Research Article

Ant Colony Optimized Routing Strategy for Electric Vehicles

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Electric vehicles (EVs) have recently attracted increasing research interest, on account of environmental issues and diminishing fuel reserves. EVs are environmentally friendly but have a short driving range. EVs must utilize energy efficiently, because they travel with limited energy. Conventional vehicle routing methods are not suitable for EVs, as they do not take energy consumption into account. This study introduces an energy efficient routing method using ant colony optimization (ER-ACO) to maximize the energy efficiency. We simulated ER-ACO and compared it with other ACO techniques, including the conventional routing method and other approaches for EVs. As a result, the proposed model improved the energy efficiency in terms of both the average distance per kW and average energy consumption.

1. Introduction

Presently, research on electric vehicles (EVs) is necessary owing to the situation of diminishing fossil fuels and climate change. There are three main types of EV [1]. The first is a hybrid vehicle (HEV), which employs a combination of electricity and fossil fuels. The second is a plug-in hybrid vehicle (P- HEV), which employs electrical power for short distances and fossil fuels for long distances. Finally, there are electric vehicles that utilize electrical energy exclusively.

EVs have three main advantages compared with conventional vehicles. First, EVs are better for the environment, as they obtain their motive power from rechargeable batteries. This means that they function as a clean source of energy. Thus, toxic gases and fumes are not emitted, which reduces CO_2 emissions [2]. Second, EVs introduce a cost-saving effect, as electrical energy is cheaper than traditional fuels such as petrol and diesel. Moreover, the mechanical structure of an EV is simpler than that of a conventional car, and so it is cheaper to maintain. Finally, EVs reduce noise pollution, and electric motors provide a softer driving experience for drivers.

Vehicle routing is to determine a traveling route of a vehicle geographically. Usually, it is defined as an optimization problem to minimize total travel time and distance. However,

EV is powered by battery which still asks long charging time, and it has the short driving range due to the limit of battery capacity [3]. Thus, for EVs routing, it needs to consider not only travel time and distance traditionally, but also energy consumption. The battery can be drained more or can be charged according to the gradients of driving roads. EV consumes less energy or even charges the battery on downhill roads, but more energy is needed on uphill roads. Therefore, EV requires its own routing method with consideration of its characteristics. In addition, considering the limited capacity of battery, it is important that EV reaches its destination using the minimum amount of energy.

Many studies focus on the energy consumption, cost, and travel time in connection with EV routing. However, the unique characteristic of an EV is its energy recuperation function. Recuperation energy is energy generated while traveling downhill or during braking, which is utilized to recharge a vehicle's battery. This study proposes an approach considering recuperation for EV routing.

Various parameters are applicable for the routing of EVs, such as the travel distance, time, cost of driving, and state of charge (SoC). There are two important characteristics of EV routing to consider. First, there is diversity because different parameters need to be controlled. In addition, there is uncertainty owing to environmental factors, such as human

driving, pedestrians, and road conditions. Therefore, many researchers have tackled EV routing using AI techniques. We propose a routing method using ant colony optimization (ACO).

The remainder of this paper is organized as follows. Section 2 introduces related work concerning EV routing. Section 3 presents the system model and proposed strategy using ACO. Section 4 presents and discusses the simulation results. Finally, Section 5 summarizes the study.

2. Related Work

In this section, we discuss routing methods divided into two main categories: routing methods only and combinations of routing and charging methods. A routing method aims to reach the destination without charging, while a combination method includes charging while driving. There have been many studies related to EV routing that have utilized several AI techniques, such as Tabu search [4], particle swarm optimization (PSO) [5], A* [6], and ACO [7, 8].

Abousleiman and Rawashdeh proposed a strategy to determine the most energy efficient route [4]. They utilized four parameters: elevation changes, battery capacity, road cost, and traffic information. Tabu search is a flexible heuristic method, which was adopted because there were very few constraints. However, it is difficult to obtain a global optimization result, because this approach searches in a direction in which the slope of the road decreases. Siddiqi et al. proposed a model that utilizes PSO techniques to determine optimized paths [5]. The authors suggested minimizing the distance by taking into account the travel time, delay time, charging time, and charging cost. PSO has the advantage of an optimization ability for complex functions. Although it achieves relatively fast convergence, it can suffer from early nonoptimal convergence. Furthermore, this study did not take into account the energy recuperation function for EVs. Sachenbacher et al. proposed a model for determining the optimal energy path using the A* algorithm [6] and also considered the recuperation energy. However, the authors did not take into account various factors such as the travel time, cost, and traffic congestion, which are important measures for vehicles.

Hooda and Kumar considered driving costs, including the travel distance from source to destination, toll fee, and battery charging cost, using ACO [7]. To calculate the probability function, the authors utilized heuristic information that contained location information between each city. Zhang et al. considered five parameters: the travel distance, travel time, temperature, battery life, and energy consumption [8]. They not only considered driving, but also the driving environment. For example, the use of air conditioning functions depends on the temperature inside and outside of a vehicle. The temperature was set as a parameter, because air conditioners consume energy. [8] defined four conversion probability functions, which consisted of two air conditioners, a charging function, and a speed function. These were chosen using the roulette wheel selection technique with heuristic information, which employs the Euclidean distance between the next node and destination.
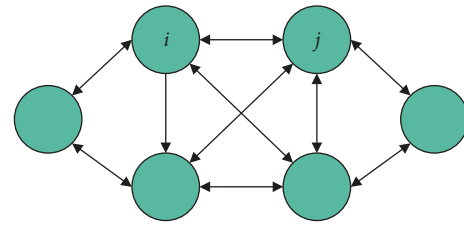

FIGURE 1: A graph representation of a network.

Studies that combine routing techniques with charging techniques, such as charging stations, are summarized as follows [9–11]. Sweda and Klabjan aimed to determine the minimum cost path when EVs need to recharge their batteries [9]. Two solutions were proposed: dynamic programming and reverse recursion techniques. In that study, the driving costs, including charging costs, were considered to minimize the driving time. Zhang et al. proposed a mathematical model that considered three parameters: the travel distance, travel time, and electricity charging cost [10]. In that study the source node, middle node, and destination node were specified. Tang et al. studied a joint optimization approach for routing and charging to maximize the consumer profit [11]. The authors proposed a distributed algorithm, which reduces the complexity of computation. In addition, they considered two types of charging station for various situations.

As discussed above, many studies have attempted to solve the EV routing problem using AI techniques. Among the available AI techniques, there are advantages to ACO. First of all, the ACO technique converges quickly. In addition, it does not select the next step using only the previous information. It selects the next step in a probabilistic manner, which can navigate various paths. Many studies have solved the EV routing using energy cost, travel distance and travel time. However, to reduce the energy cost for EV with a limited driving range, minimizing energy consumption is the most important. Energy consumption is affected by energy recuperation and driving speed. By considering recuperation in the routing, energy can be drained slowly. The driving speed also affects the energy drain speed as well as traveling time. Thus, we propose an energy efficient routing strategy utilizing ACO and considering recuperation and speed.

3. Methodology

A network can be expressed as a weighted directed graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of nodes and $\mathcal{E}$ is the set of arcs connecting the nodes, as illustrated in Figure 1.

EVs travel along the arcs from the source node to the destination node. Each arc sets the Euclidean distance as a cost.

3.1. System Model. Unlike conventional vehicle routing models, which assume that the energy consumption is a linear function of the travel distance and time, we modeled the energy consumption by considering the speed and the gradient of the road. The energy consumption of an EV has

two key features: discharge and recuperation. Discharge is the function through which an EV loses energy, whereas recuperation is the function through which the EV receives energy. Regenerative braking transforms an EV's kinetic energy into electrical energy to recharge the EV's batteries [12].

We compute the energy discharge and recuperation in three steps. First, the required mechanical power P_M of a conventional vehicle is calculated based on the speed and gradient [13].

$$
\begin{aligned}
P_M = \Big(m * a + \frac{1}{2} * c_d * \rho * \mathscr{A}^* v^2 + m * g * \sin(\alpha) \\
+ c_r * m * g * \cos(\alpha) \Big) * v,
\end{aligned}
\tag{1}
$$

where m denotes the total vehicle mass (kilograms), a is the acceleration (meter per square second), c_d is the aerodynamic drag coefficient ($0 \leq c_d \leq 1$), ρ is the air density (kilogram per cubic meter), $\mathscr{A}$ is the frontal surface of the vehicle (square meters), v is the velocity (kilometer per hour), g is the gravitational constant (meter per square second), c_r is the rolling resistance coefficient ($0 \leq c_r \leq 1$), and α is the gradient of the road (degree).

Second, the mechanical power is converted to electrical power P_E to apply to an electric vehicle, whereby an electric motor has to provide the required amount of mechanical power. The relationship between the mechanical power described by the regression parameters ϕ and the emitted electrical power is utilized. The ϕ^d is the parameter of discharge by the motor and the ϕ^r is the parameter of recuperation by the generator. The electrical power for discharge P_E^d and recuperation P_E^r is dependent on whether the mechanical power is positive or negative. When P_M was less than zero, which means downhill roads, the energy recuperation occurs.

$$
\begin{aligned}
P_E^d = \phi^d * P_M \quad (P_M \geq 0 \ kilowatts) \\
P_E^r = \phi^r * P_M \quad (P_M < 0 \ kilowatts)
\end{aligned}
\tag{2}
$$

Third, the electrical power is converted into the amount of battery power P_B. To move an EV, battery energy is converted inside the electric motor [14]. It is utilized the relationship between the electrical power P_E described by the additional regression parameters φ and the battery power P_B. The φ^d is the discharging parameter and the φ^r is the recuperation parameter. The battery power for discharge P_B^d and recuperation P_B^r is calculated when the electrical power was greater than zero and when the power was less than zero respectively. Battery power P_B is the value of unit time.

$$
\begin{aligned}
P_B^d = \varphi^d * P_E^d \quad (P_E \geq 0 \ kilowatts) \\
P_B^r = \varphi^r * P_E^r \quad (P_E < 0 \ kilowatts)
\end{aligned}
\tag{3}
$$

Battery power P_B is multiplied by the associated travel time t_{ij} to calculate the energy consumption for traveling from location i to j. The final energy consumption E_{ij} is given by

$$
E_{ij} = \begin{cases} P_B^d * t_{ij} & if \ (P_M \geq 0 \ kilowatts) \\ P_B^r * t_{ij} & if \ (P_M < 0 \ kilowatts) \end{cases}
\tag{4}
$$

3.2. Proposed Strategy Using ACO. ACO is a widely employed metaheuristic technique based on certain behavioral patterns of ants searching for food. Ants have the capability to find the optimal path between food and their nest. Ants move randomly to find food and return to the nest with it. They lay down chemical substances called pheromones τ, which are accumulated and also evaporate along their path. A path consists of arcs and nodes, as illustrated in Figure 1.

The more ants travel on the same trail, the more concentrated the pheromones on that trail become, and the trail becomes more attractive for other ants. Ants accumulate pheromones through iterations from the source to destination. Through this mechanism, ants can find the shortest path between a food source and their nest, and the shortest path is the best path for the ants. When applied to EVs, the best path is an energy efficient path.

One iteration of the ACO algorithm consists of three steps: initialize the pheromone, adjust the probability, and update the pheromone. For the pheromone initialization, all path pheromones are initialized to the same value τ_0 before starting the iteration. For the probability adjustment, each ant selects the next node according to a stochastic greedy search, which is called the state transition rule. A state transition rule utilizes both heuristic and pheromone information. The transition probability p_{ij}^k is given in

$$
p_{ij}^k = \frac{\tau_{ij}^\alpha * \mu_{ij}^\beta}{\sum_{l \in \mathscr{N}_i^k} \left(\tau_{il}^\alpha * \mu_{il}^\beta \right)}
\tag{5}
$$

An ant k placed on node i moves to node j with probability p_{ij}^k. The probability p_{ij}^k represents the probability of moving to an adjacent node j from node i, $\mathscr{N}_i^k$ denotes the set of neighboring nodes of ant k on node i, and τ_{ij} denotes the amount of pheromones between nodes i and j. We define the heuristic information μ_{ij}, which represents the energy consumption and speed. The energy consumption and speed are expressed in the form of heuristic information for the following reasons. First, the energy consumption is important for EVs with a short driving range. Second, the speed includes information on the distance and time. The heuristic function is calculated by assigning weights to the energy consumption and speed. The parameters α and β control the relative influence between the amount of pheromones and the heuristic information. For the pheromone and probability update, when an ant k arrives at a destination it returns to its source position, laying down a certain amount of pheromone, such as $\Delta \mathscr{T}^k$, in each arc, as illustrated in (6). All arcs in

```
(1)   Set the start node and the destination node
(2)   Initialize pheromones to the value τ₀ on all arcs
(3)   For iteration i = 1 to n do
(4)      For ant k = 0 to m do
(5)         let V₀ be the start node for ant k
(6)         current node = V₀
(7)         While (next node != destination node)
(8)            calculate the probabilities of the neighbors of the current node using Equation (5)
(9)            determine the next node based on the calculated probabilities
(10)           current node = next node
(11)        EndWhile
(12)     EndFor
(13)     update the pheromones on all arcs using Equation (6) and (7)
(14) EndFor
```

ALGORITHM 1: EV routing algorithm using ACO.

the path formed by the ant k have the same $\Delta\mathscr{T}^k$ value. The expression for updating the pheromone value $\mathscr{T}_{ij}$ is shown in

$$\mathscr{T}_{ij} \longleftarrow \left(1 - \rho\right)\mathscr{T}_{ij} + \Delta\mathscr{T}^k \qquad (6)$$

For each iteration, the deposited pheromones are evaporated. The decay parameter ρ determines how quickly routes are forgotten. Therefore, busy paths accumulate pheromones, whereas they evaporate on less busy paths, speeding up the convergence. If an ant gets lost, this is not reflected in the update. The ACO algorithm converges rapidly, and can explore a range of paths. Therefore, it is suitable for the EV environment, which requires quick and broad decisions. The goal of routing is to maximize the energy efficiency. We propose an objective function that considers the energy consumption and speed. The proposed energy optimization model for EV routing is presented in

$$\min f\left(x\right) = \left(w^{*}E_{sd}\right) + \left(1 - w\right) * \frac{1}{speed_{sd}} \qquad (7)$$

The proposed model aims to minimize the objective function for a path. Here, E_{sd} is the amount of energy consumed from the source to destination node, and $speed_{sd}$ is the average speed of an ant in the path. The speed influences the energy consumption, and the weight parameter w balances the energy consumption and speed. The proposed algorithm is specified in Algorithm 1.

4. Experimental Comparison

4.1. Simulation Model. As an energy efficiency routing simulation, a simple road network based on the city of Sioux Falls in South Dakota was implemented [15]. As shown in Figure 2(a), all nodes and arcs are numbered. The network is composed of 76 arcs and 24 nodes. A road network with distance information is presented in Figure 2(b). Road parameters were defined as the road length, gradient of the road, and moving speed. First, we adopted two distributions for the speed, Gaussian and uniform, with a mean of 42 km/h. Then, according to the policy concerning the structure and

facility standards of the National Highway Traffic Ministry, the gradient of the road should be between 0 and 9° [16]. Therefore, we employed a log function with a mean of 2 and standard deviations of 0.2, 0.5, and 1 for the gradient. Uphill and downhill paths are deployed randomly. Finally, we classify the length of the path into three distances of 6, 8, and 10 km from the source node to the destination. For the 6 km path, we selected the pairs (0, 4), (2, 14), and (3, 18) as the source and destination. For the 8 km path, we selected (1, 18), (2, 17), and (5, 22) and for the 10 km path (0, 17), (0, 23), and (1, 19) were selected. In this experiment, we set $\sigma = 1$ for the log function, a Gaussian distribution for the speed function, and a 10 km path length as default. The parameters α and β were set to 1, the decay parameter ρ was set to 0.7, and the acceleration was set to 0. All experiments were conducted over 300 iterations and the experimental value was the average of 200 experiments performed. The strategic parameter w was utilized to balance the energy consumption and speed. Since the speed is one of factors that affect energy consumption, it is important to give adequate weight between energy consumption and speed. Besides, the performance of ACO depends on how many ants are used in an experiment. Therefore, a preliminary experiment was conducted to determine the value of the strategy parameter, w and the number of ants. We simulated in two environment, Gaussian and uniform distribution for speed. In Figure 3, the performance according to w and the number of ants is illustrated.

In Figures 3(a) and 3(b), energy consumption is the highest when w is 0.1. This is because it puts more emphasis on the speed than on the energy consumption. For Gaussian distribution, the bigger the w value, the less energy consumed. On the other hand, in uniform distribution, the energy consumption was the lowest when w is 0.3. In terms of the travel time, the performance is the best when $w = 0.5$ in Gaussian distribution or $w = 0.1$ in uniform distribution. In terms of the travel distance, the performance is the best when $w = 0.5$ in Gaussian distribution and in uniform distribution. In Figures 3(c) and 3(d), the best energy consumption occurs with 15 ants in both distributions. When the number of ants
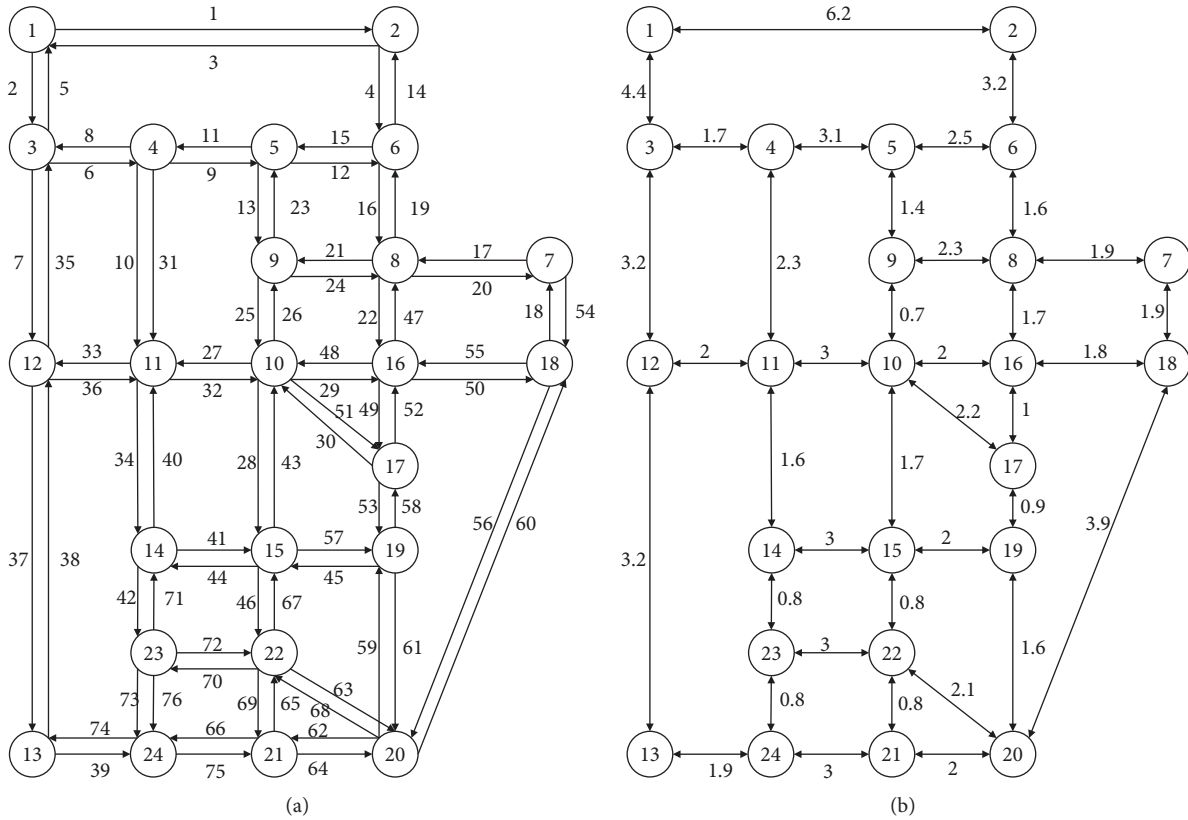
FIGURE 2: Sioux Falls in South Dakota with the adjusted distance network: (a) simple network topology; (b) network topology with distance.
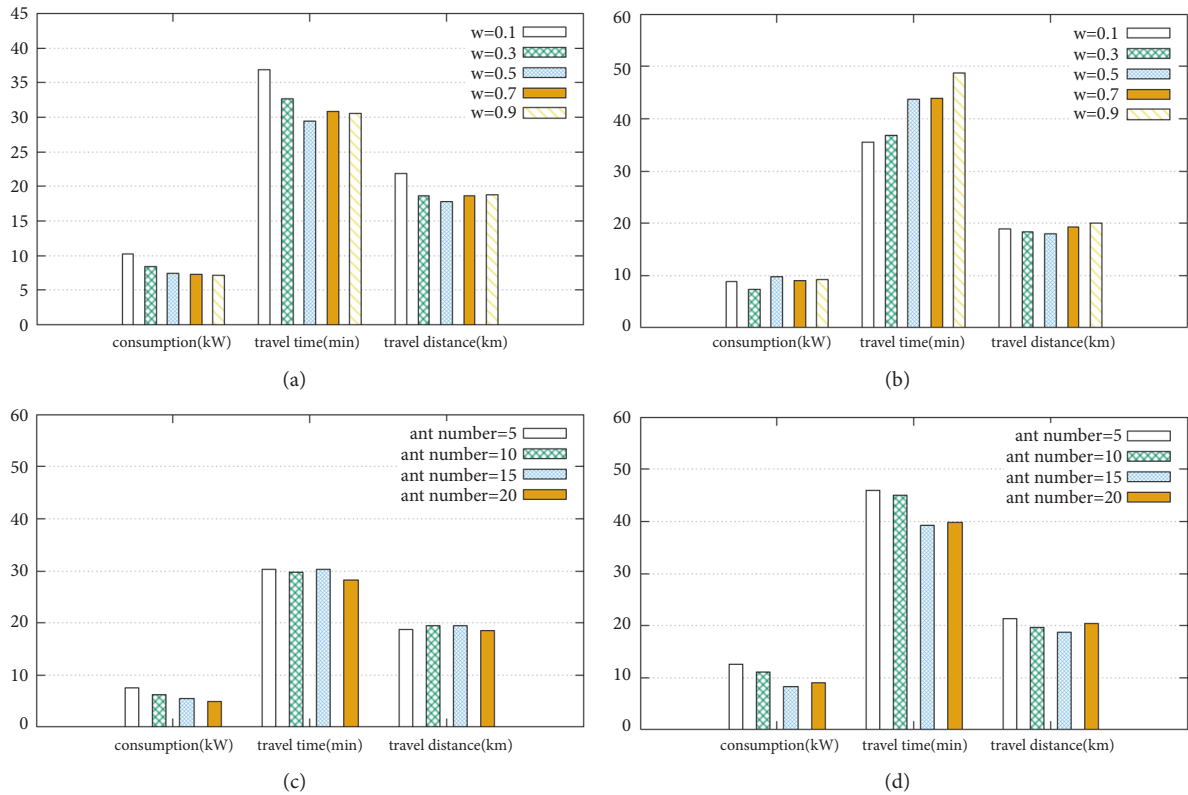

FIGURE 3: Performance comparison with varying weight and number of ants: (a) varying weight with Gaussian distribution, (b) varying weight with uniform distribution, (c) varying the number of ants with Gaussian distribution, and (d) varying the number of ants with uniform distribution.
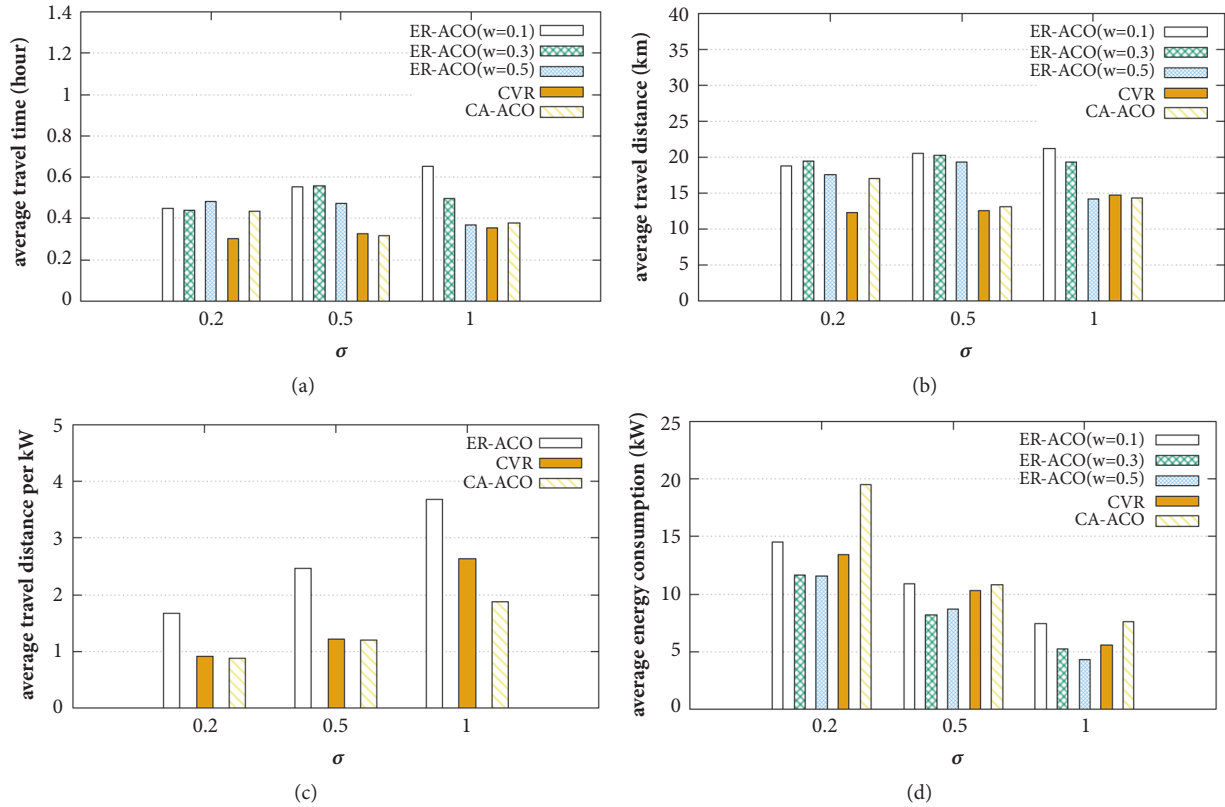
FIGURE 4: Performance comparison with varying road gradients in a Gaussian distribution: (a) travel time, (b) travel distance, (c) travel distance per unit of energy consumption, and (d) energy consumption.

is too small, such as with 5 or 10 ants, the result may be biased. When the number of ants is too large, like 20 ants or more, it can be difficult to find the optimal path because randomness increases. The travel time and distance are the least when $w = 20$ or $w = 15$. As a result, so further simulations, we experiment with a weight of 0.3 and 15 ants.

4.2. Results and Analysis. In this study, we compared the proposed model, called energy efficient routing on ACO (ER-ACO), with a routing algorithm for conventional vehicles and another routing algorithm for EVs. The routing algorithm for conventional vehicles, called conventional vehicle routing (CVR), defines a function using the distance and time costs [17]. The other routing algorithm for EVs, called compare another ACO (CA-ACO), defines a function using the time and energy costs [18]. The energy refers to the cost of charging. However, we assumed that vehicles are fully charged when they depart, and do not charge until arriving. We set up two scenarios by varying the gradients of the roads and distance between the source and destination.

As shown in Figure 4, we set the gradients of the road differently using the standard deviation σ of the log function. We adopted a Gaussian distribution for the speed. The simulation results show the difference in time, distance, energy consumption, and travel distance per kW. As shown in Figures 4(a) and 4(b), the performance of CVR is the best, because the conventional vehicle routing provides a

route for the shortest distance and the shortest time. In Figure 4(a), CVR exhibits a performance approximately 25% superior to ER-ACO ($w = 0.5$). However, the performance is similar to CVR at $\sigma = 1$. Although this approach provides a route that is not the shortest distance, there is an advantage in terms of energy owing to recuperation. In terms of the travel distance per kW, the performance of CVR is inferior to that of ER-ACO. ER-ACO ($w = 0.3$) achieved the best performance in terms of energy efficiency. ER-ACO achieved an energy efficiency that is approximately 40% and 96% better than CVR and CA-ACO, respectively, for the log function at $\sigma = 1$. It can be observed from Figure 4(d) that ER-ACO achieves a good performance. It does not consume much energy, because even though ER-ACO yields a long travel distance this does not affect the energy consumption owing to recuperation.

Figure 5 illustrates the results when utilizing a uniform distribution for thee speed. As shown in Figure 5(a), the performance of CA-ACO is the best for three standard deviations. However, as shown in Figure 5(b), the performance of CA-ACO is approximately 30% inferior to that of ER-ACO, because CA-ACO does not account for distance. It can be observed in Figure 5(c) that ER-ACO achieves the best energy efficiency, which is approximately 69% and 49% stronger than for CVR and CA-ACO, respectively, for the log function at $\sigma = 1$. The lowest energy consumption is provided by ER-ACO for all three different standard deviations.
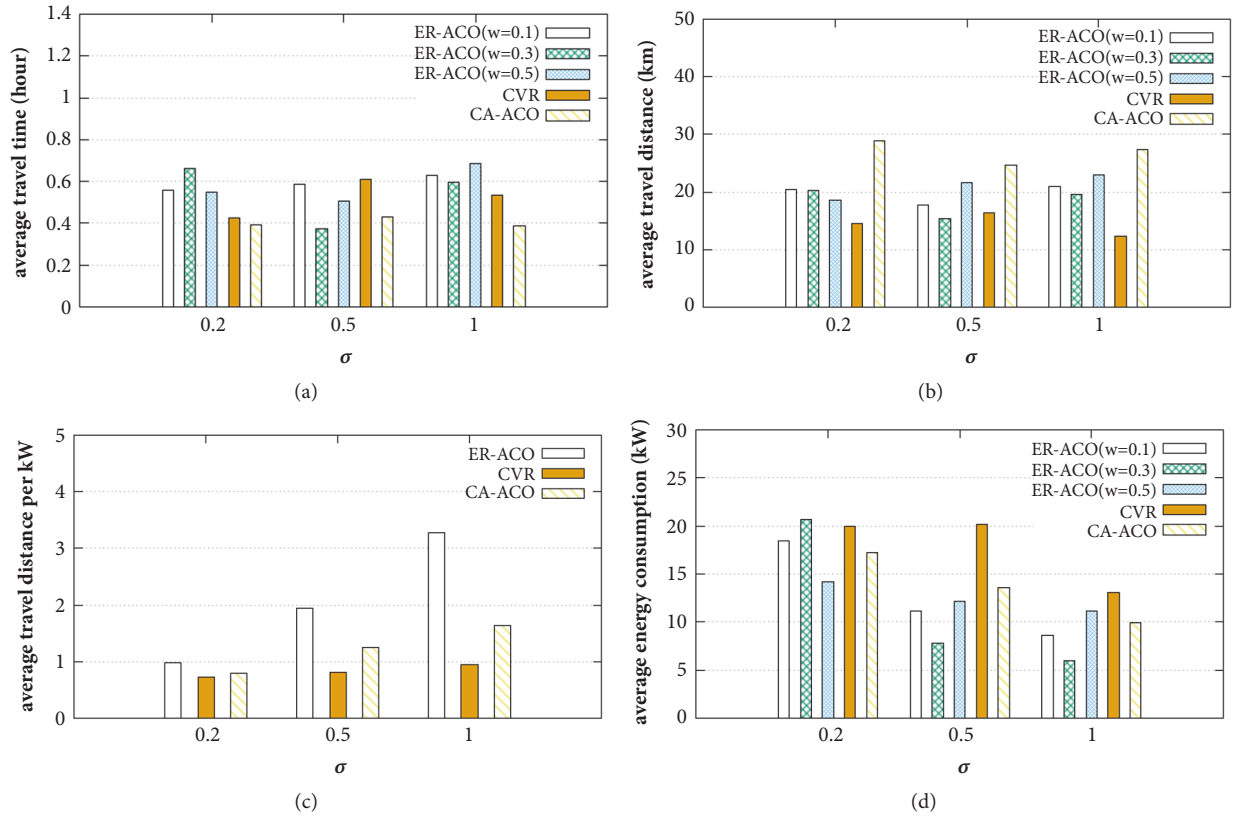
FIGURE 5: Performance comparison with varying gradients of the road in a uniform distribution: (a) travel time, (b) travel distance, (c) travel distance per energy consumption, and (d) energy consumption.

Figure 6 presents the results for three distances between the source and destination pairs. The speed distribution is defined by a Gaussian distribution. As shown in Figure 6(a), the average travel time of CA-ACO is approximately 20% better than that of ER-ACO for the 10 km path. In addition, the travel time of CVR is approximately 25% better than that of ER-ACO. In terms of the travel distance, ER-ACO achieves a travel distance around 20% further than CA-ACO for the 10 km path. In terms of the average travel distance per kW, ER-ACO achieves the best energy efficiency, even though it follows a detouring travel path. ER-ACO exhibits an energy efficiency that is approximately 41% and 47% better than those of CVR and CA-ACO, respectively, for the 10 km path. As shown in Figure 6(d), ER-ACO exhibits the best performance in terms of the average energy consumption.

For the results shown in Figure 7, we employed a uniform distribution for the speed. As shown in Figures 7(a) and 7(b), the average travel time of CA-ACO is approximately 25% better than that of ER-ACO, and the average travel distance of CA-ACO is approximately 13% shorter than that of ER-ACO for the 10 km path. On the other hand, it can be seen in Figures 7(c) and 7(d) that the energy efficiency of ER-ACO is approximately 61% and 59% better than those of CVR and CA-ACO, respectively. The average energy consumption for ER-ACO is two times lower than that of CA-ACO for the 10 km path.

We conducted four experiments under two scenarios. According to these experiments, CVR performs well in terms of the travel time and distance. CA-ACO achieves a good performance in terms of the energy consumption and travel time. Finally, ER-ACO performs well in terms of the energy. The recuperation enhances the energy efficiency, which helps EVs to achieve a further travel distance. The speed was considered because it influences the energy consumption. Therefore, ER-ACO achieves a high energy efficiency, and so it achieves a longer distance with less fuel. The methods achieving the shortest routes are CVR and CA-ACO, but ER-ACO is suitable for routing when considering energy efficiency.

5. Conclusions

This paper has presented an energy efficient routing method for EVs. The energy efficiency, energy consumption, and speed were considered as parameters. The energy consumption included recuperation functions, which in turn help to save energy. The speed is related to the energy consumption, and so this was important to suitably adjust the speed. This study proposed an ER-ACO strategy that sets the energy consumption and speed using ACO. We compared other techniques with ER-ACO under four scenarios. As a result of the experiments, it was observed that the ER-ACO strategy achieves a good performance in terms of the energy efficiency.
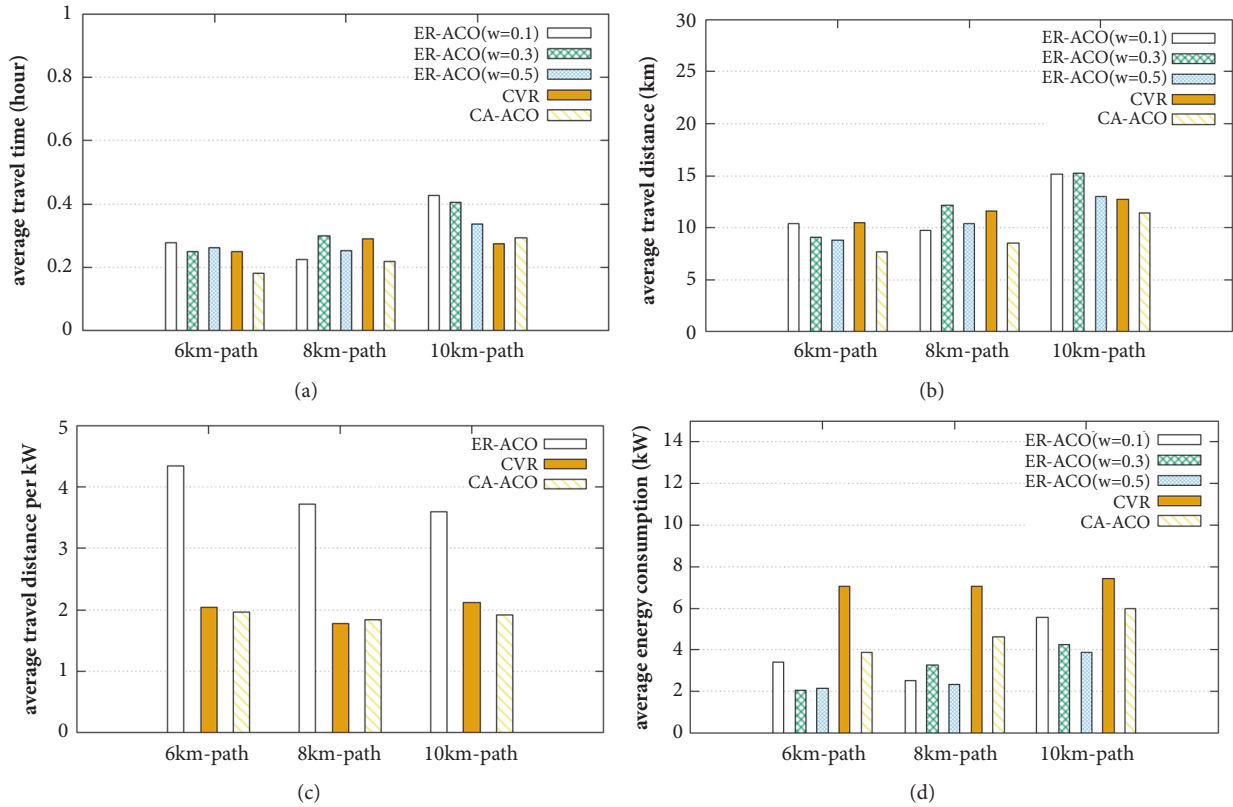
Figure 6: Performance comparison with a varying distance between the source and destination in a Gaussian distribution: (a) travel time, (b) travel distance, (c) travel distance per energy consumption, and (d) energy consumption.
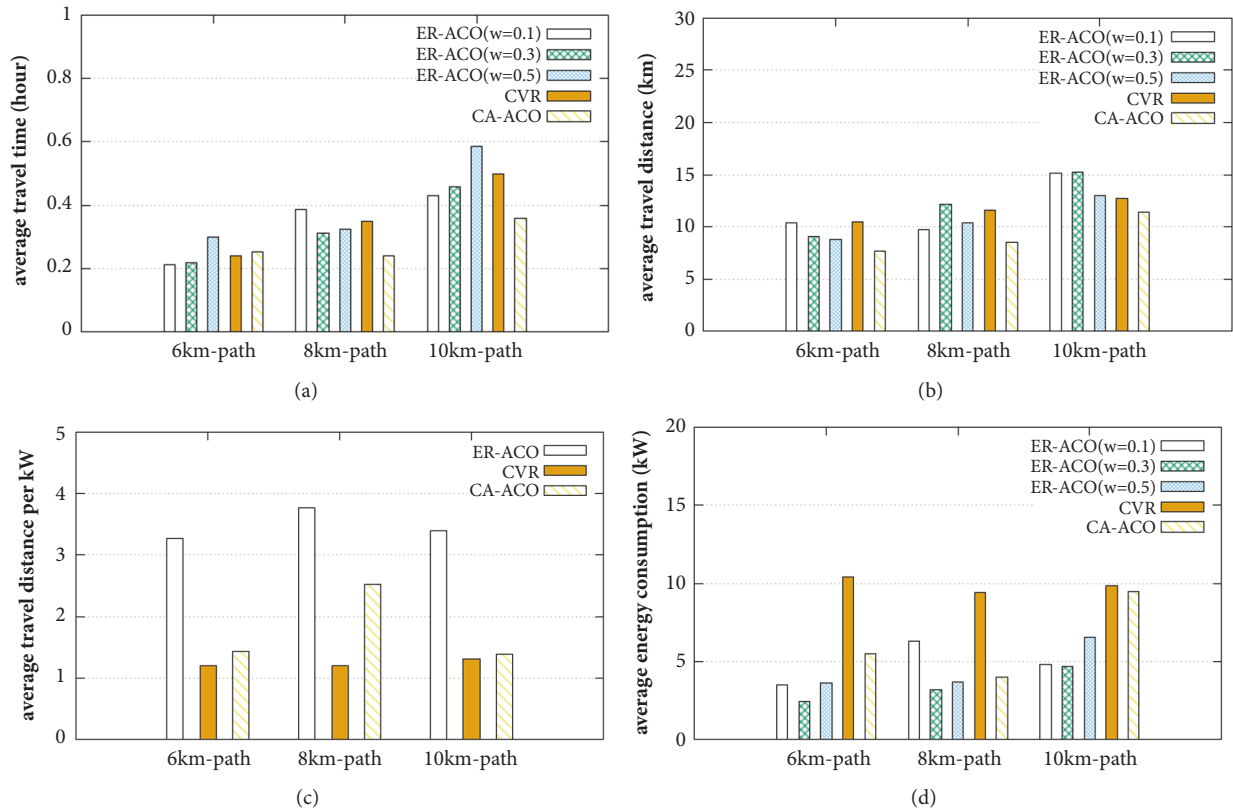

Figure 7: Performance comparison with a varying distance between the source and destination in a uniform distribution: (a) travel time, (b) travel distance, (c) travel distance per energy consumption, and (d) energy consumption.

This study considered the case of arriving at the destination without charging. In future work, this can be expanded by adding a charge in the middle of the journey. In addition, various environmental factors can be considered, such as the positions of charging stations and charging costs [19, 20].

Data Availability

The data used to support the findings of this study have not been made available, because our funding agency has not agreed to this.

Conflicts of Interest

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

Acknowledgments

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