

An Ant Colony Optimization Framework for Rural Road Network Planning to Maximize Accessibility in Facility-Based Rural Road Infrastructure

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Abstract:

Infrastructure connectivity is essential for socio-economic development and quality of life in rural areas. However, inadequate road infrastructure often limits access to healthcare, education, markets, and other essential services. Effective rural road network planning is therefore crucial for improving accessibility and network efficiency. This study presents a novel optimization framework for rural road network design by integrating a gravity-based demand model, Ant Colony Optimization (ACO), and the Minimum Spanning Tree (MST) approach. Village importance is quantified using a composite score based on population and available facilities and incorporated into a gravity model to estimate inter-village demand. In the first stage, ACO identifies high-priority routes by maximizing the Value of Path (VOP), which balances accessibility benefits and path length. In the second stage, MST ensures complete network connectivity by linking remaining unconnected villages using the Value of Edge (VOE) metric. Overall network performance is evaluated using the Value of Network (VON), which integrates accessibility and network efficiency. The proposed framework is validated using a case study of 75 villages in the Kashipur block, India. Results demonstrate a 25.46% reduction in total network length, a 17.78% decrease in the number of links, and a 16.78% improvement in VON, along with a 21.62% increase in average score per link, indicating improved network efficiency and accessibility. The proposed model provides a practical decision-support tool for planners and policymakers to develop length-efficient and accessibility-oriented rural road networks while supporting the social and economic dimensions of sustainable rural infrastructure planning.

1. Introduction

Rural areas are typically characterized as regions situated outside urban centers, where the majority of residents rely primarily on agriculture for their livelihood. In terms of living conditions, rural areas accommodate a substantial population. While many people from these regions have chosen to pursue urban jobs and lifestyles during the process of urbanization, nearly half of the population continues to reside in rural areas throughout the year.

This highlights the necessity to provide essential living conditions and fundamental public services, such as housing, transportation, and environmental considerations, for rural inhabitants [1].

The improvement of rural road networks is crucial for ensuring equitable access to critical resources like healthcare, education, and markets, especially in underserved and remote locations where infrastructure deficiencies severely obstruct socio-economic progress. A well-structured rural road system affects rural residents' daily lives, improves connectivity in rural areas, and makes it easier to access important facilities [2]. The development of the rural road network must be carefully approached to maximize user accessibility, facilitate the efficient

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transportation of goods, and link important facilities while minimizing both construction and maintenance costs [3,4]. In India, it has been demonstrated that rural connectivity plays a crucial role in determining household income, consumption patterns, and poverty alleviation [5-7]. Acknowledging this fact, programs like the Pradhan Mantri Gram Sadak Yojana (PMGSY) initiated by the Ministry of Rural Development [8], along with strategic planning guidelines created in partnership with global organizations such as the World Bank [9], highlight the importance of methodical rural road planning. These guidelines advocate for the identification of a "core network" that ensures every habitation has at least one all-weather road connection. However, financial resources are often inadequate to fulfill all connectivity demands, necessitating that policymakers and planners make investment choices based on priorities. Historically, this prioritization has relied heavily on economic cost-benefit analysis, assessing productivity through metrics like the net welfare gains resulting from lower transportation costs, increased job opportunities, and improved trade [10].

Even with these strategies, the issue persists in creating rural road networks that are both effective and fair, ensuring a balance between budget limitations and the highest social and economic benefits. This requires the implementation of sophisticated optimization models and algorithms that can tackle the complexities involved in rural road planning within a context of limited resources. Accordingly, the present study focuses primarily on improving accessibility and socio-economic connectivity through efficient rural road network planning, thereby contributing to the social and economic dimensions of sustainable rural development.

2. Literature Review

Rural road network planning has been a major area of research in transportation engineering due to its significant role in improving accessibility, regional development, and the delivery of essential services to rural communities. Various optimization techniques have been employed to design efficient road networks that balance connectivity, accessibility, and construction costs. Early studies primarily relied on classical optimization algorithms because of their mathematical simplicity, deterministic nature, and computational efficiency. Among these, the Minimum Spanning Tree (MST) algorithm has been extensively used to establish cost-effective road connections between villages and major transportation corridors while minimizing overall network length and infrastructure expenditure [11,12]. Applications of MST-based approaches have been reported in diverse geographical contexts, including rural regions of Nepal [13], mountainous and hilly terrains [14], and accessibility planning for welfare and public services [15].

These studies demonstrated the effectiveness of the MST in ensuring network connectivity with minimal investment, making it particularly suitable for resource-constrained rural development projects.

Another widely adopted approach is Dijkstra's Algorithm (DA), which has been utilized to identify optimal routes and improve accessibility within rural transportation systems. Researchers have employed DA to determine the importance of rural settlements using facility-based indices and accessibility measures [16]. The algorithm has also been used to develop need-based transportation networks that reflect the service requirements and travel preferences of local communities [17]. Similarly, Mixed Integer Linear Programming (MILP) models have been applied to rural road planning problems requiring the simultaneous consideration of multiple constraints such as connectivity, budget limitations, safety requirements, and developmental priorities. Studies conducted in countries such as India and Bangladesh have shown that MILP can effectively generate economical all-weather road networks while satisfying various planning objectives [18,19]. Although these classical approaches provide mathematically optimal solutions, their applicability often becomes limited when dealing with large-scale, highly complex, and multi-objective rural transportation problems.

To address these limitations, researchers have increasingly turned toward metaheuristic optimization techniques capable of exploring large and complex solution spaces. Genetic Algorithms (GA) have been widely used to optimize transportation infrastructure by enhancing network connectivity, accessibility, and operational performance [20]. Inspired by natural evolutionary processes, GA offers the flexibility to handle multiple conflicting objectives and nonlinear constraints, making it suitable for complex rural planning scenarios. Similarly, one of the most effective techniques for transportation network design is Ant Colony Optimization (ACO), which draws inspiration from ants' foraging habits. Several studies have integrated ACO with local search procedures and Scatter Search methodologies to generate efficient regional road networks under diverse geographical and operational conditions [21]. Furthermore, ACO-based frameworks have been proposed to support sustainable rural development by improving access to healthcare, educational institutions, and other essential services [22]. The ability of ACO to balance exploration and exploitation through pheromone-guided search enables it to identify high-quality network configurations in complex environments.

Other metaheuristic approaches have also demonstrated promising results in transportation planning applications. Simulated Annealing (SA) has been applied to optimize the spatial distribution of rural schools in China [23] and to develop demand-responsive transportation systems that

improve service accessibility in sparsely populated regions [24]. The probabilistic search mechanism of SA allows it to escape local optima and explore a broader solution space. Similarly, Tabu Search (TS) has been utilized to improve transportation networks by systematically examining alternative solutions while preventing repetitive exploration of inferior configurations [25]. Applications of TS include both rural and urban public transportation planning under various spatial and temporal constraints. More recently, Particle Swarm Optimization (PSO) and hybrid optimization frameworks have gained increasing attention due to their fast convergence characteristics and ability to combine the strengths of multiple algorithms. These methods have shown considerable potential in solving large-scale transportation planning problems characterized by dynamic conditions and multiple performance objectives.

In India, rural road development has been significantly influenced by the Pradhan Mantri Gram Sadak Yojana (PMGSY), launched in 2000 to provide all-weather road connectivity to previously unconnected rural habitations. The programme has substantially improved access to markets, healthcare facilities, educational institutions, and employment opportunities across rural areas. National guidelines increasingly emphasize the use of Geographic Information Systems (GIS), spatial databases, and evidence-based planning techniques to support route selection and prioritization [26,27]. However, planning practices at the district and project implementation levels often continue to rely on conventional methods and expert judgment. Such approaches may not adequately account for variations in population distribution, facility availability, accessibility requirements, and future transportation demand, potentially leading to suboptimal resource allocation and limited improvements in overall accessibility [28,29]. These challenges highlight the need for integrating advanced

optimization models and decision-support systems into rural road planning processes.

Despite substantial progress in rural road network optimization research, several important gaps remain. Most existing studies focus on a single objective, such as minimizing construction cost, reducing travel distance, or maximizing network coverage. Comparatively fewer studies have attempted to simultaneously address accessibility enhancement, socio-economic development, network efficiency, and sustainability within a unified framework. Furthermore, although metaheuristic algorithms have demonstrated strong performance in solving transportation planning problems, their application to rural road network design has largely concentrated on distance and cost optimization rather than accessibility-oriented development. The integration of village population characteristics, facility availability, and inter-village interaction demand into network optimization models remains relatively limited.

Another notable limitation is that many existing approaches emphasize network connectivity without adequately considering the broader benefits that transportation infrastructure provides to rural communities. As a result, the generated networks may be structurally efficient but may not necessarily maximize accessibility to essential services or contribute effectively to regional development objectives. Additionally, limited research has explored the combined application of Ant Colony Optimization, Gravity Models, and graph-theoretic approaches such as the Minimum Spanning Tree for accessibility-driven rural road planning. To highlight these differences and position the proposed framework within the existing body of research, a comparison with existing approaches is presented in Table 1. This gap is particularly significant in the context of developing countries, where resource constraints necessitate infrastructure investments that maximize social and economic benefits.

Table 1. Comparison of the proposed framework with existing approaches

Method	Minimizes Distance/Cost	Uses Population & Facility Information	Models Inter-Village Demand	Accessibility-Oriented Optimization	Ensures Complete Connectivity	Two-Stage Optimization
MST	✓	×	×	×	✓	×
Dijkstra	✓	×	×	Limited	×	×
MILP	✓	✓	×	Limited	✓	×
GA	✓	✓	Configurable	Limited	Configurable	×
PSO	✓	✓	Configurable	Limited	Configurable	×
ACO	✓	✓	Configurable	Limited	×	×
Proposed Framework	✓	✓	✓	✓	✓	✓

To address these limitations, the present study proposes an integrated framework that combines Ant Colony Optimization (ACO), the Gravity Model, and the Minimum Spanning Tree (MST) approach for rural road network planning. Unlike conventional methods that primarily focus

on cost minimization, the proposed framework incorporates village population, facility availability, and inter-village interaction demand to maximize accessibility and improve network effectiveness. By integrating these complementary methodologies, the study aims to develop a sustainable,

connected, and accessibility-oriented rural road network capable of supporting long-term regional development.

2.1 Novelty and Contribution of the Proposed Framework

Although previous studies have applied Ant Colony Optimization (ACO), Minimum Spanning Tree (MST), GIS-based analysis, and accessibility indices for rural road planning, these approaches generally optimize a single objective such as network length, construction cost, or connectivity. The proposed framework differs from existing methods in several important aspects. First, it integrates a gravity-based demand model with ACO to guide the optimization process using inter-village socio-economic interactions rather than relying solely on geometric distance or shortest paths. Second, the optimization simultaneously considers village population, facility availability, and spatial accessibility through the proposed Value of Path (VOP) metric, enabling the identification of road links that provide greater socio-economic benefits. Third, a two-stage optimization strategy is adopted in which ACO first identifies high-priority accessibility-oriented routes, while MST subsequently guarantees complete network connectivity for any remaining unconnected villages with minimum additional network length. Unlike conventional MST-based approaches that minimize distance alone, the proposed framework combines accessibility-driven optimization with graph-theoretic connectivity enhancement. Finally, the framework is implemented as an integrated GIS-based decision-support tool that enables planners to evaluate alternative rural road networks using spatial data and quantitative performance indicators. These contributions collectively provide a practical methodology for accessibility-oriented rural road planning under limited infrastructure resources.

3. Problem Statement and Objectives

3.1 Problem Definition

Rural areas in developing countries often suffer from inadequate road infrastructure, which restricts access to essential services such as healthcare, education, and markets. Despite the implementation of rural connectivity programs such as Pradhan Mantri Gram Sadak Yojana (PMGSY) in India, significant challenges persist in terms of planning, prioritization, and sustainability. Existing methodologies are often fragmented, fail to integrate socio-economic and spatial data, and overlook multidimensional factors such as demand, accessibility, cost-effectiveness, and resilience.

To overcome the limitations of conventional rural road network design, this study proposes a hierarchical two-stage optimization framework that integrates socio-economic and infrastructural factors into the rural road planning process. The framework begins by calculating inter-village demand,

which is derived from each village's population and the availability of essential facilities. This approach ensures that the planning process systematically prioritizes areas with higher needs and greater potential impact. Building upon this approach, the Ant Colony Optimization (ACO) algorithm is employed to identify optimal route configurations that enhance overall network efficiency while reflecting actual inter-village interactions. The optimization process is guided by the Value of Path (VOP) metric, which quantitatively evaluates each route in terms of connectivity, accessibility, and efficiency. To guarantee full network integration, especially in cases where certain villages remain isolated, the Minimum Spanning Tree (MST) algorithm is incorporated to establish connectivity across all nodes. Through this integrated methodology, the framework effectively balances construction cost with socio-economic benefits, resulting in an equitable, adaptive, and scalable solution for sustainable rural infrastructure development.

3.2 Research Objectives

The main objective of this research is to develop an optimization framework that maximizes accessibility and socio-economic benefits while minimizing travel distance and construction costs. Specifically, the study seeks to:

1. To estimate the inter-village demand by considering population and facility-based attractiveness, allowing the identification of potential high-demand linkages. To ensure that road network planning focuses on routes that offer the greatest socio-economic benefits and improve accessibility across rural areas.
2. To generate optimized road connections using the Ant Colony Optimization (ACO) algorithm by simulating probabilistic path exploration inspired by the adaptive behavior of ants, and to evaluate the effectiveness of the identified routes using the proposed Value of Path (VOP) metric, which quantifies network performance in terms of accessibility, efficiency, and socio-economic benefits.
3. To ensure complete and efficient network connectivity by applying the Minimum Spanning Tree (MST) approach to systematically integrate all habitations, including remote and low-demand villages, and to evaluate the effectiveness of the added links using the Value of Edge (VOE) metric, thereby enhancing inclusive accessibility, reducing geographic isolation, and promoting balanced regional development.

The proposed framework employs a hierarchical two-stage optimization strategy. In the first stage, the ACO algorithm searches the feasible road network to identify accessibility-oriented routes that maximize the Value of Path (VOP). In the second stage, the MST algorithm connects the remaining unconnected villages by selecting feasible links that maximize the Value of Edge (VOE) while minimizing additional construction length. The overall performance of the optimized rural road network is evaluated using the Value of Network (VON).

The proposed framework therefore combines accessibility-oriented optimization through ACO with connectivity enhancement through MST. Rather than optimizing a single objective function, the framework sequentially optimizes VOP and VOE, while VON serves as the final performance

indicator for evaluating the effectiveness of the optimized rural road network.

3.3 Mathematical Formulation of the Optimization Model

The proposed rural road network planning problem is formulated on an undirected graph $G=(V,E)$, where $V=\{1,2,\dots,n\}$ denotes the set of villages (nodes), and E represents the set of feasible road links (edges) obtained from the GIS database. The proposed framework employs a hierarchical two-stage optimization strategy, in which accessibility-oriented routes are first optimized using ACO, followed by connectivity optimization using MST to produce the final rural road network.

3.3.1 Decision Variables

The binary decision variable is defined as

$$x_{ij} = \begin{cases} 1, & \text{if the link } (i,j) \text{ is included in optimized network,} \\ 0, & \text{otherwise} \end{cases} \quad (1)$$

where x_{ij} represents the selection of the road segment connecting villages i and j .

3.3.2 Stage I: Accessibility-Oriented Optimization

In the first stage, the Ant Colony Optimization (ACO) algorithm searches the feasible road network to identify road links that maximize the Value of Path (VOP). The optimization objective is

$$\max VOP \quad (2)$$

Where VOP represents the accessibility and socio-economic importance of the selected routes based on village population, facility scores, and inter-village demand. The ACO algorithm probabilistically explores feasible routes and reinforces high-quality solutions through pheromone updating until convergence.

3.3.3 Stage II: Connectivity Optimization

Although the first stage identifies high-value accessibility-oriented routes, some villages may remain disconnected. Therefore, in the second stage, the Minimum Spanning Tree (MST) algorithm is applied to connect the remaining villages while minimizing the additional network length. The Value of Edge (VOE) is used to represent the socio-economic contribution of each feasible additional link relative to its length. Since the conventional MST minimizes edge weights, VOE is transformed into a minimization weight as:

$$w_{ij} = \left(\frac{1}{VOE_{ij}} \right) \quad (3)$$

where w_{ij} is the transformed weight of feasible edge $i-j$. Thus, maximizing VOE is implemented equivalently by minimizing w_{ij} . Higher VOE links receive lower transformed weights and are therefore preferentially selected by the MST, subject to the connectivity and acyclicity requirements.

3.3.4 Constraints

The optimization is subject to the following constraints.

Feasible Edge Constraint

Only feasible road links extracted from the GIS database are considered during optimization.

$$x_{ij} = 0, \quad \forall (i,j) \notin E \quad (4)$$

Connectivity Constraint

The ACO stage does not explicitly enforce global network connectivity. The constraint therefore ensures that selected links are associated with the considered villages, while complete connectivity of the final network is enforced algorithmically in Stage II using the Minimum Spanning Tree (MST). The MST stage connects all villages remaining unconnected after the ACO stage by adding the minimum necessary feasible links.

$$\sum_{j:(i,j) \in E} x_{ij} \geq 1, \quad \forall i \in V \quad (5)$$

Thus, Eq. (5) alone does not mathematically guarantee that all villages form a single connected component. Global connectivity is explicitly guaranteed by the Stage II MST procedure, which operates on the remaining feasible links after preserving the links selected by ACO.

Binary Constraint

The decision variables are binary.

$$x_{ij} \in \{0,1\} \quad (6)$$

3.3.5 Network Evaluation

After the completion of the two optimization stages, the overall performance of the optimized rural road network is evaluated using the Value of Network (VON). Unlike VOP and VOE, which assess individual optimization stages, VON provides a comprehensive network-level performance measure by integrating accessibility, socio-economic benefits, and network efficiency into a single evaluation metric.

$$VON = \left(\frac{\sum_{i,j \in N} (S_i + S_j) * (P_i + P_j)}{L_n} \right) \quad (7)$$

where:

S_i / S_j = facility-based scores of villages i and j ,

P_i / P_j = population of villages i and j ,

L_n = Total length of edges. ($i,j \in$ solution of proposed framework when path generated by ant k)

N = set of road links in the final optimized network.

The proposed optimization model follows a hierarchical two-stage strategy. In Stage I, the ACO algorithm optimizes accessibility by maximizing the Value of Path (VOP). In Stage II, the MST algorithm ensures complete network connectivity by minimizing the transformed edge weight w_{ij} , thereby preferentially selecting high-VOE links while adding the minimum necessary road links. The overall performance of the resulting rural road network is subsequently evaluated using the Value of Network (VON). The performance of the resulting rural road network is finally assessed using the Value of Network (VON), which integrates accessibility, socio-economic benefits, and network efficiency into a single evaluation metric.

4. Methodology

4.1 Ant Colony Optimization (ACO) Framework

A nature-inspired metaheuristic algorithm called Ant Colony Optimization (ACO) mimics how ants forage by depositing pheromones along their pathways to reward faster and more efficient routes [26]. This collective intelligence emerges through stigmergy, a mechanism of indirect communication in which agents modify the environment, and subsequent agents respond to those modifications, thereby guiding the system's evolution [30]. The original ACO algorithm, known as the Ant System, was first formalized by Dorigo in 1991 [31, 32]. Since then, several advanced variants have been proposed, such as the Ant Colony System, Rank-Based Ant System, and Max-Min Ant System, which enhance convergence speed, robustness, and solution quality [33-36]. Furthermore, ACO has been extended to dynamic optimization settings, such as the Dynamic Traveling Salesman Problem, where node positions or edge costs change over time [37-39].

ACO has been extensively applied in routing, transportation, and network design problems due to its inherent adaptability and ability to efficiently explore large solution spaces under complex constraints [40-41]. Compared to classical optimization techniques, ACO provides a balance between exploration (searching new paths) and exploitation (reinforcing promising routes), making it particularly suitable for spatial problems involving multiple villages and dynamic demand. In the context of this study, ACO is employed to optimize rural road connectivity by simulating probabilistic path exploration based on inter-village demand, population-based attraction, and spatial accessibility. This approach enables the generation of high-value paths that not only minimize construction length but also maximize socio-economic benefits, aligning with the proposed evaluation metric of Value of Path (VOP) and Value of Edge (VOE). The pseudocode of the entire methodology is shown in Fig. 1, and the flowchart is shown in Fig. 2.

Input: Village data (facilities, population, distance matrix)
Output: Optimized rural road network

BEGIN

Step 1: Preprocessing

Compute_Village_Scores()
 Compute_Inter-Village_Demand()

Step 2: Accessibility-Oriented Path Identification Using ACO (Stage I)

Initialize pheromone values on feasible edges
 Initialize ACO parameters: number of ants, α , β , ρ , maximum iterations, and starting village

```

FOR iter = 1 TO Max_Iterations DO

  FOR each Ant DO
    Construct Path using transition probability
    until all feasible villages are exhausted
    Evaluate VOP(Path)
  END FOR

  Best_Path = Path with Max VOP
  Update_Pheromone(top k ant paths)

  IF all ants follow the same path THEN
    BREAK
  END IF

END FOR

Step 3: Ensuring All-Village Connectivity Using MST (Stage II)

Preserve ACO-selected links as fixed connections
Identify remaining unconnected villages
Identify feasible edges not selected by ACO
Calculate VOE for remaining feasible edges

Calculate MST weight:  $w_{ij} = 1 / VOE_{ij}$ 
MST_Result = Apply_MST(Remaining_Edges,  $w_{ij}$ )
Final_Network = Merge(Best_Path, MST_Result)

Output Final_Network
END

```

Fig. 1. Pseudocode of the proposed ACO-MST framework for rural road network optimization.

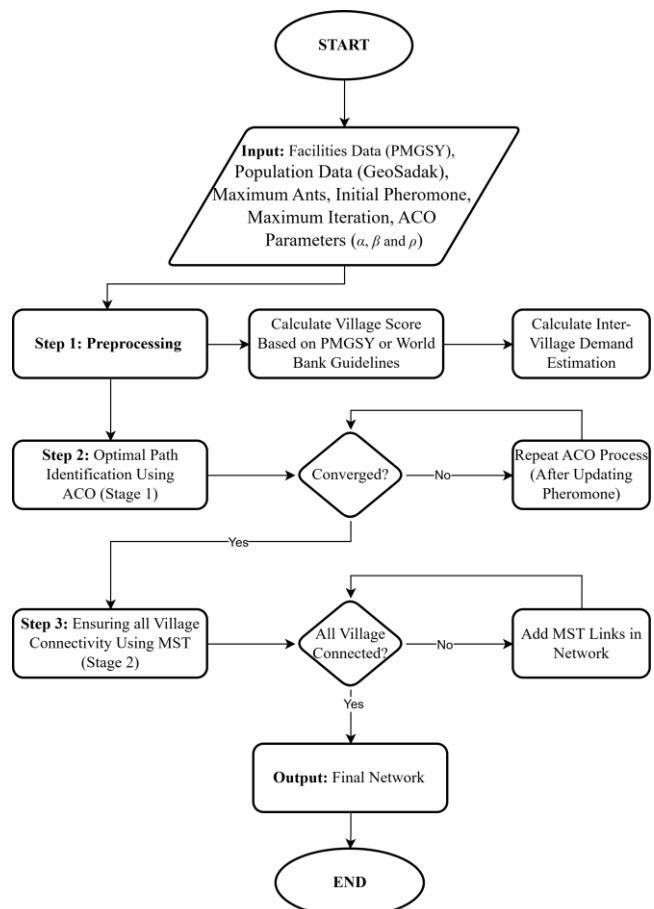


Fig. 2. Flowchart of the proposed ACO-MST framework for rural road network optimization.

The proposed framework adopts a sequential two-stage optimization strategy rather than a single integrated optimization. Stage 1 employs ACO to maximize accessibility by identifying high-value rural road paths using the Value of Path (VOP), while Stage 2 applies the Minimum Spanning Tree (MST) to connect only those villages that remain unconnected after the ACO stage. This decomposition allows each algorithm to address a distinct objective: ACO efficiently explores accessibility-oriented routes, whereas MST guarantees complete network connectivity with the minimum additional network length. During the MST stage, the links selected by the ACO algorithm are preserved as fixed connections, and MST adds only the minimum additional feasible links required to connect the remaining unconnected villages, thereby avoiding redundant edge selection. Compared with a single integrated optimization, the proposed approach reduces computational complexity and allows each optimization stage to exploit the strengths of the respective algorithm.

4.2 Village Score and Demand Estimation

The village score measures the overall availability and quality of services in a settlement. It is computed in accordance with PMGSY [42] and World Bank guidelines [43], with weights assigned to service categories such as education, health, markets, and administrative services. The cumulative facility score reflects a village's relative attractiveness and priority for road connectivity, and it is determined either by the highest-category score or by the cumulative sum of individual parameter scores, as shown in Table 2. Accordingly, the facility-based score (S) of a village is calculated as:

$$S = \sum_{c \in C_{max}} \min(\max_{1 \leq p \leq m_c} S_{c,p}, W_c) + \sum_{c \in C_{cum}} \sum_{p=1}^{m_c} \min(S_{c,p}, W_c) \quad (8)$$

Where:

- C_{max} = set of categories using the highest-category rule,
- C_{cum} = set of categories using the cumulative rule,
- $S_{c,p}$ = score of the p th sub-category in category c ,
- m_c = number of sub-categories in category c ,
- W_c = weight of category c ,

Table 2 Facilities and their proposed weightages as per PMGSY and World Bank Guidelines.

S. No.	Parameter	Category Weight/Score	Sub—category Weight/Score
1	Population (Census 2011) of the Habitation/village connected by the Through Route (score of the highest category)	30	
	5000 and above		30
	3000 to 4999		20
	1000 to 2999		10

	Less than 1000		05
2	Market facilities (cumulative score)	30	
	Mandi/GrAMs/Rurban Growth Cluster		15
	Warehouse / Cold Storage / Sugar Mills / Agro Industry		10
	Collection Centre or pack house		5
3	Educational facilities (score of the highest category)	15	
	High School		10
	Higher Secondary School / Girls High School / ITIs		12
	Degree College		15
4	Medical facilities (score of the highest category)	15	
	Primary Health Centre / Veterinary Hospital		10
	Bedded Hospital / Community Health Centre		15
5	Transport infrastructure (cumulative score)	10	
	Bus Stand		4
	Administrative Centre (Block, Panchayat Hqr)		4
	Bank/Fuel Station		2

The Gravity Model is widely used to quantify interaction or demand potential between spatial entities, drawing inspiration from Newton's law of gravitation, where the interaction force is proportional to the product of two masses and inversely proportional to the square of the distance [39]. In transportation and infrastructure planning, the model has been extensively applied to capture socio-economic linkages and spatial accessibility, particularly in the context of rural road development [44].

In this model, each village is represented as an entity with a "mass" reflecting its socio-economic importance, which is estimated as the product of its facility-based score and population. The attraction between two villages, i and j , is expressed mathematically as :

$$F_{ij} = \frac{(S_i * P_i) * (S_j * P_j)}{D_{ij}^2} \quad (9)$$

Where:

- S_i / S_j = facility-based scores of villages i and j ,
- P_i / P_j = population of villages i and j ,
- D_{ij} = distance of the feasible edge between villages i and j , expressed in kilometres.

A higher value of F_{ij} indicates stronger socio-economic interaction and thus greater connectivity demand between the two villages. These gravity-derived attraction values are subsequently incorporated into the Ant Colony Optimization (ACO) framework, serving as heuristic guidance for probabilistic path construction and enabling the design of demand-driven rural road networks.

In the proposed framework, population and facility information serve complementary roles in representing the

socio-economic importance and demand characteristics of rural settlements. The population component incorporated into the village score represents the demographic priority of a settlement according to the adopted planning criteria, whereas the actual population value represents the magnitude of the population potentially benefiting from improved connectivity. Actual population also contributes to the gravity-based interaction between villages, thereby representing potential inter-village demand. This formulation gives greater priority to highly populated settlements while retaining the influence of facility availability in determining their socio-economic importance.

4.3 Optimal Path Identification Using ACO (Stage 1)

Ant Colony Optimization (ACO) is a metaheuristic optimization framework inspired by the foraging behavior of ants, where collective intelligence emerges through pheromone-mediated communication [45]. In the context of rural road planning, ACO is employed to iteratively explore and refine path connections between villages, balancing exploration of new alternatives with exploitation of previously successful solutions [46].

Path Exploration:

At each construction step, the probability of ant k selecting a connection between village i and village j during iteration t is determined by:

$$P_{ij,k}(t) = \begin{cases} \frac{\tau_{ij}(t)^{\alpha} \eta_{ij}(t)^{\beta}}{\sum_{l \in J_{ik}} \tau_{il}(t)^{\alpha} \eta_{il}(t)^{\beta}}, & \text{if } j \in J_{ik} (\text{all possible edges}) \\ 0, & \text{if } j \notin J_{ik} \end{cases} \quad (10)$$

$$\eta_{ij}(t) = F_{ij} \quad (11)$$

where:

- $\tau_{ij}(t)$ = pheromone concentration on edge (i, j) at iteration t ,
- $\eta_{ij}(t)$ = heuristic visibility of edge (i, j) at iteration t ,
- α and β = parameters controlling the influence of pheromone trail intensity and heuristic desirability, respectively,
- J_{ik} = set of all possible edges for ant k when located at village i .

During path construction, each ant starts from an eligible village and selects the next feasible unvisited village according to the transition probability given by Eq. (10). The candidate set is updated after every selection to prevent immediate repetition of visited villages. Edges that would create a cycle are excluded from subsequent selection. The procedure continues until no further feasible unvisited village can be added to the current path. Paths with higher pheromone intensity and greater heuristic demand (gravity-based attraction) are more likely to be selected, thereby biasing the search towards socially and economically beneficial connections. If the path-construction process

terminates before all villages are reached, the resulting disconnected villages are retained as unconnected components for the subsequent connectivity stage. These villages are subsequently identified and connected through the Stage II MST procedure.

Conventional transportation network optimization methods primarily evaluate candidate routes using travel distance or construction cost. However, rural road planning also requires consideration of socio-economic importance, as villages differ in population and the availability of essential facilities. Therefore, the proposed framework uses the Value of Path (VOP) to evaluate candidate paths by jointly considering socio-economic importance, path length, and network coverage. This enables the ACO algorithm to prioritize routes that provide greater socio-economic service potential while maintaining efficient road connectivity.

Evaluation Metric:

The Value of Path (VOP) is introduced as the primary performance metric for evaluating the quality of candidate paths generated during the ACO optimization process. Unlike conventional shortest-path measures, VOP simultaneously considers socio-economic importance, accessibility, and travel efficiency. It quantifies the trade-off between maximizing access to essential services and minimizing travel distance, enabling the optimization process to identify routes that provide the greatest overall benefit to rural communities. A higher VOP indicates a path that delivers greater accessibility benefits at a relatively lower cost, making it more desirable in the optimization framework. It is computed by considering the cumulative service potential of the villages connected by the path, weighted by their accessibility and divided by the path length to penalize longer routes.

The VOP formulation ensures that the optimized road network prioritizes routes passing through villages with higher facility scores, thereby enhancing accessibility and equitable service distribution. Additionally, a coverage ratio R_c is incorporated into VOP to maximize the number of villages connected within the optimized path, ensuring wider spatial inclusivity. VOP is expressed as a relative index whose numerical magnitude depends on the adopted population, facility-scoring, and distance scales. Therefore, it is primarily used for comparative evaluation of candidate paths generated under the same study conditions. The VOP is expressed as:

$$VOP = \left[\left(\frac{\sum (S_i + S_j) * (P_i + P_j)}{L_p} \right) * R_c \right] \quad (12)$$

$$R_c = \frac{N_{ACO}}{N_T} \quad (13)$$

where:

R_c = Coverage Ratio

N_{ACO} = No. of villages connected through ACO by the k^{th} ant

N_T = Total no. of Villages

VOP = Value of Path, representing the socio-economic benefits (score and population) of villages connected by the selected roads ($i, j \in$ path generated by ant k),

L_p = Length of the path generated by ant k .

Pheromone Update:

Once all ants complete their tours, pheromone trails are updated by reinforcing shorter and more attractive paths while allowing weaker routes to evaporate. Pheromone reinforcement is restricted only to the edges of the ant paths, achieving the maximum Value of Path (VOP). The pheromone update rule is defined as:

$$\tau_{ij}(t+1) = (1 - \rho)\tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ijk}(t) \quad (14)$$

$$\Delta\tau_{ijk}(t) = \begin{cases} \frac{Q_k}{L_k(t)}, & \text{if } (i, j) \in T_k(t) \\ 0, & \text{if } (i, j) \notin T_k(t) \end{cases} \quad (15)$$

$$Q_k = 1 \quad (16)$$

Here, $\tau_{ij}(t+1)$ is the updated pheromone concentration on edge (i, j) , ρ is the pheromone evaporation rate, and $\Delta\tau_{ijk}(t)$ indicates the pheromone reinforcement contributed exclusively by the top k ants. The pheromone update incorporates the top k ants' best path solutions based on the VOP values at iteration t . For edges belonging to the top ant path and whose pheromone values have already been updated, any occurrence of these edges in the paths of subsequent ants will be excluded from further pheromone updates to prevent excessive deposition. $L_k(t)$ is the length of the k^{th} ant path, and $T_k(t)$ is its set of edges in the k^{th} ant path.

Convergence/ Optimum Path:

Through this mechanism, over successive iterations, pheromone trails are strengthened only for the most socio-economically optimal networks, while weaker solutions fade through pheromone evaporation. Convergence is considered to be achieved when the paths constructed by all ants become identical, indicating that the colony has converged to a stable best-found path. The algorithm terminates upon satisfying this condition or upon reaching the prescribed maximum number of iterations, whichever occurs first. At this point, the algorithm has identified a stable best-found solution under the selected parameter settings, and the corresponding path is retained as the best-found rural road path, balancing socio-economic service potential, network efficiency and connectivity.

Although the ACO stage effectively identifies accessibility-oriented routes with high socio-economic value, it does not explicitly enforce complete network connectivity. Consequently, some villages may remain unconnected after the optimization process. Rather than incorporating connectivity constraints directly into the ACO formulation, which would substantially increase the complexity of the optimization, the proposed framework applies the MST

algorithm as a second optimization stage. The MST is constructed only for the remaining unconnected villages using the feasible road links that were not selected during the ACO stage. As a result, redundant links are avoided, complete connectivity is guaranteed, and the accessibility-oriented network generated by ACO is preserved.

4.4 Ensuring Connectivity Using MST (Stage 2)

Following the accessibility-oriented optimization performed by the ACO algorithm, the Minimum Spanning Tree (MST) is applied to the villages that remain unconnected after Stage I. The links selected by ACO are preserved as fixed connections and excluded from the candidate edge set of the MST. The MST therefore considers only the remaining feasible links required to connect the unconnected villages to the ACO-generated network. This procedure ensures that all villages are incorporated into a single connected final network while preventing the repeated selection of ACO-selected links and unnecessary redundant connections.

In the proposed framework, the Value of Edge (VOE) represents the socio-economic value of a feasible road link relative to its length. Since the conventional MST algorithm minimizes edge weights [47], VOE is transformed into a minimization weight using:

$$w_{ij} = \left(\frac{1}{VOE_{ij}} \right) \quad (17)$$

Where w_{ij} is the transformed weight assigned to the feasible edge $i-j$. The reciprocal transformation converts the preference for higher VOE into a minimization criterion, such that edges with higher VOE values obtain lower MST weights and are preferentially selected. The MST then adds the minimum necessary feasible links to connect the remaining unconnected villages to the ACO-generated network.

Evaluation Metric:

Since the primary objective of the second optimization stage is to achieve complete network connectivity, a separate evaluation metric termed the Value of Edge (VOE) is introduced. VOE assesses the contribution of each additional road link by considering both its socio-economic importance and construction efficiency. Consequently, the MST algorithm minimizes the transformed edge weight w_{ij} , thereby preferentially selecting links with higher VOE while maintaining complete connectivity and avoiding cycles. The Value of Edge (VOE) is defined as:

$$VOE_{ij} = \left(\frac{(S_i + S_j) * (P_i + P_j)}{L_e} \right) \quad (18)$$

where:

VOE = Value of Edge,

L_e = Total length of edge “ ij ”. ($i, j \in$ solution of MST when path generated by ant k)

Unlike VOP, which evaluates complete accessibility-oriented paths during the ACO stage, VOE evaluates the relative socio-economic service potential of individual road

links considered during the connectivity stage. Higher VOE values indicate greater socio-economic benefit relative to the required edge length.

After completing the above steps, the final optimum network is obtained. Collectively, these stages result in an optimized rural road network that guarantees full connectivity while maintaining an appropriate balance between accessibility, operational efficiency and effective resource utilization.

4.5 Network Performance Evaluation Using Value of Network (VON)

After the optimized rural road network has been generated through the combined application of the ACO and MST algorithms, its overall performance is evaluated using the Value of Network (VON). VON represents the overall socio-economic service potential of the final network relative to its total network length and serves as a network-level performance indicator for comparing alternative network configurations. A higher VON indicates greater socio-economic service potential per unit network length. As a relative planning index, its numerical magnitude depends on the population, facility-scoring, and distance scales adopted in the study. Since the same villages, population data, facility-scoring system, and distance units are maintained for all alternative networks, VON provides a

consistent basis for comparative evaluation within the study area. The VON is calculated using Eq. (7).

Since VON is computed after the final network has been established, it is used solely as a network-level performance evaluation metric rather than as an optimization objective. It enables quantitative comparison of the existing, benchmark, and optimized networks based on their socio-economic service potential and network length.

5. Case Study: Design of Optimum Rural Road Network

5.1 Study Area

The Kashipur block in the Udham Singh Nagar district of the Indian state of Uttarakhand serves as the research's study area. The research requires data on village populations, available facilities, coordinates, and existing and possible road links. The study area connects 75 villages, serving a total population of 127,678. The data were primarily collected from the OMMS Portal [48] database, as shown in Fig. 3, linked to the government-initiated PMGSY (Pradhan Mantri Gram Sadak Yojana) program, and other layouts were downloaded from the PMGSY National GIS Website [49].

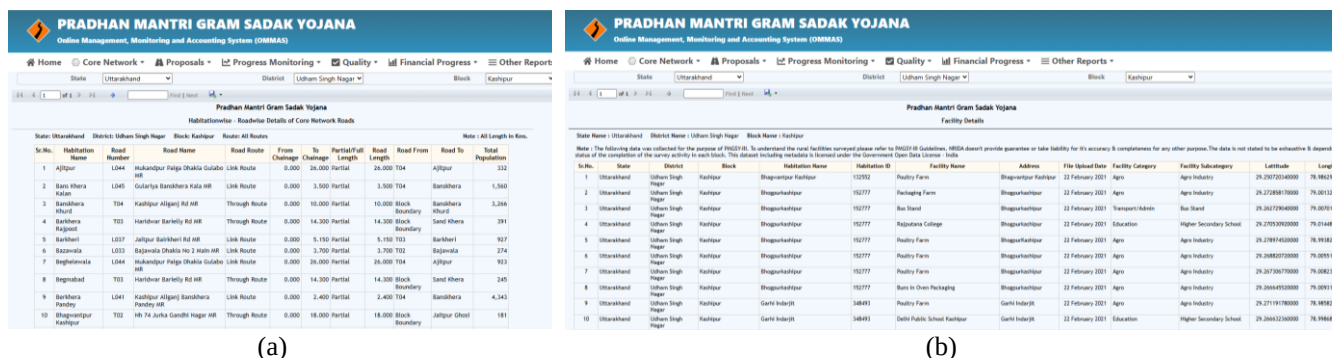


Fig. 3. OMMS Portal for efficient retrieval of population (a) and facility datasets (b).

5.2 Software Used

The implementation of the proposed methodology was carried out using Microsoft Visual Studio for algorithm development and QGIS for spatial visualization and analysis. The computations and mapping were performed on a personal computer, and the detailed system specifications are provided in Table 3.

Table 3 System Specifications

Component	Specification
Processor	Intel(R) Core (TM) i7-10700 CPU @ 2.90GHz
Installed RAM	16GB
System Type	64-bit operating system, x64-based processor
GPU	Intel (R) UHD Graphics 630

Microsoft Visual Studio

Microsoft Visual Studio is an integrated development environment (IDE) developed by Microsoft for designing, developing, debugging, and deploying software applications. It supports multiple programming languages, including C#, C++, Visual Basic, Python, HTML and JavaScript, and provides a comprehensive environment for desktop, web, mobile and cloud application development. In this study, Visual Studio was used to develop the proposed rural road network planning and decision-support application using the C# programming Language.

The model presented here was created using the C# programming language, which demonstrates the efficiency of ACO integrated with the gravity model and MST in the planning of rural road networks.

Quantum Geographic Information System (QGIS)

QGIS is an open-source Geographic Information System (GIS) software that provides advanced capabilities for spatial database management, geoprocessing, network analysis and geospatial visualization. In the proposed framework, QGIS was employed for preprocessing PMGSY GeoSadak datasets, extracting village and road network features, generating the road network graph and inter-village distance matrix, preparing the spatial database for the ACO-MST optimization model and visualizing the existing and optimized rural road networks.

5.3 Distance Matrix for Study Area

The OpenLayers plugin in QGIS was used to identify and map the villages within the study area. A point layer was created in QGIS, with each point representing the geographic location of a village. The required village and road-network information was compiled in the GIS environment. The distances of the feasible road edges considered in the study were obtained from the GeoSadak portal and expressed as ground distances. These distances were used to represent the available feasible road connections and for comparative analysis of the existing and optimized rural road networks. The existing rural road network was considered as the set of feasible road links for the optimization process. Thus, the optimized network was developed from realistic road-connectivity alternatives, enabling direct comparison with the existing network in terms of network length, connectivity and overall Performance.

5.4 Calculation of Village Score

After generating the distance matrix of the villages, the village scores were calculated for each village using the distances between villages, population data and the attribute tables obtained from PMGSY national GIS GRRIS. The village score is the summation of the sub-category weightage of all the facilities available inside the village boundary and it is calculated using Eq. (8). The category weightage and subcategory weightage are mentioned in Table 2 for the corresponding parameters. This study incorporated international guidelines of the World Bank for rural development [50], along with the PMGSY guidelines [43] for measuring village scores, by ensuring that the design met international standards of rural development.

5.5 Sensitivity Analysis of ACO Parameters

To evaluate the robustness of the proposed framework, a sensitivity analysis was performed by varying the principal ACO parameters while keeping all other parameters constant. Since ACO is a stochastic optimization algorithm, each parameter combination was independently executed 10 times using different random seeds while maintaining the same starting village and input dataset. The resulting solutions were evaluated using the same performance criteria. The mean and standard deviation across the 10 runs were calculated to assess variability and reproducibility, while the best-found solution among the 10 runs was used for parameter comparison and selection of the preferred parameter configuration. The analysis investigated the influence of pheromone importance (α), heuristic importance (β), pheromone evaporation rate (ρ), number of ants (m), and number of top-performing ants (k) on the optimized network. Network performance was evaluated using the Value of Path (VOP), total network length, convergence iterations, and execution time.

The values reported in Table 4 represent the best-found solution among the 10 independent runs for each parameter configuration. Accordingly, the reported convergence iterations, network length, VOP, and execution time correspond to the respective best-performing run.

The sensitivity analysis (Table 4 and Table 5) indicates that the proposed framework is robust to moderate variations in the ACO parameters. The base parameter combination ($\alpha = 1.0$, $\beta = 2.0$, and $\rho = 0.10$) produced the highest Value of Path (VOP = 83,297.08) while maintaining a network length of 159.22 km. Increasing the pheromone importance (α) from 1 to 2 reduced the VOP by 0.58%, whereas $\alpha = 3$ resulted in a substantial deterioration in solution quality. Similarly, $\beta = 2$ provided the best balance between exploration and heuristic guidance, while $\beta = 1$ and $\beta = 3$ yielded lower VOP values. Increasing the evaporation rate from $\rho = 0.10$ to 0.30 and 0.50 accelerated convergence but reduced solution quality because useful pheromone information dissipated more rapidly. Likewise, increasing the number of ants beyond 100 produced only marginal improvements while increasing computational time. Based on these findings, the parameter combination $m = 100$, $\alpha = 1.0$, $\beta = 2.0$, $\rho = 0.10$, and $k = 5$ was adopted for all subsequent experiments because it provided the best balance between solution quality, convergence stability and computational efficiency.

Table 4 Sensitivity analysis of ACO parameters (α , β and ρ) on the performance of the proposed framework

Case	α	β	ρ	Length (km)	VOP	Iterations	Execution Time (Sec)
Base	1	2	0.1	159.22	83297.08	182	37.81
S1	2	2	0.1	157.87	82813.26	93	18.02
S2	3	2	0.1	166.01	74721.64	57	9.28
S3	1	1	0.1	158.07	81480.92	123	21.03
S4	1	3	0.1	158.35	68787.64	158	23.47
S5	1	2	0.3	159.66	73417.77	42	6.90
S6	1	2	0.5	160.74	67851.77	25	3.85

Table 5 Selected ACO parameter values and observations from the sensitivity analysis

Parameter	Tested Values	Selected Value	Observation
Number of ants (m)	50, 100, 150, 200	100	Increasing the number of ants from 50 to 100 improved solution quality and convergence. Further increases to 150 and 200 resulted in only marginal improvements while significantly increasing computational time.
Pheromone importance (α)	1, 2, 3	1.0	Balanced exploration and exploitation, providing consistent solutions.
Heuristic importance (β)	1, 2, 3	2.0	Higher values overemphasized heuristic information, whereas $\beta = 2$ produced the best network quality.
Evaporation rate (ρ)	0.1, 0.3, 0.5	0.10	Moderate evaporation prevented premature convergence while preserving useful pheromone trails.
Top-performing ants (k)	3, 5, 10	5	Reinforcing the best five ants achieved stable convergence and improved solution quality.

The mean and standard deviation values presented in Table 6 represent the variability observed across the 10 independent runs for each tested parameter configuration. For the Base configuration, the mean convergence iteration was 184.40 ± 11.77 , whereas the best-found base-case run reported in Table 4 converged in 182 iterations. Similarly, the mean network length, VOP, VON and execution time represent the average behavior across the 10 runs and may therefore differ from the corresponding best-found solutions reported in Table 4.

The statistical summary obtained from the 10 independent runs provides additional evidence of the stability and reproducibility of the ACO-based optimization. The relatively low variability in network length across the tested configurations indicates consistent network construction, while the observed variation in VOP, convergence iterations, and execution time reflects the stochastic nature of the search process. The results indicate that the proposed framework provides stable and reproducible solutions under repeated executions, while retaining the exploratory characteristics of ACO.

Table 6 Statistical summary of 10 independent runs for the tested ACO parameter configurations

Case	Length (km)	VOP	VON	Iterations	Execution Time (s)
Base	159.51 ± 0.41	$80,609.11 \pm 4,090.19$	$158,610.55 \pm 1,904.21$	184.40 ± 11.77	37.61 ± 4.22
S1	159.49 ± 0.57	$74,357.33 \pm 2,971.11$	$157,573.50 \pm 2,011.21$	76.30 ± 6.15	13.00 ± 1.80
S2	160.30 ± 2.00	$73,548.17 \pm 412.32$	$157,419.07 \pm 2,499.56$	56.70 ± 2.11	9.32 ± 0.42
S3	159.55 ± 0.89	$75,189.95 \pm 2,699.79$	$154,658.91 \pm 3,842.66$	139.50 ± 39.35	23.85 ± 5.66
S4	158.69 ± 0.18	$62,231.12 \pm 3,455.59$	$156,318.22 \pm 74.38$	117.00 ± 18.94	14.73 ± 3.64
S5	159.00 ± 0.60	$68,181.00 \pm 5,613.27$	$157,042.98 \pm 1,006.56$	42.70 ± 6.70	6.98 ± 0.57
S6	158.84 ± 0.70	$63,776.66 \pm 4,120.26$	$156,782.14 \pm 1,543.66$	26.80 ± 4.13	4.72 ± 1.12

5.6 Finding the Optimum Network

The proposed optimization framework was developed to generate an optimal rural road network that maximizes accessibility and socio-economic benefits while ensuring complete connectivity with minimum additional road length. The framework integrates Ant Colony Optimization (ACO), a demand-based interaction model, and the Minimum

Spanning Tree (MST) algorithm within a C# implementation to identify the optimal road links. The algorithm was executed using a set of parameters and their corresponding values, as listed in Table 7. For the final network presented in this study, the selected parameter configuration was executed independently, and the reported run converged after 211 iterations, requiring a total execution time of 41.69 s.

Table 7 Input/Output values of parameters of the Rural Road Network Planning Algorithm.

Input Parameters	Value	Output Parameters	Value
Number of Ants (m)	100	Iteration Taken	211
Initial Pheromone	0.5	Execution Time	41.69 sec
Pheromone evaporation (ρ)	0.1		
Maximum Iteration	1000		
α (Pheromone trail intensity parameters)	1		
β (Heuristic desirability parameters)	2		
Top k Ants	5		

The performance of the proposed framework was subsequently evaluated against the existing rural road network and the standalone ACO and MST approaches to assess its effectiveness in terms of connectivity, network length, and Value of Network (VON).

6. Results and Discussion

6.1 Convergence Behavior of the ACO Algorithm

The convergence behavior of the proposed Ant Colony Optimization (ACO) algorithm is presented in Fig. 4(a) and Fig. 6(b), which show the variation of the Value of Path (VOP) and the total network length over successive iterations, respectively.

As shown in Fig. 4(a), the VOP increased from 56,694 in the initial iterations to a final value of 83,297. The improvement occurred in a stepwise manner, indicating that the ants progressively discovered better network configurations during the search process. Significant gains were observed during the early and intermediate iterations, where the VOP increased from approximately 61,457 to 65,515, then to 74,702, and finally reached 83,297. After the 123rd iteration, no further improvement in VOP was observed; however, the algorithm continued until the 211th iteration, when all ants followed the same path, satisfying the defined convergence

criterion. Thus, the VOP remained stable between iterations 123 and 211, and the solution at iteration 211 was considered the stable best-found solution under the selected parameter settings. The increasing trend of VOP demonstrates the ability of the pheromone updating mechanism to guide the search towards network configurations with higher socio-economic benefits and improved accessibility.

The variation of the total network length during the optimization process is presented in Fig. 4(b). Initially, the network length fluctuated around 160.2 km and temporarily increased to approximately 166.6 km during the intermediate iterations. This behavior indicates that the algorithm explored alternative network structures that offered higher accessibility benefits despite requiring slightly longer road connections. As the search progressed, the network length decreased to 159.22 km. Although the network length stabilized at approximately the 123rd iteration, the algorithm continued until the 211th iteration to satisfy the convergence criterion based on the paths followed by all ants. This behavior demonstrates that stabilization of the objective value occurred before complete colony convergence.

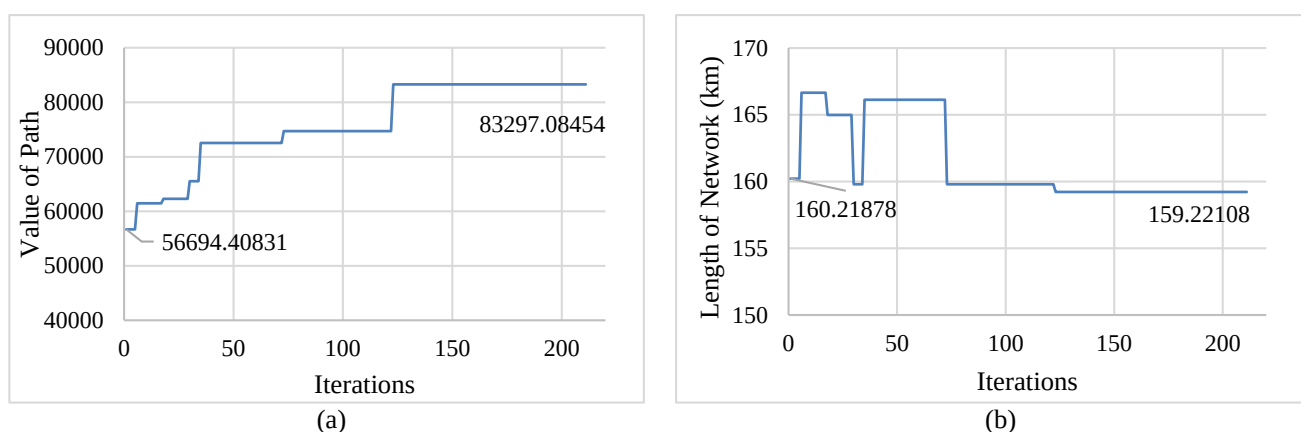


Fig. 4. Convergence behavior of the proposed ACO algorithm: (a) Value of Path (VOP) vs Iterations; (b) Network length vs Iterations.

The simultaneous increase in VOP and reduction in network length demonstrate the effectiveness of the proposed optimization framework in achieving multiple planning objectives. While maximizing the socio-economic value of the network, the algorithm was also able to minimize the overall road length, leading to a more efficient and length-efficient rural transportation network. The convergence of both performance indicators at nearly the same iteration further confirms the robustness and stability of the proposed ACO-based rural road network planning methodology.

6.2 Comparative Analysis of Existing and Optimized Networks

The existing network connects 75 villages through 90 links, serving a total population of 127,678. However, the

optimized network connects the same 75 villages using only 74 links, with a total length of 159.22 km, as shown in Fig. 5. It demonstrates a significant improvement, with the total length reduced by 25.46% from 213.60 km to 159.22 km. This reduction indicates a more efficient road network design and the potential for lower length-related construction, maintenance and future upgradation costs. However, actual project costs also depend on factors such as terrain conditions, pavement type, drainage structures, land acquisition and regional construction costs, which were not explicitly considered in the present study. It should be noted that the reduction in the number of links from 90 to 74 does not imply the removal or decommissioning of existing rural roads. In the proposed framework, the existing road network

is used only as the set of feasible links available for optimization. The optimized network represents a planning-oriented network that identifies the most efficient combination of feasible road links to maximize accessibility and socio-economic benefits while minimizing the overall network length. Therefore, the optimized network should be interpreted as a decision-support tool for future rural road planning and investment prioritization rather than a recommendation to remove or reduce the maintenance of existing roads. Furthermore, the Value of Network increased

by 16.78%, reflecting an improvement in the network's ability to connect more villages and facilities effectively, thus enhancing accessibility and service delivery across the region. The 21.62% increase in the Average Score per Link further highlights that the optimized network not only minimizes cost but also maximizes social and functional benefits, ensuring a balanced approach between economic efficiency and community welfare in rural transportation planning. Comparison and improvement between the existing and optimal networks are illustrated in Table 8.

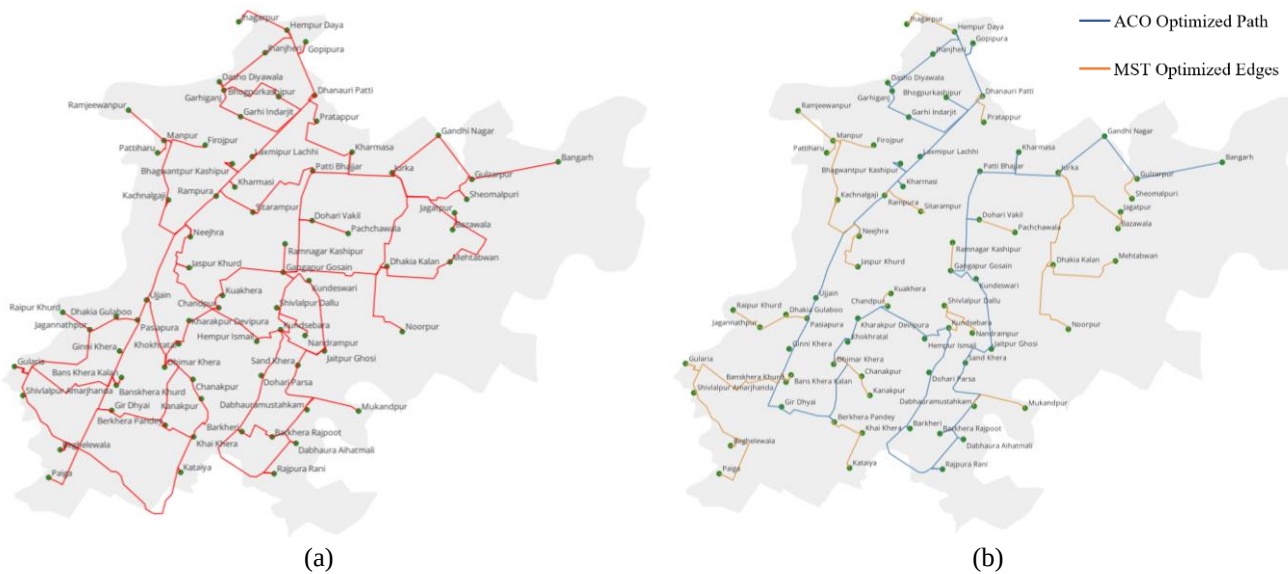


Fig. 5: (a) Existing Rural Road Network. (b) Optimized Rural Road Network generated by the proposed ACO-MST framework.

Table 8 Result of the Rural Road Network Planning Algorithm.

Parameter	Pre-existing Network	Optimized Network	Improvement (%)
Population Connected	127678	127678	-
Village Connected	75	75	-
Number of Links	90	74	17.78%
Average Score per Link	27.27	33.16	21.62%
Length of Network (km)	213.60	159.22	25.46%
Value of Network	134967.91	157618.71	16.78%

The comparative evaluation of the rural road network using the Value of Path (VOP) and Value of Edge (VOE) indicators clearly demonstrates the effectiveness of the proposed optimization framework. As presented in the results, the optimized network achieved a higher VOP,

reflecting a greater cumulative socio-economic benefit across connected villages, while VOE values ensured that even unconnected yet valuable villages were incorporated into the planning process. These improvements indicate a more efficient and equitable network design, minimizing unnecessary path lengths while maximizing overall connectivity. In addition to these indicators, the combined analysis of VOP and VOE confirms the robustness of the optimization, ensuring that the final rural road network maintains strong connectivity, cost-effectiveness, and sustainable service provision across all villages. The comparison of the existing rural road network, proposed framework, standalone MST and ACO approaches are shown in Table 9.

Table 9 Comparison of the existing rural road network, proposed framework, standalone MST and ACO approaches.

Method	Total Road Length (km)	Villages Connected	VON	Remarks
Existing Network	213.60	75	134,967.91	Existing rural road network
MST	148.73	75	146,337.31	Ensures complete connectivity with minimum network length
ACO	90.43	42	150,341.10	Maximizes accessibility but does not ensure complete connectivity
Proposed ACO-MST Framework	159.22	75	157,618.71	Balances accessibility and complete network connectivity

Table 9 compares the proposed framework with the existing rural road network and the standalone MST and ACO approaches. The standalone MST produces the shortest fully connected network (148.73 km) but yields a lower VON than the proposed framework because it primarily focuses on connectivity. In contrast, the standalone ACO achieves a higher VON (150,341.10) with the shortest network length (90.43 km); however, it connects only 42 out of 75 villages, leaving a significant number of habitations unconnected. The proposed ACO-MST framework combines the complementary strengths of both algorithms by first identifying accessibility-oriented routes using ACO and subsequently connecting only the remaining unconnected villages using MST. This sequential optimization strategy enables the ACO stage to maximize socio-economic

accessibility without imposing explicit connectivity constraints, while the MST stage guarantees complete network connectivity using the minimum additional feasible links. Consequently, the proposed framework achieves complete connectivity for all 75 villages while attaining the highest VON (157,618.71), demonstrating a superior balance between accessibility, socio-economic benefits, and network efficiency. Because the MST is applied only to the remaining unconnected villages and excludes links already selected during the ACO stage, unnecessary redundancy is avoided while preserving the accessibility-oriented routes identified during the first stage. The benchmark networks generated using the standalone ACO and MST approaches are shown in Fig. 6.

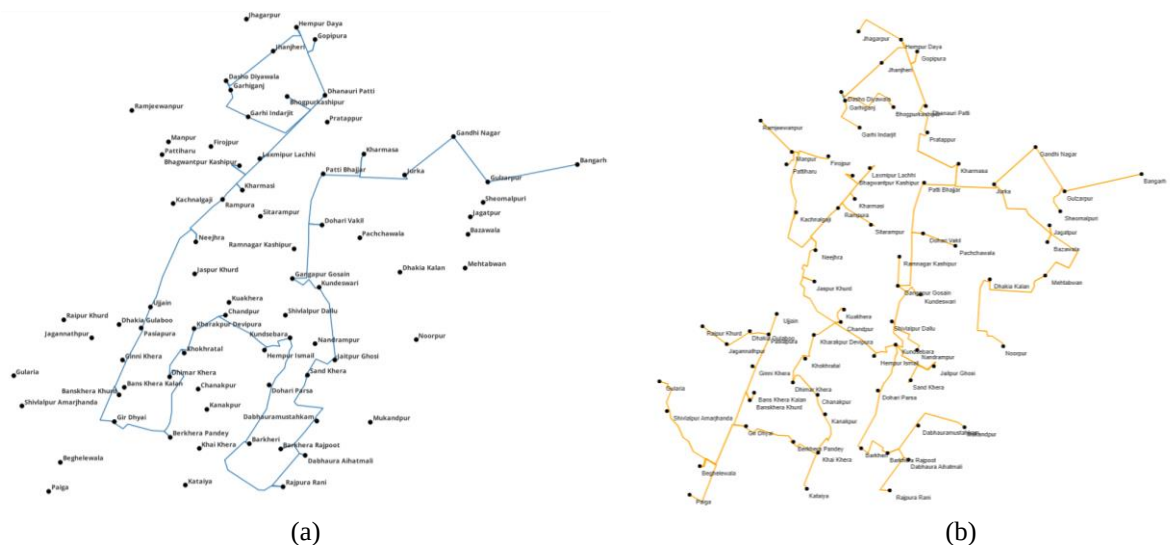


Fig. 6. (a) Rural road network generated using the standalone ACO algorithm. (b) Rural road network generated using the standalone MST algorithm.

Fig. 6 compares the benchmark networks generated using the standalone ACO and MST approaches. The standalone ACO identifies accessibility-oriented routes with a high VON but leaves several villages unconnected because connectivity is not explicitly enforced. In contrast, the standalone MST connects all villages using the minimum feasible network length but does not prioritize socio-economic accessibility. By integrating both approaches, the proposed ACO-MST framework achieves complete connectivity while maximizing the overall Value of Network (VON), thereby providing a more balanced solution for sustainable rural road planning.

Although the proposed ACO-MST framework generates an efficient and fully connected rural road network with the potential to reduce unnecessary network length and improve accessibility-oriented performance, the resulting topology is predominantly tree-based, with limited redundant links. Consequently, the network may exhibit reduced resilience and robustness under road failures, natural disasters, or emergencies where alternative routes are desirable. However, in the context of rural road planning, where construction budgets are often constrained, minimizing redundant links reduces overall network length and supports efficient infrastructure planning; however, it may also limit

alternative routes during road failures or emergency situations. Therefore, future research could extend the proposed framework by incorporating resilience, redundancy, and emergency accessibility as additional optimization objectives.

7. Conclusion

The mathematical model presented in this study is designed to develop an optimal rural road network that maximizes accessibility to settlements and essential facilities while minimizing travel distances through efficient network connectivity. This approach promotes efficient and accessibility-oriented rural infrastructure planning while contributing to the social and economic dimensions of sustainable rural development in developing countries where financial resources are limited. The model, developed using the C# programming language, demonstrates the effectiveness of integrating Ant Colony Optimization (ACO), the Gravity Model and the Minimum Spanning Tree (MST) approach for efficient rural road network planning and connectivity enhancement. Implemented in QGIS with real-world coordinates, the proposed framework is intended for new rural road network planning. Existing rural road

links are considered only as feasible connectivity alternatives during the optimization process, allowing a direct comparison between the existing and optimized networks. The proposed methodology provides a practical decision-support tool for planners to identify efficient rural road networks, thereby promoting accessibility-oriented infrastructure development and contributing to the social and economic dimensions of sustainable rural development, particularly in resource-constrained regions under programmes such as the Pradhan Mantri Gram Sadak Yojana (PMGSY).

While the model achieves an optimized and connected network, certain limitations remain. The current approach does not explicitly account for environmental constraints or variations in construction costs across different regions, which may influence the practicality of implementation. Moreover, dynamic aspects such as seasonal accessibility, traffic growth and long-term maintenance needs have not been incorporated. Moreover, although ground distances of feasible road links are used in the present study, the framework does not explicitly account for actual travel time, road conditions, seasonal accessibility, traffic growth and long-term maintenance requirements. Future research could extend this framework by integrating geographic and environmental variables, cost heterogeneity and multi-objective optimization techniques. Additionally, incorporating real-time data and machine learning approaches may further enhance the adaptability and robustness of the model for diverse rural settings.

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