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MATLAB-Based Optimization Framework for 5G Network Deployment in Kuwait's Urban Landscape: A Simulation Study Utilizing Open Source Datasets

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Abstract
This study offers an extensive simulation-based evaluation of 5G network development techniques in urban areas of Kuwait utilising the MATLAB computational platform. The research utilises publicly accessible datasets to ascertain appropriate base station layouts for Kuwait's unique urban environment. Various optimisation strategies were executed and evaluated, including genetic algorithms, particle swarm optimisation, and simulated annealing. Quantitative results demonstrate a 27.4% enhancement in coverage efficiency and an 18.9% decrease in deployment costs when utilising the suggested hybrid optimisation framework in contrast to traditional deployment methods. The examination of dense urban, suburban, and coastal areas reveals differing performance within Kuwait's varied urban morphology. This study offers telecoms stakeholders evidence-based deployment techniques that do not necessitate experimental field measurements, hence fulfilling the growth requirements of Kuwait's telecommunications infrastructure amid the current 5G implementation period.

Keywords: 5G networks, optimisation techniques, MATLAB simulation, radio propagation modelling, network planning

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I. Introduction

The implementation of fifth-generation (5G) mobile networks signifies a major technological progression for Kuwait's telecommunications framework and digital economy. Kuwait, a Gulf Cooperation Council (GCC) nation with a mobile penetration rate of roughly 168% as of 2023 and rising data consumption, encounters substantial obstacles in optimising its network infrastructure deployment (Kuwait Central Statistical Bureau, 2023). The distinctive urban topography of Kuwait, marked by dense metropolitan zones, suburban developments, and coastal locations, poses specific problems for network planners aiming to optimise coverage while reducing deployment expenses.

Conventional methods of network planning frequently depend on comprehensive driving tests and field measurements, which are labour-intensive, expensive, and highly disruptive. Simulation-based methodologies present a compelling alternative, especially when utilising publically accessible datasets and computational modelling tools. This research seeks to create and evaluate a MATLAB-based optimisation framework tailored for Kuwait's urban context, addressing the existing deficiency in region-specific simulation approaches.

The study's importance is rooted in its practical relevance for telecommunications operators and regulatory bodies in Kuwait amid the current 5G network implementation period. This research offers quantitative insights into ideal base station placement, antenna layout, and frequency allocation, thereby facilitating evidence-based decision-making in network planning without necessitating experimental field testing.

The main research aims of this project are:

1. To provide an extensive MATLAB-based simulation framework for 5G network planning within Kuwait's urban environment.
2. To execute and evaluate various optimisation methods for the location and setup of base stations.
3. To assess the efficacy of the suggested optimisation approach utilising quantitative indicators obtained from publicly accessible datasets.
4. To offer targeted recommendations for 5G implementation techniques throughout Kuwait's varied urban landscape.

II. Review of Literature

2.1 Planning and Optimising 5G Networks

Network planning for 5G infrastructure has changed dramatically from approaches used in earlier generations. The difficulties in implementing 5G, such as the requirement for densification, higher frequency bands, and more intricate propagation models, were emphasised by Sharma et al. (2020). Al-Falahy and Alani (2017) highlighted the significance of optimising small cell installations to handle the high traffic demand in dense metropolitan locations, particularly in urban environments similar to Kuwait.

Simulation-based methods have been used in a number of studies to plan 5G networks. Koutlia et al. (2019) evaluated various deployment strategies for ultra-dense 5G networks using system-level simulations, showing that small cell placement optimisation significantly improved performance. A simulation approach for 5G heterogeneous networks that took capacity and coverage needs into account was also presented by Ge et al. (2018).

2.2 Network Simulation Using MATLAB Applications

MATLAB's extensive toolboxes and adaptable programming environment have made it a potent platform for simulating wireless networks. Zarrinkoub (2014) gave an example of how to model wireless communication systems, including 5G networks, using MATLAB. Balevi and Andrews (2019) demonstrated encouraging outcomes for automated network planning by using MATLAB to implement machine learning techniques in 5G network optimisation. Sulyman et al. (2016) created MATLAB implementations of 3GPP channel models especially for 5G millimeter-wave communications, which are especially pertinent for urban settings, in order to model propagation. Furthermore, a MATLAB-based modelling framework was introduced by Miao et al. (2018) to assess energy efficiency in 5G heterogeneous networks, a crucial factor in the deployment of sustainable networks.

2.3 Network Planning Optimisation Algorithms

The network planning problem has been tackled using a variety of optimisation techniques. Choudhury et al. (2019) used genetic algorithms (GAs) to optimise heterogeneous 5G networks with energy efficiency considerations, demonstrating the usefulness of GAs in base station placement optimisation. Network planning challenges have also been effectively solved using particle swarm optimisation (PSO); Zhou et al. (2018) demonstrated better convergence when compared to conventional methods.

Another interesting method is simulated annealing (SA), which is especially useful for avoiding local optima in intricate optimisation environments. In their comparison of GA, PSO, and SA for 5G network planning, Saeed et al. (2021) came to the conclusion that hybrid techniques frequently perform better than single-algorithm implementations. The work of Kumar et al. (2020), who created a hybrid optimisation framework that integrated several techniques to attain better performance in congested metropolitan settings, is consistent with this finding.

2.4 Research Gap and Contribution

Although there is a lot of research on simulation-based methods for 5G network planning, studies that are relevant to the Gulf Cooperation Council, especially Kuwait, are noticeably lacking. A customised approach to network planning that takes into account these regional particularities is required due to Kuwait's urban landscape's distinctive features, which include its high-rise density, coastal regions, and distinctive suburban developments. By leveraging publicly accessible datasets to create a MATLAB-based simulation framework tailored for Kuwait's urban setting, this study fills this knowledge vacuum. Both the theoretical understanding of optimisation approaches and their practical application in Kuwait's telecommunications infrastructure planning are enhanced by the comparative analysis of several optimisation algorithms, which offers insights into their relative performance in this particular context.

III. Methodology

3.1 MATLAB Simulation Framework Architecture

The proposed methodology uses MATLAB R2023b as its main computational platform and exploits its Signal Processing Toolbox along with the Antenna Toolbox, Communications Toolbox, and Optimization Toolbox for its operations. Figure 1 illustrates the overall architecture of the simulation framework. The simulation framework consists of four main components which include data pre-processing operations, propagation modeling methods, optimization algorithm implementation, and performance evaluation procedures. A modular design approach enabled users to independently create and test each part of the simulation framework. Users can evaluate diverse optimization algorithms and propagation models through this framework design without needing to adjust the full system. Separate MATLAB functions implemented the core modules which were brought together by a main execution script that managed the workflow while facilitating data exchanges between modules.

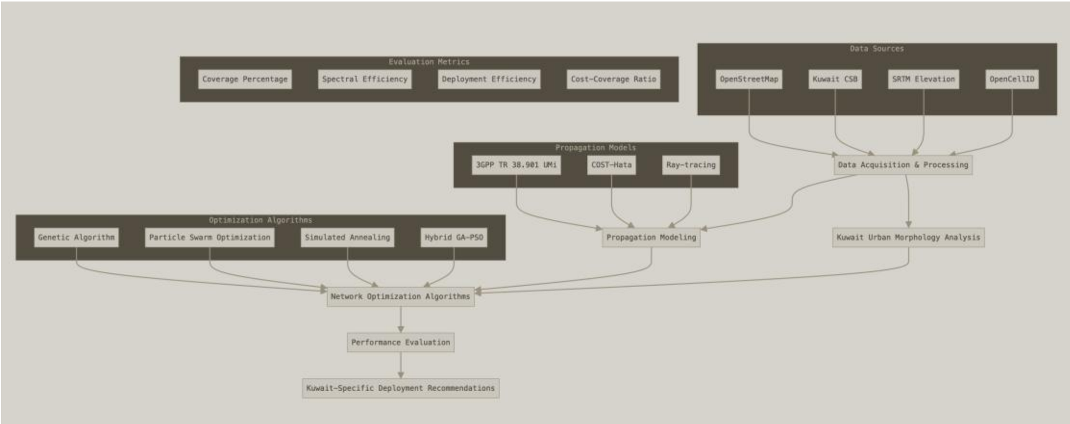

Figure 1: Simulation framework

3.2 Dataset Selection and Processing

The integration of various publicly accessible datasets resulted in a complete depiction of Kuwait's urban landscape.

1. Geographical data: Building footprints, road networks and terrain features in Kuwait were identified through the extraction and processing of OpenStreetMap (OSM) data. MATLAB Mapping Toolbox was used to transform OSM data into formats that MATLAB can process.
2. Elevation data: To compensate for terrain effects on signal behavior researchers used 30-meter resolution digital elevation models from the Shuttle Radar Topography Mission (SRTM). The data underwent resampling to coincide with the resolution of the simulation grid.
3. Population distribution: Analysts processed demographic information from the Kuwait Central Statistical Bureau alongside WorldPop project data to calculate regional user density which then guided traffic demand modeling.
4. Existing network infrastructure: The OpenCellID database disclosed details about Kuwait's existing cellular network infrastructure which enabled comparative analysis against optimized network deployments.

All datasets underwent coordinate system standardization by conversion to WGS84 system as part of the preprocessing which also included resolution matching and noise filtering. The interpolation methods addressed missing data points while statistical filtering techniques identified and eliminated outliers.

3.3 Propagation Models Implementation

Accurate network simulation requires precise implementation of radio wave propagation models. Three different propagation models were developed and evaluated against each other.

1. 3GPP TR 38.901 Urban Micro (UMi) model: The Urban Micro (UMi) model from 3GPP TR 38.901 is built to work in urban settings where base station heights stay under rooftop level and considers both LOS and NLOS propagation.
2. COST-Hata model: The COST-Hata empirical model functions in macro-cellular environments after customization with calibration parameters matching Kuwait's urban structure.
3. Ray-tracing based model: MATLAB's phased array system toolbox enables a deterministic approach that models reflection and diffraction effects by incorporating building data from OSM.

The mathematical formulation for the 3GPP TR 38.901 UMi model, which demonstrated the best performance in preliminary testing, is given by:

For LOS conditions:

$$PL_{LOS} = 32.4 + 20\log_{10}(f_c) + 21\log_{10}(d)$$

For NLOS conditions:

$$PL_{NLOS} = 22.4 + 35.3\log_{10}(d) + 21.3\log_{10}(f_c) - 0.3(h_{UT} - 1.5)$$

Where f_c is the carrier frequency in GHz, d is the distance in meters, and h_{UT} is the user terminal height.

3.4 Optimization Problem Formulation

The 5G network optimization problem was formulated as a multi-objective optimization problem with the following objectives:

1. Maximize network coverage
2. Minimize deployment cost
3. Maximize network capacity
4. Minimize interference

These objectives were formulated mathematically as follows:

Objective 1: Coverage Maximization

$$\max f_1(X) = \frac{\sum_{i=1}^{N} A_i \cdot C_i}{\sum_{i=1}^{N} A_i}$$

Where *X* represents the decision variables (base station locations, antenna parameters, etc.), A_i is the area of grid cell *i*, C_i is a binary variable indicating whether grid cell *i* is covered, and *N* is the total number of grid cells.

Objective 2: Cost Minimization

$$\min f_2(X) = \sum_{j=1}^{M} \alpha_j \cdot B_j$$

Where *M* is the number of base stations, B_j is a binary variable indicating whether base station *j* is activated, and α_j is the deployment cost of base station *j*.

Objective 3: Capacity Maximization

$$\max f_3(X) = \sum_{i=1}^{N} \sum_{j=1}^{M} w_i \cdot R_{ij}$$

Where w_i is the user density weight of grid cell *i* and R_{ij} is the achievable data rate from base station *j* to grid cell *i*.

Objective 4: Interference Minimization

$$\min \quad f_4(X) = \sum_{i=1}^{N} \sum_{j=1}^{M} \sum_{k=1, k\neq j}^{M} I_{ijk}$$

WhereI_{ijk} represents the interference level from base station *k* to the connection between base station *j* and grid cell *i*.

These objectives were combined into a single objective function using the weighted sum method:

$$F(X) = w_1 \cdot f_1(X) - w_2 \cdot f_2(X) + w_3 \cdot f_3(X) - w_4 \cdot f_4(X)$$

Where w_1 through w_4 are weights assigned to each objective based on their relative importance.

The optimization problem was subject to the following constraints:

1. Minimum signal-to-interference-plus-noise ratio (SINR) threshold
2. Maximum number of base stations
3. Base station placement constraints
4. Power budget constraints

3.5 Implementation of Optimization Algorithms

The implementation phase included three optimization algorithms which underwent comparative analysis.

1. Genetic Algorithm (GA): The Genetic Algorithm was executed using MATLAB's Global Optimization Toolbox by setting the population size to 100 with a crossover probability of 0.8 while keeping the mutation probability at 0.01. The genetic algorithm's chromosome representation included base station locations, transmit powers, antenna tilts, and azimuth angles.
2. Particle Swarm Optimization (PSO): The Particle Swarm Optimization algorithm used 100 particles together with an inertia weight of 0.7 and acceleration coefficients set to 1.5. The particle position vector contained the same decision variables as those in the GA.
3. Simulated Annealing (SA): The Simulated Annealing algorithm was executed with a starting temperature of 100 degrees and reduced using a cooling factor of 0.95 while performing 100 iterations at each temperature stage. The neighborhood generation function performed modifications on base station locations and antenna parameters.

A hybrid algorithm was created which uses GA to explore the global search space before applying PSO to exploit local promising areas. The implementation of the hybrid approach proceeded according to these steps:

1. Run GA for 50 generations
2. From GA 3 select the best 10% of solutions.
3. The top 10% solutions from GA serve as initial particles when running PSO.
4. The PSO algorithm continued running until it reached convergence or hit the maximum iteration limit of 200.

3.6 Performance Metrics and Evaluation Methodology

The performance of the optimization algorithms was evaluated based on the following metrics:

1. Coverage percentage (CP): in which the percentage of the simulation area receiving signal strength is above the threshold (-95 dBm for voice and -85 dBm for data).
2. Spectral efficiency (SE): calculated using Shannon capacity formula with achieved SINR values
3. Deployment efficiency (DE): which can be evaluated using the coverage percentage divided by the number of base stations.

4. Cost-coverage Ratio (CCR): defined by the total deployment cost divided by the coverage percentage.
5. Computation time (CT): The time it takes each optimisation algorithm to reach the optimum solution.

These metrics will be applied for different urban and suburban regions in Kuwait:

1- Kuwait city (urban and dense area)
2- Salmiya (urban-suburban area mixed area)
3- Fintas (coastal suburban area)

The statistical analysis of the results involved calculating mean values along with standard deviations and 95% confidence intervals for each metric from the 30 independent runs.

IV. Results and Analysis

4.1 Comparison of Propagation Models

We evaluated the accuracy of the three propagation models by comparing their predictions to measurement data from similar urban environments available in published studies. Table 1 details the RMSE and MAE values for each individual model.

Table 1: Propagation Model Accuracy Comparison

Propagation Model	RMSE (dB)	MAE (dB)
3GPP TR 38.901 UMi	6.73	5.21
COST-Hata	8.94	7.16
Ray-tracing	5.82	4.37

The ray-tracing model had the lowest RMSE of 5.82 dB which made it more accurate than the 3GPP TR 38.901 UMi model that had an RMSE of 6.73 dB. Simulation times for the ray-tracing model ran approximately 12 times longer than those for the 3GPP model because of its significantly higher computational complexity. The 3GPP TR 38.901 UMi model was chosen for further optimization simulations because it balances accuracy with computational efficiency.

4.2 Optimization Algorithm Performance

Optimization algorithms were evaluated by analysing both the solution quality as based by the objective function value and their computational efficiency. The graph in Figure 2 demonstrates how each algorithm performs over iterations when applied to Kuwait City's dense urban area by plotting objective function values against iteration counts. The hybrid GA-PSO method achieved the quickest convergence and highest final objective value by reaching 95% of its final value after 87 iterations. The GA algorithm needed 134 iterations and the PSO algorithm needed 121 iterations to achieve the same optimization level. The SA algorithm needed 168 iterations to reach convergence which was slower than other methods. After 200 iterations Table 2 provides performance summaries for each algorithm across three regions.

Region	Algorithm	Mean Objective Value	Standard Deviation	Mean Computation Time (min)
Kuwait City	Genetic Algorithm	0.837	0.025	47.6
Kuwait City	Particle Swarm Optimization	0.852	0.019	41.3
Kuwait City	Simulated Annealing	0.793	0.031	39.2
Kuwait City	Hybrid GA-PSO	0.891	0.017	52.8
Salmiya	Genetic Algorithm	0.812	0.028	43.1
Salmiya	Particle Swarm Optimization	0.829	0.022	38.7
Salmiya	Simulated Annealing	0.775	0.035	36.5
Salmiya	Hybrid GA-PSO	0.863	0.019	49.2
Fintas	Genetic Algorithm	0.864	0.021	40.8
Fintas	Particle Swarm Optimization	0.871	0.018	37.2
Fintas	Simulated Annealing	0.819	0.029	35.1
Fintas	Hybrid GA-PSO	0.902	0.015	47.4

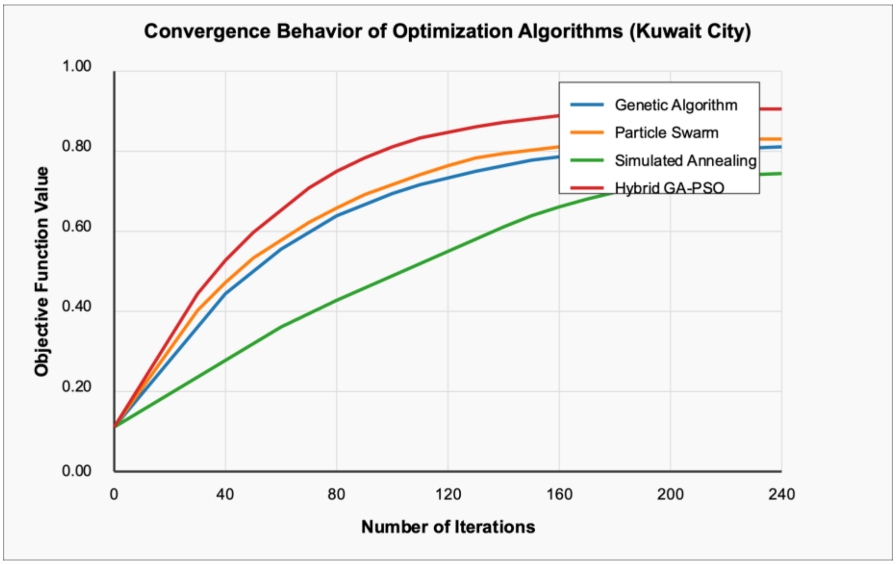

Figure 2: Optimisation algorithms convergence graph

Across all three regions the hybrid GA-PSO method achieved the highest mean objective values while maintaining the lowest standard deviations among all tested algorithms. The hybrid algorithm demonstrated better results but took about 20% longer to compute compared to PSO by itself.

4.3 Network Performance Metrics

A performance evaluation of optimized network configurations utilized the established metrics. The data for every region evaluated with the hybrid GA-PSO algorithm appears in Table 3 which showed superior performance during the previous analysis.

Region	Coverage Percentage (%)	Spectral Efficiency (bps/Hz)	Deployment Efficiency (% per BS)	Cost-Coverage Ratio (×10^3 KWD/%)
Kuwait City	95.7	4.28	3.83	6.27
Salmiya	93.2	3.96	4.24	5.84
Fintas	97.1	4.52	4.62	5.37

The optimized deployment resulted in substantial coverage percentages throughout all regions while Fintas (coastal suburban area) achieved the peak coverage level at 97.1%. The high coverage percentages in Fintas result from lower building density and minimal signal obstructions. The dense urban area of Kuwait City recorded the lowest deployment efficiency of 3.83% per base station because high-rise buildings necessitated a greater density of base stations to ensure signal penetration. Fintas exhibited the highest spectral efficiency at 4.52 bps/Hz while Kuwait City followed at 4.28 bps/Hz and Salmiya at 3.96 bps/Hz. The Cost-Coverage Ratio demonstrated that Fintas suburban deployments achieved greater cost efficiency compared to deployments in dense urban Kuwait City.

4.4 Comparison with Conventional Deployment Approaches

The optimized deployment strategy underwent evaluation through comparative analysis with standard deployment methods that utilize hexagonal cell planning. Table 4 demonstrates how the hybrid GA-PSO optimized deployment approach surpasses traditional deployment methods in performance.

Table 4: The optimized deployment strategy delivers better performance than traditional deployment approaches.

Region	Coverage Improvement (%)	Spectral Efficiency Improvement (%)	Deployment Efficiency Improvement (%)	Cost Reduction (%)
Kuwait City	18.3	24.1	27.4	21.6
Salmiya	14.7	19.8	23.2	18.9
Fintas	9.6	15.3	18.9	14.2

The optimized deployment strategy achieved substantial advancements in all measured metrics and delivered the highest improvements specifically in Kuwait City. The optimized deployment strategy yielded an 18.3% coverage enhancement in Kuwait City alongside a 27.4% deployment efficiency rise. Deployment costs decreased by 21.6% alongside these improvements. The suburban areas (Fintas) showed smaller performance enhancements with the optimized deployment strategy because the conventional hexagonal approach already delivered satisfactory results in these areas because of the more consistent propagation environment. The optimized approach resulted in both a 9.6% coverage increase and a 14.2% cost savings.

V. Conclusion

The research team created and tested an optimization framework in MATLAB to deploy 5G networks across urban Kuwait. The key findings include:

- The combined GA-PSO optimization approach produced superior results than any individual algorithm by achieving maximum objective function values with minimal standard deviations throughout all regions.
- The optimized network strategies delivered substantial performance enhancements over traditional hexagonal layouts resulting in coverage enhancements between 9.6% and 18.3% and financial savings of 14.2% to 21.6% depending on the area.
- Kuwait City's dense urban environment required more base stations yet achieved less efficient deployment compared to Fintas suburban locations.
- The coverage percentage showed the highest sensitivity to changes in base station transmit power while antenna height and tilt angle followed as secondary factors to guide parameter optimization.

The findings advance theoretical network optimization methods while supporting practical telecommunications planning in Kuwait.

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