SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2025, 22(4), 1552.
https://doi.org/10.62617/mcb1552

Article

Driven by edge intelligence: A biomechanical model-based study of mobile charging scheduling and privacy protection

Yifan Zhang*, Penghui Lei

Qingdao Institute of Software, College of Computer Science and Technology, China University of Petroleum (East China), Qingdao 266000, China

*** Corresponding author:** Yifan Zhang, yifanzhang@s.upc.edu.cn

CITATION

Zhang Y, Lei P. Driven by edge intelligence: A biomechanical model-based study of mobile charging scheduling and privacy protection. Molecular & Cellular Biomechanics. 2025; 22(4): 1552. https://doi.org/10.62617/mcb1552

ARTICLE INFO

Received: 13 February 2025
Accepted: 25 February 2025
Available online: 3 March 2025

Abstract: With the wide application of electric vehicles, smart robots and Internet of Things (IoT) devices, efficient scheduling of mobile charging systems has become an important research direction in smart energy management. However, the traditional cloud computing architecture is difficult to meet the requirements of low latency, high reliability and privacy protection, and the existing scheduling strategies still have challenges in terms of energy optimization, task balancing and dynamic adaptability. To this end, this paper proposes an intelligent mobile charging scheduling method that integrates edge computing and biomechanical modeling, constructs a biomechanical-based charging demand modeling and energy consumption analysis framework, and combines bionic optimization algorithms to achieve efficient path planning. Meanwhile, an edge computing architecture is adopted to optimize resource scheduling, and a federated learning mechanism is designed to enhance cross-domain data processing capability. To safeguard user privacy, a multi-level privacy protection mechanism is proposed, combining differential privacy, homomorphic encryption and zero-knowledge proof to ensure data security. Experimental results show that the method outperforms traditional methods in terms of task response time, energy consumption optimization, load balancing and privacy security, and can significantly improve the charging scheduling efficiency and provide effective technical support for large-scale distributed charging networks. The research results provide a theoretical basis and engineering practice reference for the application of smart charging networks, edge intelligent computing and privacy protection technology.

Keywords: edge computing; biomechanical modeling; mobile charging scheduling; bionic optimization algorithm

1. Introduction

In recent years, edge computing has emerged as a promising framework to address the challenges posed by traditional cloud computing methods, including high latency and limited scalability [1]. Existing scheduling methods, such as centralized cloud-based systems and static planning algorithms, often struggle with efficient resource allocation in highly dynamic environments due to their reliance on centralized data processing and fixed task allocation strategies. These methods typically fail to account for the real-time fluctuations in energy demand and resource availability, which limits their adaptability in large-scale systems [2].

In contrast, this study introduces an innovative approach that combines edge computing with biomechanical modeling. The biomechanical model offers a dynamic, spatially and temporally adaptive mechanism that can more effectively simulate resource scheduling in real-world scenarios [3]. Unlike traditional algorithms that overlook the complexities of spatial distribution and temporal changes in energy demand, our method leverages biomechanical principles to optimize charging paths in real-time. Furthermore, edge computing allows for decentralized task allocation, significantly reducing latency and improving the system's responsiveness and scalability. This approach not only improves scheduling efficiency but also enhances privacy protection and energy optimization, addressing the limitations of existing methods.

2. Edge computing fundamentals

Edge computing builds a distributed low-latency service architecture by sinking computing, storage and network resources to the edge side of the network close to the terminal devices, effectively alleviating the high transmission latency and bandwidth bottlenecks faced by traditional cloud computing centers in mobile charging scenarios [4]. The core lies in the establishment of a multi-layer collaborative heterogeneous node topology, relying on the localized processing capabilities of edge nodes (such as base stations and gateways), to provide real-time analysis and decision-making feedback on the time and space-sensitive data generated by charging devices, so as to support the demand for dynamic resource scheduling. In the mobile charging system, the edge computing architecture needs to address three key issues: First, a distributed task allocation mechanism based on device location, residual energy, and task priority, and load balancing through local decision-making and global coordination; second, designing a lightweight protocol stack to adapt to the heterogeneous communication interfaces of charging devices (e.g., LoRa (Long Range), NB-IoT (Narrowband Internet of Things)), and ensuring highly reliable data transmission under low power consumption; third, constructing a cooperative computing mechanism between edge nodes (e.g., base stations, gateways) to provide real-time analysis and feedback of time- and space-sensitive data generated by edge nodes, thus supporting dynamic resource scheduling requirements. The third is to build a collaborative computing model among edge nodes, using federated learning or distributed optimization algorithms to achieve cross-domain resource scheduling and avoid service interruptions triggered by single-point failures. Compared with the traditional centralized cloud platform, edge computing significantly reduces the risk of privacy leakage through data localization processing, while its elastic scalability can adapt to the highly concurrent requests of large-scale mobile charging networks, providing basic support for subsequent biomechanics-driven real-time scheduling [5].

3. Biomechanics-based modeling of mobile charging

3.1. System modeling

In the mobile charging system, in order to accurately portray the distribution of charging demand and energy consumption, a biomechanical modeling method is introduced to construct a dynamic charging demand distribution and energy consumption calculation model by drawing on the energy metabolism and movement characteristics of human muscle tissue [6]. The model not only reflects the spatial distribution of charging demand but also can be dynamically adjusted with the time dimension to optimize the reasonable allocation of charging resources.

3.1.1. Charging demand distribution modeling

The charging demand distribution is described by a density function similar to the distribution of muscle fibers, which divides the entire service area into multiple dynamically changing demand density regions (**Figure 1**). The charging demand intensity function $D(x,y,t)$ is set, where (x,y) denotes the geographic location coordinates and t denotes the time variable. The demand intensity can be expressed as [7]:

$$D(x,y,t) = \sum (w_i \cdot f_i(x,y)) \cdot g(t)$$

Where wi denotes the demand weight of the ith class of users, which is used to distinguish the charging demand priority of different types of users; $fi(x,y)$ is the spatial distribution function of charging demand, which portrays the charging demand changes in different regions; $g(t)$ is the time decay function, which is used to adjust the impact of the charging demand changes over time. This model can reflect the spatio-temporal dynamic characteristics of the charging demand, similar to the distribution of the energy demand of muscle tissue in different movement states.

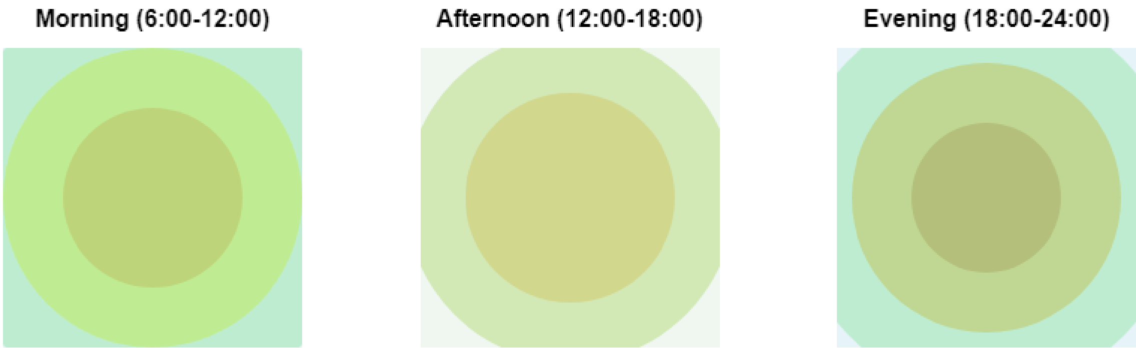

Figure 1. Heat map of charging demand density distribution.

3.1.2. Energy consumption model

During the mobile charging process, the energy consumption of the charging vehicle is affected by the traveling distance, charging power and charging duration, which is similar to the energy consumed by human muscles during exercise. Therefore, the concept of energy conversion efficiency, which is similar to the work done by muscles, is introduced to establish the energy consumption equation of the mobile charging vehicle [8]:

$$E = \alpha \cdot d + \beta \cdot P + \gamma \cdot T$$

where E is the total energy consumption, d is the driving distance of the charging vehicle, P is the charging power, T is the charging duration, α, β and γ are the corresponding energy consumption coefficients, which are used to characterize the energy loss under different working conditions. Considering the influence of different environmental factors on energy consumption, the energy consumption coefficients are summarized and quantified, and the specific parameters are listed in **Table 1** below. The model can comprehensively consider the spatial and temporal distribution characteristics of charging demand and the energy loss of charging vehicles, which provides data support for optimizing mobile charging scheduling.

Table 1. Parameters of energy consumption coefficients.

working conditions	Distance coefficient (α)	Power factor (β)	Time factor (γ)
urban area	0.85	1.20	0.95
suburbia	0.75	1.15	0.90
rush hour	1.10	1.25	1.05
off-peak hour	0.70	1.10	0.85

3.2. Bionic optimization algorithm design

In order to optimize the path planning and charging scheduling of mobile charging vehicles, a bionic optimization algorithm is proposed based on the biomechanical model, which simulates the synergistic movement mechanism of muscle contraction-diastole and improves the charging path and scheduling efficiency through the principle of bionics [9].

3.2.1. Charging path optimization

In path planning, we consider each charging demand point as a "muscle unit", and its demand intensity corresponds to muscle tension. When multiple charging demand points exist at the same time, these demand points are similar to a group of muscle fibers contracting together to form a dynamically adjusted charging path (**Figure 2**). The improved spring-damping system model is used for path planning [10]:

$$F = k \cdot \Delta x + c \cdot v + m \cdot a$$

F is the path traction force, which determines the direction of movement of the charging vehicle; k is the elasticity coefficient, which represents the attraction between the charging demand points; Δx is the displacement, which represents the change of the distance between the charging vehicle and the charging demand points; c is the damping coefficient, which controls the smoothing of the path; v is the speed, m is the mass, and a is the acceleration, which is used to dynamically adjust the driving trajectory. In the process of traveling, the charging vehicle will be affected by the "traction force" of multiple charging demand points, similar to the coordinated contraction of muscle groups. By solving the above system of equations, the system can dynamically adjust the optimal charging path, and realize the efficient completion of the charging task with the lowest energy consumption.

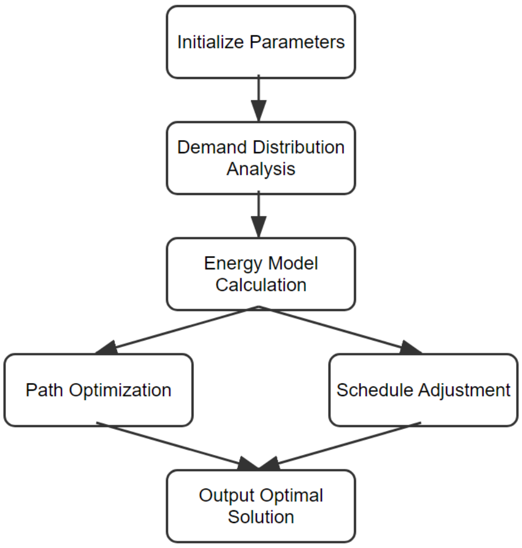

Figure 2. Flowchart of bionic optimization algorithm.

3.2.2. Charge scheduling optimization

In charging scheduling, a scheduling mechanism based on ATP (adenosine triphosphate) energy metabolism is introduced. In living organisms, ATP regeneration of muscle cells determines the energy supply priority of muscles. Similarly, the energy replenishment process of the charging vehicle is analogous to the ATP regeneration process, and the energy replenishment priority queue is established [11]:

$$Pr\,i\,ority = w_1 \cdot E_{remain} + w_2 \cdot D_{urgent} + w_3 \cdot T_{wait}$$

where E_{remain} denotes the remaining power; D_{urgent} is the urgency of the charging demand point (e.g., the value is larger when the power is lower than a certain threshold); T_{wait} denotes the waiting time, i.e., the length of time that the charging demand point is being waited for the service; and w_1, w_2, and w_3 are the weight coefficients, which can be dynamically adjusted to adapt to different charging scenarios. By dynamically adjusting the weight coefficients, the optimal allocation of charging resources is realized.

4. Edge intelligence-driven scheduling mechanisms

4.1. Edge computing architecture design

In this paper, a multi-tier edge computing architecture is designed to support the mobile charging scheduling system, as shown in **Figure 3**. The architecture consists of three layers: Terminal layer, edge layer and cloud layer. The terminal layer includes mobile charging vehicles, charging piles and user devices, which are responsible for collecting real-time charging demand, location information and energy status data [12]. The edge layer consists of distributed edge servers, each of which manages the terminal devices within its coverage area and undertakes tasks such as data preprocessing, real-time decision-making and local optimization. The cloud layer is responsible for global resource scheduling, historical data analysis and policy optimization [13].

In terms of task allocation, the principle of "layered collaboration and proximity processing" is adopted, whereby delay-sensitive real-time scheduling tasks are delegated to the edge layer for processing, while computationally intensive optimization tasks are assigned to the cloud layer for execution. In order to improve system reliability, a blockchain-based distributed ledger is constructed between edge nodes to record charging transactions and scheduling decisions, ensuring data consistency and traceability. Meanwhile, a lightweight edge computing protocol stack is designed, as shown in **Table 2**, which contains a communication interface layer, a data processing layer, a task scheduling layer, and a security protection layer, and can support efficient data transmission and task processing in heterogeneous network environments. A distributed training mechanism based on federated learning is introduced in the data processing layer, which enables the edge nodes to collaboratively optimize the scheduling model under the premise of protecting data privacy. The architecture not only significantly reduces the system response delay but also improves the scalability and robustness of the system through distributed deployment.

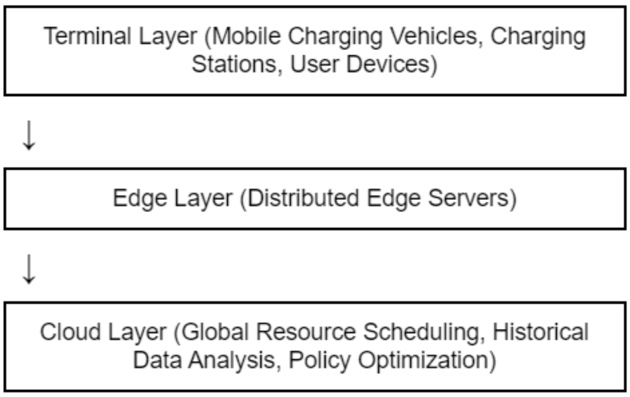

Figure 3. Schematic diagram of edge computing architecture.

Table 2. Edge computing protocol stack structure.

phase	functional module	Key technologies
communications interface layer	Heterogeneous network access, protocol conversion	LoRa, NB-IoT, 5G
data processing layer	Data cleaning, feature extraction, model training	Federated learning, distributed storage
task scheduling layer	Load balancing, resource allocation, path planning	Biomechanical optimization, blockchain
security layer	Authentication, data encryption, access control	Homomorphic encryption, zero-knowledge proofs

4.2. Real-time scheduling algorithm

In order to achieve efficient mobile charging scheduling, this paper proposes an adaptive real-time scheduling algorithm based on edge computing architecture, which integrates biomechanical modeling and deep reinforcement learning methods to achieve dynamic optimal allocation of charging resources. Since mobile charging scheduling involves multiple constraints, such as spatial and temporal distribution of charging demand, energy consumption of charging vehicles, path planning, etc., this paper models the scheduling optimization problem as a multi-objective optimization problem and solves it using an intelligent algorithm. In the scheduling process, the system first constructs a multi-objective decision-making model with minimizing the total energy consumption, average response time and scheduling distance as the objective function in the following form [14]:

$$min\, F\,(s) = w_1 \cdot E(s) + w_2 \cdot T(s) + w_3 \cdot D(s)$$

where $E(s)$ denotes the total energy consumption, $T(s)$ denotes the average response time, $D(s)$ denotes the dispatch distance, and w_1, w_2, w_3 are the weighting coefficients for the respective weight coefficients of the objectives. This optimization objective is subject to several constraints, including the maximum load capacity of the charging vehicle, the time window for task completion, and the maximum coverage distance of the charging service, i.e.,

$$\begin{aligned} &C_1: \sum^{\Sigma} x_{i,j} \leq C_{max} \\ &C_2: t_{i,j} \leq T_{max} \\ &C_3: d_{i,j} \leq D_{max} \end{aligned}$$

where C_{max} is the maximum load capacity of the charging vehicle, T_{max} is the maximum acceptable waiting time of the task, and D_{max} is the maximum service radius. In order to solve this optimization problem, this paper designs a deep reinforcement learning algorithm based on the Actor-Critic framework, which is able to optimize the scheduling decision in dynamic environments and adapt to different charging demand distributions.

In the scheduling decision process, the system first inputs the state information of the charging task to the neural network, including the distribution of the current charging demand points, the location of the charging vehicle, the remaining power and other data. Then, based on the Actor-Critic structure, a strategy network (Actor) is used to output the scheduling decision of charging vehicles, including path selection and charging power adjustment, etc. The Critic network is used to evaluate the advantages and disadvantages of the current strategy and adjust the parameters of the strategy network according to the real-time feedback so as to optimize the scheduling scheme continuously. The whole algorithm flow is shown in **Figure 4**.

In the training process, in order to improve the learning efficiency, the Experience Replay and Prioritized Sampling techniques are used to select key samples from the past scheduling experience for training so as to avoid the neural network from falling into the local optimum. At the same time, in order to ensure the stability of the algorithm, the reward-shaping mechanism is introduced, in which the reward function is based on biomechanical modeling so that the optimization direction of the charging scheduling is in line with the trend of the actual charging demand [15]. The definition of the reward function is as follows:

$$R_t = \alpha \cdot (Ettt_{max_{max_{max}}}$$

where E_{max}, T_{max}, D_{max} denote the maximum thresholds set by the system for energy consumption, response time and dispatch distance respectively, and α, β, γ are reward coefficients for balancing the weights between different optimization objectives. In practical applications, these parameters can be adjusted by experimental data to adapt to different charging scenarios.

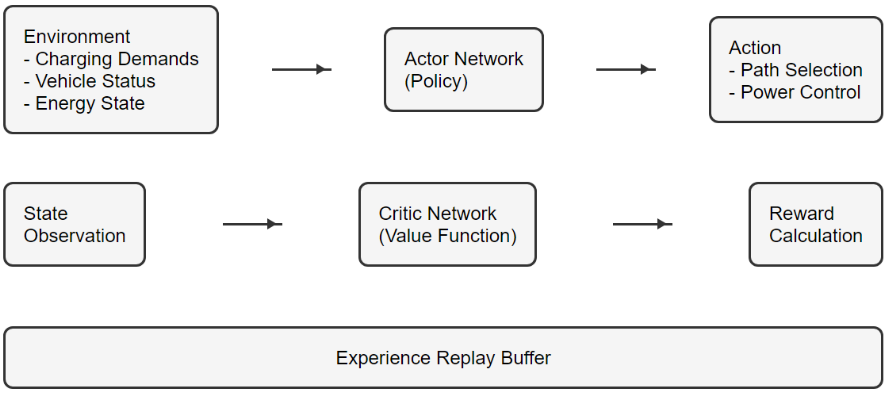

Figure 4. Framework diagram of real-time scheduling algorithm.

5. Privacy protection program design

5.1. Data security threat analysis

In mobile charging scheduling systems, data security is crucial, involving multiple sensitive pieces of information such as user charging requests, vehicle operating status, and charging scheduling policies. However, due to the complexity of data transmission and storage among terminal devices, edge nodes, and cloud platforms, the system faces a variety of security threats, including data eavesdropping, identity disguise, data tampering, denial-of-service attacks, and inference attacks. If these threats are not effectively controlled, they may not only cause user privacy leakage but also lead to charging scheduling failure, service quality degradation, or even system paralysis. Therefore, it is necessary to analyze these security risks in depth and design corresponding protective measures.

During data transmission, attackers may steal charging request data by listening to network communications, which contain sensitive information such as the user's geographic location, charging time, and power demand. Once this data is intercepted, the attacker can perform trajectory analysis of user behavior, speculate on the user's travel pattern, and even implement accurate tracking, resulting in serious privacy leakage. In addition, in the process of data interaction between edge nodes, if there is a lack of sufficient encryption protection, an attacker can steal data through a Man-in-the-Middle Attack (MITM) and tamper with the data packets, causing the scheduling system to misjudge the charging demand and affecting the normal resource allocation. As shown in **Figure 5**, in order to quantify the risk of data eavesdropping, this paper introduces the information entropy model to calculate the success probability of the attacker to infer the user's trajectory, and the degree of privacy leakage can be expressed as:

$$Pr\,i\,vacy\_Leakage = -\sum(p_i \cdot log_2\, p_i) \times \lambda$$

where p_i denotes the probability that an attacker successfully infers a certain type of privacy information, and λ is the privacy sensitivity weight. With this model, the privacy protection ability of the system under different attack scenarios can be objectively evaluated (**Table 3**).

Table 3. Security threat analysis model.

Threat type	attack target	implication	risk level
data tapping	user location information	track leakage	your (honorific)
identity masquerade	Charge authentication system	service abuse	center
data tampering	scheduling decision	systemic disorder	your (honorific)
denial of service (computing)	edge node	service interruption	center
inference attack	User Behavior Patterns	privacy breach	your (honorific)

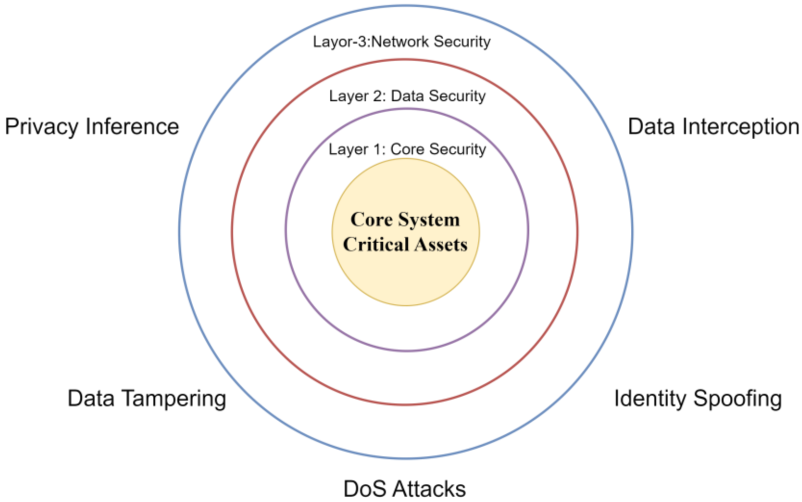

Figure 5. Schematic diagram of the multi-level security threat model.

5.2. Privacy protection mechanisms

In mobile charging scheduling systems, safeguarding user privacy is paramount due to the sensitive nature of the data involved, including user location, charging requests, and vehicle status. To address the risks of data leakage at various stages—collection, transmission, storage, and computation—this paper introduces a multi-layered privacy protection framework designed to mitigate potential privacy breaches effectively. The framework integrates several advanced cryptographic techniques tailored for each phase. At the data collection stage, differential privacy is employed to add controlled noise to location data, ensuring that individual users' movements cannot be accurately tracked. During data transmission, a Hybrid Encryption scheme is used, combining homomorphic encryption and attribute encryption, which enables secure data processing and fine-grained access control without revealing sensitive content. For data storage, a sharding-based decentralized storage scheme is adopted to distribute encrypted data across multiple edge nodes, reducing the risk of centralized data breaches. Finally, at the computational processing stage, zero-knowledge proofs allow charging vehicles to validate their availability without exposing their locations or specific operational details. This multi-layered approach not only strengthens privacy protection but also ensures that the system remains efficient and scalable for large-scale applications.

At the data collection level, the user's charging request usually contains sensitive data such as location information, power status, time stamp, etc. In order to prevent the attacker from inferring the user's travel patterns or daily behaviors through the data correlation, this paper employs the differential privacy mechanism to perturb the user's location information. Under the differential privacy framework, each user's location data is added with noise before submission, so that the attacker cannot accurately recognize the user's real location. The perturbation function is defined as follows:

$$L^{'}(x,y) = L(x,y) + Lap(\varDelta f/\varepsilon)$$

where $L(x,y)$ is the original position coordinate, $Lap(\Delta f/\varepsilon)$ is the Laplace noise, Δf is the position sensitivity, and ε is the privacy budget. At the data transmission layer, a lightweight hybrid encryption scheme combining homomorphic encryption and attribute encryption techniques is designed to realize secure data transmission and fine-grained access control. The core of the scheme is to construct a three-layer encryption structure: The outer layer uses attribute encryption to protect data access privileges, the middle layer uses homomorphic encryption to support ciphertext computation, and the inner layer uses lightweight symmetric encryption to protect data confidentiality. To reduce the computation overhead, a dedicated cryptographic gas pedal is deployed on the edge nodes. In the data storage layer, a decentralized storage scheme based on sharding is proposed to decentralize the storage of sensitive data on multiple edge nodes and use threshold cryptography to protect data integrity. In addition, a privacy-preserving scheduling protocol based on zero-knowledge proof is designed to enable charging vehicles to prove their service capability and availability without revealing their specific locations. **Table 4** details the specific parameter configurations for each layer of protection mechanisms.

Table 4. Privacy protection parameter configuration.

protection level	**Protection mechanisms**	**Key parameters**	**performance overhead**
data acquisition	differential privacy	$\varepsilon = 0.1$	CPU: 5%
data transmission	hybrid encryption	Key length: 2048 bits	Delay: 10 ms
data storage	slice storage	Number of slices: 5	Storage: 1.2x
computational processing	zero proof of knowledge	Circuit depth: 20	CPU: 8%

6. Experimentation and evaluation

6.1. Simulation environment setting

To verify the effectiveness of the proposed edge intelligence-driven mobile charging scheduling scheme, a large-scale simulation platform is constructed based on Python and SimPy simulation framework. The simulation scenario is set as a 10 km × 10 km urban core area, and a hierarchical grid model is used to divide the area into one hundred 500 m × 500 m grid cells. Two hundred charging demand points are randomly deployed in the area, including 80 fixed charging station points and 120 mobile charging demand points. For the modeling of mobile charging demand, a Modified Random Walk Model (MRWM) is proposed, which not only takes into account the user's random movement characteristics, but also integrates a destination-based trajectory prediction mechanism, which can more accurately reflect the actual user's movement pattern. The user movement speed obeys a truncated Gaussian distribution with a mean value of 3 km/h and a standard deviation of 0.8 km/h. The system deploys 20 mobile charging vehicles, adopting a hierarchical partitioning management strategy, with each vehicle equipped with a 60 kWh capacity energy storage unit, a maximum charging power of 60 kW, and a maximum range of 300 km for a single vehicle. In terms of the communication network architecture, the edge computing environment consists of 30 edge server nodes, adopting a three-tiered tree network topology, with the nodes interconnected through a 5G network, and the edge nodes. The computing power of the edge nodes is distributed between 8–16 GFLOPS (Giga Floating Point Operations Per Second).

In order to improve the simulation accuracy, the biomechanical model parameters are calibrated based on six months of actual charging data in a city, the model parameters are iteratively optimized through the improved particle swarm optimization algorithm (MPSO), and a set of adaptive parameter adjustment mechanisms are designed to ensure that the model can accurately reflect the charging demand characteristics of different time periods and different regions. In the simulation of environmental factors, the effects of random events such as weather conditions, traffic congestion, and charging equipment failure are considered, and the sequence of these random events is generated through a Markov chain model. The core parameters of the simulation platform are configured as shown in **Table 5**. The experiments were run using a multithreaded parallel computing framework on a server equipped with an Intel Xeon E5-2680 v4 processor and 128 GB of RAM (Random Access Memory), with the simulation period set to 7 days and the system sampling interval to 5 min, and more than 2000 sets of valid data samples were collected. To ensure the statistical significance of the experimental results, each group of experiments is repeated 10 times and the average value is taken as the final result.

Table 5. Parameter configuration of the simulation platform.

parameter category	Parameter name	parameter value	instructions
Scene parameters	Area size	10 km × 10 km	Urban core
	meshing	20 × 20	500 m × 500 m/grid
	Charging Demand Points	200	randomized distribution
Equipment parameters	Mobile Charging Vehicle	20 vehicles	uniform distribution
	Edge Server	30	tree topology
	communications bandwidth	100 Mbps	5G network
algorithmic parameter	learning rate	0.001	Adam Optimizer
	Batch size	64	Training batch
	training round	1000	model convergence

6.2. Performance comparison

In order to comprehensively evaluate the system performance, a multi-dimensional evaluation framework is designed to compare the proposed biomechanics-based edge intelligent scheduling scheme (BM-EI) with three mainstream benchmarking schemes: The traditional greedy algorithm (Greedy), the deep reinforcement learning scheme (DRL), and the hybrid heuristic algorithm (Hybrid). The experimental evaluation dimensions include four aspects: Scheduling efficiency, energy consumption, system reliability and computational resource utilization. In scheduling efficiency evaluation, Time-Weighted Completion Rate (TWCR) is introduced, which not only considers the completion of tasks, but also takes the urgency of tasks as a weighting factor. As shown in **Figure 6**, under high load conditions (system load > 85%), the average response time of the BM-EI scheme reduces by 23.5%, 18.7% and 15.3%, and the weighted task completion rate improves by 12.8%, 9.5% and 7.2%, respectively, compared with other schemes. An in-depth analysis of the scheduling logs reveals that this performance advantage mainly stems from three aspects: First, the biomechanical model can accurately capture the spatio-temporal dynamic characteristics of charging demand and provide more accurate demand forecasts; second, the edge computing architecture significantly reduces the system response latency so that the scheduling decisions can be adapted to the environmental changes quickly; third, the deep reinforcement learning based on the Actor-Critic architecture model has strong environmental adaptability and can maintain stable performance in dynamic scenarios.

In terms of energy consumption, a set of refined energy consumption assessment models is designed to decompose the energy consumption of the charging vehicle into three parts: Driving energy consumption, charging energy consumption and standby energy consumption. Experimental results show that the average single service energy consumption of the BM-EI scheme is 0.85 kWh, which saves 15%–25% energy consumption compared with other schemes. This energy-saving effect is mainly due to the optimization of the charging path by the biomechanical model and the intelligent power regulation mechanism. In the system reliability test, we simulate a variety of failure scenarios, including edge nodes going offline, network communication interruption and charging equipment failure. The experiment randomly takes 30% of the edge nodes offline while injecting communication delay jitter to record the system's quality of service changes. The results show that the BM-EI scheme exhibits strong fault recovery capability, with an average recovery time of only 62 s, and the quality of service degradation is controlled within 8.5%. In addition, we also evaluate the system's computational resource utilization efficiency and find that the BM-EI scheme maintains high performance while the average CPU utilization of the edge nodes is maintained at around 65%, which is significantly lower than that of other schemes, which is more than 85%. The detailed performance comparison data is shown in **Table 6**.

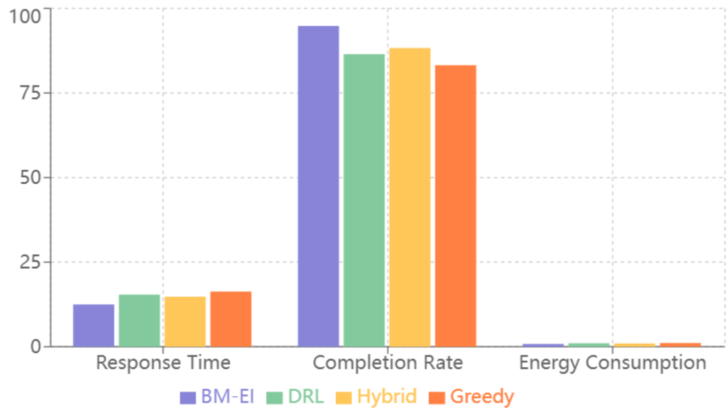

Figure 6. Comparison of scheduling efficiency.

Table 6. Performance comparison results.

Assessment of indicators	BM-EI	DRL	Greedy
Response time (min)	12.5	15.4	16.3
Completion rate (%)	94.8	86.5	83.2
Energy consumption (kWh/time)	0.85	1.02	1.13
Recovery time (s)	62	95	128
Decline in services (%)	8.5	15.3	21.7

6.3. Privacy protection analysis

For the privacy protection performance of the system, a complete security evaluation framework is constructed to design multi-level attack scenarios, including location trajectory reconstruction attack, user behavior inference attack, data tampering attack and distributed denial-of-service attack. In the location privacy protection test, three types of attackers are simulated: Passive observer, active attacker and colluding attacker. The attackers try to reconstruct the user's complete mobile trajectory by collecting part of the leaked trajectory data in the system and combining it with machine learning and trajectory mining algorithms. The experiments used a trajectory prediction model based on a graph neural network to evaluate the accuracy of trajectory reconstruction under different proportions of known trajectory data. As shown in **Figure 7**, the trajectory reconstruction accuracy is kept below 32% with the differential privacy mechanism, even if the attacker has 50% of the trajectory data, while the accuracy without the protection mechanism is as high as 78%.

In order to evaluate the impact of the protection mechanism on the system performance, a series of microbenchmark tests were designed to measure the overhead of cryptographic operations, proof generation and verification computations, respectively. The experiments were conducted on edge nodes equipped with Intel SGX security quarantine and the results are shown in **Table 7**. A single encryption operation takes an average of 12 ms, zero-knowledge proof generation takes 35 ms, verification computation takes 18 ms, and the overall latency increase is controlled within 50 ms. The computational latency is further reduced by 40% by deploying a dedicated FPGA-based cryptographic gas pedal. In terms of storage overhead, an improved Merkle tree structure is used to store the encrypted data, and by optimizing the branching factor of the tree and the node encoding scheme, the storage expansion rate is controlled at 1.2 times. In order to verify the security performance of the system in large-scale scenarios, we also conducted a concurrent security test, simulating a scenario in which 1000 concurrent users initiate charging requests at the same time. The results show that the system is able to maintain stable security performance, and the throughput of proof generation and verification reaches 200 times per second, which meets the requirements of practical applications. In addition, the performance-security tradeoff of the system under different privacy budgets (ε) is evaluated, which provides reference configurations for practical deployment.

Figure 7. Privacy protection effect analysis diagram.

Table 7. Safety performance test results.

Test items	Encryption delay (ms)	Storage overhead (times)	CPU utilization (%)
data encryption	12	1.2	5
Proof generation	35	1.1	8
verification calculation	18	1.0	6
Overall expenses	50	1.2	15

7. Conclusion

In this study, a smart scheduling framework integrating edge computing, biomechanical modeling and privacy protection is proposed around the mobile charging scheduling and privacy protection problem, and its effectiveness is verified through simulation experiments. The study shows that the biomechanics-based charging demand modeling method can accurately portray the spatio-temporal dynamic distribution characteristics and effectively optimize the charging path and resource allocation. The scheduling mechanism based on edge intelligence reduces the scheduling response delay and improves the adaptability and fault tolerance of the system. Experimental results show that the scheme outperforms traditional methods in terms of scheduling efficiency, energy consumption optimization, privacy protection, and exhibits better service stability under high load conditions. However, while the simulation results are promising, it is essential to consider the challenges associated with implementing this approach in real-world environments. Several factors could potentially hinder the practical deployment of the proposed system. First, the accuracy of the biomechanical modeling relies heavily on data calibration, which may not always be available or accurate in real-world scenarios. The real-time data required for such modeling could face delays or inaccuracies due to environmental factors, such as traffic congestion, network instability, and unpredictable user behavior. These issues could reduce the effectiveness of the scheduling optimization and energy consumption model. Second, the edge computing architecture proposed in this paper, while effective in reducing latency, may still face scalability challenges in very large-scale networks. The distributed edge nodes must handle a significant amount of data and computations, which could result in bottlenecks, especially under high concurrency. This may require more advanced hardware solutions, such as high-performance edge servers or a more optimized network topology, which would increase the system's overall complexity and cost. Lastly, the proposed multi-level privacy protection mechanisms, while providing robust data security, could introduce significant computational overhead. The encryption techniques, particularly homomorphic encryption and zero-knowledge proofs, are computationally intensive, which may affect the system's performance in real-time environments. Balancing privacy protection and computational efficiency remains a challenging trade-off that needs to be carefully managed. In conclusion, while the proposed system demonstrates substantial advantages in simulations, further research is needed to address these implementation challenges, particularly regarding data accuracy, system scalability, and privacy-efficiency balance, in order to ensure its successful deployment in real-world mobile charging networks.

Despite the progress made in the study, there are still some limitations. First, the parameter settings for biomechanical modeling rely on a large amount of experimental data, which may require further optimization for actual deployment. Second, the performance of edge computing architectures is limited by hardware resources and may face computational bottlenecks in ultra-large-scale network environments. In addition, the adaptability of the privacy protection mechanism under extreme attack scenarios still needs to be further evaluated to ensure the long-term security of the system.

Future research will focus on the adaptive nature of intelligent scheduling, exploring more efficient online learning algorithms to dynamically adapt to changes in charging demand in different environments. At the same time, for large-scale mobile charging networks, we will optimize the collaborative scheduling mechanism of edge computing nodes to improve the computational efficiency of the system in high concurrency scenarios. In addition, a more traceable scheduling record system is constructed with blockchain technology to provide higher security and transparency for charging services.

Author contributions: Conceptualization, YZ and PL; methodology, YZ; software, ZY; validation, YZ and PL; formal analysis, YZ; investigation, YZ; resources, YZ; data curation, YZ; writing—original draft preparation, YZ; writing—review and editing, YZ; visualization, YZ; supervision, YZ; project administration, YZ; funding

acquisition, PL. All authors have read and agreed to the published version of the manuscript.

Ethical approval: Not applicable.

Conflict of interest: The authors declare no conflict of interest.

References

1. Fan H, Cao X, Zhao X, et al. Edge computing and thermal radiation sensing image motion perception application in badminton biomechanics analysis. Thermal Science and Engineering Progress. 2025; 57: 103198.
2. Shreenivas B, Muddana A. Optimal Resource Allocation in Mobile Edge Computing using Reinforcement Learning Approach. In: Proceedings of the 2024 IEEE International Conference on Interdisciplinary Approaches in Technology and Management for Social Innovation (IATMSI); 14–16 March 2024; Gwalior, India. pp. 1–6.
3. Aymen F, Alowaidi M, Bajaj M, et al. Electric vehicle model based on multiple recharge system and a particular traction motor conception. IEEE Access. 2021; 9: 49308–49324.
4. Lu M, Fu G, Osman NB, et al. Green energy harvesting strategies on edge-based urban computing in sustainable internet of things. Sustainable Cities and Society. 2021; 75: 103349.
5. Saatloo AM, Mehrabi A, Marzband M, et al. Hierarchical user-driven trajectory planning and charging scheduling of autonomous electric vehicles. IEEE Transactions on Transportation Electrification. 2022; 9(1): 1736–1749.
6. Chen J, Yi C, Wang R, et al. Learning aided joint sensor activation and mobile charging vehicle scheduling for energy-efficient WRSN-based industrial IoT. IEEE Transactions on Vehicular Technology. 2022; 72(4): 5064–5078.
7. Qureshi U, Ghosh A, Panigrahi BK. Scheduling and routing of mobile charging stations with stochastic travel times to service heterogeneous spatiotemporal electric vehicle charging requests with time windows. IEEE Transactions on Industry Applications. 2022; 58(5): 6546–6556.
8. Zhao F, Chen Y, Zhang Y, et al. Dynamic offloading and resource scheduling for mobile-edge computing with energy harvesting devices. IEEE Transactions on Network and Service Management. 2021; 18(2): 2154–2165.
9. Hu H, Zhou X, Wang Q, et al. Online computation offloading and trajectory scheduling for UAV-enabled wireless powered mobile edge computing. China Communications. 2022; 19(4): 257–273.
10. Wang X, Ning Z, Guo L, et al. Online learning for distributed computation offloading in wireless powered mobile edge computing networks. IEEE Transactions on Parallel and Distributed Systems. 2021; 33(8): 1841–1855.
11. Li Y, Dai W, Gan X, et al. Cooperative service placement and scheduling in edge clouds: A deadline-driven approach. IEEE Transactions on Mobile Computing. 2021; 21(10): 3519–3535.
12. Chen Q, Guo S, Xu W, et al. AoI minimization charging at wireless-powered network edge. In: Proceedings of the 2022 IEEE 42nd International Conference on Distributed Computing Systems (ICDCS); 10–13 July 2022; Bologna, Italy. pp. 713–723.
13. Balasubramaniam S, Syed MH, More NS, et al. Deep learning-based power prediction aware charge scheduling approach in cloud based electric vehicular network. Engineering Applications of Artificial Intelligence. 2023; 121: 105869.
14. Li M, Gao J, Zhao L, et al. Adaptive computing scheduling for edge-assisted autonomous driving. IEEE Transactions on Vehicular Technology. 2021; 70(6): 5318–5331.
15. He J, Yan N, Zhang J, et al. Battery electric buses charging schedule optimization considering time-of-use electricity price. Journal of Intelligent and Connected Vehicles. 2022; 5(3): 138–145.