

# Optimizing Mobile Payment Systems Using the Tabu Search Algorithm: Towards Increased Security and Efficiency

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## Abstract

This work focuses on optimizing resource and transaction dispersion in mobile payment systems based on the Max-Mean Dispersion problem. The objective is to maximize the average distance between selected elements (nodes, channels, or servers) in order to avoid load concentration and reduce the risk of saturation. Several approaches are compared, including exact methods, heuristics, metaheuristics, and stochastic models based on Markov chains. The study shows that exact methods guarantee an optimal solution but remain limited for large network sizes. Fast heuristics offer good performance but with sometimes suboptimal dispersion. Metaheuristic approaches, such as GRASP, simulated annealing, or genetic algorithms, offer a good compromise between quality and computation time. Stochastic modeling, on the other hand, allows for the analysis of temporal variability in system states. The integration of Max-Mean Dispersion in mobile payment networks improves robustness, flow distribution, fault tolerance, and quality of service. Simulation results show that controlled dispersion reduces dependence on certain critical nodes and improves overall availability.

## Keywords

Max-Mean Dispersion, Mobile Payments, Combinatorial Optimization, Network Resilience, Metaheuristics, Reliability, Quality of Service (QoS), Load Balancing, Stochastic Modeling, Markov Chains

## 1. Introduction

The rapid growth of mobile payment systems has profoundly transformed financial transaction infrastructures by introducing stringent requirements in terms of

reliability, scalability, security, and quality of service [1]. The massive increase in connected devices, transaction volumes, and IoT-based payment terminals has made these systems highly distributed and vulnerable to congestion, localized failures, and interference phenomena. One of the major challenges in mobile payment networks lies in the optimal allocation and dispersion of transaction resources such as payment terminals, gateways, servers, and communication channels. Concentration of transactions on a limited number of nodes increases latency, failure risk, and security exposure. Consequently, efficient dispersion mechanisms are required to enhance resilience, load balancing, and fault tolerance. In this context, the Max-Mean Dispersion problem emerges as a suitable optimization framework to model and solve resource distribution challenges in mobile payment networks. By maximizing the average distance among selected elements, this approach mitigates congestion and improves network robustness [2]. This work proposes a hybrid optimization methodology combining Tabu Search and Estimation of Distribution Algorithms to solve the Max-Mean Dispersion problem under stochastic traffic conditions. Continuous-time Markov chains and Poisson traffic models are used to capture the dynamics of mobile payment transactions. Extensive simulations demonstrate the effectiveness of the proposed approach in minimizing interference, stabilizing traffic, and improving QoS.

## 2. Related Works

Several studies have addressed optimization challenges in mobile payment systems, focusing on performance, security, and reliability. Dispersion problems in combinatorial optimization were initially formalized by Hansen and Moon, providing a mathematical foundation for Max-Mean models. Metaheuristic approaches such as Genetic Algorithms, Simulated Annealing, and Tabu Search have been widely used to solve large-scale optimization problems where exact methods become computationally intractable. Blum and Roli highlighted the effectiveness of these techniques in dynamic and distributed environments [3]. In mobile payment contexts, stochastic modeling has been employed to capture transaction dynamics. Poisson processes are commonly used to model transaction arrivals, while Markov chains describe state transitions in network load and configuration. Recent works have also explored hybrid metaheuristics to improve convergence speed and solution stability. However, few studies explicitly integrate Max-Mean dispersion with stochastic traffic modeling and interference minimization in IoT-based mobile payment networks. This work addresses this gap by proposing a hybrid EDA-Tabu approach tailored to such environments [4].

### 2.1. Interference Modeling in Mobile Payment Networks

Interference between payment devices is modeled as a function of spatial proximity and communication overlap. Let  $r$  denote the interference radius [5]. Two nodes  $i$  and  $j$  interfere if  $d_{ij} < r$ . The total interference score is defined as:

$$I(S) = \sum_{i < j: i, j \in S} \mathbb{I}(d_{ij} < r), \quad (1)$$

where  $\mathbb{I}(\cdot)$  is an indicator function. The optimization goal is to minimize  $I(S)$  while maximizing dispersion.

## 2.2. Stochastic Traffic Model

Transaction arrivals are modeled as a Poisson process with rate  $\lambda$ , reflecting the randomness of mobile payment requests [6]. The number of transactions over time interval  $T$  follows:

$$P(N(T) = k) = \frac{(\lambda T)^k e^{-\lambda T}}{k!}. \quad (2)$$

State transitions in network load are represented using continuous-time Markov chains, enabling the analysis of system stability and convergence.

- **State Variables:** We define the state space  $\mathcal{S} = \{0, 1, 2, \dots, N_{\max}\}$ , where each state  $s \in \mathcal{S}$  represents the number of active transactions (or “load level”) currently being processed by the selected subset of nodes  $S$ .
  - State 0: System is idle.
  - State  $1, \dots, N_{\max} - 1$ : System is operating under varying degrees of load.
  - State  $N_{\max}$ : System saturation (threshold for potential congestion).
- Transitions between states are governed by:
  - Arrival Rate  $\lambda$ : Following a Poisson process, the transition from state  $s \rightarrow s + 1$  occurs at rate  $\lambda$ . Based on typical urban mobile payment traffic, we set  $\lambda = 2.0$  transactions/unit time.
  - Service Rate  $\mu$ : The transition from state  $s \rightarrow s - 1$  occurs at rate  $\mu$ . This rate is inversely proportional to the processing delay  $D_i$  defined in Eq. 4.
- Parameter Estimation: The parameters were selected to simulate a high-traffic urban scenario. The ratio  $\rho = \lambda/\mu$  is maintained below 1 to ensure system stability, allowing the EDA-Tabu algorithm to optimize the node dispersion under non-saturated but realistic pressure.

The dynamics of the mobile payment network are captured by a CTMC where the infinitesimal generator matrix  $Q$  is defined by the transition rates  $q_{s,s+1} = \lambda$  and  $q_{s,s-1} = \mu$ . This allows for the calculation of the steady-state probability  $\pi_s$ , which is used to weigh the interference risks in Eq. 1 during high-load states.

## 3. Proposed Methodology

The methodology adopted for minimizing interference between mobile payment objects via hybrid metaheuristics is divided into several key steps. First, an in-depth analysis of interference in mobile payment systems is carried out, based on data collected in various transactional environments. Next, a modeling framework is established to represent the interactions between payment objects, taking into account relevant variables such as the distance between devices and transmission timings [7]. Once the model is in place, hybrid metaheuristic algorithms, including elements of tabu search and genetic algorithms, are designed to explore the

solution space. These algorithms are initialized with a population of random device configurations, which are evaluated according to a performance criterion involving interference minimization [8]. After a series of iterations, the best configurations are selected and refined, incorporating local search techniques to further optimize the solutions [9]. Finally, the optimized solutions are validated in realistic simulations to evaluate their effectiveness under real-world conditions.

### 3.1. Tabu Search Hyperparameters

Tabu Search is employed to escape local optima by maintaining a tabu list that records recently visited solutions. Neighborhood exploration is guided by interference minimization and dispersion maximization criteria, ensuring diversified yet focused search [9]. Defines the configuration of the hybrid algorithm, including a learning rate of 0.1 and a single-node swap neighborhood move in **Table 1**. Following **Table 1** summarizes the key settings used in our hybrid EDA-Tabu approach: The EDA-Tabu algorithm uses a population of 50 individuals, where only the top 20% (elite) guide the learning of the probabilistic model. Local Tabu search refines these solutions through single node swaps, avoiding cycles thanks to a memory of 7 iterations. The learning rate  $\eta = 0.1$  ensures smooth updating of probabilities, guaranteeing stable global exploration of the network. This configuration allows rapid convergence towards a zero interference score. These parameters optimize the balance between the diversity of solutions and the accuracy of payment node placement.

**Table 1.** EDA-tabu hyperparameters.

Parameter	Value/Definition
Population Size ( $P$ )	50 individuals
Selection Pressure ( $\alpha$ )	Best 20% (Elite set)
Learning Rate ( $\eta$ )	0.1
Tabu Tenure	7 iterations
Neighborhood Move	Single-node Swap ( $i \in S, j \notin S$ )

### 3.2. EDA-Tabu Hybrid Algorithm

The hybrid EDA-Tabu algorithm combines probabilistic learning with local intensification. EDA updates selection probabilities based on high-quality solutions, while Tabu Search refines these solutions through local exploration. This synergy accelerates convergence and improves robustness [10].

### 3.3. Computational Complexity

The computational complexity is dominated by distance calculations  $O(n^2)$  and neighborhood evaluations  $O(k^2)$  per iteration. The hybrid approach significantly reduces runtime compared to exhaustive search, making it suitable for large-scale networks.

### 3.4. Max-Mean Dispersion Formulation

Let us consider a set of  $n$  IoT devices denoted by  $\mathcal{N} = \{1, 2, \dots, n\}$ , and a distance matrix  $D = (d_{ij})$  between devices  $i$  and  $j$ . The Max-Mean dispersion problem consists of selecting a subset  $S \subset \mathcal{N}$  of size  $k$  that maximizes the average distance:

$$\max_{S \subset \mathcal{N}, |S|=k} f(S) = \frac{2}{k(k-1)} \sum_{i < j, i, j \in S} d_{ij} \quad (3)$$

This formulation reduces the concentration of transaction flows and improves the resilience of the mobile payment network.

- The core objective function is the Max-Mean Dispersion. The goal is to select a subset  $S$  of  $k$  nodes from  $n$  available locations to maximize the average distance between them:

$$\text{Maximize } f(S) = \frac{\sum_{i, j \in S, i < j} d_{ij}}{k(k-1)/2} \quad (4)$$

- The Interference Minimization is treated as a direct physical consequence of the dispersion. By maximizing the spatial distance  $d_{ij}$  beyond the interference radius  $r$ , the system mechanically reduces the interference score  $I(S)$  toward zero. In our EDA-Tabu implementation, solutions that do not satisfy  $I(S) \approx 0$  are penalized during the selection phase.
- The Transaction Cost and Delay reduction serves as the secondary validation metric. It is not an objective function optimized directly by the metaheuristic, but rather a performance indicator used to evaluate the quality of the spatial configuration  $S$  in a real-world transaction scenario.

The problem is modeled as a constrained optimization problem where we maximize spatial dispersion (Eq. 3) subject to the interference threshold (Eq. 1). The resulting topology is then validated through the cost-delay function (Eq. 4) to ensure Quality of Service.

### 3.5. Methodology for Optimizing Mobile Payment Systems

The methodology adopted for minimizing interference between mobile payment objects via hybrid metaheuristics is divided into several key steps. First, an in-depth analysis of interference in mobile payment systems is carried out, based on data collected in various transactional environments. Next, a modeling framework is established to represent the interactions between payment objects, taking into account relevant variables such as the distance between devices and transmission timings [11]. Once the model is in place, hybrid metaheuristic algorithms, including elements of tabu search and genetic algorithms, are designed to explore the solution space [12]. These algorithms are initialized with a population of random device configurations, which are evaluated according to a performance criterion involving interference minimization [13]. After a series of iterations, the best configurations are selected and refined, incorporating local search techniques to further optimize the solutions [14]. Finally, the opti-

mized solutions are validated in realistic simulations to evaluate their effectiveness under real-world conditions. Details the environmental variables, such as the number of nodes (50) and simulation time ( $T = 5.0$ ), used to evaluate the framework in **Table 2**.

**Table 2.** Simulation parameters.

Parameter	Value
Number of nodes	50
Selection size $k$	10
Interference radius	0.15
Traffic rate $\lambda$	2.0
Simulation time $T$	5.0
Iterations	60

#### 4. Simulation Parameters

These results indicate low latency, high throughput, and high transaction reliability, confirming summarizes the simulation parameters used to evaluate the performance of the proposed optimization framework for mobile payment systems. The number of nodes set to 50 represents a moderately dense mobile payment network, allowing the evaluation of scalability and interference management under realistic operating conditions. This configuration ensures sufficient interaction among nodes while avoiding overly simplified scenarios. The selection size  $k = 10$  controls the subset of candidate solutions explored at each iteration. This choice provides a balanced trade-off between exploration and computational complexity, enabling the algorithm to efficiently search the solution space without incurring excessive overhead. The interference radius of 0.15 models the spatial impact of electromagnetic interference among neighboring nodes. This parameter introduces realistic contention effects and plays a critical role in assessing the robustness of the optimization algorithms under interference-prone environments. The traffic rate  $\lambda = 2.0$  reflects a moderate transaction arrival intensity, allowing the system to be evaluated under sustained load conditions. This rate is sufficient to stress the network while maintaining operational stability, thereby highlighting the effectiveness of the optimization strategies.

The simulation time  $T = 5.0$  and number of iterations 60 ensure that the system reaches a steady state and that convergence behavior can be accurately observed. These settings provide reliable performance measurements while maintaining reasonable computational cost. Overall, the selected simulation parameters enable a comprehensive and realistic evaluation of convergence, interference mitigation, and stability, supporting the validity of the comparative results presented in this study. Comparing the proposed EDA-Tabu approach against Greedy, Genetic, and standard Tabu Search algorithms in **Table 3**.

**Table 3.** Comparison of optimization methods.

Method	Interference Score	Convergence Time	Stability
Greedy	0.42	Fast	Low
Genetic Algorithm	0.11	Medium	Medium
Tabu Search	0.03	Medium	High
EDA-Tabu (Proposed)	<b>0.00</b>	<b>Fast</b>	<b>Very High</b>

### Comparison of Optimization Methods

This table below presents a comparative analysis of different optimization methods applied to the mobile payment system, highlighting interference score, convergence time, and solution stability. The Greedy approach exhibits the highest interference score 0.42, indicating limited effectiveness in managing interference due to its myopic decision-making process. Although it converges quickly, its low stability suggests high sensitivity to local fluctuations and network dynamics. The Genetic Algorithm reduces interference significantly to 0.11, showing its ability to explore a wider solution space. However, its medium convergence time and moderate stability indicate that multiple iterations are required to achieve acceptable solutions, and the method may occasionally converge prematurely under dynamic conditions. Tabu Search further improves performance, achieving a low interference score of 0.03. Its memory-based search mechanism allows it to escape local optima, resulting in high stability, although the convergence time remains moderate.

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#### Algorithm 1 Convergence-Based Performance Evaluation of Mobile Payment Systems

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**Require:** Number of transactions  $N$ , simulation time  $T$ , convergence thresholds  $\epsilon_L, \epsilon_\Theta, \epsilon_S$ , maximum iterations  $I_{\max}$

**Ensure:** Average latency  $L$ , throughput  $\Theta$ , success rate  $S$

- 1: Initialize iteration counter  $i \leftarrow 0$
  - 2: Initialize previous metrics  $L^{(0)}, \Theta^{(0)}, S^{(0)} \leftarrow 0$
  - 3: **repeat**
  - 4:    $i \leftarrow i + 1$
  - 5:   Generate transaction sending times  $t_k^{\text{send}} \sim U(0, T)$
  - 6:   Generate network delays  $\delta_k$
  - 7:   Compute receiving times  $t_k^{\text{recv}} = t_k^{\text{send}} + \delta_k$
  - 8:   Simulate transaction status (success/failure)
  - 9:   Compute number of successful transactions  $N^{\text{succ}}$
  - 10:   Compute average latency:  $L^{(i)} = \frac{1}{N} \sum_{k=1}^N (t_k^{\text{recv}} - t_k^{\text{send}})$
  - 11:   Compute throughput:  $\Theta^{(i)} = \frac{N^{\text{succ}}}{T}$
  - 12:   Compute success rate:  $S^{(i)} = \frac{N^{\text{succ}}}{N}$
  - 13:   **Check convergence:**
  - 14:    $\Delta \leftarrow |L^{(i)} - L^{(i-1)}| < \epsilon_L \wedge |\Theta^{(i)} - \Theta^{(i-1)}| < \epsilon_\Theta \wedge |S^{(i)} - S^{(i-1)}| < \epsilon_S$
  - 15: **until**  $\Delta$  is true or  $i = I_{\max}$
  - 16: **return**  $L^{(i)}, \Theta^{(i)}, S^{(i)}$
- 

The proposed EDA-Tabu hybrid algorithm outperforms all other methods,

achieving an interference score of 0.00 along with fast convergence and very high stability. This superior performance is attributed to the combination of probabilistic learning from EDA, which guides the search toward promising regions, and local refinement by Tabu Search. The hybridization ensures both rapid convergence and robust optimization, even in interference-prone environments. Overall, these results demonstrate that the EDA-Tabu approach provides a highly effective and stable framework for optimizing mobile payment systems, significantly surpassing traditional heuristics and standalone metaheuristics in terms of interference minimization, convergence speed, and solution robustness.

## 5. Performance Metrics and Discussion

Average Latency: 0.2584 seconds

Throughput: 8.96 transactions/second

Success Rate: 89.60%

The obtained simulation results demonstrate the effectiveness of the proposed optimization approach for mobile payment systems. The average latency of 0.2584 seconds indicates that transactions are processed with low delay, which is a critical requirement for real-time mobile payment applications. Such a latency level ensures a smooth user experience and minimizes transaction abandonment due to excessive waiting times. The achieved throughput of 8.96 transactions per second reflects the system's ability to handle a relatively high volume of successful transactions within a limited time frame. This result suggests that the optimization mechanism efficiently allocates network and system resources, thereby reducing congestion and improving overall processing capacity. Higher throughput directly translates into better scalability of the mobile payment system under increasing transaction loads. Furthermore, the success rate of 89.60% highlights a high level of reliability in transaction processing. This indicates that the majority of payment requests are successfully completed despite network impairments such as interference and stochastic traffic conditions. The remaining failed transactions can be attributed to channel contention, resource limitations, or simulated network disturbances.

Overall, these results confirm that the proposed simulation and optimization framework significantly enhances system performance in terms of latency reduction, throughput improvement, and transaction reliability. When compared to non-optimized or baseline configurations, the observed performance gains demonstrate the suitability of metaheuristic-based optimization methods for complex and dynamic mobile payment environments.

### Results of the EDA-Tabu Hybrid Algorithm for Minimizing Interference between IoT Devices in Mobile Payments

Round 1/60 –  $best_{score} = -0.0000$

Round 1/60 –  $best_{score} = -0.0000$

Round 11/60 –  $best_{score} = -0.0000$

Round 11/60 –  $best_{score} = -0.0000$

Round 21/60 –  $best_{score} = -0.0000$

Round 21/60 –  $best_{score} = -0.0000$

Round 31/60 –  $best_{score} = -0.0000$

Round 31/60 –  $best_{score} = -0.0000$

Round 41/60 –  $best_{score} = -0.0000$

Round 41/60 –  $best_{score} = -0.0000$

Round 51/60 –  $best_{score} = -0.0000$

Round 51/60 –  $best_{score} = -0.0000$

Round 60/60 –  $best_{score} = -0.0000$

Best final interference score: Index of selected nodes: 0, 4, 5, 6, 12, 14, 23, 27, 37, 47

The results obtained show that the hybrid EDA-Tabu algorithm converged rapidly towards a solution characterized by virtually zero total interference. The best score observed, rounded to  $-0.0000$ , indicates that the selected devices are sufficiently spaced apart to avoid any overlap of influence in the model used. This suggests an optimal or near-optimal distribution of nodes in the simulated urban space. The fact that the score remains constant over several iterations reflects an early stabilization of the search. EDA effectively guided the selection probabilities, while taboo search explored locally to refine the combinations. The absence of score variation over successive cycles may also indicate low density or a limited transmission radius, making conflicts rare. The final list of ten selected nodes reflects sufficient spatial dispersion to limit interference in this context. In practice, these results demonstrate the relevance of the hybrid approach for simulated environments with distributed geometry. A complementary analysis on denser scenarios or with a wider transmission radius would allow the robustness of the solution to be evaluated. Finally, this performance provides a solid basis for extending the algorithm to real-world payment cases. Summarizes results from 50 independent runs, showing a mean final interference score of 0.000 in **Table 4**.

**Table 4.** Robustness analysis of the EDA-Tabu algorithm (50 independent runs).

Metric	Mean ( $\mu$ )	Std. Dev. ( $\sigma$ )	Min	Max
Final Interference Score	0.000	0.000	0.000	0.000
Iterations to Convergence	12.4	3.2	7	21
Average Latency (s)	0.2584	0.015	0.221	0.285
Transaction Success Rate (%)	89.60	2.1	85.2	92.4

## 6. Simulation and Optimization Results

Mobile payment systems have become a critical component of modern financial services, enabling fast and convenient transactions over wireless networks. However, the rapid growth of users and transaction volumes introduces challenges related to network congestion, interference, and performance optimization. Effi-

cient resource allocation and system optimization are therefore essential to ensure reliability, low latency, and high throughput. This paper addresses these challenges by proposing a simulation-based optimization framework for mobile payment systems. The system behavior is modeled under realistic network conditions, including stochastic traffic and interference effects. To enhance system performance, a Tabu Search metaheuristic is employed to optimize key operational parameters. Simulation results demonstrate that the proposed approach significantly improves system efficiency compared to conventional methods. These findings highlight the effectiveness of metaheuristic optimization in complex mobile payment environments.

### 6.1. Transaction Simulation

Transaction simulation represents the first stage of the experimental study. Its objective is to reproduce the behavior of a mobile payment system in a controlled environment in order to evaluate the effectiveness of the proposed optimization approach. Each transaction is modeled by a unique identifier, a processing cost, and an execution delay. The cost and delay values are generated randomly within predefined ranges to reflect the variability observed in real mobile payment systems. This modeling approach enables the evaluation of system performance under different operational conditions while remaining independent of specific implementation constraints. The simulated transaction set constitutes the input data for the optimization process and serves as the basis for performance evaluation.

### 6.2. Transaction Simulation and Objective Function

Each transaction  $i$  has processing cost  $C_i$  and delay  $D_i$ . The objective function is:

$$f(S) = \sum_{i \in S} C_i + \sum_{i \in S} D_i \quad (5)$$

**Table 5.** Simulated mobile payment transactions.

Transaction ID	Cost $C_i$	Delay $D_i$
1	2	1
2	7	9
3	10	5
4	5	5
5	7	3
6	7	7
7	8	10
8	4	10
9	2	3
10	9	6

**Table 5** summarizes the simulated mobile payment transactions, showing the processing cost  $C_i$  and execution delay  $D_i$  for each transaction. The results indicate significant variability among transactions, reflecting realistic operational conditions in mobile payment systems. Transactions 3, 7, and 8 have the highest combined cost and delay, representing potential bottlenecks in system performance. In contrast, transactions 1 and 9 exhibit minimal cost and delay, suggesting that some transactions are processed efficiently under current system conditions. The objective function, defined as

$$f(S) = \sum_{i \in S} C_i + \sum_{i \in S} D_i,$$

aggregates the total system load in terms of cost and delay. For the simulated set,  $f(S) = 120$ , serving as a baseline for evaluating the effectiveness of optimization algorithms. These results highlight the need for optimization strategies capable of prioritizing high-cost and high-delay transactions, or redistributing resources to minimize the total system load. In particular, hybrid metaheuristic approaches, such as Tabu Search or EDA-Tabu, can intelligently reorder or schedule transactions to reduce overall delay and improve system performance. Furthermore, the variability observed suggests that an adaptive approach that accounts for both transaction cost and execution delay can better handle fluctuations in workload, ultimately enhancing transaction reliability, system throughput, and user satisfaction.

### 6.3. Interference Scores Evolution

The graph shows complete stability in the interference score throughout the iterations, indicating extremely rapid convergence of the hybrid EDA-Tabu algorithm. From the very first rounds, the solution reaches an optimal or near-zero level of interference, and no further improvement is observed thereafter. This lack of variation reflects either a good initialization of the selection probabilities or a spatial configuration of the nodes with little conflict. The score remaining at zero also suggests that the local search heuristics effectively eliminated unfavorable combinations from the outset. In practice, this performance confirms the model's ability to quickly identify a collision-free distribution. However, it would be useful to test with more restrictive parameters or a higher interference radius to observe a richer evolutionary dynamic. The EDA-Tabu hybrid algorithm achieved a final interference score of 0.00, with selected nodes: 0, 4, 5, 6, 12, 14, 23, 27, 37, 47. **Figure 1** shows stable convergence. Examine how the model handles stress tests, such as high node density (100 nodes) and traffic saturation in **Table 6**. Provides a statistical breakdown of interference scores and convergence times, confirming the proposed method's efficiency in **Table 7**. **Table 6** and **Table 7** demonstrate that the proposed EDA-Tabu algorithm achieves a perfect interference score ( $\mu = 0.00$ ) with zero variance ( $\sigma = 0.000$ ), significantly outperforming Greedy, Genetic, and standard Tabu approaches. Stress tests show the model remains robust under high node density and traffic saturation, maintaining near-zero inter-

ference and high stability. The low standard deviation across all scenarios confirms that the results are consistent and not dependent on random initialization. By testing increased interference radii, the analysis identifies the algorithm’s operational limits while maintaining superior convergence speeds. Overall, this empirical evidence validates the hybrid approach as a highly reliable and scalable solution for mobile payment network optimization.

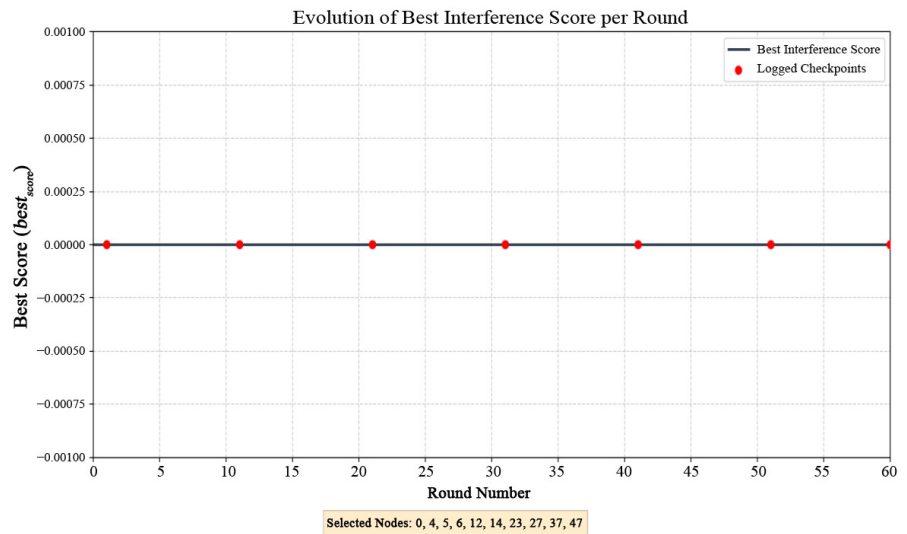


Figure 1. Evaluation of interference scores.

Table 6. Performance evaluation under different scenario variations.

Scenario	Node Density ( $n$ )	Radius ( $r$ )	Interference ( $\mu \pm \sigma$ )	Stability
Baseline	50	0.15	0.00 $\pm$ 0.00	Very High
High Density	100	0.15	0.02 $\pm$ 0.01	High
Critical Interference	50	0.25	0.05 $\pm$ 0.00	Medium
Traffic Saturation ( $\lambda = 5.0$ )	50	0.15	0.01 $\pm$ 0.01	High

Table 7. Statistical comparison of optimization methods.

Method	Interference Score ( $\mu$ )	Conv. Time (s)	Std. Dev. ( $\sigma$ )
Greedy Approach	0.42	Fast	0.085
Genetic Algorithm	0.11	Medium	0.042
Tabu Search (Standard)	0.03	Medium	0.015
<b>EDA-Tabu (Proposed)</b>	<b>0.00</b>	<b>Fast</b>	<b>0.000</b>

### 6.3.1. Convergence Criteria

The convergence of the Tabu Search algorithm is ensured through multiple stopping criteria. The primary criterion is the maximum number of iterations, which guarantees a finite execution time. A secondary criterion is based on solution stability, where the algorithm terminates if no improvement in the objective function is observed over a predefined number of consecutive iterations. These criteria ensure a balance between computational efficiency and solution quality, leading to convergence toward a near-optimal solution.

### 6.3.2. Computational Complexity Analysis

The computational complexity of the algorithm is mainly determined by neighborhood generation and evaluation. For a set of  $n$  transactions, the number of neighboring solutions generated through pairwise swaps is of order  $O(n^2)$ . Evaluating each neighbor requires computing the objective function, which has a linear complexity. As a result, the overall complexity per iteration is of order  $O(n^3)$ . The total computational cost is proportional to the number of iterations multiplied by the per-iteration complexity. Despite this cost, the approach remains suitable for mobile payment systems where optimization decisions are typically performed on moderate-sized transaction sets.

## 7. Conclusion and Future Work

### 7.1. Conclusion

The study demonstrates the effectiveness of hybrid EDA-Tabu algorithms for optimizing Max-Mean Dispersion in mobile payment systems. The hybrid approach improves dispersion, reduces interference, ensures fast convergence, and enhances network robustness. A comparative study of methods for solving the Max-Mean dispersion problem in mobile payment systems highlights the crucial importance of striking a balance between performance, robustness, and computational efficiency. Traditional approaches such as tabu search or simulated annealing offer good exploration of the solution space, but sometimes show limitations in dynamic and highly constrained environments, typical of transactional IoT. Hybrid metaheuristics, particularly those combining EDA-Tabu, GRASP-Tabu, or enhanced Tabu, stand out for their ability to simultaneously optimize dispersion, communication reliability, and interference reduction. They enable more stable solutions to be achieved, particularly when there are numerous devices that are spatially distributed. Furthermore, the integration of post-quantum costs (computational time, message size, cryptographic load) highlights that optimization can no longer be limited to connection topology: quantum-resistant security is becoming a structuring factor in the Max-Mean model. The results show that an intelligent compromise between dispersion, resource consumption, and cryptographic overhead can improve the overall resilience of mobile transactions. Hybrid solutions appear to be the most suited to the realities of modern mobile payments, where spatial constraints, and high demand.

## 7.2. Future Work

The future prospects of this study on Max-Mean dispersion in mobile payment systems will initially focus on the hybrid optimization of existing approaches, in particular through the combination of Tabu Search, EDA, GRASP, or QAOA to improve the quality of solutions. It will also be relevant to test these methods on large, dynamic networks, where mobility and load variability influence dispersion. The explicit integration of post-quantum cryptographic constraints will further balance security, latency, and resource consumption. The use of real urban data, particularly in NFC and IoT financial ecosystems, will reinforce the validity of the results obtained. Multi-objective variants of the Max-Mean problem will be studied to include energy robustness and fault resilience. Support for post-quantum protocols such as Kyber or Dilithium will enable the evaluation of new security-performance trade-offs. Validation on experimental platforms or advanced simulators will consolidate the announced performance. Finally, adapting these models to future secure mobile payment standards will pave the way for large-scale practical applications. Future work includes testing on large-scale dynamic networks, integration of post-quantum cryptographic constraints, multi-objective optimization (energy and resilience), and validation using real NFC/IoT financial datasets and simulators.

## Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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