Reinforcement Learning-Based Multiple Constraint Electric Vehicle Charging Service Scheduling

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The popularization of electric vehicles faces problems such as difficulty in charging, difficulty in selecting fast charging locations, and comprehensive consideration of multiple factors and vehicle interactions. With the increasingly mature application of navigation technology in vehicle-road coordination and other aspects, the proposal of an optimal dynamic charging method for electric fleets based on adaptive learning makes it possible for edge computing to process electric fleets to effectively execute the optimal route charging plan. We propose a method of electric vehicle charging service scheduling based on reinforcement learning. First, an intelligent transportation system is proposed, and on this basis a framework for the interaction between fast charging stations and electric vehicles is established. Subsequently, a dynamic travel time model for traffic sections was established. Based on the habits of electric vehicle owners, an electric vehicle charging navigation model and a reinforcement learning reward model were proposed. Finally, an electric vehicle charging navigation scheduling method is proposed to optimize the service resources of the fast charging stations in the area. The simulation results show that the method balances the charging load between stations, can effectively improve the charging efficiency of electric vehicles, and increases user satisfaction.

1. Introduction

With the extensive development of electric vehicles in various countries around the world, the number of electric vehicles is increasing, and problems such as difficulty in charging electric vehicles, serious line losses, voltage drops, charging safety, and severe peaks are expected [1–3]. Electric vehicle charging and charging path planning should receive more attention. For electric vehicles whose driving time is longer than the nondriving time, fast charging is an important power supplement method [4, 5]. The disorderly charging of electric vehicles would not only cause congestion of fast charging stations, which increases the burden on the regional grid, but also result in concentrated charging times causing problems such as transformer overload and increased peak-to-valley difference, which is not conducive to the safe operation of the distribution network [6, 7]. Therefore, reasonable guidance and charging scheduling for vehicles with fast charging needs are beneficial to the alleviation of the burden on the regional grid while meeting the charging needs [8, 9].

In response to the above problems, scholars at home and abroad have conducted some research. In [10], we studied the uniform charging node in [11] and extended it to the nonuniform charging node in [12] by solving the mixed integer nonlinear programming problem (MINLP) of the single vehicle. The remaining energy of the vehicle on each node is expressed as a dynamic programming (DP) problem for a single electric vehicle path problem, and a DP-based algorithm is provided to determine the optimal path and charging strategy of the electric vehicle subflow level. In [13], we proposed a distributed electric vehicle path selection system based on the distributed ant colony algorithm (ACA). The distributed architecture minimizes the total travel of electric vehicles to the destination by proposing a set of nearest fast charging stations. In [14], we proposed an improved Dijkstra method to solve the multiobjective optimization problem and obtained a multiobjective
optimization function including travel time, fast charging
station number of vehicles, and charging load, thereby
optimizing electric vehicle charging path planning and al-
leviating fast charging stations. The lack of surrounding
traffic congestion reduces waiting time and improves the
availability of charging facilities.

The above literature has its own characteristics regarding
charging route navigation and charging scheduling, but
when studying electric vehicle charging route navigation, it
only focuses on the economic benefits and waiting time of
the vehicle and ignores the impact of fast charging station
loads when charging large-scale electric vehicles. Most
charging scheduling uses a fixed strategy while ignoring
the influence of various factors, such as the increase in the
number of electric vehicles and user habits, on electric
vehicle charging scheduling for different time periods.

In this context, we propose an electric vehicle charging
service scheduling method based on reinforcement learning
to meet the needs of electric vehicle owners. The structure of
the paper is as follows. In Section 2, we propose a fast
charging station and electric vehicle system framework and
use this framework to study electric vehicle charging nav-
gination. In Section 3, we establish a dynamic travel time
model for traffic sections and propose an electric vehicle
charging navigation model. In Section 4, incorporating
reinforcement learning, we further propose an electric ve-
cicle charging navigation scheduling method to rationally
optimize the service resources of each fast charging station
in the area. In Section 5, we use a certain city as a model and
compare the simulation results of the proposed method with
those of the traditional electric vehicle charging navigation
method to demonstrate the superiority of this method.
Conclusions and further research directions are outlined in
Section 6.

2. Fast Charging Station and Electric Vehicle
System Framework

With the gradual development and application of 4G and 5G
communications, the applications of various technologies
for navigation and vehicle-road collaboration have become
increasingly mature [15, 16]. At the same time, edge com-
puting technology also provides technical guarantees for fast
response and low error rate operating environments. The
computational burden of the central scheduling node is
transferred to the user edge side, which greatly increases the
processing efficiency and enables electric vehicles and fast
charging stations to share information and synchronize
processing [17].

Currently, electric vehicles can share information with
fast charging stations and other systems through the In-
ternet, upload the status and location of electric vehicles in
real time, and navigate in real time based on the location of
electric vehicles [18, 19]. Moreover, a variety of optimal
dynamic charging methods for electric fleets based on
adaptive learning have been proposed, and the results show
that this method can basically achieve the optimal solution.
On this basis, the optimal route charging schedule can be
effectively carried out for the electric fleet of efficient and
dynamic transportation systems. Inspired by the above re-
search, this paper proposes a guidance system structure for
electric vehicles and fast charging stations. The structure of
the guidance system for electric vehicles and fast charging
stations in this article is shown in Figure 1. With the Internet
platform as the center, the system dynamically updates
intersection information and provides dynamic charging
and navigation strategies for electric vehicles by referring to
road condition information and fast charging station in-
formation. Navigation combines the road condition infor-
mation and the waiting time of each fast charging station
and chooses the fast charging station with the highest overall
efficiency for itself to charge. The fast charging station itself
further charges the electric vehicle according to various
factors, such as weather, energy supply and demand, and
user habits. At intervals, the traffic information and fast
charging station information are refreshed according to the
above selection, and the charging navigation strategy is
provided again.

3. Preliminary Model Establishment

This section first proposes a dynamic travel time model for
traffic sections and, on this basis, establishes a charging
navigation model that considers distance, time, and eco-

3.1. Dynamic Travel Time Model of Traffic Section. The
dynamic path selection model for electric vehicles in this paper
is based on the dynamic travel time model of the road
segment. First, the movement of the vehicle in the road
segment is described by the cumulative number of vehicles
$M(a, t)$, which represents the sum of the number of vehicles
passing observation point $a$ before time $t$. According to the
definition of flow and density, the traffic flow $\sigma(a, t)$ and
traffic density $\rho(a, t)$ are as follows:

$$\sigma(a, t) = \lim_{t \to a_0} \left( \frac{M(a, t) - M(a, t_0)}{t - t_0} \right) = \frac{\partial M(a, t)}{\partial t},$$

$$\rho(a, t) = \lim_{a \to a_0} \left( \frac{M(a_0, t) - M(a, t)}{a - a_0} \right) = \frac{\partial M(a, t)}{\partial a},$$

where $M(a, t_0)$ and $M(a_0, t)$ are the number of vehicles at
different positions at time $t_0$ and the number of vehicles at position
$a_0$ at time $t$, respectively.

According to the traffic volume and traffic density, the traffic
velocity $v(a, t)$ can be obtained as follows:

$$v(a, t) = \frac{\sigma(a, t)}{\rho(a, t)} = \frac{\partial M(a, t)}{\partial t} \cdot \frac{\partial a}{\partial M(a, t)}.$$

Assuming that the vehicles on the road section are evenly
distributed in the road section, the traffic density $\rho_i(t)$ of
road section $i$ is as follows:

$$\rho_i(t) = \frac{M(a^0_i, t) - M(a^l_i, t)}{L_i \cdot n_i},$$
where \( a_i^0 \) and \( a_i^f \) are the entrance and exit positions of road section \( i \), respectively; \( n_i \) is the number of vehicles that can be accommodated per unit length in road section \( i \); and \( L_i \) is the length of road section \( i \).

According to the above formula, the vehicle speed \( v_i(t) \) on road section \( i \) can be expressed as follows [20]:

\[
v_i(t) = \begin{cases} 
    v_{i,\text{free}}, & \rho_i(t) < \rho_i,\text{min}, \\
    v_{i,\text{min}} + (v_{i,\text{free}} - v_{i,\text{min}}) \left[ 1 - \frac{\rho_i(t) - \rho_i,\text{min}}{\rho_i,\text{max} - \rho_i,\text{min}} \right]^{\alpha - 1}, & \rho_i,\text{min} \leq \rho_i(t) \leq \rho_i,\text{max}, \\
    v_{i,\text{min}}^{\beta - 1}, & \rho_i(t) > \rho_i,\text{max},
\end{cases}
\]

(4)

where \( v_{i,\text{free}} \) is the free flow velocity of section \( i \); \( \rho_i,\text{max} \) and \( \rho_i,\text{min} \) are the maximum density and minimum density on section \( i \), respectively; \( v_{i,\text{min}} \) is the minimum vehicle speed; and \( \alpha \) and \( \beta \) are system model parameters.

It can be concluded that the passing time \( T_i \) of road section \( i \) is expressed as follows:

\[
T_i = \frac{L_i}{v_i(t)} = \frac{L_i}{\frac{\partial M(a, t)}{\partial t} \cdot (\partial a/\partial M(a, t))}
\]

(5)

If the road congestion signal is received halfway, the system changes the route to reduce the delay time. The subjective probability of the owner changing road section \( i \) to road section \( i' \) is \( P_{i \rightarrow i'} \):

\[
P_{i \rightarrow i'} = \int_{T_i}^{T_i,\text{max}} e^{-\left(\frac{(T_i,\text{max} - T_i)^2}{2(\eta)^2}\right)} d(T_{\text{Max}}),
\]

(6)

where \( T_i \) is the travel time of section \( i \) in the route; \( T_i,\text{max} \) is the travel time of section \( i' \) in the route; \( T_{\text{Max}} \) is the maximum travel time; and \( \eta \) is a subjective coefficient.

Therefore, the length of the driving section can be approximated by subjective probability as \( d_i \):

\[
d_i = (1 - P_{i \rightarrow i'}) L_i + P_{i \rightarrow i'} L_{i'}
\]

\[
= 1 - \int_0^{T_i} e^{-\left(\frac{(T_{\text{Max}} - T_i)^2}{2(\eta)^2}\right)} d(T_{\text{Max}}), L_i + \int_0^{T_i} e^{-\left(\frac{(T_{\text{Max}} - T_i)^2}{2(\eta)^2}\right)} d(T_{\text{Max}}), L_{i'},
\]

where \( L_{i'} \) is the length of road section \( i' \).

3.2. Electric Vehicle Charging Navigation Model. Electric vehicles need to be charged frequently during use, so there will be demand for fast charging. According to the charging needs of different vehicles, implementing different navigation schemes can effectively improve the response speed of the vehicle. This section comprehensively considers the driving distance required to reach a fast charging station, the total time of driving and charging, and the charging economy to establish a charging navigation model.
For electric vehicle owners with high total driving distance requirements, this article considers the principle that the direction of the fast charging station is the same as the destination direction when all vehicles are connected to the Internet. It is proposed that the sum of the shortest distance \( D \) from the starting point \( O \) of the vehicle to the fast charging station \( S \) and from the fast charging station \( S \) to the destination \( D \) is expressed as follows:

\[
\min D = \sum_{a=1}^{m} \sum_{b=1}^{m} d_{ab,OX}a_{ab} + \sum_{a=1}^{m} \sum_{b=1}^{m} d_{ab,SD}a_{ab},
\]

where \( a \) and \( b \) are path nodes; \( m \) is the total number of path nodes; \( d_{ab,OX} \) and \( d_{ab,SD} \) are the length of the road section from the starting point \( O \) to the fast charging station \( S \) and from the fast charging station \( S \) to the destination \( D \) with \( a \) and \( b \) as the end nodes; and \( a_{ab} \) is a variable that equals 1 for the road section with \( a \) and \( b \) as the end nodes and equals 0 otherwise.

For electric vehicle owners with high total time requirements, this article proposes the shortest total charging time as the goal to optimize the charging path:

\[
\min T = T_D + T_C + T_Q.
\]

The specific solutions of \( T_D \) and \( T_C \) are as follows:

\[
T_D = \sum_{i=1}^{\text{path}} \frac{d_i}{v_i(t)}
\]

\[
= \sum_{i=1}^{\text{path}} \frac{(1 - P_{i-1}T_i) L_i + P_{i-1}T_i L_i}{v_i(t)}
\]

\[
= \sum_{i=1}^{\text{path}} \frac{(1 - P_{i-1}T_i) L_i + P_{i-1}T_i L_i}{(\partial M(a, t)/\partial t) \cdot (\partial i/\partial M(a, t))}
\]

\[
T_c = \frac{Q_{Ex} - Q_{Re}}{P\theta}
\]

\[
= \frac{Q_{Ex} - \left(C_{car} \cdot C_{carIN1} \cdot Q \int_0^{T_p} v_i(t)dt\right)}{P \cdot \theta},
\]

where \( T_D \) is the travel time to the fast charging station; \( T_Q \) is the waiting time in the fast charging station, which is determined by the number of vehicles; \( T_C \) is the charging time; \( Q_{Ex} \) is the expected voltage at the end of charging, which is set to 95% of the full charge; \( Q_{Re} \) is the remaining power to the fast charging station; \( P \) is the charger power; \( \theta \) is the charging efficiency; \( C_{car} \) is the electric vehicle battery capacity; \( C_{carIN1} \) is the initial state of charge of the electric vehicle; and \( Q \) is the electric energy consumed by the electric vehicle per kilometer.

For electric vehicle owners with high cost requirements, this article proposes the minimum cost as the goal to optimize the charging path:

\[
\min M = M_D + M_S,
\]

where \( M_D \) is the electricity cost consumed on the charging path and \( M_S \) is the cost consumed by the fast charging station.

4. Electric Vehicle Charging Navigation Scheduling Strategy Based on Reinforcement Learning

The goal of the reinforcement learning algorithm is to find an optimal strategy based on the Markov decision process to maximize the expected cumulative return. In this section, the driving distance of the electric vehicle, the total driving and charging time, and the charging economy are optimized in parallel to provide the electric vehicle owner with the best electric vehicle charging navigation scheduling strategy [21, 22].

4.1. Strategy Gradient Algorithm. The basic principle of reinforcement learning is to learn from exploratory experiments and obtain action strategies to achieve established goals. The learning subject is the agent; the object interacting with the agent is the environment. Reinforcement learning is an abstraction of goal-oriented interactive learning problems. In a certain environment state, the agent takes action, and the environment responds to the agent’s actions, presents the new environment state to the agent, and feeds a certain reward back to the agent. The agent and the environment continue to interact to achieve the ultimate goal of maximizing returns.

The interaction process between the agent and the environment can be described by a time series: in a certain period \( t \), the agent takes a certain action \( a \) according to the current environment state \( s^n_t \); in the next period \( t + 1 \), due to the agent’s action \( a^n_t \), the environment state changes from \( s^n_t \) to \( s^n_{t+1} \), and the agent is rewarded with \( r(t) \). In each time period, the probability distribution of all actions that the agent can take in the current environment state is called the agent’s strategy \( \pi \). The agent continuously changes its strategy through interaction and finally achieves the goal of maximizing rewards.

The reinforcement learning problem satisfies the Markov characteristic; that is, the state of the next period is only related to the state \( s^n_t \) of the current period and has nothing to do with the state \( s^n_{t-1} \) of the previous period. The policy-based method is used to express a policy. Assuming that the strategy of electric vehicle charging and navigation control consists of a \( t \)-step decision, the agent obtains \( n \) corresponding training trajectories \( T_n \) by interacting with the environment as follows:

\[
\tau_n = [s^n_1, r(1)^n, a^n_1, s^n_2, r(2)^n, a^n_2, \ldots, s^n_n, r(t)^n, a^n_t],
\]

where \( a^n_t \) represents the action determined at time \( t \) during the \( n \) training, \( s^n_t \) represents the state after action \( a \) during the \( n \) training, and \( r(t)^n \) represents the reward obtained after action \( a \) during the \( n \) training. The expected return reward \( \rho_n \) for all stored trajectories is as follows:
where $R(\tau_n) = \sum_{t=0}^{T} r(t)^n$ is the reward value of trajectory $\tau_n$, $p_\theta(\tau_n)$ is the probability of trajectory $\tau_n$, $p(r(t + 1)^n, s_{n+1}^t, f_{n+1}^t, a_{n+1}^t)$ is the probability of actions at each intersection. The value range is $\mathbb{R}$, and the dimension is 3. Among them, $D_t^n, T_t^n$, and $M_t^n$ correspond to the distance, time, and cost, respectively, after the current action is executed. After obtaining the environmental state value, the corresponding reward value is calculated, and at the same time, the environment will move to the next state.

### 4.4. Reward Function Design

The reward function is designed as follows:

$$
\text{reward} = -a \cdot (D_t^n - \min D)^2 - b \cdot (T_t^n - \min T)^2 - c \cdot (M_t^n - \min M)^2,
$$

where reward represents the reward value obtained by the action performed by the electric vehicle at each time node, that is, the quality of the current trajectory $\tau_n$ action.
Among them, \( a, b, \) and \( c \) are the weighting coefficients: when the owner only cares about the distance, \( a \) equals 1, and the rest equal 0; when the owner only cares about the total time, \( b \) equals 1, and the rest equal 0; when the owner only cares about the cost, \( c \) equals 1, and the rest equal 0; and if the owner chooses to focus on all three variables, set \( a + b + c = 1 \), and assign values according to the proportion.

4.5. Controller. For electric vehicle charging navigation, a scheduling algorithm based on the policy gradient algorithm is proposed according to the personal habits of different electric vehicle owners. By observing the information to select a behavior directly for back propagation and using rewards to directly enhance and weaken the possibility of selection behavior, the probability of selecting good behavior will increase next time, and bad behavior will be weakened next time.

A three-layer wavelet neural network is used. The wavelet neural network is a multilayer feedforward neural network trained according to error back propagation [23]. This article uses a three-layer neural network, that is, one input layer, one input layer, and one hidden layer, as shown in Figure 2. The state is set as the input layer of the neural network. Its dimension is 3; the hidden layer of the neural network has 20 neurons; and the output layer contains 3 neurons, corresponding to 3 output actions.

The connection weights and bias terms between the input layer and the hidden layer and between the hidden layer and the output layer are represented by a parameter set of \( \theta \). The input and output strategies of the \( n \) training wavelet neural network of the strategy body are defined as \( \pi_n(\theta) \).

The activation function of the connection between the input layer and the hidden layer is \( \tan h, \) and its function formula is as follows:

\[
f(z) = \tan h(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}.
\]  

The activation function connecting the hidden layer and the output layer is a wavelet basis function, and its function formula is as follows:

\[
\zeta(z) = e^{-(z^2/2)} \cos(1.75z).
\]  

According to the pseudocode of the algorithm, the specific training process can be obtained as shown in Figure 3.

5. Simulation Results and Discussion

Taking the city in Figure 4 as a model, the city includes 21 nodes, 32 road sections, and 4 fast charging stations. The number marked on the road section represents the length of the road section in km. Fast charging stations are located at nodes 9, 12, 14, and 19. For electric vehicles, the battery capacity is 90 kWh, the cruising range is 400 km, and the fast charging station power is 350 kW. When the electric vehicle leaves the fast charging station, \( C_{\text{carIN}} \) is 90%; the training parameters are as follows: the number of training rounds is 1900, and the learning coefficient is 0.95. The discount rate is 0.95.

The vehicle randomly sets the initial position and target position (on 21 nodes) and randomly sets the remaining power (not higher than 30%). According to the distance selected by the user, the total time consumed, and the cost as the reward value, the vehicle is trained from the initial position to the fast charging station to charge and from the fast charging station to the target location. After the training is completed, the final reward changes are shown in Figure 5.

Figure 5 shows that as the number of training sessions increases, the training reward gradually increases. After 600 training sessions, the curve shows an oscillating trend, and the reward oscillates around 190. In the subsequent training, the reward is basically stable. Save the neural network model obtained from the last training parameter.

The 08:00 traffic flow distribution obtained through urban traffic simulation is shown in Figure 6. The green line represents smooth traffic, orange represents traffic congestion, and red represents heavy traffic congestion. For the traffic flow shown in Figure 6, the saved reinforcement learning model is used to obtain the station selection probability of the electric vehicle when each network node starts, as shown in Figure 7. It can be concluded that under the premise of considering congestion, the trained reinforcement learning model can effectively select fast charging
stations corresponding to shorter distances according to the target node.

Now, take an electric vehicle starting at node 13 and ending at node 2 as an example to analyze its dynamic station selection strategy. Consider the distance, total time, and cost required for the owner to obtain charging navigation during driving, as shown in Table 1.

Plan 1 takes the minimum distance as the goal and chooses fast charging station No. 9, and the travel route is shown as the solid line in Figure 8. Plan 2 takes the minimum time as the goal and chooses fast charging station No. 14, and the travel route is shown by the dashed line in Figure 8. Plan 3 takes the minimum cost as the goal and chooses No. 12 fast charging station, and the travel route is shown as the crossed line in Figure 8.

Multiple routes were selected for testing, and methods from [10, 13] and the charging navigation method proposed in this paper were compared. The performance comparisons under the comprehensive requirements of the research vehicle owners are shown in Figure 9.

The first graph in Figure 9 shows the change trend of the average distance with the increase in the number of test routes under the premise of considering the comprehensive performance required by the user. In this graph, the comparison between the method in this paper and the methods in the other two references is shown. With the increase in the number of routes, the average travel distance of the three methods fluctuated and finally stabilized in the vicinity of 17 km. In this process, the total distance predicted by the three methods is basically the same. The second graph in Figure 9 shows the trend of the total time as the number of test routes increases. As the number of routes increases, the total time of the method in this paper steadily decreases, and finally the time is reduced to 0.7 h, while for the other two methods, the total time consumed curve presents an oscillating situation, and the time consumed is unstable and greater than that for the method in this paper. It can be concluded from the curve that the method in this paper has the least total time consumption. The third graph in Figure 9 shows the trend of the total cost as the number of test routes increases. With the increase in the number of routes, the total cost of the method in this paper first increases, then gradually decreases, and finally stabilizes at approximately 30 yuan. For the method from [10], the total cost of the method was initially lower than that of the method in this paper. With the increase in the number of test routes, the cost began to increase and eventually was significantly higher than that of the method in this paper. The cost for the method in [13] remained higher than the cost for the method in this paper after initially oscillating lower. It can be concluded that, under the comprehensive performance requirements, the total distances of the three methods are basically the same. On this basis, with the increase in the number of route tests, the method in this paper has the least total time and cost, which indicates the superiority of the method in this paper.
In the case of the same time, initial point, and destination, we compare user satisfaction under the electric vehicle charging navigation strategy in [10, 13, 24–26]. The user satisfaction from testing electric vehicles using these methods is shown in Table 2. It can be seen in the table that, with the increase of test lines, user satisfaction under this
Figure 7: Probability of selecting a fast charging station node.

Table 1: Scheme comparison.

| Plan | Distance (km) | Total time (h) | Expenses (yuan) | Station selection |
|------|---------------|----------------|-----------------|-------------------|
| 1    | 11            | 1.5            | 76              | 9                 |
| 2    | 11            | 1              | 84              | 14                |
| 3    | 15            | 1.8            | 60              | 12                |

Figure 8: Route selection chart.
Figure 9: Distance, time, and cost comparison chart.

Table 2: User satisfaction for electric vehicle charging navigation strategies.

| Number of routes | This article (%) | [10] (%) | [13] (%) | [24] (%) | [25] (%) | [26] (%) |
|------------------|------------------|----------|----------|----------|----------|----------|
| 1                | 100              | 100      | 100      | 100      | 100      | 100      |
| 10               | 100              | 95       | 80       | 90       | 90       | 70       |
| 100              | 95               | 80       | 70       | 90       | 80       | 75       |
| 1000             | 90               | 75       | 75       | 85       | 75       | 55       |
method far exceeds other methods. It has been demonstrated that the method in the article can effectively meet the charging and navigation needs of users.

6. Conclusions

We propose an electric vehicle charging service scheduling method based on reinforcement learning to meet the needs of electric vehicle owners. First, based on an intelligent transportation system, a framework for the interaction between fast charging stations and electric vehicles is proposed. Subsequently, the dynamic travel time model of the traffic section was established, and the electric vehicle charging navigation model was proposed. Finally, combined with reinforcement learning, the electric vehicle charging navigation scheduling method is further proposed to rationally optimize the service resources of each fast charging station in the area. The results show that, compared with the existing methods, the algorithm and model proposed in this paper can effectively optimize electric vehicle charging and navigation scheduling based on the needs of the vehicle owner and can meet the various needs of the vehicle owner.

Data Availability

The MATLAB simulation data used to support the findings of this study are currently under embargo while the research findings are commercialized. Requests for data, 12 months after publication of this article, will be considered by the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this study.

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