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Machine Learning Techniques Benchmarking based on Global optimization Methods for Parameter Estimation of Log-distance Path loss model

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Abstract: Accurate parametric estimation of path loss models using distinctive machine learning techniques are crucial for ensuring reliable mobile communications. They inform network planning, help optimize resource allocation, and ultimately enhance user experience. Traditional methods of parameter estimation often struggle to adapt to the complex, dynamic environments encountered in real-world scenarios, leading to inaccuracies that can compromise network efficacy. To address these challenges, machine learning-based global optimization methods have emerged as a promising alternative, offering sophisticated techniques that can enhance the precision of parameter estimation. This paper explores the benchmarking of various machine learning algorithms based global optimization method in predictive path loss modelling at three different study locations. The methods include the Particle Swarm Optimization (PTS), Pattern search (PATS), Genetic Algorithm (GA), and Simulated Annealing (SIA). With mean square error evaluation metric, the results reveals that PTS attains better global precision credibility with lower MSE values as the iteration number increases when estimating the log-distance model parameters. The results attained by PTS clearly showcase its efficiency in finding optimal or near-optimal solutions in continuous search domains. Its adaptive nature allows it to quickly converge on good solutions, making it more suitable for the parametric path loss model estimations.

1. Introduction

Path loss modeling is a critical component in the design and optimization of wireless communication systems. It involves estimating how much of the transmitted signal power is lost as it travels from a transmitting antenna to a receiving antenna. The accuracy of these models directly affects the efficiency and effectiveness of wireless communication networks [1-3]. With the advent of machine learning, global optimization methods have emerged as powerful tools for enhancing the precision of path loss models. This paper explores how machine learning techniques can be leveraged to benchamrked for path loss modeling optimisation, discussing their benefits, methodologies, applications, and potential future developments.

Global optimization methods in machine learning focus on finding the best solution from a set of possible solutions by minimizing or maximizing a defined objective function. In path loss modeling, these methods can be used to fine-tune model parameters, which directly influence the performance of wireless communication systems. Traditional methods often rely on empirical formulas or deterministic models, which may not capture the complexities of real-world environments [3]. Machine learning provides a way to model non-linear relationships and interactions among variables, enabling more accurate and robust path loss predictions based on extensive datasets [4-7]. By selecting appropriate global optimisation algorithms to aid effective tuning of path loss models parameters, researchers can significantly improve the fidelity of cellular network planning.

The application of machine learning global optimization methods to path loss modeling is already seeing tangible results across various fields. For example, in urban environments, these methods can be utilized to account for obstacles like buildings and trees that complicate signal propagation. In rural

or suburban areas, adapting machine learning models to consider terrain variations can lead to better performance. Telecommunications companies can benefit from these optimized models by deploying more efficient network configurations, ultimately leading to enhanced user experiences and coverage. Furthermore, the use of machine learning in dynamic environments, such as vehicular networks and IoT systems, represents an exciting frontier for path loss modeling.
Particularly, the integration of machine learning global optimization methods in path loss modeling holds tremendous potential for further advancements in wireless technology. Future research may focus on the incorporation of real-time data through online learning techniques, enabling models to adapt to changing conditions in real-time.

2. Path Loss Modeling Concept

Path loss modeling is a crucial aspect in the field of wireless communications, influencing the performance of cellular networks and various wireless technologies [2-4]. It quantifies the reduction in power density of an electromagnetic wave as it propagates through space or interacts with environmental elements. The complexities present in real-world environments necessitate accurate modeling techniques that can account for various factors affecting signal strength, such as distance, frequency, terrain, and urban structures. Global optimization methods, with their ability to explore a vast search space and provide optimal solutions, have become invaluable in enhancing the accuracy and reliability of path loss models [5, 17,18].
Global optimization methods refer to a set of numerical techniques aimed at finding the global minimum or maximum of a given function, often within a specified range. These methods differ significantly from local optimization approaches, which may only identify local extrema. In the context of path loss modeling, global optimization techniques can be employed to fine-tune model parameters that best fit observational data. The application of these global optimization methods in path loss modeling presents numerous advantages. First, they can enhance the accuracy of path loss predictions by identifying the most suitable parameters for diverse environments. This is particularly important as different urban, suburban, and rural areas exhibit distinct propagation characteristics due to variations in building density, vegetation, and topography. By effectively navigating the parameter space, these optimization techniques can lead to more precise models that result in better planning and deployment of wireless networks, ultimately improving users' experiences [19-21].
Moreover, global optimization methods can facilitate the incorporation of multiple factors into path loss models, which traditional approaches may overlook. Advanced algorithms can simultaneously handle multiple objectives, such as minimizing error across various distances or frequencies while considering environmental variables.
As researchers and engineers continue to push the boundaries of wireless technology, the optimization of path loss models will remain a pivotal element in achieving efficient and reliable communication systems. Consequently, adopting and advancing global optimization methods will play a fundamental role in the future of wireless networking, ensuring its capability to meet the increasing demand for seamless connectivity.

2.1 Literature Review

Global optimization methods for parametric estimation modeling are essential for accurately estimating parameters in complex systems, particularly when traditional local optimization techniques may fail [9]. These methods ensure convergence to global optima, addressing challenges posed by non-convex cost functions and the need for robust solutions in various applications, including science and engineering.

The particle swam optimisation (PS) optimization method has been applied in several areas, including the tuned mass damper for design optimization [10] and cable-damper systems [11, 12].

In [13], the authors demonstrated that the particle swam optimisation method has the capacity to estimate parameters in spatial autoregressive models without requiring a good initial guess, thus outperforming local methods like Newton-Raphson and Nelder-Mead in terms of success rate.

In [14, 15], the genetic algorithm (GA) approach has been employed for vapour-liquid thermodynamic and wind power curve modelling based prediction. The author in [16] demonstrated the estimation capacity of simulated annealing (SIA)in nonlinear parametric determination of kinetic energy. Similar approach using simulated annealing is also shown in [17], but for Equivalent dipole parameter estimation.

This paper explores the benchmarking of various machine learning algorithms based global optimization method in predictive path loss modelling, outlining their strengths and weaknesses, and providing insights into their practical applications in modern communication networks.

3. Methodology

This study employs a comprehensive five-phased methodology. The first phase details the execution of a field test measurement campaign aimed at collecting the essential signal data necessary for tuning the propagation path loss model. and identifying its parameters. Additionally, it outlines the generic propagation model considered, along with its associated variables.
In the second phase, we define the genetic log-distance path loss model and specify its unique modeling variables. The third phase introduces the theoretical famework of the four optimization methods that have been adopted for this research. The fourth phase provides the objective function and a dual set of benchmarking criteria developed for this study. Finally, the corresponding benchmarking results which reveal the specific performance of each optimisation methods is presented in phase five. This structured approach not only enhances the clarity of our methodology but also ensures a thorough examination of the propagation loss model and its optimization

3.1 Measurement

Measurements were conducted using field test tools equipped with TEMS application software, which is renowned for its capabilities in radio spectrum analysis. TEMS is a sophisticated professional testing software designed for radio frequency cellular communication networks. It can scan, collect, and display a substantial amount of network data under realistic conditions. Additionally, it provides users with the opportunity to evaluate and analyze network performance, as well as to identify and diagnose existing network issues efficiently.
The experimental setup for the field drive test, designed for signal data collection, is illustrated in Fig. 1. This drive testing involves comprehensive measurements of signal strength and service quality parameters at the receiver terminal within the coverage area of the evaluated base station. Consequently, the drive test system serves as a valuable tool for gaining in-depth insights into the performance of cellular networks.
The tools utilized in the field drive test system include a Global Positioning System (GPS), specialized mobile phone software, two LTE mobile phones, a scanner, MapInfo software, data cards, a laptop, a power inverter, direct test cables, and an extension board. All these components will be integrated and housed within a vehicle for the drive test, as depicted in Fig1. The MapInfo software is specifically employed to display drive test location maps and generate route data. Using the field drive test system, live signal data will be collected around four Long Term Evolution (LTE) eNodeB antenna sites, each operating at a bandwidth of 10 MHz. The transceiver base station antennas, referred to as NodeBs, are sectorized to enhance coverage. This LTE network is operated by one of the leading telecom service providers in Nigeria, offering LTE services across Port Harcourt City, Nigeria.The path loos data were obtained from the measured signal power, RSRP (dBm) mathematically using the formula [4, 5, 7]:

$$Pathloo(dB) = EIRP - RSRP_{meas} \tag{1}$$

Where *EIRP* is calculated as:

$$EIRP = Pt + Gt - Fr \tag{2}$$

With Gt, bening the transmit antenna gain, Pt, is the transmitted power, and Fr, represent the transmission cable/connectionloss, all in dB. The RSRP denotes the Reference Signal Received Power.

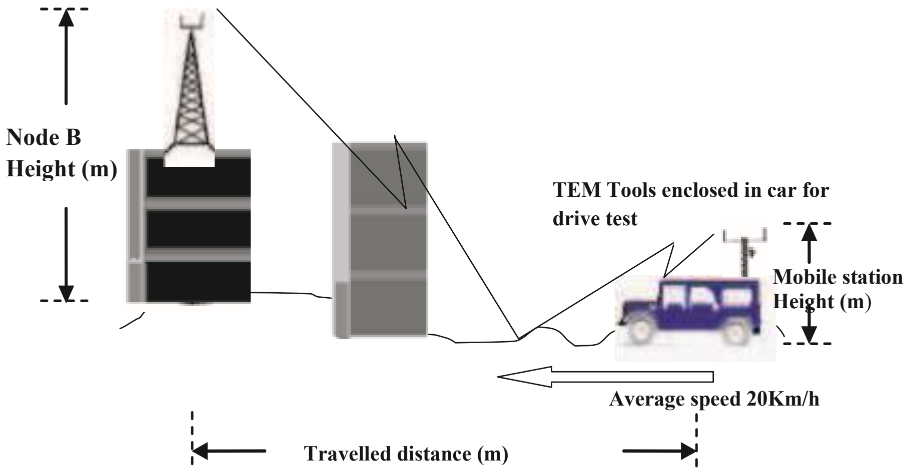

Fig.1: A Sketch of TEMS Drive Test Configuration

3.2 Log-Distance Path loss Model

The Generic Log-Distance Path Loss Model serves as a fundamental framework for understanding how radio signals attenuate over varying distances in wireless communication systems [3-6]. This model is particularly useful in predicting the path loss encountered by electromagnetic signals as they travel through different environments, which can significantly affect the performance and reliability of wireless networks. The model captures the relationship between the distance from a transmitter and the signal strength received at a specific location, thereby allowing engineers and researchers to design and optimize networks by accurately estimating coverage areas and identifying potential dead spots. At the heart of the Generic Log-Distance Path Loss Model is the logarithmic relationship between distance and path loss. The model is mathematically expressed as[1,3,5].

Thus, the parametric log-distance path loss model can expressed as:

$$PL_{(log)}=p_1+p_2*log10\ (d)\ +p_3*log10\ (f); \qquad (3)$$

where f indicate the transmission frequency of the transmitter and p ($p=p_1,p_2,\ p_3$) indicate the terrain and the offset influencing parameters.

3.3 Objective Function

An objective function is a mathematical expression that quantifies the performance of a solution based on specific criteria [17-18]. In global optimization, the objective function is evaluated repeatedly as part of the optimization process.

In this paper, we engage the four algorithms, which includes the Particle Swarm Optimization (PSO), Pattern Search (PATS), Genetic Algorithms (GA), and Simulated Annealing (SA), to conduct the search space and obtain potential solutions to the parametric log-distance propagation modelling problems. In mathematical terms, we consider a global optimisation objective function *(Obj_gl(p)),*which can be expressed as:

$$Obj\_gl(p)=min(PL_{mea}-PL_{(log)}) \qquad (4)$$

where PL_{mea} and $PL_{(log)}$ indicate the measured pathloss and the parametric log-distance path loss model whose parameters are to be determined using the four global optimisation methods.

3.4 Global Optimisation Methods: Theoretical framework

Particle Swarm Optimization (PSO), Pattern Search (PATS), Genetic Algorithms (GA), and Simulated Annealing (SA) represent a suite of powerful global optimization techniques used in various fields, including engineering, economics, and artificial intelligence. These algorithms are particularly beneficial in solving complex optimization problems where traditional approaches may struggle to find the global optimum due to the presence of multiple local minima. Each method leverages a unique approach to navigating the search space, reflecting different principles drawn from natural phenomena or mathematical theory.

Particle Swarm Optimization is inspired by the social behavior of birds and fish, where a group of individuals (particles) collaboratively explore the search space. Each particle adjusts its position based on its own experience and that of its nearest neighbors, balancing exploration and exploitation. This collective intelligence enables PSO to efficiently converge on optimal solutions, often with fewer computational resources compared to other methods. On the other hand, Pattern Search is a derivative-free optimization technique that evaluates solutions iteratively, using a pattern set to explore the space around known good points. Unlike PSO, it does not rely on gradient information, making it robust for functions that are discontinuous or noisy.

Genetic Algorithms are grounded in the principles of natural selection and genetics, operating on a population of potential solutions that undergo selection, crossover, and mutation to evolve toward better solutions over generations. This stochastic search method mimics biological evolution, factoring in survival of the fittest and genetic variability.

In contrast, Simulated Annealing is inspired by the annealing process in metallurgy, where controlled cooling allows materials to reach a minimum energy state. SA searches for optimal solutions by exploring the neighborhood of a solution and probabilistically accepting worse solutions to escape local optima. Each algorithm's distinct approach provides valuable tools for tackling a wide array of optimization challenges, emphasizing the importance of understanding their unique characteristics to apply them effectively in real-world scenarios

While these global optimization methods provide significant advantages, they may also introduce computational complexity and require careful implementation to ensure efficiency and effectiveness in various modeling scenarios.

3.5 Benchmarking Criteria

The evaluation of various performance metrics is crucial in assessing the effectiveness of different strategies in problem-solving and optimization [18-21]. To ensure a fair contest, we need solid evaluation metrics that measure accuracy, efficiency, and robustness. In this paper, the focus is on the following metrics to measure accuracy, efficiency, and robustness of the benchmarking process. The metrics include the Mean Percentage Error (MAPE), and Residual Sum of Square Error (RSE) and Mean Square Error (MSE). The MAPE is a statistical metric that estimates the average percentage difference between predicted and actual values. It provides an overview of the accuracy of a prediction method in terms of percentage deviation from the true values. The RSE measures the level of variance in the error term, or residuals, of a method or model. The smaller the residual sum of squares, the better your model fits your data; the greater the residual sum of squares, the poorer your model fits your data. The MSE measures the mean of the squared differences between the predicted values and the actual values. Fundamentally, it measure the average magnitude of the error between the predicting method and the true target values.

4. Results and Analysis

As mentioned earlier, the engagement of different performance metrics is crucial in assessing the effectiveness of various problem-solving and optimization methods. In this section we present the results for the the four bench-marked methods—Particle Swarm Optimization (PS), Pattern search (PATS), Genetic Algorithm (GA), and Simulated Annealing (SIA) by using MAPE, MAE, RSE and MSE metrics. These metrics have been extensively implemented in Matlab2024b software to evaluate the performance of the four global optimisation methods in determining the parameters of the log-distance path loss model in connection measured path loss data. A lower value in these metrics correlates directly with enhanced algorithm performance in minimizing prediction errors with respect to the log-distance parametric estimations

Shown in Figs. 2 to 4 are the graph which reveal the predictive fitting performance of the four bench-marked global machine learning PTS, PATS,GA and SIA using MAPE as a performance metric in three different study locations where field measurements were conducted. From the graphs, PTS attained 1.732, 2.388, and 2.647 MAPE values in locations 1-3, while PATS attained 2.975, 5.090 and 4.268; GA attained 2.647, 4.424 and 4.888; SIA attained 1.734, 2.555 and 2.685 MAPES values, respectively at the same locations. A Lower MAPE value with PTS indicates that its global precision credibility in estimation the the log-distance model parameters is more accurate compare to other methods that were used in the same process.

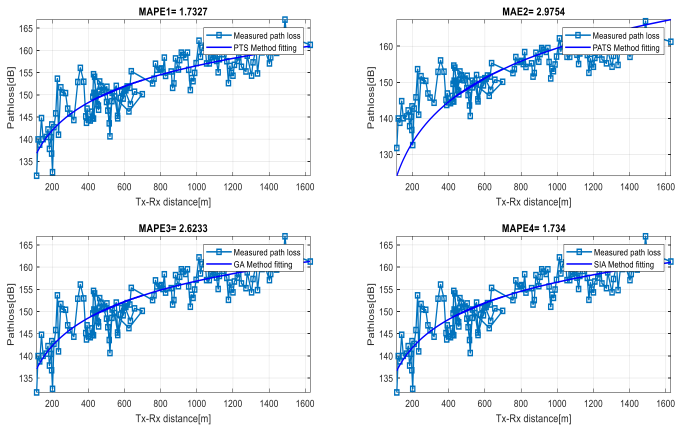

Fig.2: Pathloss data fittings with the four benchmarked PST, PATS, GA and SIA in location 1

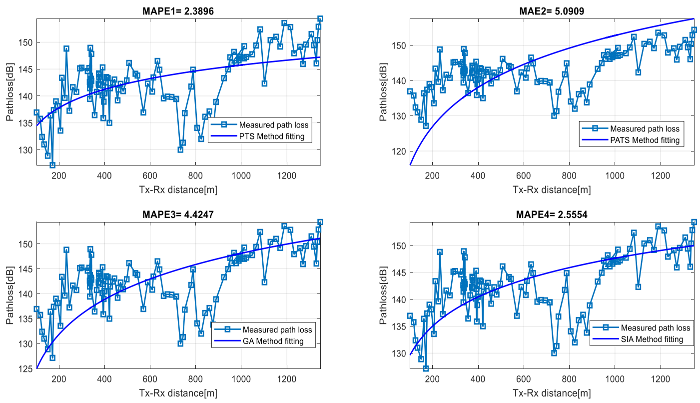

Fig.3: Pathloss data fittings with the four benchmarked PST, PATS, GA and SIA in location 2

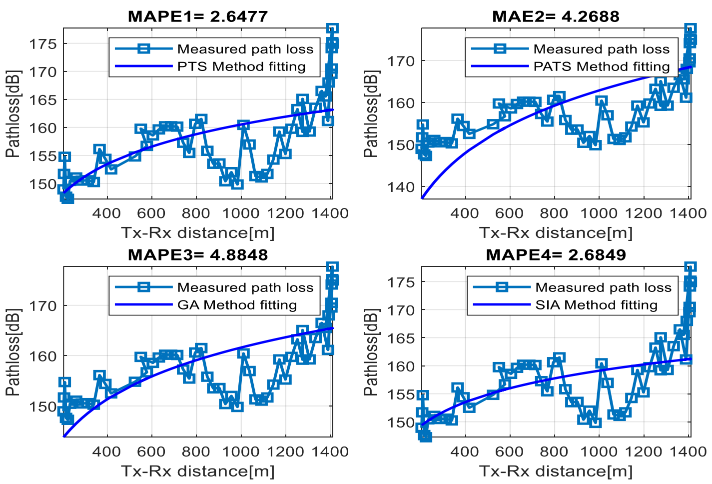

Fig.4: Pathloss data fittings with the four benchmark PST, PATS, GA and SIA in location 3

Shown in Figs. 5 to 7 are the graph which reveal the predictive fitting performance of the four bench-marked global machine learning PTS, PATS,GA and SIA using residual sum error (RSE) as a performance metric in three different study locations where field measurements were conducted. With this metric, the smaller the the value, the better its precision capacity.

From the graphs, PTS attained 5.46x10-8, 5.46x10-8, and 5.46x10-8, RSE values in locations 1-3, while the GA, PATS and SIA attained higher values at the same locations. Again, lower RSE value with PTS also indicates that its global precision credibility in estimation the the log-distance model parameters is more accurate compare to other methods that were used in the same process.

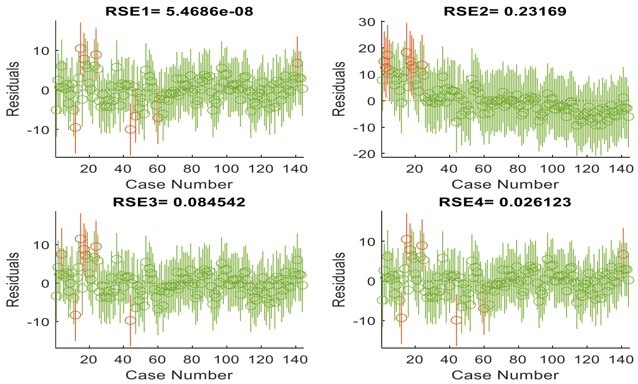

Fig.5: Residual error distribution pattern with the four benchmark PST, PATS, GA and SIA in location 1

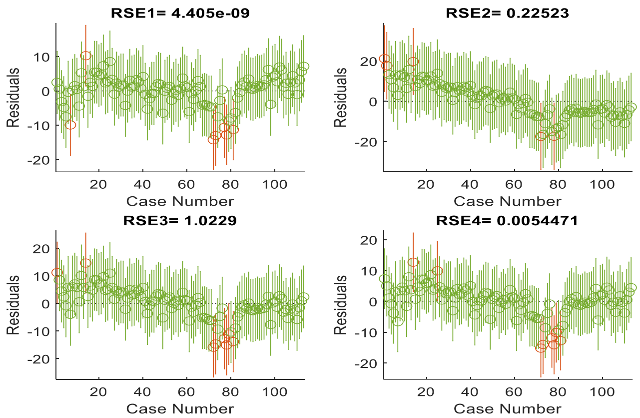

Fig.6: Residual error distribution pattern with the four benchmark PST, PATS, GA and SIA in location 2

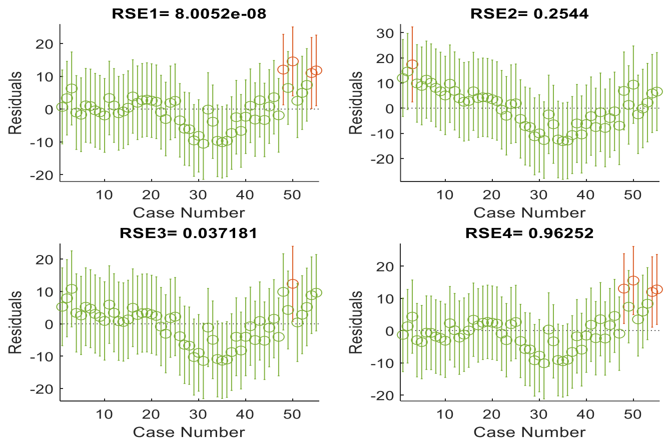

Fig.7: Residual error distribution pattern with the four benchmark PST, PATS, GA and SIA in location 1

Shown in Figs. 8 to 10 are the graph which reveal the predictive fitting performance of the four bench-marked global machine learning PTS, PATS,GA and SIA using MSE as a performance metric versus the number of iterations in the three different study locations where field measurements were conducted. In essence, MSE measures the average magnitude of the error between the predicting method and the true target values. With this metric, the smaller the the value, the better its precision credibility.

In the context of machine learning-based global optimisation methods, MSE and the number of iterations are closely related. The results reveal that as the number of iterations increases, the MSE typically decreases, indicating that each method is learning and improving its predictions over time. However, there's a point of diminishing returns where adding more iterations doesn't significantly reduce the MSE. This indicates that the optimisation methods has reached its limits in terms of performance improvements on the predicting target. Again, the graphical figures reveals that PTS attains better global precision credibility with lower MSE values as the iteration number increases when estimating the log-distance model parameters. The results attained by PTS clearly showcase its efficiency in finding optimal or near-optimal solutions in continuous domains. Its adaptive nature allows it to quickly converge on good solutions, making it more suitable for the parametric path loss model estimations. However, while PTS can effectively explore the search space, it may also suffer from premature convergence in complex landscapes with many local minima.

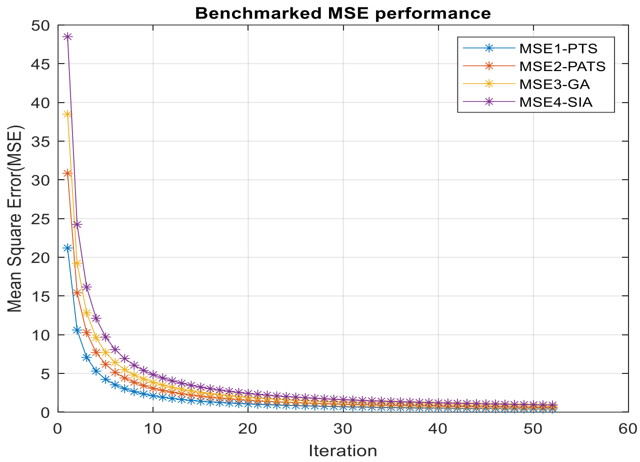

Fig.8: MSE versus iteration plots for the four benchmarked PST, PATS, GA and SIA in location 1

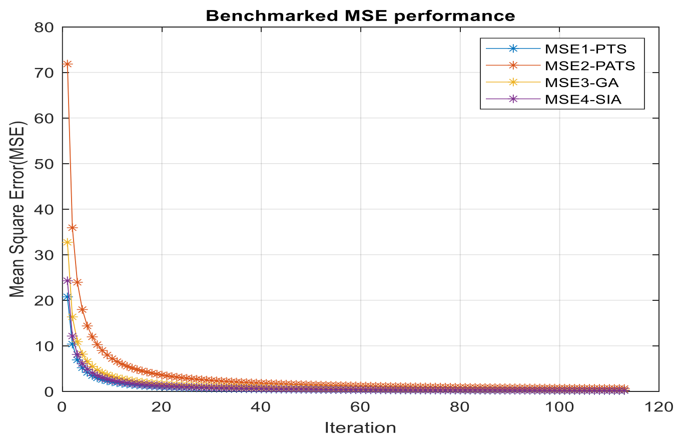

Fig.9: MSE versus iteration plots for the four benchmarked PST, PATS, GA and SIA in location 1

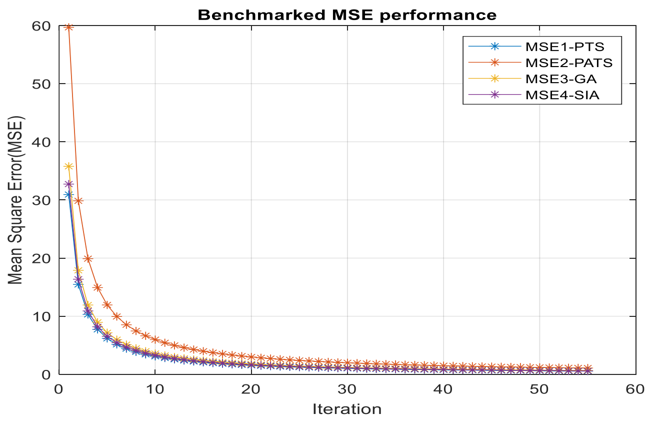

Fig.10: MSE versus iteration plots for the four benchmark PST, PATS, GA and SIA in location 1

sols			fvals	fevals
22.851	20.842	1387.7	69.773	1260
-80.586	37.422	30	41.43	640
8.9524	23.088	18.779	40.702	61186
21.544	21.056	112.94	40.71	6756

sols			fvals	fevals
72.993	11.341	-3398.4	90.096	1264
-84.277	36.953	30	60.8	640
-0.82969	23.218	18.055	48.419	49200
31.637	18.085	128.69	52.385	3164

sols			fvals	fevals
46.85	17.718	-217.34	57.297	1257
-77.188	37.422	30	44.36	640
-3.9971	25.816	-7.8499	41.244	43204
68.723	14.092	2.4833	42.427	1526

5 Conclusion

Machine learning based global optimisation enhance parameter estimation of existing path loss models by leveraging large datasets to identify complex patterns and relationships that traditional methods may overlook. This allows for more accurate predictions in varied and dynamic environments.

This paper explores the benchmarking of four machine learning techniques based global optimization method in predictive path loss modelling at three different study locations. The methods include the Particle Swarm Optimization (PTS), Pattern search (PATS), Genetic Algorithm (GA), and Simulated Annealing (SIA). By means of mean square error evaluation metric, the results reveals that PTS attains better global precision credibility with lower estimation errors when estimating the log-distance model parameters. The results attained by PTS clearly demonstrates its efficiency in finding optimal or near-optimal solutions in continuous search domains. Its adaptive nature allows it to quickly converge on good solutions, making it more suitable for the parametric path loss model estimations.

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