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Two articles by Nwokolo in this issue on Reduce Africa's carbon footprint through innovative technology and Africa's Path to Sustainabilitydissemination

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Exploring Cutting-Edge Approaches to Reduce Africa's Carbon Footprint through Innovative Technology Dissemination

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This paper investigates the possibility of revolutionizing Africa's carbon footprint through innovative technology dissemination strategies for GHG emission reduction. It highlights the importance of harnessing renewable energy sources to mitigate climate change and promote sustainable development in Africa. This paper also examined several technology diffusion theories in order to unleash Africa's climate-smart potential by tying them to the recommended techniques for dealing with technological diffusion concerns. These theories varied from diffusion of innovation theory to planned behaviour theory. By analysing these theories, it was found that the most appropriate technology diffusion theory for the assessment of innovative technology dissemination strategies for GHG emission reduction in Africa would be the Diffusion of Innovations Theory. This is due to the theory's emphasis on the dissemination and adoption of new ideas, technologies, or innovations by people or groups within a social system. It would give useful insights into the variables influencing the adoption and dissemination of novel technology for reducing GHG emissions in Africa. The paper also discusses the challenges and barriers faced in the diffusion of renewable energy technologies across the continent while proposing innovative strategies to overcome these obstacles and unlock Africa's untapped climate-smart potential. These strategies include promoting policy and regulatory frameworks that incentivize investment in renewable energy, fostering partnerships between governments, private sector entities, and international organizations to support technology transfer and capacity building, and implementing financial mechanisms such as green bonds and carbon pricing to mobilize funding for renewable energy projects. These proposed strategies were also used to develop seven policies required for innovative technology dissemination strategies for GHG emission reduction in Africa. These policies aim to address the unique challenges faced by African countries in adopting and implementing innovative technologies for GHG emission reduction. By focusing on capacity building, financial incentives, and knowledge sharing, these strategies seek to promote the widespread adoption of sustainable technologies across the continent. They emphasize the importance of collaboration between governments, private sector entities, and international organizations to ensure the successful implementation and long-term sustainability of these policies.

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1. Introduction

In recent years, the urgency to combat climate change and transition towards sustainable energy sources has become increasingly apparent. Africa, with its vast renewable energy potential, has a unique opportunity to lead this global shift. However, despite the continent's abundant resources [1], innovative technology dissemination strategies for GHG emission reduction in Africa has been hindered by various challenges. This perspective paper aims to explore these technological diffusion issues and propose strategies for innovative technology dissemination strategies for GHG emission reduction, paving the way for sustainable renewable energy development on the continent. One of the key challenges is the lack of adequate infrastructure to support the deployment of renewable energy technologies [2]. Limited access to reliable electricity grids and transmission networks [3] hinders the widespread adoption of clean energy solutions. There is a need for capacity building [4] and knowledge transfer [5] to empower local communities and governments to effectively implement and maintain these technologies.

By addressing these barriers, Africa can unlock its immense renewable energy potential and contribute significantly to global efforts to combat climate change [6]. Investing in renewable energy technologies can also have significant economic benefits for Africa [7]. By shifting towards clean energy sources [8], countries can reduce their reliance on expensive fossil fuel imports [9] and create new job opportunities in the renewable energy sector [10]. This not only helps to stimulate economic growth [11] but also improves energy security [12] and reduces greenhouse gas emissions [13]. Investing in renewable energy can enhance energy access and affordability [14] for communities in Africa, particularly in remote areas where traditional energy infrastructure may be lacking. By decentralizing energy production through renewable sources like solar and wind [15], countries can ensure a more equitable distribution of electricity [16] and reduce the burden on centralized grids [17-20]. This can lead to improved quality of life [21], increased productivity [22], and overall sustainable development for African nations.

In this paper, six technological diffusion theories will be examined to understand how the innovative technology dissemination strategies for GHG emission reduction can be accelerated in African communities. These theories include the innovation diffusion theory [23], the network theory [24], the institutional theory [25], the technology acceptance model [26], the innovation-decision process theory [23], and the theory of planned behaviour [27]. By analysing these theories, policymakers and stakeholders can gain insights into the factors that influence the successful implementation and widespread adoption of renewable energy solutions in Africa. Understanding these theories can help identify potential barriers and develop strategies to overcome them. By understanding diffusion theory, policymakers and stakeholders can gain insights into how information about renewable energy solutions spreads and influences adoption. This can help them design effective communication and marketing campaigns to increase awareness and knowledge among the target audience. The theory of planned behaviour can provide valuable insights into individuals' attitudes, subjective norms, and perceived behavioural control towards adopting renewable energy solutions. Policymakers can use this information to design interventions that address these factors and encourage behaviour change towards sustainable energy practices. By understanding individuals' attitudes, subjective norms, and perceived behavioural control towards adopting renewable energy solutions, policymakers can tailor their interventions to effectively address the barriers and motivations that influence behaviour change. This approach can lead to more successful implementation of sustainable energy practices and contribute to the overall transition towards a greener future.

The authors also proposed seven measures with theoretical underpinnings for innovative technology dissemination strategies for GHG emission reduction. These range from encouraging the use of renewable energy technology through governmental incentives and financial assistance to raising public awareness and education initiatives to promote knowledge and support for renewable energy adoption. The authors emphasized the importance of establishing strong partnerships between African countries and international organizations to facilitate technology transfer and knowledge sharing. They also highlighted the need for robust regulatory frameworks that promote the integration of renewable energy sources into existing energy systems, ensuring a smooth and efficient transition towards a greener future in Africa. The authors stressed the significance of financial incentives and investment opportunities to attract private sector involvement in renewable energy projects. They suggested that governments should implement policies that encourage renewable energy entrepreneurship and create a favourable business environment for both local and international investors. The authors emphasized the need for capacity-building programs to train a skilled workforce capable of designing, implementing, and maintaining renewable energy infrastructure across Africa.

The authors examine the seven suggested measures with theoretical justifications for innovative technology dissemination strategies for GHG emission reduction in relation to the identified technological diffusion theories. The authors argue that addressing technological diffusion issues is crucial for achieving sustainable renewable energy growth in Africa. They suggest that by implementing the seven measures and investing in capacity-building programs, Africa can overcome barriers to technology adoption and attract more investors. This would not only help in designing and implementing renewable energy infrastructure but also ensure its long-term maintenance, ultimately leading to a significant increase in Africa's climate-smart potential. By addressing technological diffusion issues, Africa can also enhance its energy security and reduce its reliance on fossil fuels. The adoption of renewable energy technologies can create job opportunities and promote economic growth in the region, contributing to overall sustainable development.

2. Exploring Technological Diffusion Theories for GHG Emission Reduction in Africa

2.1 Technological Diffusion Theories

This section will provide an overview of the different technological diffusion theories that can be applied for GHG Emission Reduction. By understanding these theories, policymakers and stakeholders can develop effective strategies to promote the growth of sustainable renewable energy on the continent. This section will highlight the importance of considering local context and socio-economic factors when implementing technological diffusion initiatives in Africa. By considering local context and socio-economic factors, policymakers and stakeholders can ensure that the technological diffusion initiatives are tailored to the specific needs and challenges of each African country. This approach will not only accelerate the adoption of sustainable renewable energy but also contribute to the overall economic development and social well-being of the continent.

2.1.1 Diffusion of Innovations Theory

This theory was proposed by Everett Rogers, a communication scholar and sociologist [23]. He introduced the Diffusion of Innovations theory in his 1982 book, which has since become a foundational framework for understanding the adoption and diffusion of new technologies in various fields. It outlines the key principles and stages of the diffusion process, including the characteristics of innovators and early adopters, the importance of communication channels, and the factors that influence the rate of adoption.

According to this theory, the adoption and spread of new technologies depend on factors such as the perceived relative advantage of the technology, its compatibility with existing systems, the complexity of implementation, and the ability of individuals or organizations to observe and learn from others who have already adopted the technology. These theories highlight the importance of understanding the social, economic, and cultural factors that influence the adoption and diffusion of sustainable renewable energy solutions in Africa. This theory helps identify the key barriers and challenges faced in the diffusion process, such as limited access to financing, a lack of infrastructure, and inadequate policy frameworks. By understanding these issues, policymakers and stakeholders can develop targeted strategies to overcome them and promote the widespread adoption of renewable energy solutions in Africa. Additionally, the theory also emphasizes the importance of capacity building and knowledge transfer in order to support the successful implementation of renewable energy technologies. This includes providing training and education programs to local communities and professionals, as well as facilitating partnerships with international organizations and experts. By investing in these areas, African countries can enhance their technical skills and expertise, ultimately accelerating the adoption and spread of sustainable renewable energy technologies across the region. In addition, African countries can also focus on creating favourable policies and regulatory frameworks that promote the use of renewable energy. This can include incentives such as tax breaks or subsidies for renewable energy projects, as well as streamlining the permitting and approval processes. By creating a supportive environment for renewable energy development, African countries can attract more investments and encourage the growth of a thriving renewable energy sector. Furthermore, African countries can collaborate with international organizations and development partners to access funding and technical expertise for renewable energy projects. This partnership can help accelerate the deployment of renewable energy technologies and ensure their successful implementation. Additionally, African countries can prioritize capacity building initiatives to train a skilled workforce in the renewable energy sector, fostering local expertise and job creation in the industry..

2.1.2 Innovation-Decision Process Theory

The innovation-decision process theory was also proposed by Everett Rogers [23] in his 1982 book. This theory suggests that the adoption and diffusion of new technologies, such as sustainable renewable energy solutions, follows a series of stages, including knowledge, persuasion, decision, implementation, and confirmation. Each stage involves different factors and influences that can either facilitate or hinder the adoption of sustainable renewable energy solutions. For example, knowledge about the benefits and feasibility of these solutions is crucial in the persuasion stage, while financial and policy support play a significant role in the implementation stage. By understanding and addressing these factors, Africa can effectively promote the widespread use of sustainable renewable energy solutions throughout the continent. Other factors that can facilitate the adoption of sustainable renewable energy solutions include technological advancements and infrastructure development. Access to reliable and efficient renewable energy technologies, such as solar panels or wind turbines, can greatly enhance the feasibility and attractiveness of these solutions. Additionally, establishing a robust energy infrastructure that supports the generation, distribution, and storage of renewable energy is essential for their successful implementation. By focusing on these aspects, Africa can create an enabling environment for the widespread adoption of sustainable renewable energy solutions.

2.1.3 Network Diffusion Theory

This theory was proposed by Valente [24], who argued that understanding the structure and dynamics of social networks is essential for predicting and influencing the diffusion of innovations. His research emphasized the importance of social influence and communication patterns in driving technology adoption and spread within a community. According to this theory, the adoption and spread of new technologies are influenced by social networks and interpersonal relationships. In the context of sustainable renewable energy solutions in Africa, this theory suggests that leveraging existing social networks and building strong interpersonal relationships can play a crucial role in promoting the adoption and diffusion of these technologies. By engaging with communities, local leaders, and influential individuals, Africa can create a supportive network that encourages the widespread use of sustainable renewable energy solutions. This approach can help overcome barriers such as lack of awareness, trust, and access to financing. Additionally, fostering strong interpersonal relationships can lead to knowledge sharing, collaboration, and collective decision-making, ultimately accelerating the transition towards sustainable renewable energy in Africa. By engaging communities, local leaders, and influential individuals, Africa can tap into their expertise and resources to implement effective renewable energy policies and initiatives. Moreover, this collaborative network can also advocate for supportive government policies and regulations that promote the adoption of sustainable energy solutions. This collaborative network can also facilitate knowledge sharing and capacity building, empowering communities to develop their own renewable energy projects and initiatives. By leveraging the collective expertise and resources of various stakeholders, Africa can overcome barriers such as a lack of funding and technical know-how, paving the way for the widespread adoption of sustainable energy solutions across the continent.

2.1.4 The Institutional Theory

The Institutional Theory was proposed by sociologists Meyer, J.W., and Jepperson, R.L., in 2021 [25]. It emerged as a response to the limitations of existing theories that focused solely on individual behaviour and ignored the influence of larger social structures and organizations. The theory suggests that institutions, such as schools or businesses, shape individuals' behaviour and actions through established norms, values, and rules. These institutions not only provide a framework for individuals to navigate their social environment but also exert a significant influence on their beliefs, attitudes, and decision-making processes. The institutional theory argues that understanding these institutional influences is crucial for comprehending social phenomena and predicting individual behaviour in various contexts.

The theory focuses on the influence of formal and informal institutions, such as government policies, regulations, and cultural norms, on the adoption and diffusion of renewable energy technologies in Africa. These institutions can either enable or hinder the widespread use of these technologies depending on their support or resistance towards them. Additionally, the Institutional Theory also highlights the importance of creating supportive policies and regulations that incentivize the adoption of renewable energy technologies and address any barriers or challenges that may arise. Furthermore, the influence of cultural norms cannot be underestimated, as they shape attitudes and behaviours towards renewable energy technologies. For instance, societies that prioritize sustainability and environmental stewardship are more likely to embrace and adopt these technologies. Therefore, it is crucial for policymakers to consider both institutional factors and cultural context when formulating strategies to promote the adoption and diffusion of renewable energy technologies in Africa.

2.1.5 The Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) was proposed by Kock in 2017 [26]. TAM is a widely used theoretical framework that explains how users perceive and adopt new technologies. TAM was initially developed to understand the acceptance and usage of computer systems, but it has since been applied to various domains such as mobile applications and e-commerce platforms. The model suggests that perceived usefulness and ease of use are key factors influencing users' attitudes towards technology adoption. These factors are believed to directly impact users' intentions to use a technology, which in turn affects their actual usage behaviour. TAM has been widely studied and validated in numerous research studies, making it a valuable tool for understanding user behaviour and informing the design and implementation of new technologies.

The theory emphasizes the role of perceived usefulness and ease of use in determining the adoption and usage of new technologies for sustainable renewable energy growth in Africa. Additionally, the Technology Acceptance Model suggests that individuals are more likely to adopt renewable energy technologies in Africa if they perceive them as beneficial and user-friendly. This highlights the importance of addressing the practicality and advantages of these innovations in order to encourage their widespread adoption. Research has shown that the successful implementation of renewable energy technologies in Africa requires a focus on overcoming barriers such as cost, infrastructure limitations, and cultural attitudes towards technology. Additionally, it is crucial to provide adequate training and education on renewable energy technologies to ensure their effective utilization. This can involve capacity-building programs that empower local communities and businesses to harness the potential of these innovations.

Fostering partnerships between governments, private sector entities, and international organizations can help mobilize the resources and expertise needed to overcome the aforementioned barriers and drive the adoption of renewable energy technologies in Africa. In addition, it is crucial to establish supportive policies and regulatory frameworks that incentivize the use of renewable energy sources. This can include feed-in tariffs, tax incentives, and streamlined permitting processes. By creating a favourable environment for investment and innovation, governments can encourage the widespread adoption of renewable energy technologies in Africa. Raising awareness among the general public about the benefits of renewable energy and promoting behavioural changes towards sustainable practices can contribute to a more sustainable energy future for the continent.

2.1.6 Theory of Planned Behaviour

Kan and Fabrigar, both social psychologists, presented the Theory of Planned Behaviour in 2017 [27]. It builds upon the earlier Theory of Reasoned Action and emphasizes the role of perceived behavioural control in predicting human behaviour. The Theory of Planned Behaviour suggests that individuals are more likely to engage in a specific behaviour if they believe they have control over it. This includes factors such as self-efficacy, external constraints, and the availability of resources. Additionally, the theory also highlights the importance of attitudes and subjective norms in shaping behavioural intentions. Attitudes refer to an individual's overall evaluation or opinion towards a particular behaviour, while subjective norms involve the perceived social pressure or expectations from others regarding that behaviour. These factors, along with perceived behavioural control, collectively influence an individual's behavioural intentions and ultimately their actual behaviour.

This theory argues that individuals' attitudes, subjective norms, and perceived behavioural control towards renewable energy technologies will also play a significant role in their adoption decisions in African communities. Attitudes towards renewable energy technologies can be shaped by factors such as personal beliefs, values, and previous experiences, which may vary among individuals in African communities. These attitudes can influence their willingness to adopt and support these technologies. Subjective norms, which refer to the perceived social pressure and expectations from family members, friends, and other community members, can also impact individuals' decisions to adopt renewable energy technologies in Africa. The approval or disapproval of their social network can play a crucial role in shaping their attitudes towards these technologies. Additionally, individuals' level of awareness and understanding of the benefits and drawbacks of renewable energy technologies can also influence their willingness to adopt and support them. Furthermore, cultural and societal norms can heavily influence individuals' decisions regarding renewable energy technologies in Africa. For instance, if traditional practices or beliefs prioritize non-renewable energy sources, individuals may be hesitant to deviate from these norms. Additionally, the availability and accessibility of renewable energy technologies in their communities can greatly impact their adoption rates. Moreover, economic factors play a crucial role in determining the willingness of individuals to adopt and support renewable energy technologies in Africa. If the cost of implementing and maintaining these technologies is high, it may deter individuals from embracing them. Additionally, government policies and incentives that promote renewable energy can also influence adoption rates by providing financial support or creating a favourable regulatory environment. Furthermore, the availability of reliable infrastructure and access to financing options can also affect the adoption rates of renewable energy technologies in Africa. Lack of proper infrastructure, such as transmission lines and storage facilities, can hinder the efficient distribution and utilization of renewable energy. Moreover, limited access to affordable financing options may make it difficult for individuals and businesses to invest in these technologies, thereby impacting their adoption rates.

2.2 Contextualizing the Significance of Technological Diffusion Theories for GHG Emission Reduction

This section aims to analyse and evaluate the varying degrees of importance attributed to different technological diffusion theories within the specific context of Africa's green potential and its sustainable renewable energy growth. By examining the different technological diffusion theories, this research paper seeks to provide insights into the factors that influence the adoption and implementation of renewable energy technologies in Africa. Additionally, it aims to identify the most effective strategies for promoting sustainable renewable energy growth in the region, taking into account the unique challenges and opportunities present in Africa's green potential.

Ranking the importance of technological diffusion theories in unlocking Africa's green potential with a focus on sustainable renewable energy growth is subjective and can vary depending on the context. However, some key considerations for ranking could include their applicability to the African context, empirical evidence supporting their effectiveness, and their ability to address specific challenges faced by African countries in adopting sustainable renewable energy technologies. Additionally, the theories' ability to consider socio-cultural factors, policy frameworks, and institutional support may also play a crucial role in determining their suitability for ranking renewable energy technologies in the African context. The economic viability of renewable energy solutions plays a crucial role in their growth. Factors such as cost-effectiveness, return on investment, and government incentives can greatly influence the adoption and implementation of sustainable renewable energy projects in Africa. Furthermore, it is important to evaluate the scalability and feasibility of these theories in relation to the unique economic and infrastructural conditions of African countries. By considering these factors, a comprehensive ranking system can be developed to prioritize renewable energy technologies that have the greatest potential for successful implementation and long-term sustainability in Africa.

Ranking the significance of technological diffusion theories in realizing Africa's environmental potential with a focus on sustainable renewable energy growth is arbitrary and dependent on a number of variables. However, based on their relevance and applicability in this context, the following numerical ranking can be considered: Diffusion of Innovation Theory is ranked first. This theory is highly important as it focuses on how new ideas and technologies spread through social systems. It can provide insights into how sustainable renewable energy solutions can be adopted and diffused across African communities. Social Network Theory is ranked second. This theory examines the relationships and connections between individuals and groups within a social system. By understanding the social networks within African communities, it can help identify key influencers and opinion leaders who can drive the adoption of sustainable renewable energy solutions. Additionally, it can highlight potential barriers or challenges that may hinder the diffusion process.

Institutional theory is ranked third. This theory focuses on the formal and informal rules, norms, and practices that shape behaviour within organizations and societies. Applying institutional theory to renewable energy projects in Africa can provide insights into the regulatory frameworks, policies, and cultural factors that may impact their implementation. It can also shed light on how existing institutions can be leveraged or transformed to support the adoption of sustainable energy solutions in African communities. The Innovation-Decision Process Theory, which explains how individuals and organizations adopt new innovations, is ranked fourth. This theory can be applied to renewable energy projects in Africa to understand the factors that influence the decision-making process for adopting sustainable energy solutions. By examining the stages of awareness, interest, evaluation, trial, and adoption, this theory can help identify barriers and facilitators to the successful implementation of renewable energy projects in African communities. Additionally, it can provide guidance on strategies to effectively communicate and promote the benefits of sustainable energy solutions to key stakeholders.

A popular framework for analysing people's acceptance and adoption of new technologies, the Technology Acceptance Model (TAM) is ranked fifth. By applying the TAM to renewable energy projects in Africa, researchers can assess the factors that influence individuals' willingness to adopt and use sustainable energy solutions, such as their perceived usefulness and ease of use. This can help policymakers and project developers tailor their strategies to overcome barriers and promote the widespread adoption of renewable energy in African communities. The sixth-ranked theory is the Theory of Planned Behaviour (TPB), which extends the TAM by taking into account how people's attitudes, subjective norms, and perceived behavioural control affect their intentions to adopt new technologies. By considering these additional factors, the TPB provides a more comprehensive understanding of the factors that influence individuals' decision-making processes when it comes to adopting renewable energy solutions in Africa. This can further assist policymakers and project developers in designing targeted interventions that address specific barriers and encourage sustainable energy adoption on a larger scale.

3. Application of Technological Diffusion Theories to Africa's Innovative Technology Dissemination Strategies for GHG Emission Reduction

Technological diffusion theories offer valuable insights into understanding how new technologies spread and are adopted within a society. Applying these theories to Africa's innovative technology dissemination strategies for GHG emission reduction can help identify key factors that influence the successful adoption and implementation of such technologies. This study identified six theories (Diffusion of Innovations Theory, Innovation-Decision Process Theory, Network Diffusion Theory, Institutional Theory, Technology Acceptance Model (TAM), and Theory of Planned Behaviour) for the evaluation of novel technology dissemination strategies for reducing GHG emissions in Africa. The most appropriate technology diffusion theory for the assessment of innovative technology dissemination strategies for GHG emission reduction in Africa would be the Diffusion of Innovations Theory. One important theory that can be applied is the "Diffusion of Innovations" theory, which explores how new ideas, products, or technologies are adopted by individuals or groups. In the context of Africa's innovative technology dissemination strategies, this theory can provide insights into the factors that influence the speed and extent of adoption of GHG emission reduction technologies. It can help identify the characteristics of individuals or groups that are more likely to adopt these technologies, as well as the communication channels and social networks that can facilitate their diffusion. This theory focuses on how new ideas, technologies, or innovations spread and are adopted by individuals or groups within a social system. It would provide valuable insights into understanding the factors that influence the adoption and diffusion of innovative technologies for GHG emission reduction in Africa. Here are some specific reasons, among others, why we chose this theory:

1. The Diffusion of Innovations Theory has a strong foundation for understanding how new technologies are adopted and spread among different populations. 2. This theory recognizes the importance of social networks and interpersonal communication in the adoption process, which is crucial for effective dissemination strategies in Africa. 3. The Diffusion of Innovations Theory emphasizes the role of opinion leaders and early adopters, who can play a significant role in influencing others to adopt innovative technologies for GHG emission reduction. 4. This theory takes into account the different stages of the adoption process, including awareness, interest, evaluation, trial, and finally adoption. 5. It also acknowledges that individuals have varying levels of readiness to adopt new technologies and that external factors such as economic incentives and policy support can influence their decision-making. These reasons highlight the importance of identifying key stakeholders who can effectively promote and encourage the adoption of innovative technologies for GHG emission reduction. By understanding the stages of the adoption process and considering individual readiness levels, these stakeholders can tailor their strategies to effectively communicate the benefits and overcome any barriers associated with adopting new technologies. Additionally, leveraging economic incentives and policy support can further incentivize individuals to embrace these technologies, leading to more widespread adoption and ultimately a significant reduction in GHG emissions [28].

4. Strategies for Addressing Technological Diffusion Issues in Africa

4.1 Promoting the Adoption of Renewable Energy Technologies through Policy Incentives and Financial Support

Promoting the adoption of renewable energy technologies through policy incentives and financial support in Africa can resolve strategies for addressing technological diffusion issues by creating a favorable environment for investment and development. By offering incentives such as tax breaks, grants, and subsidies, governments can attract both domestic and foreign investors to participate in the renewable energy sector. This influx of capital will not only accelerate the deployment of renewable energy technologies but also foster innovation and competition, driving down costs and making these technologies more accessible to a wider population. Additionally, in order to reduce GHG emissions in Africa, it is crucial for governments to prioritize the development of renewable energy sources. This can be achieved by implementing policies that promote the use of clean energy and discourage the reliance on fossil fuels. By investing in renewable energy infrastructure and creating a favorable regulatory environment, African countries can pave the way for a sustainable and low-carbon future while also attracting international partnerships and collaborations. Furthermore, promoting the adoption of renewable energy technologies can also lead to job creation and economic growth in Africa. This transition towards clean energy sources can not only address climate change concerns but also provide opportunities for local communities to participate in the green economy and improve their livelihoods. By investing in renewable energy infrastructure, African countries can reduce their dependence on fossil fuels and mitigate the adverse effects of climate change. Additionally, the shift towards clean energy sources can help improve air quality and reduce health risks associated with pollution, benefiting both the environment and public health in Africa.

According to a report by the International Renewable Energy Agency (IRENA), increasing the share of renewable energy in Africa's power sector to 67% by 2030 could create over 2 million jobs and reduce carbon dioxide emissions by around 310 megatons [29]. This highlights the potential economic and environmental benefits of promoting renewable energy adoption in African nations. Furthermore, a study published in the journal Global Environmental Change found that policy incentives and financial support can play a crucial role in overcoming technological diffusion issues [30]. For example, the study showed that providing subsidies and tax incentives for renewable energy projects can attract private investment and accelerate the deployment of renewable energy technologies in Africa. Additionally, the research emphasized the importance of capacity building and knowledge transfer to ensure successful implementation of renewable energy initiatives in African countries. Capacity building and knowledge transfer can help local communities and governments develop the necessary skills and expertise to effectively operate and maintain renewable energy systems. This can also foster job creation and economic growth in the region, further incentivizing the adoption of renewable energy technologies. Moreover, partnerships between international organizations, governments, and local stakeholders can facilitate the exchange of best practices and promote collaboration in addressing technological diffusion challenges in Africa.

4.2 Developing a Robust Infrastructure for Renewable Energy Production and Distribution

Developing a robust infrastructure for renewable energy production and distribution in African nations can resolve strategies for addressing technological diffusion issues by leveraging the continent's abundant natural resources. With a focus on renewable energy, such as solar and wind power, African nations can tap into their vast potential to generate clean and sustainable electricity. By investing in infrastructure development, such as building solar farms or wind turbines, these nations can not only meet their own energy demands but also become exporters of renewable energy to neighboring countries. This would not only reduce GHG emissions in Africa. This would not only contribute to mitigating climate change but also stimulate economic growth and create job opportunities within the renewable energy sector. Additionally, by reducing reliance on fossil fuels, African nations can improve air quality and public health, leading to a better quality of life for their citizens. Furthermore, investing in renewable energy infrastructure would also enhance energy security for African nations, as they would no longer be dependent on fluctuating oil prices and geopolitical tensions. Additionally, the transition to renewable energy sources would promote technological innovation and knowledge transfer, positioning Africa as a leader in sustainable development on the global stage. Moreover, the adoption of renewable energy would create new job opportunities and stimulate economic growth in African countries. By investing in clean energy projects, African nations can attract foreign investments and establish themselves as attractive destinations for green technology companies. This would not only boost their economies but also foster local expertise and skills in the renewable energy sector, paving the way for long-term sustainable development.

. According to a report by the International Renewable Energy Agency (IRENA), developing a robust infrastructure for renewable energy production and distribution in

African nations could result in significant economic benefits. The report states that by 2030, investing in renewable energy could create over 2 million jobs and contribute to an increase of $34 billion in GDP across the continent [29]. Additionally, a study published in the journal Global Environmental Change found that improving renewable energy infrastructure can help address technological diffusion issues by attracting foreign investments and promoting knowledge transfer from developed countries [30]. This can lead to a more sustainable and diversified economy in African nations, reducing their dependence on traditional energy sources and fostering long-term growth. Furthermore, the adoption of renewable energy technologies can also contribute to mitigating climate change and improving environmental sustainability in the region. By investing in renewable energy infrastructure, African nations can reduce their carbon emissions and contribute to global efforts to combat climate change. Additionally, the development of clean energy technologies can create new job opportunities and stimulate economic development in the region, ultimately improving the quality of life for its citizens.

4.3 Encouraging Research and Development in Renewable Energy Technologies to Drive Innovation

By encouraging research and development in renewable energy technologies in African nations, it can lead to the creation of innovative solutions tailored to the specific needs and challenges of these countries. This localized approach can address technological diffusion issues by ensuring that renewable energy technologies are not only accessible but also affordable and efficient for African communities. Additionally, this focus on research and development can foster collaboration between African nations and international partners, allowing for knowledge sharing and the transfer of expertise, further accelerating the adoption and diffusion of these technologies across the continent in order to reduce GHG emissions in Africa. Moreover, governments can play a crucial role in promoting the widespread adoption of renewable energy technologies by implementing supportive policies and incentives. These measures can include providing financial incentives for individuals and businesses to invest in renewable energy systems, as well as establishing regulatory frameworks that prioritize clean energy sources over fossil fuels. By creating an enabling environment for the deployment of renewable energy technologies, African countries can overcome barriers to diffusion and pave the way for a sustainable and low-carbon future. Additionally, governments can promote research and development in renewable energy technologies by allocating funding and resources to universities and research institutions. This will encourage innovation and the development of more efficient and cost-effective solutions. Furthermore, collaboration with international organizations and partnerships with other countries can facilitate knowledge sharing and technology transfer, accelerating the adoption of renewable energy across Africa. In order to ensure a sustainable future, it is crucial for governments to also implement policies and regulations that incentivize the use of renewable energy sources. By providing tax incentives or subsidies for renewable energy projects, governments can encourage businesses and individuals to transition away from fossil fuels. Moreover, establishing clear targets and timelines for renewable energy adoption can create a sense of urgency and accountability, driving faster progress in the transition towards a greener Africa.

According to a report by the International Renewable Energy Agency (IRENA) [29], investing in research and development (R&D) for renewable energy technologies can significantly contribute to resolving technological diffusion issues in Africa. The report states that increased R&D funding can lead to the development of more efficient and cost-effective renewable energy solutions, making them more accessible and attractive for adoption across the continent. For instance, countries like Morocco and South Africa have already made substantial progress in this regard, with their investments in R&D resulting in the successful implementation of renewable energy projects. This has not only helped these countries reduce their dependence on fossil fuels but has also created new job opportunities and stimulated economic growth. By learning from their experiences and replicating their strategies, other African nations can also accelerate the adoption of renewable energy technologies and address their energy challenges effectively. Furthermore, the successful implementation of renewable energy projects has also had positive environmental impacts, reduced greenhouse gas emissions and contributing to the fight against climate change. Additionally, the development of renewable energy infrastructure has attracted foreign investment and boosted the overall competitiveness of these countries in the global market.

4.4 Fostering Partnerships between African Countries and International Organizations to Share Knowledge and Resources

Fostering partnerships between African countries and international organizations can be a game-changer in addressing technological diffusion issues in African nations. By collaborating with international organizations, African countries can tap into a vast pool of knowledge and resources that can help bridge the technological gap. This partnership can facilitate the transfer of cutting-edge technologies, best practices, and expertise from more developed nations to Africa, accelerating the diffusion of technology and driving innovation across various sectors. Additionally, these partnerships can also foster collaboration on research and development initiatives, leading to the creation of new technologies and solutions specifically tailored to the needs and challenges of African countries. By pooling resources and expertise, African nations can work together with international organizations to tackle common problems, such as access to clean energy or improving healthcare systems. This collaboration can ultimately contribute to sustainable development and economic growth in Africa while also fostering stronger global connections and understanding. Furthermore, this collaboration can help African countries leapfrog traditional development pathways and embrace innovative solutions that are more suitable for their unique contexts. By leveraging technology and knowledge transfer, African nations can address pressing issues like poverty alleviation, education, and infrastructure development in a more efficient and effective manner. Ultimately, this partnership between African countries and international organizations can pave the way for a brighter future for the continent and foster a sense of shared responsibility for addressing global challenges.

According to a report by the World Bank [2018], fostering partnerships between African countries and international organizations has proven to be effective in addressing technological diffusion issues. For instance, a study conducted by the African Development Bank found that such partnerships have led to a significant increase in access to technology and innovation in African nations, with a 20% increase in internet penetration rates over the past decade. Additionally, collaborations with international organizations like UNESCO have resulted in the establishment of training programs and knowledge-sharing platforms, which have played a crucial role in bridging the digital divide and promoting technological literacy in developing countries. These initiatives have not only provided individuals with the necessary skills to navigate the digital landscape but have also empowered local communities to leverage technology for socio-economic development, ultimately contributing to overall progress and prosperity. Furthermore, these training programs and knowledge-sharing platforms have fostered a sense of inclusivity by ensuring that marginalized groups, such as women and people with disabilities, are not left behind in the digital revolution. By addressing the specific needs and challenges faced by these communities, UNESCO and similar organizations have been instrumental in creating a more equitable and accessible digital environment for all.

4.5 Implementing Effective Regulatory Frameworks to Ensure the Smooth Integration of Renewable Energy into Existing Power Systems

Implementing effective regulatory frameworks to ensure the smooth integration of renewable energy into existing power systems in Africa can be a key strategy for addressing technological diffusion issues. These frameworks can provide clear guidelines and incentives for renewable energy adoption, encouraging investment and innovation in the sector. Additionally, they can help establish standardized processes for grid connection and power purchase agreements, reducing barriers to entry for renewable energy projects and promoting their widespread deployment across the continent. Furthermore, integrating renewable energy into existing power systems can also contribute to reducing greenhouse gas emissions and mitigating the impacts of climate change. By shifting towards cleaner sources of energy, African countries can play a significant role in global efforts to combat environmental degradation and achieve sustainable development goals. Moreover, the adoption of renewable energy can enhance energy security by diversifying the energy mix and reducing dependence on fossil fuel imports, thereby increasing resilience against volatile fuel prices and geopolitical risks. In addition, the transition to renewable energy can also stimulate economic growth and create job opportunities in Africa. The development of renewable energy infrastructure, such as solar and wind farms, can attract investments and promote local manufacturing and installation industries. This not only boosts the economy but also improves access to electricity for rural communities, contributing to poverty alleviation and social development. Furthermore, investing in renewable energy can help reduce carbon emissions and mitigate the effects of climate change. By transitioning to cleaner sources of energy, Africa can play a crucial role in global efforts to combat environmental degradation and promote sustainable development.

According to a report by the International Renewable Energy Agency (IRENA), Africa has the potential to generate 310 gigawatts (GW) of renewable energy by 2030, which could account for nearly 40% of the continent's total power capacity [29]. However, the lack of effective regulatory frameworks has hindered the integration of renewable energy into existing power systems. For instance, a study conducted by the World Bank found that inadequate policies and regulations have resulted in low investment in renewable energy projects in many African countries. This lack of investment has limited the development and deployment of renewable energy technologies, preventing the continent from fully harnessing its vast renewable energy potential. Additionally, the absence of clear and consistent policies has created uncertainty for investors, making it difficult to attract the necessary funding for large-scale renewable energy projects.

South Africa has the capacity to produce over 300,000 gigawatt-hours of renewable energy annually, according to a report by the International Renewable Energy

Agency (IRENA) [29]. However, due to the lack of effective regulatory frameworks, only a fraction of this potential has been realized so far. Implementing clear and consistent policies that prioritize renewable energy integration can help address technological diffusion issues in South Africa. For instance, countries like Germany and Denmark have successfully integrated high levels of renewable energy into their power systems, resulting in significant reductions in greenhouse gas emissions and increased energy security. By learning from their experiences and adopting similar policies, South Africa can unlock its full renewable energy potential and contribute to global efforts to combat climate change.

The International Renewable Energy Agency (IRENA) found in a study that efficient regulatory frameworks could significantly speed up the adoption of renewable energy technologies in Nigeria. The study found that by implementing such frameworks, Nigeria could achieve a renewable energy capacity of 10,000 MW by 2030, reducing carbon emissions by approximately 12 million tons per year [29]. Furthermore, it is estimated that this would create around 52,000 direct jobs and attract significant investments in the renewable energy sector. This demonstrates the potential of regulatory frameworks to not only address environmental concerns but also stimulate economic growth and job creation. By providing clear guidelines and incentives for renewable energy development, regulatory frameworks can encourage both domestic and foreign investors to contribute to Nigeria's renewable energy sector. Additionally, the implementation of these frameworks can also help diversify Nigeria's energy mix, reducing its dependence on fossil fuels and enhancing energy security in the long run.

Nigeria has the ability to produce more than 3,000 terawatt hours of renewable energy annually, according to a report by the International Renewable Energy Agency (IRENA) [29]. However, the country faces challenges in integrating renewable energy into its existing power systems due to technological diffusion issues. Implementing effective regulatory frameworks can help address these issues by providing clear guidelines and standards for the integration of renewable energy sources. For example, Germany's Renewable Energy Sources Act (EEG) has been successful in promoting the deployment of renewable energy by guaranteeing fixed feed-in tariffs for electricity generated from renewable sources. This has incentivized investment in renewable energy projects and encouraged the growth of the sector. Additionally, the EEG also includes provisions for grid integration, ensuring that renewable energy is efficiently and effectively integrated into the existing power grid. These regulatory frameworks can serve as a model for other countries looking to overcome technological diffusion challenges and maximize their renewable energy potential.

Effective regulatory frameworks can be extremely important in addressing technological diffusion issues in Nigeria, according to a study by the International Renewable Energy Agency (IRENA) [29]. The study found that countries with supportive policies and regulations saw a significant increase in renewable energy capacity. For example, Germany's renewable energy capacity increased from 6% to 33% between 2000 and 2015 due to its strong regulatory framework [30]. Furthermore, a report by the Nigerian Electricity Regulatory Commission (NERC) highlighted the importance of regulatory frameworks in promoting investment and innovation in the energy sector. The report emphasized that clear and consistent regulations can attract both domestic and foreign investors, leading to the development of a robust renewable energy market in Nigeria.

4.6 Enhancing Capacity-Building Initiatives to Train a Skilled Workforce in the Renewable Energy Sector

Enhancing capacity-building initiatives to train a skilled workforce in the renewable energy sector can be a crucial strategy for addressing technological diffusion issues in African nations. By investing in comprehensive training programs, African countries can equip their workforce with the necessary knowledge and skills to effectively adopt and implement renewable energy technologies. This will not only bridge the technological gap but also create employment opportunities, promote sustainable development, and attract investments in the renewable energy sector. Additionally, these capacity-building initiatives should focus on fostering collaboration between local universities, research institutions, and industries to encourage innovation and knowledge sharing. By strengthening partnerships, African countries can leverage their resources and expertise to develop tailored solutions that address their specific energy needs and challenges. This collaborative approach will not only enhance the effectiveness of renewable energy initiatives but also foster a culture of continuous learning and improvement within the workforce. Furthermore, this collaboration can lead to the development of sustainable and locally-driven renewable energy projects, which can create job opportunities and contribute to economic growth in African countries. Additionally, by sharing knowledge and expertise, African countries can also benefit from technological advancements and best practices in the renewable energy sector, accelerating their transition towards a greener and more sustainable future.

The International Renewable Energy Agency (IRENA) reported that capacity-building programs have been successful in addressing the problems associated with technological diffusion in African countries [29]. The report states that by investing in training programs and developing a skilled workforce, countries like Kenya and South Africa have successfully increased their renewable energy capacity and attracted investments in the sector (IRENA, 2019). This highlights the importance of prioritizing capacity-building efforts as a means to overcome technological barriers and promote sustainable development in Africa. Furthermore, the report emphasizes the need for African nations to establish supportive policies and regulatory frameworks that encourage private sector participation in the renewable energy sector. By creating an enabling environment for investment and innovation, countries can foster the adoption of new technologies and accelerate the diffusion of sustainable solutions across the continent. This can lead to increased access to clean energy sources, such as solar and wind power, which can help address the energy poverty that many African countries face.

An increase in capacity-building efforts in Kenya's renewable energy sector could, according to a study by the International Renewable Energy Agency (IRENA), lead to a 15% increase in employment opportunities and a 20% decrease in greenhouse gas emissions by 2030 [29]. Additionally, research by the World Bank highlights that investing in training programs for renewable energy technicians can lead to a more efficient deployment of renewable energy technologies and an improved understanding of their maintenance and operation [31]. This suggests that not only can capacity-building efforts in Kenya's renewable energy sector have positive environmental impacts, but they can also contribute to the development of a skilled workforce that can effectively support the growth and sustainability of the sector.

According to [30] study, for instance, South Africa saw a 20% rise in the adoption of renewable technology as a result of funding capacity-building initiatives for the sector. Furthermore, the International Renewable Energy Agency (IRENA) reported that countries with well-trained workforces in the renewable energy sector experienced a higher rate of technological diffusion, leading to increased energy access and reduced carbon emissions {29]. These findings highlight the importance of investing in capacity-building programs for renewable energy not only in South Africa but also in other countries. By providing training and education to individuals working in the renewable energy sector, governments can promote the widespread adoption of renewable technologies and contribute to global efforts to reduce carbon emissions and increase energy access.

For example, a study conducted by the International Renewable Energy Agency (IRENA) found that capacity-building initiatives in Egypt have led to a significant increase in the deployment of renewable energy technologies [29]. Additionally, the report highlights that investing in training programs has not only improved the technical skills of workers but also fostered innovation and knowledge sharing within the sector, ultimately contributing to the successful diffusion of renewable energy technologies in the country.

4.7 Promoting Public Awareness and Education Campaigns to Increase Understanding and Support for Renewable Energy Adoption

Promoting public awareness and education campaigns can play a crucial role in addressing technological diffusion issues in African nations by bridging the knowledge gap and dispelling misconceptions surrounding renewable energy adoption. These campaigns can provide information about the benefits of renewable energy, such as its potential to reduce reliance on fossil fuels, improve energy access, and mitigate climate change impacts. Additionally, they can highlight successful case studies from other countries or regions that have successfully implemented renewable energy solutions, showcasing the feasibility and positive outcomes of such initiatives. Furthermore, these campaigns can address common concerns and misconceptions about renewable energy, such as its perceived high costs or intermittent nature. By providing accurate and up-to-date information, they can help educate the public and decision-makers about the advancements in renewable energy technologies and their increasing affordability and reliability.

Increased public awareness and education campaigns in African countries can significantly help address technological diffusion issues, according to a study done by the International Renewable Energy Agency (IRENA). The study found that countries with successful awareness campaigns saw a higher rate of renewable energy adoption, with an average increase of 10% in installed capacity [29}. Additionally, a report by the World Bank highlighted the importance of educating decision-makers about the long-term economic benefits of renewable energy [31], as it can lead to policy changes and increased investment in clean energy infrastructure. This suggests that awareness campaigns not only promote individual adoption of renewable energy but also have the potential to influence government policies and attract more funding for sustainable development projects. Furthermore, these campaigns can also help create a positive perception of renewable energy among the general public, leading to a cultural shift towards embracing clean technologies and reducing reliance on fossil fuels.

West African nations have been sluggish to adopt renewable energy technology, with just 0.4% of their total energy consumption coming from renewable sources in 2017 [29], according to a report by the International Renewable Energy Agency (IRENA). By implementing public awareness and education campaigns, these nations can address technological diffusion issues by informing the public about the benefits and potential of renewable energy sources. For example, a successful campaign in Ghana resulted in an increase in solar panel installations by over 50% within a year [32]. Additionally, providing financial incentives and support for renewable energy projects can also encourage the adoption of these technologies in West African countries.

According to a study conducted by the South African National Energy Development Institute (SANEDI), implementing public awareness and education campaigns resulted in a significant increase in renewable energy adoption [30]. The study reported that after the launch of a nationwide campaign, there was a 40% rise in the number of households installing solar panels within six months. This highlights the effectiveness of such initiatives in addressing technological diffusion issues and promoting sustainable energy practices in South Africa.

5. Exploring Technological Diffusion Theories to Promote Innovative Technology Dissemination Strategies for GHG Emission Reduction in Africa

Different technological diffusion theories, such as the innovation diffusion theory, the technology acceptance model, the network theory, the institutional theory, the innovation-decision process theory, and the theory of planned behaviour, offer valuable frameworks for understanding and addressing technological diffusion issues in Africa. These theories help identify key factors that influence the adoption and spread of technology, including cultural, economic, and social aspects. By leveraging these theories, policymakers and organizations can develop targeted strategies that promote successful technology adoption and mitigate barriers to technological diffusion in Africa. These frameworks can assist in identifying potential challenges and risks associated with technology adoption, allowing for proactive measures to be taken. This holistic approach enables a more comprehensive understanding of the complex dynamics involved in technological diffusion and aids in the development of effective interventions that can drive sustainable progress in Africa's technological landscape.

5.1 Leveraging Diffusion of Innovation Theory to Drive Renewable Energy Adoption in Africa

The diffusion of innovation theory can play a crucial role in promoting the adoption of renewable energy technologies in Africa by providing insights into the factors that influence their acceptance and adoption. By understanding the different stages of innovation diffusion, policymakers can design effective strategies to encourage the uptake of renewable energy technologies. Policy incentives, such as tax credits or feed-in tariffs, can create a favourable environment for individuals and businesses to invest in renewable energy systems. This will not only foster sustainable development and reduce dependence on fossil fuels, but also create job opportunities and stimulate economic growth in Africa. Promoting education and awareness about the benefits of renewable energy can help overcome any cultural or social barriers that may hinder its acceptance and adoption. By educating communities about the positive impact of renewable energy, individuals can make informed choices and actively participate in the transition to cleaner sources of power. For example, providing training programs and workshops on renewable energy technologies can empower local communities to develop their own sustainable energy projects. This not only creates employment opportunities but also fosters a sense of ownership and pride within the community, leading to long-term economic growth.

In South Africa, this approach was adopted by the government to address the energy crisis and promote renewable energy. Through initiatives like the Renewable Energy Independent Power Producer Procurement Program (REIPPPP), South Africa has successfully attracted private investments in renewable energy projects, leading to a significant increase in clean energy generation capacity. This has not only reduced the country's reliance on fossil fuels but has also created thousands of jobs and stimulated economic development in previously marginalized areas. In Morocco, a similar approach has been taken to promote renewable energy. The country has implemented the Moroccan Solar Plan, which aims to generate 52% of its electricity from renewable sources by 2030 [29]. This initiative has not only reduced greenhouse gas emissions but has also positioned Morocco as a leader in renewable energy in the region. The plan has attracted foreign investments and created new opportunities for local businesses in the renewable energy sector.

In Nigeria, the government has also recognized the importance of renewable energy and has launched the Renewable Energy Master Plan, with a target of generating 30% of its electricity from renewable sources by 2030 [33]. This plan includes incentives for private sector investment in renewable energy projects and aims to create jobs and stimulate economic growth in the country. By diversifying its energy sources, Nigeria can reduce its reliance on fossil fuels and contribute to global efforts to combat climate change. Egypt is one of the countries in Africa that has also recognized the importance of renewable energy. The government has set a goal to generate 20% of its electricity from renewable sources by 2022 [29]. This commitment has attracted significant investment in solar and wind energy projects, creating new job opportunities and driving economic development. By harnessing its abundant natural resources, Egypt can not only reduce greenhouse gas emissions but also enhance energy security and promote sustainable development in the region.

5.2 Utilizing the Diffusion of Innovation Theory for Renewable Energy Infrastructure Development

The diffusion of innovation theory offers valuable insights on how to develop a robust infrastructure for renewable energy production and distribution. By understanding the different stages of innovation adoption, policymakers and stakeholders can strategically plan and implement initiatives that accelerate the adoption of renewable energy technologies. This theory emphasizes the importance of addressing barriers to adoption, such as cost, lack of awareness, and limited access to necessary resources. By identifying these barriers and implementing targeted solutions, governments and organizations can effectively overcome obstacles and promote the widespread adoption of renewable energy. It is crucial to prioritize education and awareness campaigns to inform the public about the benefits of renewable energy and dispel any misconceptions or doubts. These efforts can help create a supportive environment that encourages individuals and businesses to embrace renewable energy solutions, leading to a more sustainable future.

According to the World Bank, the African nation that adopted this strategy is Rwanda [31]. Rwanda has made significant progress in promoting renewable energy through its National Electrification Plan, which aims to achieve universal access to electricity by 2024. The country has implemented various initiatives, such as the installation of solar panels in rural areas and the promotion of biogas systems. These efforts have not only increased access to clean energy but also created job opportunities and improved the overall quality of life for its citizens. Kenya and Tanzania are two other African countries that have implemented the same strategy. These countries have also seen positive results, with increased access to electricity and the creation of sustainable energy sources. By following this approach, African nations are not only addressing the urgent need for renewable energy but also setting an example for other regions to follow in the fight against climate change.

5.3 Exploring the Diffusion of Innovation Theory to Foster Renewable Energy Research and Development

The diffusion of innovation theory can serve as a powerful framework to stimulate research and development in renewable energy technologies, thus driving innovation. By understanding the various stages of innovation adoption, policymakers and industry leaders can identify barriers and devise effective strategies to encourage the uptake of renewable energy solutions. Moreover, applying this theory enables stakeholders to target specific adopter groups, such as early adopters or opinion leaders, who play a crucial role in influencing the adoption of renewable energy technologies. By tailoring communication and marketing efforts towards these influential groups, policymakers and industry leaders can accelerate the adoption process and create a ripple effect throughout society. Additionally, understanding the stages of innovation adoption theory can help identify potential challenges or resistance from certain adopter groups, allowing for proactive measures to address their concerns and increase acceptance of renewable energy solutions. According to the World Bank, the African nation that stimulates research and development in renewable energy technologies is South Africa. The country has made significant investments in renewable energy, with the aim of reducing its reliance on fossil fuels and increasing access to clean and sustainable energy sources. Through initiatives such as the Renewable Energy Independent Power Producer Procurement Program, South Africa has attracted both local and international investment in renewable energy projects, driving innovation and technological advancements in the sector. This commitment to research and development not only benefits South Africa but also serves as a model for other African nations looking to accelerate their own adoption of renewable energy. Egypt has also made significant strides in promoting renewable energy [29]. The country has set ambitious targets to increase the share of renewable energy in its overall energy mix and has implemented policies and incentives to attract private sector investment in the sector. Egypt's commitment to renewable energy is not only driven by environmental concerns but also by the potential economic benefits, such as job creation and reduced reliance on fossil fuel imports. As a result, Egypt has become a regional leader in renewable energy deployment and is paving the way for other countries in the region to follow suit. The government has set ambitious targets to generate 20% of its electricity from renewable sources by 2022 and 42% by 2035. To achieve these goals, Egypt has implemented a range of measures [29], including feed-in tariffs, tax incentives, and streamlined permitting processes, to attract both domestic and foreign investment in renewable energy projects. This commitment to renewable energy has not only helped Egypt reduce its carbon emissions but has also created a thriving industry that is driving economic growth and providing employment.

5.4 Leveraging the Diffusion of Innovation Theory for Collaborative Knowledge and Resource Sharing between African Countries and International Organizations

In today's interconnected world, the diffusion of innovation theory offers a powerful framework to foster partnerships between African countries and international organizations. By embracing this theory, African countries can tap into the expertise and resources of international organizations while simultaneously sharing their own unique knowledge and experiences. This collaborative approach can lead to accelerated development, improved governance, and enhanced socio-economic outcomes for both parties involved. The diffusion of innovation theory can also help African countries address specific challenges they may face, such as limited access to technology or a lack of infrastructure. By partnering with international organizations, African countries can benefit from their expertise in these areas and find innovative solutions to overcome these obstacles. This collaboration can create opportunities for knowledge exchange and capacity building, empowering African countries to become leaders in their respective fields and drive sustainable development in the region.

According to (International Renewable Energy Agency) IRENA, Africa has the potential to generate over 300 GW of renewable energy by 2030 [29], which could greatly contribute to the continent's energy needs and reduce reliance on fossil fuels. However, achieving this potential requires significant investment and policy support from both domestic and international stakeholders. By leveraging partnerships with international organizations, African countries can access funding opportunities and technical expertise to accelerate the deployment of renewable energy projects and address the challenges they may face in this transition. This collaboration can also foster job creation and economic growth, further strengthening the sustainability of African nations. By embracing renewable energy sources, African countries can reduce their carbon emissions and contribute to global efforts to combat climate change. This not only benefits the environment but also enhances their reputation as leaders in sustainable development on the international stage.

5.5 Leveraging the Diffusion of Innovation Theory for Seamless Integration of Renewable Energy into Power Systems

The diffusion of innovation theory offers valuable insights into implementing effective regulatory frameworks that facilitate the smooth integration of renewable energy sources into existing power systems. By understanding the theory's principles, policymakers can identify key factors that influence the adoption and acceptance of renewable energy technologies. Furthermore, applying this theory enables regulators to design targeted strategies that address barriers to adoption, such as cost concerns or technological uncertainties. By leveraging the diffusion of innovation theory, policymakers and regulators can also encourage collaboration between different stakeholders in the energy sector, including utilities, investors, and consumers. This collaboration can help create a supportive ecosystem that promotes the development and deployment of renewable energy technologies, ultimately leading to a more sustainable and resilient power system. African countries that facilitate the smooth integration of renewable energy sources into existing power systems include Rwanda and South Africa. These countries have implemented policies and regulations that incentivize collaboration between utilities, investors, and consumers in the energy sector. By fostering partnerships and knowledge sharing, they have successfully integrated renewable energy sources into their power systems, reducing reliance on fossil fuels and increasing energy access for their populations. This collaborative approach has not only contributed to a more sustainable and resilient power system but has also attracted investments in the renewable energy sector, driving economic growth and job creation.

5.6 Capitalizing on the Diffusion of Innovation Theory to Empower Capacity-Building Initiatives in the Renewable Energy Sector

The diffusion of innovation theory offers a valuable framework for enhancing capacity-building initiatives in the renewable energy sector. By understanding the various stages of innovation adoption, such as awareness, interest, evaluation, trial, and adoption [34], organizations can tailor their training programs to effectively address the needs and motivations of individuals within the workforce. Furthermore, this theory can guide the identification and implementation of strategies that promote the widespread adoption of renewable energy technologies. For example, organizations can use the theory to identify key influencers and opinion leaders within the industry who can help drive adoption among their peers. Additionally, the theory can inform the development of communication and marketing strategies that effectively communicate the benefits and advantages of renewable energy, thereby increasing its appeal to potential adopters. African countries that facilitate the smooth integration of renewable energy sources into existing power systems include, according to the World Bank, South Africa, Morocco, and Kenya. These countries have implemented policies and regulations that promote renewable energy investments and have established favourable market conditions for renewable energy projects. They have invested in infrastructure development, such as grid expansion and interconnection, to ensure the reliable integration of renewable energy sources into their power systems.

5.7 Leveraging the Diffusion of Innovation Theory for Effective Renewable Energy Advocacy and Education Campaigns

The diffusion of innovation theory offers a valuable framework for designing public awareness and education campaigns that can drive increased understanding and support for renewable energy adoption. By identifying and targeting different segments of the population based on their innovativeness and readiness to adopt new ideas, campaigns can be tailored to address specific barriers and motivations that influence renewable energy adoption. The theory emphasizes the importance of utilizing influential individuals or opinion leaders within each segment to help spread the message and create a ripple effect of positive change. This approach not only increases the credibility and trustworthiness of the campaign but also taps into existing social networks and communities, amplifying the reach and impact of the message. By incorporating interactive and engaging communication strategies such as storytelling, visual aids, and hands-on experiences, campaigns can effectively capture attention and inspire individuals to take action towards renewable energy adoption. According to World Bank data, African nations that have developed public education and awareness initiatives to promote better knowledge of and support for the use of renewable energy sources include Kenya, Ethiopia, and South Africa. These countries recognized the importance of educating their citizens about the benefits of renewable energy and implemented programs to raise awareness and encourage its adoption. By implementing public education, these countries are not only empowering their citizens with knowledge but also paving the way for a sustainable future.

6. Policy for Assessing Novel Technology Dissemination Strategies for Lowering GHG Emissions in Africa

Africa holds immense potential for climate-smart initiatives, particularly in the realm of renewable energy. However, the continent faces significant challenges when it comes to the diffusion and adoption of these technologies. To effectively address this issue and unlock Africa's sustainable energy growth, a comprehensive policy framework is needed that focuses on enhancing technological diffusion strategies and overcoming barriers to implementation. This section discusses the seven comprehensive policy frameworks that were developed from the seven suggested strategies for addressing technological diffusion issues in Africa.

6.1 Promoting the Adoption of Renewable Energy Technologies through Policy Incentives and Financial Support

One way the government can promote the adoption of renewable energy technologies in Africa is by implementing policy incentives. These incentives can include tax breaks, subsidies, and grants for individuals and businesses that invest in renewable energy projects. Financial support can be provided through low-interest loans or venture capital funds specifically dedicated to renewable energy initiatives. By utilizing the diffusion of innovation theory, the government can create an environment that encourages the widespread adoption of renewable energy technologies, ultimately leading to a more sustainable future for Africa.

6.2 Developing a Robust Infrastructure for Renewable Energy Production and Distribution

The government recognizes the urgent need to develop a robust infrastructure for renewable energy production and distribution in African countries. To achieve this, it has implemented several key policies. Firstly, it is actively investing in research and development to drive innovation in renewable energy technologies. This includes funding for the development of more efficient solar panels, wind turbines, and energy storage systems. The government is providing financial incentives and tax breaks to encourage private sector investment in renewable energy infrastructure. By offering grants and subsidies for the construction of renewable energy facilities, the government aims to increase the overall capacity and availability of clean energy sources. It is implementing regulations and standards to promote the adoption of renewable energy in various sectors, such as transportation and manufacturing. These comprehensive efforts are aimed at reducing greenhouse gas emissions and transitioning towards a more sustainable and environmentally friendly energy system.

6.3 Encouraging Research and Development in Renewable Energy Technologies to Drive Innovation

One government policy to encourage research and development in renewable energy technologies and drive innovation is to provide financial incentives such as tax credits or grants for companies and individuals involved in these sectors in African countries. This can help offset the costs of research and development, making it more attractive for businesses to invest in renewable energy technologies. Governments can establish partnerships with universities and research institutions to promote collaboration and knowledge sharing, fostering a supportive environment for innovation in the renewable energy sector. Governments can implement policies that require a certain percentage of energy to be generated from renewable sources, creating a guaranteed market for renewable energy technologies. This not only stimulates demand but also encourages companies to invest in the development and production of these technologies to meet the growing need. Governments can prioritize renewable energy in public procurement processes, further driving the adoption and advancement of renewable energy technologies.

6.4 Fostering Partnerships between African Countries and International Organizations to Share Knowledge and Resources

The government recognizes the importance of fostering partnerships between African countries and international organizations to share knowledge and resources. To achieve this, the government has implemented a comprehensive policy framework that promotes collaboration and cooperation. This includes establishing platforms for regular dialogue and information exchange, facilitating joint projects and initiatives, and providing financial support for capacity-building programs. The government encourages the participation of African countries in international forums and conferences to enhance networking opportunities and promote cross-border collaboration. By actively engaging with international organizations, the government aims to strengthen the bonds between African countries and the global community. This can lead to increased knowledge sharing, technological advancements, and access to resources that can contribute to the sustainable development of African nations. By actively participating in international forums, African countries can have a voice in shaping global policies and agendas that directly impact their interests and priorities.

6.5 Implementing Effective Regulatory Frameworks to Ensure the Smooth Integration of Renewable Energy into Existing Power Systems

The government recognizes the importance of integrating renewable energy into existing power systems and has implemented a comprehensive set of policies to ensure its effective implementation in African countries. These policies include conducting thorough assessments of the current power system infrastructure, identifying potential barriers and challenges, and developing strategies to overcome them. The government promotes collaboration between relevant stakeholders, such as energy regulators, utility companies, and renewable energy developers, to foster knowledge sharing and facilitate a seamless transition towards a more sustainable energy future.

6.6 Enhancing Capacity-Building Initiatives to Train a Skilled Workforce in the Renewable Energy Sector

The government recognizes the importance of enhancing capacity-building initiatives to train a skilled workforce in the renewable energy sector in African countries. To achieve this, it has implemented various policies aimed at promoting vocational training programs and partnerships with educational institutions. The government offers financial incentives and subsidies to individuals and businesses that invest in renewable energy training programs, ensuring a steady supply of skilled workers for the sector. These initiatives not only address the immediate need for a skilled workforce but also contribute to long-term sustainability by creating a pipeline of trained professionals. The government actively collaborates with industry experts and stakeholders to continuously update and improve these capacity-building initiatives, ensuring that they remain relevant and effective in meeting the evolving demands of the renewable energy sector.

6.7 Promoting Public Awareness and Education Campaigns to Increase Understanding and Support for Renewable Energy Adoption

One effective government policy to promote public awareness and education campaigns for renewable energy adoption is to allocate funds for comprehensive and widespread advertising campaigns in African countries. These campaigns can utilize various media platforms, such as television, radio, and social media, to reach a wide audience and educate them about the benefits of renewable energy. The government can collaborate with educational institutions to develop curriculum and training programs that incorporate renewable energy concepts, ensuring that future generations are well-informed about its importance and potential.

CONCLUSIONS

In conclusion, it is evident that addressing technological diffusion issues is crucial for the sustainable growth of renewable energy in Africa. By overcoming barriers such as lack of access to financing, inadequate infrastructure, and limited technical expertise, Africa can unlock its climate-smart potential and engage in renewable energy innovation. The report also examined several technology diffusion theories in order to unleash Africa's climate-smart potential by tying them to the recommended techniques for dealing with technological diffusion concerns. These theories varied from diffusion of innovation theory to planned behaviour theory. By understanding and applying these theories, policymakers and stakeholders can develop targeted strategies to overcome the barriers mentioned earlier. For example, by leveraging the diffusion of innovation theory, they can identify early adopters and opinion leaders within communities to promote the adoption of renewable energy technologies. Incorporating planned behaviour theory can help in understanding the factors that influence individuals' intentions to adopt climate-smart solutions, enabling tailored interventions to increase uptake across Africa.

The appropriate proposed strategies for addressing technological diffusion issues in Africa range from encouraging the adoption of renewable energy technologies through policy incentives and financial support to increasing public awareness and support for renewable energy adoption. These strategies can be complemented by promoting collaboration and knowledge sharing among African countries, as well as fostering partnerships with international organizations and investors. Investing in capacity-building programs and providing training opportunities for local communities can empower them to actively participate in the renewable energy sector and contribute to sustainable development in Africa.

With the right policies proposed in this study, ranging from how the government can promote the adoption of renewable energy technologies in Africa by implementing policy incentives to promote public awareness and education campaigns for renewable energy adoption to allocating funds for comprehensive and widespread advertising campaigns, investments, and collaborations, Africa has the opportunity to revolutionize its energy sector and contribute significantly to global efforts in combating climate change. By implementing these policies, Africa can not only reduce its reliance on fossil fuels but also create new job opportunities in the renewable energy sector. The promotion of renewable energy adoption can improve energy access and reliability for communities across the continent, leading to socio-economic development and improved quality of life.

In addition to addressing technological diffusion issues, further research could explore the potential of public-private partnerships in promoting sustainable renewable energy growth in Africa. This could involve examining successful case studies from other regions and identifying strategies that can be adapted to the African context. Investigating the role of policy frameworks and regulatory mechanisms in facilitating the adoption and diffusion of climate-smart technologies could provide valuable insights for policymakers and stakeholders in driving sustainable energy transitions across the continent.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

AUTHOR CONTRIBUTIONS

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Big Data and Neural Networks in Smart Grid - Part 1: The Impact of Measurement Differences on the Performance of Neural Network Identification Methodologies of Overhead Low-Voltage Broadband over Power Lines Networks

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Until now, the neural network identification methodology for the branch number identification (NNIM-BNI) and the neural network identification methodology for the distribution line and branch line length approximation (NNIM-LLA) have approximated the number of branches and the distribution line and branch line lengths given the theoretical channel attenuation behavior of the examined overhead low-voltage broadband over powerlines (OV LV BPL) topologies [1], [2]. The impact of measurement differences that follow continuous uniform distribution (CUDs) of different intensities on the performance of NNIM-BNI and NNIM-LLA is assessed in this paper. The countermeasure of the application of OV LV BPL topology databases of higher accuracy is here investigated in the case of NNIM-LLA. The strong inherent mitigation efficiency of NNIM-BNI and NNIM-LLA against CUD measurement differences and especially against those of low intensities is the key finding of this paper. The other two findings that are going to be discussed in this paper are: (i) The dependence of the approximation Root-Mean-Square Deviation (RMSD) stability of NNIM-BNI and NNIM-LLA on the applied default operation settings; and (ii) the proposal of more elaborate countermeasure techniques from the literature against CUD measurement differences aiming at improving NNIM-LLA approximations.

Keywords: Smart Grid; Broadband over Power Lines (BPL) networks; Power Line Communications (PLC); Distribution and Transmission Power Grids; Neural Networks; Big Data; Modeling; Measurements

1. Introduction

During the recent years, the evolution of the traditional power grid, which represents an omnipresent widely branched hierarchical network structure with relatively few one-way communications modalities, to a modern power grid that is upgraded with an intelligent IP-based communications network of two-way information flows may support a myriad of broadband applications [1]-[9]. The supported broadband applications can facilitate the today's digital transformation of power utilities and consumers, namely: (i) power utilities' operations and management -e.g., real-time

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monitor, meter and control of the power grid equipment and wired infrastructure-; and (ii) customers' needs and demands -e.g., real-time monitor and control of their power flows-. To implement the two-way information flow across the smart grid, Broadband over Power Lines (BPL) networks exploit the available wired power grid infrastructure while permitting their integration with other communications solutions, such as Radio Frequency (RF) mesh, modified Long Term Evolution (LTE), Code Division Multiple Access (CDMA) at sub GHz bands, dedicated fiber along high voltage lines and 5G communications, through their BPL wireline / wireless interfaces [3], [7], [8], [10].

A plethora of channel models has been applied for characterizing BPL channels; say, deterministic, statistical, bottom-up, top-down, hybrid BPL channel models and. more recently, BPL channel models that exploit artificial intelligence (AI), machine learning (ML) and neural network (NN) capabilities [1], [11]-[26]. On the basis of the deterministic hybrid model (DHM) of [1], [2], which describes BPL signal propagation and transmission across the topologies of the overhead low voltage (OV LV) BPL networks, critical DHM broadband performance metrics, such as the channel attenuation of the OV LV BPL topologies, may be further exploited by the BPL broadband applications of the smart grid. Indeed, Topology Identification Methodology (TIM), which has been proposed in [27], [28] and is among the BPL broadband applications of the smart grid, can approximate the exact topological characteristics (*i.e.*, number of branches, length of branches, length of main lines and branch terminations) of an examined BPL topology by comparing the available channel attenuation measurements of the examined BPL topology with the theoretical DHM channel attenuation results of various OV LV BPL topologies stored in the TIM BPL topology database. By exploiting the available big data of the TIM BPL topology database for the OV LV BPL topologies and AI - ML - NN capabilities, the neural network identification methodology for the branch number identification (NNIM-BNI) and the neural network identification methodology for the distribution line and branch line length approximation (NNIM-LLA) have been proposed for the OV LV BPL topologies in [1] and [2], respectively. More specifically, NNIM-BNI aims at identifying the number of branches and NNIM-LLA tries to approximate the distribution line and branch line lengths for a given OV LV BPL topology *theoretical* channel attenuation behavior when the corresponding OV LV BPL topology does not lie among the ones of the TIM BPL topology database in both methodology cases.

However, measurement differences between experimental and theoretical OV LV BPL topology channel attenuation values may occur due to several practical reasons and "real" life conditions while these measurement differences may significantly affect the performance of the BPL broadband applications of the smart grid [28]-[32]. In this paper, the effect of the measurement differences observed between the experimental and theoretical OV LV BPL topology channel attenuation values on the performance of NNIM-BNI and NNIM-LLA is first assessed. In accordance with [28], [29], [32], [33], a typical scenario to take into account the measurement differences during the BPL topology channel attenuation analysis is their handling as error distributions such as Continuous Uniform Distributions (CUDs) and Normal Distributions (NDs) that are superimposed to the coupling scheme transfer function theoretical numerical results of DHM. In this paper, measurement differences are going to be simulated as CUDs of various intensities. The procedure that is going to be followed so as to assess the impact of measurement differences as CUDs on the NNIM-BNI and NNIM-LLA approximation performance consists of two Phases, namely: (i) *Phase 1*: Exploiting the list of indicative

OV LV BPL topologies of [1], [2], the representative database sets of the TIM OV LV BPL topology database and the default operation settings A presented in [1], the branch number approximations of NNIM-BNI are compared against the corresponding best branch number approximation without measurement differences and the real branch number for given indicative OV LV BPL topology when CUD measurement differences of various intensities are assumed; and (ii) *Phase 2*: Focusing on the same list of indicative OV LV BPL topologies of [1], [2], the default operation settings B of [2], are here applied. In order to improve the NNIM-LLA performance and cope with the insidious effect of measurement differences, the default operation settings C, that are a more elaborate version of the default operation settings B of [2], are here proposed as a fine countermeasure against measurement differences. First, the NNIM-LLA approximations of the distribution line and branch line lengths, when CUD measurement differences of various intensities and default operation settings B are assumed, are compared against the corresponding approximations without measurement differences of default operation settings B so that the performance of NNIM-LLA is assessed against the measurement differences. Second, the performance of NNIM-LLA approximations of the distribution line and branch line lengths is benchmarked when CUD measurement differences of the same intensities and default operation settings C are assumed. Here, the role of the default operation settings of higher accuracy against the CUD measurement differences is investigated. In accordance with [1], [2], the performance metric that is going to be applied in both Phases of this paper is the Root-Mean-Square Deviation (RMSD) so that the impact of the CUD measurement differences on the NNIM-BNI and NNIM-LLA approximation performance can be assessed. Conversely to [1], [2], it should be noted that the theoretical channel attenuation measurements of the examined OV LV BPL topologies will be included in the TIM BPL topology database of this paper as well as the topological characteristics of the corresponding OV LV BPL topologies.

The rest of this paper is organized as follows: Section 2 briefly presents DHM, NNIM-BNI and NNIM-LLA. Certain aspects that highlight the operation points of NNIM-BNI and NNIM-LLA, which are vulnerable to measurement differences, are presented in this Section. In addition, the mathematics concerning the involvement of measurement differences during the NNIM-BNI and NNIM-LLA operation are reported. In Section 3, the numerical results regarding the impact of measurement differences on the approximation performance of NNIM-BNI and NNIM-LLA are given. Section 4 concludes this paper.

2. DHM, TIM OV LV BPL Topology Database, NNIM-BNI and NNIM-LLA

In this Section, DHM and TIM OV LV BPL topology database that are responsible for the big data pool of NNIM-BNI and NNIM-LLA are first presented in this Section. Here, DHM is presented by focusing on its output of OV LV BPL topology channel attenuation that is appropriately included into TIM OV LV BPL topology database as the theoretical coupling scheme channel transfer functions. Also, the effect of CUD measurement differences on the DHM output is mathematically presented. Second, NNIM-BNI and NNIM-LLA, which have been proposed in [1] and [2], respectively, are briefly discussed as well as the corresponding useful conclusions of [1], [2] that are going to be exploited in this pair of papers and may further affect the operation and performance of NNIM-BNI and NNIM-LLA.

2.1 DHM and the Mathematics of the Measurement Differences

DHM is a synthetic BPL channel model of three concatenated modules; say, the bottom-up, the top-down and the coupling scheme modules [1], [2], [9], [11]-[13], [34]-[36]. More specifically, the bottom-up and top-down modules of DHM address the propagation and transmission issues of the BPL signal across the OV LV BPL topologies. To deal with the aforementioned propagation / transmission problem, the bottom-up and top-down modules of DHM require details about the applied OV LV Multi-conductor Transmission Line (MTL) configurations and the OV LV BPL topologies, namely:

1. As the OV LV MTL configuration that is applied in this paper is concerned, the typical OV LV MTL configuration of Fig. 1(a) is assumed. The examined OV LV MTL configuration consists of four parallel non-insulated conductors (i.e., $n^{\mathrm{OVLV}}=4$) of vertical distance that is equal to Δ_{OVLV}. The upper conductor of radius $r_{\mathrm{OVLV,n}}$ is the neutral conductor while the lower three conductors of radius $r_{\mathrm{OVLV,p}}$ are the three LV phases. The lowest phase conductor is hung at height h_{OVLV} above the ground. The exact dimensions, the material of the conductors and the structure of the conductors are detailed in [9], [11], [13], [15], [37], [38]. The reference conductor of the OV LV MTL configuration is assumed to be the imperfect lossy ground of properties reported in [39]-[41].
2. As the OV LV BPL topologies that are used in this paper are concerned, the typical OV LV BPL topology of Fig. 1(b) is assumed. With reference to Fig. 1(b), the typical OV LV BPL topology is bounded by the transmitting and receiving ends while N branches of open-circuit terminations are encountered across the transmitting path. The arbitrary k, k=1,…,N branch has length equal to $L_{\mathrm{b}k}$ and is located at distance $\sum_{i=1}^{k} L_i$ from the transmitting end. The same length $\sum_{i=1}^{N+1} L_i$ of 1000m is assumed between the transmitting and receiving ends for all the applied OV LV BPL topologies of this paper [1], [25]. In accordance with [1], [2], [13], [34] the topological characteristics and the number of branches for five indicative OV LV BPL topologies –i.e., Line-Of-Sight (LOS), rural, suburban, urban A and urban B– are listed in Table 1. The indicative OV LV BPL topologies that are included in Table 1 may offer a general study of all OV LV BPL topology classes that are encountered in BPL networks. The indicative OV LV BPL topologies of Table 1 have already been used as OV LV BPL topology case studies during the benchmark of TIM-BNI, NNIM-BNI, TIM-LLA and NNIM-LLA in [1], [26].

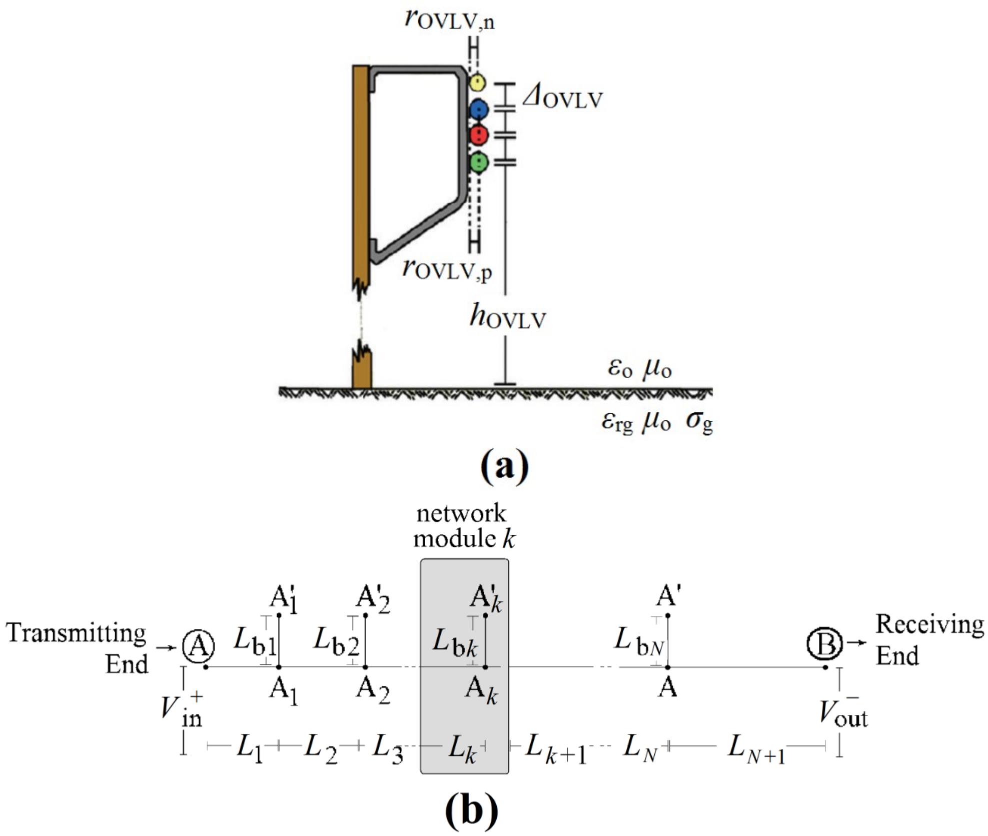


Figure 1. (a) OV LV MTL configuration [1], [9], [13]. (b) Typical OV LV BPL topology with *N* branches [1], [25].

Table 1
Indicative OV LV BPL Topologies [1], [13], [26], [34]

OV LV BPL Topology Name	**Branch Number (*N*)**	**Length of Main Lines**	**Length of Branches**
Urban case A (Typical urban case)	3	L_1=500m, L_2=200m, L_3=100m, L_4=200m	L_{b1}=8m, L_{b2}=13m, L_{b3}=10m
Urban case B (Aggravated urban case)	5	L_1=200m, L_2=50m, L_3=100m, L_4=200m, L_5=300m, L_6=150m	L_{b1}=12m, L_{b2}=5m, L_{b3}=28m, L_{b4}=41m, L_{b5}=17m
Suburban case	2	L_1=500m, L_2=400m, L_3=100m	L_{b1}=50m, L_{b2}=10m
Rural case	1	L_1=600m, L_2=400m	L_{b1}=300m
LOS case	0	L_1=1000m	-

By the interconnection of the bottom-up and the top-down modules of DHM, the $n^{\mathrm{OVLV}} \times n^{\mathrm{OVLV}}$ line channel transfer function matrix $\mathbf{H}^{\mathrm{OVLV}}\{\cdot\}$ of the typical OV LV BPL topology of Fig. 1(b) is given by [1], [2], [9], [11]-[13], [34]-[36]

$$\mathbf{H}^{\mathrm{OVLV}}\{\cdot\} = \mathbf{T}_{\mathrm{V}}^{\mathrm{OVLV}} \cdot \mathbf{H}^{\mathrm{OVLV,m}}\{\cdot\} \cdot \left(\mathbf{T}_{V}^{\mathrm{OVLV}}\right)^{-1} \tag{1}$$

where $\mathbf{H}^{\mathrm{OVLV,m}}\{\cdot\}$ is the $n^{\mathrm{OVLV}} \times n^{\mathrm{OVLV}}$ modal channel transfer function matrix and $\mathbf{T}_{\mathrm{V}}^{\mathrm{OVLV}}$ is the $n^{\mathrm{OVLV}} \times n^{\mathrm{OVLV}}$ transformation matrix. With reference to [1], [2], [9], [11]-[13], [34]-[36] and observing eq. (1), the line channel transfer function matrix depends on the examined OV LV MTL configuration (i.e., physical properties and geometry of the OV LV MTL configuration) and the examined OV LV BPL topology.

By the concatenation of the bottom-up and the top-down modules with the coupling scheme module of DHM, the theoretical coupling scheme channel transfer function is given by [42], [43]

$$H^{\mathrm{OVLV},C}\{\cdot\} = \left[\mathbf{C}^{\mathrm{out}}\right]^{\mathrm{OVLV},C} \cdot \mathbf{H}^{\mathrm{OVLV}}\{\cdot\} \cdot \left[\mathbf{C}^{\mathrm{in}}\right]^{\mathrm{OVLV},C} \tag{2}$$

for given coupling scheme where $[\cdot]^{c}$ denotes the applied coupling scheme, $\mathbf{C}^{\mathrm{in}}$ is the input coupling $n^{\mathrm{OVLV}} \times 1$ column vector dealing with the BPL signal injection process and $\mathbf{C}^{\mathrm{out}}$ is the ouput coupling $1 \times n^{\mathrm{OVLV}}$ line vector dealing with the BPL signal extraction process. Actually, the coupling scheme channel transfer function of eq. (2) relates the output BPL signal $V^{\mathrm{out},-}$ with the input one $V^{\mathrm{in},+}$ of Fig. 1(b). It should be noted that the coupling scheme transfer function of eq. (2) is a frequency dependent function due to the involved frequency dependent function elements from eq. (1) (i.e., the modal channel transfer function and the transformation matrices) and also depends on the applied coupling scheme for the BPL signal injection / extraction across the examined OV LV BPL topology. It should be noted that the theoretical coupling scheme channel transfer function of eq. (2) is of interest for the preparation of the TIM OV LV BPL topology database of the next subsection of this paper since for given OV LV MTL configuration and coupling scheme, the corresponding theoretical coupling scheme channel transfer functions can be computed by DHM and stored in the TIM OV LV BPL topology database by only adjusting the topological characteristics of OV LV BPL topologies. With reference to [42], [43], it should be noted that the applied coupling scheme is the WtG[1] one.

The computation of the DHM coupling scheme transfer function of eq. (2) is a rather theoretical issue since no measurement differences are taken into account. However, a set of practical reasons and "real life" conditions, which can be grouped into six categories [28], [30], [44], [45], can create measurement differences during the practical determination of the coupling scheme transfer function. To assess the effect of the measurement differences during the determination of the coupling scheme transfer functions of the OV LV BPL topologies, in accordance with [28], [30], [44], [45] and with reference to eq. (2), the measured coupling scheme transfer function $\overline{H_{d1,d2,\iota}^{\mathrm{OVLV},C,D}}\{\cdot\}$ is determined by

$$\overline{H_{d1,d2,\iota}^{\mathrm{OVLV},C,D}}\left(f_q\right) = H^{\mathrm{OVLV},C}\left(f_q\right) + e_{d1,d2,i}^{D}\left(f_q\right),\ q=1,\ldots,Q,\ i=1,\ldots,I \tag{3}$$

where $[\cdot]^{D}$ denotes the applied measurement difference distribution (i.e., CUD in this paper), $d1$ is the first parameter of the applied measurement difference distribution (i.e., the minimum value $-a_{\mathrm{CUD}}$ of CUD in this paper), $d2$ is the second parameter of the applied measurement difference distribution (i.e., the maximum value a_{CUD} of CUD in this paper), $e_{d1,d2,i}^{D}\left(f_q\right)$ is the measurement difference at frequency f_q for given measurement difference distribution, I is the number of different $1 \times Q$ line vectors of measurement differences per applied measurement difference distribution, first and second parameter and i indicates the i^{th} among I line vectors of measurement differences. In this paper, 1 representative line vector of measurement differences are going to be assumed per applied measurement difference distribution, first and second parameter; say, i=I=1. It should be noted that the measured coupling scheme channel transfer function of eq. (3) is of interest for the NNIM-BNI and NNIM-LLA since for given OV LV MTL configuration and coupling scheme, the corresponding I measured coupling scheme channel transfer functions are approximated in terms of the branch number and main / branch line lengths.

2.2 TIM OV LV BPL Topology Database

In accordance with [1], [2], TIM OV LV BPL topology database acts as the big data pool for NNIM-BNI and NNIM-LLA. In fact, TIM OV LV BPL topology database is the core part of TIM and is borrowed by the NNIM-based methodologies due to its big data detail concerning the correspondence among topological characteristics and coupling scheme transfer function behavior of the OV High-Voltage (HV), Medium-Voltage (MV) and LV topologies [27]. Combining the database requirements of [1], [2], TIM OV LV BPL topology database consists of the following fields for each OV LV BPL topology: (i) the ID number p of the OV LV BPL topology when the number of all OV LV BPL topologies in the TIM OV LV BPL topology database is equal to P; (ii) the actual number of branches N of the OV LV BPL topology; (iii) the actual lengths of the distribution lines $\mathbf{L} = [L_1 \quad L_2 \quad \cdots \quad L_{N+1}]$ of the OV LV BPL topology; (iv) the actual lengths of the branch lines $\mathbf{L_b} = [L_{\text{b}1} \quad L_{\text{b}2} \quad \cdots \quad L_{\text{b}N}]$ of the OV LV BPL topology; and (v) the theoretical coupling scheme channel transfer function values with respect to the frequency of the OV LV BPL topology as given in eq. (2). The size of the TIM OV LV BPL topology database depends on the default operation settings that are applied during its preparation (see Sec. 2.3).

2.3 Default Operation Settings

With reference to [1], [2], the applied default operation settings have a direct impact on the size of the TIM OV LV BPL topology database and, thus, on the performance of the NNIM-based methodologies. Actually, the default operation settings define the values of the maximum number of branches $N_{\max}$, the length spacing L_{s} for both the branch distance and the branch length, the maximum branch length $L_{\text{b,max}}$ and the operation frequency range that are anyway essential factors for the five fields of TIM OV LV BPL topology database [27], [28]. The following values of the default operation settings of this paper are concerned, namely:

- *The Default Operation Settings A for NNIM-BNI*: In accordance with [1], the number of branches for the OV LV BPL topologies of the TIM OV LV BPL topology database ranges from 0 (say, “LOS” case of Table 1) up to 3 branches (say, urban case A of Table 1). The length spacings for the branch distance and the branch length are assumed to be equal to 100m and 25m, respectively, while the branch line length may range from 0m to 100m. Note that the total distribution line length is assumed to be equal to 1,000m in all the OV LV BPL topologies of the TIM OV LV BPL topology database. The amplitudes of the coupling scheme channel transfer functions in dB are stored in the TIM OV LV BPL topology database for the OV LV BPL topologies with respect to the frequency. The frequency range is assumed to be equal to 3-30MHz while the flat-fading subchannel frequency spacing is equal to 1MHz. In accordance with [1], representative sets of the TIM OV LV BPL topology database (database representativeness) are assumed during the operation of the NNIM-BNI for the branch number approximation of the urban case A (3 branches), suburban case (2 branches) and rural case (1 branch). Especially, in this paper, the following improvements are additionally assumed after the observation of the NNIM-BNI operation and performance of [1]: (i) The urban case A, suburban case, rural case and LOS case will be included into the TIM OV LV BPL topology database. Conversely to [1], NNIM-BNI does not blindly operate in this paper; and (ii) for NNIM-BNI branch number approximations that are not in the range from 0 (minimum acceptable branch number value) to 4 (maximum acceptable branch number value with respect to the preparation of the TIM OV LV BPL topology database), NNIM-BNI approximation is again executed.

- *The Default Operation Settings B and C for NNIM-LLA:* As the default operation settings B are concerned in [2], the number of branches for the OV LV BPL topologies of the TIM OV LV BPL topology database are going to range from 0 (say, “LOS” case) up to 2 branches in this paper due to time delay reasons regarding the application of the following default operation settings C; from [1], [2], it has been verified that the preparation time of the TIM OV LV BPL topology database exponentially increases with the increase of the demanded accuracy of the default operation settings thus establishing a relationship between the approximation performance and total duration time of the NNIM-based methodologies. The length spacings for the branch distance and the branch length are assumed to be equal to 100m and 100m, respectively, while the branch line length may range from 0m to 300m. Note that the total distribution line length is assumed to be equal to 1,000m in all the OV LV BPL topologies of the TIM OV LV BPL topology database. The amplitudes of the coupling scheme channel transfer functions in dB are stored in the TIM OV LV BPL topology database for the OV LV BPL topologies with respect to the frequency. The frequency range is assumed equal to 3-88MHz while the flat-fading subchannel frequency spacing is equal to 1MHz. By comparing default operation settings A and B, it is evident that default operation settings B are more elaborate in comparison with the default operation settings A and this is due to the fact that the approximation of the distribution line and branch line lengths remains a difficult challenge where higher accuracy is expected from the TIM OV LV BPL topology database that is going to be exploited by the NNIM-based methodology. To examine the further improvement tomography potential of NNIM-LLA and its behavior when measurement differences are applied, default operation settings C, which are proposed in this paper, are more elaborate in comparison with the default operation settings B. Anyway, the application of the default operation settings C is also examined in this paper to act as a countermeasure again the measurement differences. Hence, as the default operation settings C are concerned in this paper, the length spacings for the branch distance and the branch length are assumed to be equal to 100m and 30m, respectively, while the branch line length may range from 0m to 300m. Similarly to default operation settings B, the total distribution line length, the frequency range and the flat-fading subchannel frequency spacing are assumed to be the same. In addition, the following assumptions are made: (i) The number of branches of the examined indicative OV LV BPL topologies is assumed to be known; and (ii) the database representativeness, which is analyzed in [2] for the operation of NNIM-LLA, is assumed during the application of the default operation settings B and C. In accordance with [2], only one of the symmetrical OV LV BPL topologies is stored in the OV LV BPL topology database so as not to disrupt the approximations due to the symmetry of BPL topologies described in [64], [46]. Especially, in this paper, the following improvements are assumed with respect to the NNIM-LLA operation and its performance of [2]: (i) The suburban case, rural case and LOS case will be included into the TIM OV LV BPL topology database in default operation settings B and C while only the distribution line and branch line lengths of the suburban case and rural case are going to be approximated by NNIM-LLA. Conversely to [2], NNIM-LLA does not blindly operate in this paper; (ii) for NNIM-LLA distribution line fragment length approximations that are not in the range from 0m (minimum acceptable distribution line length) to 1000m (total distribution line length), NNIM-LLA approximation is again executed; and (iii) for NNIM-LLA branch line fragment length approximations that are not in the range from 0m (minimum acceptable branch line length) to 150m or 300m for the default operation settings B or C, respectively (maximum acceptable branch line length), NNIM-LLA approximation is again executed. Note that the last two improvements cope with the unacceptable NNIM-LLA approximations of [2] (i.e., at least one of the approximated distribution and branch line lengths is below zero given the fixed length of 1000m between the transmitting and receiving ends for all the applied OV LV BPL topologies of this paper).

Finally, it should be noted that the default participation percentages of the three phases of NNIM-based methodologies of [1], [2], [47], [48] are assumed in this paper; say, training, validation and testing phases during the operation of NNIM-BNI and NNIM-LLA are respectively assumed to be equal to 70%, 15% and 15%.

2.4 NNIM-BNI and NNIM-LLA in a Measurement Difference Environment

NNIM-BNI lies in the research fields of AI, ML and NNs [47], [49]-[51]. NNIM-BNI has been proposed and numerically assessed in [1] against TIM-BNI, which is its alternative deterministic BNI methodology. NNIM-BNI approximates the branch numbers $N_{\mathrm{NNIM-BNI}}$ of the examined indicative OV LV BPL topology per *hl* hidden layer by comparing its coupling scheme channel transfer function values against the respective ones of the available OV LV BPL topologies of the TIM OV LV BPL topology database. Actually, the operation of NNIM-BNI depends on: (i) the TIM OV LV BPL topology database; and (ii) the MATLAB NN program of [47], [48] that programmatically supports the fully connected neural network architecture of Figure 2 of [1] as well as the involved training, validation and testing phases. The factors that affect the accuracy performance of the NNIM-BNI approximations and have been identified in [1] are: (i) the default operation setting values that affect the accuracy and size of the TIM OV LV BPL topology database; (ii) the representativeness of the TIM OV LV BPL topology database; (iii) the number *HL* of the hidden layers assumed; and (iv) the participation percentage of the three phases. Another factor that may affect the accuracy performance of the NNIM-BNI approximations when measurement differences occur is the inclusion of the examined indicative OV LV BPL topologies in the TIM OV LV BPL topology database. Until now, NNIM-BNI has exploited the performance metric of RMSD of the amplitude of the coupling scheme channel transfer function in dB, as expressed in eq. (2) since the scenario of the existence of measurement differences is first examined in this paper. In this paper, NNIM-BNI is again going to exploit the performance metric of RMSD of the amplitude of the coupling scheme channel transfer function in dB but via the eq. (3) where measurement differences occur and are mathematically taken into account.

In [2], NNIM-BNI has been extended to NNIM-LLA so that the lengths of the distribution lines and branch lines for a given OV LV BPL topology coupling scheme channel transfer function behavior with respect to frequency can be approximated; say, NNIM-LLA achieves the tomography of the examined OV LV BPL topology. Indeed, NNIM-LLA adopts the same fully connected NN architecture of NNIM-BNI while it depends on the same factors with NNIM-BNI, say: (i) the default operation setting values that affect the TIM OV LV BPL topology database; (ii) the representativeness of the TIM OV LV BPL topology database when the number of branches for the examined OV LV BPL topology is *a priori* known; (iii) the deliberate ignorance of symmetrical OV LV BPL topologies during the preparation of the TIM OV LV BPL topology database; (iv) the number *HL* of the assumed hidden layers; and (v) the participation percentage of the three phases. The output of the NNIM-LLA approximates the distribution and branch line lengths of the examined indicative OV LV BPL topology (i.e., the NNIM-LLA approximation lengths of the distribution and branch lines are $\mathbf{L}_{\mathrm{NNIM-LLA}} = [L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad \cdots \quad L_{N+1,\mathrm{NNIM-LLA}}]$ and $\mathbf{L}_{\mathrm{b,NNIM-LLA}} = [L_{\mathrm{b1,NNIM-LLA}} \quad L_{\mathrm{b2,NNIM-LLA}} \quad \cdots \quad L_{\mathrm{b}N,\mathrm{NNIM-LLA}}]$, respectively). Similarly to NNIM-BNI, the scenario of the inclusion of the examined indicative OV LV BPL topologies in the TIM OV LV BPL topology database is first examined in this paper when measurement differences are considered. Extending the application of NNIM-LLA of [2], NNIM-LLA here exploits the performance metric of RMSD of the amplitude of the coupling scheme channel transfer function in dB when measurement differences are included, as expressed in eq. (3). In this paper, NNIM-LLA is again going to exploit the performance metric of RMSD of the amplitude of the coupling scheme channel transfer function in dB through the eq. (3) where measurement differences occur and are mathematically taken into consideration. At the NNIM-LLA output, apart from the approximation for the lengths of the distribution and branch lines, NNIM-LLA presents its approximation RMSDs per hidden layer.

3. Numerical Results and Discussion

In this Section, numerical results concerning the performance of NNIM-BNI and NNIM-LLA are presented as well as their evaluation when CUD measurement differences of different intensities are applied. The higher accuracy of the applied default operation settings is treated as the simplest countermeasure technique against measurement differences in NNIM-LLA.

3.1 NNIM-BNI – Base Scenario and Measurement Differences

As the operation of the NNIM-BNI is concerned, NNIM-BNI is based on the MATLAB NN training program of [47], [48] while the default operation settings A of Sec. 2.3 are assumed. Given the amplitudes of coupling scheme channel transfer functions in dB for the urban case A, suburban case and rural case of Table 1, NNIM-BNI gives as output in Table 2 the respective NNIM-BNI approximation of the branch

Table 2
Branch number approximation of NNIM-BNI without CUD Measurements

Indicative OV LV BPL Topologies of Table 1		Urban case A (Typical urban case)	Suburban case	Rural case	RMSD (m)	Notes
Actual Number of Branches N		**3**	**2**	**1**	-	-
NNIM-BNI (Approximated Number of Branches) $N_{\text{NNIM-BNI}}$	1st execution	2.67	1.80	1.13	0.24	Default Operation Settings A + 1 hidden layer
	2nd execution	3.02	2.01	1.12	0.07	
	3rd execution	3.64	2.16	1.05	0.38	
	1st execution	3.06	2.16	1.28	0.19	Default Operation Settings A + 2 hidden layers
	2nd execution	2.78	2.08	1.34	0.24	
	3rd execution	3.32	2.14	1.08	0.21	
	1st execution	2.82	1.87	1.18	0.17	Default Operation Settings A + 3 hidden layers
	2nd execution	2.78	1.97	1.21	0.18	
	3rd execution	2.06	1.78	1.44	0.61	
	1st execution	2.66	2.51	1.22	0.37	Default Operation Settings A + 4 hidden layers
	2nd execution	3.12	2.02	1.10	0.09	
	3rd execution	2.94	2.01	1.12	0.08	
	1st execution	2.99	2.08	1.10	0.08	Default Operation Settings A + 5 hidden layers
	2nd execution	2.99	2.00	1.24	0.14	
	3rd execution	3.01	2.05	1.26	0.15	

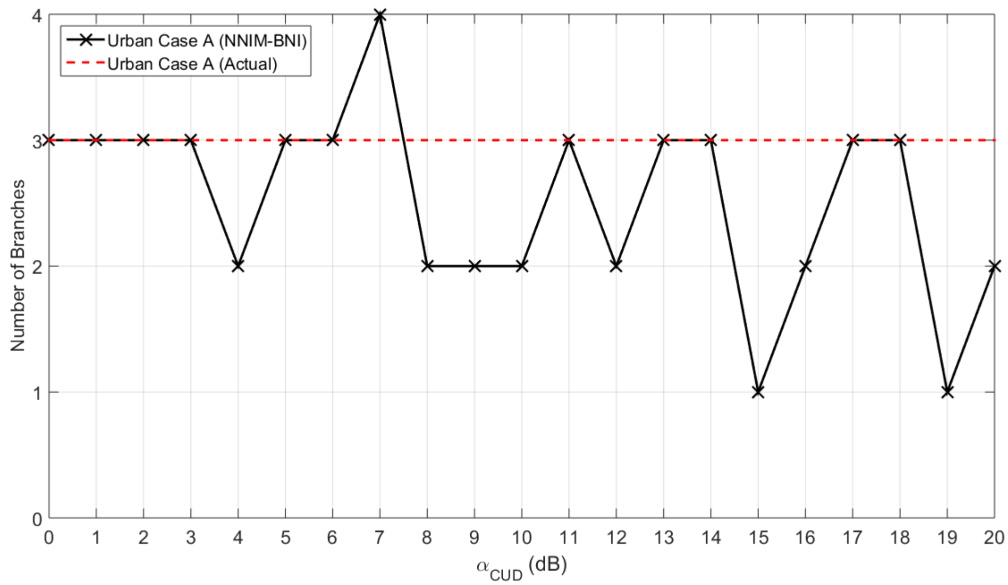
numbers $N_{\text{NNIM-BNI}}$ per hidden layer where the maximum number of hidden layers HL is assumed to be equal to 5. Since the results of Table 2 are going to act as the basis scenario for the effect study of measurement differences, CUD measurements are omitted in the basis scenario (i.e., a_{CUD} of CUD measurements is assumed to be equal to 0dB). Apart from the branch number approximations, the actual branch numbers of the three examined OV LV BPL topologies of Table 1 are presented for comparison reasons while the RMSDs of NNIM-BNI approximations for these three examined OV LV BPL topologies are also computed. Note that three executions of NNIM-BNI are reported for each of the three examined OV LV BPL topologies.

From Table 2, it is evident that the RMSD per hidden layer remains satisfactorily stable when different executions occur for the default operation settings A and the three examined OV LV BPL topologies of this paper. In fact, by assessing the RMSD values of Table 2, reliable NNIM-BNI approximations can occur even if 1 hidden layer and only one execution are assumed for given indicative OV LV BPL topology of Table 1. Since no CUD measurement differences are applied in the basis scenario of Table 2, the RMSD values may act as the benchmark for assessing the impact of higher a_{CUD} values of CUD measurements on the NNIM-BNI approximation performance, apart from the approximated branch numbers per OV LV BPL topology.

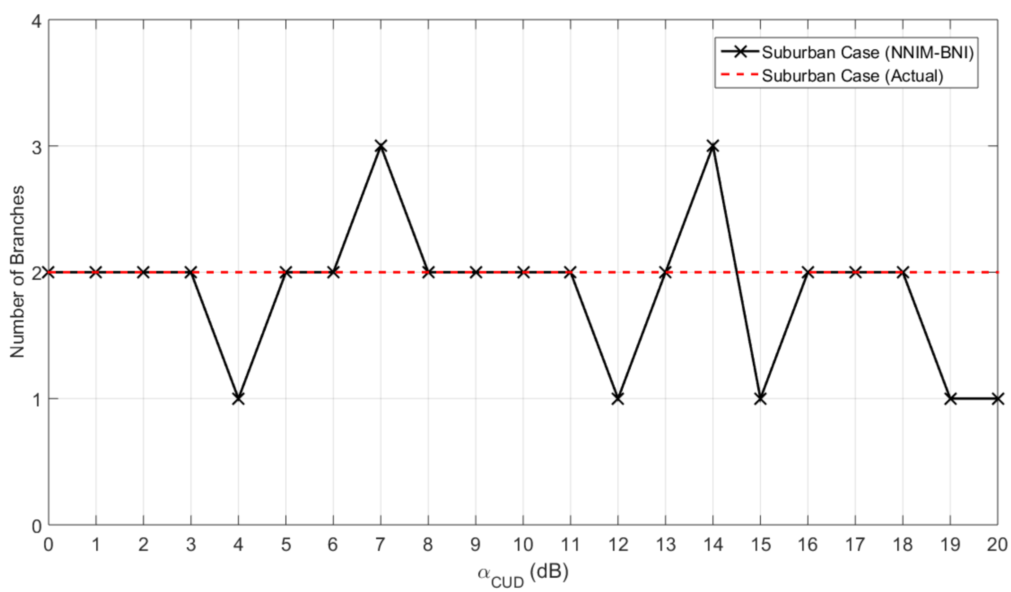
Similarly to Table 2, in Table 3, given the amplitudes of coupling scheme channel transfer functions contaminated with measurements in dB for the urban case A, suburban case and rural case of Table 1, NNIM-BNI gives as output the respective NNIM-BNI approximations of the branch numbers $N_{\text{NNIM-BNI}}$ when various a_{CUD} values of CUD measurements are assumed. Note that: (i) one hidden layer is assumed during the NN preparation of NNIM-BNI in this subsection; (ii) one execution is performed in each NNIM-BNI approximation case; and (iii) one measurement difference $1 \times Q = 1 \times (30-3) = 1 \times 27$ line vector is superimposed to the amplitudes of the coupling scheme channel transfer functions of the aforementioned three OV LV BPL topologies in each NNIM-BNI approximation case. Apart from the branch number approximations, the actual branch numbers of the three examined OV LV BPL topologies of Table 1 are presented for comparison reasons while the RMSD values assess the approximation performance for given a_{CUD} of CUD measurements for the aforementioned BPL topologies. More analytically, to graphically examine the performance of NNIM-BNI for the various a_{CUD} values of CUD measurements of Table 3, the rounded branch number approximation of NNIM-BNI and the actual branch number are plotted in Fig. 2(a) for the urban case A with reference to Table 3. Similar figures with Fig. 2(a) are given in Figs. 2(b) and 2(c), but for the suburban and rural case of Table 3, respectively.

Table 3
Branch number approximation of NNIM-BNI for Different a_{CUD} Values of CUD Measurements

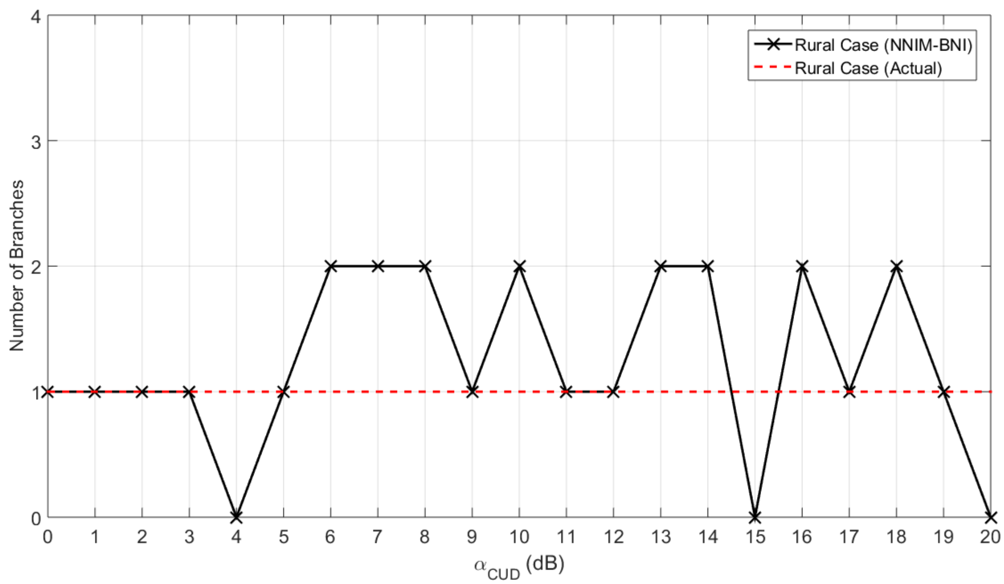
Indicative OV LV BPL Topologies of Table 1		**Urban case A (Typical urban case)**	**Suburban case**	**Rural case**	**RMSD (m)**	**Notes**
Actual Number of Branches N		**3**	**2**	**1**	-	-
NNIM-BNI (Approximated Number of Branches) $N_{\mathrm{NNIM-BNI}}$	$\boldsymbol{a_{\mathrm{CUD}}}$ **of CUD Measurememts (dB)**					Default Operation Settings A + 1 hidden layer
	0	2.88	1.97	1.13	0.11	
	1	3.42	2.13	1.27	0.30	
	2	3.19	2.21	1.28	0.23	
	3	3.02	1.97	0.98	0.03	
	4	2.12	1.24	0.41	0.75	
	5	2.68	1.90	0.98	0.19	
	6	2.52	2.01	1.57	0.43	
	7	3.91	2.86	1.89	0.89	
	8	2.33	1.95	1.60	0.52	
	9	2.15	1.51	1.14	0.58	
	10	2.23	2.04	1.93	0.70	
	11	2.68	1.61	0.91	0.29	
	12	2.34	1.47	0.73	0.51	
	13	3.37	1.92	1.61	0.41	
	14	2.94	2.62	2.26	0.81	
	15	1.30	0.64	0.32	1.32	
	16	2.50	2.06	1.57	0.44	
	17	2.71	1.51	0.66	0.38	
	18	2.81	2.32	1.98	0.61	
	19	1.49	1.31	0.88	0.96	
	20	2.02	0.85	0.20	0.99	


Urban Case A (NNIM-BNI)
Urban Case A (Actual)
Number of Branches
α_{CUD} (dB)

(a)


Suburban Case (NNIM-BNI)
Suburban Case (Actual)
Number of Branches
α_{CUD} (dB)

(b)



(c)

Figure 2. The rounded branch number approximations of NNIM-BNI with respect to a_{CUD} of CUD measurements. (a) Urban case A. (b) Suburban case. (c) Rural case.

From Table 3 and Figs. 2(a)-(c), several interesting remarks concerning the performance of NNIM-BNI can be pointed out when CUD measurement differences are superimposed. More specifically:

- As the RMSD results of the NNIM-BNI branch number approximation of the three indicative OV LV BPL topologies are examined, fluctuating RMSD values can be observed when the a_{CUD} of CUD measurements increases. In fact, the highest RMSD values of Table 3 that are equal to 0.99m and 0.96m are observed when a_{CUD} of CUD measurements is equal to 20dB and 19dB, respectively.
- When the a_{CUD} of CUD measurements increases the aforementioned RMSD behavior is reflected on Figs. 2(a)-(c); say, given the actual number of branches in each one of the three indicative OV LV BPL topologies, the rounded NNIM-BNI branch number approximation is almost equal to the actual number of branches for each one of the indicative OV LV BPL topologies when the a_{CUD} of CUD measurements remains lower or equal to 5dB. When a_{CUD} of CUD measurements becomes greater than 5dB, fluctuations of the rounded NNIM-BNI branch number approximations are observed in all the indicative OV LV BPL topologies. The highest deviations between the actual numbers of branches and the rounded NNIM-BNI branch number approximations, which are equal to 2 branches, is observed in the urban case A of Fig. 2(a) when a_{CUD} of CUD measurements is equal to 15dB and 19dB.

When a_{CUD} of CUD measurements remains low (i.e., below 5dB), NNIM-BNI can intrinsically mitigate measurement differences thus giving accurate rounded NNIM-BNI branch number approximations in the majority of the cases examined. Conversely, higher a_{CUD} values imply that appropriate mitigation techniques for the measurement differences should be externally applied to the measured coupling scheme transfer functions of eq.(3) prior to its consideration by NNIM-BNI.

3.2 NNIM-LLA – Base Scenario and Measurement Differences

As the base scenario of the operation of NNIM-LLA is concerned, the default operation settings B of Sec. 2.3 are assumed. Already been mentioned, the number of branches for the OV LV BPL topologies of the TIM OV LV BPL topology database are going to range from 0 (say, “LOS” case) up to 2 branches in this paper so as to allow the application of the default operation settings C bypassing: (i) the extremely high preparation time delay of the TIM OV LV BPL topology database when 3 branches need to be examined; and (ii) the high execution time of the MATLAB NN program of [47], [48] due to the high number of OV LV BPL topologies and the mechanism of avoiding the unacceptable NNIM-LLA approximations. Note that the suburban case, rural case and LOS case will be included into the TIM OV LV BPL topology database in contrast with [2] while only the distribution line and branch line lengths of the suburban case and rural case are going to be approximated by NNIM-LLA.

As the base scenario without measurement differences is concerned, the length approximations of the distribution and branch lines of NNIM-LLA are reported in Table 4 when the default operation settings B are assumed and the suburban case of Table 1 is examined. Apart from the original approximations that are given in black font color, the symmetrical approximations of NNIM-LLA for the suburban case are also given in blue font color. Similarly to [2] and for comparison reasons, the real lengths of the distribution and branch lines of the suburban case are presented while the RMSDs of NNIM-LLA approximations for the suburban case are also computed. Similarly to [1], [2], three executions of NNIM-LLA are reported for the suburban case per hidden layer. Table 5 is the same with Table 4 but for the rural case of Table 1. Similarly to [2], note that RMSD is computed in Tables 4 and 5 when 4 distribution line segments and 3 branches are assumed for the two examined indicative OV LV BPL topologies so that the RMSD effect of the inclusion of the two indicative OV LV BPL topologies during the preparation of the TIM OV LV BPL topology database can be assessed through the comparison of RMSD values with the respective ones of [2] where the two examined indicative OV LV BPL topologies are excluded from the TIM OV LV BPL topology database.

Table 4
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case and Default Operation Settings B with no measurement differences (the symmetrical approximations are reported in blue font color and the suburban case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1		**Suburban case**	**RMSD**	**Notes**
Distribution Line Length L =$[L_1 \quad L_2 \quad L_3 \quad 0]$ **Branch Line Length** $\mathbf{L_b}$ =$[L_{b1} \quad L_{b2} \quad 0]$		[500m 400m 100m 0m] [50m 10m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\text{NNIM-LLA}} = [L_{1,\text{NNIM-LLA}} \quad L_{2,\text{NNIM-LLA}} \quad L_{3,\text{NNIM-LLA}} \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\text{b,NNIM-LLA}} = [L_{\text{b1,NNIM-LLA}} \quad L_{\text{b2,NNIM-LLA}} \quad 0]$	1st execution	[61.95m 689.88m 248.17m 0m] [134.76m 158.64m 0m] [248.17m 689.88m 61.95m 0m] [158.64m 134.76m 0m]	216.18m 158.68m	Default Operation Settings B + 1 hidden layer
	2nd execution	[102.86m 509.38m 387.76m 0m] [143.86m 156.92m 0m] [387.76m 509.38m 102.86m 0m] [156.92m 143.86m 0m]	201.03m 87.77m	
	3nd execution	[106.12m 518.35m 375.53m 0m] [147.26m 162.89m 0m] [375.53m 518.35m 106.12m 0m] [162.89m 147.26m 0m]	199.25m 93.44m	
	1st execution	[109.41m 550.49m 340.10m 0m] [52.35m 48.63m 0m] [340.10m 550.49m 109.41m 0m] [48.63m 52.35m 0m]	182.97m 84.60m	Default Operation Settings B + 2 hidden layers
	2nd execution	[108.39m 532.83m 358.78m 0m] [228.83m 252.06m 0m] [358.78m 532.83m 108.39m 0m] [252.06m 228.8m 0m]	216.65m 134.36m	
	3nd execution	[57.82m 726.80m 216.30m 0m] [92.06m 94.40m 0m] [216.30m 726.80m 57.82m 0m] [94.40m 92.06m 0m]	215.39m 168.09m	
	1st execution	[113.61m 522.69m 363.59m 0m] [18.35m 4.77m 0m] [363.59m 522.69m 113.61m 0m] [4.77m 18.35m 0m]	183.17m 71.68m	Default Operation Settings B + 3 hidden layers
	2nd execution	[136.05m 516.21m 347.74m 0m] [19.02m 18.74m 0m] [347.74m 516.21m 136.05m 0m] [18.74m 19.02m 0m]	172.54m 74.68m	
	3nd execution	[99.88m 498.15m 402.01m 0m] [105.41m 149.07m 0m] [402.01m 498.15m 99.88m 0m] [149.07m 105.41m 0m]	201.19m 73.83m	
	1st execution	[207.41m 487.87m 305.00m 0m] [117.01m 143.02m 0m] [305.00m 487.87m 207.41m 0m]	150.02m	Default Operation Settings B

		[143.02m 117.01m 0m]	105.15m	+ 4 hidden layers
	2nd execution	[138.22m 515.74m 346.14m 0m] [41.75m 40.02m 0m] [346.14m 515.74m 138.22m 0m] [40.02m 41.75m 0m]	171.48m 75.25m	
	3rd execution	[100.93m 573.22m 329.81m 0m] [25.96m 22.40m 0m] [329.81m 573.22m 100.93m 0m] [22.40m 25.96m 0m]	186.24m 92.57m	
	1st execution	[106.50m 527.93m 365.66m 0m] [227.01m 217.69m 0m] [365.66m 527.93m 106.50m 0m] [217.69m 227.01m 0m]	212.55m 125.17m	Default Operation Settings B + 5 hidden layers
	2nd execution	[152.23m 505.47m 313.49m 0m] [15.87m 20.17m 0m] [313.49m 505.47m 152.23m 0m] [20.17m 15.87m 0m]	159.87m 84.14m	
	3rd execution	[103.04m 522.04m 377.05m 0m] [43.48m 47.36m 0m] [377.05m 522.04m 103.04m 0m] [47.36m 43.48m 0m]	189.23m 66.70m	

Table 5
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case and Default Operation Settings B with no measurement differences (the symmetrical approximations are reported in blue font color and the rural case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1		**Rural case**	**RMSD**	**Notes**
Distribution Line Length L =$[L_1 \quad L_2 \quad 0 \quad 0]$ **Branch Line Length** $\mathbf{L}_b$ =$[L_{b1} \quad 0 \quad 0]$		[600m 400m 0m 0m] [300m 0m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}} = [L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad 0 \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}} = [L_{\mathrm{b1,NNIM-LLA}} \quad 0 \quad 0]$	1st execution	[278.75m 770.31m 0m 0m] [232.13m 0m 0m] [770.31m 278.75m 0m 0m] [232.13m 0m 0m]	187.06m 83.08m	Default Operation Settings B + 1 hidden layer
	2nd execution	[205.33m 796.69m 0m 0m] [164.04m 0m 0m] [796.69m 205.33m 0m 0m] [164.04m 0m 0m]	217.65m 116.54m	
	3rd execution	[280.44m 719.56m 0m 0m] [299.50m 0m 0m] [719.56m 280.44m 0m 0m] [299.50m 0m 0m]	170.81m 63.91m	
	1st execution	[266.99m 733.42m 0m 0m] [215.69m 0m 0m] [733.42m 266.99m 0m 0m] [215.69m 0m 0m]	180.94m 78.01m	Default Operation Settings B +

	2nd execution	[297.29m 700.86m 0m 0m] [276.04m 0m 0m] [700.86m 297.29m 0m 0m] [276.04m 0m 0m]	161.57m 55.16m	2 hidden layers
	3nd execution	[308.12m 692.59m 0m 0m] [278.26m 0m 0m] [692.59m 308.12m 0m 0m] [278.26m 0m 0m]	156.42m 49.98m	
	1st execution	[278.28m 631.75m 0m 0m] [112.72m 0m 0m] [631.75 278.28m 0m 0m] [112.72m 0m 0m]	165.74m 85.27m	Default Operation Settings B + 3 hidden layers
	2nd execution	[239.99m 760.01m 0m 0m] [299.979397173821m 0m 0m] [760.01m 239.99m 0m 0m] [299.97m 0m 0m]	192.43m 85.53m	
	3nd execution	[296.21m 731.66m 0m 0m] [210.946885278590m 0m 0m] [731.66m 296.21m 0m 0m] [210.95m 0m 0m]	173.30m 71.75m	
	1st execution	[250.02m 749.98m 0m 0m] [300.00m 0m 0m] [749.98m 250.02m 0m 0m] [300.00m 0m 0m]	187.07m 80.17m	Default Operation Settings B + 4 hidden layers
	2nd execution	[350.10m 649.68m 0m 0m] [295.77m 0m 0m] [649.68m 350.10m 0m 0m] [295.77m 0m 0m]	133.53m 26.66m	
	3nd execution	[349.94m 628.11m 0m 0m] [275.66m 0m 0m] [628.11m 349.94m 0m 0m] [275.66m 0m 0m]	128.26m 23.57m	
	1st execution	[234.69m 781.13m 0m 0m] [325.14m 0m 0m] [781.13m 234.69m 0m 0m] [325.14m 0m 0m]	199.77m 93.17m	Default Operation Settings B + 5 hidden layers
	2nd execution	[349.82m 649.66m 0m 0m] [300.21m 0m 0m] [649.66m 349.82m 0m 0m] [300.21m 0m 0m]	133.59m 26.68m	
	3nd execution	[299.03m 686.21m 0m 0m] [310.08m 0m 0m] [686.21m 299.03m 0m 0m] [310.08m 0m 0m]	157.03m 50.33m	

By comparing Tables 4 and 5 with the respective Tables 3 and 4 of [2], it is evident that the inclusion of the examined indicative OV LV BPL topologies in the TIM OV LV BPL topology database affects the accuracy of NNIM-LLA. Also, the mechanism for encountering the unacceptable NNIM-LLA approximations fills the missing approximations in Tables 4 and 5, especially those when the high number of hidden layers is assumed. In total, apart from the elimination of the unacceptable NNIM-LLA approximations, the RMSD values get significantly improved regardless of the examined indicative OV LV BPL topology and the number of the applied hidden layers. To graphically validate the aforementioned RMSD improvement, the best RMSD values of the NNIM-LLA approximations (say, the minimum RMSD value between the original and symmetrical approximated OV LV BPL topology given the number of execution and the number of hidden layers) of Table 4 are plotted in Fig. 3(a) with respect to the number of hidden layers when the default operation settings B are assumed. In Fig. 3(b), the same plot with Fig. 3(a) is presented but for the rural case of Table 5.

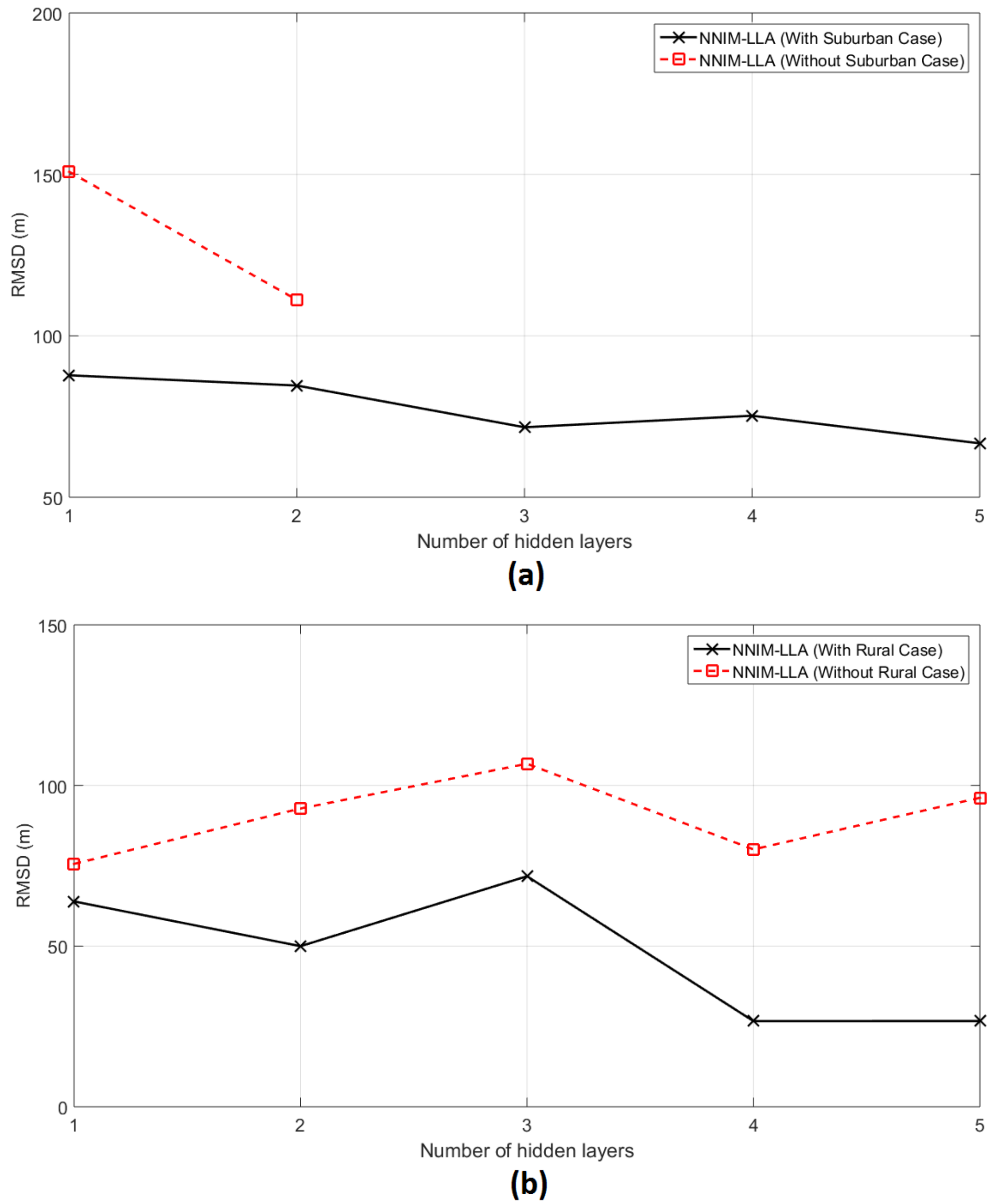


Figure 3. Best RMSD values of NNIM-BNI approximations whether the examined indicative OV LV BPL topology is included in the preparation of the TIM OV LV BPL topology database or not. (a) Suburban case. (b) Rural case.

Already been observed in Tables 3-5, the inclusion of the indicative OV LV BPL topologies in the TIM OV LV BPL topology database and the mechanism for preventing unacceptable approximations significantly improve the performance and accuracy of NN related approximations of this paper, say, NNIM-BNI and NNIM-LLA. Also, the following assumptions are made for the following CUD measurement study during the application of NNIM-LLA, namely:

- The best RMSD values of NNIM-BNI approximations imply that the selection between the original and symmetrical approximations can be fulfilled. Anyway, in accordance with [2], additional topological pieces of information or empirical observations so that the distinction between these approximated OV LV BPL topologies may help towards the selection between the original and symmetrical approximations.
- Similarly to Sec.3.1 and without affecting the generality of the analysis, only one repetition and two hidden layers are going to be applied in the following CUD measurement analysis. As the one repetition is considered, best RMSD values of Tables 4 and 5 can be considered to be relatively close for the different repetitions for given examined indicative OV LV BPL topology and number of hidden layers. As two hidden layers are assumed, best RMSD values of Figs. 3(a) and 3(b) can be considered to be relatively close for the different numbers of hidden layers for given examined indicative OV LV BPL topology. Anyway, only one hidden layer is assumed to be sufficient in general, but one and five hidden layers are assumed so that the NNIM-LLA performance against the measurement differences and the total duration time for the different default operation settings can be investigated in the rest of this paper.

As the impact of CUD measurement differences on the performance of NNIM-LLA is investigated, similarly to Table 4, in Table 6, given the amplitudes of coupling scheme channel transfer functions contaminated with measurements in dB for the suburban case of Table 1, NNIM-LLA gives as output its respective approximations of the distribution and branch line lengths when various a_{CUD} values of CUD measurements are assumed. Note that one $1 \times Q = 1 \times (88 - 3) = 1 \times 85$ measurement difference line vector for each a_{CUD} value that ranges from 0dB to 20dB is superimposed to the amplitudes of the coupling scheme channel transfer functions of the suburban case for the respective NNIM-LLA approximation cases. Also, the best RMSD value between the approximated original and symmetrical OV LV topologies and the respective OV LV BPL topology are presented per a_{CUD} in Table 6. Table 7 is similar to Table 6 but for the rural case of Table 1. Note that the same 21×85 measurement difference vector with Table 6 is here superimposed to the amplitudes of the coupling scheme channel transfer functions of the rural case for all the examined NNIM-LLA approximation cases. In Tables 6 and 7, the default operation settings B of Sec.2.3 are applied when one hidden layer is assumed during the NNIM-LLA simulations.

Table 6
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case and Default Operation Settings B for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the suburban case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1		**Suburban Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad L_3 \quad 0]$ **Branch Line Length** $\mathbf{L_b}=[L_{b1} \quad L_{b2} \quad 0]$		[500m 400m 100m 0m] [50m 10m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}} = [L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad L_{3,\mathrm{NNIM-LLA}} \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}} = [L_{\mathrm{b1,NNIM-LLA}} \quad L_{\mathrm{b2,NNIM-LLA}} \quad 0]$	$\boldsymbol{a_{\mathrm{CUD}}}$ **of CUD Measurements (dB)**			Default Operation Settings B + 1 hidden layer
	0	[514.49m 335.46m 150.05m 0m] [119.28m 106.45m 0m]	54.75m	
	1	[225.07m 718.12m 56.81m 0m] [168.35m 152.43m 0m]	174.42m	
	2	[263.82m 653.95m 82.22m 0m] [81.64m 75.23m 0m]	134.08m	
	3	[511.72m 343.71m 144.57m 0m] [161.23m 157.85m 0m]	75.14m	
	4	[221.28m 716.98m 61.75m 0m] [162.76m 139.54m 0m]	172.84m	
	5	[238.17m 707.35m 54.49m 0m] [174.80m 150.64m 0m]	169.22m	
	6	[229.59m 711.73m 58.68m 0m] [158.89m 141.56m 0m]	169.53m	
	7	[752.89m 34.22m 212.89m 0m] [147.32m 142.86m 0m]	184.24m	
	8	[513.37m 380.09m 131.32m 0m] [182.12m 137.55m 0m]	71.00m	
	9	[154.58m 805.21m 40.18m 0m] [152.33m 138.91m 0m]	211.85m	
	10	[210.15m 723.15m 66.70m 0m] [156.13m 146.19m 0m]	177.02m	
	11	[239.26m 694.45m 66.28m 0m] [162.12m 155.94m 0m]	164.62m	
	12	[214.29m 732.38m 53.34m 0m] [153.16m 141.86m 0m]	178.21m	
	13	[739.43m 47.12m 213.45m 0m] [155.50m 149.49m 0m]	179.41m	
	14	[756.80m 28.69m 214.51m 0m] [147.00m 146.54m 0m]	187.07m	
	15	[232.00m 716.22m 51.77m 0m] [169.73m 155.13m 0m]	173.01m	
	16	[231.56m 704.34m 64.10m 0m] [166.45m 147.98m 0m]	168.42m	
	17	[734.08m 66.52m 199.40m 0m] [146.32m 139.96m 0m]	169.89m	
	18	[709.93m 87.39m 202.67m 0m] [155.54m 158.97m 0m]	162.86m	
	19	[217.50m 713.43m 69.07m 0m] [162.53m 144.14m 0m]	173.06m	

	20	[219.18m 708.39m 72.43m 0m] [162.78m 132.21m 0m]	170.03m	

Table 7
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case and Default Operation Settings B for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the rural case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1		**Rural Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad 0 \quad 0]$ **Branch Line Length** $\mathbf{L_b}=[L_{b1} \quad 0 \quad 0]$		[600m 400m 0m 0m] [300m 0m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}} = [L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad 0 \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}} = [L_{\mathrm{b1,NNIM-LLA}} \quad 0 \quad 0]$	$\boldsymbol{a_{\mathrm{CUD}}}$ **of CUD Measurements (dB)**			Default Operation Settings B + 1 hidden layer
	0	[591.84m 410.07m 0m 0m] [39.52m 0m 0m]	98.58m	
	1	[785.00m 216.36m 0m 0m] [204.93m 0m 0m]	104.87m	
	2	[839.77m 207.39m 0m 0m] [329.55m 0m 0m]	116.78m	
	3	[804.46m 108.34m 0m 0m] [75.35m 0m 0m]	159.17m	
	4	[890.85m 109.17m 0m 0m] [7.61m 0m 0m]	190.74m	
	5	[701.77m 421.63m 0m 0m] [250.88m 0m 0m]	43.49m	
	6	[740.00m 260.00m 0m 0m] [0m 0m 0m]	135.86m	
	7	[734.26m 223.51m 0m 0m] [101.29m 0m 0m]	112.54m	
	8	[983.99m 23.43m 0m 0m] [218.82m 0m 0m]	205.58m	
	9	[745.74m 241.63m 0m 0m] [189.25m 0m 0m]	91.49m	
	10	[787.87m 212.13m 0m 0m] [151.87m 0m 0m]	114.97m	
	11	[660.41m 338.10m 0m 0m] [202.32m 0m 0m]	49.31m	
	12	[765.06m 238.30m 0m 0m] [160.25m 0m 0m]	102.07m	
	13	[665.00 474.69 0m 0m] [257.86m 0m 0m]	40.67m	
	14	[573.36m 426.64m 0m 0m] [328.51m 0m 0m]	17.86m	
	15	[737.08m 114.20m 0m 0m] [197.60m 0m 0m]	125.90m	
	16	[590.81m 196.27m 0m 0m] [144.09m 0m 0m]	97.03m	
	17	[722.22m 277.78m 0m 0m] [144.45m 0m 0m]	87.89m	

	18	[750.02m 249.98m 0m 0m] [162.60m 0m 0m]	95.54m	
	19	[641.08m 353.70m 0m 0m] [242.41m 0m 0m]	31.96m	
	20	[605.22m 309.40m 0m 0m] [368.12m 0m 0m]	42.89m	

From Tables 6 and 7, NNIM-LLA presents a similar behavior with NNIM-BNI concerning the intrinsic mitigation of the measurement differences; although measurement differences affect RMSD values of the NNIM-LLA approximations, a strong correlation between RMSD values and a_{CUD} values of CUD measurements is not observed in the examined suburban and rural cases. Similarly to Table 3 and Figs. 2(a)-(c), a highly fluctuating RMSD trend can be observed when the a_{CUD} of CUD measurements increases in suburban and rural cases. Indeed, with reference to Table 4, the maximum difference between the best RMSD values of the three executions is equal to 70.91m for the suburban case when one hidden layer is assumed (i.e. RMSD of the 1st execution minus the RMSD of the 3rd execution). With reference to Table 6, the maximum RMSD difference between the best values of the 21 different measurement difference cases is equal to 157.10m for the suburban case when one hidden layer is again assumed (i.e. RMSD of the measurement difference case of a_{CUD}=9dB minus the RMSD of the measurement difference case of a_{CUD}=0dB). As the rural case is concerned, the aforementioned maximum differences are equal to 52.63m and 187.72m with reference to Tables 5 and 7, respectively. Therefore, a successful mitigation technique against the measurement differences should be benchmarked through the prism of its performance to reduce the maximum difference between the best values of the 21 different measurement difference cases thus stabilizing the fluctuating behavior of the RMSD values of the NNIM-LLA approximations. Finally, for comparison reasons, the total duration time for preparing both Tables 6 and 7 is equal to 3,505s for the default operation settings B and 21 different measurement difference cases when one hidden layer is assumed. For the time computations of this paper, the used PC consists of an 1.86GHz Intel Pentium with 4GB RAM while the worst case scenario of the preparation of TIM OV LV BPL topology database is applied where the appropriate TIM OV LV BPL topology is prepared per indicative OV LV BPL topology and CUD measurement difference case in compliance with the database representativeness, which is analyzed in [2] for the operation of NNIM-LLA and mentioned in Sec.2.3.

3.3 NNIM-LLA – Default Operation Settings against Measurement Differences

In accordance with [1], the accuracy degree of the TIM OV LV BPL topology database, which is affected by the selection of the applied default operation settings, has significantly improved RMSDs of the branch number approximations of NNIM-BNI. In this paper, default operation settings C, which allow higher accuracy degree of the TIM OV LV BPL topology database in comparison with the one of default operation settings B, are applied in order to improve the performance of NNIM-LLA against the measurement differences. But the higher accuracy degree of the TIM OV LV BPL topology requires higher time duration times of NNIM-LLA that can be a prohibitive task when the required accuracy is set to be very high.

Similarly to Tables 6 and 7, in Table 8, NNIM-LLA gives approximations of the distribution and branch line lengths when the same a_{CUD} values of CUD measurements of

Table 6 are applied given the amplitudes of coupling scheme channel transfer functions contaminated with measurements in dB for the suburban case of Table 1. The same 21×85 measurement difference vector with Tables 6 and 7 is here superimposed to the amplitudes of the coupling scheme channel transfer functions of the suburban case for all the 21 NNIM-LLA approximation cases. Similarly to Table 6, the best RMSD value between the approximated original and symmetrical OV LV topologies and the respective OV LV BPL topology are presented per a_{CUD} value in Table 8. Conversely to Table 6, the default operation settings C are adopted during the preparation of Table 8 instead of the default operation settings B. Table 9 is similar to Table 8 but for the rural case of Table 7. To graphically examine the impact of the default operation settings that support a more elaborate version of the TIM OV LV BPL topology database on the mitigation of the measurement differences, the best RMSD values of the NNIM-LLA approximations (say, the minimum RMSD value between the original and symmetrical approximated OV LV BPL topology given the execution and the number of hidden layers) of Tables 6 and 8 are plotted in Fig. 4(a) with respect to the a_{CUD} of the applied CUD measurements when the default operation settings B and C are assumed, respectively. In Fig. 4(b), the same plot with Fig. 4(a) is given but for the rural case and with respect to Tables 7 and 9.

Table 8
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case and Default Operation Settings C for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the suburban case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1		**Suburban Case**	**RMSD**	**Notes**
Distribution Line Length L =$[L_1 \quad L_2 \quad L_3 \quad 0]$ **Branch Line Length** $\mathbf{L}_\mathrm{b}$ =$[L_{\mathrm{b1}} \quad L_{\mathrm{b2}} \quad 0]$		[500m 400m 100m 0m] [50m 10m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}} =$ $[L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad L_{3,\mathrm{NNIM-LLA}} \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}} =$ $[L_{\mathrm{b1,NNIM-LLA}} \quad L_{\mathrm{b2,NNIM-LLA}} \quad 0]$	$\boldsymbol{a}_{\mathbf{CUD}}$ **of CUD Measurements (dB)**			Default Operation Settings C + 1 hidden layer
	0	[715.32m 71.28m 213.39m 0m] [151.51m 147.17m 0m]	167.50m	
	1	[284.39m 650.09m 65.52m 0m] [156.12m 143.70m 0m]	141.10m	
	2	[687.71m 110.29m 202.00m 0m] [149.84m 144.56m 0m]	150.07m	
	3	[724.46m 62.99m 212.54m 0m] [151.86m 145.33m 0m]	171.26m	
	4	[716.60m 72.80m 210.60m 0m] [153.16m 143.41m 0m]	166.75m	
	5	[282.40m 656.36m 61.24m 0m] [154.76m 149.40m 0m]	143.91m	
	6	[706.15m 81.71m 212.15m 0m] [152.85m 144.42m 0m]	162.58m	
	7	[265.15m 676.45m 58.40m 0m] [157.69m 150.64m 0m]	153.38m	
	8	[720.49m 70.19m 209.32m 0m] [153.10m 144.78m 0m]	168.24m	
	9	[720.59m 67.92m 211.48m 0m] [152.64m 144.57m 0m]	169.03m	

	10	[280.41m 654.99m 64.61m 0m] [156.07m 148.88m 0m]	143.94m	
	11	[283.95m 649.47m 66.58m 0m] [152.87m 146.65m 0m]	141.06m	
	12	[281.65m 659.43m 58.93m 0m] [154.30m 149.01m 0m]	144.85m	
	13	[272.07m 670.23m 57.71m 0m] [156.43m 147.97m 0m]	149.82m	
	14	[700.18m 93.36m 206.46m 0m] [155.07m 148.79m 0m]	158.45m	
	15	[283.23m 653.08m 63.69m 0m] [155.45m 142.52m 0m]	141.94m	
	16	[719.25m 67.76m 212.99m 0m] [151.70m 143.67m 0m]	168.79m	
	17	[280.28m 652.45m 67.27m 0m] [156.30m 148.75m 0m]	143.24m	
	18	[271.65m 670.15m 58.20m 0m] [151.95m 149.16m 0m]	149.58m	
	19	[281.00m 654.80m 64.20m 0m] [155.11m 147.51m 0m]	143.49m	
	20	[270.20m 672.51m 57.29m 0m] [154.15m 147.87m 0m]	150.60m	

Table 9
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case and Default Operation Settings C for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the rural case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1		**Rural Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad 0 \quad 0]$ **Branch Line Length** $\mathbf{L}_{\mathrm{b}}=[L_{\mathrm{b1}} \quad 0 \quad 0]$		[600m 400m 0m 0m] [300m 0m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}}=[L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad 0 \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}}=[L_{\mathrm{b1,NNIM-LLA}} \quad 0 \quad 0]$	$\boldsymbol{a_{\mathrm{CUD}}}$ **of CUD Measurements (dB)**			Default Operation Settings C + 1 hidden layer
	0	[790.25m 189.38m 0m 0m] [202.45m 0m 0m]	113.44m	
	1	[750.59m 225.04m 0m 0m] [223.77m 0m 0m]	91.88m	
	2	[716.01m 283.97m 0m 0m] [191.34m 0m 0m]	74.38m	
	3	[732.49m 267.51m 0m 0m] [261.42m 0m 0m]	72.30m	
	4	[665.20m 334.66m 0m 0m] [11.30m 0m 0m]	114.56m	
	5	[740.38m 245.13m 0m 0m] [145.37m 0m 0m]	98.27m	
	6	[670.96m 329.03m 0m 0m] [126.16m 0m 0m]	75.87m	
	7	[739.60m 260.40m 0m 0m] [322.50m 0m 0m]	75.10m	

	8	[779.41m 220.59m 0m 0m] [121.76m 0m 0m]	117.20m	
	9	[620.96m 379.04m 0m 0m] [655.98m 0m 0m]	135.01m	
	10	[748.68m 251.30m 0m 0m] [94.85m 0m 0m]	111.04m	
	11	[833.91m 164.90m 0m 0m] [170.90m 0m 0m]	134.51m	
	12	[829.14m 166.38m 0m 0m] [142.01m 0m 0m]	137.34m	
	13	[776.44m 223.03m 0m 0m] [95.56m 0m 0m]	122.03m	
	14	[685.64m 93.61m 0m 0m] [50.95m 0m 0m]	152.71m	
	15	[730.21m 269.73m 0m 0m] [93.68m 0m 0m]	104.54m	
	16	[808.70m 313.49m 0m 0m] [94.36m 0m 0m]	115.47m	
	17	[751.79m 248.21m 0m 0m] [46.39m 0m 0m]	125.58m	
	18	[760.09m 235.28m 0m 0m] [95.14m 0m 0m]	116.33m	
	19	[691.35m 358.99m 0m 0m] [153.33m 0m 0m]	67.12m	
	20	[727.00m 202.77m 0m 0m] [165.94m 0m 0m]	102.12m	

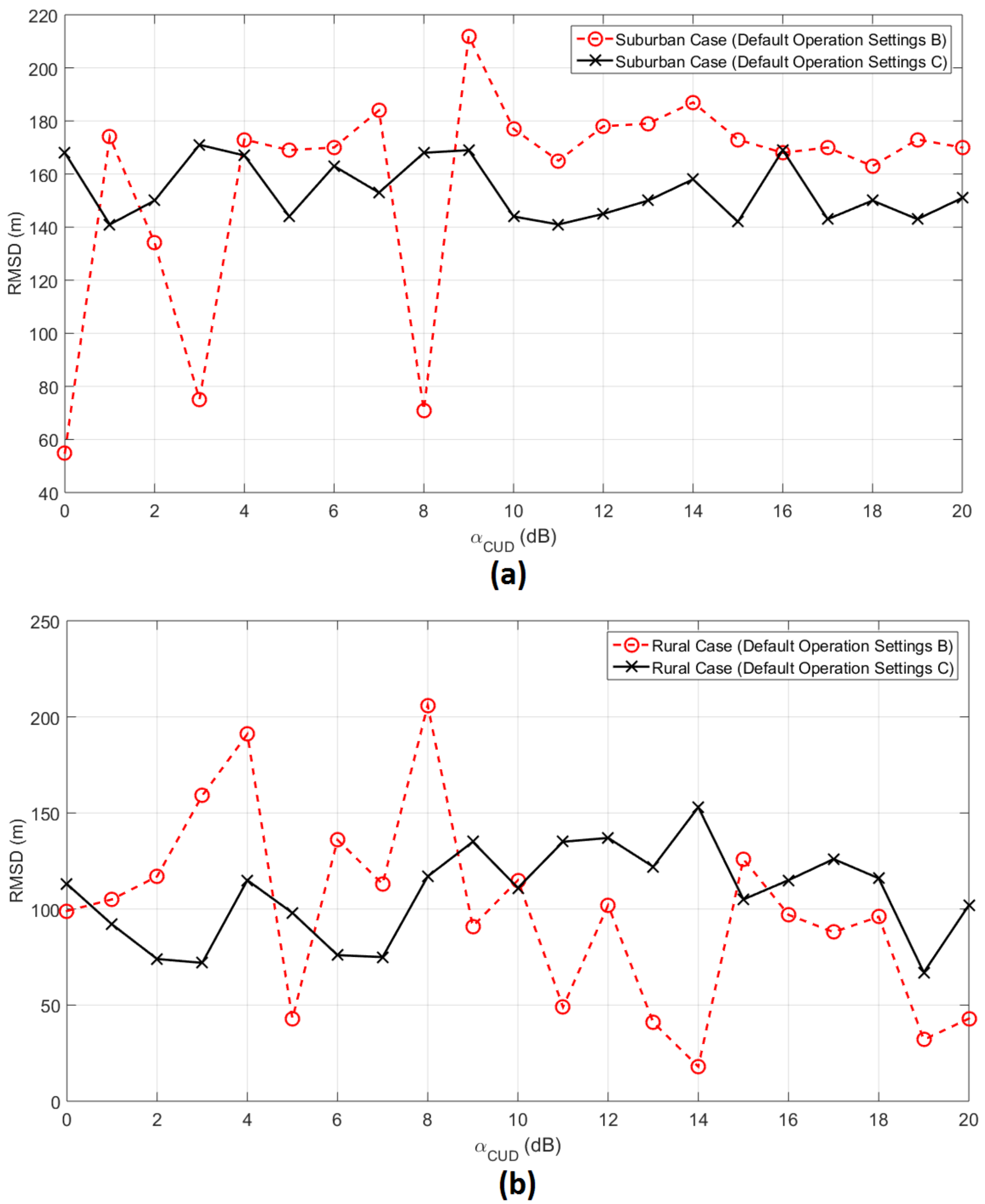


Figure 4. Best RMSD values of NNIM-LLA approximations with respect to a_{CUD} of the applied CUD measurements when the default operation settings B and C are applied and one hidden layer is assumed. (a) Suburban case. (b) Rural case.

Comparing Tables 8 and 9 and examining Figs. 4(a) and 4(b), it is obvious that the adoption of default operation settings that create more elaborate version of the TIM OV LV BPL topology database, such as the default operation settings C of this Section, reduces the mean RMSD of the NNIM-LLA approximations but the aforementioned reduction is constrained by the representativeness of the OV LV BPL topologies in the

TIM OV LV BPL topology databases that remains unaffected either in the suburban case or in rural one [1], [2]. In addition, the default operation settings C critically reduce the fluctuations of NNIM-LLA approximations with respect to a_{CUD} of the applied CUD measurements either in suburban case or in rural one; for the suburban case and with reference to Table 8, the maximum difference between the best values of the 21 different measurement difference cases gets improved from 157.10m to 30.20m when one hidden layer is assumed and the default operation settings B and C are applied, respectively. Similarly, for the rural case and with reference to Table 9, the maximum difference between the best values of the 21 different measurement difference cases gets improved from 187.72m to 85.59m when one hidden layer is assumed and the default operation settings B and C are applied, respectively. As already been mentioned, a trade-off between the improved performance of NNIM-LLA when more elaborate default operation settings are applied and the total duration time of NNIM-LLA simulation occurs; the total duration time for preparing both Tables 8 and 9 increases up to 29,364s in comparison with the total duration time of 3,505s for preparing both Tables 6 and 7.

To validate the beneficial role of the default operation settings C against the CUD measurement differences when various a_{CUD} are applied, the same procedure, which is followed in Table 8, Table 9 and Figure 4 for one hidden layer, is repeated when five hidden layers are applied during the NNIM-LLA approximations. Similarly to Fig. 4(a), the best RMSD values of the NNIM-LLA approximations for the suburban case are plotted in Fig. 5(a) with respect to the a_{CUD} of the applied CUD measurements when the default operation settings B and C are assumed, respectively, and five hidden layers are applied. In Fig. 5(b), the same plot with Fig. 5(a) is given but for the rural case. Note that the same 21×85 measurement difference vector, which is applied across the latter NNIM-LLA approximations, is again used for the NNIM-LLA approximation cases of Figs. 5(a) and 5(b). For the sake of the paper size reduction, the respective Tables to Tables 8 and 9 for preparing Figs. 5(a) and 5(b) are not analytically presented in this subsection.

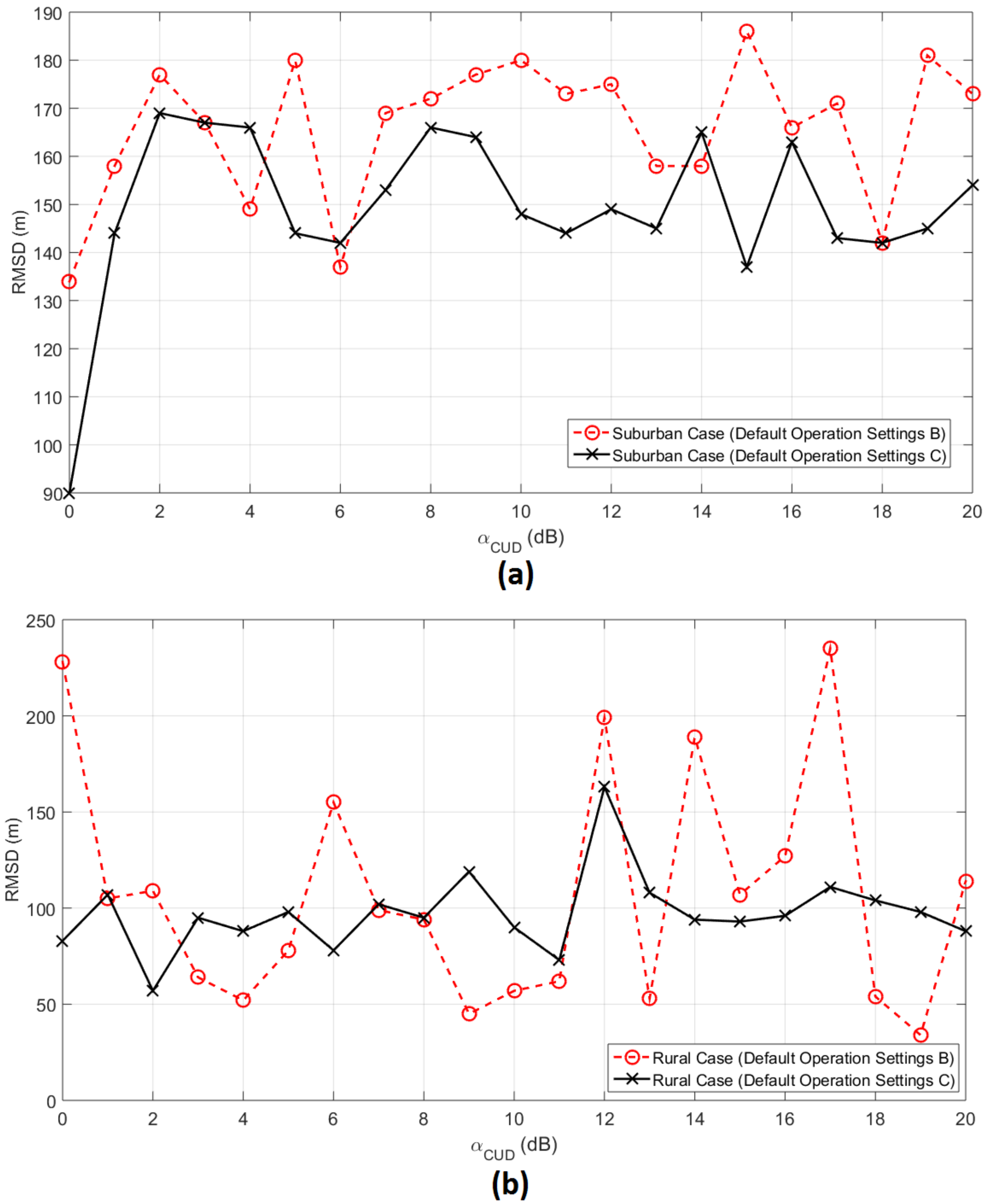


Figure 5. Best RMSD values of NNIM-LLA approximations with respect to a_{CUD} of the applied CUD measurements when the default operation settings B and C are applied and five hidden layers are assumed. (a) Suburban case. (b) Rural case.

Observing Figs. 5(a) and 5(b), the mitigation efficiency of the default operation settings C against CUD measurement differences is again validated in the suburban and rural cases, respectively, when five hidden layers are assumed. Apart from the similar RMSD general image and RMSD values of Figs. 5(a) and 5(b) with the respective Figs. 4(a) and 4(b), the application of the default operation settings C indeed reduces the mean

RMSD and the RMSD fluctuations when compared to the ones of the default operation settings B; for the suburban case of Fig. 5(a), the maximum difference between the best RMSD values of the 21 different measurement difference cases gets improved from 52m to 32m when five hidden layers are assumed and the default operation settings B and C are applied, respectively (note that the best RMSD value of default operation settings C when a_{CUD} is equal to 0dB is excluded during the previous maximum difference computation due to its extremeness). Similarly, for the rural case and with reference to Table 9, the maximum difference between the best values of the 21 different measurement difference cases gets improved from 201m to 106m when five hidden layers are assumed and the default operation settings B and C are applied, respectively. The trade-off between the improved performance of NNIM-LLA and the total time duration time of NNIM-LLA simulation also occurs; the total time duration time for the suburban and rural case plots of Figs. 5(a) and 5(b) when the default operation settings C are applied increases up to 45,556s in comparison with the total duration time of 11,270s for preparing the suburban and rural case plots of Figs. 5(a) and 5(b) when the default operation settings B have been applied. Note that the two improvements of Sec.2.3 that deal with the unacceptable NNIM-LLA approximations of [2] have achieved the elimination of the unacceptable NNIM-LLA approximations in Figs. 5(a) and 5(b) but the increased total duration times of Figs. 5(a) and 5(b) with comparison to the ones of Figs. 4(a) and 4(b) are explained by the fact that the latter total time duration times also include the required repetitions of the MATLAB NN program of [47], [48] that programmatically supports the NNIM-LLA approximations so that the unacceptable NNIM-LLA approximations can be eliminated. Surely, the worst case scenario of the preparation of TIM OV LV BPL topology database per indicative OV LV BPL topology and CUD measurement difference case significantly deteriorates the aforementioned total time duration times thus indicating the significant delays that may be present if more elaborate restrictions concerning the possible database representativeness improvements that may be applied during the preparation of TIM OV LV BPL topology database per examined case. This clearly unveils the need for: (i) smarter countermeasure techniques against measurement differences prior to the application of the MATLAB NN program of NNIM-LLA; and (ii) tailored-made and representative segments of the TIM OV LV BPL database that holds per case groups and not per examined case.

After the previous observations, the companion paper of [52] starts the challenge of searching and adopting of appropriate countermeasure techniques against measurement differences from the literature so that the performance of NNIM-LLA could be improved in terms of their RMSD fluctuations and, at the same time, the mean RMSD gets improved and the total duration time remains close to the total duration time of the default operation setting basis. From the literature, the application of piecewise monotonic data approximation methods, such as L1PMA, L2WPMA and L2CXCV which have theoretically been presented and experimentally verified in [30], [53]-[59] as output module, is assessed as the intermediate module after the DHM module and before the NNIM-LLA module when CUD measurement differences of various a_{CUD} values occur during the operation of the OV LV BPL networks.

5. Conclusions

In this paper, the impact of CUD measurement differences on the performance of NNIM-BNI and NNIM-LLA has been assessed as well as the countermeasure role of the adoption of diverse default operation settings against measurement differences. First, the effect of the presence of CUD measurement differences of various a_{CUD} values has been examined. Both NN methodologies have presented a strong inherent mitigation efficiency against CUD measurement differences and especially those of low a_{CUD} values (i.e., a_{CUD} values lower than approximately 5dB). CUD measurement differences of high a_{CUD} values primarily affect the stability of the NNIM-BNI and NNIM-LLA approximations in terms of their RMSD fluctuations rather than mean RMSD that depends on the accuracy of the applied TIM OV LV BPL topology database and its representativeness. Second, the adoption of default operation settings that allows more elaborate versions of the applied TIM OV LV BPL topology significantly improves the stability of the approximations by reducing the RMSD approximation fluctuations. Hence, the adoption of the aforementioned default operation settings can act as a countermeasure technique in environments where unknown or high CUD measurement differences are observed. However, a trade-off between the accuracy of the applied default operation settings and the total duration time of NNIM-LLA has been revealed. Third, improvements for the finer operation of NN identification methodologies have been examined, such as the BPL topology database representativeness, the BPL topology inclusion into the BPL topology database and the unacceptable approximation elimination technique. The application of more elaborate countermeasure techniques against measurement differences and / or representative segments of the TIM OV LV BPL database should be further investigated so that more accurate and stable NNIM-BNI and NNIM-LLA approximations can occur.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Big Data and Neural Networks in Smart Grid - Part 2: The Impact of Piecewise Monotonic Data Approximation Methods on the Performance of Neural Network Identification Methodology for the Distribution Line and Branch Line Length Approximation of Overhead Low-Voltage Broadband over Powerlines Networks

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The impact of measurement differences that follow continuous uniform distributions (CUDs) of different intensities on the performance of the Neural Network Identification Methodology for the distribution line and branch Line Length Approximation (NNIM-LLA) of the overhead low-voltage broadband over powerlines (OV LV BPL) topologies has been assessed in [1]. When the α_{CUD} values of the applied CUD measurement differences remain low and below 5dB, NNIM-LLA may internally and satisfactorily cope with the CUD measurement differences. However, when the α_{CUD} values of CUD measurement differences exceed approximately 5dB, external countermeasure techniques against the measurement differences are required to be applied to the contaminated data prior to their handling by NNIM-LLA. In this companion paper, the impact of piecewise monotonic data approximation methods, such as L1PMA and L2WPMA of the literature, on the performance of NNIM-LLA of OV LV BPL topologies is assessed when CUD measurement differences of various α_{CUD} values are applied. The key findings that are going to be discussed in this companion paper are: (i) The crucial role of the applied numbers of monotonic sections of the L1PMA and L2WPMA for the overall performance improvement of NNIM-LLA approximations as well as the dependence of the applied numbers of monotonic sections on the complexity of the examined OV LV BPL topology classes; and (ii) the performance comparison of the piecewise monotonic data approximation methods of this paper against the one of more elaborated versions of the default operation settings in order to reveal the most suitable countermeasure technique against the CUD measurement differences in OV LV BPL topologies.

Keywords: Smart Grid; Broadband over Power Lines (BPL) networks; Power Line Communications (PLC); Distribution and Transmission Power Grids; Neural Networks; Big Data; Modeling; Measurements; Piecewise Monotonic Data Approximations

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1. Introduction

The emerging smart grid that is the upgraded version of the traditional power grid is characterized by its intelligent IP-based communications network of two-way information flows, which may further support a plethora of broadband applications [1]-[10]. Among the communications solutions that can be integrated across the smart grid to support the two-way information flows, Broadband over Power Lines (BPL) networks exploit the available wired power grid infrastructure without the need for investing in extra networking cable across the entire equipment. The integration of the BPL networks with the other communications solutions of the smart grid is feasible through the installation and operation of the BPL wireline / wireless interfaces [4], [8], [11].

Deterministic Hybrid Model (DHM), which describes the BPL signal propagation and transmission across the topologies of the overhead low voltage (OV LV) BPL networks [12]-[20], has acted as the channel model basis while artificial intelligence (AI), machine learning (ML) and neural network (NN) features have been concatenated after it in [1]. Indeed, exploiting the available big data of the Topology Identification Methodology (TIM) BPL topology database for the OV LV BPL topologies of [21], [22] and AI - ML - NN functionalities, the neural network identification methodology for the distribution line and branch line length approximation (NNIM-LLA) has been proposed for the OV LV BPL topologies in [23] while its performance has been assessed in [1] when measurement differences of various intensities may occur. In fact, measurement differences between experimental and theoretical OV LV BPL topology channel attenuation values may be observed due to several practical reasons and "real" life conditions, as shown in [22], [24]. In accordance with [1], [22], [24]-[27], a typical scenario to take into account the measurement differences during the BPL topology channel attenuation analysis is their handling as error distributions, such as the Continuous Uniform Distributions (CUDs) of various amplitudes that are superimposed to the coupling scheme transfer function theoretical numerical results from DHM. In [1], NNIM-LLA has been deployed and benchmarked by exploiting the already knowledge and experience of [3], [23], namely: (i) the list of the indicative OV LV BPL topologies; (ii) default operation settings B of [23]; (iii) default operation settings C of [1]; (iv) the assumption of *a priori* knowledge of the number of branches of the examined indicative OV LV BPL topologies in each case (i.e. not-blind NNIM-LLA approximations); (v) the database representativeness, which is analyzed in [23] for the operation of NNIM-LLA; and (vi) the mechanism proposed in [1] against the unacceptable NNIM-LLA approximations of [23]. In accordance with [3], [23], Root-Mean-Square Deviation (RMSD) has been chosen as the performance metric so that the impact of the measurement differences on the NNIM-LLA approximation performance can be evaluated as well as the countermeasure techniques against them. In [1], it has been revealed that NNIM-LLA presents an inherent mitigation efficiency against CUD measurement differences of low a_{CUD} values (i.e., a_{CUD} values that remain lower than 5dB). In contrast, CUD measurement differences of high a_{CUD} values primarily affect the stability of the NNIM-LLA approximations in terms of their RMSD fluctuations rather than mean RMSD approximations. Also, the adoption of more elaborate default operation settings or representative TIM OV LV BPL topology database sets that are applied separately in each simulation case can significantly improve the stability of the approximations by reducing the RMSD approximation fluctuations but the total duration time of NNIM-LLA significantly increases. In [1], it has been recognized that the search and the adoption of appropriate countermeasure techniques against measurement differences, such as: (i) smarter countermeasure techniques against measurement differences prior to the application of the NNIM-LLA module; and (ii) tailored-made and representative segments of the TIM OV LV BPL database that holds per case groups and not per examined case. Among the available countermeasure techniques against measurement differences prior to the application of the NNIM-LLA module, the piecewise monotonic data approximation methods are assessed in this companion paper so as to improve the performance of NNIM-LLA approximations in terms of the RMSD fluctuations, mean RMSD and the total duration time.

From the literature, the application of piecewise monotonic data approximation methods, such as L1PMA and L2WPMA which have theoretically been presented and experimentally verified in [28]-[33], may successfully cope with the measurement differences. In accordance with [25], L1PMA and L2WPMA are formally categorized in the piecewise monotonic data approximations with predefined monotonic sections. L1PMA and L2WPMA have been proposed in [31]-[35] while their performance regarding the mitigation of measurement differences in transmission and distribution BPL networks has been assessed in [22], [24], [25], [27], [28], [36], [37] as output module after the DHM one. Already been identified in [22], [24], [25], [27], [36], the performance of L1PMA and L2WPMA mainly depends on the predefined number of monotonic sections while their best approximation performance against measurement differences is achieved when a specific number of monotonic sections can be identified and applied per measurement difference case. Acknowledging that the right selection of the number of monotonic sections plays the key role during the application of L1PMA and L2WPMA, the findings of [25], [27] concerning the adaptive number of monotonic sections during the operation of L1PMA and L2WPMA are going to be checked in this companion paper. Hence, the piecewise monotonic data approximation module (PMDAM), which consists of either L1PMA or L2WPMA, is concatenated after the DHM module but before the NNIM-LLA one in this companion paper. NNIM-LLA performance against CUD measurement differences is going to be assessed in terms of RMSD fluctuations, mean RMSD and total duration time when the PMDAM is added. Useful conclusions are expected through the comparison of RMSD fluctuations, mean RMSD and total duration time achieved by L1PMA and L2WPMA with the respective ones of [1], say, achieved by the application of default operation settings B (default operation settings basis) and default operation settings C.

The rest of this companion paper is organized as follows: Section 2 briefly presents L1PMA and L2WPMA as well as their integration in the NNIM-LLA operation through the PMDAM and DHM. In Section 3, the numerical results regarding the impact of measurement differences on the approximation performance of NNIM-LLA are given. The mitigation role of the three scenarios against the CUD measurement differences is assessed in terms of the RMSD fluctuations, mean RMSD and NNIM-LLA total duration time. Section 4 concludes this companion paper.

2. PMDAM

In this Section, the adoption of L1PMA and L2WPMA is detailed under the aegis of the PMDAM. As the PMDAM is considered as a countermeasure technique module against the CUD measurement differences of [1], its location across the NNIM-LLA operation flowchart stands right after the theoretical coupling scheme channel transfer function results of DHM that are contaminated by CUD measurement differences (say, measured coupling scheme channel transfer function results) for given examined OV LV BPL topology. Depending on the applied piecewise monotonic data approximation method of PMDAM, PMDAM input is the aforementioned measured coupling scheme channel transfer function results while PMDAM output is the respective approximated coupling scheme channel transfer function results, which are ideally equal to the theoretical coupling scheme channel transfer function results of the examined OV LV BPL topology [22], [24], [25], [27], [28], [36]. Practically, instead of the measured coupling scheme channel transfer function results of the examined OV LV BPL topology, NNIM-LLA receives as input the respective approximated coupling scheme channel transfer function results without affecting the applied representative sets of the TIM OV LV BPL topology database and the operation of the MATLAB NN program of [38], [39], which programmatically supports the fully connected NN architecture of Figure 2 of [3] as well as the involved training, validation and testing phases. The efficient performance of piecewise monotonic data approximations entails lower RMSD fluctuations that ideally tend to zero. As the total duration time is concerned, the representative sets of the TIM OV LV BPL topology database are prepared per each examined case and the default operation settings B are assumed as the default operation settings basis, it is expected that the total duration time after the application of piecewise monotonic data approximation methods as countermeasure technique against the CUD measurement differences of [1] remains closer to the one after the application of default operation settings B rather than the one of default operation settings C. In the following two subsections, a brief presentation of L1PMA and L2WPMA is given.

2.1 L1PMA

L1PMA is the first one of the two piecewise monotonic data approximations supported by PMDAM in this companion paper. L1PMA is going to exploit the piecewise monotonicity property of the theoretical coupling scheme channel transfer function results of DHM by decomposing the previous results into separate monotonous sections between their adjacent turning points (primary extrema) for given OV LV BPL topology [28], [32], [33], [36]. Aiming at minimizing the moduli sum of the CUD measurement differences, L1PMA is going to mitigate the uncorrelated measurement differences by neglecting the existence of few large ones [28]. A detailed analysis concerning the extensive application of L1PMA to transmission and distribution BPL networks is given in [22], [24], [25], [27], [28], [36], [40]. Already been reported for PMDAM, L1PMA receives as inputs the measured coupling scheme channel transfer function results of the examined OV LV BPL topology, the measurement frequencies and the number of monotonic sections (i.e., either user- or computer-defined) and gives as output the best fit of the measured OV MV BPL coupling transfer function results; say, the respective L1PMA approximated coupling scheme channel transfer function results. Note that the measurement frequencies and the findings concerning the applied number of monotonic sections, which have been presented in [40] and treat with the application of L1PMA to OV LV BPL topologies, are going to be exploited in this companion paper.

2.2 L2WPMA

L2PMA is the second one of the two piecewise monotonic data approximations supported by PMDAM in this companion paper. In accordance with [37] and similarly to L1PMA of Sec.2.1, L2WPMA is going to decompose the examined input data of the measured coupling scheme channel transfer function of the examined OV LV BPL topology into separate monotonous sections between its primary extrema [25], [35], [36]. Apart from the measured data, L2WPMA software receives as input the measurement frequencies and the number of monotonic sections, similarly to L1PMA, and gives as output a spline representation of the measured data. Conversely to L1PMA, L2WPMA focuses on the first divided of the input measured data by demanding the minimization of the weighted sum of the square of the measurement differences via the constraint of specific number of sign changes [25], [27], [35], [36]. The number of sign changes is equal to the number of monotonic sections minus one where the number of monotonic sections is either user- or computer-defined in a similar way to L1PMA.

3. Numerical Results and Discussion

In this Section, the mitigation role of the piecewise monotonic data approximations, say, L1PMA and L2WPMA, against the CUD measurement differences of different intensities is investigated. In fact, the default operation settings that are adopted in this companion and remain almost identical to the ones of the original paper of [1] are initially detailed. The small differences in default operation settings B (basis) and default operation settings C are due to the restrictions in software use of L1PMA and L2WPMA. Then, the L1PMA and L2WPMA of different number of monotonic sections, in compliance with the findings of [25], [27], are deployed against the CUD measurement differences of different intensities. The results of the application of the piecewise monotonic data approximations of PMDAM of this companion paper are presented and discussed in terms of the RMSD approximation fluctuations and the total duration time of NNIM-LLA when are compared against the results produced by the simple application of the default operation settings B (basis) and default operation settings C.

3.1 Default Operation Settings

According to [1], the default operation settings define the values of the maximum number of branches $N_{\max}$, the length spacing L_{s} for both the branch distance and the branch length, the maximum branch length $L_{\mathrm{b,max}}$ and the operation frequency range that are anyway essential factors for the five fields of TIM OV LV BPL topology database that are used during the operation of NNIM-LLA. As the maximum number of branches, the length spacing and the maximum branch length are concerned, these remain the same when the default operation settings B and C are applied in this companion paper. However, in order to comply with the requirement of the Fortran software that supports the piecewise monotonic data approximations of this companion paper [33], [35], small changes are required in the frequency range and the flat-fading subchannel frequency spacing; say, the BPL frequency range and flat-fading subchannel frequency spacing are assumed equal to 1-30MHz and 1MHz, respectively, in [25], [36]. To prevent the misunderstanding of the results of the following subsections with the results of the original paper, default operation settings B’ and C’ are denoted hereafter for the default operation settings B and C of [1], respectively.

Except for the previous default operation settings, the following assumptions of [1] are also taken into account in this companion paper, namely: (i) The number of branches of the examined indicative OV LV BPL topologies (say, suburban and rural cases of Table 1 of [1]) is assumed to be known; (ii) the database representativeness, which is analyzed in [23] for the operation of NNIM-LLA, is assumed during the application of the default operation settings B' and C'; (iii) the exclusion of the symmetrical OV LV BPL topologies from the OV LV BPL topology database so as not to disrupt the approximations due to the symmetry of BPL topologies described in [41], [42]; (iv) the inclusion of the examined suburban and rural cases into the TIM OV LV BPL topology database; and (v) the mechanism described in [1] for preventing the unacceptable NNIM-LLA approximations of [23] (i.e., at least one of the approximated distribution and branch line lengths is below zero given the fixed length of 1000m between the transmitting and receiving ends for all the applied OV LV BPL topologies).

Finally, it should be noted that the default participation percentages of the three phases of NNIM-based methodologies of [3], [23], [38], [39] are assumed in this paper; say, training, validation and testing phases during the operation of NNIM-LLA are assumed to be equal to 70%, 15% and 15%, respectively.

3.1.1 Default Operation Settings B'

As the impact of CUD measurement differences on the performance of NNIM-LLA is investigated, similarly to Table 6 of [1], in Table 1, given the amplitudes of coupling scheme channel transfer functions contaminated with measurements in dB for the suburban case, NNIM-LLA gives as output its respective approximations of the distribution and branch line lengths when various a_{CUD} values of CUD measurements are assumed. Conversely to Table 6 of [1], note that one $1 \times Q = 1 \times (30-1) = 1 \times 29$ measurement difference line vector for each a_{CUD} value that ranges from 0dB to 20dB is superimposed to the amplitudes of the coupling scheme channel transfer functions of the suburban case for the respective NNIM-LLA approximation cases. Also, the best RMSD value between the approximated original and symmetrical OV LV topologies and the respective OV LV BPL topology are presented per a_{CUD} value in Table 1. Table 2 is similar to Table 1 but for the rural case. Note that the same 21×29 measurement difference vector with Table 1 is here superimposed to the amplitudes of the coupling scheme channel transfer functions of the rural case for all the examined NNIM-LLA approximation cases. In Tables 1 and 2, the default operation settings B' are applied when one hidden layer is assumed during the NNIM-LLA simulations, as analyzed in [1].

From Tables 1 and 2, the fluctuating RMSD value trend that is not directly correlated with the examined a_{CUD} values, which has first been observed in [1], is also seen in this companion paper when different a_{CUD} values for the CUD measurements are applied in the suburban and rural cases. Indeed, with reference to Table 1, the maximum RMSD difference between the best values for the suburban case is equal to 137.95m when one hidden layer is assumed and a_{CUD} values range from 1dB to 20dB. As the rural case is concerned in Table 2, maximum RMSD difference between the best values is equal to 127.26m when one hidden layer is assumed and a_{CUD} values range from 1dB to 20dB. Note that the respective maximum RMSD difference of Tables 6 and 7 in [1] was equal to 157.10m.and 187.72m for the suburban and rural cases, respectively, when a_{CUD} values range from 0dB to 20dB. Similarly to [1], the intrinsic mitigation characteristic of

Table 1
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case and Default Operation Settings B' for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the suburban case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		**Suburban Case**	**RMSD**	**Notes**
Distribution Line Length L =[L_1 L_2 L_3 0] **Branch Line Length $\mathbf{L}_{\mathrm{b}}$** =[L_{b1} L_{b2} 0]		[500m 400m 100m 0m] [50m 10m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}}$ = [$L_{1,\mathrm{NNIM-LLA}}$ $L_{2,\mathrm{NNIM-LLA}}$ $L_{3,\mathrm{NNIM-LLA}}$ 0] **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}}$ = [$L_{\mathrm{b1,NNIM-LLA}}$ $L_{\mathrm{b2,NNIM-LLA}}$ 0]	**a_{CUD} of CUD Measurements (dB)**			Default Operation Settings B' + 1 hidden layer
	0	[36]4.46m 72.13m 213.41m 0m] [148.890m 147.42m 0m]	166.91m	
	1	[213.23m 731.29m 55.49m 0m] [171.73m 135.05m 0m]	179.06m	
	2	[405.62m 491.25m 103.13m 0m] [157.74m 147.86m 0m]	82.68m	
	3	[224.99m 717.42m 57.59m 0m] [169.55m 150.48m 0m]	174.11m	
	4	[213.40m 736.27m 50.33m 0m] [157.45m 120.47m 0m]	177.86m	
	5	[721.98m 65.59m 212.43m 0m] [147.66m 137.09m 0m]	168.79m	
	6	[706.71m 80.54m 212.75m 0m] [164.17m 172.26m 0m]	167.70m	
	7	[147.59m 830.84m 21.53m 0m] [143.29m 136.76m 0m]	220.63m	
	8	[744.82m 33.54m 221.64m 0m] [162.64m 151.99m 0m]	185.88m	
	9	[700.03m 103.25m 196.72m 0m] [156.13m 147.66m 0m]	154.75m	
	10	[701.72m 97.38m 200.90m 0m] [135.33m 141.61m 0m]	154.48m	
	11	[666.52m 134.99m 198.50m 0m] [152.01m 141.36m 0m]	139.04m	
	12	[618.06m 201.75m 180.19m 0m] [161.76m 153.20m 0m]	115.06m	
	13	[231.12m 708.62m 60.26m 0m] [158.41m 129.19m 0m]	166.94m	
	14	[708.95m 83.73m 0m] [151.95m 153.28m 0m]	163.06m	
	15	[267.66m 159.70m 174.12m 0m] [301.11m 165.48m 0m]	170.90m	
	16	[690.06m 118.57m 191.37m 0m] [132.96m 149.55m 0m]	146.40m	
	17	[162.82m 818.26m 18.85m 0m] [127.85m 128.08m 0m]	212.21m	
	18	[677.14m 132.21m 190.65m 0m] [145.84m 144.05m 0m]	140.64m	
	19	[36]9.34m 64.14m 216.52m 0m] [158.07m 139.60m 0m]	170.28m	

	20	[214.14m 739.62m 46.24m 0m] [166.20m 141.49m 0m]	181.56m	

Table 2
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case and Default Operation Settings B' for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the rural case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		**Rural Case**	**RMSD**	**Notes**
Distribution Line Length L =[L_1 L_2 0 0] **Branch Line Length $\mathbf{L}_\mathrm{b}$** =[L_{b1} 0 0]		[600m 400m 0m 0m] [300m 0m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}} = [L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad 0 \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}} = [L_{\mathrm{b1,NNIM-LLA}} \quad 0 \quad 0]$	**a_{CUD} of CUD Measurements (dB)**			Default Operation Settings B' + 1 hidden layer
	0	[36]1.15m 288.85m 0m 0m] [167.16m 0m 0m]	77.78m	
	1	[700.35m 299.69m 0m 0m] [18.16m 0m 0m]	119.26m	
	2	[628.82m 255.02m 0m 0m] [320.21m 0m 0m]	56.39m	
	3	[732.97m 267.31m 0m 0m] [157.15m 0m 0m]	89.20m	
	4	[582.56m 417.44m 0m 0m] [29.11m 0m 0m]	102.81m	
	5	[678.36m 320.46m 0m 0m] [135.46m 0m 0m]	75.16m	
	6	[824.04m 382.54m 0m 0m] [181.65m 0m 0m]	96.00m	
	7	[548.71m 318.94m 0m 0m] [62.44m 0m 0m]	96.83m	
	8	[635.77m 281.28m 0m 0m] [80.30m 0m 0m]	95.35m	
	9	[780.97m 218.95m 0m 0m] [356.41m 0m 0m]	99.08m	
	10	[630.51m 346.01m 0m 0m] [483.88m 0m 0m]	73.35m	
	11	[888.77m 119.76m 0m 0m] [193.03m 0m 0m]	157.37m	
	12	[700.03m 300.01m 0m 0m] [208.74m 0m 0m]	63.62m	
	13	[748.51m 251.49m 0m 0m] [106.72m 0m 0m]	107.88m	
	14	[700.61m 275.78m 0m 0m] [143.78m 0m 0m]	84.48m	
	15	[741.43m 258.36m 0m 0m] [158.01m 0m 0m]	92.76m	
	16	[904.25m 95.90m 0m 0m] [74.08m 0m 0m]	183.65m	
	17	[720.42m 512.40m 0m 0m] [309.69m 0m 0m]	62.37m	

	18	[800.02m 223.20m 0m 0m] [158.85m 0m 0m]	114.14m	
	19	[524.16m 507.58m 0m 0m] [614.82m 0m 0m]	128.97m	
	20	[737.50m 262.50m 0m 0m] [150.00m 0m 0m]	92.82m	

NNIM-LLA against the measurement differences is more affected by the TIM OV LV BPL topology database representativeness in terms of the topology characteristics rather than the accuracy of the assumed frequency range. The latter observation is verified by the comparable maximum RMSD differences between the best values when the two different frequency range of 3-88MHz of [1] and 1-30MHz of this companion paper are assumed for the suburban and rural cases of Tables 1 and 2, respectively. As the mean RMSD values of Tables 1 and 2 are concerned for the a_{CUD} values that range from 1dB to 20dB, these are equal to 163.60m and 99.57m for the suburban and rural case, respectively. Note that the total duration time for preparing both Tables 1 and 2 is equal to 1,342s for the default operation settings B' of the frequency range of 1-30MHz while the respective total duration time for the default operation settings B of the frequency range of 3-88MHz was equal to 3,505s as reported in [1]. The previous total duration time difference is mainly due to the operation of the MATLAB NN program of [38], [39] that programmatically supports the fully connected NN architecture of NNIM-LLA as well as the involved training, validation and testing phases.

3.1.2 Default Operation Settings C'

In accordance with [1], the higher accuracy degree of the TIM OV LV BPL topology database, which is affected by the adoption of the default operation settings C, has significantly improved the RMSD fluctuations by reducing the maximum RMSD differences of the NNIM-LLA approximations when the a_{CUD} values range from 1dB to 20dB. Also, the default operation settings C has slightly improved mean RMSD values for given examined indicative OV LV BPL topology. But the adoption of the default operation settings C entailed higher duration times of NNIM-LLA in [1] when the preparation of the TIM OV LV BPL topology database is made from the beginning in each examined case.

Similarly to Table 1, NNIM-LLA gives approximations of the distribution and branch line lengths in Table 4 when the default operation settings C' are adopted and the same a_{CUD} values of CUD measurements of Table 1 are assumed. The same 21×29 measurement difference vector with Tables 1 and 2 is here superimposed to the amplitudes of the coupling scheme channel transfer functions of the suburban case for all the 21 NNIM-LLA approximation cases. Similarly to Table 1, the best RMSD value between the approximated original and symmetrical OV LV topologies and the respective OV LV BPL topology are presented per a_{CUD} value in Table 3. Table 4 is similar to Table 3 but for the rural case.

Table 3
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case and Default Operation Settings C' for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the suburban case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		Suburban Case	RMSD	Notes
Distribution Line Length L =[L_1 L_2 L_3 0] **Branch Line Length $\mathbf{L}_\mathrm{b}$** =[L_{b1} L_{b2} 0]		[500m 400m 100m 0m] [50m 10m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}}$ = [$L_{1,\mathrm{NNIM-LLA}}$ $L_{2,\mathrm{NNIM-LLA}}$ $L_{3,\mathrm{NNIM-LLA}}$ 0] **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}}$ = [$L_{\mathrm{b1,NNIM-LLA}}$ $L_{\mathrm{b2,NNIM-LLA}}$ 0]	**a_{CUD} of CUD Measurements (dB)**			Default Operation Settings C' + 1 hidden layer
	0	[627.845m 189.99m 182.16m 0m] [147.73m 140.07m 0m]	115.68m	
	1	[573.93m 265.68m 160.39m 0m] [158.32m 147.37m 0m]	90.83m	
	2	[630.92m 189.36m 179.72m 0m] [148.02m 139.35m 0m]	116.01m	
	3	[567.68m 270.96m 161.36m 0m] [156.08m 149.47m 0m]	89.20m	
	4	[234.82m 724.03m 41.16m 0m] [125.29m 111.39m 0m]	166.79m	
	5	[303.84m 620.03m 76.12m 0m] [135.79m 127.45m 0m]	124.57m	
	6	[567.25m 272.78m 159.97m 0m] [157.14m 149.64m 0m]	88.87m	
	7	[571.01m 266.27m 162.71m 0m] [156.06m 146.84m 0m]	90.10m	
	8	[223.63m 731.26m 45.11m 0m] [168.40m 159.68m 0m]	179.50m	
	9	[575.78m 259.46m 164.76m 0m] [148.27m 138.48m 0m]	89.33m	
	10	[239.14m 711.14m 49.72m 0m] [128.35m 122.70m 0m]	163.11m	
	11	[569.29m 266.80m 163.91m 0m] [156.69m 148.66m 0m]	90.43m	
	12	[567.31m 272.21m 160.48m 0m] [157.04m 149.03m 0m]	88.89m	
	13	[569.82m 269.94m 160.24m 0m] [159.05m 150.65m 0m]	90.31m	
	14	[572.51m 263.54m 163.95m 0m] [153.36m 144.36m 0m]	90.00m	
	15	[272.11m 665.07m 62.82m 0m] [126.67m 117.14m 0m]	141.89m	
	16	[629.36m 189.32m 181.31m 0m] [146.02m 142.22m 0m]	116.15m	
	17	[569.76m 269.09m 161.15m 0m] [157.22m 149.08m 0m]	89.91m	
	18	[566.49m 273.58m 159.93m 0m] [156.31m 149.37m 0m]	88.42m	
	19	[632.95m 188.14m 178.91m 0m] [147.73m 142.46m 0m]	117.03m	

	20	[210.58m 743.53m 45.89m 0m] [145.86m 130.88m 0m]	180.68m	

Table 4
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case and Default Operation Settings C' for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the rural case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		**Rural Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad 0 \quad 0]$ **Branch Line Length** $\mathbf{L}_{\mathrm{b}}=[L_{\mathrm{b1}} \quad 0 \quad 0]$		[600m 400m 0m 0m] [300m 0m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}}=[L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad 0 \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}}=[L_{\mathrm{b1,NNIM-LLA}} \quad 0 \quad 0]$	$\boldsymbol{a_{\text{CUD}}}$ **of CUD Measurements (dB)**			Default Operation Settings C' + 1 hidden layer
	0	[726.55m 251.36m 0m 0m] [108.88m 0m 0m]	103.26m	
	1	[748.48m 251.54m 0m 0m] [346.36m 0m 0m]	81.27m	
	2	[793.83m 206.16m 0m 0m] [202.98m 0m 0m]	109.91m	
	3	[767.26m 246.89m 0m 0m] [154.48m 0m 0m]	101.84m	
	4	[735.21m 277.30m 0m 0m] [116.69m 0m 0m]	97.79m	
	5	[373.28m 605.60m 0m 0m] [16.22m 0m 0m]	157.75m	
	6	[730.68m 269.01m 0m 0m] [180.13m 0m 0m]	83.33m	
	7	[772.27m 227.73m 0m 0m] [204.96m 0m 0m]	98.84m	
	8	[627.09m 421.38m 0m 0m] [155.14m 0m 0m]	56.29m	
	9	[694.73m 302.17m 0m 0m] [175.22m 0m 0m]	69.81m	
	10	[706.80m 296.86m 0m 0m] [157.79m 0m 0m]	77.705m	
	11	[733.03m 266.97m 0m 0m] [41.41m 0m 0m]	120.87m	
	12	[795.07m 204.92m 0m 0m] [339.34m 0m 0m]	105.33m	
	13	[788.62m 206.09m 0m 0m] [162.14m 0m 0m]	114.76m	
	14	[605.60m 373.28m 0m 0m] [16.22m 0m 0m]	107.75m	
	15	[654.23m 374.86m 0m 0m] [149.29m 0m 0m]	61.28m	
	16	[764.86m 235.14m 0m 0m] [125.68m 0m 0m]	110.03m	
	17	[674.54m 276.29m 0m 0m] [53.44m 0m 0m]	108.00m	

	18	[27]2.63m 317.37m 0m 0m] [441.75m 0m 0m]	69.44m	
	19	[877.89m 276.24m 0m 0m] [191.15m 0m 0m]	122.12m	
	20	[737.27m 258.02m 0m 0m] [152.23m 0m 0m]	93.22m	

According to [1], the adoption of default operation settings that create more elaborate versions of the TIM OV LV BPL topology database, such as the default operation settings C' of this Section against the default operation settings B' of Sec.3.1.1, improves the NNIM-LLA approximation performance but the preparation of the TIM OV LV BPL topology database, which is assumed in [1] and this companion paper, entails prohibitive total duration times when even more elaborate default operation settings need to be assumed. With reference to Table 3, the maximum RMSD difference between the best values for the suburban case is equal to 92.26m when the default operation settings C' are applied, one hidden layer is assumed and a_{CUD} values range from 1dB to 20dB while the respective maximum RMSD difference between the best values is equal to 137.95m when the default operation settings B' has been applied in Table 1. Similarly to the suburban case, as the rural case is concerned in Table 4, maximum RMSD difference between the best values is equal to 93.71m when the default operation settings C' are applied, one hidden layer is assumed and a_{CUD} values range from 1dB to 20dB while the respective maximum RMSD difference between the best values is equal to 127.26m when the default operation settings B' has been applied in Table 2. Apart from the maximum RMSD difference between the best values, the default operation settings C' also improve the mean RMSD metrics; say, the mean RMSDs between the best values for the suburban case of Table 3 and rural case of Table 4 are equal to 114.60m and 96.98m, respectively, when the default operation settings C' are applied, one hidden layer is assumed and a_{CUD} values range from 1dB to 20dB while the respective mean RMSDs of Tables 1 and 2 are equal to 163.60m and 99.57m when the default operation settings B' has been applied. Therefore, it is evident that the adoption of more elaborate default operation settings is a fine countermeasure technique against the measurement differences of various a_{CUD} values that anyway enhances the intrinsic mitigation characteristics of NNIM-LLA. However, the slight positive impact of the elaborate default operation settings on the RMSD metrics is explained by the representativeness of the OV LV BPL topologies in the TIM OV LV BPL topology databases that remains unaffected either in the suburban case or in rural one [1], [3], [23]. Note that the total duration time for preparing both Tables 3 and 4 is equal to 10,048s for the default operation settings C' of the frequency range of 1-30MHz while the respective total duration time for the default operation settings C of the frequency range of 3-88MHz was equal to 29,364s as reported in [1]. Again, similarly to the default operation settings C and B of [1], the total duration time for preparing both Tables 3 and 4 is increased by approximately three times in comparison with the total duration time for preparing both Tables 1 and 2 and this is clearly due to the operation of the NNIM-LLA as well as the involved training, validation and testing phases.

3.2 L1PMA and L2WPMA of PMDAM

Already been identified in [22], [24], [25], [27], [36], the mitigation performance of L1PMA and L2WPMA against measurement differences mainly depends on the predefined number of monotonic sections. In accordance with [25], [27], different numbers of monotonic sections can be applied depending on the examined BPL topology class and the applied a_{CUD} value when deterministic and statistic systems are examined. Here, the mitigation performance of L1PMA and L2WPMA against measurement differences is assessed when the measurement differences of various a_{CUD} values are applied and default operation settings B' are assumed but PMDAM, which consists of piecewise monotonic data approximations, precedes the NNIM-LLA module. Except for the mitigation performance, the total duration time of the integration of the default operation settings B', PMDAM and NNIM-LLA is compared against the total duration time of the operation of the default operation settings C' and NNIM-LLA.

As the effect of the number of monotonic sections is investigated in L1PMA, in Table 5, the maximum RMSD difference between the best values and mean RMSD for the suburban case is reported per monotonic section, which ranges from 1 to 20, when L1PMA is applied and a_{CUD} values of measurement differences range from 1dB to 20dB. In Table 6, similar approximation performance metrics are given but for the rural case. Note that the same measurement difference vector with Tables 1 and 2 is here superimposed to the amplitudes of the coupling scheme channel transfer functions of the suburban and rural cases for all the NNIM-LLA approximation cases. Apart from the aforementioned approximation performance metrics, for comparison reason, the maximum RMSD difference between the best values and mean RMSD are reported when the default operation settings B' and C' are applied in each examined case.

In Tables 5 and 6, the maximum RMSD difference between the best values and the mean RMSD that are lower than the respective values of the default operation settings B' per case are shown in green color while the cases with the lowest maximum RMSD difference between the best values are highlighted in yellow color. As the suburban case of Table 5 is concerned, L1PMA mainly helps towards the improvement of mean RMSD rather than of the maximum RMSD difference between the best values while the opposite holds in the rural case of Table 6. In accordance with [25], [27], the careful selection of the number of monotonic sections is critical for achieving the measurement difference mitigation and this number primarily depends on the examined BPL topology complexity; say, for the suburban and rural cases, 20 and 6 monotonic sections have been respectively applied in [25], [27]. Due to the higher complexity of the suburban case concerning the number of the branches, higher number of monotonic sections is here required in contrast with the rural case. Indeed, with reference to Tables 5 and 6, 10 and 6 monotonic sections achieve the lowest maximum RMSD difference between the best values for the suburban and rural case, respectively; the previous values for the monotonic sections agree with the concept presented in [25], [27].

Table 5
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case and Default Operation Settings B' for Different L1PMA Numbers of Monotonic Sections when a_{CUD} Values of CUD Measurements range from 1dB to 20dB

L1PMA Number of Monotonic Sections	**Maximum RMSD Difference between the Best Values (m)** **(Default Operation Settings B': 137.95m)** **(Default Operation Settings C': 92.26m)**	**Mean RMSD (m)** **(Default Operation Settings B': 163.60m)** **(Default Operation Settings C': 114.60m)**
1	209.74	166.42
2	213.38	163.84
3	133.41	164.72
4	186.07	180.41
5	186.82	153.33
6	146.45	173.01
7	335.68	156.29
8	202.05	147.61
9	217.04	159.22
10	132.31	158.89
11	193.60	163.39
12	143.01	165.39
13	174.36	158.81
14	188.72	150.15
15	170.42	164.38
16	550.68	203.93
17	191.52	148.08
18	190.31	155.58
19	148.37	157.85
20	180.33	166.42

Table 6
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case and Default Operation Settings B' for Different L1PMA Numbers of Monotonic Sections when a_{CUD} Values of CUD Measurements range from 1dB to 20dB

L1PMA Number of Monotonic Sections	**Maximum RMSD Difference between the Best Values (m)** **(Default Operation Settings B': 127.26m)** **(Default Operation Settings C': 93.71m)**	**Mean RMSD (m)** **(Default Operation Settings B': 99.57m)** **(Default Operation Settings C': 96.98m)**
1	100.24	95.82
2	116.38	97.78
3	252.16	100.47
4	178.65	106.13
5	237.15	89.21
6	94.16	101.73
7	128.24	101.48
8	217.56	105.02
9	189.85	99.59
10	224.98	115.85

11	98.55	102.35
12	120.74	90.33
13	145.04	87.71
14	181.69	103.53
15	145.69	98.98
16	181.15	104.00
17	120.28	103.75
18	116.41	104.33
19	114.11	93.58
20	144.43	95.82

Similarly to Tables 1 and 3, NNIM-LLA gives approximations of the distribution and branch line lengths of the suburban case in Table 7 when the default operation settings B' are adopted, L1PMA of PMDAM with 10 monotonic sections is activated prior to the NNIM-LLA and the same a_{CUD} values of CUD measurements of Tables 1 and 3 are assumed. Also, the best RMSD value between the approximated original and symmetrical OV LV topologies and the respective OV LV BPL suburban topology are presented per a_{CUD} value. Table 8 is similar to Table 7 but for the rural case when L1PMA of PMDAM with 6 monotonic sections is activated.

From Tables 7 and 8, it is verified that the L1PMA application may allow better mitigation performance of the measurement differences in comparison with the performance of only applying default operation settings B' but a careful selection of monotonic sections is required, which is anyway a difficult task when NN algorithms follow the PMDAM operation. Conversely, the L1PMA application does not achieve better mitigation performance of the measurement differences in comparison with the performance of only applying default operation settings C'. But, it should be noted that the total duration time for preparing both Tables 7 and 8 is equal to 1416s when L1PMA and default operation settings B' are adopted that is anyway significantly lower than 10,048s of preparing the respective Tables 3 and 4 when the default operation settings C' are adopted.

Table 7
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case, Default Operation Settings B' and L1PMA of 10 Monotonic Sections for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the suburban case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		**Suburban Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad L_3 \quad 0]$ **Branch Line Length** $\mathbf{L}_b=[L_{b1} \quad L_{b2} \quad 0]$		[500m 400m 100m 0m] [50m 10m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}}=[L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad L_{3,\mathrm{NNIM-LLA}} \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}}=[L_{\mathrm{b1,NNIM-LLA}} \quad L_{\mathrm{b2,NNIM-LLA}} \quad 0]$	$\boldsymbol{a_{\mathrm{CUD}}}$ **of CUD Measurements (dB)**			Default Operation Settings B' + 1 hidden layer +L1PMA (10 monotonic sections)
	0	[36]1.25m 92.91m 195.84m 0m] [146.14m 139.60m 0m]	157.73m	
	1	[721.59m 70.38m 208.02m 0m] [168.39m 171.17m 0m]	172.96m	
	2	[36]6.27m 78.62m 205.11m 0m] [151.49m 148.70m 0m]	165.03m	
	3	[750.48m 34.69m 214.82m 0m] [151.82m 149.2m 0m]	184.82m	
	4	[700.04m 99.81m 200.14m 0m] [143.47m 141.51m 0m]	154.08m	
	5	[701.93m 100.58m 197.49m 0m] [139.43m 143.54m 0m]	153.89m	
	6	[36]7.19m 71.79m 211.02m 0m] [145.24m 154.62m 0m]	167.84m	
	7	[211.77m 728.54m 59.69m 0m] [155.44m 152.73m 0m]	178.94m	
	8	[36]4.05m 37.94m 248.01m 0m] [34.47m 54.02m 0m]	169.45m	
	9	[731.75m 59.54m 208.71m 0m] [156.03m 157.09m 0m]	174.98m	
	10	[223.17m 724.06m 52.79m 0m] [155.63m 139.29m 0m]	173.93m	
	11	[27]3.94m 70.41m 245.12m 0m] [117.71m 127.27m 0m]	161.18m	
	12	[709.64m 85.87m 204.49m 0m] [148.06m 147.70m 0m]	161.30m	
	13	[225.25m 723.82m 50.92m 0m] [173.68m 145.01m 0m]	175.78m	
	14	[27]9.01m 97.95m 213.04m 0m] [189.25m 197.95m 0m]	166.67m	
	15	[265.06m 658.55m 76.39m 0m] [143.67m 126.54m 0m]	143.90m	
	16	[36]7.72m 56.28m 225.99m 0m] [65.79m 67.21m 0m]	162.54m	
	17	[215.08m 738.84m 46.08m 0m] [153.77m 122.19m 0m]	178.19m	
	18	[448.78m 434.41m 116.81m 0m] [192.89m 185.16m 0m]	88.79m	
	19	[477.56m 376.06m 146.39m 0m] [132.08m 118.15m 0m]	55.63m	

	20	[200.05m 754.74m 45.21m 0m] [170.11m 128.41m 0m]	187.94m	

Table 8
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case, Default Operation Settings B' and L1PMA of 6 Monotonic Sections for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the rural case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		**Rural Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad 0 \quad 0]$ **Branch Line Length** $\mathbf{L}_{\mathrm{b}}=[L_{\mathrm{b1}} \quad 0 \quad 0]$		[600m 400m 0m 0m] [300m 0m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\mathrm{NNIM-LLA}} = [L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad 0 \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}} = [L_{\mathrm{b1,NNIM-LLA}} \quad 0 \quad 0]$	$\boldsymbol{a}_{\mathbf{CUD}}$ **of CUD Measurements (dB)**			Default Operation Settings B' + 1 hidden layer +L1PMA (6 monotonic sections)
	0	[567.23m 340.47m 0m] [43.93m 0m 0m]	100.14m	
	1	[901.25m 174.66m 0m 0m] [219.91m 0m 0m]	145.38m	
	2	[799.60m 200.49m 0m 0m] [2.95m 0m 0m]	154.87m	
	3	[658.73m 339.81m 0m 0m] [128.19m 0m 0m]	72.30m	
	4	[777.12m 246.59m 0m 0m] [167.58m 0m 0m]	101.73m	
	5	[730.17m 287.42m 0m 0m] [186.08m 0m 0m]	78.01m	
	6	[742.86m 257.14m 0m 0m] [142.86m 0m 0m]	96.74m	
	7	[814.28m 185.72m 0m 0m] [157.14m 0m 0m]	126.63m	
	8	[640.86m 363.36m 0m 0m] [127.33m 0m 0m]	68.48m	
	9	[661.92m 420.99m 0m 0m] [113.90m 0m 0m]	74.55m	
	10	[889.51m 149.91m 0m 0m] [190.40m 0m 0m]	150.41m	
	11	[694.01m 293.40m 0m 0m] [225.18m 0m 0m]	60.71m	
	12	[709.27m 260.91m 0m 0m] [187.81m 0m 0m]	79.17m	
	13	[815.67m 184.49m 0m 0m] [81.02m 0m 0m]	141.88m	
	14	[743.26m 249.32m 0m 0m] [59.21m 0m 0m]	120.24m	
	15	[707.03m 354.37m 0m 0m] [130.14m 0m 0m]	77.82m	
	16	[704.34m 303.33m 0m 0m] [122.22m 0m 0m]	86.05m	
	17	[779.61m 217.71m 0m 0m] [183.32m 0m 0m]	106.30m	

	18	[743.38m 192.28m 0m 0m] [219.24m 0m 0m]	100.17m	
	19	[772.08m 216.12m 0m 0m] [138.79m 0m 0m]	113.02m	
	20	[750.02m 250.11m 0m 0m] [298.27m 0m 0m]	80.16m	

As L2WPMA of PMDAM is concerned, similarly to Table 5 of L1PMA, in Tables 9, the maximum RMSD difference between the best values and mean RMSD for the suburban case is reported per monotonic section, which ranges from 1 to 20, when L2WPMA and default operation settings B' are applied and a_{CUD} values of measurement differences range from 1dB to 20dB. Similarly to Table 6 of L1PMA, in Table 10, similar approximation performance metrics are given but for the rural case when L2WPMA and default operation settings B' are applied. Similarly to Tables 6 and 7, the maximum RMSD difference between the best values and the mean RMSD that are lower than the respective values of the default operation settings B' per case are shown in green color while the cases with the lowest maximum RMSD difference between the best values are highlighted in yellow color in Tables 9 and 10.

Table 9
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case and Default Operation Settings B' for Different L2WPMA Numbers of Monotonic Sections when a_{CUD} Values of CUD Measurements range from 1dB to 20dB

L1PMA Number of Monotonic Sections	**Maximum RMSD Difference between the Best Values (m)** **(Default Operation Settings B': 137.95m) (Default Operation Settings C': 92.26m)**	**Mean RMSD (m)** **(Default Operation Settings B': 163.60m) (Default Operation Settings C': 114.60m)**
1	238.68	161.43
2	133.91	166.17
3	166.44	150.33
4	503.18	165.03
5	179.32	161.39
6	153.12	169.48
7	166.76	166.20
8	112.38	150.10
9	112.74	156.24
10	140.70	179.77
11	178.16	159.96
12	53.48	173.48
13	248.88	169.05
14	141.12	169.79
15	181.97	163.25
16	213.50	156.58
17	156.26	185.69
18	102.97	166.37
19	137.95	170.37
20	111.46	161.43

Table 10
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case and Default Operation Settings B' for Different L2WPMA Numbers of Monotonic Sections when a_{CUD} Values of CUD Measurements range from 1dB to 20dB

L1PMA Number of Monotonic Sections	**Maximum RMSD Difference between the Best Values (m)** **(Default Operation Settings B': 127.26m)** **(Default Operation Settings C': 93.71m)**	**Mean RMSD (m)** **(Default Operation Settings B': 99.57m)** **(Default Operation Settings C': 96.98m)**
1	142.50	79.87
2	189.54	115.42
3	135.63	110.10
4	317.46	109.18
5	94.38	108.50
6	187.90	115.80
7	187.20	113.90
8	164.55	89.29
9	147.96	100.75
10	235.47	105.82
11	171.38	109.40
12	117.72	109.60
13	162.39	125.97
14	872.65	147.28
15	233.67	125.19
16	219.60	92.21
17	127.40	106.80
18	128.80	88.18
19	127.26	99.68
20	98.61	79.87

In Table 9 where the suburban case is investigated, L2WPMA helps towards the improvement of either the maximum RMSD difference between the best values (i.e. 7 out of 20 cases examined) or the mean RMSD (i.e. 9 out of 20 cases examined) when the careful selection of monotonic sections is made. Actually, in 3 examined cases of Table 9, the application of L2WPMA achieves to improve both the maximum RMSD difference between the best values and the mean RMSD. Similar performance results are observed in the rural case of Table 10. As the numbers of monotonic sections with the lowest maximum RMSD difference between the best values, 12 and 5 monotonic sections are concerned for the suburban and rural cases, respectively, while 20 and 6 monotonic sections have been respectively applied in [25], [27]. Already been mentioned and identified in [25], [27], L1PMA and L2WPMA are both piecewise monotonic data approximations and components of the PMDAM that present similar behavior concerning the selection of the monotonic sections per examined OV LV BPL topology despite their theoretical definition differences; say, higher numbers of monotonic sections are expected when OV LV BPL topologies of more and shorter branches are encountered.

Similarly to Tables 7 and 8, NNIM-LLA gives approximations of the distribution and branch line lengths of the suburban case in Table 11 when the default operation settings B' and L2WPMA with 12 monotonic sections are applied and the same a_{CUD} values of CUD measurements of Tables 1, 3 and 7 are assumed. Also, the best RMSD value between the approximated original and symmetrical OV LV topologies and the respective OV LV BPL suburban topology are presented per a_{CUD} value. Table 12 is similar to Table 11 but for the rural case when the default operation settings B' and L2WPMA of 5 monotonic sections are applied.

Table 11
Distribution and Branch Line Length Approximations of NNIM-LLA for the Suburban Case, Default Operation Settings B' and L2WPMA of 12 Monotonic Sections for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the suburban case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		**Suburban Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad L_3 \quad 0]$ **Branch Line Length $\mathbf{L_b}$** $=[L_{b1} \quad L_{b2} \quad 0]$		[500m 400m 100m 0m] [50m 10m 0m]	-	-
NNIM-LLA **Approximated Distribution Line Length** $\mathbf{L}_{\text{NNIM-LLA}} = [L_{1,\text{NNIM-LLA}} \quad L_{2,\text{NNIM-LLA}} \quad L_{3,\text{NNIM-LLA}} \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\text{b,NNIM-LLA}} = [L_{\text{b1,NNIM-LLA}} \quad L_{\text{b2,NNIM-LLA}} \quad 0]$	**a_{CUD} of CUD Measurements (dB)**			Default Operation Settings B' + 1 hidden layer +L2WPMA (12 monotonic sections)
	0	[188.04m 771.39m 40.57m 0m] [150.63m 128.97m 0m]	193.86m	
	1	[36]5.07m 71.50m 213.43m 0m] [149.51m 142.19m 0m]	166.65m	
	2	[752.06m 36.74m 211.20m 0m] [157.03m 145.04m 0m]	184.22m	
	3	[214.46m 743.14m 42.40m 0m] [172.75m 149.09m 0m]	184.01m	
	4	[700.94m 76.41m 222.65m 0m] [139.91m 151.19m 0m]	163.95m	
	5	[213.49m 740.01m 46.51m 0m] [143.54m 147.21m 0m]	180.53m	
	6	[181.03m 782.64m 36.23m 0m] [154.65m 145.29m 0m]	200.53m	
	7	[213.55m 745.46m 40.99m 0m] [166.60m 122.28m 0m]	181.69m	
	8	[224.62m 722.36m 53.03m 0m] [167.81m 113.32m 0m]	171.76m	
	9	[36]5.06m 74.02m 210.93m 0m] [141.77m 148.54m 0m]	165.80m	
	10	[233.92m 704.59m 61.48m 0m] [169.93m 145.51m 0m]	168.10m	
	11	[36]0.63m 80.57m 208.80m 0m] [146.69m 147.52m 0m]	163.23m	
	12	[223.02m 723.78m 53.21m 0m] [173.72m 141.00m 0m]	175.75m	
	13	[223.15m 736.73m 40.11m 0m] [173.50m 127.07m 0m]	178.32m	
	14	[690.93m 115.86m 193.21m 0m] [139.01m 142.52m 0m]	147.05m	
	15	[36]4.54m 78.36m 207.10m 0m] [145.28m 154.86m 0m]	165.19m	
	16	[212.69m 738.15m 49.17m 0m] [166.44m 118.70m 0m]	179.22m	

	17	[213.24m 728.84m 57.92m 0m] [162.19m 146.09m 0m]	178.58m	
	18	[222.91m 722.87m 54.23m 0m] [161.27m 152.80m 0m]	175.62m	
	19	[734.82m 40.68m 224.50m 0m] [164.86m 148.24m 0m]	182.07m	
	20	[707.92m 97.29m 194.79m 0m] [152.97m 147.45m 0m]	157.36m	

Table 12
Distribution and Branch Line Length Approximations of NNIM-LLA for the Rural Case, Default Operation Settings B' and L2WPMA of 5 Monotonic Sections for Different a_{CUD} Values of CUD Measurements (the symmetrical approximations are reported in blue font color and the rural case is included in the TIM OV LV BPL topology database)

Indicative OV LV BPL Topologies of Table 1 of [1]		**Rural Case**	**RMSD**	**Notes**
Distribution Line Length L $=[L_1 \quad L_2 \quad 0 \quad 0]$ **Branch Line Length** $\mathbf{L_b}=[L_{b1} \quad 0 \quad 0]$		[600m 400m 0m 0m] [300m 0m 0m]	-	-
NNIM-LLA Approximated Distribution Line Length $\mathbf{L}_{\mathrm{NNIM-LLA}} = [L_{1,\mathrm{NNIM-LLA}} \quad L_{2,\mathrm{NNIM-LLA}} \quad 0 \quad 0]$ **Approximated Branch Line Length** $\mathbf{L}_{\mathrm{b,NNIM-LLA}} = [L_{\mathrm{b1,NNIM-LLA}} \quad 0 \quad 0]$	$\boldsymbol{a_{\mathrm{CUD}}}$ **of CUD Measurements (dB)**			Default Operation Settings B' + 1 hidden layer +L2WPMA (5 monotonic sections)
	0	[726.69m 283.12m 0m 0m] [178.69m 0m 0m]	79.67m	
	1	[725.80m 274.20m 0m 0m] [151.94m 0m 0m]	87.48m	
	2	[501.71m 497.64m 0m 0m] [181.40m 0m 0m]	68.93m	
	3	[779.14m 238.37m 0m 0m] [66.48m 0m 0m]	126.91m	
	4	[538.48m 210.80m 0m 0m] [135.55m 0m 0m]	97.56m	
	5	[811.12m 177.45m 0m 0m] [27].65m 0m 0m]	145.22m	
	6	[699.43m 270.02m 0m 0m] [189.01m 0m 0m]	74.74m	
	7	[801.41m 199.45m 0m 0m] [187.32m 0m 0m]	155.56m	
	8	[823.41m 763.60m 0m 0m] [254.69m 0m 0m]	162.21m	
	9	[794.92m 272.25m 0m 0m] [171.80m 0m 0m]	100.53m	
	10	[762.50m 237.50m 0m 0m] [150m 0m 0m]	103.73m	
	11	[732.72m 269.18m 0m 0m] [32.17m 0m 0m]	123.32m	
	12	[780.04m 220.83m 0m 0m] [143.68m 0m 0m]	112.73m	
	13	[575.14m 559.29m 0m 0m] [76.26m 0m 0m]	104.23m	
	14	[836.89m 124.36m 0m 0m] [301.10m 0m 0m]	137.37m	

	15	[773.05m 223.89m 0m 0m] [7.56m 0m 0m]	144.66m	
	16	[425.06m 375.05m 0m 0m] [268.79m 0m 0m]	67.83m	
	17	[704.19m 295.81m 0m 0m] [86.19m 0m 0m]	98.15m	
	18	[656.53m 309.71m 0m 0m] [102.55m 0m 0m]	84.80m	
	19	[728.78m 271.18m 0m 0m] [4.14m 0m 0m]	131.32m	
	20	[36]2.50m 287.50m 0m 0m] [150m 0m 0m]	82.65m	

From Tables 11 and 12, it can be generalized that the application of piecewise monotonic data approximations may allow better mitigation performance of the measurement differences in comparison with the performance of only applying default operation settings B' but this performance cannot surpass the one of only applying more elaborate default operation settings, such as default operation settings C'. Known the number of monotonic sections, which remains a challenge anyway, the main advantage of deploying piecewise monotonic data approximations against measurement differences is their light total duration time aggravation; the total duration time for preparing both Tables 11 and 12 is equal to 1,423s for L2WPMA and default operation settings B' that is almost equal to the duration time of applying L1PMA and default operation settings B' but it is again significantly lower than 10,048s of preparing the respective Tables 3 and 4 when the default operation settings C' are adopted.

3.3 Piecewise Monotonic Data Approximations against Measurement Differences in a NN Environment - Discussion

To graphically validate the mitigation performance of the application of L1PMA against the CUD measurement differences when various a_{CUD} values are applied, which has been reported in Tables 5-12, the best RMSD values of the NNIM-LLA approximations for the suburban case are plotted in Fig. 1(a) with respect to the a_{CUD} of the applied CUD measurements when the default operation settings B', the default operation settings C' and the combined operation of L1PMA of 10 monotonic sections with the default operation settings B' are applied. In Fig. 1(a), Tables 1, 3 and 7 are exploited for curving the plots of the default operation settings B', the default operation settings C' and the combined application of L1PMA with the default operation settings B', respectively, when one hidden layer is applied. In Fig. 1(b), the same plot with Fig. 1(a) is given but for the rural case by exploiting Tables 2, 4 and 8 for the application of the default operation settings B', the default operation settings C' and the combined operation of L1PMA of 6 monotonic sections with the default operation settings B', respectively. As the application of L2WPMA against the CUD measurement differences is concerned, the best RMSD values of the NNIM-LLA approximations for the suburban case are plotted in Fig. 2(a) with respect to the a_{CUD} of the applied CUD measurements when the default operation settings B', the default operation settings C' and the combined operation of L2WPMA of 12 monotonic sections with the default operation settings B' are applied. In Fig. 2(a), Tables 1, 3 and 11 are exploited for curving the plots of the default operation settings B', the default operation settings C' and the combined application of L2WPMA with the default operation settings B', respectively, when one hidden layer is applied. In Fig. 2(b), the same plot with Fig. 2(a) is given but for the rural case by exploiting Tables 2, 4 and 12 for the application of the default operation settings B', the default operation settings C' and the combined operation of L2WPMA of 5 monotonic sections with the default operation settings B', respectively.

In Figs. 1 and 2, the mitigation performance of the default operation settings B', the default operation settings C' and the combined operation of L1PMA with the default operation settings B' is graphically synopsized. Concluding this companion paper and with reference to Figs. 1 and 2, the following remarks are pointed out:

- The maximum RMSD difference between the best values has been applied as the criterion or the main mitigation performance metric against the CUD measurement differences of various a_{CUD} values for assessing the default operation settings B', the default operation settings C' and the combined operation of L1PMA / L2WPMA with the default operation settings B'. This performance metric has been chosen so as to focus on the stability of the NNIM-LLA approximations thus bypassing the high number of executions [1]. Figs. 1 and 2 validate that the combined operation of L1PMA / L2WPMA with the default operation settings B' achieves more stable NNIM-LLA approximations in comparison with the ones of simply applying the default operation settings B' with small total duration time increase. However, the selection of the appropriate number of monotonic sections in both piecewise monotonic data approximation methods remains a challenging issue for the different BPL topologies and BPL topology classes. Conversely, Figs. 1 and 2 also verify that the combined operation of L1PMA / L2WPMA with the default operation settings B' achieves less stable NNIM-LLA approximations in comparison with the ones of simply applying the default operation settings C'. Apart from the better maximum RMSD differences between the best values achieved, the default operation settings C' allow better mean RMSDs for the NNIM-LLA approximations but significantly higher total duration times when different segments of the TIM OV LV BPL topology database are required to be prepared in each case.
- Already been identified, other mitigation performance metrics against the CUD measurement differences of various a_{CUD} values that should be taken into account during the assessment of various methodologies are the mean RMSD and the total duration time. In fact, the main mitigation performance metric against the CUD measurement differences of various a_{CUD} values could be the mean RMSD when the accuracy of NNIM-LLA approximations is of interest rather than the NNIM-LLA approximation stability of this companion paper. Anyway, a fair compromise of all the aforementioned mitigation performance metrics is promoted during the assessment in the future works.

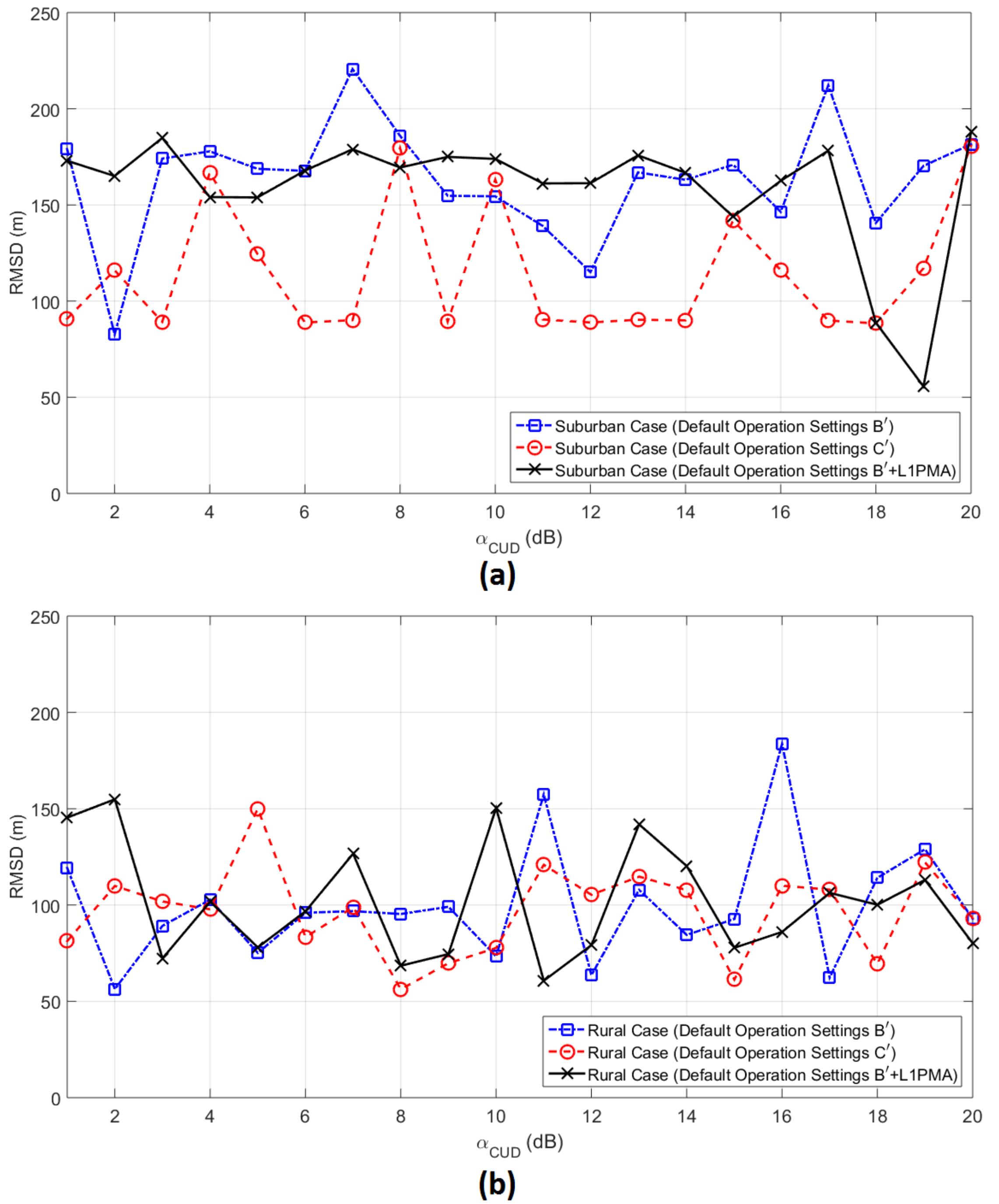
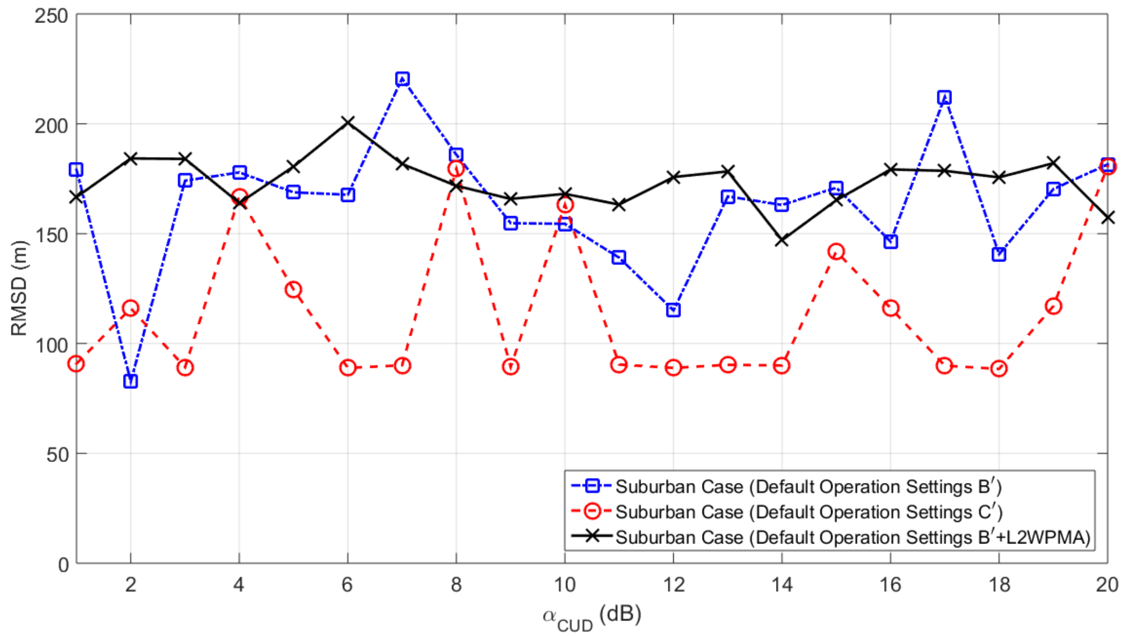
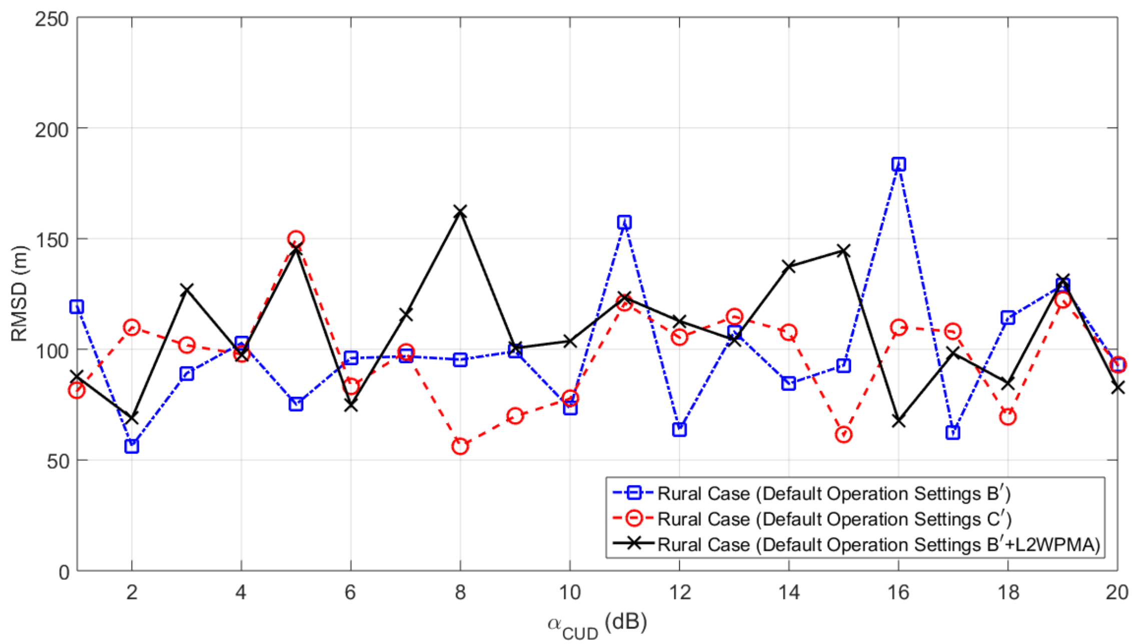


Figure 1. Best RMSD values of NNIM-LLA approximations with respect to a_{CUD} of the applied CUD measurements when the default operation settings B', the default operation settings C' and the combined operation of the default operation settings B' with L1PMA are applied and one hidden layer is assumed. (a) Suburban case -10 monotonic sections for L1PMA-. (b) Rural case -6 monotonic sections for L1PMA-.



(a)



(b)

Figure 2. Best RMSD values of NNIM-LLA approximations with respect to a_{CUD} of the applied CUD measurements when the default operation settings B', the default operation settings C' and the combined operation of the default operation settings B' with L2WPMA are applied and one hidden layer is assumed. (a) Suburban case -12 monotonic sections for L2WPMA-. (b) Rural case -5 monotonic sections for L2WPMA-.

- The main constraint of successfully applying piecewise monotonic data approximations, such as L1PMA or L2WPMA of this companion paper, against measurement differences during the operation of NN methodologies is the right selection of monotonic sections. Already been identified in [25], [26], [28], [36], [37], [40], [43], the higher complexity of the examined BPL topologies concerning the number and the length of the branches requires higher number of monotonic sections by the piecewise monotonic data approximations due to the occurred number and depth of notches across the coupling scheme transfer function theoretical numerical results from DHM that are further contaminated with the measurement differences. Although the aforementioned correlation between the complexity of BPL topology classes and the number of monotonic sections still occurs during the combined operation of DHM, PMDAM and NNIM-LLA of this companion, further study and investigation are required towards the use of the adaptive number of monotonic sections, which has been proposed in [25], [27].
- Piecewise monotonic data approximation methods, such as L1PMA and L2WPMA, have theoretically been presented and experimentally verified in [28]-[31], [44]-[46]. Until now, when piecewise monotonic data approximation methods have been applied as the output module they have successfully mitigated the measurement differences in transmission and distribution BPL networks. In this companion paper, piecewise monotonic data approximation methods, which are contained in the PMDAM module, are located prior to the NNIM-LLA module and feed the latter module with the approximated coupling scheme channel transfer function results. However, the applied representative sets of the TIM OV LV BPL topology database, the assumed default operation settings and the operation specifications of the MATLAB NN program of [38], [39] mainly affect the NNIM-LLA approximation performance thus limiting the PMDAM performance improvement.

4. Conclusions

In this companion paper, the mitigation role of the piecewise monotonic data approximation methods against CUD measurement differences of various a_{CUD} values has been assessed when NNIM-LLA approximations are expected for OV LV BPL topologies. In fact, PMDAM module, which contains L1PMA and L2WPMA that are the piecewise monotonic data approximations of interest in this companion paper, acts as the intermediate module after the DHM module and before the NNIM-LLA module. In accordance with the existing literature of piecewise monotonic data approximation methods, the crucial issue of the right selection of the number of monotonic sections of L1PMA and L2WPMA has been recognized while the correlation of the number of monotonic sections with the complexity of the examined OV LV BPL topology classes has also been revealed in this companion paper. It has been shown that the right selection of the applied number of monotonic sections in L1PMA and L2WPMA may improve either the stability of NNIM-LLA approximations through the improvement of the maximum RMSD difference between the best values or the overall performance of NNIM-LLA approximations through the improvement of the mean RMSD. At the same time, the total duration time of NNIM-LLA operation is not significantly affected by the operation of PMDAM. However, it has been verified that the default operation settings, which affect the preparation of the TIM OV LV BPL topology database and the NNIM-LLA operation, are the dominant factor of the NNIM-LLA approximation performance; say, the best tuning of L1PMA and L2WPMA can improve the NNIM-LLA approximation performance for given default operation settings but it cannot improve the NNIM-LLA approximation performance in comparison with the one of applying more elaborated default operation settings and this is due to: (i) the PMDAM position prior to the NNIM-LLA module; and (ii) the NN definition and operation inside the NNIM-LLA module.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Africa's Path to Sustainability: Harnessing Technology, Policy, and Collaboration

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This paper explores the significant role of technological advancements, strategic policies, and collaborations in driving Africa towards a more sustainable future. It highlights how the continent's increasing adoption of innovative technologies, such as renewable energy solutions and digital infrastructure, coupled with well-crafted strategic policies and international collaborations, is transforming various sectors and fostering a sustainable future. These advancements have not only improved access to basic services like healthcare and education but have also created new opportunities for economic growth and job creation. The paper emphasizes the importance of ongoing collaborations between African countries and international partners in sharing knowledge, expertise, and resources to accelerate sustainable development efforts across the continent. The paper discusses different international organizations that have collaborated with and assisted Africa in the areas of technical innovation, finance, and knowledge exchange necessary to achieve a full-scale sustainable future. Despite their humanitarian efforts, Africa faces tremendous hurdles in attaining a sustainable future. These challenges range from a lack of access to technology and digital infrastructure in rural areas to difficulties in harnessing technological advancements due to infrastructure and connectivity constraints. These challenges have hindered Africa's ability to fully leverage the potential of technical innovation and digital solutions for a sustainable future. Limited financial resources and investment opportunities have further impeded progress in achieving the necessary infrastructure and connectivity upgrades. The continent is vulnerable to the impacts of climate change, which further hinders its development progress. Therefore, it is crucial for ongoing collaborations between African countries and international partners to address these challenges collectively and work towards long-term solutions for a sustainable future in Africa.

Keywords: Sustainability; Innovation; Renewable Energy; Digital Transformation; African Context; Technological Barriers

1. Introduction

In recent years, Africa has witnessed a remarkable surge in technological innovations that are not only transforming the continent but also driving it towards a more sustainable future. These innovations have the potential to address some of the

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pressing challenges faced by African nations, such as access to clean energy [1], efficient agriculture practices [2], and improved healthcare systems [3]. By harnessing the power of technology, Africa is paving the way for sustainable development. These technological innovations are not only benefiting African nations but also attracting global attention [4] and investment [5]. With increased collaboration and support, Africa has the opportunity to further accelerate its progress towards a more sustainable future and become a model for other regions facing similar challenges [6]. With advancements in renewable energy technologies, African nations are able to tap into their vast natural resources [7] and provide clean and affordable energy solutions to their populations [8]. The use of smart farming techniques and precision agriculture is enabling farmers to maximize crop yields while minimizing environmental impact. These technological advancements not only improve food security [7] but also promote sustainable land management practices [7]. The use of mobile technologies has enhanced agricultural practices by providing farmers with real-time weather updates [8], market prices, and access to financial services for loans and insurance [8]. This has resulted in increased productivity and income for farmers, ultimately contributing to food security [7] and poverty reduction in rural communities[8].

The adoption of digital platforms and mobile technologies in Africa has revolutionized access to financial services, allowing for greater financial inclusion and economic empowerment. This has led to increased entrepreneurship and job opportunities, contributing to overall economic growth in the region. These technological advancements have also facilitated improved healthcare delivery through telemedicine and remote monitoring, especially in rural areas with limited access to medical facilities. The use of mobile technologies has also transformed the education sector in Africa. With access to online learning platforms and educational apps, students in remote areas can now access quality education and resources, bridging the educational gap between urban and rural areas [9]. This has not only improved literacy rates but also enhanced the skills and knowledge of individuals, leading to a more skilled workforce and increased productivity in various industries.

These advancements have the potential to address some of Africa's pressing challenges, such as access to clean energy [10], financial inclusion, food security, healthcare delivery, and efficient resource management. By embracing these technologies, Africa can not only improve the quality of life for its citizens but also contribute to global efforts to mitigate climate change [11] and achieve sustainable development goals [12]. The adoption of these technologies can also foster economic growth and create job opportunities in Africa. By investing in renewable energy sources [13] and promoting green industries [14], African countries can reduce their dependence on fossil fuels [15] and attract investments from international organizations and businesses that prioritize sustainability [16]. This will not only strengthen Africa's economy but also position it as a leader in sustainable development on the global stage.

We will also distinctively explore the role of strategic policies in driving Africa towards a more sustainable future [17]. As the continent faces various challenges such as climate change [18], rapid urbanization [8], and resource depletion [8], it is crucial to examine how well-designed policies [19] can effectively address these issues and pave the way for long-term sustainability [20]. By analysing successful case studies and examining key strategies implemented by African nations, we aim to highlight the importance of strategic policies in shaping a brighter future for Africa and its people [21]. These policies should prioritize renewable energy sources, promote sustainable agriculture practices, and encourage investment in green technologies [22]. It is essential for these policies to prioritize education and awareness programs that empower communities to actively participate in sustainable practices [23]. Fostering partnerships between governments [24], private sectors [25], and international organizations can ensure the successful implementation [26] and monitoring of these policies [27, 28], leading to a more resilient and prosperous Africa.

In this paper, the seven proposed strategic policies driving Africa toward a more sustainable future. By engaging in these efforts, African countries can work towards achieving the Sustainable Development Goals and creating a more sustainable future for all. Additionally, it is important to involve local communities and indigenous peoples in decision-making processes to ensure their voices are heard and their rights are respected in sustainable development initiatives.

We will also explore the significant role that collaborations and partnerships play in driving Africa towards a more sustainable future. With the continent facing numerous environmental, social, and economic challenges, it has become increasingly evident that no single entity can address these issues alone. Therefore, this paper aims to highlight the power of collective action and cooperation in achieving sustainable development goals across Africa. By examining successful collaborations and partnerships in various sectors such as renewable energy, conservation, education, and entrepreneurship, we will shed light on the transformative potential of working together towards a common goal. These partnerships not only leverage resources and expertise but also foster knowledge sharing and innovation, leading to more effective and impactful solutions. Ultimately, by promoting collaboration and cooperation, Africa can overcome its challenges and pave the way for a sustainable future that benefits all its people. Foster collaborations among various stakeholders, including the African Union's Agenda 2063, the United Nations Sustainable Development Goals, the African Renewable Energy Initiative, the Great Green Wall Initiative, the African Circular Economy Alliance, the African Union's Climate Change Strategy, and the Renewable Energy for Africa program, are proposed to propel Africa toward a more sustainable future. These initiatives aim to address key challenges such as poverty, inequality, climate change, and energy access in Africa. By leveraging the collective efforts of these stakeholders, Africa can unlock its vast potential for renewable energy, promote circular economy practices, and build resilience to climate change impacts.

This paper also proposes that it is crucial to engage with international partners and organizations to leverage resources and expertise in promoting sustainable technologies in Africa. This can be achieved through partnerships with institutions such as The African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank to secure funding and technical assistance for sustainable energy projects across the continent [29]. By collaborating with these international partners and organizations, African countries can access financial support and knowledge transfer to implement renewable energy solutions. This not only helps in reducing greenhouse gas emissions but also enhances energy security and fosters economic growth in the region. These partnerships can also facilitate knowledge exchange and capacity building, allowing African countries to learn from successful experiences in other regions and adapt them to their specific contexts. Engaging with international partners can help African countries access global networks and platforms that promote sustainable technologies, enabling them to showcase their own innovations and attract further investment in the sector.

Generally, we will explore how technological advancements, strategic policies, and collaborations are playing a crucial role in driving Africa towards a more sustainable future. By examining the various initiatives and efforts undertaken by governments, organizations, and individuals across the continent, we will shed light on the transformative potential of these factors in addressing pressing environmental challenges and promoting socio-economic development. We will analyse the key opportunities and challenges that arise from this journey towards sustainability, highlighting the need for continued innovation and cooperation to ensure that progress is sustained and amplified. This exploration will also delve into the importance of education and awareness in driving sustainable practices, as well as the role of technology and research in finding innovative solutions. In addition, we will examine the role of government policies and regulations in creating an enabling environment for sustainable development. This includes exploring how governments can incentivize businesses and individuals to adopt sustainable practices through tax incentives, subsidies, and other economic measures.

We also examine areas the African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank have all determined that Africa's future is poised to become more sustainable as a result of significant technological advancements. In spite of these, there are still challenges that need to be addressed in order to fully harness the potential of technology for sustainable development in Africa. These difficulties are the hallmarks of the research question in this paper. This paper aims to explore the specific challenges that hinder the full utilization of technology for sustainable development in Africa. By identifying and addressing these obstacles, it is possible to unlock the true potential of technological advancements and ensure a more sustainable future for the continent. Thus, the major research question of this study is: what are the potential factors impeding Africa's progress toward a more sustainable future, despite technological advancements? By understanding these factors, policymakers and stakeholders can develop targeted strategies and interventions to overcome them. Additionally, this research will contribute to the existing body of knowledge on sustainable development in Africa and provide insights for future policy decisions and investments in technology.

2. Approach

This section investigates seven reputable international technological organizations that have recognized that Africa is moving toward a more sustainable future as a result of technological advancements, strategic policies, and collaborations, as documented in our recent research findings [29]. These organizations have acknowledged Africa's efforts in harnessing renewable energy sources such as solar and wind power, which are contributing to the continent's sustainable development goals. They have commended Africa's focus on digital innovation and connectivity, which is driving economic growth and improving access to essential services for its population. These organizations include Google, Microsoft, the World Bank, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), the African Development Bank (AfDB), and the United Nations Development Programme (UNDP).

Why do the authors of this study select these international technological organizations as the ideal entities to recognize Africa's progress toward a more sustainable future as a result of technological advancements? The World Bank and the United Nations Development Programme (UNDP) are considered the best organizations to acknowledge Africa's sustainable future due to their extensive experience and expertise in global development issues. With their vast networks and resources, these organizations have been actively involved in supporting African countries in implementing sustainable technologies and promoting inclusive growth. Their recognition carries significant weight in the international community, lending credibility to Africa's progress towards sustainability. These organizations have a proven track record of successfully implementing sustainable projects in various sectors, such as renewable energy, agriculture, and healthcare. Their expertise in navigating complex challenges and finding innovative solutions makes them invaluable partners in Africa's journey towards a sustainable future. Furthermore, their collaborations with local communities and governments ensure that the initiatives are tailored to the specific needs and aspirations of African nations, fostering long-term development and resilience. By leveraging their extensive network and resources, these organizations are able to mobilize funding and technical expertise to support the implementation of sustainable projects. Their commitment to capacity building and knowledge sharing empowers local communities to take ownership of these initiatives, ensuring their long-term success and impact.

Another prominent international technological group that has recognized Africa's advancement towards a more sustainable future is Google. Google has been actively investing in various initiatives across the continent, such as providing internet access to remote areas through projects like Project Loon and supporting local entrepreneurs through programs like Google for Startups Africa. These efforts highlight Google's belief in the transformative power of technology to drive sustainable development in Africa. By leveraging its expertise in technology and innovation, Google aims to bridge the digital divide in Africa and empower communities with access to information and opportunities. Through partnerships with local governments and organizations, Google is working towards creating a more inclusive and connected Africa, paving the way for economic growth and social progress. Another notable international technological group acknowledging Africa's potential for sustainable development is Microsoft. Microsoft has been working closely with African governments and organizations to provide digital skills training and empower local communities. Their initiatives, such as the Africa Development Center and the 4Afrika Initiative, aim to foster innovation, create job opportunities, and address social challenges through technology. Through the Africa Development Center, Microsoft is not only investing in talent and innovation but also supporting local startups and entrepreneurs. By providing access to resources and mentorship, they are helping to build a thriving tech ecosystem in Africa. Additionally, the 4Afrika Initiative focuses on bridging the digital divide by providing affordable access to technology and internet connectivity, ensuring that more Africans can participate in the digital economy and benefit from its opportunities. By collaborating with local partners and investing in infrastructure, Microsoft is actively contributing to Africa's journey towards a more sustainable future.

The African Development Bank (AfDB) has been instrumental in financing and supporting various sustainable development projects across the continent. Through its investments in renewable energy, agriculture, and infrastructure, the AfDB has helped create jobs, improve access to clean energy, and enhance food security in Africa. This not only benefits the local communities but also contributes to global efforts to combat climate change and promote sustainable development worldwide. The AfDB's commitment to sustainable development is evident in its efforts to promote gender equality and empower women in Africa. By providing financial support and technical assistance to women-led businesses and initiatives, the AfDB is helping to bridge the gender gap and foster inclusive economic growth. These initiatives not only have a positive impact on the lives of women but also contribute to overall social and economic development in the region.

For instance, the United Nations Environment Programme (UNEP) and the World Wildlife Fund (WWF) have collaborated with African nations to develop innovative conservation initiatives, such as the Great Green Wall project. This initiative aims to combat desertification and promote sustainable land management practices across the Sahel region, demonstrating Africa's commitment to environmental preservation. Additionally, UNEP and WWF have supported capacity-building efforts in Africa, empowering local communities and governments to take ownership of their sustainable development agenda and drive positive change at the grassroots level. These capacity-building efforts have resulted in the implementation of various sustainable development projects, such as renewable energy installations and water conservation programs. By empowering local communities and governments, Africa is fostering a sense of ownership and responsibility towards environmental preservation, leading to long-term positive impacts on the region's ecosystems and natural resources. In addition, these capacity-building efforts have also led to increased awareness and education on sustainable practices, promoting a shift towards more environmentally friendly lifestyles. As a result, local communities are now actively involved in decision-making processes and are taking proactive measures to protect their natural surroundings. This holistic approach to development not only benefits the environment but also enhances the overall well-being and resilience of African communities in the face of climate change and other environmental challenges.

3. Prominent International Organizations Recognition of Africa's Advancement towards a Sustainable Future

3.1 Technological Advancement Paves the Way for Africa's Sustainable Future

The African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank have all determined that Africa's future is poised to become more sustainable as a result of significant technological advancements [29]. These organizations recognize that the continent's adoption of innovative technologies holds immense potential for addressing key challenges such as poverty [30], inequality[31], and environmental degradation [32]. By leveraging these advancements, Africa can unlock new opportunities for economic growth [33], improve social well-being [34], and protect its natural resources [35]. The integration of innovative technologies can enhance the continent's resilience to climate change and promote sustainable development practices [36]. This collaborative effort between the African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank aims to support Africa in harnessing the power of technology to create a more sustainable and prosperous future for its people. According to the six selected organizations detailed in Nwokolo et al. [29], substantial technological developments are set to make Africa's future more sustainable include:

3.1.1 Improved Access to Education

In recent years, the proliferation of mobile devices and internet connectivity in Africa has revolutionized access to educational resources. With the help of smartphones and tablets, Africans can now easily access online courses, e-books, and educational videos from anywhere, even in remote areas with limited infrastructure [37]. This has not only contributed to increased literacy rates but has also empowered individuals to acquire new skills and knowledge [38], ultimately creating a more skilled workforce that can drive economic growth and development in the region. In addition, the availability of online educational resources has also fostered a culture of lifelong learning [39] in Africa. Individuals can now pursue higher education degrees or acquire specialized skills through online platforms, expanding their career opportunities and contributing to personal growth. Furthermore, the accessibility of educational resources has opened up avenues for collaboration and knowledge sharing among African students and educators, facilitating cross-cultural exchanges and fostering innovation in various fields [40]. Moreover, the availability of educational resources has played a crucial role in bridging the education gap in Africa. With online platforms, individuals in remote areas can now access quality education and receive training that was previously inaccessible to them. This has not only empowered individuals but has also contributed to the overall development and progress of the continent. According to World Bank statistics, the number of internet users in Africa has increased significantly over the past decade, reaching approximately 453 million users in 2019 [41]. According to the World Bank, this information shows that internet access has a positive impact on education because it has increased the literacy rate of African countries from 52% in 2010 to 65% in 2019 [41].

3.1.2 Enhanced Healthcare Services

Telemedicine and mobile health applications have revolutionized healthcare delivery by bridging the gap between patients and healthcare providers in remote areas [42]. Through telemedicine, individuals living in underserved regions can access medical consultations [43], receive diagnoses [44], and even undergo remote monitoring of their health conditions [45]. This not only saves time and money for patients who would otherwise have to travel long distances for medical care but also allows healthcare professionals to reach a wider patient population, ultimately improving overall health outcomes in these areas. Mobile health applications provide convenient access to healthcare information and resources [46]. These apps allow users to track their symptoms, manage medications, and even connect with healthcare providers through virtual consultations. This technology empowers individuals to take control of their own health [47] and make informed decisions about their care [48], regardless of their location or access to traditional healthcare facilities. According to World Bank statistics, improved healthcare services as a result of technological applications in Africa have decreased the mortality rate by 10% in the past decade [41]. Additionally, these apps have also helped bridge the healthcare gap in rural areas, where access to medical professionals is limited. These technological applications have revolutionized healthcare delivery by providing remote consultations, telemedicine services, and access to medical information through mobile devices. This has not only saved lives but also empowered individuals to actively participate in managing their health and seeking timely medical assistance, ultimately leading to better health outcomes in African countries.

3.1.3 Increased Agricultural Productivity

Precision farming techniques and advanced machinery have revolutionized agriculture in Africa, enabling farmers to optimize their use of resources such as water, fertilizers, and pesticides [8]. By employing precision planting and irrigation systems, farmers can ensure that crops receive the exact amount of nutrients and water they need, reducing waste and maximizing yields. Furthermore, advanced machinery like GPS-guided tractors and drones allows for more efficient land management and pest control, minimizing crop damage and increasing overall productivity [8]. As a result of these technological advancements, African farmers have been able to increase their crop yields and improve their overall agricultural productivity. This has not only helped in addressing food security challenges but has also contributed to economic growth in the region [7]. Additionally, the adoption of these technologies has empowered farmers by providing them with valuable data and insights, enabling them to make informed decisions and optimize their farming practices for long-term sustainability. According to the World Bank, agricultural productivity on the African continent increased between 2010 and 2020 as a result of climate change [41]. This can be attributed to the utilization of advanced technologies such as precision agriculture, which has helped farmers overcome the adverse effects of climate change and improve their crop yields. Moreover, the adoption of these technologies has also attracted investment in the agricultural sector, creating employment opportunities and boosting economic development in Africa.

3.1.4 Expanded Financial Inclusion

The use of mobile banking and digital payment platforms in Africa has revolutionized the way people access financial services. By providing convenient and secure ways to transfer money, make payments, and manage their finances, these technologies have empowered millions of Africans who previously had limited or no access to traditional banking services. As a result, the reliance on cash transactions has significantly reduced, leading to increased transparency, efficiency, and financial inclusion. This shift towards digital financial services has not only improved the lives of individuals but has also played a crucial role in driving economic growth and development in Africa. With increased access to financial services, individuals and businesses can now participate more actively in the formal economy, access credit facilities, and make investments. This has led to job creation, increased productivity, and overall economic stability in the region.

Digital financial services have also enabled governments to better track and monitor financial transactions, reducing the risk of corruption and promoting good governance. Furthermore, the availability of digital financial services has fostered financial inclusion by reaching previously underserved populations, such as those in rural areas or without traditional banking infrastructure. This has empowered individuals to save money, manage their finances more effectively, and build a foundation for long-term economic growth. Additionally, the use of digital platforms for financial transactions has also facilitated cross-border trade and increased economic integration within Africa and with the global economy. The World Bank predicts that a rapid increase in digital financial services in Africa could contribute to a 3% increase in the continent's GDP by

2025 [41]. This growth is expected to create new job opportunities and attract foreign investments, further stimulating economic development.

The adoption of digital financial services has the potential to reduce poverty and inequality by providing access to credit and insurance products, enabling individuals and businesses to invest in education, healthcare, and other essential needs. They also predicted that access to digital financial services in Africa could contribute an additional $3.7 trillion to the continent's GDP by 2025 [41]. This growth is driven by the convenience and efficiency of digital transactions, which have reduced the cost and time involved in conducting business across borders. The increased financial inclusion has also opened up opportunities for entrepreneurship and innovation, as individuals now have access to capital and resources that were previously out of reach. This has led to the emergence of new businesses and industries, creating jobs and stimulating economic growth. Additionally, digital financial services have also improved financial transparency and accountability, reducing the risk of corruption and promoting a more stable business environment in Africa.

3.1.5 Increased Job Opportunities

The digital revolution has enabled the rise of online marketplaces and e-commerce platforms, allowing individuals and businesses to reach a global customer base. This has led to the creation of new job roles in areas such as online retail management, logistics, and customer support. Additionally, the demand for IT professionals and digital marketers has surged as companies seek to establish their online presence and effectively market their products or services. These employment opportunities have not only provided income for individuals but also stimulated economic growth by attracting investments in technology infrastructure and promoting innovation in the digital space. As companies expand their online operations, they require robust technology systems and networks, leading to increased investments in data centers, cloud computing, and cybersecurity. This has not only created jobs in these sectors but also encouraged advancements in technology and improved connectivity worldwide.

The growth of online operations has also led to an increase in demand for skilled professionals in fields such as software development, digital marketing, and e-commerce. This has resulted in a positive ripple effect on the overall economy, as individuals with these skills are able to find employment opportunities and contribute to the growth of various industries. Advancements in technology and improved connectivity have facilitated global collaboration and communication, allowing businesses to expand their reach and tap into new markets around the world. The rise of remote work and flexible work arrangements has allowed professionals in these fields to work from anywhere, increasing their job satisfaction and work-life balance. This has also led to the emergence of a gig economy, where individuals can take on freelance projects and diversify their income streams.

As a result, the overall economy has become more dynamic and resilient, with a greater emphasis on innovation and entrepreneurship. According to Bank World, the digital revolution has the potential to increase Africa's employment rate by 20–30% by 2030 against the backdrop of high unemployment rates [41]. This is due to the fact that digital technologies can bridge the gap between job seekers and employers, making it easier for individuals to find work opportunities. The digital revolution has also facilitated the growth of remote work, allowing individuals in rural or underserved areas to access job opportunities that were previously unavailable to them. This is due to the fact that digital technologies can create new job opportunities and improve productivity in various sectors, such as agriculture, healthcare, and education. Additionally, the digital revolution can also bridge the gap between urban and rural areas, providing equal access to employment opportunities for individuals in remote regions.

3.1.6 Improved Skill Sets

The adoption of digital technologies has also led to an improvement in the skill sets of Africans, as they have had to learn how to use and navigate these platforms effectively. This has opened up new opportunities for Africans to participate in the global digital economy and has helped bridge the digital divide between Africa and other regions. The increased use of digital technologies has sparked innovation and entrepreneurship in Africa, with many individuals and businesses leveraging these tools to create innovative solutions to local challenges and drive economic growth. These digital platforms have also facilitated the growth of e-commerce in Africa, allowing businesses to reach a wider customer base and expand their market presence. The use of digital technologies has improved access to education and healthcare services in remote areas, contributing to the overall development and empowerment of communities across the continent. Digital technologies have played a crucial role in promoting financial inclusion in Africa. Mobile banking and digital payment systems have made it easier for individuals to access and manage their finances, especially those who were previously excluded from traditional banking services. This has not only increased financial stability but also fostered entrepreneurship and economic opportunities for individuals in underserved communities. The adoption of digital technologies has enhanced communication and collaboration among different sectors, enabling more efficient coordination and cooperation in addressing social and environmental challenges in Africa. The increased access to digital technologies has also facilitated the growth of e-commerce and online marketplaces, allowing small businesses in Africa to reach a wider customer base and expand their operations. The use of digital platforms has streamlined administrative processes and reduced paperwork, leading to cost savings and increased productivity for organizations across various industries. According to the World Intellectual Property Organization (WIPO), the use of digital technologies has also led to an increase in intellectual property filings in Africa [49]. This indicates a growing recognition of the importance of protecting innovative ideas and creations, which can further stimulate economic growth and investment in the region. The digitization of information has improved access to education and knowledge sharing, empowering individuals and communities to learn and develop new skills that can contribute to sustainable development in Africa. However, the World Bank predicts that the digital divide in Africa may widen if the necessary infrastructure and policies are not put in place. This could hinder the potential benefits of digitization, such as increased connectivity and access to markets, for marginalized communities and remote areas. Therefore, it is crucial for governments and stakeholders to prioritize investments in digital infrastructure and promote inclusive policies to ensure equal opportunities for all Africans in the digital era.

3.1.7 Examples of Technological Innovations Driving Africa toward a More Sustainable Future

One data-based example of how advancements in technology are assisting Africa's transition to a more sustainable future is the use of solar power. According to the

International Renewable Energy Agency (IRENA), Africa has the highest solar irradiation levels globally, making it an ideal region for harnessing solar energy [50]. With the help of technological advancements in solar panels and energy storage systems, African countries are increasingly adopting solar power as a clean and sustainable energy source. For instance, in 2019, Egypt inaugurated the world 's largest solar park, the Benban Solar Park, which has a capacity of 1.8 gigawatts and is expected to reduce carbon emissions by 2 million tons annually [50]. This project not only demonstrates Africa's commitment to renewable energy but also showcases its potential to become a global leader in solar power generation. As more African countries invest in solar infrastructure and develop policies to promote renewable energy, the continent is poised to make significant progress towards a greener and more sustainable future.

For example, in South Africa, the Renewable Energy Independent Power Producer Procurement Program (REIPPPP) has been critical in attracting private investment and accelerating the deployment of solar energy projects. This program has successfully added over 6,000 MW of renewable energy capacity to the country's grid, reducing carbon emissions and creating job opportunities in the process [29]. As other African nations follow suit and implement similar initiatives, the continent's solar power potential will continue to be unlocked, paving the way for a cleaner and more prosperous future. In Nigeria, solar parks such as the 75 MW Katsina Solar Power Plant have been established, further contributing to the country's renewable energy goals [29]. These solar parks not only provide clean and sustainable electricity to remote areas but also stimulate economic growth by attracting investments and creating employment opportunities in the solar industry. With the continuous development of solar parks, Nigeria is on track to achieve its target of generating 30% of its electricity from renewable sources by 2030 [29].

The use of mobile banking is one data-driven example of how technological advancements are assisting Africa's transition to a more sustainable future. In Africa, mobile banking has become increasingly popular, allowing individuals to access financial services and make transactions using their mobile phones. This technology has not only improved financial inclusion but also reduced the reliance on traditional brick-and-mortar banks, making it easier for people in remote areas to manage their finances and contribute to economic growth. Additionally, mobile banking has also helped reduce the environmental impact by minimizing the need for paper-based transactions and physical infrastructure. In South Africa, mobile banking technology is being utilized to provide financial services to the unbanked population, who previously had limited access to traditional banking services. This has empowered individuals to save money, access credit, and engage in other financial activities that were previously out of reach. Moreover, mobile banking has also played a crucial role in promoting entrepreneurship and small business growth by enabling easy and secure payment solutions for customers. As a result, it has contributed to the overall economic development of the country.

Numerous banks in South Africa, including Standard Bank, Absa, Capitec, First National Bank, and Nedbank, are using mobile banking technology to provide financial services to the unbanked population. These banks have introduced mobile banking apps that allow users to open accounts, transfer money, and make payments using their smartphones. This has greatly improved financial inclusion in the country, as individuals who were previously excluded from the formal banking sector now have access to a range of financial services. Additionally, mobile banking has also helped reduce the cost of financial transactions for both customers and businesses, leading to increased efficiency and productivity in the economy.

In Nigeria, mobile banking technology is being utilized to provide financial services to the unbanked population by numerous banks, including Guaranty Trust Bank, Access Bank, First Bank, United Bank for Africa, Ecobank, Fidelity Bank, and Zenith Bank. These banks have developed user-friendly mobile banking applications that allow individuals to open bank accounts, transfer funds, and make payments using their mobile phones. This has significantly expanded the reach of financial services in the country, especially in rural areas where traditional banking infrastructure is limited. Furthermore, these mobile banking solutions have also facilitated the growth of small businesses by providing them with convenient and secure means of accepting payments from customers. Equity Bank, Safaricom's M-Pesa, Airtel Money, KCB M-Pesa, Tala, and T-Kash by Telkom Kenya are just a few of the banks in Kenya using mobile banking technology to offer financial services to the unbanked population. These mobile banking platforms have not only increased financial inclusion but have also revolutionized the way people manage their money. With just a mobile phone, individuals can now access a range of financial services, such as savings accounts, loans, and insurance, empowering them to take control of their finances and improve their economic well-being.

Precision agriculture practices, like remote sensing and data analytics, that assist farmers in optimizing their crop production, leading to higher yields and less negative environmental impact, are one data-based example of how technological advancements are assisting Africa's transition to a more sustainable future. These techniques allow farmers to monitor soil conditions, weather patterns, and crop health in real-time, enabling them to make informed decisions and minimize the use of water, fertilizers, and pesticides. As a result, not only do these advancements contribute to a more sustainable agricultural sector in Africa, but they also support food security and economic growth in the region. By utilizing precision agriculture technologies, farmers can precisely apply resources such as water and fertilizers to specific areas of their fields, ensuring efficient usage and minimizing waste. Additionally, these advancements enable farmers to detect and address potential crop diseases or pest infestations early on, preventing significant yield losses and reducing the need for chemical interventions. Ultimately, the integration of these technologies promotes long-term sustainability in African agriculture while simultaneously boosting productivity and profitability for farmers.

In Kenya, precision agriculture techniques, such as remote sensing and data analytics, that help farmers optimize their crop production, leading to increased yields and reduced environmental impact, are employed by numerous agricultural firms, including Twiga Foods and UjuziKilimo. These companies provide farmers with real-time data on soil moisture levels, weather patterns, and crop health, allowing them to make informed decisions about irrigation and pest control. By implementing precision agriculture practices, these firms are not only helping farmers increase their productivity and profitability but also reducing the overall environmental footprint of agriculture in Kenya. Others include AgriTech Solutions and Green Solutions Ltd. These companies provide farmers with real-time data on soil moisture levels, nutrient content, and pest infestations, allowing them to make informed decisions about irrigation and pesticide application. By adopting precision agriculture techniques, farmers in Kenya have been able to improve their crop yields by up to 30% while reducing water usage by 40% [41]. These advancements not only benefit the farmers themselves but also contribute to the overall sustainability and resilience of the agricultural sector in Kenya.

The Internet of Things (IoT) technology is one data-based illustration of how technological advancements are facilitating Africa's transition to a more sustainable future. In South Africa, the Internet of Things (IoT) technology is being utilized to monitor and optimize energy consumption by numerous corporations, including mining companies such as Anglo American and manufacturing plants like Sasol. Others include transportation companies like Transnet and telecommunications providers like MTN. By using IoT technology, these companies are able to track and analyse their energy usage in real-time, identifying areas of inefficiency and implementing strategies to reduce their carbon footprint. This not only helps them save costs but also contributes to the overall goal of achieving a more sustainable future by minimizing energy waste and promoting responsible resource management. Others include Exxaro Resources and Gold Fields in the mining sector, and ArcelorMittal South Africa and Nampak in the manufacturing industry. These companies have implemented IoT technology to track energy usage, identify inefficiencies, and make data-driven decisions to reduce their environmental impact and improve operational efficiency. By leveraging IoT devices and real-time data analytics, these corporations can effectively manage their energy consumption, leading to cost savings and a more sustainable approach to resource utilization.

Several businesses in Algeria, including mining firms like Algerian Mining Corporation and Energy Solutions Ltd., are using the Internet of Things (IoT) technology to monitor and optimize energy consumption. These companies have implemented IoT sensors and monitoring systems to track energy usage in real-time, allowing them to identify areas of inefficiency and implement targeted solutions. This data-driven approach has not only resulted in significant cost savings but has also helped reduce their carbon footprint by optimizing energy utilization. Additionally, by analysing the collected data, these corporations can make informed decisions about equipment upgrades or process improvements, further enhancing their operational efficiency and sustainability efforts. Others include manufacturing companies like Algerian Manufacturing Solutions and logistics companies such as Algerian Logistics Services. These corporations are implementing IoT solutions to track and analyse energy usage patterns, identify areas of inefficiency, and make data-driven decisions to reduce energy waste. By doing so, they not only save costs but also contribute to a greener and more sustainable future for Algeria's resource utilization.

Several corporations in Nigeria, including mining companies such as Shell and Chevron, are using Internet of Things (IoT) technology to monitor and optimize energy consumption. These mining companies are using IoT devices to collect real-time data on energy usage, allowing them to identify areas of high consumption and implement strategies to reduce waste. By leveraging IoT technology, these corporations are not only improving their operational efficiency but also minimizing their environmental impact by reducing energy consumption and emissions. This demonstrates the potential of IoT in promoting sustainable practices across various industries in Nigeria. Others include manufacturing companies like Dangote Group and telecommunications companies such as MTN. These companies are leveraging IoT solutions to remotely monitor their energy usage in real-time, identify areas of high consumption, and implement energy-saving measures. This not only helps them reduce their carbon footprint but also leads to significant cost savings in the long run.

Many Egyptian companies, including mining firms like the Egyptian Mining Company and oil and gas firms like Petro Egypt, are using Internet of Things (IoT) technology to monitor and optimize energy consumption. By implementing IoT solutions, these companies can track their energy usage patterns, detect inefficiencies, and make data-driven decisions to improve energy efficiency. This not only reduces their environmental impact but also enhances their operational efficiency and reduces overall costs. Others include manufacturing companies, such as Egypt Aluminium and Egyptian Cement, and telecommunications companies like Telecom Egypt. By leveraging IoT technology, these companies are able to gather data on their energy usage patterns, identify inefficiencies, and make informed decisions to reduce their overall energy consumption. This not only benefits the environment but also improves their operational efficiency and reduces operational costs.

The Internet of Things (IoT) technology is being used by many businesses in Morocco, including mining firms like phosphate mining firms, to monitor and optimize energy consumption. By implementing IoT devices, these companies can track their energy usage in real-time, allowing them to identify areas of high consumption and implement strategies to reduce waste. This not only helps to conserve energy resources but also enhances the sustainability of their operations and reduces their carbon footprint. Others include the OCP Group. Through IoT devices and sensors, these companies are able to track energy usage in real-time, identify areas of high consumption, and implement strategies to reduce waste. This not only helps them meet sustainability goals but also saves them significant costs in the long run. Additionally, IoT technology allows for remote monitoring and control of energy systems, enabling proactive maintenance and minimizing downtime for these companies.

Numerous corporations in Kenya, including mining companies such as Kenya Gold Mines Ltd, are using Internet of Things (IoT) technology to monitor and optimize energy consumption. By using IoT technology, these mining companies are able to track their energy usage in real-time and identify areas where energy efficiency can be improved. This not only helps them reduce their carbon footprint but also allows them to save on energy costs, ultimately increasing their profitability. Moreover, IoT sensors can detect potential equipment failures or malfunctions, allowing for timely repairs and preventing costly downtime in mining operations. Others include manufacturing companies like Kenya Steel Industries Ltd. and telecommunications companies such as Safaricom. These companies are leveraging IoT technology to track energy usage in real-time, identify areas of inefficiency, and implement energy-saving measures. By doing so, they are not only reducing their environmental impact but also improving their operational efficiency and ultimately increasing their profitability..

3.2 Africa's Strategic Policies: Catalysts for a Sustainable Future

The World Bank, the African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank have identified several key reasons why they concluded that Africa's strategic policies have played a crucial role in propelling the continent towards a more sustainable future. These organizations have highlighted that Africa's strategic policies have successfully promoted economic growth, social development, and environmental sustainability. Additionally, they have emphasized that these policies have fostered regional integration, strengthened governance systems, and encouraged investment in renewable energy sources. Furthermore, these organizations have pointed out that Africa's strategic policies have effectively addressed key challenges such as poverty reduction, job creation, and access to basic services. Moreover, they have underscored the positive impact of these policies on promoting peace and stability within the continent, leading to increased regional cooperation and collaboration. In this section, the following strategic policies are considered.

3.2.1 Prioritize Sustainable Development

Africa's strategic policies prioritize sustainable development by placing a strong emphasis on economic growth that is environmentally friendly. This approach recognizes the need to balance economic progress with the preservation of natural resources and ecosystems. By promoting green industries, renewable energy sources, and sustainable agriculture practices, Africa aims to achieve long-term economic growth while minimizing negative environmental impacts. Additionally, these policies also prioritize investments in education and capacity-building to ensure that the benefits of sustainable development are shared equitably across the continent. This approach not only addresses immediate environmental concerns but also acknowledges the importance of social development. By investing in education and capacity-building, Africa aims to empower its citizens with the knowledge and skills necessary to participate in and contribute to a sustainable economy. Moreover, by prioritizing equitable distribution of benefits, Africa strives to reduce inequalities and promote social cohesion, fostering a more inclusive and resilient society.

According to environmental assessment by international organizations like the United Nations Environment Programme (UNEP), sustainable development in Africa requires a holistic approach that takes into account the interdependence of social, economic, and environmental factors [51]. This means addressing not only education and capacity-building but also promoting sustainable agriculture, renewable energy, and conservation efforts to protect natural resources. By integrating these principles into their development strategies, African countries can work towards achieving long-term sustainability and ensuring a better future for their people. Furthermore, it is crucial for African countries to prioritize the inclusion of marginalized communities and empower women in their development efforts. By ensuring equal access to education, healthcare, and economic opportunities, these countries can create a more inclusive and equitable society. Additionally, fostering strong partnerships with international organizations and neighbouring countries can facilitate knowledge sharing and resource mobilization, ultimately strengthening Africa's collective efforts towards sustainable development.

3.2.2 Effective Environmental Governance Frameworks

African nations have long acknowledged the significance of preserving their rich biodiversity and natural resources for the benefit of future generations. They understand that these resources are not only crucial for their own economic development but also play a vital role in maintaining the overall health of the planet. Therefore, they have implemented various conservation measures and policies to safeguard their unique ecosystems and ensure the sustainable use of their natural resources. These efforts include establishing protected areas, promoting sustainable tourism, and supporting local communities in their conservation efforts. Additionally, African nations have also actively participated in international agreements and collaborations to address global environmental challenges and promote the conservation of biodiversity on a larger scale. The Central African nation is currently receiving funds as a result of preserving its forest ecosystem, which is home to a rich diversity of plant and animal species. These funds not only support the local economy but also incentivize the government and communities to continue their conservation efforts. This financial support enables the nation to invest in research, education, and infrastructure for sustainable resource management, ensuring the long-term preservation of its natural resources. It is also recognized as a vital carbon sink and is home to numerous endangered species. These funds are being used to further invest in sustainable development projects, improve local livelihoods, and strengthen conservation efforts. This not only benefits the nation's economy but also contributes to global efforts to mitigate climate change and preserve biodiversity. Furthermore, the investment in sustainable development projects and conservation efforts in this country has led to the creation of green jobs and increased income opportunities for local communities. By promoting sustainable resource management practices, the country is setting an example for other nations to follow, encouraging a global shift towards a more environmentally conscious future. The World Bank predicts that between 2010 and 2030, the country's sustainable development efforts could lead to a significant reduction in greenhouse gas emissions and a halt in the loss of biodiversity [41]. This not only benefits the country itself but also contributes to global efforts to combat climate change and protect ecosystems. Additionally, the country's commitment to sustainable development has attracted international investments and partnerships, further strengthening its position as a leader in environmental conservation and sustainable growth.

3.2.3 Embraced Renewable Energy Sources

African countries have embraced renewable energy sources, such as solar and wind power, to reduce their reliance on fossil fuels and mitigate the effects of climate change. This shift towards renewable energy has not only helped diversify their energy mix but has also created new job opportunities and improved access to electricity in remote areas. Comparatively to sub-Saharan African nations, North Africa places a higher priority on this. North Africa has been at the forefront of renewable energy adoption, with countries like Morocco and Egypt leading the way. These nations have implemented ambitious renewable energy projects, such as large-scale solar power plants and wind farms, to meet their growing energy demands while reducing carbon emissions. Additionally, North African countries have also attracted significant investments in the renewable energy sector, further driving economic growth and technological advancements in the region. However, in sub-Saharan African nations, the adoption of renewable energy has been slower due to various challenges. Limited access to financing, inadequate infrastructure, and political instability have hindered the development and implementation of large-scale renewable energy projects in these countries. Despite these obstacles, some sub-Saharan African nations, like Kenya and South Africa, have made notable progress in promoting renewable energy through policies and incentives. Efforts are being made to address the barriers and accelerate the transition towards clean energy in the region. IRENA reports predict that sub-Saharan Africa has the potential to generate more than 1,000 gigawatts of renewable energy by 2030, which could meet the region's growing electricity demand and contribute to economic growth [50]. However, North Africa has the potential to generate an even larger amount of renewable energy due to its favourable climate conditions and vast solar resources. Countries like Morocco and Egypt have already made significant investments in solar power plants and are leading the way in the region's renewable energy transition. With continued support and collaboration, North Africa has the potential to become a major exporter of clean energy to neighbouring countries and beyond. It is crucial for governments and international organizations to continue supporting and investing in renewable energy projects in order to unlock this potential and overcome the existing challenges.

3.2.4 Promote Inclusive and Equitable Access to Clean Water and Sanitation, Transforming Lives

Africa's strategic policies prioritize the development and implementation of sustainable water management systems, ensuring that all citizens have access to clean water and sanitation facilities. These policies focus on building infrastructure, such as water treatment plants and sewage systems, in both urban and rural areas. Africa actively promotes community engagement and participation in decision-making processes related to water and sanitation, ensuring that the needs of marginalized groups are addressed. By prioritizing inclusive access to clean water and sanitation, Africa's strategic policies contribute to improved health outcomes and overall well-being for its population. Access to clean water and proper sanitation reduces the risk of waterborne diseases, such as cholera and diarrhea, which are major causes of illness and death in many African countries. Furthermore, these policies also have a positive impact on education and economic development, as children are able to attend school regularly without falling ill and adults can focus on productive activities instead of spending time searching for clean water sources. According to World Bank statistics, in Sub-Saharan Africa, over 40% of the population lacks access to clean water and proper sanitation facilities [41]. This lack of access not only hinders health outcomes but also perpetuates the cycle of poverty, as families are forced to allocate a significant portion of their income towards medical expenses and water procurement. Additionally, investing in clean water and sanitation infrastructure can lead to job creation and stimulate economic growth through increased agricultural productivity and tourism opportunities. The World Bank also predicted that improving access to clean water and sanitation can reduce the prevalence of waterborne diseases such as diarrhea and cholera, which are major causes of morbidity and mortality in developing countries like Africa. This, in turn, can improve overall productivity and educational outcomes, as children are less likely to miss school due to illness.

3.2.5 Progress in Waste Management and Recycling Initiatives

Africa's has made significant progress in waste management and recycling initiatives, further contributing to its sustainable development goals. For instance, many African countries have implemented innovative waste-to-energy projects, harnessing the potential of organic waste to generate electricity and reduce reliance on fossil fuels. Additionally, community-led recycling programs have been established, creating employment opportunities and promoting a circular economy by transforming waste materials into valuable resources. These countries include Kenya, where the government has launched the "Waste to Wealth" program, encouraging citizens to separate their waste and providing incentives for recycling [29]. This initiative has not only reduced the amount of waste going to landfills but has also created new businesses in the recycling industry. Another example is Rwanda, which has implemented a nationwide ban on single-use plastic bags and promotes the use of biodegradable alternatives. These efforts have significantly reduced plastic pollution and increased awareness about sustainable waste management practices among its citizens. Most African countries could transition to a future that is more sustainable, with less waste and a thriving recycling industry, if progress is made in this direction. By adopting similar initiatives and policies, African nations can not only address the environmental challenges posed by waste but also stimulate economic growth and create job opportunities in the recycling sector. Additionally, it would contribute to global efforts to combat plastic pollution and promote sustainable development across the continent.

3.2.6 Examples of Strategic Policies Driving Africa toward a More Sustainable Future

The use of solar energy is one evidence-based illustration of how strategic policies are aiding Africa's transition to a more sustainable future. Solar power has become increasingly popular in Africa due to strategic policies that promote its adoption. For instance, in Morocco, the Noor Ouarzazate Solar Complex is one of the world's largest solar power plants, providing clean energy to over a million people [29]. This project not only reduces greenhouse gas emissions but also creates job opportunities and stimulates economic growth in the region. Strategic policies in Africa are also focusing on other renewable energy sources, such as wind and hydroelectric power. These policies aim to diversify the energy mix and reduce dependency on fossil fuels, ultimately contributing to a more sustainable future for the continent. Additionally, these initiatives are attracting foreign investments and fostering international collaborations, further accelerating Africa's transition towards a greener and more prosperous future.

Strategic policies in Africa are also focusing on promoting renewable energy sources other than solar power. For example, countries like Kenya and Ethiopia are investing heavily in wind power projects, harnessing the strong winds in their regions to generate clean electricity. These initiatives not only contribute to a more sustainable future but also enhance energy security and reduce dependence on fossil fuels. In addition to wind power, hydropower is another renewable energy source that African countries are exploring. With abundant rivers and water resources, countries like Zambia and Mozambique are developing large-scale hydropower projects to meet their growing energy demands. By diversifying their renewable energy portfolio, these countries are not only reducing greenhouse gas emissions but also creating new job opportunities and attracting foreign investments in the clean energy sector.

In southern Africa, the Lesotho Highlands Water Project is a prime example of harnessing hydropower for both energy generation and water supply. This project has not only helped meet South Africa's electricity needs but has also improved access to clean drinking water for millions of people in the region. Additionally, the development of hydropower infrastructure in South Africa has the potential to strengthen regional cooperation and promote sustainable economic growth across the region. In Nigeria, Kamji Dam and the Zungeru hydropower project are notable examples of harnessing hydropower for energy generation [29]. These projects have significantly increased Nigeria's electricity capacity and have the potential to reduce reliance on fossil fuels, contributing to a more sustainable energy mix. Furthermore, the development of hydropower infrastructure in Nigeria can create job opportunities and stimulate economic development in rural areas, improving the livelihoods of local communities.

3.3 Role of Cooperation in Advancing Africa's Sustainable Future

The World Bank, the African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank have all determined that significant technological advancements are poised to make Africa's future more sustainable. They cited three main grounds for concluding that cooperation between African governments and international organizations or private sector entities has played an important role in moving the continent toward a more sustainable future. By implementing innovative technologies such as renewable energy solutions, Africa can reduce its reliance on fossil fuels and mitigate the environmental impact of traditional energy sources. This transition to cleaner energy not only helps combat climate change but also creates new job opportunities and stimulates economic growth in the renewable energy sector. Investing in digital infrastructure can improve access to information, education, and healthcare services, empowering communities and driving economic development across the continent. Moreover, promoting sustainable agriculture practices can enhance food security and reduce the vulnerability of African nations to climate-related shocks. By adopting techniques such as agroforestry and precision farming, Africa can increase crop yields while minimizing the use of chemical inputs and preserving natural resources. These efforts not only contribute to environmental sustainability but also strengthen the resilience of rural communities and foster inclusive economic growth. The World Bank record reveals that Africa has made significant progress in implementing these practices. For example, in Ethiopia, the use of agroforestry has helped farmers increase their crop yields by up to 128% [29]. Additionally, precision farming techniques have been successfully adopted in countries like Kenya, resulting in improved soil fertility and reduced water usage. These success stories demonstrate the potential for African nations to achieve food security and climate resilience through sustainable agricultural practices.

The World Bank and other international organizations working to advance sustainability in Africa noted that collaboration between African governments and non-governmental or for-profit organizations has been crucial in guiding the continent toward a more sustainable future. By working together, these partnerships have been able to leverage resources, expertise, and technology to implement innovative solutions that address the unique challenges faced by African farmers. These collaborations have fostered knowledge exchange and capacity building, empowering local communities to take ownership of their agricultural practices and drive sustainable development. They also predicted that these partnerships will continue to play a crucial role in shaping the future of African agriculture, as they provide a platform for ongoing collaboration and learning. Through these collaborations, African farmers can access new technologies, market opportunities, and training programs that will enable them to improve productivity, reduce environmental impact, and enhance resilience in the face of climate change. As a result, not only will these partnerships contribute to a more sustainable future for Africa, but they will also contribute to the overall economic growth and well-being of the continent. By fostering partnerships between African farmers and organizations, governments, and international stakeholders, there will be increased investment in agricultural infrastructure and research, leading to improved access to resources such as irrigation systems and advanced farming techniques. This will not only boost agricultural productivity but also create employment opportunities and stimulate economic growth in rural areas. Ultimately, these partnerships have the potential to transform the agricultural sector in Africa, ensuring food security and improving the livelihoods of millions of people.

3.3.1 Examples of Collaborations Driving Africa toward a More Sustainable Future

Give data-based examples of how collaborations are assisting Africa's transition to a more sustainable future. The partnership between the African Development Bank (AfDB) and the Global Environment Facility (GEF) is one data-driven example of how collaborations are assisting Africa's transition to a more sustainable future. Through this collaboration, they have supported numerous projects across Africa aimed at promoting renewable energy, sustainable agriculture, and climate resilience. For instance, in Nigeria, the AfDB and GEF collaborated to finance the Off-Grid Energy Access Fund, which has provided solar power to over 1 million people in rural areas, reducing reliance on fossil fuels and improving access to clean energy. This collaboration not only contributes to the achievement of the United Nations Sustainable Development Goals, particularly Goal 7 (Affordable and Clean Energy) and Goal 13 (Climate Action), but also empowers local communities by creating job opportunities in the renewable energy sector [29]. Additionally, the partnership between AfDB and GEF has facilitated knowledge sharing and capacity building initiatives, enabling African countries to develop their own sustainable solutions to address climate change challenges.

The partnership between the African Union and the United Nations Development Programme (UNDP) to implement the Africa Renewable Energy Initiative (AREI) is another data-driven example of how collaborations are assisting Africa's transition to a more sustainable future. Through this collaboration, over 10,000 megawatts of new renewable energy capacity have been installed across Africa [41], providing clean and affordable electricity to millions of people. Additionally, the AREI has attracted over $10 billion in investments, creating job opportunities and stimulating economic growth in the region [41]. This partnership has not only contributed to the sustainable development of Africa but has also played a crucial role in reducing the continent's carbon footprint. The implementation of the Africa Renewable Energy Initiative has paved the way for a greener and more resilient future, ensuring access to clean energy for generations to come. The alliance between the African Development Bank (AfDB) and the Green Climate Fund (GCF) is yet another evidence-based example of how partnerships are assisting Africa's transition to a more sustainable future. Through this collaboration, the AfDB has received significant funding from the GCF to support various sustainable development projects across Africa. For instance, in 2019, the AfDB and GCF jointly launched the Africa NDC Hub, which aims to assist African countries in implementing their Nationally Determined Contributions (NDCs) under the Paris Agreement. This collaboration has helped mobilize resources and expertise to address climate change and promote sustainable development in Africa. The AfDB and GCF have worked together to fund renewable energy projects, improve climate resilience in vulnerable communities, and support the transition to low-carbon economies. Additionally, this collaboration has facilitated knowledge sharing and capacity building among African countries, enabling them to better respond to the challenges posed by climate change.

4. Investigating the Challenges for Major Organizations in Supporting Africa's Sustainable Future

4.1 Exploring the Constraints of Key Organizations in Promoting Technological Innovations for Africa's Sustainable Future

The limitations of the African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank in advancing technological innovations and driving Africa toward a more sustainable future include the following: 1) limited financial resources and funding opportunities for technological projects; 2) inadequate infrastructure and access to reliable electricity, hindering the implementation of advanced technologies; 3) lack of skilled workforce and technical expertise in emerging fields; 4) regulatory challenges and bureaucratic hurdles that slow down the adoption of innovative solutions; 5) insufficient collaboration and coordination among different stakeholders to effectively leverage technology for sustainable development. 6. Limited awareness and understanding of the potential benefits and applications of technology, leading to a reluctance to invest in and embrace new technological solutions 7. The limited availability of affordable and reliable internet connectivity further exacerbates the digital divide and hinders the widespread adoption of technology in various sectors. 8. Furthermore, the lack of digital literacy and skills among individuals and communities further hampers their ability to fully utilize and benefit from technological advancements. 9. Inadequate infrastructure and outdated policies also pose significant barriers to the effective integration of technology for sustainable development. 10. Moreover, the high cost of technology devices and software limits access for marginalized communities, perpetuating the inequality in digital opportunities. 11. the limited availability of technical support and maintenance services in underserved areas hinders the sustainability and long-term effectiveness of technology implementation.

However, despite these limitations, these organizations continue to work towards overcoming these barriers and are actively seeking partnerships and innovative solutions to bridge the digital divide. They are collaborating with government agencies, non-profit organizations, and private sector companies to develop affordable and accessible technology solutions tailored to the needs of marginalized communities. They are advocating for policy changes that prioritize digital inclusion and allocate resources for infrastructure development in underserved areas. By leveraging their expertise and resources, these organizations are working towards empowering individuals with digital skills and knowledge, enabling them to fully participate in the digital economy. They understand that closing the digital divide requires a multi-faceted approach that combines technological advancements with community engagement and education initiatives. These organizations also recognize the importance of addressing affordability barriers to ensure that individuals in underserved areas can access and afford digital technologies and internet services. They collaborate with local governments and stakeholders to develop policies and programs that promote digital literacy and provide equal opportunities for all individuals to thrive in the digital age. By offering training programs and workshops, these organizations empower individuals with the necessary skills to navigate the digital landscape effectively. They also work towards bridging the digital divide by advocating for increased internet infrastructure in underserved areas and supporting initiatives that provide affordable devices and connectivity options. Through their comprehensive approach, these organizations strive to create a more inclusive and equitable digital society for everyone.

4.2 Analyzing the Impact of Key Institutions on Africa's Sustainable Future: Unveiling the Constraints and Strategic Policy Implications

The shortcomings of the World Bank, the African Development Bank (AfDB), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the United Nations Development Programme in offering strategic policies to move Africa toward a more sustainable future. Despite their significant contributions and efforts, these organizations face certain limitations in providing strategic policies for Africa's sustainable future. One major challenge is the complex and diverse nature of the African continent, with its varying socio-economic conditions, cultural contexts, and political landscapes. Additionally, the lack of adequate funding and resources often hinders these organizations from implementing comprehensive and long-term strategies that can effectively address Africa's sustainability needs. While these institutions play a crucial role in advancing sustainable development in Africa, their limitations stem from various factors such as limited funding, bureaucratic processes, and differing priorities among member countries. Moreover, the complex socio-economic and political landscape of Africa requires a more comprehensive and context-specific approach to address the continent's unique challenges and maximize the potential impact of these institutions' strategic policies. Despite their significant contributions, these organizations face certain limitations that hinder their ability to fully drive Africa toward a more sustainable future. For instance, the AfDB and UNDP may struggle with limited funding and resources, while Google and Microsoft might face challenges in reaching remote areas with limited internet connectivity. The World Wildlife Fund (WWF) and the World Bank might encounter difficulties in navigating complex political landscapes and securing cooperation from various governments. The WWF and World Bank may also face challenges in effectively addressing cultural differences and local community engagement, which are crucial for successful conservation and development efforts. Furthermore, the WWF and World Bank may struggle with limited funding and resources, hindering their ability to implement large-scale projects in remote areas. They may face resistance from local communities who may be skeptical of external organizations and their intentions. The WWF and World Bank might encounter difficulties in navigating complex political landscapes and bureaucratic processes, which can delay or impede their conservation and development initiatives. Ensuring the long-term sustainability of their projects could pose a challenge, as they may need to find innovative ways to secure ongoing funding and support from stakeholders

4.3 Exploring Collaborative Efforts for Africa's Sustainable Future: Assessing the Limitations of Key Organizations

The limitations of the African Development Bank (AfDB), the United Nations Development Programme (UNDP), Google, Microsoft, the United Nations Environment Programme (UNEP), the World Wildlife Fund (WWF), and the World Bank in collaborations for driving Africa toward a more sustainable future include their limited financial resources and capacity to implement large-scale projects. These organizations may face challenges in coordinating efforts and aligning their respective agendas and priorities. These challenges may arise due to differences in organizational cultures, bureaucratic processes, and decision-making structures. Geographical and logistical constraints can also hinder effective collaboration among these organizations, making it difficult to achieve a cohesive and unified approach towards sustainability in Africa. Limited resources and funding can further exacerbate these challenges, as organizations may compete for the same pool of resources and struggle to secure the necessary funding for their sustainability initiatives. Political instability and conflicts in certain regions of Africa can create additional barriers to collaboration, as organizations may be hesitant to work together in volatile environments. In addition, cultural and linguistic diversity in Africa can also pose challenges to achieving a cohesive and unified approach towards sustainability. Different cultural norms and languages may require tailored approaches and effective communication strategies to ensure effective collaboration among organizations. Addressing these challenges requires strong leadership and coordination among stakeholders to overcome barriers and foster a collective effort towards sustainable development in Africa.

5. Exploring the Limitations of Technological Advancements in Africa's Journey towards Sustainability

Exploring the limitations of technological advancements in Africa's journey towards sustainability is crucial for achieving long-term success. While technology has the potential to greatly improve various aspects of sustainability, it is important to acknowledge and address the specific challenges and constraints that Africa faces in adopting and implementing these advancements. By exploring these limitations, such as limited access to reliable electricity or internet connectivity, policymakers and stakeholders can develop tailored strategies that leverage technology effectively while also considering the unique context of the continent. This holistic approach will help ensure that technological advancements contribute meaningfully to Africa's journey towards sustainability, ultimately improving the quality of life for its people. This section examines these limitations and their potential impact on the implementation of technology-driven solutions in Africa.

5.1 Lack of Access to Technology and Digital Infrastructure in Rural Areas

The lack of access to technology and digital infrastructure in rural areas of Africa poses significant challenges to connectivity and information sharing. Without proper infrastructure, communities are unable to benefit from the advantages of digital connectivity, such as accessing educational resources, healthcare information, or economic opportunities. This digital divide further exacerbates existing inequalities between rural and urban areas, limiting the potential for growth and development in these regions. The absence of reliable internet connections hampers communication and collaboration among individuals and organizations, hindering their ability to connect and share ideas, knowledge, and resources. This lack of connectivity can also impede the delivery of essential services, such as emergency response systems or online government services, leaving these communities at a disadvantage compared to their digitally connected counterparts. Without access to reliable internet, individuals in these communities may struggle to acquire the necessary digital skills and knowledge needed for participation in today's increasingly digital world, widening the gap between those who have access to opportunities and those who do not. This digital divide can have significant implications for economic and educational opportunities in these communities. Without access to reliable internet, businesses may struggle to compete in the digital marketplace, limiting their potential for growth and success. Students in these communities may face challenges in accessing online educational resources and opportunities, hindering their ability to acquire the skills needed for future employment. The lack of internet access can also widen the gap between those who have access to information and those who do not, exacerbating existing inequalities. This can result in limited access to crucial services such as healthcare information, government resources, and job opportunities, further marginalizing these communities and hindering their overall development.

5.2 Insufficient Research and Development Investment Hinders Tailored Innovation for Africa

This limited investment in research and development has hindered the development of innovative solutions that specifically address the unique challenges faced by African countries. As a result, many of the existing solutions are not effectively adapted to the local context, leading to inefficiencies and missed opportunities for growth and development. Moreover, this lack of tailored innovation also hampers Africa's ability to compete globally and limits its potential for economic advancement. In order to overcome these challenges, it is crucial for African countries to prioritize and allocate more resources towards research and development initiatives. By doing so, they can foster the creation of innovative solutions that are specifically designed to tackle the region's unique obstacles and promote sustainable growth. Investing in tailored innovation will not only enhance Africa's competitiveness on a global scale but also unlock its untapped potential for economic advancement and prosperity. By focusing on research and development, African countries can also address pressing social issues such as healthcare, education, and poverty alleviation. These innovative solutions have the potential to improve the quality of life for millions of people in the region and contribute to overall human development. Ultimately, prioritizing research and development will enable African countries to chart their own path towards self-reliance and reduce their dependence on external aid or solutions.

5.3 Insufficient Access to Education and Training Hinders Technological Skill Development

Inadequate education and training opportunities can hinder individuals from acquiring the necessary skills to effectively leverage technology. This can result in a significant digital skills gap where people struggle to adapt to the rapidly evolving technological landscape. As technology continues to advance, it becomes crucial for educational institutions and training programs to prioritize equipping individuals with the knowledge and abilities needed to navigate and utilize technology effectively. Bridging this gap is essential for ensuring equal access and opportunities for all individuals in an increasingly digital world. Without the necessary digital skills, individuals may face difficulties finding employment or advancing in their careers. Moreover, the digital skills gap can exacerbate existing inequalities, as those who are already disadvantaged may be further marginalized without access to technology and the ability to use it effectively. Therefore, addressing this gap is not only important for personal success but also for promoting social and economic equity.

5.4 Barriers to Accessing Advanced Technologies in Africa

The high costs associated with adopting and maintaining advanced technologies pose a significant barrier, limiting accessibility for many Africans. This financial burden not only includes the initial investment required to acquire these technologies but also encompasses ongoing expenses such as training, maintenance, and upgrades. Consequently, this creates a digital divide, exacerbating the existing inequality gap and hindering the potential benefits that advanced technologies can bring to African societies. The lack of reliable infrastructure, such as stable electricity and internet connectivity, further hampers the adoption and utilization of advanced technologies in Africa. Without a consistent power supply and fast internet access, it becomes even more challenging for individuals and businesses to fully leverage the potential of these technologies.

Consequently, this perpetuates the cycle of limited accessibility and hinders Africa's progress in various sectors such as education, healthcare, and economic development. In education, the lack of advanced technologies prevents students from accessing online resources and participating in virtual learning platforms, limiting their educational opportunities. In healthcare, the absence of reliable electricity and internet connectivity hinders the implementation of telemedicine and remote healthcare services, depriving many people of essential medical care. The limited utilization of advanced technologies in Africa's economic sectors restricts innovation and productivity, hindering the region's overall economic growth and competitiveness on a global scale. The lack of access to advanced technologies also hampers Africa's ability to participate fully in the digital economy, limiting its potential for job creation and economic diversification. This digital divide further exacerbates existing inequalities and widens the gap between Africa and other regions in terms of technological advancements and economic development.

5.5 Need for Strengthening Regulatory Frameworks and Governance Structures in Africa's Technology Sector

Weak regulatory frameworks and governance structures in Africa have significant implications for the ethical and social aspects of technology use. These shortcomings often result in a lack of accountability, transparency, and protection for individuals and communities affected by technological advancements. The absence of comprehensive regulations can lead to the exploitation of personal data, privacy breaches, and unequal access to technology resources, exacerbating existing social inequalities. The lack of frameworks and governance structures also hinders innovation and limits the potential benefits that technology can bring to African societies. Without clear guidelines and oversight, there is a risk of unethical practices such as surveillance, discrimination, and the spread of misinformation through technology platforms. Therefore, it is crucial for African countries to prioritize the development of robust frameworks and governance structures that address these ethical and social concerns while fostering a fair and inclusive technological landscape. These frameworks should include provisions for data protection and privacy, ensuring that individuals' personal information is safeguarded from misuse. They should promote transparency and accountability in the use of technology, holding both private companies and government entities responsible for any unethical practices. By establishing these frameworks, African countries can harness the full potential of technology to drive economic growth, improve access to education and healthcare, and empower their citizens.

5.6 Impediments to Technological Advancement Due to Inadequate Internet Accessibility

Limited access to reliable and affordable internet connectivity poses a significant challenge to the widespread adoption and utilization of technology in various sectors. Without proper internet access, individuals and businesses struggle to leverage the full potential of technology, hindering progress and development. In education, for example, students in remote areas may not have access to online learning resources or virtual classrooms, limiting their educational opportunities. Similarly, healthcare services heavily rely on technology for telemedicine and remote patient monitoring, but without reliable internet connectivity, these services become inaccessible to those in underserved areas. This lack of access can result in a disparity in healthcare outcomes, as patients are unable to receive timely medical advice or monitoring. Businesses in remote locations face challenges in conducting online transactions and reaching wider markets, hindering their growth and economic potential. In addition, the lack of reliable internet connectivity in underserved areas can also hinder educational opportunities for students.

Online learning platforms and resources are increasingly important in today's digital age, and without access to these tools, students in remote locations may struggle to keep up with their peers. This further exacerbates the educational divide between urban and rural areas, limiting the future prospects of individuals in underserved communities. The limited availability of educational facilities and qualified teachers in underserved areas adds to the challenges faced by students. Without proper infrastructure and skilled educators, students may not receive the quality education they need to thrive academically. This disparity in resources and opportunities perpetuates a cycle of inequality, making it even more difficult for individuals in underserved communities to break free from poverty and achieve their full potential. As a result, these students may lack the necessary skills and knowledge to compete in the job market, further widening the economic gap between underserved communities and more privileged areas. The lack of access to quality education can also lead to higher dropout rates and lower graduation rates, limiting future opportunities for these students and perpetuating generational poverty.

5.7 Need for Enhanced Collaboration and Knowledge-Sharing in African Countries for Sustainable Technological Development

This lack of collaboration and knowledge-sharing hinders the ability of African countries to effectively address common challenges and capitalize on opportunities presented by technology. By working together, African nations can pool their resources, expertise, and experiences to develop innovative solutions that address their unique needs and drive sustainable development across the continent. Fostering a culture of collaboration can promote cross-learning and enable African countries to avoid duplicating efforts, leading to more efficient use of resources and accelerated progress towards sustainable development goals. Collaboration can also facilitate the sharing of best practices and lessons learned, allowing African nations to learn from each other's successes and failures. This exchange of knowledge can help accelerate the development and implementation of effective technological solutions, ultimately benefiting all countries involved. By leveraging collective expertise and resources, African nations can negotiate better deals with technology providers and attract more investment in their digital infrastructure, further enhancing their capacity for innovation and sustainable development.

5.8 Risks of Relying Solely on Foreign Technology without Local Adaptation or Customization

Dependence on foreign technology without local adaptation or customization in Africa can have detrimental effects on the continent's long-term development. While importing technology from other countries can provide initial benefits, it often fails to address the specific needs and challenges faced by African nations. Without local adaptation or customization, foreign technology may not be suitable for the unique socio-economic and environmental conditions of African countries. This can result in inefficiencies, limited scalability, and a lack of sustainability. It hinders the growth of local innovation and entrepreneurship as African countries become dependent on foreign technology rather than developing their own solutions. This reliance on imported technology also leads to a drain of resources, as funds are spent on purchasing and maintaining foreign products instead of investing in local research and development. To truly drive long-term development in Africa, it is crucial for countries to prioritize the development and utilization of homegrown technologies that are tailored to their specific needs and can contribute to sustainable growth. By investing in local research and development, African countries can foster innovation and create job opportunities within their own borders.

Developing homegrown technologies can also help to address unique challenges and issues that are specific to the African context, ultimately leading to more effective and sustainable solutions for the continent. These solutions can range from improving access to clean water and energy to enhancing agricultural practices and healthcare systems. By nurturing a culture of innovation and entrepreneurship, African countries can attract foreign investment and foster economic diversification, ultimately reducing their reliance on traditional sectors such as natural resources. By focusing on these specific challenges and finding innovative solutions, African countries can not only address immediate needs but also build a foundation for long-term development. This approach can help create jobs, improve living standards, and empower local communities to take charge of their own futures. By leveraging technology and digital advancements, African countries can leapfrog traditional development models and find unique solutions that are tailored to their specific needs.

5.9 Political Instability and Insufficient Government Support for Technological Innovation act as Impediments to Africa's Long-term Viability

Political instability in Africa has been a major obstacle to sustainable development. Constant changes in leadership, corruption, and conflicts have resulted in a lack of long-term planning and commitment to addressing environmental challenges. The lack of government support for technological innovation further hinders progress towards sustainability. Insufficient funding, limited access to resources, and a lack of policies that promote research and development prevent the continent from harnessing the full potential of technology to tackle environmental issues effectively. As a result, Africa struggles to implement sustainable solutions and adapt to the rapidly changing climate. This is particularly concerning as Africa is one of the most vulnerable regions to the impacts of climate change, including droughts, floods, and desertification. Without adequate support and investment in technology-driven solutions, Africa may continue to face significant environmental challenges that hinder its social and economic development. These challenges not only affect the continent's natural resources and ecosystems but also have severe consequences for its population, especially those who rely on agriculture and livestock for their livelihoods. It is crucial for Africa to prioritize the development and implementation of innovative strategies that promote renewable energy, sustainable agriculture, and efficient resource management to mitigate the adverse effects of climate change and ensure a brighter future for its people. By investing in renewable energy sources, Africa can reduce its dependence on fossil fuels and decrease greenhouse gas emissions. Promoting sustainable agricultural practices like crop rotation and water conservation can help farmers adapt to changing climate conditions and ensure food security for the growing population. Efficient resource management strategies such as waste reduction and recycling can minimize environmental degradation and promote a circular economy in Africa. These efforts will not only contribute to mitigating climate change but also create new job opportunities and foster economic growth across the continent.

5.10 Challenges in Harnessing Technological Advancements due to Infrastructure and Connectivity Constraints

Inadequate infrastructure and limited access to electricity and internet connectivity hinder the effective implementation and utilization of technological advancements. Without a reliable power supply, it becomes difficult to sustain the operation of technological devices and systems. Limited internet connectivity restricts access to online resources, hindering the ability to leverage technology for educational, economic, and social development. These barriers disproportionately affect marginalized communities and exacerbate existing inequalities. In order to bridge this digital divide, governments and organizations must prioritize investments in infrastructure development and expand access to electricity and internet connectivity in underserved areas. Efforts should be made to provide digital literacy training and skills development programs to ensure that individuals have the necessary knowledge and abilities to navigate the digital world effectively. Collaboration between governments, organizations, and private sector entities is crucial in order to create sustainable solutions that address the unique challenges faced by marginalized communities in accessing technology. By working together, these stakeholders can pool resources and expertise to develop innovative strategies that prioritize the needs of underserved areas. This collaborative approach will not only bridge the digital divide but also empower individuals and communities to fully participate in the digital economy and access educational opportunities, healthcare services, and other essential resources.

6. CONCLUSIONS

While technological advancements have undoubtedly played a significant role in Africa's journey towards sustainability, it is important to acknowledge their limitations. One key limitation is the lack of access to technology in many rural areas [52], where basic infrastructure and connectivity are still major challenges. The high cost of implementing and maintaining advanced technologies can pose a barrier for many African countries with limited financial resources. By focusing on inclusive and affordable solutions, investing in infrastructure development, and promoting digital literacy, Africa can overcome these limitations and leverage the potential of technology to drive economic growth and social development [53]. By bridging the digital divide and ensuring equal access to technology, African countries can empower their citizens, improve education and healthcare systems, and foster innovation and entrepreneurship.

By fostering partnerships with international organizations and leveraging the expertise of local tech entrepreneurs, Africa can tap into global knowledge and resources to accelerate its technological advancement. This can lead to the creation of new industries and job opportunities, ultimately contributing to poverty reduction and overall economic prosperity. The integration of technology in various sectors such as agriculture, finance, and transportation can enhance efficiency and productivity, further boosting Africa's competitiveness in the global market. This can lead to the creation of new industries and job opportunities, ultimately boosting economic growth and reducing poverty. The adoption of technology can also enhance government efficiency and transparency, leading to better governance and public service delivery for African citizens. Technology can play a crucial role in improving access to education and healthcare in Africa. With the use of digital platforms and telemedicine, individuals in remote areas can receive quality education and medical assistance, bridging the gap between urban and rural areas. The integration of technology in governance can also empower citizens by providing them with easier access to government services and information, promoting citizen engagement and participation in decision-making processes.

It is therefore recommended that more sophisticated strategic policies and collaboration with foreign partners be implemented in order to fully utilize technological innovations and expertise in advancing the African economy and improving the quality of life for its citizens. By leveraging technology, governments can streamline administrative processes and reduce bureaucratic inefficiencies, leading to cost savings and improved service delivery. Additionally, the integration of technology can enhance transparency and accountability in governance, fostering trust between citizens and their governments. It is recommended that researchers conduct additional research into the potential of emerging technologies such as artificial intelligence and blockchain to transform key sectors of the African economy. These technologies have the potential to revolutionize industries such as agriculture, healthcare, and finance, leading to increased productivity, better access to services, and greater financial inclusion.

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CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

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Assessment of Temporal Trend in Surface Air Temperatures across Some Selected Eco-Climatic Zones in Nigeria

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Temporal trends in surface air temperatures across some selected eco-climatic zones in Nigeria from 1981 to 2018 were assessed using the Merra-2 reanalysis dataset. A total of 15 stations spread across the eco-climatic zones in Nigeria were used for this study. The Mann-Kendall (M-K) trend test was used to detect direction, significance, coefficients of time trends, while the linear regression and the Sen's slope trend tests were used to estimate the trend magnitudes. The M-K trend test showed that the surface air maximum temperature of 14 stations had monotonic increasing trends, of which 13 stations were statistically significant at the 0.01 significance level, and 1 station was statistically significant at the 0.05 significance level. However, the M-K trend test also showed that surface air minimum temperature for all the 15 stations (representing 100%), showed monotonic upward trends, statistically significant at the 0.01 significance level. The Sen's slope and linear trend tests showed higher trend magnitudes at most stations, particularly stations in the Guinea-wooded, Sudan and Sahel savannas. The estimated mean trend magnitudes of maximum and minimum air surface temperatures increased by approximately 0.035°C/year and 0.036°C/year, respectively. The estimated mean air surface temperature increased by approximately 0.036°C/year and approximately 1.4°C for Nigeria over the 38-year period. The study then presents a linear trend projection of mean air surface temperature increase in Nigeria of approximately 4.3°C by 2100. This is 0.2°C below maximum levels and within the range of approximately 1.5 to 4.5°C that global air surface temperature is projected to rise by 2100 in the Intergovernmental Panel on Climate Change (IPCC) 2007 report. The M-K and linear trend tests were fully consistent with the standardized time series anomaly plots. Mean annual values of the air surface temperatures showed latitudinal dependence. The manifestation of significant long-term trends at high confidence levels in the air surface temperatures over the period, provides a clear evidence that the climate of Nigeria is witnessing a possible human-induced radiative forcing and a strong tendency for the occurrences of climate-related extreme events and their resulting adverse implications.

Keywords: Trend; Temporal, Maximum temperature; Minimum temperature; Radiative forcing; Nigeria

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1. Introduction

A trend is generally a long-term movement in a chronologically ordered observation (*i.e.*, a time series), having a period exceeding the length of the time series. Stephenson [1] defines a trend as a long-term variation in the average level, a smooth regular component having a period exceeding the length of a time series. There is generally a basic tendency either for data to go upward, downward or remain stable over a considerable period of time. Most importantly, analyzing temporal trends and changes in air surface temperature can indirectly reveal the "health" of the environment. A rising and/or declining trend may be quite instructive for different segments of human and natural systems.

The detection of time series trends in hydroclimatic parameters has become the most popular technique for detecting local, regional and global climate change and variability, and spatial or temporal changes in climate parameters appear to be non-uniform. Yue and Hashino [2] pointed out that there may be considerable and significant spatiotemporal changes between regions with different climates.

Many researchers analyzed surface air temperature-time series from various climate change perspectives across a wide range of temporal and spatial scales. Their analysis indicates significant increases in surface air temperature in different parts of the world [3-5]. Climate change scenarios for Nigeria as examined by Abiodun *et al.* [3], using a 30-year data distribution that spanned from 1971-2000, reported upwards trends in surface air maximum and minimum temperatures. Many studies have shown positive trends in surface air temperatures, although the changes vary from one region to another [6-9]. Analysis of 30 years' data for temperature and rainfall variability in Nigeria spanning from 1971-2000 conducted by Akinsanola and Ogunjobi [10], indicated that surface temperatures and rainfall increased significantly at a considerable number of the sites they studied. Their results further suggested a sequence of alternately upward and downward trends in the two parameters. Oguntunde *et al.* [11] conducted a study to assessed the possible occurrence of trends in air surface temperature across Nigeria from 1901-2000. Their results showed that the change in the minimum air surface temperature was higher than the change in the maximum air surface temperature. Amadi *et al.* [12] conducted a trend and variation study of basic atmospheric parameters including but not limited to mean annual air surface temperatures. Their findings showed trends in the parameters across Nigeria from 1950-2012.

The contemporary focus of applied climate science is on enhancing knowledge at local, regional and global scales. The more limited this information is available, the more relevant it will be to most users of the application. Studying trends and changes in a region's weather and climate elements is critical for sustainable agriculture, water management, power generation, marine and aviation safety, and more. Most communities in Nigeria are vulnerable to the vagaries of climate change and variability since they are exposed to several environmental hazards associated with climate change and variability. The effective use of weather and climate information to manage climate-related risks and prepare adaptive and mitigation measures to face future challenges is very vital. According to the IPCC report [13], high temperatures leaves in its wake, incidences of heatwaves. High temperatures can trigger off incidences of diseases linked to high temperatures such as Cerebra-spinal meningitis, heat stroke etc. Also, changes in surface air temperatures influences quite a number of hydrological processes, including precipitation.

Some trend studies in Nigeria focus on individual towns over relatively short periods of time [14-18]. Most of these studies carried out in Nigeria focused on the last century, while others focused on small spatial scales, mostly using in-situ meteorological data. Therefore, there is a need to study current trends in annual mean air surface temperatures at representative stations of selected eco-climatic zones in Nigeria using an Integrated Earth System Analysis (IESA) approach using decades of global reanalysis data. Reanalysis is a process in which a data assimilation system provides a consistent reprocessing of meteorological observations, typically covering an extended period of the historical data record. Milestones in achieving the objectives of this study are: 1. Assessing the historical recorded trends of the selected parameters at the site and period studied; 2. Assessing the temporal trends and possible causes of spatial variation of the selected parameters.

2. Location and Brief Geography of the Study Area

Nigeria is sandwiched between latitudes 4° and 14°N and between longitudes 3° and 15°E of the Equator and Greenwich Meridian respectively. The climate of Nigeria is made up of various ecotypes and climate zones and is influenced by the interaction of the Tropical Maritime and the Tropical Continental air masses and their associated Planetary Winds-the South-east and the North-east trade winds respectively. The Tropical Maritime air mass emanates from the Sub-tropical High Pressure belt, centered about 30°S of the equator, and off the coast of Namibia while the Tropical Continental air mass emanates from the Sub-tropical High pressure belt., centered about 30°N, north of the equator and over the Sahara Desert [3] The Tropical Maritime air mass is warm and moist while the Tropical Continental air mass is cold and dry, even as it travels across the Sahara Desert, towards Nigeria. The interactions of these two air masses defines the Wet and Dry season pattern in Nigeria. Teleconnection influences on the Nigerian landscape are imposed by the strong North Atlantic Oscillation (NAO) during the dry season and the El Nino-Southern Oscillation (ENSO) during the wet season [11].

Adefolalu [19] has pointed out that Nigeria may be divided into five eco-climatic zones - the Mangrove-swamp rainforest, the Tropical rainforest, the Guinea, Sudan and the Sahel Savannas. The characteristic of the eco-climatic zones is essentially defined by the vegetation pattern. Other factors such as rainfall, relief, soil type and human activity, may have significant impacts. Fig. 1: shows the meteorological stations for the study and the eco-climatic zones.

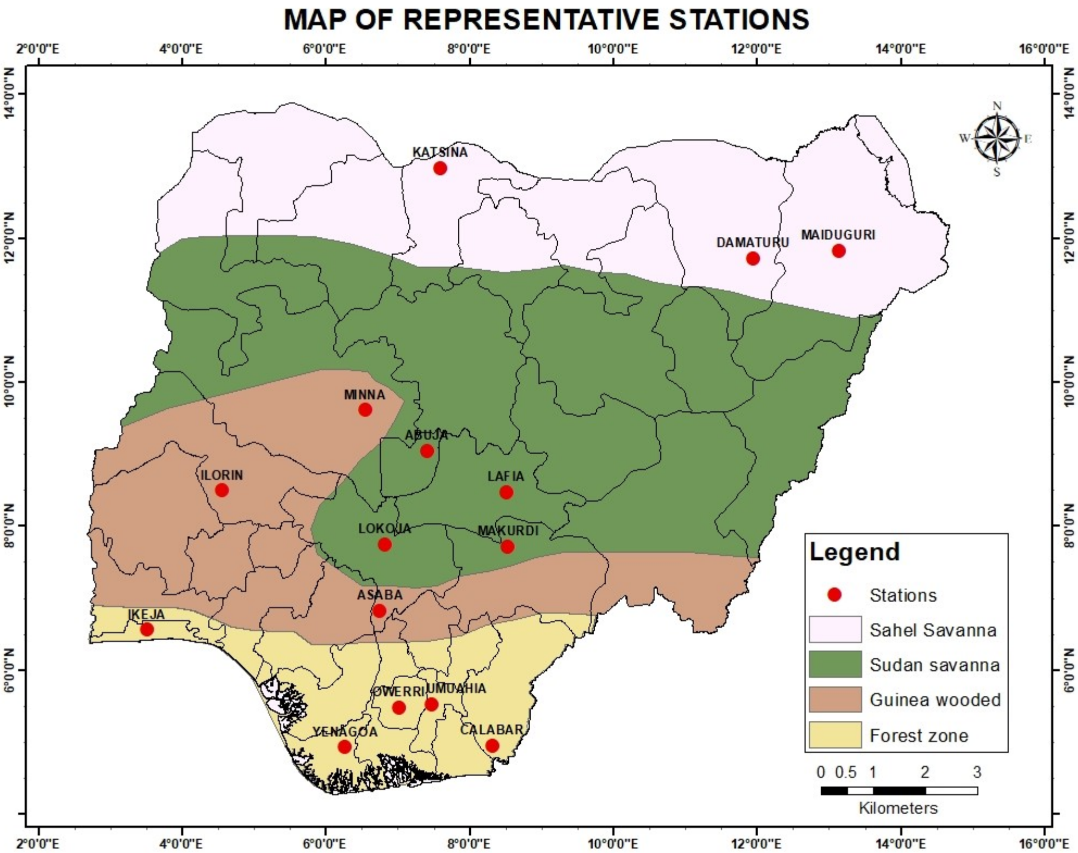

Fig. 1. Map of Nigeria showing the meteorological stations for the study and eco-climatic zones

Table 1. Summary information on the meteorological stations [3, 19, 20]

Station name	Latitude (°N)	Longitude (°E)	Altitude (m)	Eco-climatic Zones
Katsina	12.98	7.60	163.91	Sahel Savanna
Maiduguri	11.83	13.15	331.51	
Damaturu	11.73	11.95	388.54	
Abuja	9.05	7.41	404.65	Sudan savanna
Lafia	8.48	8.52	163.91	
Lokoja	7.75	6.82	198.15	
Minna	9.62	6.55	346.62	Guinea-wooded Savanna
Ilorin	8.50	4.55	283.03	
Makurdi	7.72	8.53	139.21	
Asaba	6.83	6.75	136.69	Tropical rainforest
Umuahia	5.53	7.48	92.84	
Owerri	5.48	7.02	60.61	
Ikeja	6.56	3.51	55.68	Mangrove-swamp rainforest
Calabar	4.95	8.32	34.68	
Yenagoa	4.93	6.26	13.06	

3. Data and Methodology

3.1 Dataset

The data for the assessment of mean annual air surface temperatures for trends across some representative stations of the selected eco-climatic zones in Nigeria is MERRA-2, which is obtained from the National Aeronautics and Space Administration (NASA) database. The GEOS Atmospheric model and the Grid Point Statistical Interpolation analysis scheme are considered as the important components of this system [21-23]. Reanalysis products are increasingly used in climate monitoring because appropriate and careful consideration is given to their inherent uncertainties [20]. The stations are the representative stations of the selected eco-climatic zones in Nigeria. The data represents the mean monthly values of air surface temperatures remotely sensed at 2 meters above the ground surface from the space-borne observation systems, spanning from 1981 to 2018. The parameters of interest are the air surface maximum and minimum temperatures. Summary information on the representative stations, meteorological parameters measured at the representative stations are presented in Table 1.

3.2 Data Check and Smoothening

Data was checked for incompleteness, outliers, and homogeneity. The data had no missing values. Quality checks help to remove outliers (genuine freak events or single data errors) and their biases. According to Longobardi & Villani [24], long-term climate analysis should be based on homogenous data, since there is a large variability in space and time of climate variables. Climate datasets are homogeneous datasets with fluctuations/variations caused only by weather and climate changes. Non-climatic factors can introduce fluctuations/homogeneities that create progressive biases in the data distribution [12]. Hence, normality and homogeneity tests were conducted on the datasets.

3.3 Methodology

The original mean monthly datasets were converted to mean annual datasets. This study synergistically embraced the parametric linear trend test and the non-parametric Mann-Kendall (M-K) and Sen's slope trend tests. According to Kundzewicz & Robson [25] and Sonali & Kumar [26], multiple statistical tests should be used to accurately interpret the data and test hypotheses when each statistical test addresses a specific question.

The M-K trend test was used to evaluate the trend direction, significance of the trend and the M-K tau b. The linear regression model using the least squares method and the Sen's slope trend tests were used to estimate the magnitudes of the trend. Many authors have pointed out that non-parametric tests have statistical advantages over the parametric test. Therefore, non-parametric tests are superior because of the following advantages: they are insensitive to the presence of outliers (*i.e.*, being robust to rogue events and incomplete data) and they exhibit a degree of monotonicity [27-29].

In cases where the non-parametric tests showed disparity in results with the parametric linear trend test, the M-K and Sen's slope trend tests results were held superior to the parametric test.

3.3.1 The Mann-Kendall (M-K) Trend Test

The M-K trend test statistics is computed using the sign of differences between successive values rather than on the values of the randomly selected variables [35]. This non-parametric statistical tool has been widely used to assess trends in hydro-climatic data [30, 31, 36, 37]. Hence, it was adopted in this study.

Given a time series of n-sized dataset, such that n is greater than or equal to 10, the M-K test statistic (S) is computed with the formula [28, 32].

$$S = \sum_{k=1}^{n-1} \sum_{j=k+1}^{n} sgn(x_j - x_k) \qquad 1$$

where x_j and x_k are the sequential data values for the j^{th} and k^{th} terms (j > k)

$$\text{Sgn}\,(x_j - x_k) = \begin{cases} 1 \; if \; x_j - x_k > 0 \\ 0 \; if \; x_j - x_k = 0 \\ -1 \; if \; x_j - x_k < 0 \end{cases} \qquad 2$$

An increasing (upward) trend (later values exceeding earlier values) is denoted by a large positive value of test statistic (*S*). A decreasing (downward) trend (later values not exceeding earlier values) is denoted by a large negative value of the test statistic (*S*). A small absolute M-K test statistic(*S*) value implies that a trend does not exist.

The variance of *S, VAR(S)* (σ2) where ties are not present (*i.e.,* j=k does not exist) is defined as

$$VAR(S) = \frac{n(n-1)(2n+5)}{18} \qquad 3$$

where ties are present, the variance of S is defined as

$$VAR(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p=1}^{q} t_p \; (t_p - 1)(2t_p + 5)\right] \qquad 4$$

From Eqn. 4, q denotes the number of tied (*i.e.*, j=k), t_p denotes the number of data values in the p^{th} group.

Computation of Z test statistic is done using the values of M-K test statistic(*S*) and the variance of the M-K test statistic *AR(S)* as follow

$$Z = \begin{cases} \frac{S-1}{\sqrt{VAR(S)}} \; if \;\; S > 0 \\ 0 \qquad\quad if \; S = \; 0 \\ \frac{S+1}{\sqrt{VAR(S)}} \; if \;\; S < 0 \end{cases} \qquad 5$$

An upward or downward trend is denoted by a positive or negative value of *Z,* respectively. For a two-tailed test, the null hypothesis H_o implies that a linear trend does not exist and that the data distribution is randomly ordered and independent. An alternative hypothesis H_1 implies that a linear trend does exists. For the null hypothesis H_0 to be rejected., the absolute value of Z evaluated using Eqn. 5 must be greater than the critical value $Z_{\alpha/2}$, at the selected significance level, for the null hypothesis H_0 to be rejected. Other than that, the null hypothesis is accepted.

3.3.2 The Linear Trend Test

The linear trend and Sen's slope trend tests were synergistically used in determining the trend magnitudes. A test for linear trend is given by the linear regression of y on time t.

$$y = \beta_0 + \beta_1 x + \varepsilon \qquad 6$$

The slope is denoted by β_1, and the intercept on y is denoted by β_0, which is the value of y at x = 0. The dependent variable is y, the independent variable is x, and ε is the error, residual, or bias, which can be positive, negative, or zero and is caused by random effects. The dependent variable y value corresponding to a given independent variable x value is estimated by finding the value of y from the least-squares line that fits the data.

The null hypothesis is that slope coefficient $\beta_1 = 0$ (*i.e.,* lack of linear dependence) and the alternative hypothesis is that slope coefficient $\beta_1 \neq 0$ (*i.e.,* linear dependence exists). A significant slope different from zero is the condition for rejecting the null hypothesis and accepting the alternative hypothesis that y has a linear trend over time with a ratio equal to β_1.

3.3.3 The Sen's Slope Trend Test

Estimation of trend magnitude in hydro-meteorological time series has been widely carried out using the Sens slope trend test [2, 18, 29].

Demonstration of the presence of a monotonic trend and the linearity of the trend allows for the estimation of the trend magnitude using the Sen's line. The non-parametric Sen's line models how the median data changes linearly with time, and the trend magnitude for the entire period covered by the study is obtained by multiplying the estimated slope per year by the total number of years involved. Following the method of Sen [33], the slope magnitude can be obtained as follows:

$$b_{sen} = Median\left[\frac{Y_i - Y_J}{(i-j)}\right] \text{for all j < i} \qquad 7$$

where Y_i and Y_j are data at time points i and j, respectively.

If the total number of data points in the series is *n*, then the corresponding slope estimates will be $\frac{n(n-1)}{2}$ and the test statistic b_{sen} will be the median of all slope estimates. Increasing or decreasing trend is shown by a positive or negative value of the test statistic respectively.

3.3.4 The p-value

The p-value defines a region in the probability distribution tail beyond the noticeable values of the selected test statistic. When the p-value is small, the corresponding selected test statistic value will be seen to be particularly high and when the p-value is large, the corresponding selected test statistic will be seen to be very small. The null hypothesis is rejected if the p-value is smaller than the selected significance level, assuming that the data is not consistent with the null hypothesis at the selected significance level and vice versa.

4. Results

4.1 Results of Mean Air Surface Temperatures

4.1.1 Temporal Trend in Mean Annual Air Surface Temperatures

Tables 2 and 3 show the temporal trend for mean annual air surface maximum temperatures. The Mann-Kendall's test statistic (*S*) ranges from -113 to 398, the coefficients of time trends range from -0.161 to 566, and the trend magnitude increase ranges from 0.015° to 0.073°C/year for mean annual air surface maximum temperatures across the selected eco-climatic zones in Nigeria. The highest trend magnitude in mean annual air surface maximum temperature is noticeable in Lafia (*i.e.,* 073 °C/year) while the lowest value is observed in Yenagoa (*i.e.,* 0.015 °C/year) (Table 2). The temporal trend for mean annual air surface minimum temperatures are shown in Tables 4 and 5. The Mann-Kendall's test statistic (*S*) ranges from 280 to 446, the coefficients of time trends (*i.e.*, the Kendall's tau b) range from 0.398 to 0.634, and the trend magnitude increase ranges from 0.024° to 0.069 °C/year for mean annual air surface minimum temperatures across the selected eco-climatic zones in Nigeria. The highest trend magnitude in mean annual air surface minimum temperature is noticeable in Abuja (*i.e.*, 0.069 °C/year), while the lowest value is noticeable in Katsina and Ikeja (*i.e.*, 0.024 °C/year). (Table 4).

Figs. 2 to 6 are the standardized anomaly time series plots for mean annual air surface maximum temperatures, showing monotonic positive (upward) trends in the plots of 14 stations. A monotonic negative (downward) trend is shown by one station (*i.e.,* Ikeja).

Table 2. Results of Mann-Kendall's and Sen's slope trend tests for mean annual air surface maximum temperatures

Station name	S	Kendall's tau b	Z	Sen's slope estimates (°C/year)	p-value
Maiduguri	255	0.363**	3.1938	0.039**	1.404E-03
Damaturu	284	0.404**	3.5587	0.043**	3.727E-04
Katsina	196	0.279*	2.4529	0.020*	1.417E-02
Ilorin	129	0.184	1.6098	0.019	0.1074420
Lafia	398	0.566**	4.9914	0.073**	5.993E-07
Lokoja	320	0.455**	4.0114	0.051**	6.036E-05
Minna	365	0.519**	4.5762	0.065**	4.736E-06
Abuja	364	0.518**	4.5640	0.069**	5.019E-06
Makurdi	388	0.552**	4.8665	0.058**	1.136E-06
Owerri	316	0.450**	3.9632	0.019**	2.925E-04
Asaba	269	0.383**	3.3698	0.028**	7.522E-04
Ikeja	-113	-161	4.6035	-0.006	0.1587637
Umuahia	318	0.452**	3.9869	0.020**	6.695E-05
Yenagoa	284	0.404**	3.5594	0.015**	8.041E-03
Calabar	345	0.491**	4.3270	0.017**	1.511E-05

For Kendall's tau b, ** means that Kendall's tau b is significant at the 0.01 level (2-tailed), while means that *Kendall's tau b is significant at the 0.05 level (1-tailed). For Sen's slope, ** means that the slope is significant at the 0.01 level (2-tailed), while * means that the slope is significant at the 0.05 level (1-tailed).

Figs. 7 to 11 are the standardized anomaly time series plots for mean annual air surface minimum temperatures, showing monotonic positive (upward) trends in all the 15 stations.

Table 3. Results of linear trend estimation for mean annual air surface maximum temperature

Station name	Parameters	Slope estimates (°C/year)	Standard error	Students t-test	p-value
Maiduguri	Slope	0.039**	0.011	3.5862	4.77E-04
	Intercept	34.933	0.131	272..412	4.36E-02
Damaturu	Slope	0.048**	0.011	4.3837	8.50E-05
	Intercept	33.628	0.146	236.828	7.46E-03
Katsina	Slope	0.022*	0.009	2.4022	1.60E-02
	Intercept	33.465	0.103	330.044	5.58E-01
Ilorin	Slope	0.016	0.011	1.2883	1.25E-01
	Intercept	31.674	0.113	283.215	9.90E-01
Lafia	Slope	0.0075**	0.010	7.8234	2.01E-09
	Intercept	29.939	0.170	184.621	2.92E-07
Lokoja	Slope	0.052**	0.012	4.5241	3.71E-05
	Intercept	29.96	0.151	205.252	2.23E-03
Minna	Slope	0.069**	0.012	5.8302	6.22E-07
	Intercept	29.331	0.175	175.050	3.83E-05
Abuja	Slope	0.073**	0.012	6.0492	2.68E-07
	Intercept	29.157	0.182	167.914	1.54E-05
Makurdi	Slope	0..059**	0.008	7.1710	1.54E-08
	Intercept	29.384	0.137	222.263	4.90E-06
Asaba	Slope	0.028**	0.004	3.4982	6.87E-04
	Intercept	29.069	0.096	310.227	9.02E-02
Owerri	Slope	0.018**	0.004	4.7703	2.03E-05
	Intercept	28.3323	0.051	570.588	3.66E-01
Umuahia	Slope	0.020**	0.004	4.8984	1.21E-05
	Intercept	228.72	0.055	528.139	1.92E-01
Ikeja	Slope	-0.0069	0.044	-1.7697	1.11E-01
	Intercept	29.017	0.048	606.314	1.37E-07
Yenagoa	Slope	0.014**	0.004	3.8055	5.30E-04
	Intercept	28.468	0.045	633.952	8.00E-01
Calabar	Slope	0.018**	0.004	4.1381	8.17E-06
	Intercept	27.79	0.050	560.224	7.46E-01

**Slope is significant at the 0.01 level (2-tailed)
*Slope is significant at the 0.05 level (1-tailed)

Table 4. Mann-Kendall and Sen's slope trend tests for mean annual air surface minimum temperatures

Station name	S	Kendall's tau b	Z	Sen slope (°C/year)	p-value
Maiduguri	289	0.411**	3.6219	0.027**	2.925E-04
Damaturu	345	0.491**	4.3261	0.031**	1.518E-06
Katsina	280	0.398**	3,5089	0.024**	4.499E-04
Ilorin	366	0.521**	4.5906	0.029**	4.421E-06
Lafia	415	0.590**	5.2056	0.048**	1.934E-07
Lokoja	385	0.548**	4.8284	0.043**	1.132E-06
Minna	407	0.579**	5.1050	0.045**	2.735E-07
Abuja	364	0.518**	4.5640	0.069**	1.285E-07
Makurdi	388	0.552**	4.8673	0.038**	1.132E-06
Asaba	394	0.560**	4.9419	0.033**	7.735E-07
Owerri	410	0.583**	5.1439	0.033**	1.323E-04
Umuahia	391	0.556**	4.9038	0.033**	9.399E-07

Yenagoa	414	0.589**	5.1953	0.031**	2.043E-07
Calabar	446	0.634**	5.6340	0.030**	1.761E-08
Ikeja	348	0.495**	4.3651	0.024**	1.271E-05

**Kendall's tau b is significant at the 0.01 level (2-tailed)
**Slope is significant at the 0.01 level (2-tailed)

Table 5. Results of linear trend estimation for mean annual air surface minimum temperature

Station name	Parameters	Slope estimates (°C/year)	Standard error	Students t-test	p-value
Maiduguri	Slope	0.027**	0.006	4.2017	7.65E-05
	Intercept	20.671	0.08005	264.667	1.10E-02
Damaturu	Slope	0.031**	0.006	5.1639	6.93E-06
	Intercept	20.044	0.08490	243.210	1.25E-03
Katsina	Slope	0.024**	0.006	4.0525	1.33E-04
	Intercept	19.368	0.07586	261.603	1.32E-04
Ilorin	Slope	0.031**	0.005	5.49899	1.11E-06
	Intercept	20.903	0.07665	280.258	6.55E-04
Lafia	Slope	0.047**	0.006	7.9952	8.95E-10
	Intercept	20.876	0.10506	207.447	2.66E-07
Lokoja	Slope	0.041**	0.006	6.6786	4.39E-08
	Intercept	21.05	0.09876	221.315	1.18E-05
Minna	Slope	0.046**	0.007	6.5024	6.69E-08
	Intercept	19.418	0.11102	183.002	6.51E-06
Abuja	Slope	0.046**	0.006	7.0835	8.86E-09
	Intercept	19.44	0.10720	189.767	1.28E-06
Makurdi	Slope	0.039**	0.006	6.8273	3.24E-08
	Intercept	20.834	0.09194	234.822	1.28E-08
Asaba	Slope	0.034**	0.005	6.6422	5.06E-08
	Intercept	21.20	0.08097	269.966	4.5E-05
Owerri	Slope	0.033**	0.044	7.3927	6.52E-09
	Intercept	21.753	0.07659	292.493	1.51E-05
Umuahia	Slope	0.032**	0.005	6.8802	2.93E-08
	Intercept	21.52	0.07664	289.009	4.66E-05
Ikeja	Slope	0.025**	0.004	5.7450	1.23E-06
	Intercept	23.035	0.06338	370.915	4.62E-03
Yenagoa	Slope	0.031**	0.0042	7.4115	8.71E-09
	Intercept	22.768	0.0724	322.836	4.23E-05
Calabar	Slope	0.029**	0.004	8.8284	1.35E-10
	Intercept	23.767	0.6238	389.961	1.08E-05

**Slope is significant at the 0.01 level (2-tailed)

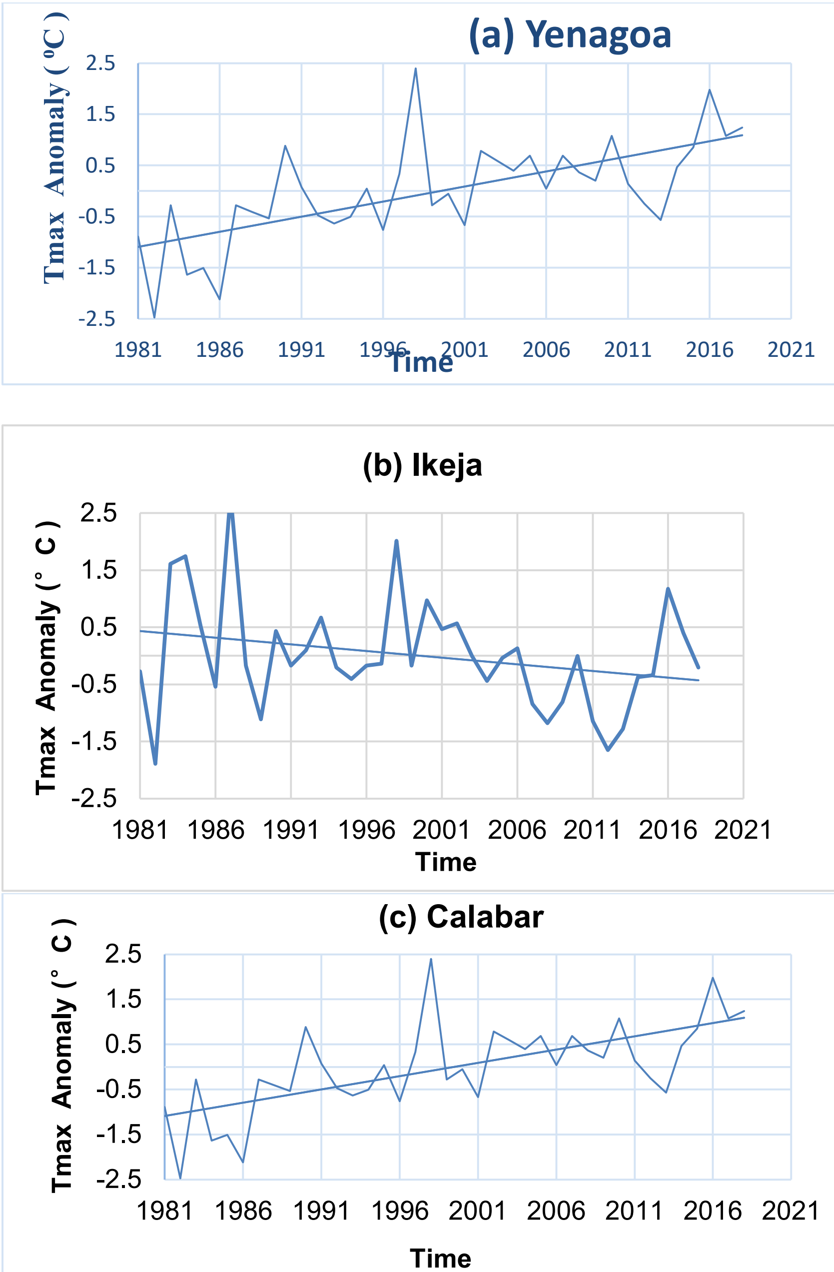

Fig. 2. Standardized anomaly time series plots for mean annual air surface maximum temperatures for representative stations (a: Yenagoa, b: Ikeja and c: Calabar) of the Mangrove-swamp rainforest eco-climatic zone

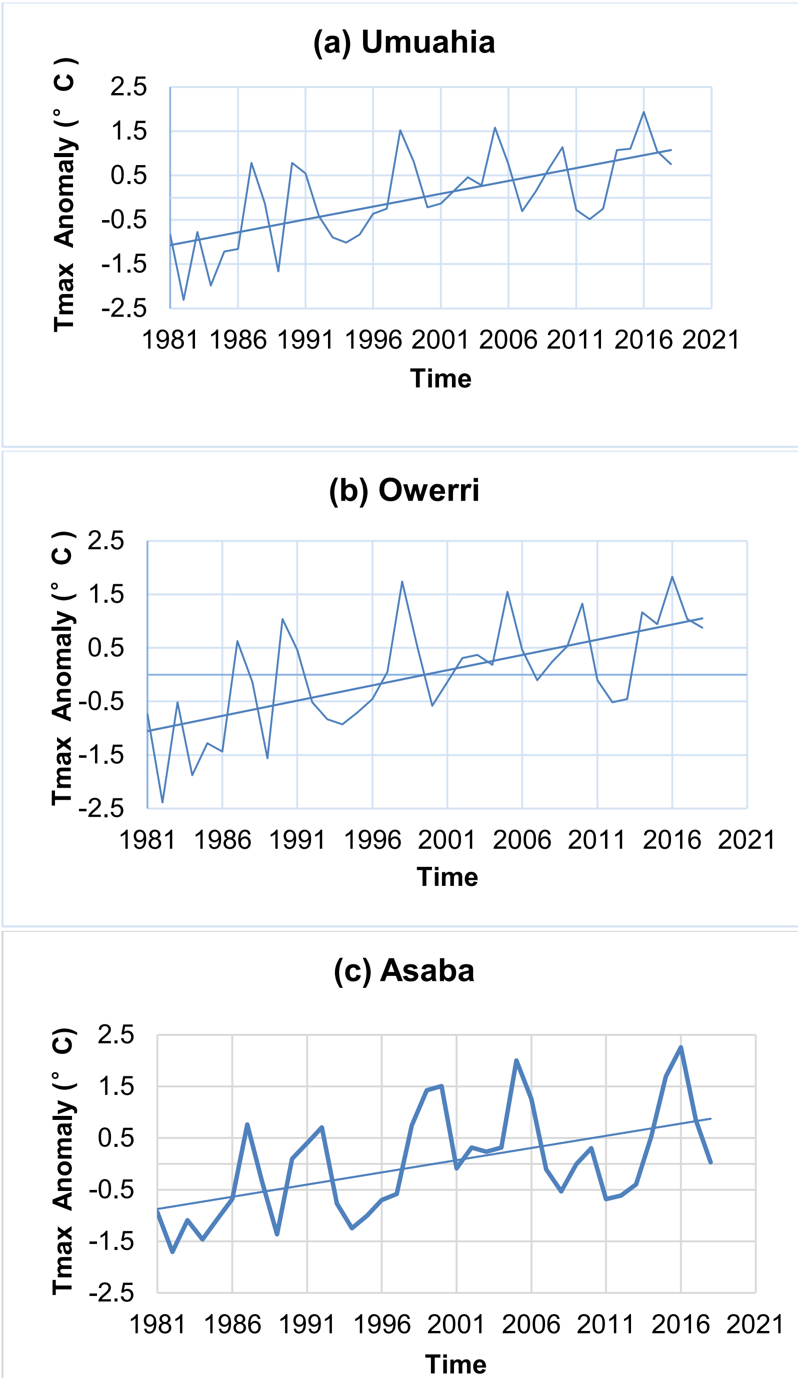

Fig. 3. Standardized anomaly time series plots for mean annual air surface maximum temperatures for representative stations (a: Umuahia, b: Owerri and c: Asaba) of the Tropical rainforest eco-climatic zone

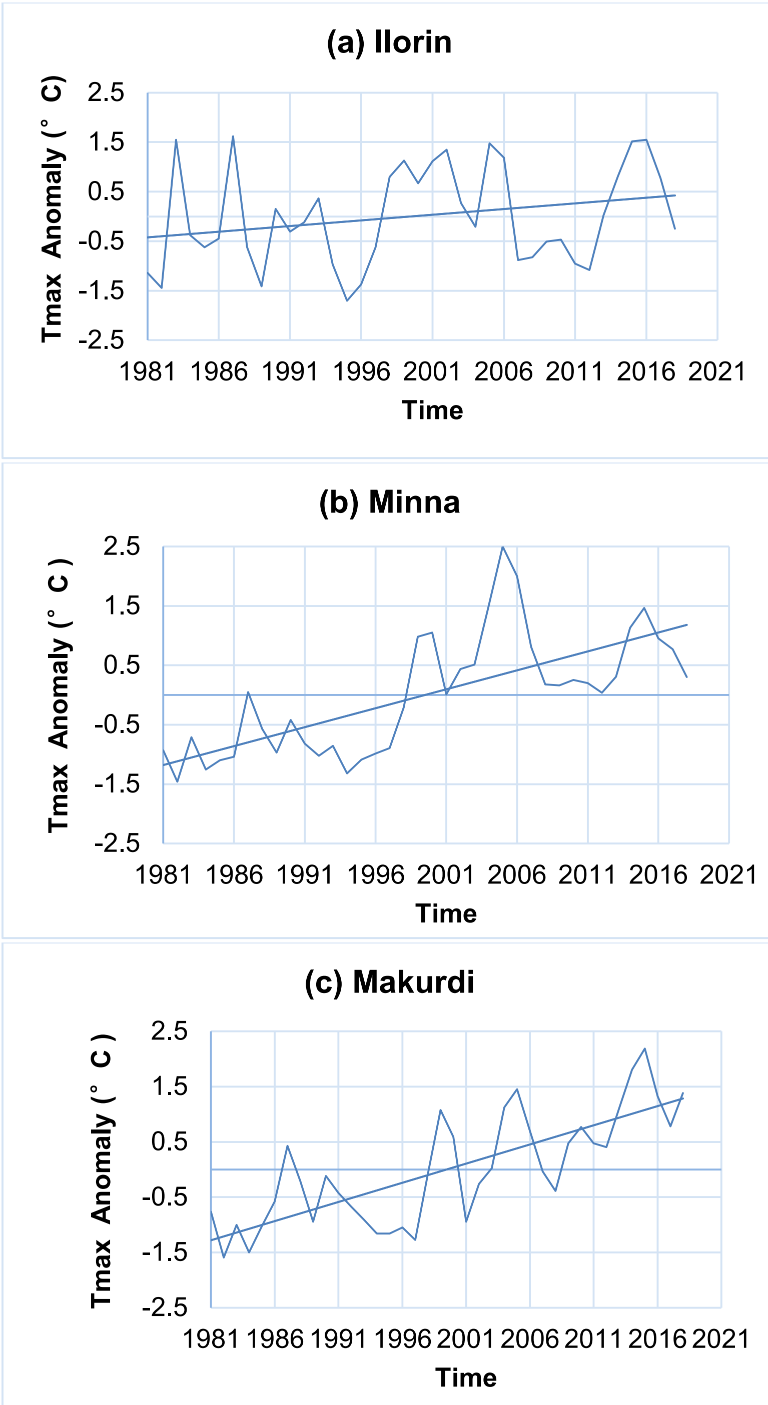

Fig. 4. Standardized anomaly time series plots for mean annual air surface maximum temperatures for representative stations (a: Ilorin, b: Minna and c: Makurdi) of the Guinea-wooded savanna eco-climatic zone

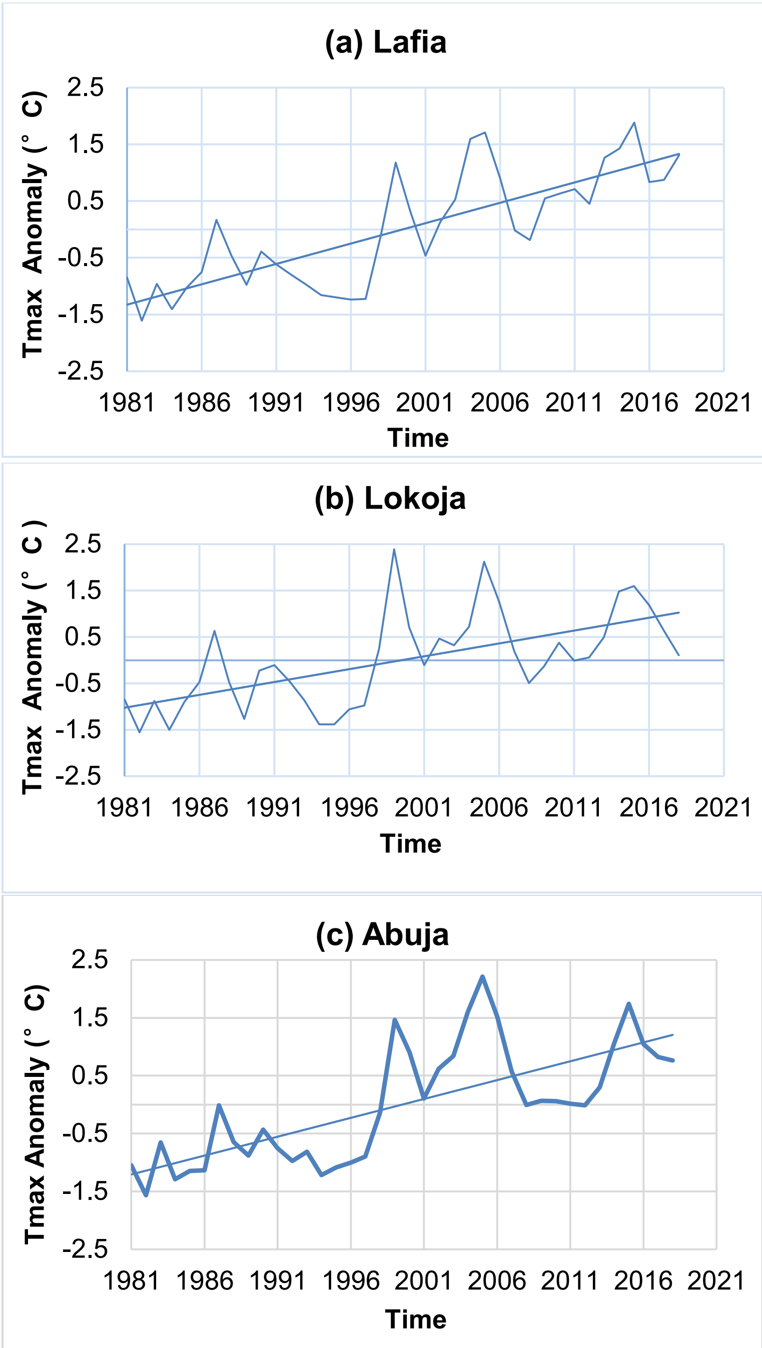

Fig. 5. Standardized anomaly time series plots for mean annual air surface maximum temperatures for representative stations (a: Lafia, b: Lokoja and c: Abuja) of the Sudan savanna eco-climatic zone

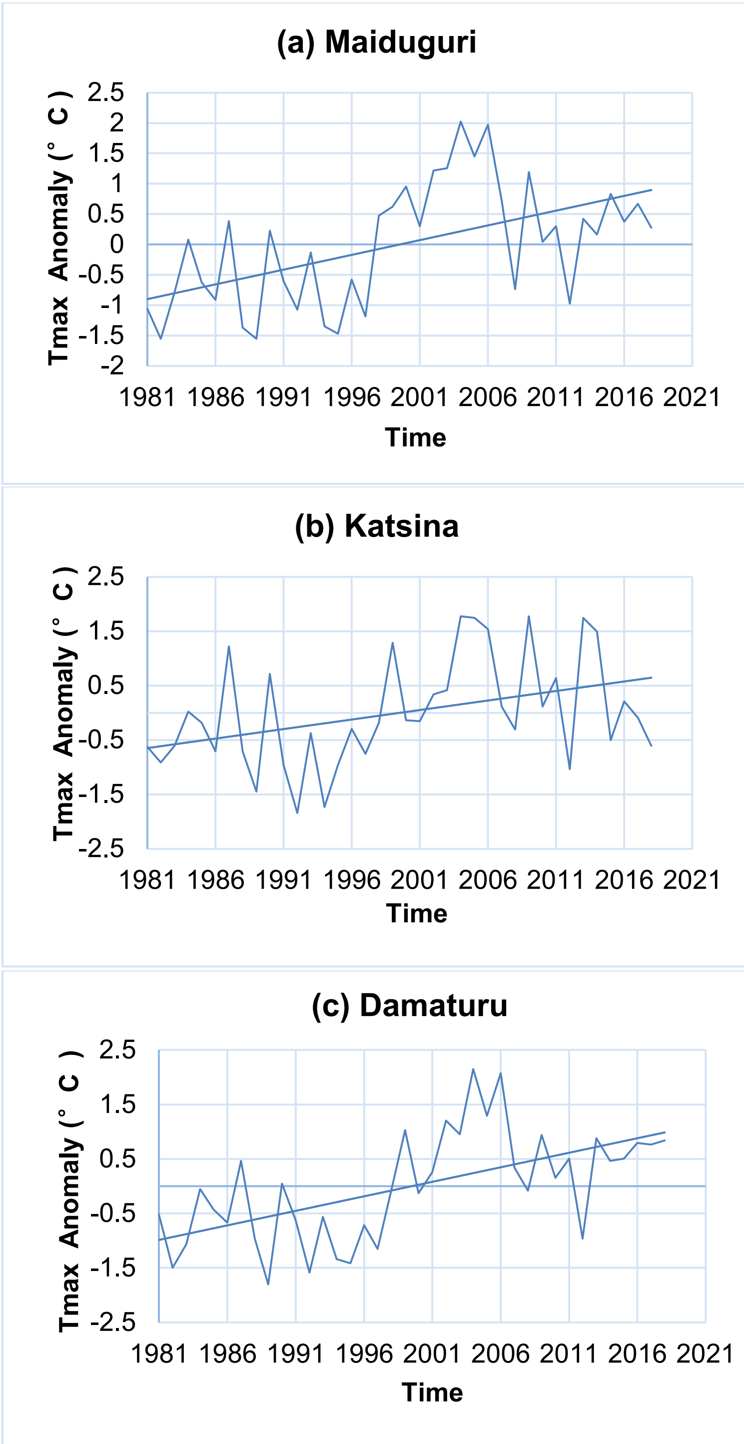

Fig. 6. Standardized anomaly time series plots for mean annual air surface maximum temperatures for representative stations (a: Maiduguri, b: Katsina and c: Damaturu) of the Sahel savanna eco-climatic zone

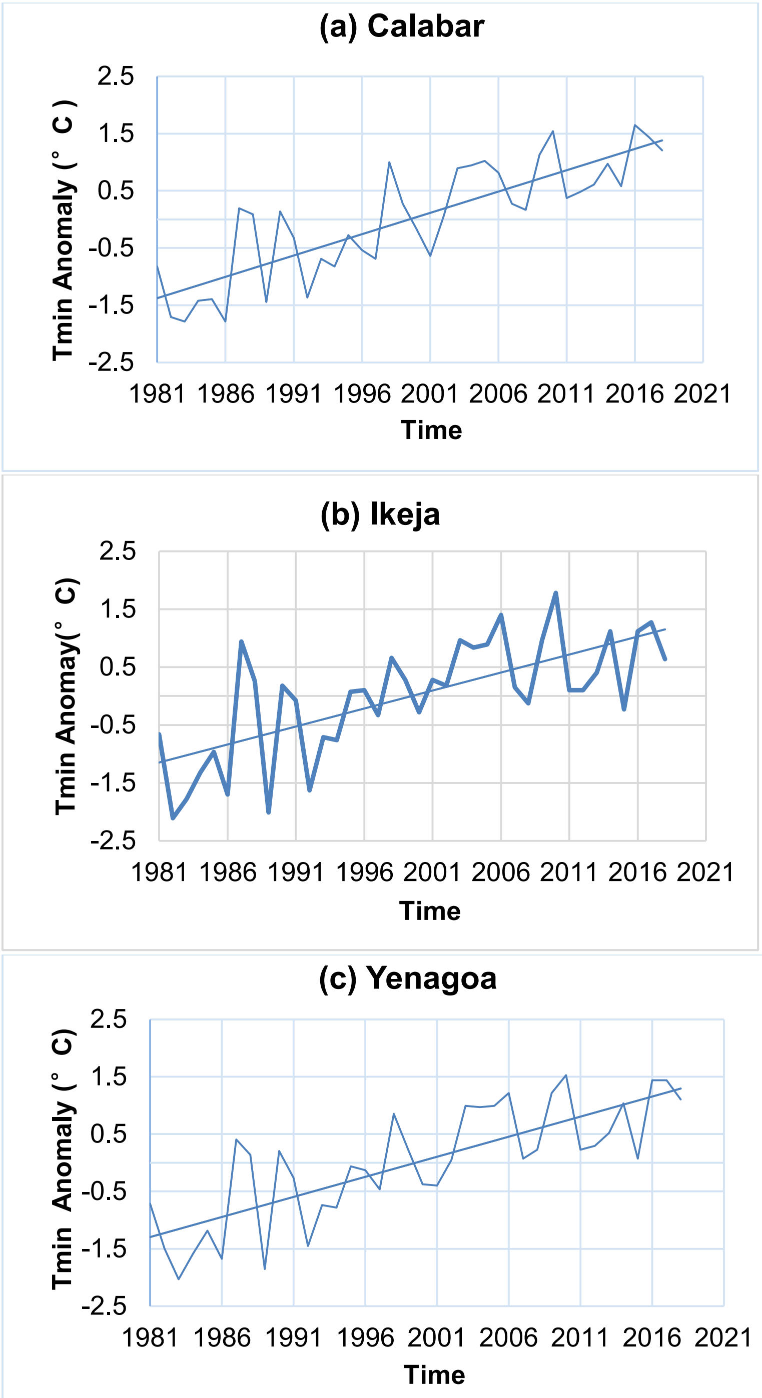

Fig. 7. Standardized anomaly time series plots for mean annual air surface minimum temperatures for representative stations (a: Calabar, b: Ikeja and c: Yenagoa) of the Mangrove-swamp rainforest eco-climatic zone

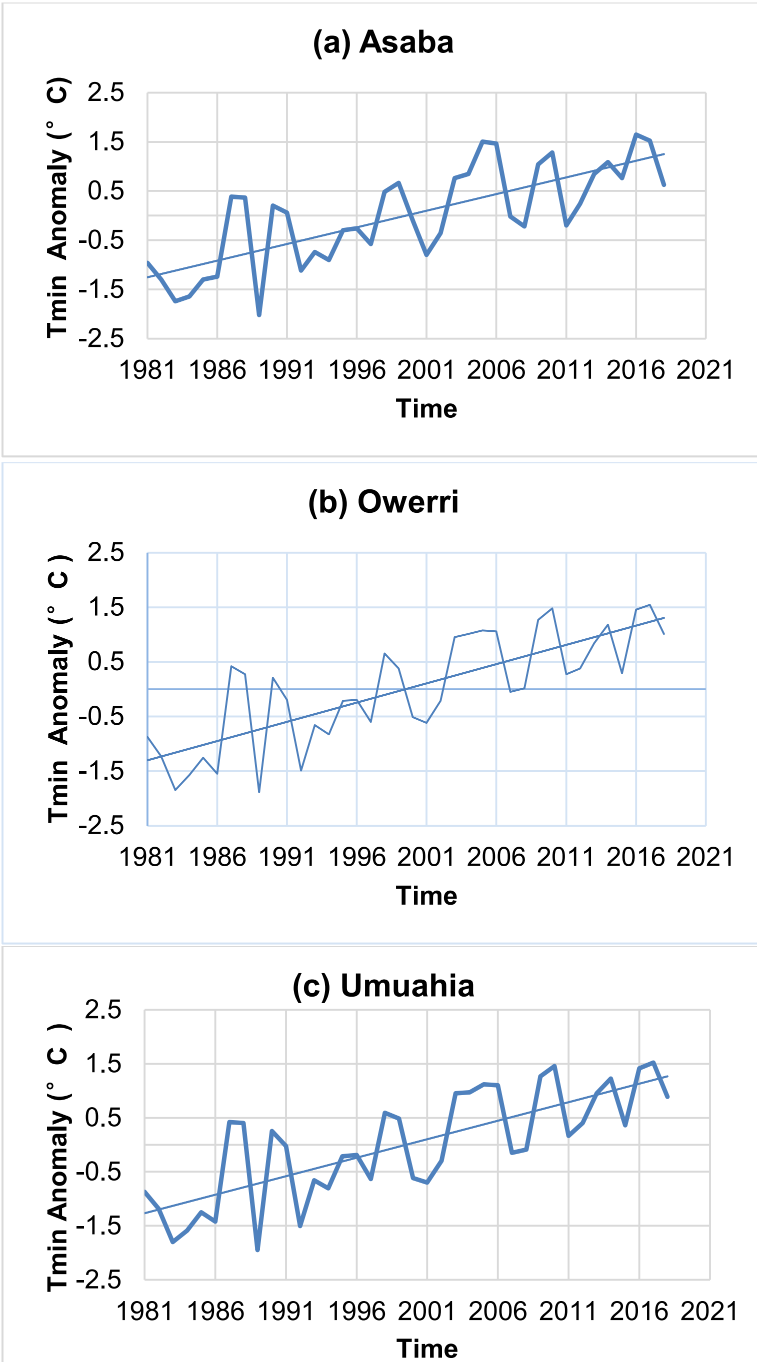

Fig. 8. Standardized anomaly time series plots for mean annual air surface minimum temperatures for representative stations (a: Asaba, b: Owerri and c: Umuahia) of the Tropical rainforest eco-climatic zone

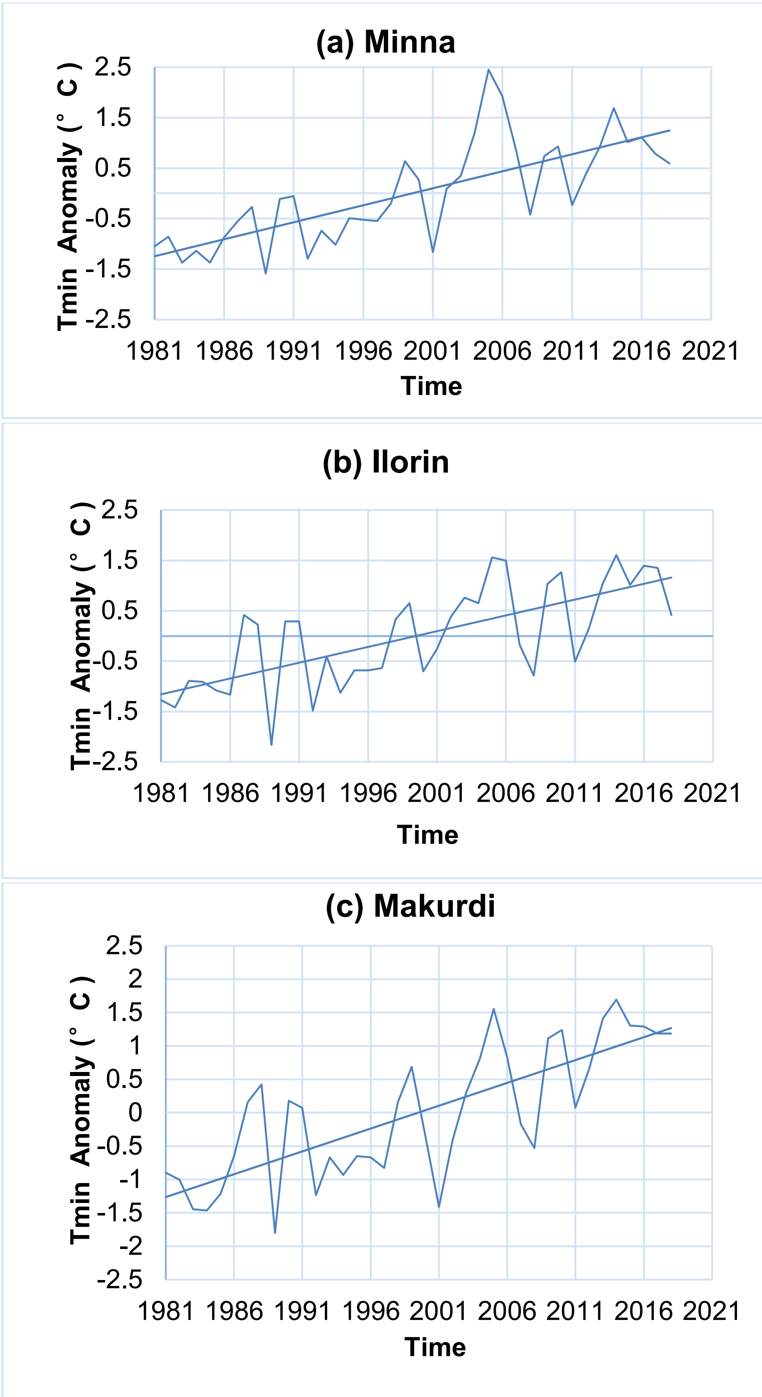

Fig. 9. Standardized anomaly time series plots for mean annual air surface minimum temperatures for representative stations (a: Minna, b: Ilorin and c: Makurdi) of the Guinea-wooded savanna eco-climatic zone

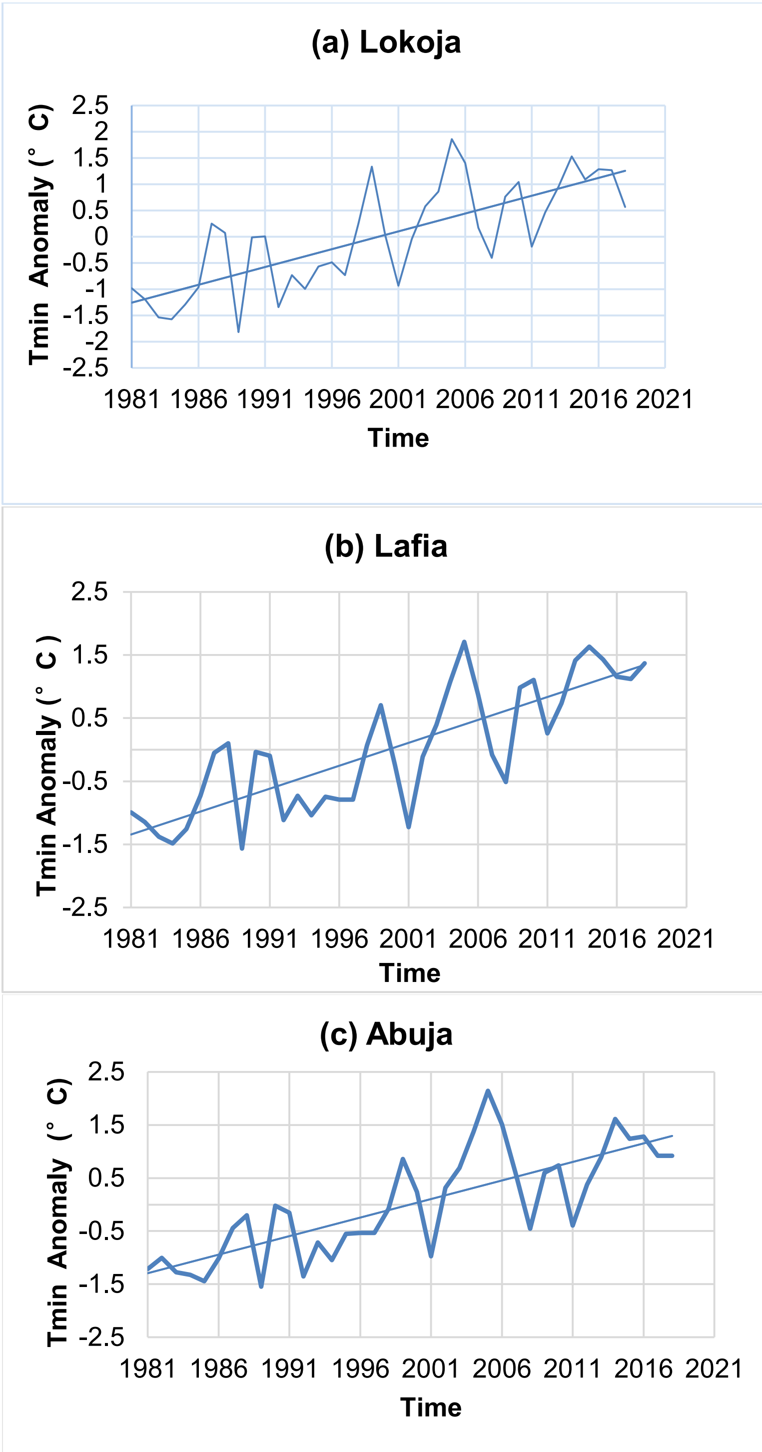

Fig. 10. Standardized anomaly time series plots for mean annual air surface minimum temperatures for representative stations (a: Lokoja, b: Lafia and c: Abuja) of the Sudan savanna eco-climatic zone

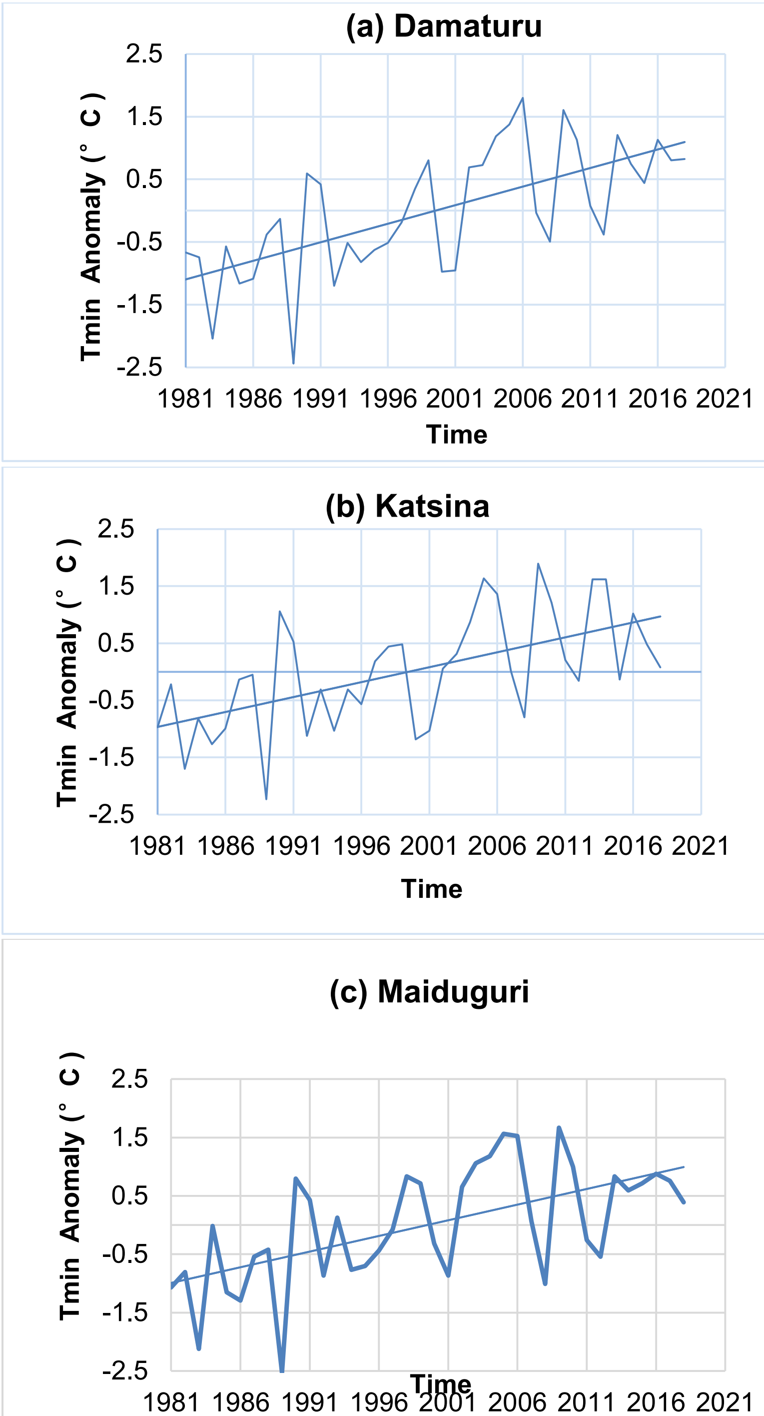

Fig. 11. Standardized anomaly time series plots for mean annual air surface minimum temperatures for representative stations (a: Katsina, b: Damaturu and c: Maiduguri) of the Sahel savanna eco-climatic zone

4. Discussion

Long-term monotonic trends were manifested in the historical records of the studied parameter. The highlights of the findings are hereby presented.

The temporal trend analysis of mean annual air surface maximum temperature in Tables 2 and 3 reveals that 14 stations have monotonic positive (upward) trends in mean annual air surface maximum temperature as shown by the positive values of the M-K test statistic (*S*). Ikeja however, shows a monotonic negative (downward) trend as observed by the negative value of the Mann-Kendall's test statistic (*S*). The highest value in the M-K test statistic for mean annual air surface maximum temperature was observed in Lafia, while the lowest value was observed in Ilorin. The M-K coefficients of time trend (*i.e.*, Kendall's tau b) for mean annual air surface maximum temperature for 12 stations are statistically significant at the 99% confidence interval (*i.e.*, 0.01 significance level) and one station (*i.e.*, Katsina) is statistically significant at the 95% confidence interval (*i.e.*, 0.05 significance level).

Similarly, the long-term temporal trend analysis of mean annual air surface minimum temperature in Tables 4 and 5 shows that all the stations have monotonic positive (upward) trends in mean annual air surface minimum temperature as revealed by the positive values of the M-K test statistic(*S*). The highest value was observed in Calabar, while Katsina revealed the lowest value. The trends for all the stations are statistically significant at the 0.01 significance level as revealed by the coefficients of time trends values. Comparing Tables 2 and 4, it was observed that mean annual air surface minimum temperature has a higher change rate than mean annual air surface maximum temperature. The results of this study long-term temporal trend analysis are in line with the findings of [11], in which mean annual air surface minimum temperature has a higher rate of change than mean annual air surface maximum temperature. Majority of the stations in the Guinea-wooded (*i.e.,* Makurdi and Minna), Sudan (Abuja, Lafia and Lokoja) and Sahel savanna (*i.e.,* Maiduguri and Damaturu) zones have higher trend magnitudes. The highest trend magnitude in mean annual air surface maximum temperature is noticeable in Lafia (*i.e.,* 073 °C/year), while the lowest value was noticeable in Yenagoa (*i.e.,* 0.015 °C/year). The highest trend magnitude in mean annual air surface minimum temperature was noticeable in Abuja (*i.e.,* 0.069 °C/year), while the lowest value is noticeable in Katsina and Ikeja (*i.e.,* 0.024 °C/year). Mean estimated trend magnitude increase for mean annual air surface maximum temperature is about 0.035 °C/year and about 0.036 °C/year for mean annual air surface minimum temperature. Thus, this study gives an estimated mean trend magnitude increase in mean annual air surface temperature of about 0.036 °C/year (*i.e.,* 0.36 °C/decade) and an estimated mean annual air surface temperature increase in Nigeria of about 1.4°C from 1981-2018.

The standardized chronologically ordered anomaly plots for mean annual air surface maximum temperature show monotonic positive (upward) trends in 14 stations (Figs 2 a-c to 6 a-c). Extreme temperature events such as that of 1998 are shown in some of the standardized anomaly time series plots (*i.e.,* Calabar, Owerri, Umuahia and Yenagoa). The outstanding years (*i.e.,* 2005, 2009 and 2010) which are amongst the 10 warmest years in the global record relative to the 1961-1990 reference period [34], were observed in the plots of some stations. No significant long-term trends were observed in Ikeja (Fig. 2b) and Ilorin (Fig. 4a). The results of the plots are in line with the M-K and the linear trend tests results (Tables 2 and 3 respectively)

Additionally, the standardized chronologically ordered anomaly plots for mean annual air surface minimum temperature showing monotonic positive (upward) trends in all the 15 stations were observed (Figs. 7 a-c to 11 a-c). The standardized anomaly time series plots also displays the years with records of extreme events in mean annual air surface minimum temperatures during the period of this study. All the station's time series plots depict monotonic trends that are in complete agreement with the results of the M-K and the linear trend tests (Tables 4 and 5, respectively). The plots for the mean annual air surface temperatures depict chronologically ordered meteorological observations of air surface temperatures for the period covered by this study. The trend line fitted into the plots shows that mean annual air surface maximum temperature had increased monotonically for 14 stations as shown by the positive (upward) trend lines. Excerpt one station (*i.e.,* Ikeja) where the mean annual air surface maximum temperature had decreased monotonically as shown by the negative(downward) trend line over the period covered by this study. Similarly, the plots for mean annual air surface minimum temperature shows that mean annual air surface minimum temperature had increased monotonically across all the representative stations of the eco-climatic zones over the period covered by this study. The magnitudes of the increase in both mean annual air surface maximum and minimum temperatures are shown by the Sen's slope (Table 2 and 4) and the linear trend tests (Tables 3 and 5).

The synergistic use of more than one method to analyze the trends in mean annual air surface temperatures in Nigeria from 1981 to 2018, in this study is in line with the findings of [25, 26]. According to them, proper care should be taken to arrive at correct interpretation of data and test assumptions during trend analysis using statistical tests, and the conclusions should be made by using more than one statistical test as each statistical test addresses a specific question.

This study suggests that increasing population, urbanization, increased evapotranspiration rates, severe drought, deforestation and desertification may be culpable for the upward and high trend magnitudes in air surface temperature observed in the Guinea-wooded, Sudan and Sahel savannas. The result of this study trend magnitude and direction is in line with that of Akinsanola & Ogunjobi [10], who reported an increase of about 0.036 °C/year in air surface temperatures and upward trends in most stations in Nigeria, a decreasing trend of about -0.02°C in Jos over the period 1971-2000 and a decreasing air surface temperature trend in Ikeja and Oshodi from 1991-2000. The result of this study is also in line with the findings of Abiodun *et al.*, [3], who found a trend in increasing mean annual air surface temperature in Nigeria which are statistically significant at the 95% confidence interval (*i.e.,* 0.05 significance level) from 1971 to 2000 historical record.

This research results agrees in part with that of Amadi *et al.* [12], which found upward trends in mean annual air surface maximum and minimum temperatures in Nigeria which are statistically significant at the 95% and 99% confidence intervals (*i.e.,* 0.05 and 0.01 levels of significance) and monotonic positive (upward) trends, in most of the stations covered by this study, a statistically non -significant downward trend in mean annual air surface maximum temperature in Ilorin and a significant, monotonic positive (upward) trend in both mean annual air surface maximum and minimum temperatures in Ikeja. The disagreements in Ilorin mean annual air surface maximum temperature result could be as a result of differences in data length. The disagreements in Ikeja's mean annual air surface maximum temperature result could be as a result of the possible build-up in the atmosphere over Ikeja, of a layer of air that tends to attenuate the intensity of the downwelling solar radiation reaching the earth's surface but traps the thermal Infrared radiation upwelling from the earth's surface and lower atmosphere at night. This study suggests that this may be culpable for the reducing mean annual air surface maximum temperature but increasing mean annual air surface minimum temperature noticeable in

Ikeja. Therefore, further studies should be carried out to unravel the cause of the downward trend in mean annual air surface maximum temperature noticeable in Ikeja.

5. CONCLUSIONS

This study provides an invaluable insight on the temporal trend in mean annual air surface temperatures across the representative stations of the selected eco-climatic zones in Nigeria. The study revealed monotonic positive (upward) trends significant at the 0.01 and 0.05 significance levels across the representative stations whose estimated mean trend magnitude increase over the 38-year period is 1.3°C and 1.4°C for mean annual air surface maximum and minimum temperatures respectively. The estimated mean trend magnitude increase for mean annual air surface temperature in Nigeria is about 1.4°C for the period 1981-2018. With an estimated increase in mean trend magnitude of about 0.035 °C/year for mean annual air surface maximum temperature and an estimated increase in mean trend magnitude in mean annual air surface minimum temperature of about 0.036 °C/year, the estimated mean magnitude increase for both mean annual air surface maximum and minimum temperatures is about 0.036°C/year (*i.e.,* 0.36 °C/decade). This study, then gives a projected estimated mean linear trend magnitude increase of about 4.3°C in mean annual air surface temperature by year 2100 in Nigeria. This is 0.2°C less than the highest regime and within the range of the projected global increase of about 1.5 to 4.5°C in air surface temperature up to year 2100 by the IPCC 2007 report.

The observed trends in this study indicates changes in the net balance between the downwelling solar and the upwelling thermal infrared radiation from the earth's surface and lower atmosphere due to radiative forcing caused by increasing concentrations of greenhouse gases (GHG's) and aerosols, land surface properties changes, urbanization and increasing population. The manifestation of long-term significant temporal trend in the mean annual air surface temperatures at the 99% and 95% confidence intervals (*i.e.,* 0.01 and 0.05 significance levels, respectively) over the period covered by this study provides a clear evidence of possible future increase in air surface temperature and a strong indication of the tendency for the occurrence of climate-related hazards and their resulting adverse impacts in Nigeria. The results have serious consequences for Nigeria, a developing country with a large population. There is cogent need to respond proactively rather than reactively, so as to tackle the attendant resulting adverse impacts of increasing air surface temperatures in Nigeria before they become overwhelming.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interests regarding the publication of this paper.

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