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RESEARCH ARTICLE

Optimized Deployment Strategy for Roadside Units Based on Accident Risk Assessment and Simulation Validation

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ABSTRACT Intersections are crucial and high-risk areas in urban road networks due to dense traffic and complex scenarios. Deploying Roadside Units (RSUs) can enhance safety and efficiency by providing real-time traffic information. However, the impact of traffic accident risks on RSU deployment is largely ignored. This study introduces an innovative RSU deployment strategy that prioritizes the risk of traffic accidents at intersections. The approach begins with analyzing environmental conditions, traffic patterns, and historical accident data at target intersections to identify key risk dimensions: road, accident, and environmental. The Analytic Hierarchy Process (AHP) and Entropy Weight Method (EWM) are used to weigh the indicators to evaluate their importance in accident risk assessment. Then, construct an objective function based on the accident risk value of the intersection. To overcome the redundancy problem in risk assessment, this study proposes an improved 0-1 knapsack algorithm that considers the redundancy of intersection accident risk to determine the optimal deployment location of RSUs. Simulations with SUMO, TraCI, Veins, and OMNeT++ demonstrate the algorithm's superiority over traditional methods in all metrics. The results show that the vehicle coverage of this strategy is on average 2.63% and 2.86% higher than that of the IIA-ORD and UDA algorithms, respectively. It also leads by about 5.04% in traffic accident coverage and 5.72% in accident risk coverage. This intersection-focused RSU deployment method ensures timely information dissemination after incidents, providing valuable insights and practical guidelines for improving urban intersection safety and efficiency.

INDEX TERMS Accident risk, intelligent transportation systems, optimized deployment strategy, roadside unit (RSU), improved 0-1 knapsack algorithm.

I. INTRODUCTION

Intersections, recognized as critical nodes within urban road networks, are pivotal areas where vehicular flows converge. However, due to the dense presence of vehicles, multidirectional flows, and complex traffic environments, intersections often become hotspots for traffic accidents. In recent years, with the continuous development of vehicle-to-infrastructure collaboration, the deployment of Roadside Units (RSUs) [1], [2], [3] has emerged as a key element in enhancing the safety and efficiency of intersections. This paper aims to investigate RSU deployment methods based on the risk of traffic accidents at intersections, to improve the safety and efficiency of traffic operations at these critical points.

From a safety perspective, although traffic accidents are sporadic and random, they exhibit certain inherent patterns over an extended period, influenced by the surrounding built environment and traffic organization [4]. For drivers

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traversing areas with a high risk of accidents, accident risk warnings are promptly transmitted before any incident occurs. This ensures drivers are aware of the risks and adhere to driving regulations in these high-incidence areas. Additionally, accident information must be disseminated through vehicle-to-RSU (V2R) communication to prevent secondary accidents [5]. The diagram of V2R communication is shown in Fig 1. From an efficiency standpoint, areas with a high incidence of accidents signify a higher probability of accidents occurring. The timely release of accident information helps other drivers optimize their routes [6], avoiding congested areas, thereby significantly enhancing travel efficiency.

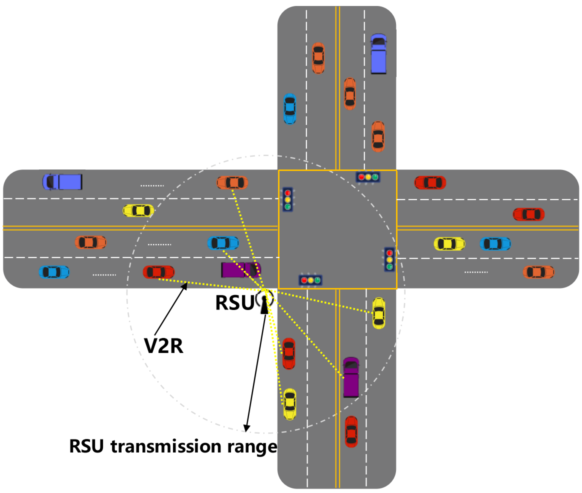


FIGURE 1. V2R communication.

In the current landscape of intelligent transportation systems, the deployment locations and quantity of RSUs impact the Quality of Service (QoS) of the transportation system. This paper proposes an RSU deployment method based on the risk of intersection accidents, integrating the urban road network topology and intersection accident risk coefficients. A thorough analysis of intersection accident risks from the perspectives of road dimensions, accident dimensions, and environmental dimensions is conducted, proposing fifteen risk source evaluation indicators. A combined Analytic Hierarchy Process (AHP) and Entropy Weight Method (EWM) are employed to assign weights to these evaluation indicators, calculating the risk of intersection accidents based on actual traffic accident data. Priority is given to deploying RSUs at intersections with higher accident risks. To address the issue of benefit redundancy within the overlapping coverage areas of different RSUs, an improved 0-1 knapsack algorithm is introduced. This algorithm incorporates a coverage benefit redundancy constraint to reduce resource wastage within the overlapping coverage areas of different RSUs. Experimental validation shows that the improved 0-1 knapsack algorithm effectively addresses the issue of RSU benefit redundancy, and the deployment method proposed in this study demonstrates significant advantages in vehicle coverage, traffic accident coverage, and intersection accident risk coverage.

The organization of the paper is as follows: Section II discusses related work conducted in this field to date. Section III introduces the intersection accident risk evaluation based on AHP-EWM, the RSU deployment model, and the improved 0-1 knapsack algorithm considering coverage redundancy. Section IV describes the experimental scenarios and related parameter settings. Section V discusses the performance evaluation of the proposed method. Finally, Section VI offers conclusive remarks on this study and its findings.

II. LITERATURE REVIEW

A well-conceived RSU deployment strategy is crucial not only for enhancing the performance of vehicle-to-infrastructure systems but also for minimizing deployment costs. Researchers have developed various RSU deployment strategies tailored to different application scenarios in recent years [7]. These strategies are designed to deploy RSUs purposefully, based on the specific needs of the scenarios, to better meet the requirements of drivers and the urban traffic system.

The first category of RSU deployment strategies focuses on the significance of the deployment locations. These methods begin by identifying criteria to evaluate the importance of potential RSU deployment sites. Subsequently, sites are selected iteratively for RSU deployment until a specified performance indicator meets the desired criteria. Research by Dubey et al. [8] highlighted that deploying RSUs at intersections, compared to other locations, could increase their coverage area by approximately 15%. Nidhi [9] have demonstrated the advantages of deploying RSUs in areas with a high density of intersections through various statistical indicators, including packet transmission rates, packet loss, routing overhead, and end-to-end delay. Ghosh et al. [10] addressed the challenge of prioritizing RSU deployment through the introduction of an intersection impact analysis system, aimed at optimizing RSU placement.

The second category emphasizes coverage rate within the deployment area,intending to achieve efficient traffic flow and optimal overall benefits by deploying RSUs. Yu et al. [11] proposed a balance-focused approach, creating an RSU deployment strategy based on traffic demand. Their simulations showed that covering 25% of the road network with RSUs could serve most vehicles while reducing communication delays. Zhang et al. [12] introduced a deployment scheme based on an improved multi-objective quantum-behaved particle swarm optimization algorithm, targeting maximum coverage with the minimum number of RSUs. Feng et al. [13] offered a density-based heuristic method, assuming RSUs are deployed on static public streetlights, minimizing costs while ensuring comprehensive wireless coverage. Ghosh et al. [14] developed an optimal RSU deployment algorithm within the Memetic Framework, aiming to maximize vehicle coverage while minimizing overlap between RSUs. Based on extensive urban vehicular mobility data from Beijing, Kui et al. [15] proposed a uniformity-considerate RSU deployment algorithm. Wang et al. [16] presented a centrality-based deployment method tailored for urban and suburban road scenarios.

The third category considers the Quality of Service (QoS) in the deployment area. Ghorai et al. [17] proposed a constraint Delaunay-based strategy for RSU deployment, focusing on covering convex areas with obstacles to maximize vehicle-to-infrastructure communication probability. Ni et al. [18] designed a linear programming-based clustering algorithm (URDA) to address effective RSU deployment meeting anticipated data transmission delays and task allocations. Yang et al. [19] employed a method based on the Dijkstra algorithm, modeling the problem as a variant of the 0-1 knapsack issue, to propose a binary differential evolution-based RSU deployment scheme. This algorithm was shown to achieve high road coverage and low packet loss rates within limited delay and budget constraints.

In conclusion, while existing RSU deployment strategies primarily aim to optimize RSU placement for enhanced information transmission, installation, maintenance costs, and broader service coverage, they often overlook the impacts of traffic accidents and urban road scene factors on RSU deployment. Studies indicate that traffic accidents directly and significantly affect traffic flow, potentially impacting fluidity, speed, capacity, and overall efficiency of the traffic system. Traffic accidents can cause road blockages and congestion [20], [21], reduce traffic capacity [22], [23], slow down traffic flow [24], [25], and disrupt traffic due to emergency service vehicles [26], [27]. Thus, when developing RSU deployment strategies, it is imperative to consider the risk of traffic accidents and their potential aftermath comprehensively to effectively tackle and manage issues related to intersection traffic safety and vehicular passage.

III. METHODS

A. SELECTION OF EVALUATION INDICATORS

Based on a comprehensive review of relevant literature [28], [29], [30] and indicators both domestically and internationally, and starting from actual traffic accident data, we establish 15 evaluation indicators across road dimensions, accident dimensions, and environmental dimensions as Table 1.

Roads play an important role in the transportation system, and their condition has a crucial impact on traffic safety. The state of the road affects risk factors during the entire traffic flow process. Therefore, when evaluating road traffic risks, potential risks caused by the roads themselves must be considered. In terms of road dimensions, the focus is primarily on the characteristics of the roads connected to intersections. Roads of different grades and numbers of lanes may have different impacts on intersection accidents. For example, roads of higher grades and with more lanes are usually associated with higher speeds and more complex crossing flows, which may increase the risk of accidents. By assessing the road dimensions, a deeper understanding of how road structures influence the probability of intersection accidents can be obtained.

In the accident dimension, the focus is on the specific types of accidents that occur at intersections and their characteristics. Analyzing indicators such as the number of large vehicle collisions, number of fatal accidents, and number of injury accidents can provide insight into the frequency of different types of accidents at intersections, helping to identify potential high-risk intersections.

In the environmental dimension, factors related to the environmental conditions at the time of the accident are considered. For example, ambulance accessibility, traffic congestion index, and number of adverse weather events during traffic accidents. These factors can affect the severity of the accident and the effectiveness of emergency response. By comprehensively considering environmental factors, a more complete understanding of intersection accident risks can be gained, offering strong support for the implementation of corresponding traffic management and safety measures.

B. INDICATOR WEIGHTING

In the process of determining the weights of evaluation indicators, to reflect the decision-maker's level of interest in different indicators and to minimize the influence of subjectivity on weight determination, ensuring the authenticity and credibility of decision outcomes, it is customary to integrate subjective and objective weighting methods. This approach considers both the intrinsic relationships among the data of the indicators and incorporates the subjective experience of experts, thereby deriving a comprehensive weight for each indicator. By using this integrated weighting method, the importance of each evaluation indicator can be more comprehensively and objectively represented, providing a more scientific and rational basis for decision-making.

In this paper, in order to more accurately evaluate the importance of each indicator, a comprehensive weighting method combining the AHP and the EWM was adopted to determine the weights of the evaluation indicators. This approach takes into account both the subjective judgments of experts and the objectivity of the data, making the evaluation results more comprehensive and reliable.

The AHP is a subjective method for determining weights. This method involves establishing a hierarchical structure model, breaking down complex decision-making issues into the goal, criteria, and alternative layers. In the criteria layer, factors are compared pairwise, and numerical values are assigned based on their relative importance to form a judgment matrix. Subsequently, the weights of the factors are determined by calculating the eigenvectors of the judgment matrix, followed by a consistency test to assess the matrix's consistency. If the consistency ratio (CR) is within an acceptable range (typically $CR < 0.1$), these weights will be used to synthesize the basis for the final decision. The results of the AHP subjective weights are presented as shown in Table 2. After constructing the judgment matrices for the evaluation indicators of each dimension in Table 2,

TABLE 1. Significant indicator.

Dimension	Indicator
Road dimension	Average grade of the road section connected to the intersection
	Average number of lanes in the road section connected to the intersection
	Number of intersections within the intersection coverage area
Accident dimension	Number of traffic accidents within the intersection coverage area
	Number of large vehicle accidents
	Number of fatal accidents
	Number of injury accidents
	Number of pedestrian accidents
	Number of vehicle accidents
	Number of incidents of illegal driving by drivers
	Average speed at the time of the accident
Environmental dimension	Ambulance accessibility
	Traffic congestion index
	Number of adverse weather events
	Average visibility

all dimensions pass the consistency test, with the Consistency Ratio CR < 0.1.

The EWM, as an objective weighting approach, starts from the data perspective to avoid the influence of subjective human factors on the weighting of indicators. To determine the weights of the evaluation indicators using the entropy weight method, a decision matrix is initially constructed based on the evaluation indicators as follows:

$$B = \begin{bmatrix} & B_1 & B_2 & \cdots & B_{15} \\ R_1 & 3 & 5 & \cdots & 0 \\ R_2 & 2 & 2 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ R_{55} & 2 & 4 & \cdots & 0 \end{bmatrix} \tag{1}$$

As indicated by Eq (1), the research divides intersections into a total of 55 segments, encompassing 15 indicators within the multidimensional risk source evaluation. Due to the different dimensions of various indicators, the decision matrix is first standardized. Subsequently, the entropy values for each evaluation indicator are calculated. The results of the objective weights using the EWM are presented as shown in Table 2.

Based on the two different weighting methods described above, after importing the selected evaluation indicators and their corresponding data, the calculation results for both subjective and objective weighting methods are obtained separately. However, as both subjective and objective weighting methods have certain limitations, a combined weighting approach is used to effectively integrate the advantages of both methods and to compensate for their respective shortcomings. The calculation formula is as follows, represented as Eq (2).

$$w_i = \alpha w_{i,1} + (1 - \alpha) w_{i,2} \tag{2}$$

In Eq (2), i represents the index of the evaluation indicator; $w_{i,1}$ and $w_{i,2}$ respectively represent the weight values obtained from the AHP subjective weighting method and the EWM objective weighting method; the value of α ranges is [0, 1]. The value of α can be dynamically adjusted according to the characteristics of the evaluation object in different application scenarios. In this paper, focusing on the evaluation of road traffic risk, α is set to 0.5. The calculation yields the final combined weights for each evaluation indicator as shown in Table 2.

C. DEPLOYMENT MODEL

Based on the risk of accidents at intersections in the deployment area, this article constructs an RSU deployment model that considers traffic safety risks, which can be expressed as Eq (3).

$$F(X) = \sum_{j=0}^{N} x_j \times t_j \tag{3}$$

$$x_j \in \{0, 1\}, \forall i = 1, 2, \ldots, N \tag{4}$$

Eq (3) represents the objective optimization function for the optimal deployment model of RSUs considering the comprehensive benefit. N is the number of RSU pre-deployment positions selected in the deployment area; x_j is a binary variable indicating whether an RSU is deployed at the current intersection; t_j represents the accident risk value of the intersection indexed by j; the deployment scheme X serves as the decision variable. By adjusting the deployment scheme, the comprehensive benefit F(X) is maximized. Eq (4) sets the variable constraint for the deployment scheme. This variable is a binary variable, where when $x_j = 1$, it indicates that an RSU is deployed at the location; when $x_j = 0$, it indicates that no RSU is deployed at the location.

D. SOLUTION ALGORITHM

When deploying a new RSU, it is essential to consider its impact on the accident risk assessment at intersections for already pre-deployed RSUs, especially when the new RSU coverage area overlaps with that of existing RSUs. This overlap in coverage areas means that when selecting new RSU deployment locations, it is necessary to recalculate the

TABLE 2. Weights of significant indicators.

Dimension	Indicator	AHP weight	EWM weight	Combined weight
Road dimension	Average grade of the road section connected to the intersection	0.0361	0.0696	0.0529
	Average number of lanes in the road section connected to the intersection	0.0321	0.0297	0.0309
	Number of intersections within the intersection coverage area	0.0945	0.0834	0.0890
Accident dimension	Number of traffic accidents within the intersection coverage area	0.1247	0.0387	0.0817
	Number of large vehicle accidents	0.0440	0.1312	0.0876
	Number of fatal accidents	0.1346	0.1964	0.1655
	Number of injury accidents	0.0770	0.0787	0.0741
	Number of pedestrian accidents	0.0706	0.0775	0.0741
	Number of vehicle accidents	0.0207	0.0390	0.0299
	Number of incidents of illegal driving by drivers	0.0408	0.0150	0.0279
	Average speed at the time of the accident	0.0404	0.0171	0.0288
Environmental dimension	Ambulance accessibility	0.0186	0.0222	0.0204
	Traffic congestion index	0.0478	0.0400	0.0813
	Number of adverse weather events	0.0910	0.0813	0.0862
	Average visibility	0.1272	0.0802	0.1037

benefits of other pre-deployed RSUs to take into account the accident risk within the intersecting areas.

To precisely adjust the traffic accident risk values, it is assumed that the accident risk is uniformly distributed within each RSU's coverage area. Therefore, the accident risk value for pre-deployed RSUs can be adjusted by comparing the ratio of the intersecting area to the total coverage area of two RSUs. Through this method, the impact of newly deployed RSUs on the coverage benefits of other RSUs can be quantitatively assessed.

In the Deployment Model section, the task of positioning RSUs within a designated deployment area is formulated as a 0-1 knapsack problem. The model defines the number of required RSUs, represented by the integer m, which must be strategically placed from among N potential pre-deployment positions. Each position is associated with a predetermined benefit value. The primary objective is to select m positions that collectively maximize the total benefit derived from these RSUs. An advanced version of the 0-1 knapsack algorithm is employed to solve this optimization problem, incorporating considerations for risk coverage redundancy. This approach is formalized in the state transition equation presented as Eq (5).

$$dp\,[i]\,[j] = Max\,(dp\,[i-1]\,[j]\,,dp\,[i-1]\,[j-1] + v_i) \quad (5)$$

In Eq (5), $dp\,[i-1]\,[j]$ and $dp\,[i-1]\,[j-1] + v_i$ represent the two choices of selecting or not selecting the RSU, with the optimal strategy determined by using the Max function. When the RSU with index i is selected, the capacity of the knapsack decreases by 1, and the total benefit of the knapsack should be increased by the comprehensive benefit of the selected RSU; when the RSU with index i is not selected, the capacity of the knapsack remains unchanged, as does the total benefit of the knapsack. Unlike the traditional 0-1 knapsack problem, when selecting the RSU with index i, the traffic accident risk values for other pre-deployed RSUs are updated. The pseudocode for the improved 0-1 knapsack algorithm considering risk coverage redundancy is presented as shown in Algorithm 1.

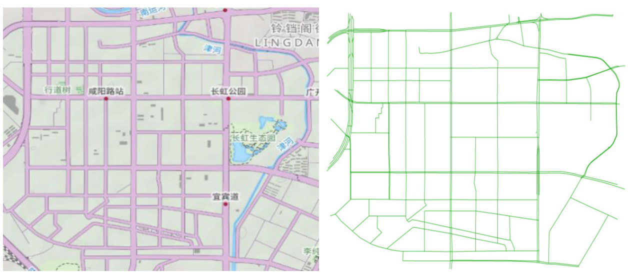
Algorithm 1 Improved 0-1 Knapsack Solving Algorithm

Input: N; m; $T=\{t_1, t_2, t_3, \cdots, t_N\}$
Initialize: RSUSet=∅; State transition matrix dp;
for $i = 1$ to $N + 1$ do
    for $j = 1$ to $m + 1$ do
        if $j <= i$ then
            Make $d_{i,j} = Max(d_{i-1,j}, d_{i-1,j-i} + F\,(x_i))$
            Update traffic accident risk values for unselected RSUs
        else
            Make $d_{i,j} = d_{i-1,j}$
while $m, j > 0$ do
    $k = 0$
    if $d_{i,j}! = d_{i-1,j}$ then
    Put index $i - 1$ to join RSU set
    make $k = k + 1$ and $j = j - 1$
Output: RSU set of the selected RSU when the F(X) is maxed.

IV. SIMULATION SCENARIO AND PARAMETER SET-UP

To evaluate the proposed methodology, the Intersection Influence Analysis System for Optimal RSU Deployment (IIA-ORD) [10], the Uniform-based Deployment Approach (UDA) [15], and the Centrality-based Deployment Approach (CDA) [16], which have been explored in previous literature, are employed as comparative algorithms. The IIA-ORD algorithm conceptualizes the traffic network as a connected graph and employs a modified K-shell method combined with the TOPSIS framework for its execution. By analyzing a range of statistical measures using real-time traffic data, it effectively identifies key intersections for the strategic deployment of RSUs. Meanwhile, the UDA coverage algorithm strives for uniformity in RSU placement, ensuring an even distribution across the deployment area while accommodating the varying traffic volumes at different intersections. Additionally, the CDA coverage algorithm integrates the concept of centrality, derived from social network analysis, into the deployment of RSUs to enhance the network's overall efficiency.

The OMNeT++ network simulator and SUMO traffic simulator are selected as the simulation environment for this study. Integration is achieved through the Veins framework, and synchronization of traffic and vehicle behaviors is facilitated by the TraCI interface. Additionally, real map data from OpenStreetMap (OSM) for Tianjin, China, is utilized, specifically focusing on a real road network spanning 3km × 2.6km located between the coordinates (117.117°E, 39.119°N) and (117.154°E, 39.146°N), as illustrated in Fig 1(a). The characters in the figure represent the names of roads and regional landmarks. The SUMO road network is created based on the road network from Fig 2(a), as depicted in Fig 2(b). Road preprocessing is required for the SUMO road network, where routes unsuitable for vehicle passage are removed based on road types. Subsequently, the corresponding traffic flows and building information are generated using SUMO tools for utilization in OMNeT++.



(a) (b)

FIGURE 2. The real road network and SUMO road network in the target area. (a) Real road network. (b) SUMO road network.

The traffic accident data used in this paper is sourced from the judicial appraisal organizations of Tianjin City, encompassing a total of 12,726 traffic accidents from the year 2012. All utilized traffic accident data do not involve any personal privacy issues. To assess the performance differences between the RSU deployment method that takes into account the risk of accidents at intersections, as described in this paper, and baseline algorithms, six different network scenarios are considered which are depicted in Fig 3(a) to 3(f). The specific simulation parameters are presented in Table 3.

TABLE 3. Simulation parameters used.

Parameter	Values
Network simulator	OMNet++
Traffic simulator	SUMO
Framework	Veins
Map	OpenStreetMap
Simulation location	Tianjin
Area of map	3km×2.6km
Physical layer radio	IEEE 802.11p
Path loss model	Two ray
Channel frequency	5.9GHz
RSU transmission range	300m,500m
Num of RSUs	10,15,20,25,30,35

V. RESULTS

A. ALGORITHM

Fig 4 illustrates the variation in traffic accident risk coverage under a 300m RSU coverage range, comparing the traditional 0-1 knapsack algorithm with the improved 0-1 knapsack algorithm that considers coverage redundancy. As shown, the traffic accident risk coverage of the improved 0-1 knapsack algorithm, which incorporates coverage redundancy, surpasses that of the traditional 0-1 knapsack algorithm. This indicates that through handling coverage redundancy, the algorithm utilizes resources more effectively, covering a greater number of potential risk areas.

Specifically, it can be observed that under each RSU deployment scheme, the traffic accident risk coverage when considering coverage redundancy consistently outperforms scenarios where redundancy is not considered. This difference stems from the improved 0-1 knapsack algorithm flexibility in choosing RSUs when taking into account coverage redundancy, aiming to maximize risk coverage. In contrast, the traditional 0-1 knapsack algorithm is more likely constrained by resource limitations, unable to effectively cover all potential risk areas. This approach to handling coverage redundancy not only enhances the coverage rate of traffic accident risks but also makes the deployment strategy more reliable and robust. Therefore, the 0-1 knapsack algorithm that considers coverage redundancy is more suited to the prevention and management of traffic accident risks.

B. VEHICLE COVERAGE

Vehicle coverage refers to the proportion of vehicle nodes within the RSU coverage area relative to the total number of vehicle nodes. A higher vehicle coverage rate indicates that more vehicle nodes can effectively communicate with the RSUs in the experiment.

Fig 5 shows the vehicle coverage rates of three methods by varying the number of RSUs from 10 to 35 and their transmission ranges of 300 meters and 500 meters. The simulation results demonstrate that as the number of RSUs and their transmission ranges increase, the vehicle coverage rate of the proposed method also increases.

In terms of vehicle coverage rate, within a 300m transmission range, the proposed method is 3.29% lower than the CDA coverage algorithm, but it is 2.72% and 3.13% higher than the IIA-ORD and UDA algorithms, respectively. Within a 500m transmission range, the proposed method is 2.56% lower than the CDA coverage algorithm, but 2.53% and 2.58% higher than the IIA-ORD and UDA algorithms, respectively.

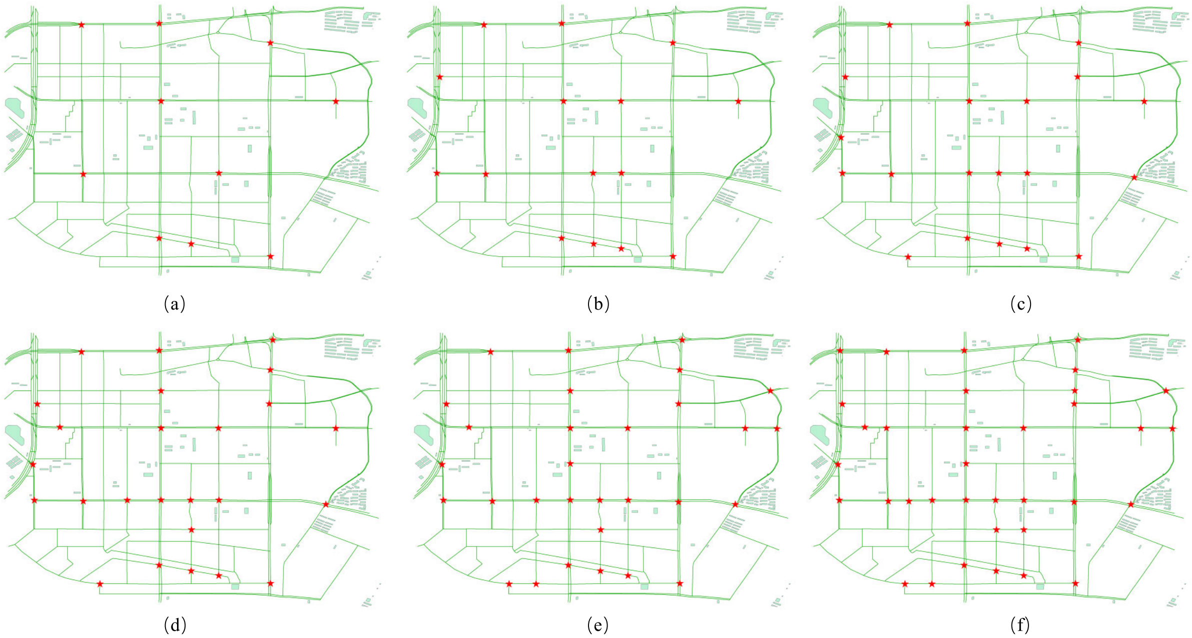


FIGURE 3. Simulation Scenarios. (a) 10 RSUs deployment scenario. (b) 15 RSUs deployment scenario. (c) 20 RSUs deployment scenario. (d) 25 RSUs deployment scenario. (e) 30 RSUs deployment scenario. (f) 35 RSUs deployment scenario. The red asterisk indicates the location of RSU deployment.

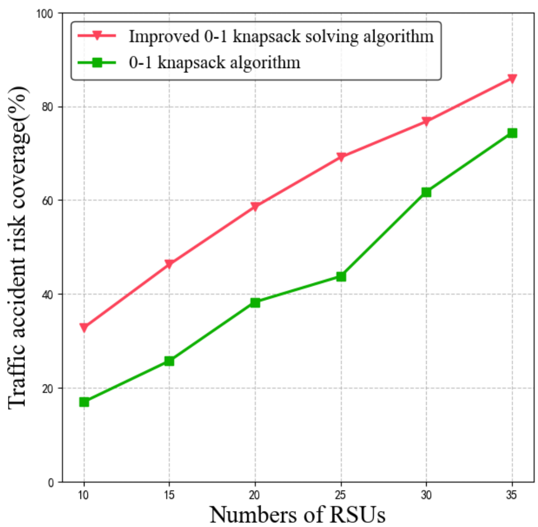


FIGURE 4. Algorithm comparison.

C. TRAFFIC ACCIDENT COVERAGE

The traffic accident coverage refers to the proportion of historical traffic accidents within the RSU coverage area relative to the total number of accidents in the simulation scenario. A higher traffic accident coverage rate indicates that within the RSU coverage area, RSUs provide more communication support to enhance information dissemination at accident sites and reduce the impact of traffic accidents on traffic flow.

Fig 6 displays the traffic accident coverage rates of three methods by varying the number of RSUs from 10 to 35 and their transmission ranges of 300 meters and 500 meters. In terms of traffic accident coverage, within a 300m transmission range, the method proposed in this paper has increased the traffic accident coverage rate by approximately 3.67%, 4.6%, and 8.2% compared to the IIA-ORD, UDA, and CDA algorithms, respectively. Within a 500m transmission range, the proposed method has improved the traffic accident coverage rate by approximately 4.13%, 5.02%, and 8.69% compared to the IIA-ORD, UDA, and CDA algorithms, respectively.

D. ACCIDENT RISKS COVERAGE

The accident risk coverage refers to the proportion of intersection risk values within the RSU coverage area relative to all accident risk values within the deployment area. A higher accident risk coverage rate aids in the timely identification and management of traffic accidents, thereby reducing the potential threat of accidents to traffic safety. By providing alerts to drivers or intervention for autonomous vehicles, the rate of traffic accidents can be effectively reduced.

Fig 7 shows the accident risk coverage of three methods by varying the number of RSUs from 10 to 35 and their transmission ranges of 300 meters and 500 meters. In terms of accident risk coverage rate, within a 300m transmission range, the method proposed in this paper has increased the accident risk coverage rate by approximately 1.86%, 4.45%, and 8.04% compared to the IIA-ORD, UDA, and CDA algorithms, respectively. Within a 500m transmission range, the proposed method has improved the accident risk coverage rate by approximately 2.21%, 4.76%, and 8.9% compared to the IIA-ORD, UDA, and CDA algorithms, respectively.

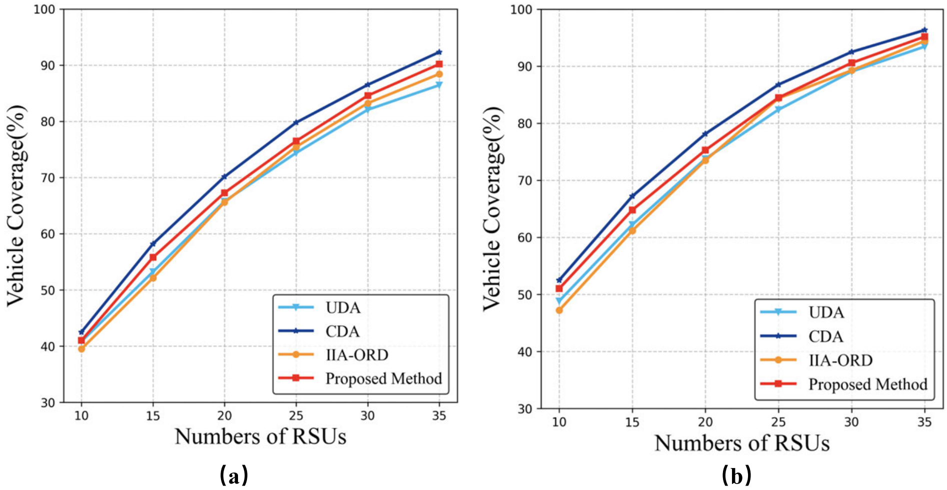


FIGURE 5. **Vehicle coverage under different transmission range of RSUs. (a) Transmission range of RSUs=300m. (b) Transmission range of RSUs=500m.**

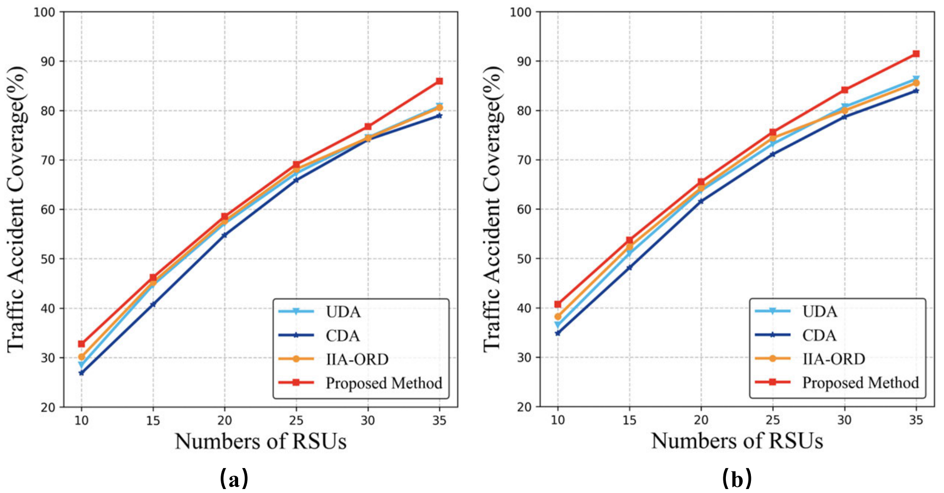


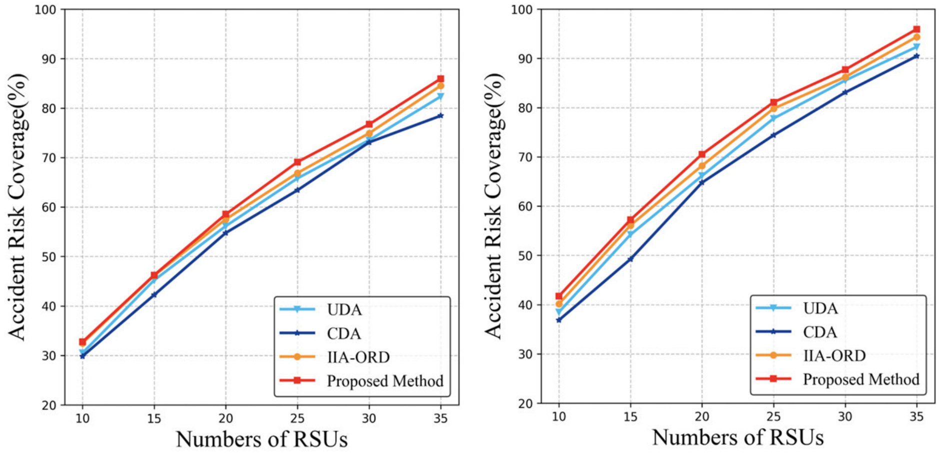
FIGURE 6. **Traffic accident coverage under different transmission range of RSUs. (a) Transmission range of RSUs=300m. (b) Transmission range of RSUs=500m.**

E. DISCUSSION

The deployment method proposed in this paper underperforms the CDA algorithm in terms of vehicle coverage rate, primarily because the CDA algorithm selects deployment locations based on centrality, focusing on areas with high vehicle density. This results in some areas having excessively high RSU density, thus leading to a higher vehicle coverage rate. On the other hand, the UDA algorithm employs a uniform deployment mechanism, where the number of deployments and the intervals between them are related. Therefore, as the number of deployments increases, the density of RSUs uniformly increases. This means that the RSU deployment locations are more evenly distributed across the deployment area, with some locations potentially situated at remote intersections with lower traffic flow, thus limiting vehicle node coverage. Meanwhile, the IIA-ORD algorithm primarily deploys at intersections and does not consider the overlap of different RSUs' coverage areas, leading to significant coverage redundancy.

The deployment method introduced in this article exhibits superior performance in both traffic accident coverage and accident risk coverage, showing significant advantages over the IIA-ORD, UDA, and CDA algorithms. The proposed method primarily considers traffic accident risk and incorporates coverage redundancy management. By taking into account the risk level of intersections during deployment and strategically placing RSUs, it successfully avoids the waste of resources that might result from deploying in dense areas.

Specifically, compared to the IIA-ORD, UDA, and CDA algorithms, the method introduced here pays more attention to covering traffic accident risks, rather than merely



(a) (b)

FIGURE 7. Accident risks coverage under different transmission range of RSUs. (a) Transmission range of RSUs=300m. (b) Transmission range of RSUs=500m.

covering areas. By incorporating coverage redundancy management, the system selects RSU deployment locations more flexibly, especially at high-risk intersections. This approach allows for more comprehensive and efficient coverage of potential risk areas, enhancing the traffic accident coverage rate.

Furthermore, by focusing on RSU deployment at intersections with higher risk levels, the problem of resource wastage in densely deployed areas is avoided. This intelligent and effective resource allocation ensures good vehicle coverage, as well as improved traffic accident and accident risk coverage, effectively reducing the risk of traffic accidents at intersections.

VI. CONCLUSION

This study aims to enhance the safety and efficiency of traffic operations at intersections by optimizing the deployment of RSUs. It considers three main dimensions: road, accident, and environment, and selects 15 evaluation indicators. By integrating the AHP and the EWM for weight distribution, the weights of the evaluation indicators are determined, which are then used to calculate the risk of accidents at intersections. Furthermore, this research applies an improved 0-1 knapsack algorithm that considers coverage redundancy, achieving effective RSU deployment. Finally, validated through real traffic accident data in actual simulation scenarios, the experimental results demonstrate that the improved 0-1 knapsack algorithm, considering coverage redundancy, outperforms the traditional 0-1 knapsack algorithm in various aspects. The RSU deployment method based on intersection accident risk surpasses the IIA-ORD and UDA algorithms by an average of 2.63% and 2.86% in vehicle coverage rate, respectively. It also outperforms the IIA-ORD, UDA, and CDA algorithms by an average of 5.04% in traffic accident coverage rate and by 5.72% in accident risk coverage rate. In summary, this study provides a viable path for RSU deployment research within intelligent transportation systems. It not only aids traffic management authorities in better planning and deploying RSUs but also promises to make a significant contribution to reducing traffic accident risks and enhancing the overall efficiency of the transportation system.

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REFERENCES

[1] D. Wang, Y. Yi, S. Yan, N. Wan, and J. Zhao, "A node trust evaluation method of vehicle-road-cloud collaborative system based on federated learning," *Ad Hoc Netw.*, vol. 138, Jan. 2023, Art. no. 103013.

[2] K. Cao, Y. Liu, G. Meng, and Q. Sun, "An overview on edge computing research," *IEEE Access*, vol. 8, pp. 85714–85728, 2020.

[3] S. Anbalagan, A. K. Bashir, G. Raja, P. Dhanasekaran, G. Vijayaraghavan, U. Tariq, and M. Guizani, "Machine-learning-based efficient and secure RSU placement mechanism for software-defined-IoV," *IEEE Internet Things J.*, vol. 8, no. 18, pp. 13950–13957, Sep. 2021.

[4] I. Dirnbach, T. Kubjatko, E. Kolla, J. Ondruš, and Ž. Šarić, "Methodology designed to evaluate accidents at intersection crossings with respect to forensic purposes and transport sustainability," *Sustainability*, vol. 12, no. 5, p. 1972, Mar. 2020.

[5] R. Cai, Y. Feng, D. He, Y. Xu, Y. Zhang, and W. Xie, "A combined cable-connected RSU and UAV-assisted RSU deployment strategy in V2I communication," in *Proc. IEEE Int. Conf. Commun. (ICC)*, Jun. 2020, pp. 1–6.

[6] B. L. Nguyen, D. T. Ngo, N. H. Tran, M. N. Dao, and H. L. Vu, "Dynamic V2I/V2V cooperative scheme for connectivity and throughput enhancement," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 2, pp. 1236–1246, Feb. 2022.

[7] A. Guerna, S. Bitam, and C. T. Calafate, "Roadside unit deployment in Internet of Vehicles systems: A survey," *Sensors*, vol. 22, no. 9, p. 3190, Apr. 2022.

[8] B. B. Dubey, N. Chauhan, and S. Pant, "Effect of position of fixed infrastructure on data dissemination in VANETs," *Int. J. Res. Rev. Comput. Sci.*, vol. 2, no. 2, p. 482, 2011.

[9] D. K. Lobiyal, "Performance evaluation of RSUs deployment at dense intersections," *Int. J. Inf. Technol.*, vol. 13, no. 3, pp. 1095–1099, Jun. 2021.

[10] S. Ghosh, I. Saha Misra, and T. Chakraborty, "Optimal RSU deployment using complex network analysis for traffic prediction in VANET," *Peer-Peer Netw. Appl.*, vol. 16, no. 2, pp. 1135–1154, Mar. 2023.

[11] H. Yu, R. Liu, Z. Li, Y. Ren, and H. Jiang, "An RSU deployment strategy based on traffic demand in vehicular ad hoc networks (VANETs)," *IEEE Internet Things J.*, vol. 9, no. 9, pp. 6496–6505, May 2022.

[12] L. Zhang, L. Wang, L. Zhang, X. Zhang, and D. Sun, "An RSU deployment scheme for vehicle-infrastructure cooperated autonomous driving," *Sustainability*, vol. 15, no. 4, p. 3847, Feb. 2023.

[13] Y. Feng, N. Ge, and T. Xiang, "A density-based RSU deployment and optimization heuristic method for vehicular networks," in *Proc. 25th Int. Conf. Adv. Commun. Technol. (ICACT)*, Feb. 2023, pp. 154–157.

[14] D. Ghosh, H. Katehara, O. Rawlley, S. Gupta, N. Arulselvan, and V. Chamola, "Artificial intelligence-empowered optimal roadside unit (RSU) deployment mechanism for Internet of Vehicles (IoV)," in *Proc. IEEE 23rd Int. Symp. a World Wireless, Mobile Multimedia Netw. (WoWMoM)*, Jun. 2022, pp. 495–500.

[15] X. Kui, H. Du, X. Xiao, and Y. Li, "Realistic vehicular mobility trace driven RSU deployment scheme," *J. Beijing Univ. Posts Telecommun.*, vol. 38, no. 1, p. 114, 2015.

[16] Z. Wang, J. Zheng, Y. Wu, and N. Mitton, "A centrality-based RSU deployment approach for vehicular ad hoc networks," in *Proc. IEEE Int. Conf. Commun. (ICC)*, May 2017, pp. 1–5.

[17] C. Ghorai and I. Banerjee, "A constrained Delaunay triangulation based RSUs deployment strategy to cover a convex region with obstacles for maximizing communications probability between V2I," *Vehicular Commun.*, vol. 13, pp. 89–103, Jan. 2018.

[18] Y. Ni, J. He, L. Cai, J. Pan, and Y. Bo, "Joint roadside unit deployment and service task assignment for Internet of Vehicles (IoV)," *IEEE Internet Things J.*, vol. 6, no. 2, pp. 3271–3283, Apr. 2019.

[19] H. Yang, Z. Jia, and G. Xie, "Delay-bounded and cost-limited RSU deployment in urban vehicular ad hoc networks," *Sensors*, vol. 18, no. 9, p. 2764, Aug. 2018.

[20] A. E. Retallack and B. Ostendorf, "Current understanding of the effects of congestion on traffic accidents," *Int. J. Environ. Res. Public Health*, vol. 16, no. 18, p. 3400, Sep. 2019.

[21] S. Sánchez González, F. Bedoya-Maya, and A. Calatayud, "Understanding the effect of traffic congestion on accidents using big data," *Sustainability*, vol. 13, no. 13, p. 7500, Jul. 2021.

[22] Z. Zheng, Z. Wang, L. Zhu, and H. Jiang, "Determinants of the congestion caused by a traffic accident in urban road networks," *Accident Anal. Prevention*, vol. 136, Mar. 2020, Art. no. 105327.

[23] Y. Lin and R. Li, "Real-time traffic accidents post-impact prediction: Based on crowdsourcing data," *Accident Anal. Prevention*, vol. 145, Sep. 2020, Art. no. 105696.

[24] Y. Lin, L. Li, H. Jing, B. Ran, and D. Sun, "Automated traffic incident detection with a smaller dataset based on generative adversarial networks," *Accident Anal. Prevention*, vol. 144, Sep. 2020, Art. no. 105628.

[25] B. Vijayalakshmi, K. Ramar, N. Jhanjhi, S. Verma, M. Kaliappan, K. Vijayalakshmi, S. Vimal, and U. Ghosh, "An attention-based deep learning model for traffic flow prediction using spatiotemporal features towards sustainable smart city," *Int. J. Commun. Syst.*, vol. 34, no. 3, p. e4609, Feb. 2021.

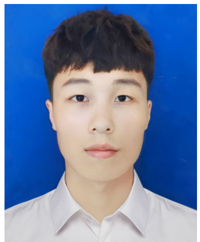
[26] M. Humayun, M. F. Almufareh, and N. Z. Jhanjhi, "Autonomous traffic system for emergency vehicles," *Electronics*, vol. 11, no. 4, p. 510, Feb. 2022.

[27] M. Shelke, A. Malhotra, and P. N. Mahalle, "Fuzzy priority based intelligent traffic congestion control and emergency vehicle management using congestion-aware routing algorithm," *J. Ambient Intell. Humanized Comput.*, vol. 2019, pp. 1–18, Oct. 2019.

[28] T. Champahom, P. Wisutwattanasak, K. Chanpariyavatevong, N. Laddawan, S. Jomnonkwao, and V. Ratanavaraha, "Factors affecting severity of motorcycle accidents on Thailand's arterial roads: Multiple correspondence analysis and ordered logistics regression approaches," *IATSS Res.*, vol. 46, no. 1, pp. 101–111, Apr. 2022.

[29] C. Se, T. Champahom, S. Jomnonkwao, N. Kronprasert, and V. Ratanavaraha, "The impact of weekday, weekend, and holiday crashes on motorcyclist injury severities: Accounting for temporal influence with unobserved effect and insights from out-of-sample prediction," *Analytic Methods Accident Res.*, vol. 36, Dec. 2022, Art. no. 100240.

[30] S. Wang, J. Yu, and J. Ma, "Identifying the heterogeneous effects of road characteristics on motorcycle-involved crash severities," *Travel Behav. Soc.*, vol. 33, Oct. 2023, Art. no. 100636.



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