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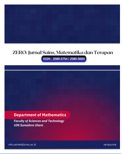

Optimizing Electric Vehicle Charging Station Placement in Banyumas Using Graph Domination Theory

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ABSTRACT

This study applies graph theory to optimize the placement of electric vehicle (EV) charging stations in Banyumas Regency, Indonesia, using real geospatial data from 27 sub-districts. Each sub-district is modeled as a vertex, with edges defined by a 10 km coverage radius. The domination number is employed to identify the minimum number of charging stations required to ensure full spatial coverage. Unlike prior EV infrastructure studies in Indonesia that primarily rely on demand-based heuristics or clustering methods, this research explicitly guarantees coverage through graph domination theory. To enhance robustness, the domination-based solution is compared with a Set Covering Problem solved using Ant Colony Optimization (ACO). Both approaches consistently identify six strategic locations, achieving 100% coverage while reducing infrastructure requirements by approximately 78% compared to a one-station-per-sub-district strategy. The results provide practical guidance for policymakers and urban planners by supporting cost-efficient, scalable, and equitable EV charging infrastructure deployment in regions with early-stage EV adoption.

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1. INTRODUCTION

Graph theory plays a vital role in computer science and applied mathematics by providing a rigorous framework for modeling complex systems and solving optimization problems, particularly in network-based decision making and facility location planning. Rather than emphasizing its broad theoretical scope, graph theory is increasingly valued for its ability to support applied optimization tasks such as infrastructure planning, resource allocation, and spatial coverage problems. Within this discipline, graph domination theory represents an important approach concerned with selecting a minimal subset of vertices, known as a dominating set, such that every vertex in the graph is either included in this set or adjacent to one of its members. The domination number, defined as the minimum cardinality of all dominating sets, is especially relevant in optimization contexts where facilities must be placed efficiently to ensure complete service coverage.

In recent years, domination theory has been applied in a range of optimization and resource allocation problems. Gayathri et al. (2020) used domination principles to optimize school transportation routes, while Hamidi and Taghinezhad (2023) applied them to improve communication and healthcare network reliability.

Similarly, Bibi et al. (2017) and Yegnanarayanan et al. (2013) utilized distance-based domination to enhance signal coverage in wireless and sensor networks. Ahmad and Batool (2023) implemented domination concepts in city-level commodity distribution, and Rehman et al. (2023) optimized hospital location planning using domination-based models. These studies demonstrate that domination numbers are effective optimization tools for minimizing infrastructure redundancy while guaranteeing coverage, yet most existing works rely on abstract graph structures or simulated networks. Consequently, the application of domination theory using real geospatial data, particularly in transportation infrastructure planning, remains limited.

In Indonesia, the rapid growth of the electric vehicle (EV) market has created a pressing need for efficient and accessible charging infrastructure. According to the AC Ventures Electric Vehicle Outlook (July 2023), the country currently operates 1,431 charging stations, with a target of 2,500 by 2025. Distributed evenly across 514 regencies and cities, this implies a minimum of five stations per region. Yet, Banyumas Regency covering 1,327.59 km² and home to approximately 1.77 million residents currently operates only two charging stations. This disparity highlights the need for an optimization-driven planning framework that determines not only how many stations are required, but also where they should be strategically located to maximize coverage and cost efficiency.

To address this challenge, this study applies graph domination theory to determine the minimum number of EV charging stations required to cover all sub-districts within Banyumas Regency. The 27 sub-districts are modeled as vertices in a graph, and edges are established between pairs of sub-districts. The domination number derived from this model represents the minimal number of stations needed to ensure that every sub-district is either directly served or within range of a nearby station. This approach provides a mathematically grounded framework for spatial decision-making using real geographic data.

For comparison and validation, the results obtained from the dominating set model are evaluated against those generated by the Set Covering Problem (SCP) solved using the Ant Colony Optimization (ACO) algorithm. The Set Covering Problem is a classical optimization model that seeks the smallest number of facilities required to ensure that every demand vertex in a region is covered by at least one facility. The ACO algorithm, a population-based metaheuristic inspired by the foraging behavior of ants, is used to solve this problem efficiently through iterative pheromone updating and heuristic selection. By contrasting domination theory with an ACO-based SCP approach, this study situates graph-based optimization within a broader applied optimization context, balancing theoretical rigor and heuristic adaptability.

Accordingly, this research aims to answer the following question:

How can graph domination theory be applied to determine the optimal placement of EV charging stations in Banyumas Regency, and how do its results compare with those produced by the Set Covering Problem solved using Ant Colony Optimization (ACO)?

Through this approach, the study contributes both theoretically and practically. From a theoretical perspective, it demonstrates one of the first applications of domination number theory using real geospatial infrastructure data in Indonesia. Practically, it provides comparative insights into how graph-based and metaheuristic optimization models can support policymakers and urban planners in designing efficient, equitable, and sustainable EV charging networks aligned with Indonesia's energy transition goals.

2. RESEARCH METHOD

2.1 Dominating Set in the Context of EV Charging Station Placement

In a graph $G = (V, E)$, the domination number $\gamma(G)$refers to the smallest cardinality of a dominating set, which is a subset of vertices ensuring that every vertex outside the set is adjacent to at least one member within it. Thus, $\gamma(G)$represents the minimum number of vertices required to dominate the entire graph (Khan et al., 2024). Recent studies have increasingly applied graph-based and metaheuristic methods to optimize electric vehicle charging infrastructure. Chen et al. (2024) utilized spatial graph clustering to determine efficient station placement in urban environments, emphasizing accessibility and network balance. Complementing this, Mousavi et al. (2024) proposed a hybrid metaheuristic algorithm that accounts for demand uncertainty when determining optimal charging locations. Metaheuristic approaches continue to gain traction; for example, Gautam and Singh (2024) demonstrated that ant colony optimization can effectively balance installation cost and spatial coverage in smart city environments.

In this application, we aim to determine the optimal locations for EV charging stations in a city by modeling the city's road network as a graph. In this graph, each vertex (V) represents a city center or a strategic location, while each edge (E) represents a road connecting two locations. For example, consider the graph $V = \{A,\ B, C, D, E\}$, which represents five strategic locations, and $E = \{(A, B), (B, C), (C, D), (D, E), (E, A), (B, D)\}$, which represents the roads connecting these locations. In this context, a dominating set refers to a subset of locations where charging stations will be installed. The goal is to ensure that every location in the network either has a charging station or is adjacent to a location with a charging station.

To determine the minimum number of locations required for charging stations, we follow a structured approach:

1. Select Candidate Locations: We begin by identifying possible subsets of vertices as candidate locations for the charging stations. These subsets represent potential sets of locations where charging stations might be installed.
2. Validate the Set: For each candidate set, we check if every vertex in the graph is either part of the candidate set or has a neighboring vertex in the set. This ensures that all locations are covered by the charging stations, either directly or through adjacency.
3. Find the Minimum Set: We then determine the smallest subset of vertices that satisfies the coverage condition. This is the optimal set of locations where charging stations should be installed to minimize the total number of stations required.
4. Calculate the Domination Number: The size of this minimum subset is called the domination number, which represents the minimum number of charging stations needed to cover the entire network.

The following Python pseudocode illustrates this approach:

```
from itertools import combinations

# Function to check if a candidate set is a dominating set
def is_dominating_set(G, S):
    for vertex in G:
        if vertex not in S and all(neighbor not in S for neighbor in G[vertex]):
            return False
    return True

# Function to find the domination number
def find_dominating_number(G):
    vertices = list(G.keys())
    n = len(vertices)
    for k in range(1, n+1):
        for subset in combinations(vertices, k):
            if is_dominating_set(G, subset):
                return subset, k
    return vertices, n # Worst case, the whole set is required

# Example graph for a transportation network
G = {
    'A': ['B', 'E'],
    'B': ['A', 'C', 'D'],
    'C': ['B', 'D'],
    'D': ['B', 'C', 'E'],
    'E': ['A', 'D']
}

# Find the domination number and optimal locations for charging stations
dominating_set, domination_number = find_dominating_number(G)
print(f"Optimal locations for charging stations: {dominating_set}")
print(f"The domination number of the transportation network is:
 {domination_number}")
```

Interpreting the Results:

Suppose the results of the above code are as follows: Optimal Locations: $\{A, B\}$ and Domination Number: 2. This means that placing EV charging stations at locations A and B ensures that all other locations (C, D, E) are either directly equipped with a station or are adjacent to a location that is. The domination number of 2 indicates that only two charging stations are required to cover the entire network. This minimizes infrastructure costs while maintaining full accessibility for EV users. By applying this method, we can efficiently determine the optimal placement of EV charging stations, ensuring that the network is fully covered with the least number of stations.

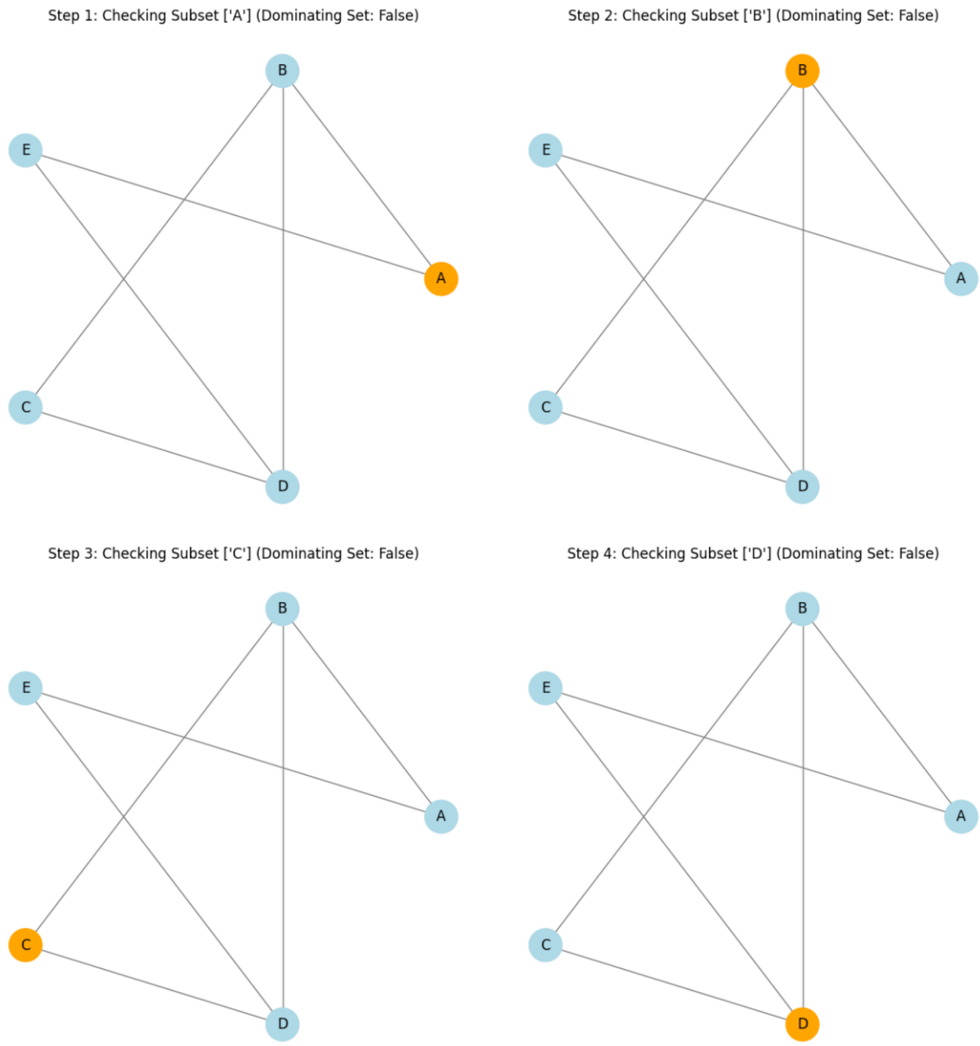
This approach can be scaled to larger networks and adapted for practical applications in urban planning and transportation infrastructure development.

The step-by-step procedure used to determine the domination number is illustrated in Figure 1, which provides a clear visual representation of how candidate vertex subsets are evaluated. The process begins by examining all possible subsets in an incremental manner, starting from the smallest subset size to ensure that the minimum dominating set is identified.

In Steps 1 to 5, the algorithm evaluates all single-vertex subsets, namely $\{A\}$, $\{B\}$, $\{C\}$, $\{D\}$, and $\{E\}$. For each subset, the algorithm checks whether all vertices in the graph are either included in the subset or adjacent to at least one vertex within it. As shown in Figure 1, none of these single-vertex subsets are able to dominate the entire graph, because at least one vertex remains uncovered in each case. Consequently, these subsets are classified as invalid and marked as False.

The algorithm then proceeds to Step 6, where it evaluates the two-vertex subset $\{A, B\}$. At this stage, the coverage condition is satisfied: every vertex in the graph is either a member of the subset or directly adjacent to vertex Aor B. As a result, this subset is identified as a valid dominating set and marked as True.

Because the algorithm evaluates subsets in ascending order of size, the identification of $\{A, B\}$as a valid dominating set guarantees that no smaller subset can achieve full domination. Therefore, the algorithm terminates at this point and concludes that the domination number of the graph is 2. This stepwise evaluation, as depicted in Figure 1, demonstrates how the domination number is derived in a systematic and exhaustive manner.



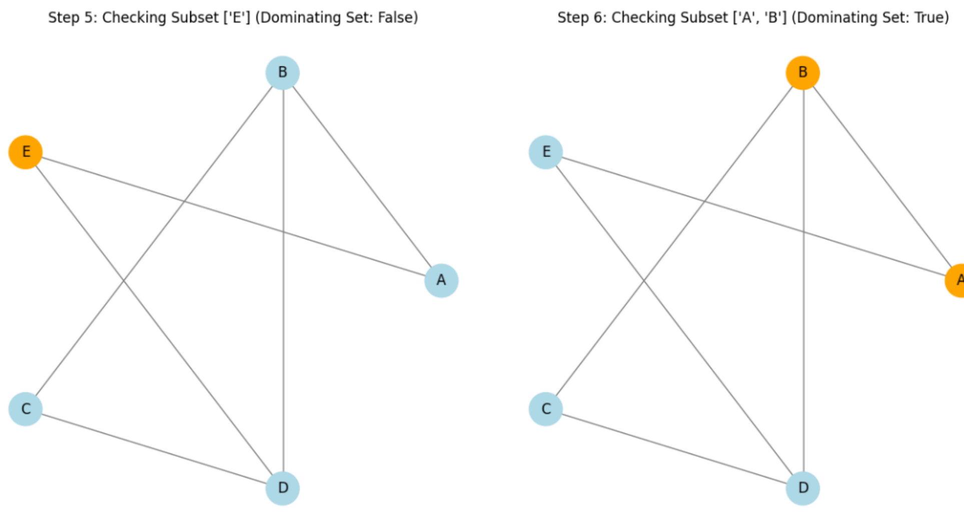


Figure 1. Step-by-step Evaluation of Dominating Set Candidates in the Graph

2.2 Set Covering Problem and Ant Colony Optimization in Comparison with the Dominating Set Approach

The Set Covering Problem (SCP) is one of the fundamental models in facility location and public infrastructure optimization. It aims to determine the smallest number of facilities needed to ensure that all demand vertices are served within a specific coverage distance. In practical terms, the SCP ensures that every city, neighborhood, or service area lies within the operational range of at least one facility, such as a hospital, bus stop, or EV charging station. This model is widely used by planners and policymakers to balance accessibility and installation cost (Daskin & Schilling, 2011).

Mathematically, the SCP is expressed as follows:

$$\begin{aligned} \text{Minimize} \quad & Z = \sum\nolimits_{j \in J} c_j x_j \\ \text{subject to} \quad & \sum\nolimits_{j \in N_i} x_j \geq 1, \forall i \in I \\ & x_j \in \{0,1\}, \forall j \in J \end{aligned} \tag{1}$$

where I represents demand vertices, J is the set of candidate facility sites, c_j denotes the installation cost at site j, and x_j is a binary decision variable (1 if a facility is placed, 0 otherwise). The constraint ensures that each demand vertex i is covered by at least one facility within the service radius.

In this study, the SCP is applied to determine optimal locations for EV charging stations in Banyumas Regency. Each candidate site represents a subset of demand vertices within a specified radius, and the objective is to minimize the number of stations while ensuring complete regional coverage. Compared with the dominating set approach which focuses on network adjacency and ensures that each vertex is either selected or connected to a selected vertex the SCP emphasizes spatial coverage based on distance. The dominating set approach supports network connectivity, whereas the SCP enhances spatial efficiency. Together, they provide a complementary framework for developing EV infrastructure that is both robust and equitable (Yang et al., 2023; Awasthi & Venkitachalam, 2021).

To solve the SCP efficiently, this research employs the Ant Colony Optimization (ACO) algorithm, a metaheuristic inspired by the foraging behavior of ants. ACO is particularly effective for solving combinatorial problems with large and interdependent search spaces. In this context, each potential EV charging station acts as a "set," and artificial ants construct feasible solutions by selecting subsets of stations that ensure complete coverage.

The probability that an ant k moves from location i to j at iteration t is defined as:

$$P_{ij}^k(t) = \begin{cases} \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}(t)]^\alpha [\eta_{il}]^\beta}, & \text{if } j \in N_i^k, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

where $\tau_{ij}(t)$ is the pheromone intensity, η_{ij} is the heuristic desirability (often the inverse of distance), and α and β control their relative influence. The pheromone update follows:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t), \tag{3}$$

where ρ is the evaporation rate, m is the number of ants, and $\Delta\tau_{ij}^{k}(t)$ is defined as:

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L_k}, & \text{if } (i,j) \text{ is part of ant } k\text{'s solution,} \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

Here, Q is a constant pheromone quantity and L_k represents the cost (or total number of stations) of the solution generated by ant k. Over several iterations, pheromone trails guide ants toward promising solutions while evaporation prevents premature convergence.

In this study, the ACO parameters α, β, ρ, and Q were selected based on established practices in transportation and infrastructure optimization literature and refined through trial-based experimentation (Armond et al., 2022; Yang et al., 2023). Parameters $\alpha$and βwere configured to balance pheromone exploitation and heuristic exploration, while the evaporation rate $\rho$was used to prevent premature convergence. Several parameter combinations were evaluated, and the final configuration was chosen due to its stable convergence and consistent number of selected charging stations, in line with the domination number obtained from the graph-based analysis.

By integrating ACO with the SCP formulation, this study complements the dominating set approach. While the dominating set provides a theoretical lower bound based on adjacency, the ACO–SCP framework introduces adaptive learning to explore alternative spatial configurations within the same coverage constraints. This combination results in an efficient and practically adaptable strategy for EV charging station placement.

2.3 Integrated Framework of Dominating Set, SCP, and ACO

Figure 2 illustrates how the domination number analysis, Set Covering Problem (SCP), and Ant Colony Optimization (ACO) are integrated in this study. The domination number analysis is first applied to establish a theoretical baseline based on graph adjacency. The problem is then reformulated as an SCP to incorporate distance-based spatial coverage constraints. Finally, the SCP is solved using ACO, which applies heuristic and iterative optimization to efficiently identify feasible solutions. The results from these three components are compared and integrated to derive an optimal and practical EV charging station placement strategy.

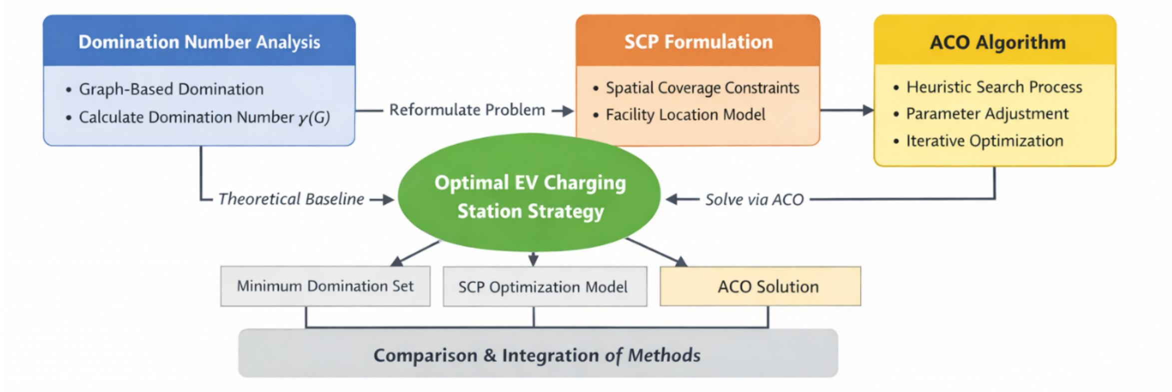


Figure 2. Integrated Framework of Dominating Number, Set Covering Problem, and Ant Colony Optimization

2.4 Data Source and Distance Computation

The dataset used in this study consists of latitude and longitude coordinates of 27 sub-districts in Banyumas Regency, Indonesia. The coordinates were obtained exclusively from Google Maps and represent the approximate geographic centers of each sub-district. Google Maps was chosen as the data source because this research focuses on the application of dominating graph theory, which requires spatial point representations to model vertices and adjacency relationships. Unlike studies that depend on detailed administrative boundaries or road-network structures, this approach does not require polygon-based data or routing information; therefore, point-based coordinates from Google Maps are sufficient and appropriate. Prior to analysis, all coordinate data were standardized into decimal degree format to ensure consistency. The dataset contained no missing or duplicate entries, and no additional preprocessing steps were required.

Adjacency between sub-districts was defined based on a fixed coverage radius of 10 km, reflecting the assumed service range of an electric vehicle charging station. Pairwise distances between sub-districts were calculated using the haversine formula, which computes geodesic distances on the Earth's surface based on latitude and longitude coordinates. GIS-based distance tools were not employed, as the haversine formula provides sufficient accuracy for regional-scale analysis and aligns well with the abstract graph representation adopted in dominating set theory. Two sub-districts were considered adjacent if their computed distance was less than or equal to 10 km.

All computational experiments were conducted using Python 3.12. Graph construction and domination set evaluation were implemented using custom Python scripts. Standard scientific libraries were employed, including NumPy for numerical operations, itertools for systematic subset generation, and NetworkX for graph representation and traversal.

3. RESULT AND ANALYSIS

The rapid rise of EVs around the world has created an urgent need for charging infrastructures that are both efficient and strategically located. In Banyumas Regency, Central Java, Indonesia, the growing movement toward sustainable transportation calls for thoughtful planning to ensure that EV users have convenient access to charging facilities. To address this challenge, the present study uses geospatial data from 27 sub-districts, including their geographic coordinates and coverage areas, to determine where charging stations should be placed. Graph theory particularly the concept of dominating sets is applied to minimize the number of required stations while still ensuring that every sub-district is adequately covered within a given radius.

The purpose of this analysis is to design a charging network that not only meets sustainability goals but also enhances the experience of EV users, both residents and travelers. The findings aim to offer useful guidance for local governments and planners in developing EV infrastructure in a data-driven and cost-efficient way. The latitude and longitude information for each sub-district used in this analysis is shown in Table 1.

Table 1. Latitude and Longitude of Sub-district in Banyumas Regency

City Number	Sub-district	Latitude, longitude
1	Lumbir	-7.444511296981006, 108.95857112326865
2	Wangon	-7.514867419643897, 109.05745812889467
3	Jatilawang	-7.53025650215728, 109.12234472584886
4	Rawalo	-7.5366286417874395, 109.17930846741757
5	Kebasen	-7.530963266717582, 109.20159819625306
6	Kemranjen	-7.592977031978278, 109.30726972324067
7	Sumpiuh	-7.612277969650419, 109.36492176741862
8	Tambak	-7.612265143879308, 109.40829027906337
9	Somagede	-7.5186389704498895, 109.3369437232398
10	Kalibagor	-7.47400886499621, 109.29720562323921
11	Banyumas	-7.514876622165727, 109.29373965207522
12	Patikraja	-7.487863269711498, 109.21436352139064
13	Purwojati	-7.493643197279994, 109.1217479790617
14	Ajibarang	-7.4075924603849135, 109.07845902693585
15	Gumelar	-7.37574115168661, 108.98088077906023
16	Pekuncen	-7.366960546982623, 109.07218783857994
17	Cilongok	-7.403108286425383, 109.13638953673167
18	Karanglewas	-7.417469711538135, 109.1842191078964
19	Kedungbanteng	-7.390394358794332, 109.20059459440267
20	Baturraden	-7.362349125418204, 109.23827494042867
21	Sumbang	-7.380081553352308, 109.27684555207361
22	Kembaran	-7.401543164426998, 109.28734515207388
23	Sokaraja	-7.457269106964582, 109.30014308091
24	Purwokerto Selatan	-7.44414080921876, 109.23835359440332
25	Purwokerto Barat	-7.420553490978125, 109.21175859440288
26	Purwokerto Timur	-7.4210137184294105, 109.25502357906085
27	Purwokerto Utara	-7.415922898099641, 109.24453652323841

Each sub-district is identified by its coordinates, which are used to calculate the geodesic distance between cities. This ensures that all spatial measurements represent the actual distance on the Earth's surface. The dataset spans both urban and rural areas from densely populated regions like Purwokerto Selatan to remote areas such as Lumbir and Ajibarang illustrating the geographic diversity of Banyumas Regency. Because of this variation, placing charging stations evenly across the region would not be effective. Instead, a customized strategy is required, one that adapts to the population density and spatial characteristics of each sub-district. Using accurate coordinates allows the results to be implemented directly in real-world planning.

A 10 km coverage radius was chosen to represent a realistic distance for EV users to travel to the nearest station. This distance provides a good balance between accessibility and infrastructure costs: it ensures convenience for drivers without requiring an excessive number of stations to be built. The optimization process uses the dominating set approach, where each city is represented as a vertex, and two cities are connected if they are within the 10 km coverage radius. The goal is to find the smallest set of cities that can cover all others either directly or through their connections. By checking every possible subset, the algorithm identifies the configuration that ensures complete coverage with the fewest stations. Using geodesic distance calculations helps maintain accuracy by accounting for the Earth's curvature.

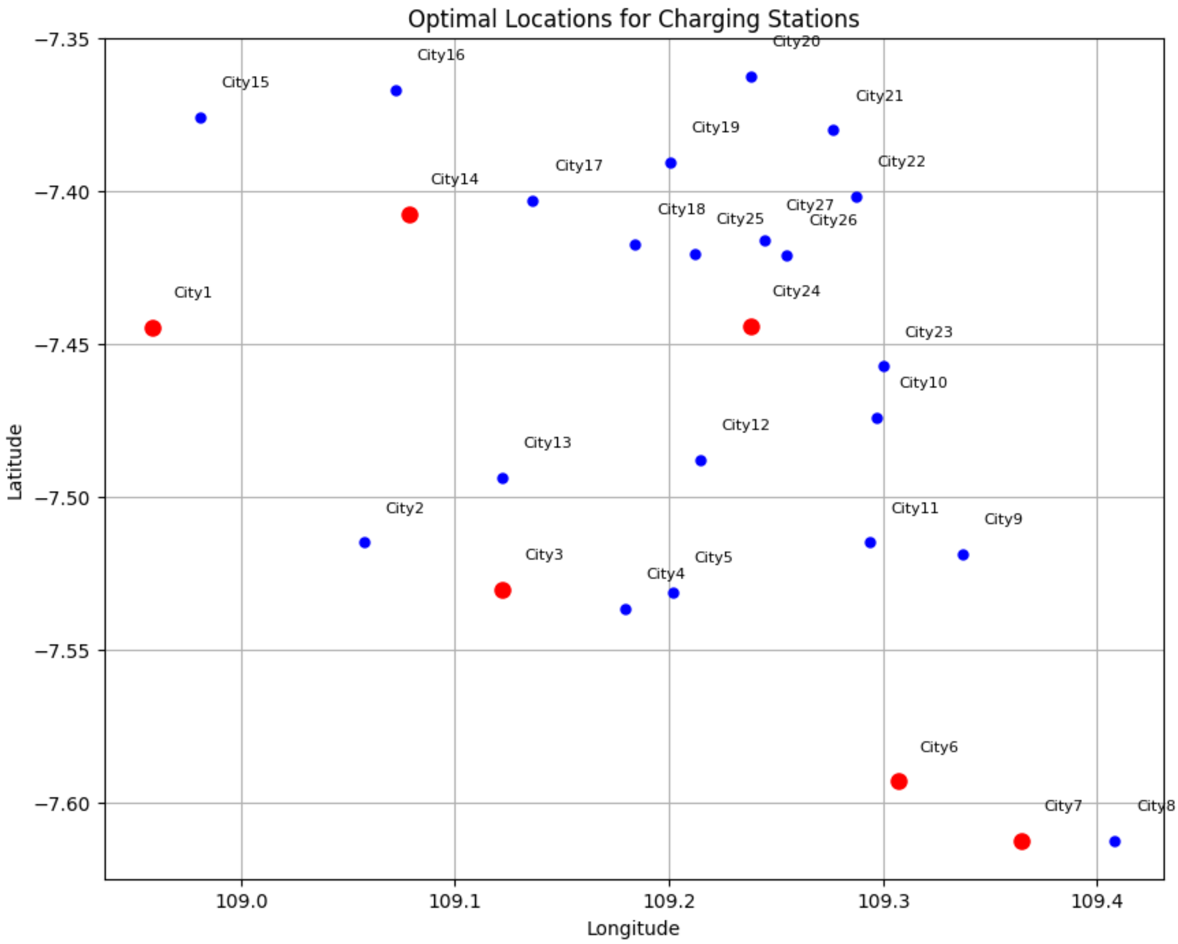


Figure 3. Optimal Locations of EV Charging Stations Using the Dominating Set Method

As shown in Figure 3, the map visualizes the spatial distribution of all 27 sub-districts in Banyumas Regency and highlights the optimal charging station locations identified using the dominating set method. Each point on the map represents a sub-district, plotted according to its geographic coordinates. The selected charging station locations are distinguished visually from the remaining sub-districts, allowing a clear comparison between covered and uncovered areas.

This figure was generated directly from the output of the Python-based implementation of the dominating set algorithm, where geodesic distances were computed and adjacency relationships were constructed programmatically. The visualization reflects the final solution produced by the algorithm rather than a conceptual illustration, thereby providing a direct link between the computational results and their spatial interpretation.

While Figure 3 provides a spatial overview of the optimal solution for a fixed coverage radius, further analysis is required to examine how changes in the coverage radius influence the number of selected locations and computational performance. To address this, Table 2 presents a quantitative comparison of the dominating set results under different coverage radius scenarios.

Table 2. Comparison of Optimal Locations with Different Coverage Radius Using Dominating Set

Trial	Coverage Radius (km)	Number of Selected Cities	Selected Cities	Computing Time
1	5	No result	[No result]	> 5h (process terminated)
2	7.5	8	[City1, City2, City4, City7, City10, City14, City15, City27]	23m
3	10	6	[City1, City3, City6, City7, City14, City24]	2m
4	15	3	[City1, City6, City18]	0s

At a 5 km radius, the algorithm could not produce a valid solution even after five hours of processing, indicating that the radius was too small to cover all cities effectively. Increasing the radius to 7.5 km allowed coverage with eight stations after 23 minutes of computation. When the radius was extended to 10 km, only six stations were required, and the computation time dropped sharply to two minutes. At a 15 km radius, the model needed only three stations, completing the process almost instantly. These results show that larger radii make coverage easier and faster, but at the expense of accessibility, especially for users in remote areas who might have to travel longer distances to charge.

To further evaluate the solution, the Ant Colony Optimization (ACO) algorithm was implemented, formulated as a Set Covering Problem (SCP). ACO mimics the behavior of ants searching for food and depends on parameters such as the number of ants, the number of iterations, and weighting factors (α, β, ρ, and Q). The algorithm was initialized with the following parameters: number of ants = 20, number of iterations = 100, $\alpha = 1$, $\beta = 2$, $\rho = 0.1$, and $Q = 1$. The coverage radius was set to 10. Different parameter combinations were tested to see how they affect the final result. The outcomes are summarized in Table 3.

Table 3. Comparison of Optimal Locations with Different ACO parameters Using The Set Covering Problem

Trial	Parameter (num_ants, num_iter, α, β, ρ, Q)	Number of Selected Cities	Selected Cities
1	(30, 50, 1, 3, 0.2, 1)	6	[City27, City13, City8, City11, City17, City1]
2	(50, 30, 1, 4, 0.3, 1)	6	[City27, City13, City6, City17, City15, City8]
3	(100, 20, 1, 5, 0.5, 1)	6	[City25, City3, City11, City1, City8, City14]

Across all three trials, the algorithm consistently produced six selected cities, even though the exact locations varied slightly. This indicates that the solution is robust to changes in parameter settings and that six stations form a stable optimum for the Banyumas case. Figure 4 shows the spatial distribution of all sub-districts and the optimal EV charging station locations selected by the ACO-based set covering model. Blue points represent all candidate cities, while red star markers indicate the selected charging station locations. This figure was generated from the final output of the Python-based ACO implementation using the selected parameter configuration. The visualization confirms that the configuration with 100 ants, 20 iterations, $\alpha = 1$, $\beta = 5$, $\rho = 0.5$, and $Q = 1$ produces a well-balanced solution, achieving full regional coverage with six strategically distributed stations. This result demonstrates stable convergence and supports the effectiveness of the chosen ACO parameters.

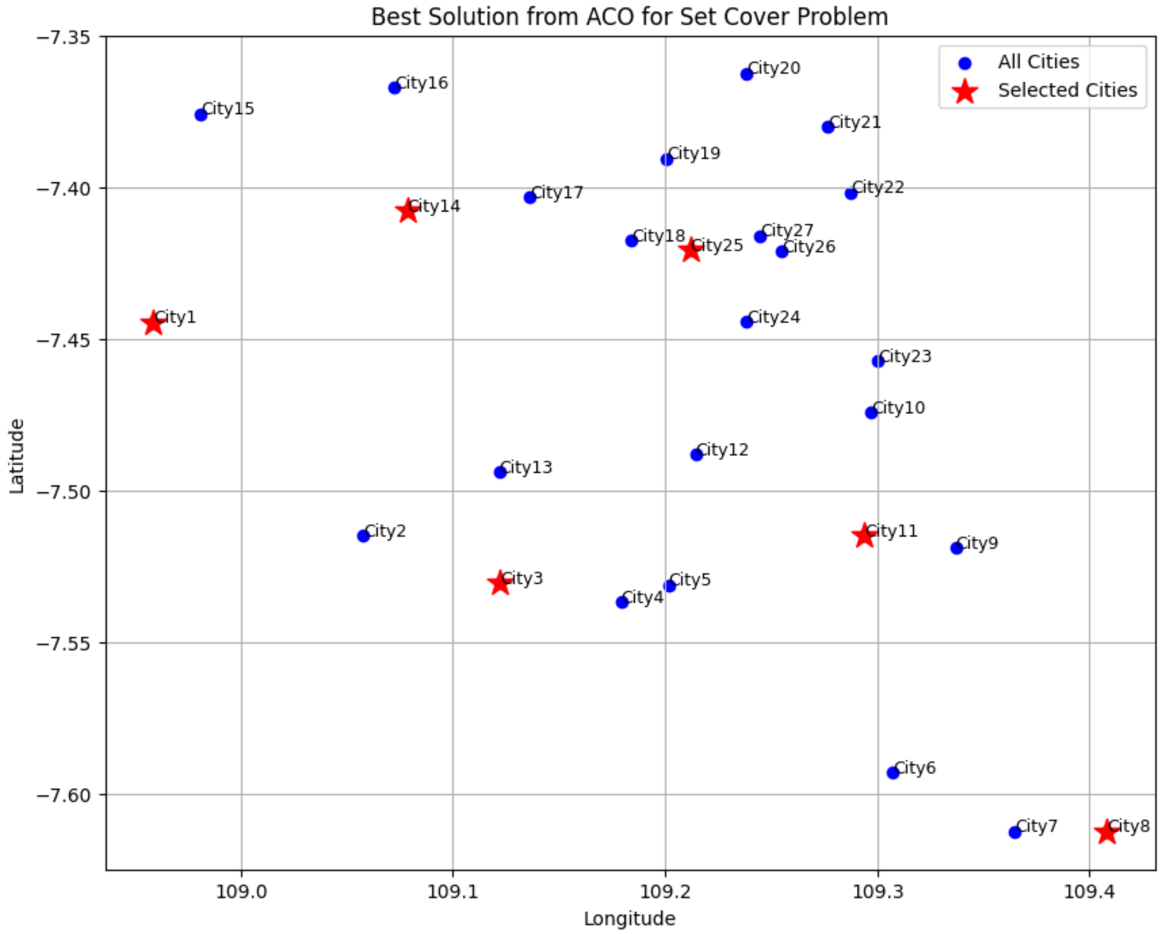


Figure 4. Best Solution from ACO Using the Set Cover Problem

To better understand how algorithmic settings interact with spatial constraints, the selected ACO parameters were tested with varying coverage radii. The combined results are displayed in Table 4.

Table 4. Comparison of Optimal Locations with Different ACO parameters and Different Coverage Radius Using The Set Covering Problem

Trial	Parameter (num_ants, num_iter, α, β, ρ, Q)	Coverage Radius (km)	Number of Selected Cities	Selected Cities
1	(100, 20, 1, 5, 0.5, 1)	5	13	[City25, City14, City21, City8, City11, City13, City5, City2, City, City10, City15, City1, City17]
2	(100, 20, 1, 5, 0.5, 1)	7.5	8	[City27, City4, City11, City14, City7, City3, City15, City1]
3	(100, 20, 1, 5, 0.5, 1)	10	6	[City25, City3, City11, City1, City8, City14]
4	(100, 20, 1, 5, 0.5, 1)	15	3	[City12, City9, City14]

The results confirm the same pattern observed earlier: when the coverage radius increases, fewer stations are needed. Specifically, 13 stations were required for a 5 km radius, eight for 7.5 km, six for 10 km, and only three for 15 km. These findings demonstrate an inverse relationship between coverage radius and network density. However, while a larger radius reduces costs, it may limit equal access for users in peripheral areas.

Therefore, a 10 km radius with six charging stations represents the most balanced and practical configuration, combining cost efficiency with adequate accessibility.

The robustness of the proposed solution is evaluated through sensitivity analysis rather than statistical validation. Specifically, the number of selected charging stations is examined under varying coverage radii and ACO parameter configurations. As shown in Tables 2–4, the solution consistently converges to six charging stations for the 10 km coverage radius across both the dominating set and SCP–ACO approaches. This consistent outcome demonstrates that the identified configuration is stable within the defined spatial and algorithmic assumptions and is not dependent on a single parameter setting.

In terms of performance metrics, the selected configuration achieves 100% spatial coverage, as all sub-districts fall within the specified service radius of at least one charging station. The maximum and average travel distances are inherently bounded by the coverage radius, which represents a realistic accessibility constraint for EV users. These metrics are consistent with the theoretical objectives of dominating set and set covering formulations, which emphasize guaranteed coverage rather than demand-weighted distance minimization.

Due to the early stage of EV adoption in Banyumas Regency, validation using actual charging demand data remains limited. Currently, only two charging stations are operational, both located at the state-owned electricity company office. As a result, this study is positioned as a strategic planning and theoretical optimization analysis rather than an operational demand-based evaluation. This approach is consistent with prior graph-based and optimization-driven studies conducted in regions with low EV penetration, where spatial coverage serves as the primary planning criterion.

The consistent identification of six optimal charging locations across different methods and parameter settings provides internal robustness and serves as a form of comparative benchmarking within the study scope. From a practical perspective, reducing the number of charging stations from a one-per-sub-district strategy to six strategically located hubs offers substantial potential for cost savings in infrastructure deployment and long-term maintenance. For implementation, local governments and the state-owned electricity company can apply the proposed framework to support phased deployment, prioritizing the identified locations and expanding the network incrementally as EV adoption increases. Although emission reductions are not directly quantified, improved charging accessibility supports long-term EV uptake and aligns with broader sustainability and transportation decarbonization policies.

4. CONCLUSION

This study presents a practical integration of graph domination theory, the set covering problem, and Ant Colony Optimization (ACO) to identify optimal locations for EV charging stations using real geospatial data from Banyumas Regency, Indonesia. Unlike prior domination-based studies that are largely theoretical, this research demonstrates the applicability of graph-based optimization for real-world infrastructure planning, thereby bridging mathematical theory and sustainable urban development.

The results show that six strategically located charging stations are sufficient to achieve 100% spatial coverage of all 27 sub-districts within a 10 km service radius. Compared to a baseline scenario of deploying one station per sub-district, this configuration reduces infrastructure requirements by approximately 78%, indicating substantial potential savings in installation, grid connection, and maintenance costs while maintaining equitable accessibility.

From a policy and implementation perspective, the identified locations provide a clear reference for phased deployment. Local governments and the state-owned electricity company can prioritize these high-impact hubs and expand the network incrementally as EV adoption increases. While previous empirical studies in Indonesia have mainly relied on demand-based heuristics or clustering approaches, this study contributes a coverage-guaranteed framework based on domination and set covering formulations.

Several limitations remain. The model assumes homogeneous demand and static conditions and does not account for population density, traffic flow, or power grid constraints. Future research should incorporate multi-criteria and dynamic models, as well as hybrid machine learning–metaheuristic approaches, to enhance scalability and practical applicability across broader regions.

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