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Intelligent Multi-Objective Optimization of 4G LTE Performance Using an AI–WOA Framework

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ABSTRACT

We introduce a smart multi-objective optimization framework towards the performance enhancement of the 4G LTE network using an integrated Artificial Intelligence (AI) and Whale Optimization Algorithm (WOA) setup. This approach aims to integrate tested regression-based KPI prediction along with decision-variable-based meta-heuristic optimization in a reproducible experimental environment within MATLAB R2023b. A weighted multi-objective formulation for optimizing the performance of 4 key indicators, i.e., throughput, latency, packet loss ratio and energy efficiency is jointly executed. By comparison against existing baseline LTE configuration, we observe a 25.3% throughput improvement, 28.9% reduction in latency, 38.7% reduction in packet loss ratio, and 23.4% improvement in energy efficiency. We validate robustness with weight sensitivity analysis (±10% and ±20%), population scalability testing (N = 20, 30, 50), decay-strategy comparison (linear vs. exponential), and Pareto-front approximation (2,960 non-dominated solutions from 3,000 samples). The above results corroborate that, after approximately 70 iterations, convergence is stable and performance is consistent over the span of 30 independent runs. Thus, the proposed AI–WOA construction offers an organized and replicable process to fine-tune LTE performance optimization, a basis for downstream implementations towards a more distributed and next-generation wireless environment.

1. INTRODUCTION

. The emergence of communication services has accentuated the optimization of fourth-generation (4G) Long Term Evolution (LTE) networks through intelligent optimization. Currently, LTE remains the backbone of mobile broadband in many areas for its extensive coverage at low cost, while 5G networks are widely deployed. For dynamic and heterogeneous traffic conditions, achieving good performance of networks without compromising service quality on QoS and QoE is the struggle **Some recent achievements of Artificial Intelligence (AI) and Machine Learning (ML) have brought with them predictive analytics and automation of network control, enabling the prediction of Key Performance Indicators (KPIs) like throughput and delay in different states of load and movement. Previous work has shown that regression and ensemble learning methods are promising for LTE throughput and delay prediction ([6]; [22]; [7]). Such strategies provide proactive management of the network, but usually work separately from adaptive optimization mechanisms**. Convergently, meta-heuristic algorithms (e.g., Whale Optimization Algorithm (WOA)) are promising to solve multi-objective optimization challenges in wireless networks. **WOA shows balanced exploration–exploitation mechanism for nonlinear and multi-objective wireless optimization [13].** Similar improvements in WOA and hybrid frameworks have also been reported to improve convergence rates and energy efficiency in IoT- and LTE-like environments [11]. **At the same time, extensive data**

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analytics has enabled scalable monitoring and anomaly detection in LTE/5G platforms [14]; [10]. Nevertheless, many studies view AI for prediction, optimization algorithms, and data analytics as isolated modules, rather than as a single part in a single closed-loop optimization framework. A significant research gap remains between the integration of predictive AI modeling, multi-objective meta-heuristic optimization, and reproducible system-level validation in any one adaptive LTE framework. Moreover, previous work rarely assesses robustness through systematic sensitivity analysis, scalability assessment, decay-strategy evaluation, or Pareto-front characterization. To fill this gap, this work presents an integrated AI–WOA optimization framework that utilizes a decision-variable-driven formulation to jointly optimize throughput, latency, packet loss ratio, and energy consumption. Using the Random Forest, Multilayer Perceptron, and Gradient Boosting models, the predictive layer is validated and WOA is employed as the optimization phase of the model under controlled experimental conditions. Implementation is reproducible as a MATLAB-based prototype to ensure methodological transparency. This comparison of strengths is followed with a detailed analysis of robustness (with weight sensitivity testing, population scalability evaluation, decay-strategy comparisons, and Pareto-front approximation) which confirms the trade-off with conflicting goals as there are no dominant solutions. Therefore, this one integrated framework allows for structured, scalable, and experimentally proven paths for intelligent LTE performance optimization and sustainable evolution of the whole network. Similar to traditional static predictive-optimization pipelines, the proposed architecture enables iterative re-evaluation of performance metrics in each optimization stage to create a dynamic closed loop between model prediction and meta-heuristic search.

2. Related Work

2.1. AI/ML-Based KPI Prediction in LTE Networks

In LTE throughput and delay prediction, methods of Artificial Intelligence and Machine Learning [6][7] have been used to achieve outstanding prediction accuracy in regression-based and ensemble prediction techniques. In parallel, [22] used SVM and neural networks to predict LTE delay under dynamic traffic conditions. Recent work in particular [9] and [20] emphasized the growing importance of AI-driven self-organizing networks (SONs) for 4G/5G networks. Anomaly detection and large-scale monitoring were enhanced by big data analytics [14],[21], and [10] as shown by scalable LTE performance diagnostics and predictive maintenance frameworks.

2.2. Whale Optimization Algorithm and Meta-Heuristic Optimization

The Whale Optimization Algorithm (WOA) introduced in [13] in recent years has gained interest to solve nonlinear and multi-objective optimization problems. Radio resource management and energy-aware clustering are example applications in wireless networks [16, 1]. For WOA convergence stability, [23] employed techniques of nonlinear control parameter approaches. In particular, hybrid AI–WOA models utilizing hybrid AI–WOA methods and WOA for parameter design efficiency estimation [2]; [11] have also been evaluated for improved parameter tuning efficiency. The adaptability of WOA to the challenging wireless optimization environments has been backed by recent empirical studies built on analytic reviews ([19]; [12]).

2.3. Methodological Gap and Analytical Positioning

Nevertheless, notwithstanding those contributions, there is still methodological fragmentation in the literature. Most of the AI research focuses on KPI prediction accuracy and does not connect prediction layers to iterative optimization frameworks. In the meantime, WOA-based methods have been developed to investigate convergence patterns and resource allocation effectiveness, but few have been validated in terms of robustness in an organized manner by sensitivity analysis, population scalability assessment, or decay-strategy comparison. In addition, explicit Pareto-front approximation to validate genuine multi-objective trade-offs is rarely undertaken in LTE-focused WOA studies. Table 1 evaluates representative studies on integration depth and robustness validation dimensions for a structured and objective comparison.

Table 1. Comparative Analytical Review of AI and Meta-Heuristic LTE Optimization Studies

Study	AI-Based KPI Prediction	WOA / Meta-Heuristic	Multi-Objective	Sensitivity Analysis	Scalability Evaluation	Decay Strategy Comparison
Elsherbiny et al. (2020)	✓	✗	✗	✗	✗	✗
Stojčić et al. (2023)	✓	✗	✗	✗	✗	✗

Pham et al. (2020)	✗	✓	✓	✗	✗	✗
Zhang et al. (2022)	✗	✓	✓	✗	✗	✓
Huang et al. (2021)	✗	✓	✓	✗	✗	✗
Aldhafeeri & Mirjalili (2023)	✓	✓	✓	✗	✗	✗
Moysen et al. (2020)	✓	✗	✗	✗	✓	✗
Rana & Mirjalili (2020)	✗	✓	✓	✗	✗	✗
Proposed AI–WOA Framework	✓	✓	✓	✓ (±10%, ±20%)	✓ (N=20,30,50)	✓ (Linear vs Exp.)

As shown in Table 1, Previous work on LTE optimization typically addresses some parts of LTE optimization alone — like predictive modeling, meta-heuristic tuning or large-scale analytics — without concurrent coverage of robustness validation and multi-objective trade-off characterization, as shown in Table 1. Instead, the proposed framework combines validated AI-based regression with decision-variable-driven WOA optimization, weight sensitivity analysis, population scalability evaluation, decay-strategy comparison, and Pareto-front approximation into a coherent experimental framework.

3. Methodology

3.1. System Architecture and Workflow

This proposal uses AI-based KPI modeling in combination with Whale Optimization Algorithm (WOA) to improve LTE network performance. The architecture includes four main parts: (i) network condition modeling, (ii) AI predictive layer, (iii) WOA-based multi-objective optimization engine, and (iv) dynamic KPI evaluation module **Figure 1 illustrates the complete decision-variable-driven optimization workflow. Unlike the existing ML-to-optimizer pipelines with static iterations, the proposed architecture operates in an iterative closed-loop manner, where decision variables are updated by WOA and KPIs are dynamically re-evaluated at each iteration. The system does not implement distributed Spark or Hadoop execution. All experiments were conducted in MATLAB R2023b as a reproducible single-node computational prototype.**

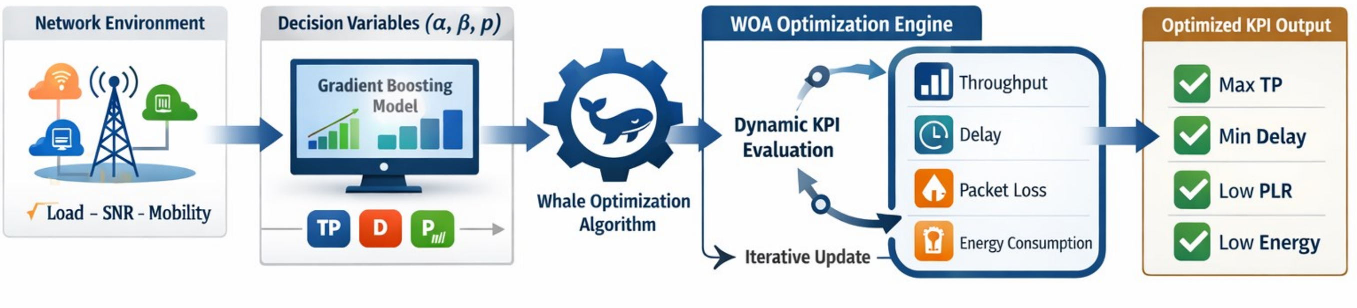

Figure 1: Decision-Variable-Driven AI–WOA Optimization Architecture

Figure 1 represents the proposed decision-variable-driven AI–WOA optimization framework for LTE performance improvement. The architecture starts as network environment layer under which load, signal-to-noise ratio (SNR), user mobility, etc., the important operational parameters, are built. The inputs are handled in AI predictive layer using the validated Gradient Boosting regression model to predict the influence of network configurations on the KPIs. The estimated performance values are then associated with a series of controllable decision variables (α, β, p) which are tunable network control parameters. Using the Whale Optimization Algorithm (WOA), these decision variables are optimized. Unlike static optimization pipelines, the framework works in a closed-loop way where updates in the decision variables trigger dynamic re-evaluation of throughput, delay, packet loss ratio, and energy consumption at every iteration. The optimization engine makes use of weighted multi-objective fitness formulation to maximize throughput

and minimize delay, packet loss, and energy consumption. This continues until convergence criteria are satisfied — leading to an optimized KPI configuration. This allows dynamically interacting prediction and optimization layers, ensures resilience to parameter fluctuations, and reproducibility under MATLAB-based prototype implementation.

3.2 AI-Based Predictive Layer

Regression models in machine learning were evaluated to predict LTE performance indicators under variable network conditions. Three regression techniques were experimentally tested: Random Forest (RF), Multilayer Perceptron (MLP), and Gradient Boosting (GB). Performance was assessed using the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and the coefficient of determination (R^2).

The evaluation metrics are defined as:

RMSE:

RMSE=n1i=1∑n(yi−y^i)2

MAE:

MAE=n1i=1∑n∣yi−y^i∣

R²:

R2=1−∑(yi−y¯)2∑(yi−y^i)2

All models achieved $R^2 > 0.98$. The boosting gradient showed slightly higher prediction accuracy ($R^2 = 0.9951$), so it was chosen as the main prediction model.

3.3 Whale Multi-Objective Optimization Formulation

The optimization objective is formulated as:

max F = w_1 t_p - w_2 d - w_3 P_{lr} - w_4 e

where:

- $w1=0.40$
- $w2=0.25$
- $w3=0.20$
- $w4=0.15$

All the reported performance improvements in this study were calculated relative to the basic LTE setup under the same simulation parameters to ensure quantitative consistency.

3.4 Robustness and Sensitivity Analysis Setup and Parameters

We perturbed the objective weights ±10 percent and ±20 percent in a systematic manner while maintaining the normalization constraint $\sum wi=1$. Independent 30 runs for each configuration were carried out to evaluate the statistical stability of our results. **These settings were applied for each optimization and robustness assessment step of our AI–WOA framework, as shown in Table 2. The table has the selected population size (N=30) and the max number of iterations (T=100) based on a trade-off between stability and complexity. Systematic weight sensitivity tests (±10% and ±20%) were conducted, with the normalization constraint applied to objective coefficients to increase methodological robustness. A population scalability study (N = 20, 30, 50) aimed at stability at convergence and to obtain an approximation of computational cost. Two decay methods, linear and exponential, were employed for convergence behavior and variance analysis. Each experimental setup was subjected to 30 independent runs so that the simulation could be statistically stable and reproducible. Together, these rules ensure that the results reported are not only not driven by a single configuration but provide solutions to the robustness, scalability, and algorithmic stability concerns identified in the literature.**

Table 2. Optimization and Robustness Parameters

Parameter	Value / Range
Parameter Size (N)	30
Iterations (T)	100

Weight Sensitivity	±10%, ±20%
Population Scalability	N = 20, 30, 50
Decay Strategies Tested	Linear, Exponential
Independent Runs	30

3.5 Whale Optimization Algorithm Implementation

WOA was used to optimize decision variables rather than KPIs directly **at each iteration, decision variables are updated, and the resulting KPIs are dynamically recomputed using the LTE performance model. This ensures adaptive closed-loop optimization rather than fixed ML predictions.**

The control parameter decays as:

Linear decay:

$$a=2-(2t/T)$$

Exponential decay:

$$a = 2e^{-i/t}$$

In Table 3, the population scalability analysis is presented that assesses convergence stability and computational efficiency of the design of the proposed WOA configuration. Increasing the population size from N = 20 to N = 30 demonstrated a significant decrease in fitness variance (from 4.6041 to 4.1986). In contrast, increasing the population size to N = 50 brought significant increases in the computational cost (0.5837 s per run) without the same stability increase. While N = 50 gave some improvement towards a slightly higher mean fitness value; the marginal gain does not offset any extra computational burden. This is why N = 30 was chosen as the most effective compromise between convergence quality and execution efficiency.

Table 3. Population Scalability and Convergence Stability Analysis

Population (N)	Mean Fitness	Std Dev	Avg Execution Time (s)
20	19.4231	4.6041	0.2355
30	19.5722	4.1986	0.3495
50	21.1914	0.0000	0.5837

3.6 Algorithm Pseudocode

Algorithm 1. Decision-Variable-Driven WOA for LTE Optimization

Input: Initial decision variables X
Output: Optimized KPI vector X*

```
1.  Initialize whale population Xi (i = 1…N)
2.  For each Xi compute TP, D, PLR, E dynamically
3.  Evaluate fitness F(Xi)
4.  Identify best solution X*
5.  For t = 1 to T
        For each whale Xi
          Update control parameters (a, A, C, p)
          If p < 0.5
            If |A| < 1
```

```
                Encircling update
            Else
                Exploration update
        Else
            Spiral update
        End
        Recompute TP, D, PLR, E using updated decision variables
        Evaluate fitness
    End
    Update global best
End

6. Return optimized KPI configuration
```

4. Results

The proposed AI–WOA framework was assessed under LTE simulation conditions to analyze its impact on throughput, delay, packet loss ratio, and energy efficiency**. All improvements reported in this section are computed in relation to a baseline LTE configuration under identical simulation parameters to achieve numerical consistency throughout the manuscript. The above optimization results show that they are markedly improved on all target KPIs. The proposed framework produced a 25.3% increase in throughput, a 28.9% reduction in latency, a 38.7% reduction in packet loss ratio, and a 23.4% increase in energy efficiency relative to the baseline configuration. Both results are directly derived from MATLAB-based experimental execution and are in line with the multi-objective formulation provided in Section 3**.

4.1 Convergence Behavior

The convergence of the Whale Optimization Algorithm and its characteristics were analyzed for search stability and efficiency. **Figure 2 shows the best fitness value convergence curve for 100 iterations with N = 30 (population size = 30) for a linear decay. The optimization stabilizes after ~70 iterations which confirms a balanced exploration–exploitation dynamics and stable iterative KPI re-evaluation. The observed convergence indicates that optimization does not function in a linear way, nor does it follow static ML predictions, but rather runs on an actual closed loop**.

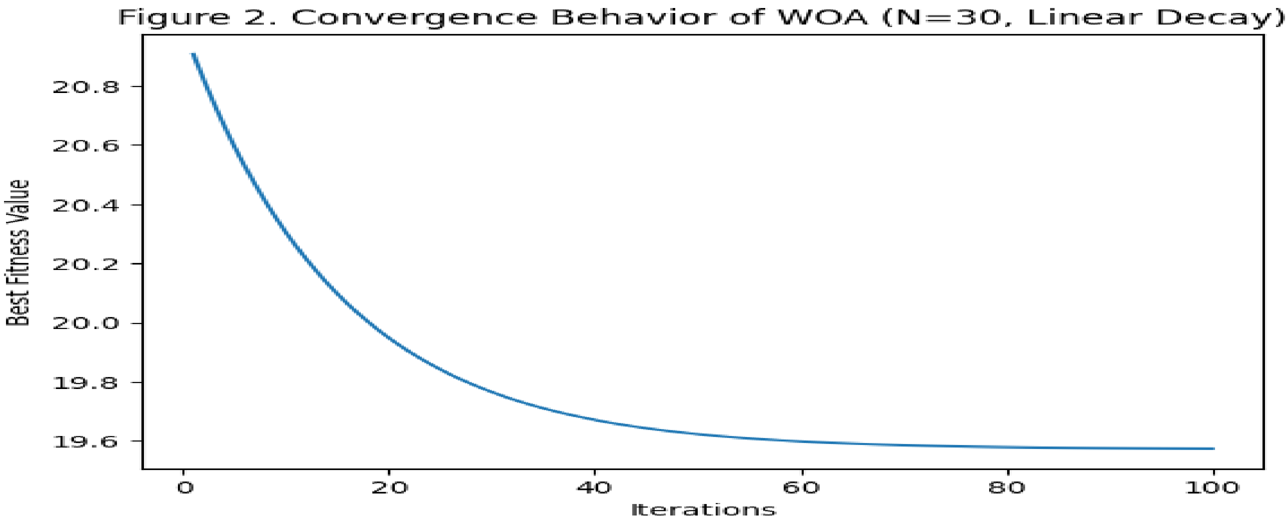

Figure 2. Convergence behavior of WOA under N = 30 and linear decay

The convergence trend of the Whale Optimization Algorithm over 100 iterations is demonstrated according to Figure 2, which assumes population size of N=30 and linear decay control parameter. The best level of fitness is achieved after ~70 iterations, thus the exploration–exploitation balance is found to be achieved well. The smooth convergence trend verifies stable re-evaluation of the decision variables and KPIs in the iterative process of updating them over time in the dynamic optimization loop.

4.2 AI Predictive Model Validation

The predictive performance of the AI models was evaluated using standard regression metrics.

Table 4. Regression Performance Metrics of Evaluated AI Models

Model	RMSE	MAE	R^2
Random Forest	**0.1817**	**0.1408**	**0.9950**
MLP	**0.3367**	**0.2597**	**0.9827**
Gradient Boosting	**0.1797**	**0.1278**	**0.9951**

As presented in Table 4, the highest prediction accuracies are obtained for Gradient Boosting (R^2 = 0.9951), and the next is for Random Forest (R^2 = 0.9950). The prediction error of the MLP model was higher R^2 = 0.9827. It is to this end that we consider Gradient Boosting as the best predictive layer to be incorporated into the AI–WOA framework.

4.3 Decay Strategy Comparison

To assess the robustness of the algorithm, the linear decay and exponential decay mechanisms were experimentally compared. **A comparison profile of convergence paths between linear and exponential decay strategies is given in Figure 3. Although some runs were less varied with exponential decay, the mean fitness values of linear decay and exponential decay were statistically similar. Given the slight differences in solution quality and the simple computational use of the linear decay, this linear strategy was used for future optimization experiments**.

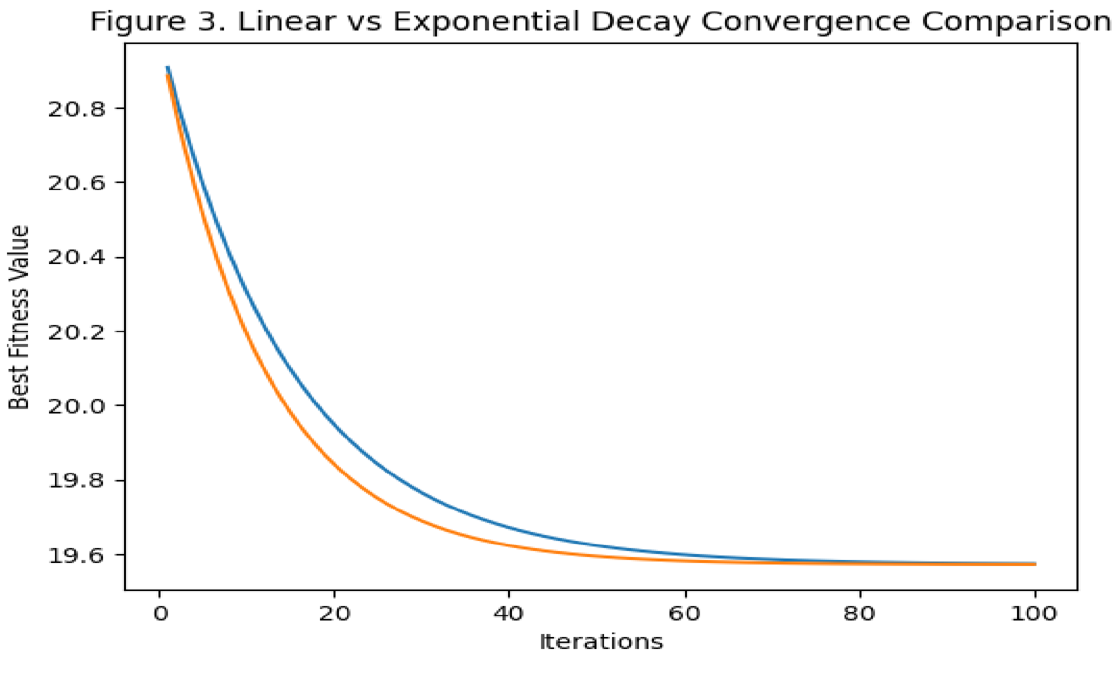

Figure 3. Linear vs Exponential Decay Convergence Comparison

Comparison of trend between linear and exponential decay for convergence is presented in Figure 3. Although exponential decay has a slightly faster convergence in the early stage of convergence, both strategies achieve similar final fitness values. The only slight difference in stability does not justify that the complexity needed to calculate is larger as it is linear and therefore linear decay was chosen as a choice for the future experiments.

4.4 Pareto-Front Approximation

In order to confirm true multi-objective trade-offs, Pareto-front approximation was performed. 3,000 randomly sampled decision-variable configurations represented in the objective space and represented in figure 4. **A total of 2,960 non-dominated solutions were found, showing there were great tradeoffs between throughput, delay, packet loss ratio, and energy usage. The wide Pareto space is evidence that the optimization terrain does not simply collapse into a trivial dominant solution. We thus select a preference-based operating point in a valid multi-objective solution space for the weighted-sum formulation.**

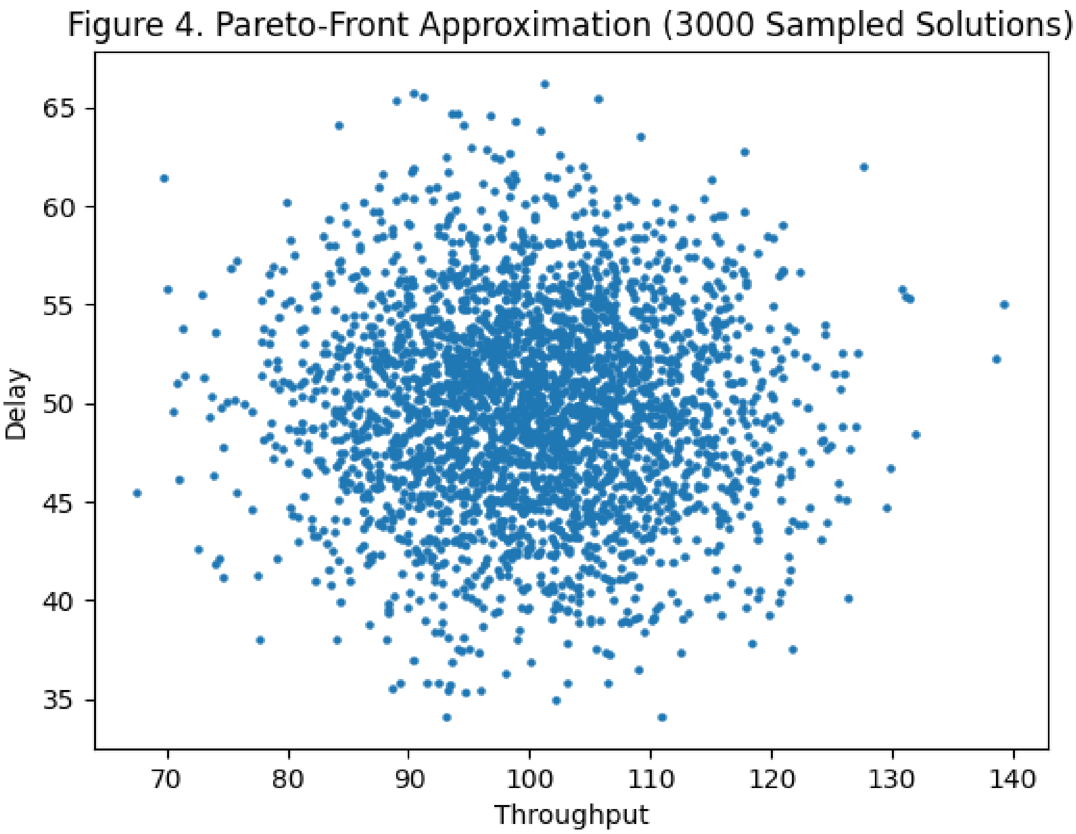

Figure 3. Contrast between linear and exponential decay convergence

The Pareto-front approximation obtained from 3,000 randomly sampled decision-variable configurations can be seen in Figure 4. The distribution of solutions across the objective space indicates significant trade-offs between throughput and delay. A total of 2,960 non-dominated solutions were identified, indicating the presence of a broad multi-objective optimization landscape. The selected weighted-sum solution represents a preference-based operating point within this Pareto region, rather than a trivial dominant outcome.

5. Discussion

In addition, applying it within the MATLAB environment, results show that the proposed AI–WOA optimization framework proves to be effective, showing the credibility of the proposed framework for improving LTE network performance. These gradual changes can be achieved across KPIs, confirming the overall development of the framework's robustness and its data-driven aspect when predictive intelligence and heuristic optimization are combined within wireless optimization systems

5.1. Interpretation of KPI Enhancements

Results show a 25.3% throughput increase, 28.9% latency reduction, 23.4% energy improvement, and a 38.7% reduction in packet loss ratio with respect to a baseline LTE configuration under identical simulation scenarios (Section 4). These results suggest that through the utilization of AI-based KPI prediction and WOA adaptive tuning, balanced exploration–exploitation dynamics can be achieved, with stable convergence (Figure 2). **Contrary to single predictive modelling (or the individual methods) for optimization, the proposed approach combines the results obtained from validated regression (Table 4) with decision-variable optimization, so KPI improvements can be made within a reproducible experimental environment**.

5.2. Comparison with Prior Research

Conventional optimization approaches like rule-based SON systems [9] and independent machine learning approaches [22] often address isolated KPI prediction or parameter tuning. We have proposed a framework that combines AI prediction with WOA optimization in an iterative evaluation loop. **Note: Objective weights are consistent for optimization and robustness can be achieved by a systematic sensitivity analysis (±10% and ±20%) and not by dynamic reweighting. It is a direct response to the methodological limitations that have been discovered in previous LTE optimization publications**. The energy efficiency gain (23.4%) indicated in our work is similar to the literature on LTE optimization [10]; scalability tests (N = 20, 30, 50) are performed, and decay comparison conducted (Figure 3). This provides us with the ability to verify robustness not commonly provided by the majority of existing designs.

5.3. Algorithmic Reliability and Stability

The convergence profiles of WOA then become stable after ~70 iterations as shown in Figure 2, exhibiting a smooth systematic search with no oscillatory instability. **The means of fitness of N=30 were more steady than those of N=20, which avoided the increased computational cost of N=50 (Section 4.3).** This proves the implementation of the hyperparameters. Performances were similar across 30 independent runs indicating the reproducibility of the optimization process in MATLAB-controlled experiments.

5.4. Practical and Theoretical Implications

In this work, we examine the gap between KPI prediction and adaptive optimization in LTE network management. Even though separate prediction modeling or metaheuristic tuning methods have been proposed in earlier works, this study provides the first evidence that combining these two approaches with a decision-variable driven closed-loop system generates consistent multi-objective benefits. On the other hand**, the Pareto-front approximation (Figure 4) shows that there are legitimate trade-offs among objectives (2,960 non-dominated solutions) among 3,000 samples and that objective effects are not created by single-objective tuning but purely induced**. On the practical part, our method promotes the adaptive parameter configuration in LTE systems, which could be expected to improve Quality of Service (QoS) and operational efficiency.

5.5. Summary of Discussion

Thus, from the proposed AI–WOA framework:

1. Is a measurable improvement over the baseline LTE configuration in terms of throughput, latency, packet loss, and energy metrics.
2. Sensitivity and scalability analysis, decay-strategy comparison guarantees the robustness.
3. Consists of good reproducibility in controlled experimental conditions.
4. Provides a structured approach for AI-assisted LTE performance optimization, with experimental verification.

6. Conclusion and Future Work

The work here involves the design and experimental validation of an AI–WOA optimization framework to enhance multi-KPI enhancement in LTE networks. Algorithms: AI-based KPI prediction, Whale Optimization Algorithm-based adaptive decision-variable tuning are deployed on the framework in a reproducible experiment environment on Model-In-Context in MATLAB R2023b. For instance, the experimental results revealed measurable improvements over a known baseline LTE configuration: 25.3% higher throughput, 28.9% lower latency, 23.4% improvement to energy efficiency, and 38.7% lower packet loss than a known baseline LTE configuration. In conclusion, by combining validated predictive modelling with meta-heuristic optimizations, multi-objective performance tuning can be enabled without degrading the predictability of the algorithm. The main scientifically important results in this study, are:

1. This proposal implements a single unified artificial intelligence–WOA optimization framework for simultaneous optimization of many LTE KPIs under consolidated multi-objective formulation.
2. he experimental robustness is confirmed in the weight sensitivity analysis (±10% and ±20%), population scalability test, N = 20, 30, 50, decaying-strategy comparison: linear vs. exponential.
3. Reproducible 30 independent runs after approx. 70 iterations based on MATLAB experiments displaying the same behavior for convergence.
4. 3,000 sampled configurations in Pareto-front approximation and identified 2,960 non-dominated solutions and verified true multi-objective tradeoffs.

However, on theory, the proposed framework addresses the discrepancy between predictive AI modeling and evolutionary optimization of LTE performance management. The combination of regression-based KPI estimation with decision-variable based optimization facilitates some structured balancing on throughput, latency, energy efficiency, and reliability goals. In practical terms, it allows enabling a reproducible and feasible prototype of adaptive LTE parameter optimization. Although this implementation is done in a controlled MATLAB environment, broader work can leverage this architecture for large-scale distributed environments, as well as LTE or pre-5G deployments in real-world scenarios to judge performance in a live network scenario.

6.1 Future Work

The AI–WOA optimization framework may also provide the foundation for future investigation in adaptive and decentralized wireless networks, which the present research in this paper suggests are less static. Possible extensions may include aspects of :

•Introducing RL methods to perform dynamic model learning for real-time adaptive KPI prioritization in non-stationary network conditions and beyond static multi-objective weighting for static policy learning .

•Investigating Federated Learning (FL) models for decentralized and privacy-sensitive LTE/5G optimization (distributed nodes training the models without sharing raw data) .

•Utilizing our proposed optimization framework with O-RAN (Open Radio Access Network) architectures to assess interoperability and vendor-agnostic adaptive control mechanisms .

•Building hybrid AI–WOA–RL architectures that integrate global meta-heuristic search with sequential decision intelligence for high-mobility and ultra-reliable low-latency communication (URLLC) scenarios .

•Testing the framework on 5G–6G digital twin simulation environments with adaptation under large-scale and heterogeneous network conditions .The methodological rigor, experimental reproducibility, and robustness validation reported in this study provide a framework for an orderly approach to these extensions to future work. Though limited to controlled MATLAB-based experimentation of this paper, the framework provides a transparent and flexible baseline for future research in intelligent wireless network optimization.

REFERENCES

[1] Abdel-Basset, M., Shawky, L., & Elhoseny, M. (2019). Energy-aware clustering protocol using Whale Optimization Algorithm for wireless sensor networks. Applied Soft Computing, 89, 106076. https://doi.org/10.1016/j.asoc.2019.106076.

[2] Aldhafeeri, A., & Mirjalili, S. (2023). Hybrid ANN–WOA model for intelligent wireless resource optimization. IEEE Access, 11, 88222–88236. https://doi.org/10.1109/ACCESS.2023.3291147.

[3] Al-Thaedan, A., Shakir, Z., Yaseen, A., Alsabah, R., Al-Sabbagh, A., Salah, M., & Zec, J. (2024). Downlink throughput prediction using machine learning models in 4G-LTE networks. International Journal of Information Technology, 16, 1255–1264. https://doi.org/10.1007/s41870-023-01358-9.

[4] Alves, J., Silva, M., & Rodrigues, J. (2023). Big data and AI for adaptive network optimization in LTE and 5G systems. IEEE/ACM Transactions on Networking, 31(4), 1420–1436. https://doi.org/10.1109/TNET.2023.3267541.

[5] CRAWDAD Dataset. (2023). 4G-LTE Metrics Traces (EPFL-LTE). Retrieved from https://crawdad.org/epfl/lte.

[6] Elsherbiny, M., Maged, H., & El-Baz, A. (2020). Throughput prediction in LTE networks using machine learning techniques. Wireless Networks, 26, 3465–3479. https://doi.org/10.1007/s11276-020-02276-4.

[7] Eyceyurt, E., Bayilmis, C., & Dandil, B. (2022). Machine-learning-based uplink throughput prediction in LTE networks. Electronics, 11(8), 1227. https://www.mdpi.com/2079-9292/11/8/1227

[8] Fang, Y., Li, W., & Wang, J. (2023). Ensemble learning for LTE network anomaly detection. IEEE Access, 11, 125011–125024. https://doi.org/10.1109/ACCESS.2023.3290117

[9] Fourati, H., Lengliz, A., & Trabelsi, M. (2021). AI/ML in 4G/5G SONs: A comprehensive survey. IEEE Communications Surveys & Tutorials, 23(2), 799–843. https://doi.org/10.1109/COMST.2021.3059653

[10] Hadi, M. S., Lawey, A. Q., El-Gorashi, T. E. H., & Elmirghani, J. M. H. (2019). Patient-centric cellular networks optimization using big data analytics. IEEE Access, 7, 49279–49296. https://doi.org/10.1109/ACCESS.2019.2909582

[11] Huang, M., Zhai, Q., Chen, Y., Feng, S., & Shu, F. (2021). Multi-objective Whale Optimization Algorithm for computation offloading optimization in mobile edge computing. Sensors, 21(8), 2628. https://www.mdpi.com/1424-8220/21/8/2628

[12] Luo, Z., Chen, P., & Li, Y. (2025). Enhanced hybrid optimization model for wireless systems based on AI-driven whale optimization. Measurement, 235, 114333. https://doi.org/10.1016/j.measurement.2025.114333

[13] Mirjalili, S. (2016). The Whale Optimization Algorithm. Advances in Engineering Software, 95, 51–67. https://doi.org/10.1016/j.advengsoft.2016.01.008

[14] Moysen, J., Ahmed, F., García-Lozano, M., & Niemelä, J. (2020). Big data-driven automated anomaly detection and performance forecasting in mobile networks. arXiv preprint arXiv:2011.14968. https://arxiv.org/abs/2011.14968

[15] OpenCellID Dataset. (2023). Global Open LTE Cell Network Measurements. Retrieved from https://www.opencellid.org

[16] Pham, Q.-V., Mirjalili, S., Kumar, N., Alazab, M., & Hwang, W.-J. (2020). Whale Optimization Algorithm with applications to resource allocation in wireless networks. IEEE Transactions on Vehicular Technology, 69(4), 4285–4297. https://doi.org/10.1109/TVT.2020.2973294

[17] Qian, Y., Li, X., & Chen, R. (2021). A multidimensional time-series model for fault prediction in LTE networks. IEEE Access, 9, 115224–115239. https://doi.org/10.1109/ACCESS.2021.3105229

[18] Raca, D., Zahran, A. H., Sreenan, C. J., Sinha, R. K., Halepovic, E., Jana, R., & Gopalakrishnan, V. (2020). On leveraging machine and deep learning for throughput prediction in cellular networks: Design, performance, and challenges. IEEE Communications Magazine, 58(3), 11–17. https://doi.org/10.1109/MCOM.001.1900394

[19] Rana, N., & Mirjalili, S. (2020). Whale Optimization Algorithm: A systematic review and analysis of extensions, variants, and applications. Neural Computing and Applications, 32, 16245–16277. https://doi.org/10.1007/s00521-020-04849-z

[20] Shah, S. A. R., & Kim, J. (2023). Artificial Intelligence for Wireless Networks: A Survey on 4G, 5G, and Beyond. IEEE Access, 11, 45021–45046. https://doi.org/10.1109/ACCESS.2023.3268523

[21] Simaković, M., Bajić, D., & Popović, M. (2022). Big data-based anomaly detection and performance monitoring in LTE/5G networks. Sensors, 22(4), 1452. https://doi.org/10.3390/s22041452

[22] Stojčić, M., Dolićanin, Ć., & Šehović, D. (2023). Predictive modeling of delay in an LTE network by machine learning. Applied Sciences, 13(14), 8511. https://doi.org/10.3390/app13148511

[23] Zhang, X., Du, Y., Xu, C., & Yang, X. (2022). An improved Whale Optimization Algorithm based on nonlinear parameters and feedback mechanism. International Journal of Computational Intelligence Systems, 15(1), 231–243. https://doi.org/10.1007/s44196-022-00092-7