Co-Evolutionary Optimization Algorithm Based on the Future Traffic Environment for Emergency Rescue Path Planning

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ABSTRACT Emergency rescue plays a key role in accident remediation and prevention. It has been the most critical factor to control the negative impacts of accident deterioration, which can save more lives and reduce property loss in time. As an essential component, emergency rescue path planning can effectively shorten the travelling time and improve the robustness of the rescue path. However, there still exist various uncertainties that may make a great impact on selecting the rescue path, which is less successful and still requires further research. To address the problem of low rescue efficiency, a co-evolutionary optimization algorithm (CEOA) is proposed in this study. Meanwhile, this study presents how the sub-path weight function co-evolves with the future traffic environment dynamics using the evolution mechanism, considering the complex vehicle running characteristics in the urban roads. Three sets of simulation experiments are conducted to test the comprehensive performance of CEOA under various scenarios. Experimental results show that the proposed CEOA is superior to traditional and emerging path optimization methods in terms of the travelling time and its stability, such as on-line re-optimization (OLRO) and co-evolutionary path optimization (CEPO). The proposed CEOA integrates the advanced advantages of regular re-optimization and co-evolutionary optimization, and opens the door to develop new path optimization technology. The findings provide powerful technology support and a theoretical basis for emergency rescue management improvement.

INDEX TERMS Emergency rescue, future traffic environment, path planning, co-evolutionary algorithm.

I. INTRODUCTION
In the urban networks, the traffic flow is often fluctuating with a lot of variable factors, such as signalized control, traffic congestions, sudden accidents, unstable driving behaviors and so on. The accident events tend to happen suddenly and less predictable, especially for traffic accidents in road networks. It is essential to implement a more efficient and reliable emergency rescue under the complex and dynamic traffic environment [1]–[3]. Path planning as part of one of the most critical, also as an increasingly important role in emergency rescue, because it can help to save lives in time and decrease economic losses as much as possible.

For the emergency rescue, rescue vehicles tend to require the planned path with the smallest travelling time under dynamic traffic environment. There are a tremendous number of methods concentrating on path planning, and the popular optimization methodologies can be classified as static path optimization (SPO) and dynamic path optimization (DPO). As a fundamental optimization method, SPO focus on how to solve the best path under static routing networks and ignores the changes in traffic environments [4]–[7]. There are numerous researches based on SPO, and most of them are designed for specific situations or problems to achieve practical applications [8]–[11]. Under the dynamic routing environments, a lot of sophisticated and stochastic uncertainties seriously affect path optimization, such as regular traffic congestions, signalized intersections and so on [12]–[15]. To overcome the traffic environmental dynamics, most researches usually pay more attention to DPO, which is often applying some on-line re-optimization (OLRO) algorithms. For instance, heuristic algorithms, deterministic algorithms, deep learning
theory and so on [16]–[23]. However, as a mainstream optimization idea, OLRO-based methods are usually adopted to resolve traffic environment dynamics and uncertainties in DPO [24], [25]. The basic idea of OLRO is to search for the best path based on the current traffic environment. It means OLRO-based methods just simply employ several SPO to modify the remaining path as environment changes. In other words, OLRO-based methods still lack of comprehensive consideration for the future routing environmental dynamics and may cause extra detour with larger travelling time.

To resolve this problem, Hu et al firstly proposed co-evolutionary path optimization (CEPO) to resolve the path optimization in a given dynamic routing environment (POGDRE). The experiments were conducted to prove the effectiveness of CEPO and its superiority [26]. To overcome the uncertainties of predicted traffic environment, Wen et al proposed a methodology of timing co-evolutionary path optimization (TCEPO) to enhance the emergency rescue efficiency by modifying the best path timely [27]. From the experimental analysis, one can see that CEPO can avoid congestion areas and unnecessary detour to reduce the travelling time. It is believed that CEPO is quite efficient in searching the best path under POGDRE. To further research the uncertainties in the traffic environment, this article focuses on how to make the rescue path more closed to the optimal travelling trajectory and raise its accuracy and reliability. Inspired by CEPO, this article combines the advanced advantages of OLRO and CEPO, and proposes a co-evolutionary optimization algorithm (CEOA) to raise the emergency rescue efficiency [28]–[30]. The proposed CEOA considers the vehicle running characteristics in urban road, and integrates the features of re-optimization and co-evolutionary optimization. Compared with other OLRO-based methods, it is a significant improvement for CEOA to avoid traffic congestions that pose negative effects on path optimization. Due to the co-evolutionary optimization mechanism, CEOA tends to select effective decisions to avoid regular traffic congestion and wrong detour, which can reduce the travelling time to a great extent. Compared with other existing algorithms such as CEPO, CEOA has better optimization performance and stronger robustness under the predicted traffic environment with uncertainties. In other words, the path optimized by CEOA is more reliable and its travelling time is more stable under the traffic environment with various prediction errors.

Research contents of this article are further divided into the following chapters: Chapter 2 describes the temporal and spatial running characteristics of urban networks, which provides the basis for modelling the co-evolutionary optimization implementation. Chapter 3 gives the basic idea of CEOA and explains how it works. Experiments and results analysis are shown in Chapter 4. Chapter 5 further discusses more details about the optimization performance of CEOA as shown in experiments. Finally, this article draws some conclusions and concludes the promising prospects in Chapter 6.

II. URBAN TRAFFIC RUNNING CHARACTERISTICS

A. THE DELAY OF INTERSECTIONS

In urban networks, most intersections are strictly managed by signalized control systems. Generally speaking, when a rescue vehicle reaches a signalized intersection, it tends to cause some travel delay because of decelerations, queuing or other restrictions [31]–[33]. For a vehicle, the travel delay of a different turn caused by signalized control is also quite different, such as left, straight and right turn. If an intersection is the non-signalized management, the generation of travelling delay tends to be more complicated. (1) Due to the lack of right-of-way assignment management, it is difficult to achieve effective communication and cooperation among different traffic participants. This means that they are easy to compete with each other for road rights, which leads to non-signal intersections developing to a disorderly and chaotic bottleneck. Thus, traffic conflicts may occur frequently and regular congestions will be generated in that. (2) Some traffic participants may lack traffic safety awareness and do not look around before crossing the road, such as pedestrians, bicycles and motorcycles. However, vehicles have to slow down or stop at the intersection, to avoid a dangerous crash.

The travel delay is usually inevitable when rescue vehicles pass through the intersections. Emergency rescue path planning aims to find out the optimal path considering actual vehicle running characteristics. That is, the rescue vehicle must obey some essential traffic rules to ensure travel safety, when it encounters a potential collision.

B. THE TEMPORAL AND SPATIAL DIFFERENCES OF TRAFFIC FLOW FOR DIFFERENT LINKS

The traffic flow of different links tends to be stochastic, time-varying and complicated, due to different driving behaviors, geographical locations, road length, speed limits, road condition and connectivity. The temporal differences in traffic flow can be defined that traffic flow varies with time because of the uncertainty of driving behaviors and travel habits. The spatial differences of traffic flow tend to be caused by different geographical locations, road structure, speed management, population density and so on [34], [35].

To imitate the practical emergency rescue, three crucial factors must be considered in path optimization. Firstly, there are no emergency lanes for most of the urban roads. Therefore, the rescue vehicle is possible to be affected by surrounding social vehicles. The interference from social vehicles mainly caused by drivers who have different driving styles [36]–[39]. Some undesirable driving behaviors may cause traffic congestion and greatly affect traffic speed, such as sudden lane change. Secondly, the traffic flow is time-varying, which means the traffic speed may change in different periods. If a road starts to suffer from spreading congestion, the related traffic speed will drop rapidly. As time goes by, the traffic congestion may begin to gradually dissipate, the traffic speed will return to a normal level. Finally,
there are different traffic speeds for different roads, or different travel directions of a road. For instance, if a road is located in the central area of the city, the associated traffic speed may be relatively low due to the intensive traffic flow. If it is located in suburban areas where the traffic environment is relatively simple and stable, the associated traffic speed may be high and even close to the top of the speed limit.

III. METHODOLOGY

A. PROBLEM DESCRIPTION

In the urban network, although the distance between two adjacent nodes is static, the traffic environment is dynamic. Hence, the travelling distance and the travelling time tend to be inconsistent, which means the short path may along with large travelling time. Due to the efficiency demand for emergency rescue, rescue time is often regarded as the primary object in path planning. Path planning is transformed into solving the following minimization problem:

$$\min T_r = f(O, R(D))$$  \hspace{1cm} (1)

where $T_r$ is the total travelling time of rescue path. $R(D)$ shows the best path from the origin $O$ to the destination $D$. $f$ is the cost function to calculate the travelling time of the path $R(D)$. Table 1 lists all the major symbols and variables that will be used in this article.

| Symbols | Meanings | Symbols | Meanings |
|---------|----------|---------|----------|
| $O$      | Rescue origin. | $D$      | Rescue destination. |
| $C_{list}$ | The list of all nodes in the optimal path. | $N$      | The number of nodes in the network. |
| $R(i,j)$ | The best path from node $i$ to node $j$. | $R(i,j)_n$ | The $n$th node in $R(i,j)$. |
| $n_c$    | The current node of the rescue vehicle. | $T$      | Time unit that used to update the road network. |
| $M$      | The node-set of all adjacent nodes of $n_c$. | $n_m$    | The nodes belonging to node set $M$. |
| $n_F$    | A node with the minimal $F$ value in $M$. | $n_a$    | A node that vehicle intends to travel. |

B. BASIC IDEA OF CEOA

In this article, any changes in the routing network will be quantized and recorded in a time unit $T$. Let $T+k|T$ denotes the time unit $T+k$ that predicted at time unit $T$. $S(T)$ denotes traffic states of routing network at time unit $T$, and $S(T+k|T)$ is the traffic states of routing network at the predicted time unit $T+k|T$.

Considering dynamic characteristics of the traffic flow, the path planning process must adapt to the changes of the traffic environment, which is called co-evolutionary optimization. To realize the dynamic modification and co-evolutionary optimization mechanism, CEOA employs the extended framework of the A* algorithm. The basic formulation of CEOA, which is composed of two key parameters:

$$F(i) = G(i) + H(i)$$  \hspace{1cm} (2)

where $i$ is the index of the adjacent node that is related to the current node. $G(i)$ indicates the actual cost from the current node to the adjacent node. $H(i)$ represents the cost from the adjacent node to the destination. Dynamic Dijkstra is introduced to calculate $G(i)$, while the ripple spreading algorithm (RSA) is adopted to optimize $H(i)$.

As shown in Fig. 1, the basic idea of CEOA is, under a predicted or given routing environmental dynamics, Dijkstra and RSA are employed to calculate the best path in each run, while the optimization step co-evolves with the dynamic of routing networks. To be specific, the fundamental optimization process of CEOA is to select the next node that will be travelled, by searching the minimum $F(i)$ among all adjacent nodes of the current node at each iteration. If the optimization process reaches the destination, the best path will be determined by tracking back the visiting order of nodes. In CEOA, the best path will be optimized regularly at each calculation step to evolve with the changes in the dynamic traffic environment.

![FIGURE 1. The illustration of the basic idea for the proposed CEOA.](image-url)

C. CEOA ALGORITHM STEPS

To find the best path, the optimization steps of CEOA focus on how to calculate the cost of moving from the origin to the destination. The cost can be expressed by distance, time, expense and so on. Considering the special research background of emergency rescue, travelling time is always
the primary optimization target in path planning. Thus, this article selects the travelling time as the calculation cost of CEOA.

How to precisely deduce $F(i)$ is a critical problem, because CEOA needs it to determine which node will be travelled next. According to equation (2), $G(i)$ and $H(i)$ are the important components to calculate $F(i)$. Thus, before calculating $G(i)$ and $H(i)$, it is necessary to find out which node will be chosen as the next node. Let $M$ denotes the node-set of all adjacent nodes that used to calculate $G(i)$. $l$ indicates the search scope. To avoid falling into local optimality and reduce the times of recalculation, CEOA expands the search scope (i.e. $l \geq 1$) when calculating $G(i)$, and let more nodes add to $M$. More rules are summarized as follows:

1. The current node will not be added in $M$, although it is an adjacent node for other nodes.
2. For each search step, if an adjacent node has not been searched, it is regarded as a new node and added to $M$.
3. CEOA finds out all unvisited adjacent nodes of $M$, and updates $M$ according to rule (2). Let $l = l + 1$ until it reaches the default value. The final set $M$ is used to calculate $G(i)$.

Fig. 2 shows the search results of $M$ for different values of $l$.

Due to the expansion of the search scope, it is necessary to develop a method to calculate the smallest $G(i)$ between nodes. As a mature algorithm, Dijkstra algorithm has advantages of accuracy and computational efficiency in solving small-scale network problems. Therefore, the Dijkstra algorithm is introduced to achieve the calculation of $G(i)$. However, the original Dijkstra algorithm usually regards the weight of links as a fixed value and tends to be applied in a static network. To address these shortcomings, CEOA considers the changes in road weights soon, and gives the comprehensive weights of road considering the weights of a few time units.

Fig. 3 shows how the improved Dijkstra algorithm figures out the weight of each link, gives an exact example to explain the deduction process, more hypotheses as follows:

1. The length of the road is 2160 m; (2) The duration of a time unit is 60 s; (3) The vehicle speed varies with the changes of the time unit. Let $L$ denote the total travel distance of the vehicle. It is observed that travel speeds are respectively 36, 43.2, 50.4 km/h, while travel distances are 600, 720, 840 m at time unit $T = 1$, 2, 3. Due to the speed is time-varying, the travel distance of the vehicle at each time unit is quite different. Hence, it is necessary to record the travel speed and distance of the vehicle in each time unit until the vehicle reaches the destination.

Under the dynamic routing networks, some uncertain factors are affecting path selection [40]. The estimation accuracy of $H(i)$ poses a significant impact on the effectiveness of CEOA. Thus, an improved RSA is adopted to calculate $H(i)$ in CEOA. Due to the ripple relay race of RSA is a time-unit-oriented process, it will co-evolves with the dynamics of the traffic environment and ensure the optimal calculation accuracy of $H(i)$.

The implementation procedure of RSA is given in Fig. 4. There are four states for each node: inactive, waiting, active and dead. If a node is active, it will trigger some ripples to its inactive adjacent nodes. When a ripple reaches an inactive
node, it will wait at the node to imitate the travel delay of the intersection. If all adjacent nodes of an active node are triggered, the node will transform into dead from active. All active or dead nodes will not be triggered by any ripple. As the ripple relay race goes on, the optimization process will be terminated once a ripple reached the destination in the first place. The best path will be determined by tracking back the visiting order of nodes, which is used to record which node triggers the ripple and activates its adjacent nodes.

The flowchart of CEOA is given in Fig. 5. Step 1 initializes all variables and gives the value of $l$. Step 2 sets the origin as the current node for the following calculation. Step 3 finds out all adjacent nodes that used to calculate $G(n_m)$ based on the current node and search scope. Step 4 adopts Dijkstra and RSA to calculate their $F(n_m)$ based on Eq. (2), Eq. (4) and Eq. (5). Step 5 compares all $F(n_m)$ and find out the minimum one, and gives the best path by tracking back the visiting order of nodes. Step 6 determines the next node that will be travelled by the vehicle soon. Step 7 judges whether the next node is the destination. Step 8 clears $M$, then add $n_m$ in $C_{loc}$ and set $n_a$ as $n_c$. Step 9 outputs the actual travelling trajectory based on $C_{loc}$.

As an important component to calculate $F(n_m)$, $G(n_m)$ can be obtained by the following formula.

$$G(n_m) = G(n_c) + C_T(n_c, n_m)$$

where $C_T(n_c, n_m)$ denotes the travelling time from $n_c$ to $n_m$ calculated by Dijkstra under the dynamic routing network. At the beginning, the origin $O$ is set as $n_c$, and $G(n_c) = G(O) = 0$.

On the basis of $G(n_m)$, $H(n_m)$ can be obtained:

$$H(n_m) = C_{T+k[T]}(n_m, D)$$

where $C_{T+k[T]}(n_m, D)$ denotes the predicted travelling time from $n_m$ to $D$ calculated by RSA at the predicted time unit $T + k[T]$. Actually, time unit $T + k$ will be updated as the changes of $G(n_m)$. From time unit $T + k$, RSA is applied to estimate the travelling time from the node $n_m$ to the destination, and eventually gives $H(n_m)$.

IV. EXPERIMENT AND ANALYSIS

A. ROUTE NETWORK DESIGN

The route networks are constructed by randomly generating $N$ nodes in a rectangular area. There are two network scales with $N = 400$ and $N = 900$. To imitate a real urban network and traffic environment, some experimental hypotheses are proposed as follows:

- To enhance the visualization and maximize the number of nodes between the origin and the destination, the origin and the destination are always set as the left bottom and the right top of the network.
To simulate the actual travel delay caused by signalized or non-signalized intersections, this article let $d(i)$ denotes the travel delay at node $i$. According to the common signal period, $d(i)$ is limited to [20, 60] seconds. When the moving vehicle reaches the node $i$, it will wait for $d(i)$ and the travelling time will increase by $d(i)$.

Congestion areas will change over time, and the evolutionary processes are divided into spreading and shrinking states. The traffic environment of the routing network will vary with each time unit (60s). During the spreading process of congestion areas, all adjacent nodes of central nodes would be transformed into congested nodes. These new congested nodes will make their adjacent nodes transform into congested nodes in the next time unit. Conversely, the shrinking process starts from the most peripheral nodes of congestion areas to the central nodes, and the congested nodes would be converted into the normal states. The spreading and shrinking process of congestion areas in the network with the scale of $N = 400$ is shown in Fig. 6.

With the evolution of congestion areas, this study generates the traffic speeds of all links in the network at each time unit. Due to the common speed limit in the urban roads, at the first time unit, the initial traffic speed is generated by a normal distribution of $V_0 \sim N(40, 5)$ ranging from 20 km/h to 60 km/h. Considering temporal and spatial characteristics of traffic flow in the city, traffic speed will change randomly within the range of $[-4, 4]$ at each time, as time unit goes on. The traffic speed of links in congestion areas will drop significantly, and it is selected from 0 km/h to 5 km/h.

### B. EVALUATION INDICATORS

Under the dynamic routing network, travelling time (TT), calculation time (CT) and path length (PL) are selected as evaluation indexes to assess the performance of CEOA. To observe the optimization stability of different scales of routing networks, several experiments are conducted to compare the performance of CEOA, CEPO and OLRO. The algorithm realizations of CEPO and OLRO are significant to reflect the scientific nature of the results. Thus, the emerging RSA is adopted to realize CEPO, while the popular Dijkstra algorithm is employed to realize OLRO [26], [27]. To further analyze the results, this article uses average value and 85% quantile as the detailed evaluation indicators, and shows box figures to evaluate the stability. The average value is a universal indicator and used to reflect the average performance of a method, while box figures refer to the degree of data fluctuation. 85% quantile illustrates the value that is greater than 85% of all results for the associated index, which is used to evaluate the reliability of experimental results.

### C. EXPERIMENT 1: SELECTION OF SEARCH SCOPE

For the CEOA, a good search scope can make the travelling time as short as possible, and ensure the practical application of the proposed approach. Usually, there is an unavoidable contradiction between optimization performance and computational efficiency. To strike a balance between them, it is essential to choose an appropriate search scope. In this experiment, the search scope of CEOA ranges from 1 to 8, the results of that are shown in Fig. 7.

![FIGURE 7. The performance analysis of different search scopes in terms of TT and CT.](image)

As shown in Fig. 7, a larger search scope tends to along with shorter travelling time, but also with longer calculation time. When the search scope begins to increase, the travelling time also decreases smoothly. Once it reaches a certain value $l = 4$, the optimization performance seems to achieve a peak, and the travelling time will no longer decrease. Furthermore, it is easy to observe that the calculation time gradually goes up as the growth of the search scope. If the calculation time is too large, it may fail to meet the real-time requirement of path planning. In the practical situation, there is a strict real-time requirement that, the path planning algorithm should be able to output the optimized path before the vehicle reaches the next node. To sum up, when $l = 4$, the optimization performance of CEOA will reach a peak and the calculation time...
of that is also relatively small, which can satisfy the real-time requirement. Therefore, the search scope is temporarily set as $l = 4$.

D. EXPERIMENT 2: RESULT ANALYSIS WITHOUT CONSIDERING UNCERTAINTIES

This sub-section mainly focuses on how to assess the performance among CEOA, CEPO and OLRO without considering uncertainties. The simulation scenarios aim to maximize the optimization performance of three methods, and find out which one is the best under an ideal situation. Some results are given in Fig.8.

Fig. 8 (a), Fig. 8 (b) and Fig. 8 (c) respectively show the travelling trajectories of CEOA, CEPO and OLRO without considering uncertainties. Although the PL of OLRO is slightly shorter than CEOA, the TT of CEOA is the shortest and much less than that of OLRO. In terms of TT, the gap between CEOA and CEPO is very tiny, it is believed that CEOA is better than CEPO. Fig. 8 (a) and Fig. 8 (b) reveal that the travelling trajectory of CEOA and CEPO is quite different. This is because CEOA can effectively avoid some traffic congestions and waiting at a blocked node until the congested state disappears, so as to obtain shorter travelling time.

Table 2 gives the average results of 20 tests without considering uncertainties. In terms of TT, CEOA still outperforms CEPO and OLRO. Remarkably, the TT of CEOA is approximately $0.4\% \sim 0.8\%$ smaller than that of CEPO, as well as $22.2\% \sim 22.69\%$ smaller than OLRO. The main reason for this result is that, the sub-path optimization of CEOA co-evolves the dynamics of the traffic environment at each time unit. Thus, CEOA can avoid the congestion areas or wrong detour and find out the best sub-path. In terms of CT, it is observed that CEOA has the largest CT for a single run. It is completely understandable because CEOA needs to compare all nodes in the search scope and determine the next node with a minimal cost in a single run. Meanwhile, the expansion of the search scope boosts the complexity of the computation. This search process refers to a great amount of computation and data storage, which leads to longer calculation time. In terms of PL, CEOA is just a little longer than the CEPO and $3.5\%$ shorter than OLRO under $N = 400$, while it is $0.15\%$ shorter than CEPO and still much shorter than OLRO under $N = 900$. It might be the reason that CEOA tends to choose the sub-paths with fewer detours when the vehicle meets regular traffic congestion.

E. EXPERIMENT 3: RESULT ANALYSIS WITH UNCERTAINTIES

Although the traffic flow of different links is affected by complicated factors, the temporal and spatial characteristics of the traffic flow determine its predictability. A great number of tests were conducted under the condition of uncertainties.

| TABLE 2. Average results of 20 tests for CEOA, CEPO and OLRO without considering uncertainties. |
|-------------|-------------|-------------|
|             | $N = 400$   | $N = 900$   |
| TT(min)     | CEOA 81.08  | 122.13      |
|             | CEPO 81.8   | 122.65      |
|             | OLRO 104.22 | 157.97      |
| CT(s)       | CEOA 6.99   | 23.51       |
|             | CEPO 0.61   | 1.97        |
|             | OLRO 0.06   | 0.11        |
| PL(km)      | CEOA 44.04  | 67.13       |
|             | CEPO 43.8   | 67.23       |
|             | OLRO 45.64  | 70.38       |
of researchers have developed a series of models and methods to predict short-term traffic flow and traffic speed [41]–[47]. In reality, it is extremely difficult to achieve a completely precise prediction with no error due to the interferences of uncertainties, and tend to lose some accuracy. However, it is essential to test the robustness performance and calculation reliability of CEOA in a practical situation. To reflect the uncertainties of traffic flow directly, the traffic speed of the links is introduced, and it can be obtained as follows:

\[
\begin{align*}
    v_{T+k}(i,j) &= v_{T|T+k}(i,j) \times (1 \pm \varphi(T+k)) \quad (5) \\
    \varphi(T+k) &= \alpha \times k + \beta \times v_{T|T+k}(i,j) \quad (6)
\end{align*}
\]

where \(v_{T+k}(i,j)\) represents the actual traffic speed of the link \((i,j)\) at time unit \(T+k\). \(v_{T|T+k}(i,j)\) denotes the predicted traffic speed at the predicted time unit \(T\). \(\varphi\) defines the magnitude of uncertainties, \(\alpha\) determines the cumulative rate of the error over time, and \(\beta\) denotes the initial error of the traffic speed for each link.

Due to the special demand for rescue efficiency in the urban emergency rescue, the travelling time far outweighs the path length for a rescue route. Thus, this sub-section mainly concentrates on analyzing the TT among CEOA, CEPO and OLRO considering uncertainties. Set \(\alpha = [0.05, 0.1]\) and \(\beta = [0.05, 0.1]\). Then, this study carries out 20 tests for CEOA, CEPO and OLRO, and gives the average results of TT, as shown in Table 3 and Table 4.

Table 3 and Table 4 show the average results in the case of \(\alpha = 0.05\) and \(\alpha = 0.1\), respectively. There are the following observations:

**TABLE 3. Average results of 20 tests for CEOA, CEPO and OLRO under \(\alpha = 0.05\).**

|               | \(\beta = 0.05\) | \(\beta = 0.1\) |
|---------------|-------------------|------------------|
|               | \(N = 400\) | \(N = 900\) | \(N = 400\) | \(N = 900\) |
| **TT(min)**   | 82.02  | 125.12  | 81.98   | 126.05  |
| CEOA          | 84.79  | 130.44  | 86.26   | 131.57  |
| CEPO          | 107.69 | 162.84  | 108.04  | 167.42  |
| OLRO          | 7.63   | 28.14   | 8.27    | 30.02   |
| **CT(s)**     | 4.32   | 67.77   | 4.49    | 67.84   |
| **PL(km)**    | 46.85  | 71.28   | 46.22   | 72.34   |
| CEOA          | 44.55  | 67.39   | 44.45   | 67.17   |
| CEPO          | 0.62   | 2.26    | 0.62    | 2.05    |
| OLRO          | 0.06   | 0.13    | 0.07    | 0.16    |

- **TABLE 4. Average results of 20 tests for CEOA, CEPO and OLRO under \(\alpha = 0.1\).**

- In terms of TT, the average results of CEOA are slightly better than CEPO without considering uncertainties. Under the dynamic traffic environment with uncertainties, the advantages of CEOA in TT are magnified. Moreover, CEOA still outperforms the OLRO-based methods in TT. This application scenario is more closed to the actual situation, which means that CEOA has stable and excellent features in actual path planning.
- Under the real scenario with uncertainties, CEOA outperforms CEPO and OLRO in terms of TT. On one hand, the re-optimization mechanism of CEOA determines that the accumulated prediction error will be eliminated at each optimization step, which can control the growth of the prediction error. Conversely, in CEPO, the prediction error accumulates over time and seriously affects the reliability of the results. On the other hand, compared to OLRO, CEOA can find out a better solution at each recalculation step through co-evolutionary optimization, leading to the shorter travelling time.
- In terms of PL, CEOA is basically consistent with CEPO, but it always shorter than OLRO. One can see that co-evolutionary optimization has a great advantage in avoiding the wrong detour decision.

Despite the average results of TT show that CEOA is superior to CEPO, there are some details needed to be discussed. To further explore the advantages of CEOA, the reliability and robustness of the results are considered in this experiment, as shown in Fig. 9 and Fig. 10.
FIGURE 10. Comparative results between three algorithms ($N = 900$).

Fig. 9 and Fig. 10 shows comparative results of TT among CEOA, CEPO and OLRO under $N = 400$ and $N = 900$. One can see that: When the cumulative parameter $\alpha = 0.05$, the stability of CEOA and CEPO is similar, while OLRO is the most unstable among them. However, it is observed that the box of CEPO are more discrete than that of CEOA, which means that CEOA tends to slightly outperforms CEPO in robustness. In the case of $\alpha = 0.1$, it is obvious that the number of large outliers of CEPO is more than CEOA. This means that CEOA can keep the results within a more stable range. With the expansion of network, the advantages of CEOA tend to become more remarkable.

To further analyze the reliability of CEOA, the 85% quantile of TT is given in Fig. 11 under different combinations of prediction error parameters. In terms of TT, the 85% quantile of CEOA is the smallest, and that of CEPO is closed to CEOA, while OLRO is the largest and much more than others. The gap between CEOA and CEPO is relative small, which means that CEOA has a great optimization performance without losing the reliability of TT. Therefore, one can see that CEOA can pose a positive impact on improving effectiveness of path planning in emergency rescue, under dynamic traffic environment with uncertainties.

V. DISCUSSION

To improve the efficiency and reliability of emergency rescue, this article proposed CEOA to find out the best path with less travelling time and strong reliability. The reason why CEOA has better performance can be analyzed from three aspects:

1. Under the dynamic traffic environment, CEOA takes full use of the advantages of co-evolutionary optimization.

The future traffic environmental dynamics are considered in CEOA at each run, because the optimization step will co-evolves with the changes of traffic environment. It can provide a right driving strategy for rescue vehicle when meeting a predictable traffic congestion, and allows the vehicle wait at a shrinking congestion area.

2. To achieve strong robustness of path planning, CEOA allows the re-optimization measure to update the real traffic data during the travelling. However, the remaining sub-paths are modified regularly to eliminate the cumulative prediction error, which makes the actual travelling trajectory better.

3. Based on a heuristic calculation framework, CEOA expands the search scope of $G(i)$ and adopts Dijkstra to solve the best weight value. Thus, CEOA can find out the best next node until reach the destination. Furthermore, RSA is introduced to precisely estimate the travel cost when selecting the sub-path, which causes a more reliable judgment of the best path.

As the major evaluation indicators, TT is the priority consideration in path planning of emergency rescue. In terms of TT, experimental results show that CEOA outperforms CEPO and OLRO. In CEOA, the optimization process co-evolves with dynamics of traffic environment in the network, and takes full use of the evolution of future traffic environment. Unlike that, OLRO-based algorithms rely on the current traffic environment and the optimization process ignores the future dynamics, which leads to extra detour behaviors.
Under the dynamic routing networks with uncertainties, the prediction error will accumulate over time and poses a negative on CEPO, resulting in losing accuracy. In terms of PL, the smallest travelling time may not correspond to the shortest path. If the vehicle reaches a congestion area, CEOA can help decide to wait or not, which can avoid some unnecessary detours, while OLRO-based algorithms tend to take action to detour. As for CT, more computation work and data storage are needed to handle in CEOA. Thus, it takes more time to obtain an accurate result, but still without losing practicality in the actual situation.

Although this study has achieved several aspects of achievement in shortening the travelling time and improving its robustness, there still exist some shortages. (1) The larger calculation time is one of the obvious limitations. Although it has less influence on the application of CEOA, smaller calculation time is still more popular. (2) The experiment in this article puts great reliance on the predicted traffic information, while the actual situation may be way more complicated. (3) The experiment just compares to the emerging CEOA and typical OLRO algorithms without consideration of other algorithms.

VI. CONCLUSION

This article proposed a co-evolutionary algorithm (CEOA) to solve the emergency rescue path planning problem. The efficiency and reliability of the proposed algorithm have been proved by simulation experiments. The results show that CEOA has a better performance compared to CEPO and OLRO, and it can be applied in more complicated emergency rescue situation. Conclusions and significance of this article can be summarized as follows:

(1) In order to improve the accuracy and efficiency of path planning in emergency rescue, this article considers the temporal and spatial characteristics of traffic flow in the urban networks and introduces a co-evolutionary optimization mechanism in path planning.

(2) To reduce recalculation times while planning the sub-path, this article improves the method of selecting nodes with a larger search scope. It is proved to be applicable by experimental results that an appropriate search scope effectively reduces the travelling time of rescue.

(3) Dijkstra and RSA are introduced in this article to obtain more accurate results at each run. The co-evolutionary optimization and re-optimization are well combined to make the actual travelling trajectory better.

(4) Experimental results show that CEOA outperforms CEPO and OLRO-based algorithms in terms of TT and PL. Compared to CEPO, the TT of CEOA is shortened by 0.4% to 4.96%. Compared to OLRO, the reduction rate of TT of CEOA can reach 22.2% to 25.04%, respectively, while the path length is shortened by 3.4% to 6.22%. Although CEOA possesses the largest calculation time, it has almost no impact on its application because it can meet the real-time requirement.

Despite CEOA has better performance in path planning considering the evolution of the future traffic environment, more work needs to be explored in the future. Firstly, the algorithm framework and data structure need to be further ameliorated to reduce the calculation time of CEOA. Secondly, the traffic flow prediction algorithm should be considered in the experiment. Additionally, the hypothetical state and evolution of the network should be more complicated to simulate the actual network, and the simulation experiment needs to compare CEOA with more algorithms. Finally, this research will continue to improve the proposed CEOA under a more complex and uncertain routing environment, to make the path planning closer to the actual situation.

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