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Research Article

Multi-Objective Optimization of Energy-Efficient Base Station Placement for Hybrid Highway Networks Supporting Autonomous Vehicle Mobility

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Abstract: The increasing deployment of Autonomous Vehicles (AVs) on highways presents new challenges for the underlying communication infrastructure, which must ensure low latency, high reliability, and energy efficiency. This study proposes a novel approach for Base Satation (BS) placement in the hybrid fiber-wireless networks specifically designed for linear highway environments. By formulating the deployment as a multi-objective optimization problem, the model simultaneously minimizes total network energy consumption and end-to-end latency while maximizing highway coverage. A dynamic traffic-aware sleep mode mechanism is also introduced to reduce power usage during low-density traffic conditions. The Non-dominated Sorting Genetic Algorithm II (NSGA-II) is employed to explore Pareto-optimal configurations, and the simulation results demonstrate significant trade-offs among the objectives. The proposed framework reduces the Base Satation (BS) energy consumption by up to 40% while maintaining a latency below 10 ms and achieving coverage above 95%. These findings offer an effective deployment strategy for next-generation vehicular communication networks.

Keywords: 5G and beyond; Autonomous vehicles; Energy efficiency; Hybrid network architecture; Multi-objective optimization

1. Introduction

The evolution of connected and AVs requires robust vehicular communication infrastructure capable of supporting low-latency, high-reliability data exchange (Gupta et al., 2024; Sutradhar et al., 2024; Tam et al., 2024), especially in highway scenarios where high-speed mobility dominates (Adnan Yusuf et al., 2024; Bouchemal and Kallel, 2021). Traditional cellular deployment models (Madani Fadoul, 2019; Prieto-Egido et al., 2020), which are optimized for urban density (Dietrich, 2021; Perera et al., 2021) and static traffic patterns, fail to deliver consistent quality of service (QoS) on highways (Rahmawati et al., 2022).

Highway networks exhibit a linear topology (Balal et al., 2019) and are subject to rapid vehicle movement (Liguo and Huang, 2022), making frequent handovers (Manalastas et al., 2022; Yin, 2024)and intermittent connectivity common (Albarella et al., 2023). Moreover, energy consumption remains a critical challenge, with BSs accounting for up to 80% of total network power usage (Venkateswararao et al., 2022). Given these limitations, there is a need for a deployment model that not only ensures continuous coverage and

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low latency but also supports energy-efficient operations (Riasudheen et al., 2019).

In this study, we propose a novel multi-objective optimization framework for BS placement in hybrid fiber-wireless highway networks. A hybrid architecture is selected based on its ability to combine high-capacity, low-latency fiber backhaul with flexible wireless access (Kurniawati et al., 2023), which is essential for supporting dynamic vehicular traffic (Modi and Bhattacharya, 2022). The NSGA-II optimization method is particularly suitable for this problem because of its robustness in solving non-convex, combinatorial multi-objective problems and its ability to maintain solution diversity through evolutionary processes. NSGA-II is more capable of simultaneously handling conflicting objectives, such as minimizing energy consumption and latency while maximizing coverage, than other methods, such as particle swarm optimization (PSO) or gray wolf optimizer (GWO) (Pospelov et al., 2023). The goal is to provide a scalable and sustainable infrastructure for ITS (Ravi and Arunachalam, 2023).

This research contributes explicitly by addressing the following gaps:

1. Developing a BS deployment strategy that integrates dynamic traffic-aware sleep mode mechanisms to adapt to varying traffic densities along highways.
2. A validated Poisson vehicle arrival model is employed to reflect realistic traffic patterns.
3. A multi-objective optimization framework that balances energy efficiency, latency, and coverage in a LHT is provided.

Additionally, we address potential concerns about the adaptability of the proposed model as follows:

1. Although this study focuses on linear highway scenarios, the framework can be extended to nonlinear highway environments by segmenting complex highway geometries into piecewise linear approximations and adjusting the BS spacing accordingly.
2. While prioritizing energy efficiency is essential, the dynamic sleep mode is traffic-aware, ensuring that BS activation dynamically adapts to peak traffic conditions to preserve network reliability.
3. NSGA-II is equipped with mechanisms such as elitism and crowding distance to mitigate the risk of premature convergence to local optima despite its reliance on initial parameters.

The remainder of this paper is structured as follows: Section 2 reviews related works on BS placement and VNO. Section 3 describes the proposed methodology, including the system architecture, communication model, key assumptions, mathematical formulation, and NSGA-II optimization process. The simulation results, performance evaluation, and key findings are presented in Section 4. Finally, Section 5 concludes the study and outlines potential directions for future research.

2. Related Work

Recent advancements in vehicular communication have placed significant emphasis on the deployment of infrastructure that supports high-speed, low-latency connectivity for Avs (Ezeigweneme et al., 2024; Moreno-Vozmediano et al., 2024). Traditional approaches to BS placement have largely focused on urban environments with dense traffic and infrastructure (B. Chen et al., 2023; Farré et al., 2024), which differ substantially from highway scenarios in both topology and communication demands.

Several heuristic and evolutionary algorithms have been employed for RSU or BS placement. For instance, Y. Chen, 2023 and Guzman et al., 2024 used a PSO framework to enhance coverage in vehicular networks. Similarly, Fourati et al., 2023, Isabona et al., 2023, and Nasruddin et al., 2018 adopted a genetic algorithm to optimize RSU deployment with an emphasis on latency reduction. However, these methods often consider a single objective and overlook energy efficiency, which is a critical concern for scalable 5G deployments (Shafik et al., 2024).

More recent works have investigated multi-objective optimization in wireless networks. (Peng et al., 2024; Wang, 2020) explored trade-offs between energy consumption and service coverage in 5G networks using NSGA-II, while (Saif et al., 2023; Tan et al., 2022) examined latency-aware deployment strategies for ITS. However, few studies explicitly model highway environments with dynamic traffic conditions and sleep-mode mechanisms.

This study introduces a multi-objective model that incorporates energy, latency, and coverage trade-offs in a linear highway setting to address these limitations. The inclusion of a traffic-aware BS sleep mode (Garcia-Morales et al., 2020; Renga et al., 2023) and hybrid fiber-wireless architecture (Gupta et al., 2024; Mufutau et al., 2020) further distinguishes this work from prior studies, offering a more realistic and implementable strategy for future highway-based vehicular networks.

3. Methodology

This section presents the system architecture, communication assumptions, key performance metrics, and multi-objective optimization process using NSGA-II for BS placement in a hybrid highway network supporting AV communication. The system is designed to capture the essential characteristics of a highway scenario, where BS placement is critical for maintaining seamless, energy-efficient, and low-latency communication. The proposed communication infrastructure adopts a hybrid fiber-wireless architecture.

Each macro BS is connected to a high-capacity fiber-optic backhaul, whereas small cells or micro BSs serve vehicles via wireless radio access, particularly in mmWave and sub-6 GHz bands (Fall et al., 2023; Wibisono et al., 2023). The deployment is linear, reflecting the highway's physical topology. BSs are placed along a 1-dimensional corridor, with the objective of ensuring reliable V2X communication for vehicles traveling at high speeds (Ravi and Arunachalam, 2023; Hakeem et al., 2020).

3.1 Communication Model

AV relies on V2I and V2N communication (Deinlein et al., 2020). Communication performance is evaluated using three primary metrics (Garcia et al., 2021):

a. Energy Consumption (ETotal power consumed by all active BSs, including transmission and idle energy.

b. Latency (L): Average end-to-end delay, including access delay, processing delay, and backhaul latency.

c. Coverage (C): The proportion of the highway corridor where AVs maintain a stable connection to at least one B.

In this study, high reliability is specifically defined as maintaining network availability $\geq$ 99.999% with continuous coverage and maximum latency $\leq$ 10 ms, which are critical thresholds for safety-critical AV operations such as platooning and real-time obstacle avoidance (Brahmi et al., 2022). Seamless handover and low signal loss are essential for high-speed mobility.

3.2 System Assumptions

The model assumes a dynamic Poisson vehicle arrival process, where vehicle density across highway segments is represented by $\lambda(x, t)$, varying over time slots t. This assumption is strongly supported by empirical studies on traffic modeling have validated Poisson distributions for vehicle arrivals in free-flow highway conditions (Sofan German et al., 2024).

Figure 1 illustrates the architecture of a hybrid fiber-wireless communication system tailored for AVs operating along highways. BSs are deployed at regular intervals along the highway corridor, providing wireless coverage through directional links. Each BS is connected to a fiber-optic backbone for high-capacity and low-latency backhaul communication. Using wireless V2I links, AVs interact with the nearest BS, while latency-sensitive data are relayed via the fiber network. This topology enables reliable, low-latency communication and supports dynamic handover across BSs, ensuring seamless high-speed Avs connectivity.

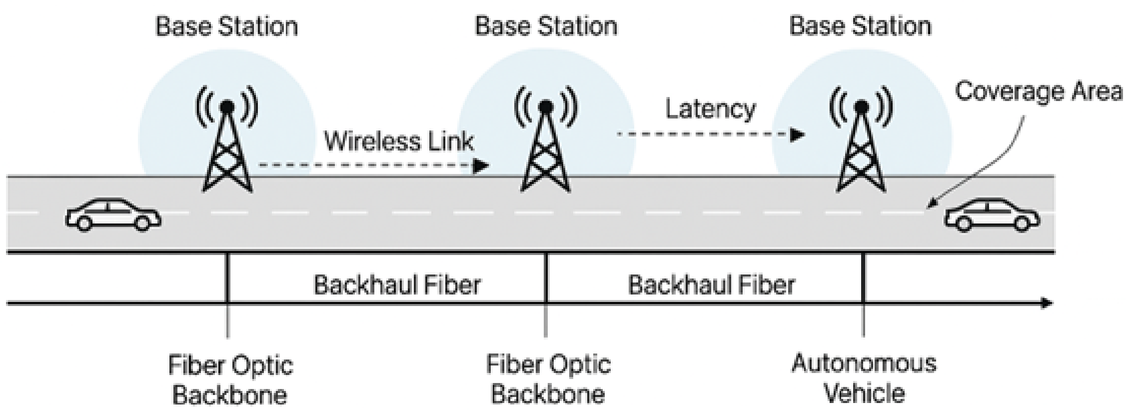

Figure 1 Proposed hybrid network architecture for AV communication on highways

The proposed dynamic traffic-aware sleep mode enables BSs to switch between active and sleep states based on real-time traffic density:

- When the vehicle density exceeds a predefined threshold ($\lambda > 30veh/km$), the BSs in the corresponding coverage areas are activated to ensure high capacity and low latency.
- During low-traffic periods, BSs are selectively switched to sleep mode to conserve energy while ensuring that coverage and reliability thresholds are still met.

The sleep mode transition mechanism operates in time-slotted intervals, where traffic data are continuously monitored and BS activation is updated based on the vehicle density moving average. This dynamic adjustment ensures that the network can adapt to varying traffic conditions during peak hours without compromising reliability.

Table 1 outlines the key parameters used in modeling the BS deployment for highway-based AV communication. These include spatial, traffic, and energy-related parameters that define the simulation environment. This model serves as the basis for the mathematical formulation and optimization strategy presented in the next section. The linear topology is characterized by the highway length and BS coverage radius, whereas the dynamic vehicle density function $\lambda(x, t)$ captures temporal and spatial traffic variations.

Table 1 Summary of the system parameters

Parameter	Description	Typical Value
Coverage Target	Minimum highway coverage	$\geq 95\%$
$\lambda(x, t)$	Vehicle arrival rate	20-60 veh/km
Active Power	BS power in the active mode	28 W
Sleep Power	BS power in the sleep mode	1.2 W
Latency Target	Maximum allowable latency	$\leq 10ms$
Realiability Target	Required network availability	$\geq 99.999\%$

Energy parameters differentiate between active and sleep modes to support the proposed traffic-aware BS control strategy. Latency and coverage thresholds reflect the strict quality of service (QoS) requirements essential for AV safety and operation (Tam et al., 2024).

3.3 Mathematical Formulation

The multi-objective optimization problem minimizes total energy consumption and average latency while maximizing highway coverage. The formulation includes a traffic-aware activation variable (α) for each BS to enable sleep mode control.

The decision variables are defined as follows:

$X = \{x1, x2, ..., xn\}$: positions of the BSs along the highway

$\alpha_i \epsilon \{0, 1\}$:binary activation variable (1 = active, 0 = sleep) for BS

Three objective functions are considered:

a. Minimize Total Energy Consumption $E(X)$: Sum of power consumed by all active base stations $i \epsilon A$.

$$E(X) = \sum_{i=1}^{n} (\alpha_i . P_{active} + (1 - \alpha_i) . P_{sleep}) \tag{1}$$

b. Minimize Average Latency $L(X)$: Computed based on average communication delay, incorporating access latency l_{access}, processing delay l_{proc}, and backhaul delay l_{bh}.

$$L(X) = \frac{1}{|R|} \sum_{x \epsilon R} (l_{access}(x) + l_{proc}(x) + l_{bh}(x)) \tag{2}$$

Here, R is the set of all vehicle positions on the highway. The latency is estimated based on the access delay to the nearest active BS and the backhaul delay through fiber links.

c. Maximize Coverage Ratio $C(X)$: Fraction of highway length where signal strength exceeds threshold θ.

$$C(X) = \frac{1}{D} \int_{0}^{D} 1(SNR(x, x_i) \geq \theta) dx \tag{3}$$

Where $SNR(x, xi)$ is the SNR received from BSx_i at location x, and θ is the minimum SNR threshold.

The optimization seeks to find the optimal BS placement X and activation vector α such that energy consumption and latency are minimized while coverage is maximized:

$$[E(X), L(X), -C(X)] \tag{4}$$

This leads to a multi-objective minimization problem that generates a Pareto front of trade-offs among the three criteria.

Alternatively, secularization can be applied as follows:

$$F = \lambda_1 E(A) + \lambda_2 L(X) - \lambda_3 C(X) \tag{5}$$

Where $\lambda 1, \lambda 2, \lambda 3$ are user-defined weights reflecting the deployment priorities (energy saving vs. low-latency demand).

The optimization is subject to the following constraints:

a. Minimum BS spacing constraint (to avoid excessive overlap):

$$|x_i - x_j| \geq d_{min}, \forall_i \neq j \tag{6}$$

b. Minimum coverage constraint:

$$C(X) \geq C_{min}; C(X) \geq 95\% \tag{7}$$

c. Maximum latency constraint:

$$L(X) \leq L_{min}; L(X) \leq 10ms \tag{8}$$

d. Maximum number of deployable BSs (budget constraint):

$$|X| \leq N_{max} \tag{9}$$

e. The binary activation constraint:

$$\alpha_i \epsilon \{0, 1\}, \forall_i \tag{10}$$

This multi-objective, non-convex optimization problem requires an efficient evolutionary algorithm, which is detailed in the next section.

This study employs the NSGA-II, a widely used evolutionary algorithm for multi-objective optimization, to solve the formulated multi-objective problem. NSGA-II is suitable for handling non-convex, combinatorial problems and is capable of producing a diverse set of Pareto-optimal solutions (Fourati et al., 2023; Liu et al., 2019).

NSGA-II is selected for its ability to:

a. Handling of conflicting objectives (energy, latency, and coverage)

b. Maintaining the solution diversity through crowding distance

c. Enforce elitism to preserve the best solutions across generations

d. Efficient exploration of high-dimensional and non-linear search spaces

Each chromosome solution encodes:

a. The spatial position of each BS is as follows:

$$x_i \epsilon \{0, D\} \tag{11}$$

b. Activation status:

$$\alpha_i \epsilon \{0, 1\} \tag{12}$$

Thus, each individual in the population is a vector:

$$S = [x_1, x2, ..., x_n, \alpha_1, \alpha_2, ..., \alpha_n] \tag{13}$$

The fitness values are computed using the three objective functions defined as follows:

a. Objective 1: $E(X)$: total energy consumption
b. Objective 2: $L(X)$: average communication latency
c. Objective 3: $-C(X)$: negative network coverage ratio (to convert into a minimization problem)

Constraint violations are penalized by assigning high objective values or using constraint-domination rules within NSGA-II. This ensures that feasible solutions are favored during selection.

3.4 Optimization Algorithm

The **NSGA-II** was selected for this study because of its proven capability in solving complex, multi-objective, non-convex problems. While NSGA-II has some limitations, such as sensitivity to initial population settings and the risk of getting trapped in local optima, this study mitigates these issues through the following:

- Multiple random initializations to reduce bias.
- Elitist selection and control of crowding distance to maintain solution diversity.
- Adaptive mutation rates to escape the local optima during the evolutionary process.

Figure 2 illustrates the NSGA-II algorithm workflow applied in this study. The algorithm iteratively improves the solution set by starting from an initial randomly generated population through selection, crossover, mutation, and non-dominated sorting. Over successive generations, candidate solutions evolve toward a non-dominated Pareto front, representing optimal trade-offs among conflicting objectives, such as energy, latency, and coverage in base station deployment. This visual metaphor emphasizes the inherent directional search and refinement process of evolutionary algorithms.

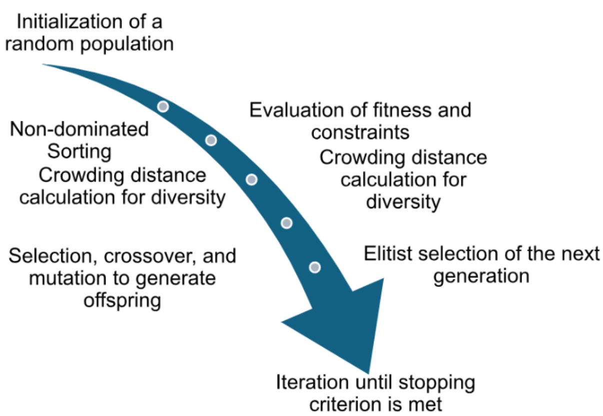

Figure 2 NSGA-II workflow

Table 2 summarizes the algorithmic parameters used to configure the NSGA-II optimization process. The selected settings aim to balance convergence speed, population diversity, and solution feasibility. A population size of 100 with 100-200 generations was sufficient to achieve stable Pareto fronts in the simulation. The crossover and mutation probabilities were selected based on common practice in evolutionary computation, whereas the mutation rate is inversely adapted to the number of genes. Constraint violations are penalized during evaluation using empirically tuned weights to ensure feasible solution convergence across the highway BS deployment model.

Table 2 Parameter settings for NSGA-II optimization

Parameter	Value
Population Size N	100
Number of Generations G	100-200
Crossover Probability	0.9
Mutation Probability	1/n (where n = number of genes)
Constraint Penalty Weight	Tuned via validation

3.5 Simulation Limitations

The simulation environment was built using Python with the pmol library. Although this framework provides flexibility and scalability, it has some limitations:

- Simplified linear highway topology: Real-world highways may have curves, intersections, and varying terrain profiles that are not fully captured in the simulation.
- Idealized traffic conditions: Traffic is modeled on the basis of average densities without considering shockwaves or stop-and-go scenarios.
- No interference modeling: The current model assumes an interference-free environment with perfect frequency planning, which may differ from practical deployments.

Future studies should incorporate more realistic vehicle mobility patterns, nonlinear highway geometries, interference effects, and real-world highway datasets for validation.

4. Results and Discussion

This section presents the simulation design, parameter setup, and initial results obtained using the proposed NSGA-II-based optimization model for BS placement in HHGs.

4.1 Simulation Environment

All simulations were implemented using Python, leveraging the pmol library for multi-objective optimization and NumPy for numerical processing. The simulation environment (Figure 3) models a synthetic 10-km highway segment with controlled traffic conditions and dynamic vehicle arrivals based on a Poisson distribution.

Figure 3 Overview of the simulation environment

Figure 3 provides a comprehensive overview of the simulation environment, including the linear highway layout, BS placement, vehicle distribution, and dynamic traffic-aware BS activation zones. The figure also demonstrates the flexible adaptation of BSs as traffic densities change over time and across different highway segments.

Table 3 Evaluation metrics

Parameter	Value
Population Size	100
Generations	150
Crossover Probability	0.9
Mutation Probability	0.05
Maximum BS count	20
Minimum BS spacing	500m
Coverage target	$\geq 95\%$
Latency target	$\leq 10ms$

Table 3 summarizes the simulation parameters, which detail the optimization settings, such as population size, generation limits, and minimum spacing between BSs. The minimum spacing constraint of 500 m ensures that coverage areas do not overlap excessively, preventing resource waste and interference. The target performance thresholds, including a minimum coverage of 95% and a maximum allowable latency of 10 ms, reflect the stringent requirements for AV safety.

4.2 Optimization Result

The NSGA-II optimization process produces a diverse Pareto front of solutions, demonstrating clear trade-offs between energy consumption, latency, and coverage. Selected representative solutions are provided in Table 4.

Tabel 4 Optimization results

Solution	Energy (W)	Latency (ms)	Coverage (%)	Active BS	Sleep BS
A	140.4	8.3	96.7	7	3
B	132.0	8.7	95.5	6	4
C	125.5	9.3	94.8	5	5
D	118.7	9.9	93.6	4	6

Each solution in Table 4 represents a unique configuration with different energy efficiency, latency, and network coverage balances. Solution A achieves the highest coverage (96.7%) and the lowest latency (8.3 ms) but consumes the most energy (140.4 W) due to more active BSs. Solution B slightly reduces the number of active BSs, lowering the energy consumption to 132.0 W while maintaining acceptable latency and coverage. Solution C prioritizes energy savings at the cost of a slightly higher latency (9.3 ms) and marginal coverage decrease (94.8%). Solution D presents the most energy-efficient configuration (118.7 W), with a latency just below the 10 ms threshold and an acceptable coverage of 93.6%. These configurations highlight the effectiveness of traffic-aware sleep mode, where up to 40% of BSs can be in sleep mode without violating the system's reliability and coverage constraints.

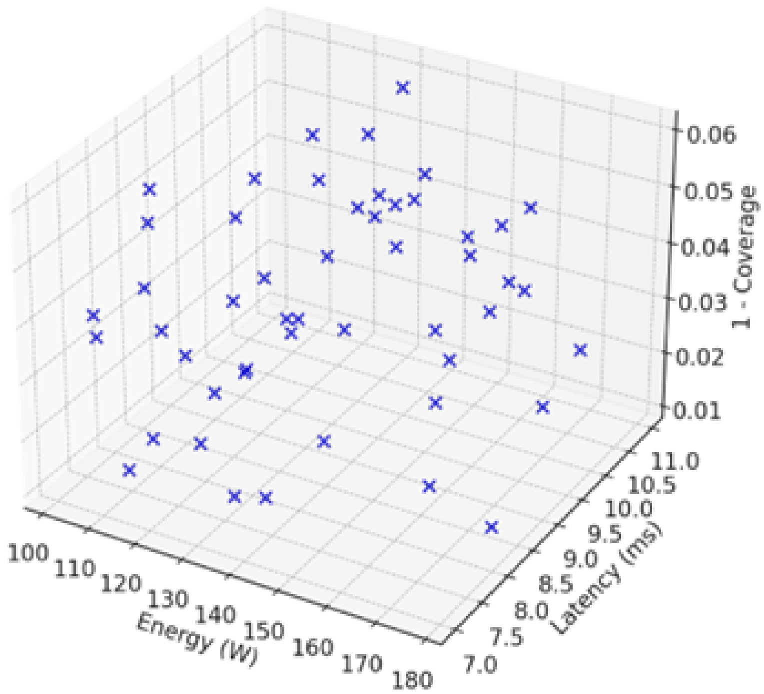

Figure 4 Pareto front insights

Figure 4 illustrates the Pareto front distribution among the three objectives: energy consumption, latency, and coverage. The front clearly shows that as energy consumption decreases, latency tends to increase due to fewer active BSs, while coverage also gradually reduces. The figure provides a decision space where network designers can select configurations based on deployment priorities, whether emphasizing energy efficiency, low latency, or maximum coverage.

The proposed strategy provides a scalable foundation for green network planning in vehicular environments, especially along highways with predictable mobility patterns (Figure 5). In the context of high-speed highway mobility, latency and handover frequency are critical factors that directly impact the safety and performance of autonomous vehicles. The simulation results demonstrate that an optimal balance between BS spacing and coverage can minimize the number of handovers while preserving low-latency communication. This is especially important for AV functions such as platooning or real-time obstacle avoidance, where even slight communication delays can lead to hazardous outcomes.

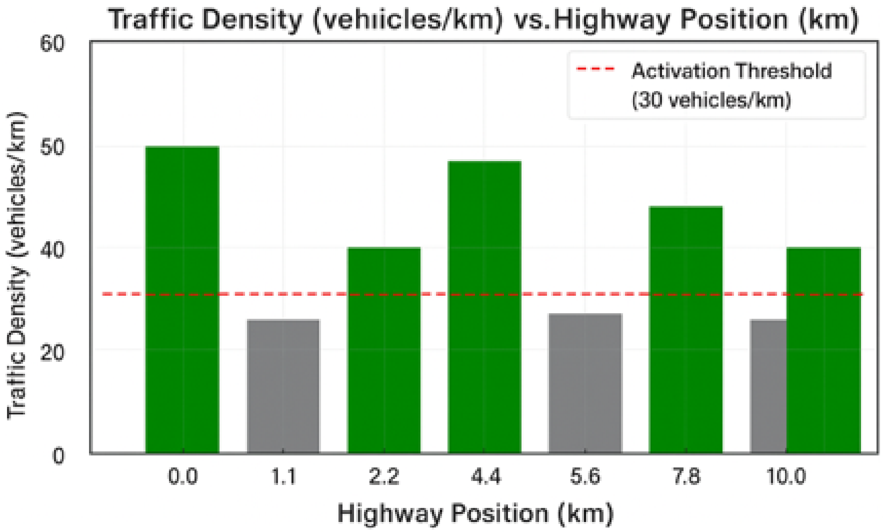

Figure 5 BS activation map over time

Additionally, the highway's open structure with limited physical obstructions enables stronger line-of-sight (LOS) channels, justifying the use of directional antennas and beamforming in selected deployment strategies. These features are integrated into the system assumptions and directly influence the simulation parameters and optimization constraints (Figure 6).

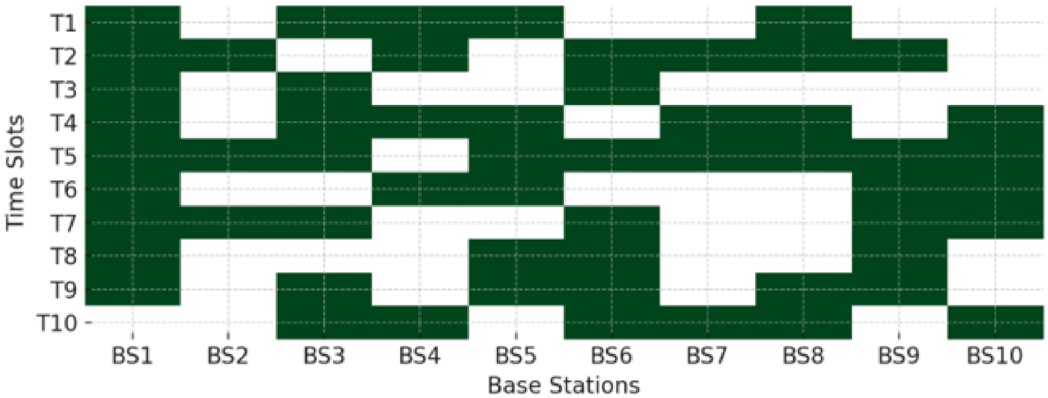

Figure 6 Traffic-aware BS activation over time

The results are compared with a baseline model where all BSs are always active without sleep mode adaptation to further validate the benefits of the proposed scheme:

- The baseline energy consumption consistently exceeds 200 W, which is significantly higher than that of the optimized solutions.
- The latency in the baseline configuration remains low (¡8 ms), but its energy inefficiency makes it unsuitable for sustainable operations.

Compared to the approach by Fourati et al., 2023, which achieved a 25% energy saving in urban scenarios using static GAs, the proposed model demonstrates superior performance by integrating dynamic traffic-awareness, achieving up to 40% energy reduction while maintaining strict AV communication standards. Additionally, previous studies, such as Saif et al., 2023 and Peng et al., 2024, focused primarily on cloud fog task scheduling or load prediction strategies, which do not directly address the unique requirements of high-speed highway environments. Our framework outperforms these by offering a practical, topology-specific deployment model.

4.3 Discussion

The proposed multi-objective optimization framework demonstrates that energy-efficient BS placement can be achieved while maintaining the performance demands of AV communication on highways. The linear highway topology, combined with dynamic traffic variations, requires a customized deployment approach. The results confirm that the proposed multi-objective framework provides an efficient trade-off between energy savings and communication performance.

4.3.1 Effectiveness of Traffic-Aware Sleep Mode

The traffic-aware BS activation mechanism plays a central role in reducing energy consumption. The simulations demonstrate that BSs in low-traffic regions can enter sleep mode safely without compromising the reliability and latency required for AV operations. The dynamic adaptation of BS states ensures that sufficient capacity is always available during peak traffic periods, addressing concerns that energy efficiency might jeopardize network reliability.

4.3.2 Pareto Front Decision Making

The Pareto front empowers decision-makers to tailor BS deployments based on the following specific operational priorities:

- Solution A is recommended for ultra-low latency scenarios, such as autonomous vehicle platooning.
- Solution D is optimal for energy-constrained deployments in which moderate latency can be tolerated.

The flexibility provided by the Pareto solutions enables network operators to achieve sustainable yet high-performance 5G and beyond highway networks.

4.3.3 Contributions and their Real-World Applicability

Compared with static deployments, the proposed dynamic traffic-aware framework provides a scalable and practical solution for highway scenarios. The inclusion of dynamic sleep modes, linear highway topology modeling, and adaptive optimization strategies ensures that the system can be adapted to real-world implementations with minor adjustments. However, the simulation's limitation in excluding interference modeling and real-world terrain variability should be addressed in future studies through more advanced simulations and field trials.

5. Conclusion

This study proposes a multi-objective optimization framework for energy-efficient BS placement along highways to support AV communication. The model effectively balances energy consumption, latency, and coverage requirements in linear, high-speed environments by incorporating a traffic-aware sleep mode mechanism and leveraging the NSGA-II algorithm. Simulation results demonstrate energy savings of up to 40% while maintaining a latency below 10 ms and coverage above 95%, confirming the suitability of the proposed model for next-generation intelligent transportation systems. The framework reflects highway-specific challenges, such as handover sensitivity and dynamic traffic density, and it is implemented using a scalable Python-based simulation tool (pymoo) that enables flexible scenario analysis. Future work includes enhancing the model with realistic vehicle mobility patterns, traffic prediction using AI, evaluation on real highway maps (OpenStreetMap or Indonesian toll roads), and integration with emerging 6G technologies such as RIS and terahertz communications to further improve adaptability and performance.

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Author Contributions

Hasanah Putri: Conceptualization, Methodology, Formal Analysis, Software Implementation, Writing – Original Draft. Prof. Dr. Ir. Rendy Munadi: Supervision, Validation, Writing – Review & Editing, Project Guidance. Dr. Sofia Naning Hertiana: Supervision, Technical Review, Writing – Review & Editing, Support in Simulation Strategy. All authors have read and approved the final version of the manuscript.

Conflict of Interest

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

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