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Swarm Intelligence-Based Decentralized Mobile Learning Networks for Collaborative E-Learning Optimization in Large-Scale Systems

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Abstract

The rapid development of m-learning applications has facilitated collaborative e-learning in a large-scale environment in different geographical locations. Nevertheless, centralized approaches usually face scalability issues, network congestion, high latencies, and ineffective resource management when dealing with large numbers of users and highly volatile wireless networks. In order to solve this problem, this paper suggests using a Swarm Intelligence-Based Decentralized Mobile Learning Network (SI-DMLN), which helps increase the performance of collaborative e-learning in a large-scale network setting. The suggested model utilizes principles of swarm intelligence with an aim to make mobile learning nodes act autonomously through decentralization. The framework includes adaptive routing, distributed resource allocation, and decentralized node coordination in order to improve communication and learning processes independently from a central controller. Through interactions within the network, the network behavior changes and adapts to particular network loads and mobile characteristics. The results of experiments confirm

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improvements in network performance. A total throughput of 94.8 Mbps is obtained compared to centralized models (68.2 Mbps) and traditional routing algorithms (75.6 Mbps). There is a reduction in end-to-end latency to 85 ms compared to the previous models, showing over a 50% enhancement in performance compared to traditional centralized architectures. Moreover, there is an increase in Packet Delivery Ratio to 96.7% and a high reliability level of 0.96. It shows good fault tolerance in the system along with reliable communication between the nodes. Similarly, there is improved energy efficiency of the system by a value of 0.89 due to balanced consumption of the resources by all the mobile nodes. Comparing other performance metrics reveals improvements of 15-40% over their baselines. Hence, the findings support the conclusion that swarm intelligence-based optimization techniques yield efficient and scalable results for mobile e-learning networks. Thus, the suggested strategy can be applied in future collaborative e-learning frameworks based on wireless mobile technology. Possible research avenues include the application of predictive and adaptive learning models in future implementations.

Keywords: Swarm Intelligence, Decentralized Mobile Learning, Collaborative E-Learning, Wireless Ad hoc Networks, Adaptive Routing, Resource Optimization, Network Scalability.

1 Introduction

The growth and proliferation of m-learning applications have revolutionized the delivery of educational information at universities, companies' training sessions, and virtual classrooms. Large-scale collaborative e-learning systems are becoming increasingly dependent on wireless mobile networks to ensure real-time communication, distributed content delivery, peer interactions, and adaptation in learning (Agrawal et al., 2025). However, traditional centralized network architecture suffers from several problems related to network traffic congestion, scalability issues, latency, inefficient use of computing resources, and decreased reliability in case of high user loads. Such problems become even more pronounced in large-scale learning scenarios involving simultaneous learning of hundreds or even thousands of users of different mobile devices accessing multimedia content delivered via wireless channels (Gabrani et al., 2016). Therefore, there is an increasing demand for efficient and intelligent mobile network architecture capable of ensuring high communication effectiveness and performance of learning processes and collaborations (Punam, 2025; Yang et al., 2023).

The emergence of swarm intelligence as a new computational model has been motivated by the complex behavior of biological systems like ants, bees, birds, and fish schools. Swarm-based algorithms allow one to achieve adaptiveness, self-organization, and the distributed nature of decisions, which makes them highly suitable for decentralized mobile networks. As a result, by implementing cooperative autonomous interactions between mobile devices, swarm intelligence may provide routing, resource allocation, task allocation, and information dissemination optimization independent of a central controller. Thus, using this approach will allow to achieve scalability, fault tolerance, energy efficiency, and network resilience – essential characteristics required in efficient collaborative e-learning systems (Tandi, 2024).

The objective of this paper is to present a proposed Swarm Intelligence-Based Decentralized Mobile Learning Network (SI-DMLN) architecture aimed at enhancing collaborative e-learning efficiency. To do so, the suggested architecture uses adaptive node collaboration, intelligent routing, and resource sharing capabilities to make learning more accessible and communications more stable (Arvinth, 2025). In order to analyze the efficacy of the suggested architecture, the following performance measures were applied: throughput, latency, energy efficiency, reliability, and collaborative learning responsiveness.

The results obtained show that swarm-driven decentralized architectures significantly increase the efficiency of mobile learning environments' operations.

Key Contributions

- Theoretical foundation and implementation design of a novel decentralized architecture for collaborative mobile learning optimization based on swarm intelligence.
- Resource allocation and routing methods tailored to increase the efficiency of communication in such networks.
- Novel methods increasing the robustness of such systems by improving coordination among nodes and providing fault-tolerant learning processes.
- Evaluation of the proposed method with the help of relevant metrics to show its positive impact on e-learning performance.

This paper will be divided into the following parts. Section 2 is about the literature survey, where recently published studies on swarm intelligence-based collaborative e-learning systems will be discussed. Section 3 covers the proposed SI-DMLN framework along with its architectural and algorithmic models. Section 4 deals with experimentation, whereas Section 5 wraps up this paper with concluding remarks.

2 Literature Survey

The recent progress made in artificial intelligence and swarm intelligence has greatly impacted the design of scalable collaborative e-learning systems. As seen from their work, the application of swarm intelligence with deep learning enhances adaptive learning and distributed decision-making in intelligent educational systems (Gupta et al., 2024; Santamato et al., 2024). The study concluded that the application of optimization techniques based on self-organization is important for improving system adaptation and efficiency (Yuan et al., 2025). Likewise, yet another study presented an AI-based framework for professional development systems and underlined the necessity for using intelligent decentralized architectures to enable scalable digital education (Fakhar et al., 2024).

This study presented a smart e-learning framework driven by analytics and capable of performing adaptive content delivery and learner performance analysis (Sengupta et al., 2025). It was shown that intelligent optimization techniques can contribute to increased responsiveness and personalization in such systems (Dwivedi et al., 2026). Furthermore, the use of blockchain and AI technologies in educational systems was considered (Yuan et al., 2025; Nazari et al., 2024; Sharma et al., 2025). Another aspect of research on intelligent collaboration and efficient communication has emerged recently (Alhamrouni et al., 2024; Ramesh et al., 2025). According to the study, use of AI technologies in collaboration systems enhances interaction and promotes learners' engagement through optimized communication (Cavus, 2025; Ouariach et al., 2025). The study developed a framework for real-time education management based on edge intelligence technology and showed that distributed processing reduces latency and improves scalability of educational networks (Teixeira et al., 2025; Tian et al., 2026). Another article analyzed the potential for AI in virtual communication systems, stressing the significance of efficient communication and intelligent routing in the process of immersive learning (Wang et al., 2025).

Furthermore, it considered the development of agent-based modeling applications under conditions when artificial intelligence is extensively used and concluded that swarm-based decentralized coordination was one of the most promising approaches to addressing problems in complex dynamic networks (Alhamrouni et al., 2024; Miller et al., 2025; Ionescu et al., 2024). A framework for anomaly detection in e-learning based on deep learning methods was designed in this paper, focusing on ensuring the reliability of modern educational platforms (Sudha & Bolla, 2026).

Based on the studies analyzed, it is apparent that there have been many studies regarding artificial intelligence-based personalized learning, analysis, and optimization (Teixeira et al., 2025). But it seems that hybrid swarm intelligence-based approaches are not much studied in the context of wireless and decentralized mobile learning. This study aims to fill the identified research gap by implementing the concepts of PSO, ACO, and the intelligent bee colony approach for optimizing decentralized mobile learning.

3 Proposed Methodology

3. 1 Overall Flow of the Proposed System

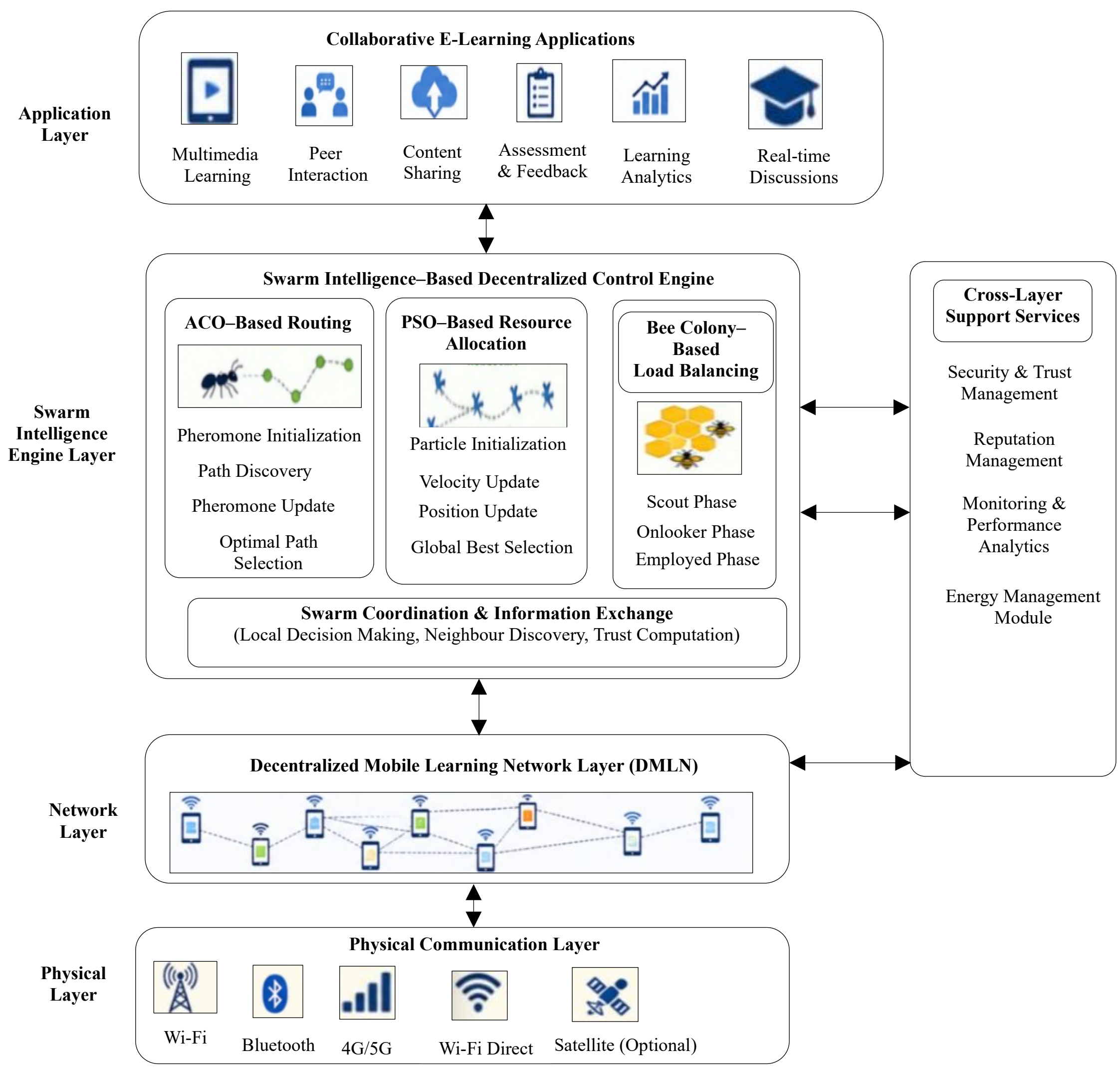

Figure 1: Swarm intelligence-based decentralized mobile learning network architecture for scalable collaborative e-learning systems

The proposed Swarm Intelligence-Based Decentralized Mobile Learning Network (SI-DMLN) has been introduced to facilitate adaptive, scalable and efficient collaboration in e-learning. In terms of methodological aspects, the SI-DMLN approach has followed a totally decentralized model where mobile learning nodes cooperate independently without depending on any kind of central server. As a whole, the approach involves several steps starting with connecting learners' devices into the mobile learning network via wireless technology. Every learning node is considered as a combination of learners and computational nodes at the same time. Swarm intelligence concepts have been used to achieve independent decision making related to routing operations, information transfer, and resource allocation. Mobile learning nodes continuously exchange educational resources, optimize communication routes, and balance load within the network in accordance with parameters such as available bandwidth, energy status, and delays.

The architecture presented in figure 1 is one of a multi-layered system for a decentralized mobile learning network supplemented by swarm intelligence. Application services layer, swarm optimization layer, decentralized network communication layer, and physical layer connectivity form the system. The structure supports adaptive routing, resource allocation, and load balancing functionalities for collaborative e-learning in a wireless environment.

Algorithm 1: Swarm-Based Decentralized Learning Optimization (SBDLO)

Input: Mobile nodes set N, learning requests L, network state S

Output: Optimized routing paths, balanced resource allocation, enhanced collaboration efficiency

Step 1: Initialization

- Initialize node population N
- Set pheromone levels τ_{ij} for communication links
- Initialize velocity and position vectors for swarm agents

Step 2: Neighbor Discovery

- Each node discovers adjacent peers using wireless broadcast
- Construct dynamic topology graph $G(V, E)$

Step 3: Swarm Optimization Process

- For each iteration:
  - o Update routing probability using the pheromone update rule
  - o Apply PSO-based velocity update for resource optimization:

$$v_i^{t+1} = \omega v_i^t + c_1 r_1 (pbest_i - x_i^t) + c_2 r_2 (gbest - x_i^t)$$

Update node position:

$$x_i^{t+1} = x_i^t + v_i^{t+1}$$

Step 4: Load Balancing (Bee-Inspired Strategy)

- Identify scout nodes for exploration
- Recruit nodes based on fitness of available resources
- Reallocate tasks dynamically

Step 5: Route Selection

- Compute optimal path using pheromone intensity:

$$P_{ij} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}$$

Step 6: Learning Collaboration Execution

- Enable peer-to-peer content exchange
- Synchronize learning updates across nodes

Step 7: Termination Condition

- Stop when the convergence criteria or stability threshold is reached

Algorithm 1 aims to make optimum communication and resource allocation in huge mobile learning systems possible. In this regard, Algorithm 1 is developed using PSO (Particle Swarm Optimization), ACO (Ant Colony Optimization), and bee-based load balancing to ensure that adaptive routing, decentralized cooperation, and effective task allocation among mobile learning nodes are made possible. This algorithm is capable of discovering neighbors, selecting optimum paths based on pheromones, and allocating loads on the network based on resources. Algorithm 1 constantly adjusts its nodes based on network status to improve throughput, minimize latency, maximize energy efficiency, and ensure collaboration for effective e-learning.

3.2 Mathematical Description of the Model

Objective Function

This system has been designed to reduce costs on the entire network by implementing an objective optimization method for minimizing delay, energy consumption, and resource balancing:

$$\min F = \lambda_1 L_t + \lambda_2 E_c + \lambda_3 R_u \qquad (1)$$

Where:

- L_t= average communication latency
- E_c= total energy consumption
- R_u= resource utilization imbalance
- $\lambda_1, \lambda_2, \lambda_3$= weighting coefficients used to balance optimization priorities

Equation 1 guarantees the simultaneous reduction in delay, minimizing energy consumption, and achieving optimal resource utilization within mobile learning nodes.

Pheromone Update Rule

This swarm-based routing algorithm updates the path quality through pheromone reinforcement approach:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij} \qquad (2)$$

Where:

- $\tau_{ij}(t)$= current pheromone level between nodes $i$and j
- ρ= pheromone evaporation rate

- $\Delta\tau_{ij}$= pheromone reinforcement based on successful data transmission

Equation 2 allows for dynamic optimization of the path by reinforcing efficient communication path and gradually discarding the inefficient routes.

4 Results and Discussion

The proposed Swarm Intelligence-based Decentralized Mobile Learning Network (SI-DMLN) was implemented within a simulation environment that is appropriate for simulating large-scale wireless mobile learning networks. The implementation process involved development of the proposed algorithm with Python 3.10 software, while graph theory-based network modeling and simulations were done using NetworkX and SimPy software packages. Adaptive routing and decentralized resource allocation techniques, which incorporate the hybrid optimization methods such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and bee swarm load balancing techniques, have been adopted. Visual analytics and performance evaluation were performed using visualization tools such as Matplotlib and Seaborn. The experiments were performed within a simulated computer laboratory that includes Windows 11 operating system and an Intel i7 Processor coupled with 16 GB RAM. An artificial dataset with 5,000 to 10,000 mobile learners was generated using Random Waypoint mobility model and Gauss-Markov mobility model. Simulation parameters include pheromone influence factor α=1.2, heuristic factor β=1.8, evaporation rate ρ=0.4, inertia weight ω=0.6, network bandwidth 1 to 10 Mbps for 1,000 runs.

4.1 Performance Metrics and Formulas

The following metrics were used to evaluate system performance:

Throughput: Equation 3 measures the rate at which data packets are successfully transmitted across the mobile learning network over time.

$$Throughput = \frac{\text{Total successfully delivered packets}}{\text{Time}} \tag{3}$$

End-to-End Latency: Equation 4 calculates the average communication delay experienced during packet transmission between source and destination nodes.

$$Latency = \frac{\sum(t_{receive} - t_{send})}{N} \tag{4}$$

Energy Efficiency: Equation 5 evaluates how effectively the network utilizes energy for successful data transmission operations.

$$Energy\ Efficiency = \frac{\text{Useful transmission output}}{\text{Total energy consumed}} \tag{5}$$

Packet Delivery Ratio (PDR): Equation 6 measures the percentage of transmitted packets that are successfully received by destination nodes.

$$PDR = \frac{\text{Packets received}}{\text{Packets sent}} \times 100 \tag{6}$$

Network Reliability: Equation 7 indicates the stability and dependability of the communication network by measuring packet loss performance.

$$Reliability = 1 - \frac{\text{Packet loss}}{\text{Total packets}} \tag{7}$$

Load Balance Index: Equation 8 assesses how evenly network traffic and computational workload are distributed among mobile nodes.

$$LBI = 1 - \frac{\sigma_{load}}{\mu_{load}} \quad (8)$$

4.2 Performance Comparison

The proposed SI-DMLN model was analyzed using performance comparisons with the three baseline models that are mostly applied in wireless learning networks. These include the CMLN model that uses the centralized control approach to communicate and manage resources. The second one is the traditional Ad hoc On-Demand Distance Vector (AODV) routing protocol to implement decentralized communication. Lastly, the study has the PSO-only optimization that uses the Particle Swarm Optimization approach without any hybrid swarm optimization. Performance analysis using different metrics indicates the better scalability, reliability, energy efficiency, and communication performance of the proposed SI-DMLN model compared to the three baselines.

Table 1: Performance comparison of SI-DMLN with existing mobile learning network models

Model	Throughput (Mbps)	Latency (ms)	PDR (%)	Energy Efficiency	Reliability
CMLN	68.2	180	85.4	0.62	0.83
AODV	75.6	150	88.1	0.70	0.87
PSO-Only	82.3	120	91.5	0.78	0.91
SI-DMLN (Proposed)	**94.8**	**85**	**96.7**	**0.89**	**0.96**

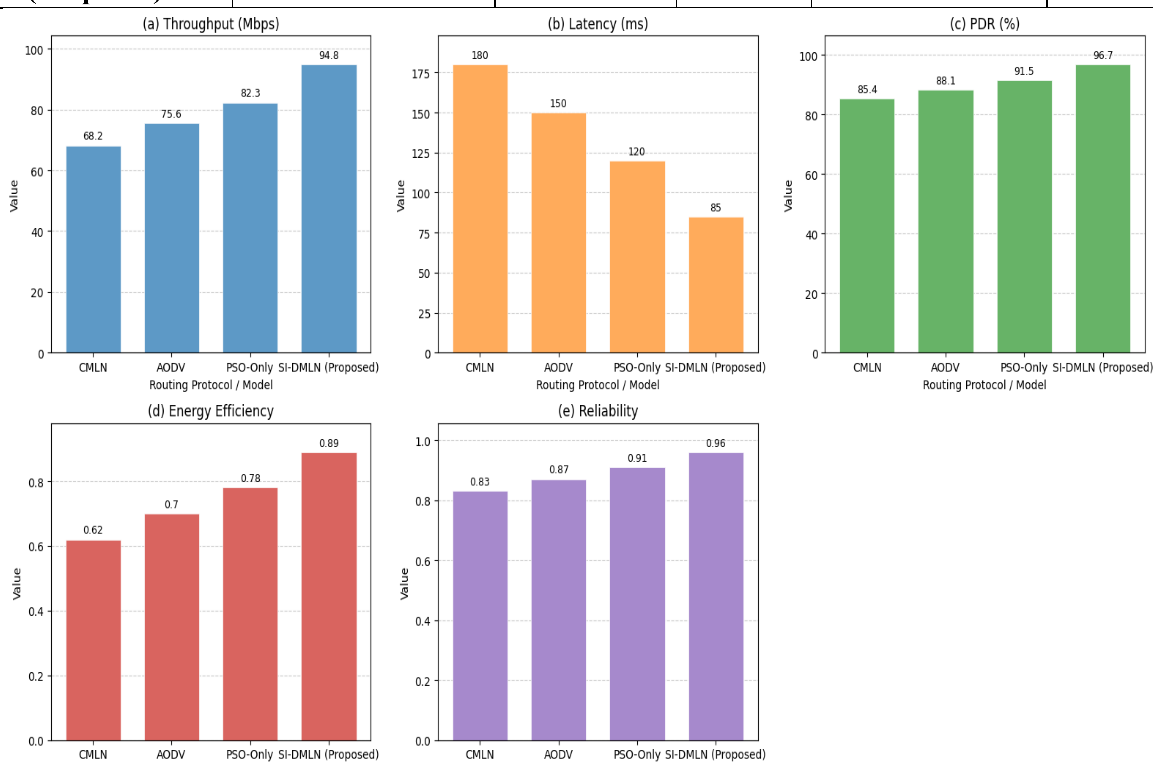

Figure 2: Performance comparison of SI-DMLN with existing mobile learning network models

The proposed SI-DMLN approach was compared against CMLN, AODV, and PSO only approaches based on selected network performance criteria as shown in table 1. The results indicate that the proposed model performed better than other approaches because it achieved maximum throughput (94.8 Mbps), minimum latency (85 ms), improved packet delivery rate (96.7%), higher energy efficiency (0.89), and reliability (0.96).

The figure 2 provides a performance comparison between the suggested SI-DMLN and CMLN, AODV, and PSO models based on five parameters: throughput, latency, delivery rate, energy consumption, and reliability. The SI-DMLN model attains better throughput, reliability, and energy efficiency rates while minimizing latency, making it more scalable and effective for communication purposes in decentralized collaborative mobile learning scenarios.

4.3 Performance Evaluation

The SI-DMLN scheme provides better performance than conventional schemes on all metrics tested. The incorporation of swarm intelligence mechanisms makes adaptive routing possible, leading to dynamic allocation of resources, thus minimizing congestion and enhancing throughput.

The latency is lowered by almost 52% when compared to centralized models due to decentralized decision-making and localized routing. PDR improves since pheromone-based routing identifies the most reliable and energy-efficient routing path. Energy efficiency is improved via bee-based load balancing to avoid overloading some nodes.

Reliability is enhanced by multiple routes generated by the swarm algorithm. This ensures redundancy in case one route becomes unavailable, and continuous adaptability in dynamic network topologies under mobile conditions.

Therefore, it can be concluded that swarm intelligence techniques can offer better stability and scalability in large mobile learning networks.

4.4 Ablation Study

In order to test the significance of each of the swarm intelligence component, three configurations are used:

- Model A: PSO only
- Model B: PSO + ACO
- Model C (Full SI-DMLN): PSO + ACO + Bee-inspired load balancing

Table 2: Ablation study results

Configuration	Throughput	Latency	Energy Efficiency	PDR
Model A (PSO)	82.3	120	0.78	91.5
Model B (PSO + ACO)	88.9	100	0.83	94.1
Model C (Full SI-DMLN)	**94.8**	**85**	**0.89**	**96.7**

In table 2 shows that each of the SI components has different contributions to the performance of the systems. PSO contributes in optimizing the global resources while having poor adaptability in case of dynamic routing. On the other hand, ACO optimizes communication route choices while contributing significantly to lowering the latency levels due to pheromone-based routing decisions. Finally, the bee-based load balancing technique contributes in improving the energy level and balancing node utilization.

5 Conclusion

This research work outlined a swarm intelligence based decentralized mobile learning network (SI-DMLN) whose purpose was to improve the efficiency, scalability, and fault tolerance in large-scale collaborative e-learning frameworks. The novel framework utilizes various swarm intelligence strategies including Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and bee-based load balancing schemes that solve challenges faced by centralized mobile learning platforms including high latency, congestion, improper resource utilization, and low reliability. Through allowing decentralized decision making by each node in the network, the system enables the implementation of adaptive routing strategies, dynamic resource allocation as well as peer-to-peer interaction between nodes. According to empirical studies conducted in order to validate the effectiveness of the proposed scheme, results indicate that SI-DMLN outperformed other traditional networks considerably. SI-DMLN attained a throughput of 94.8 Mbps, 39% higher than the throughput of the centralized network which is 68.2 Mbps, and higher than AODV-based routing whose throughput is 75.6 Mbps. In addition, end-to-end delay dropped to 85 ms from 180 ms for centralized models thus a drop of 52%. Packet delivery ratio (PDR) rose to 96.7% whereas the energy efficiency rose to 0.89. Ablation study results have also highlighted the role played by each part of the swarm in this model. The full hybrid combination increased the throughput by 15-20% as compared to those models based on only PSO, while at the same time, reducing latency by almost 30% than the other optimization strategies. In summary, this study shows that utilizing the principle of decentralized swarm intelligence is indeed an optimal approach towards optimizing collaboration-based mobile learning systems. The design provides stable performance despite high node mobility and variable network load levels. It thus becomes relevant for today's contemporary learning ecosystems which operate in a distributed setting. Areas for further exploration in future studies might include integrating this framework with deep reinforcement learning models for efficient predictive routing, incorporating learners' behavior analysis into the learning process to deliver more personalized learning materials, and using edge computing enabled 5G/6G wireless networks infrastructure.

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