SCIENTIFIC OASIS

Decision Making: Applications in Management and Engineering

Journal homepage: www.dmame-journal.org
ISSN: 2560-6018, eISSN: 2620-0104

Design of a Cognitive Decision Support System Using Knowledge Graphs and Deep Reinforcement Learning for Real-Time Emergency Response

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ARTICLE INFO

Article history:
Received 25 April 2024
Received in revised form 29 May 2024
Accepted 27 June 2024
Available online 29 December 2025

Keywords:
Cognitive Decision Support System, Knowledge Graphs, Deep Q-Network, Emergency Response, Reinforcement Learning

ABSTRACT

Emergency response scenarios are inherently complex and rapidly evolving, necessitating immediate and well-informed decision-making. Traditional decision support systems, however, often struggle to effectively integrate heterogeneous data sources and adapt to continuously changing conditions. To address these challenges and enhance both the speed and quality of decision-making in emergency contexts, this study proposes a Cognitive Decision Support System for Emergency Response (CDSS-ER), which combines Knowledge Graphs (KGs) with Deep Reinforcement Learning (DRL), specifically Deep Q-Networks (DQN). The system constructs a dynamic KG by aggregating and semantically aligning data from multiple emergency-related sources, thereby capturing contextual and relational information in real time. These structured knowledge representations are then vectorised to depict the current state of the emergency environment. Leveraging these representations, the DQN component determines optimal response policies through iterative trial-and-error interactions, continuously refining its strategies based on real-time feedback. Experimental results demonstrate that CDSS-ER substantially outperforms conventional rule-based systems with respect to both the efficiency of resource allocation and the accuracy of decisions. The framework provides a scalable and adaptive solution for emergency management and holds promise for application in other domains requiring real-time cognitive decision support.

1. Introduction

Emergency response systems play a critical role in minimising the impact of disasters, public health crises, and industrial incidents on lives and property [7]. Conventional systems, however, frequently encounter difficulties in responding promptly, maintaining situational awareness, and facilitating effective inter-agency coordination [31]. Such deficiencies often arise from the fragmented availability of information, overly rigid response protocols, and the inability to adjust dynamically to evolving circumstances [3]. In situations where rapid and informed decisions are essential, these limitations can lead to severe consequences [33]. The increasing unpredictability and complexity of emergencies have therefore intensified the demand for systems capable of

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https://doi.org/10.31181/dmame8220251605

delivering relevant, adaptable guidance to decision-makers [26].

AI-driven CDSS present a promising approach to these challenges [32]. Unlike traditional systems that remain static and inflexible, CDSS can analyse historical data, interpret current conditions, and provide informed recommendations through adaptive learning processes [17]. Central to this capability are KG, which structure data by capturing entities and their interrelations [13]. During emergencies, diverse data streams—such as meteorological forecasts, geographical and infrastructural maps, social media inputs, and sensor readings—can be integrated within KG [21]. This integration enables the system to query complex relationships, identify connections between events, and reveal insights, such as links between power outages and nearby healthcare facilities [2]. In recent years, the frequency and complexity of emergencies, including natural disasters and large-scale public health incidents, have increased, placing additional pressure on response mechanisms [23]. Effective emergency management now depends on rapid information processing, coordinated multi-stakeholder action, and flexible strategies that adapt to changing scenarios [25]. Traditional siloed models, characterised by slow data flows, are unable to meet these expectations [22]. As emergencies become more interdependent and unpredictable, the demand has grown for systems capable of handling large volumes of data efficiently, facilitating real-time analysis, and supporting inter-sector communication to enhance response agility and preparedness [16].

To address these persistent challenges, this study proposes a CDSS-ER that leverages the capabilities of KG and DRL to support intelligent and flexible decision-making. The principal gap targeted by this research is the lack of context-aware, real-time, and dynamically adaptable decision support in conventional emergency response systems. The focus of this work is on designing and implementing a system that integrates dynamic knowledge representation with a learning-based decision engine to improve both the speed and accuracy of emergency responses. The proposed system establishes a cognitive framework in which KG provide structured situational awareness while DQN facilitates sequential decision-making, continuously updated with incoming data. This approach offers a scalable, intelligent solution capable of overcoming the rigidity of traditional systems, thereby enhancing emergency preparedness and supporting multi-agency coordination during critical incidents.

2. Literature Survey

Advancements in artificial intelligence are driving significant improvements in emergency response decision support systems, enabling the timely allocation of resources, continuous situational awareness, and informed decision-making even when objectives conflict under uncertain conditions. DRL is particularly well-suited to these scenarios, as it allows systems to acquire adaptive strategies through interaction with complex and dynamic environments. By employing iterative trial-and-error processes, DRL progressively refines decisions based on real-time feedback, rendering it highly effective in contexts that demand rapid, context-sensitive, and flexible responses—areas in which conventional rule-based systems frequently underperform. Concurrently, KG are increasingly employed to integrate heterogeneous data sources, providing a structured semantic framework that enhances decision-making quality. Table 1 summarises recent studies employing AI techniques for emergency management, detailing the principal methodologies, their advantages in addressing specific challenges, and potential limitations. This evaluation highlights the critical role of AI-driven learning and knowledge representation in developing sophisticated and effective decision support systems for emergency situations.

Recent investigations into emergency response systems have focused on enhancing essential capabilities, including the optimisation of resource allocation, situational awareness, multi-agent coordination, and evacuation planning. Within the area of resource distribution, both the reinforcement learning model [9] and the many-objective decision-making framework [19] have been developed to improve the efficiency of aid delivery under high-pressure conditions. While the model in [9] demonstrates strengths in managing uncertainty and ensuring fairness during supply distribution, it is associated with significant computational demands. Conversely, the framework in Li et al. [19] employs knowledge graphs to balance competing objectives, although the maintenance and scalability of such semantic structures present ongoing challenges.

Table 1
Summary of Key AI Techniques and their Roles in Emergency Response Decision Support Systems

Author(s)	Techniques Involved	Advantages	Disadvantages	Relation to Emergency Response & Decision Support
Fan et al. [9]	Deep Reinforcement Learning (DRL)	Adaptive supply distribution; handles dynamic environments	High training cost; complex tuning	Optimizes emergency supply logistics for timely decisions
Li et al. [19]	Knowledge Graphs + Multi-Objective Optimization	Rich context understanding; supports complex decisions	KG construction is resource-intensive	Enables multi-criteria emergency aid decision support
Yang et al. [34]	Multi-Agent DRL (DQN Variants)	Collaborative resource allocation; models decentralized agents	Coordination overhead; scalability limits	Supports distributed decision-making in post-disaster recovery
Zhao et al. [36]	DRL (Improved DQN) + Cloud-Edge Computing	Real-time evacuation optimization; scalable	Infrastructure dependency; latency issues	Provides adaptive crowd evacuation support in emergencies
Li et al. [15]	Multimodal Knowledge Graphs	Integrates diverse data for situational awareness	Data quality and integration challenges	Enhances flood emergency decision support with semantic data

For situational awareness, the semantic integration proposed in Li et al. [19] facilitates a comprehensive understanding of emergency environments, whereas the Aegis system [36] provides near real-time responsiveness by combining cloud-edge computing with deep learning techniques. Nevertheless, the dependency of Zhao et al. [36] on specific infrastructural components introduces potential concerns regarding latency and operational resilience. In the domain of distributed decision-making, the agent-based approach described in [34] supports decentralised recovery planning, aligning with practical requirements for coordination among multiple actors. However, limitations remain in inter-agent synchronisation and system scalability. Additionally, the study in Li et al. [15] on urban flood response highlights the effectiveness of combining temporal, spatial, and behavioural data to support timely decision-making, though its performance is closely tied to the quality and integration of the underlying datasets.

Collectively, these studies illustrate significant progress across various aspects of emergency response, yet each method encounters specific technical or operational constraints that warrant further investigation. The evidence indicates an increasing utilisation of deep reinforcement learning to enhance emergency supply distribution, improve responsiveness under dynamic logistics conditions, and support real-time decision-making in disaster scenarios. Knowledge graphs also demonstrate substantial potential for integrating heterogeneous data to improve situational awareness and prioritisation. However, most existing approaches treat these technologies independently, limiting their ability to provide adaptive, context-aware, and scalable solutions under uncertain and evolving conditions. Notably, few studies have effectively combined knowledge graphs with deep reinforcement learning, particularly DQN, to form a unified framework capable of both capturing complex relationships across multimodal data and deriving optimal decision policies in real time. This study aims to address this gap by developing a hybrid model that integrates the semantic reasoning capabilities of knowledge graphs with the adaptive learning potential of DQN, thereby enabling intelligent, interpretable, and responsive emergency management, particularly in high-stakes scenarios such as large-scale evacuations or urban flood responses, where both precision and adaptability are critical.

3. System Framework

The initial configuration of the CDSS-ER architecture is founded upon the integration of semantic reasoning via KG and adaptive decision-making through DQN. The system first constructs a multi-relational KG that represents emergency-specific entities, including incident categories, geographic coordinates, temporal factors, infrastructure characteristics, and available resources. These entities are interconnected through semantic relations to form a contextualised graph, facilitating efficient data retrieval and inference. The KG functions as the cognitive layer of the CDSS-ER, enabling real-time understanding and reasoning over complex emergency scenarios. Concurrently, the DQN component is established to manage sequential decision-making within this dynamic environment. The state space is defined by contextual information derived from the KG, such as incident severity, location, and resource availability, while the action space encompasses a range of response strategies, including resource deployment, traffic rerouting, and authority notifications. The Q-network approximates the optimal action-value function Q(s,a), allowing the system to identify actions that maximise cumulative rewards under conditions of uncertainty. The integration mechanism permits the DQN to access KG-derived contextual insights, while the KG itself is continuously updated as actions are executed and new information is received. This configuration establishes a hybrid CDSS-ER framework in which KG provide structured situational understanding and DQN facilitates learning-based optimisation, supporting resilient, real-time decision-making during emergency response operations.

4. Methodology

The proposed CDSS-ER establishes a robust framework for contextual reasoning and adaptive decision-making by integrating KG with DQN. This section addresses three core components: the modelling of emergency knowledge via KG, the training of decision-making processes through DQN, and the synthesis of these elements into a unified cognitive architecture. The framework is designed to enable emergency responders to operate intelligently and rapidly by combining structured knowledge representation with adaptive capabilities. KG technology is employed to organise diverse emergency-related data into a dynamic knowledge structure. Essential entities and their interactions, such as those linking incidents, locations, and required resources, are encoded within the KG, facilitating inference and the generation of new insights from existing information. These relationships are further converted into quantitative representations or metrics that capture how different factors affect and respond to evolving emergency conditions [14].

The state inputs for DQN are derived from KG embeddings, enabling DQN to interpret the decision environment as a sequence of actions and associated outcomes. Through iterative interaction with the environment, DQN identifies optimal strategies, adjusting its actions based on feedback to improve future decision-making. Whenever an action is executed, such as deploying units or redirecting movement, the resulting information is incorporated into the KG in real time [5]. This continuous interaction forms a feedback loop in which knowledge reasoning informs state representation, and adaptive learning refines decision policies. Owing to this hybrid design, the system can address multiple challenges simultaneously, prioritize effectively, and respond swiftly in high-pressure emergency situations. Figure 1 presents the flow diagram of the proposed architecture.

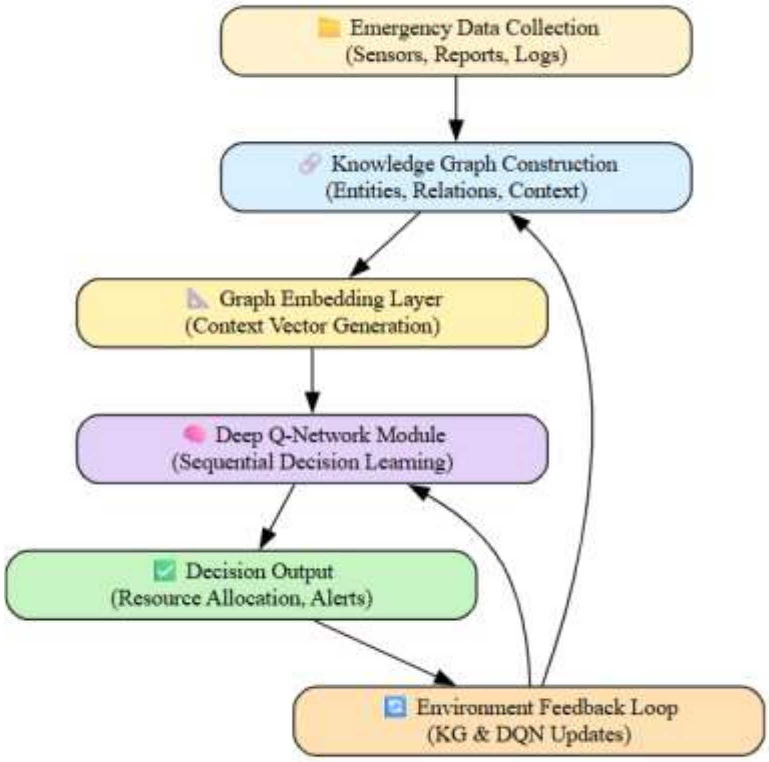

Fig.1: Proposed Architecture

Step 1: Emergency Data Acquisition

Prior to activating the core components of the architecture, emergency information is collected from a wide array of sources. These include sensor readings from GPS devices, traffic and surveillance cameras, and environmental monitoring systems, alongside data obtained from incident logs, emergency service databases, and user-generated reports from online platforms. The diversity and richness of these data streams provide a comprehensive foundation for situational analysis. To ensure data quality and suitability for semantic modelling and subsequent processing, the collected information is subjected to cleaning, normalisation, and transformation procedures [28].

Step 2: Knowledge Graph (KG) Construction

Following data pre-processing, the system constructs a KG to organise and represent the critical elements required for emergency management. Individual nodes correspond to incident types, such as fires or accidents, as well as locations, infrastructure, resources, and temporal attributes, while edges depict the relationships between these entities. CDSS-ER relies on this KG to facilitate informed decision-making tailored to specific scenarios. As the KG is continuously updated with incoming information, the system can infer missing details and identify significant patterns that are vital for effective emergency management [27].

Step 3: Knowledge Embedding and State Representation

The subsequent stage entails translating the semantic KG into a numerical representation suitable for integration with DQN. Through knowledge embedding, entities and their interrelations within the KG are converted into continuous vector forms, preserving both structural and semantic information [4]. These embeddings form the basis of the state space within the reinforcement learning model. Each state vector encodes essential details regarding the current incident type and severity, the availability of response teams, location, and temporal information. By utilizing these embeddings, DQN gains a comprehensive understanding of the emergency environment, enabling the selection of effective decision strategies [10].

Step 4: Deep Q-Network (DQN) Decision Learning

At this stage, DQN is employed within CDSS-ER to make informed decisions in dynamic emergency situations. The DQN models the environment according to a Markov Decision Process (MDP) framework, utilising the embedded state vectors to select optimal actions from a predefined set [35]. Such actions may include deploying specific response teams, directing traffic along alternate routes, issuing emergency alerts, or redistributing medical supplies. Through continual interaction with the environment, DQN evaluates the effectiveness of its actions and reinforces those yielding positive outcomes. Over time, the model converges on a policy that maximises long-term benefits while minimising operational inefficiencies and resource wastage [12].

Step 5: Hybrid Integration and Adaptive Decision Cycle

The final critical stage involves fully integrating KG and DQN into a continuous feedback loop. The KG is continually updated with incoming emergency information, enhancing the semantic representation of each state. These updated embeddings are supplied to DQN, informing the selection of subsequent actions. As DQN executes and evaluates its decisions, it becomes progressively more effective, simultaneously triggering updates to the KG based on the insights gained. This continuous adaptive cycle enables the system to respond more rapidly and accurately in real time. Consequently, the hybrid CDSS-ER exhibits high reactivity, comprehensive situational awareness, and the capacity to manage evolving emergency scenarios effectively [8].

4.1 Knowledge Graphs (KGs)

Within an emergency response system, KG represent various categories of information by modelling entities—such as incidents, resources, and locations—as nodes, with edges illustrating the relationships between them. This structured collection of contextual data enables the system to interpret complex factors relevant to emergency management [1]. Formally, relationships in a KG are expressed as triples (h,r,t), where the head and tail correspond to entities and r denotes the relationship connecting them. To facilitate efficient reasoning and similarity computation, these entities and relationships are embedded within a continuous vector space. In many applications, the TransE model is employed, with its scoring function defined as shown in equation 1:

$$f(h,r,t) = \|h + r - t\|_2 \qquad (1)$$

$h, r, t \epsilon \mathbb{R}^d$ are the vector embeddings for the head, relation and tail and $\|.\|_2$ is the Euclidean norm. When $f(h,r,t)$ is smaller, the system is able to find new and correct connections between emergency information and use them to improve decision accuracy [11].

4.2 Deep Q-Networks (DQN)

DQN are designed to support decision-making by determining optimal actions in uncertain and dynamic environments, such as those encountered during emergency response operations [30]. The model views the task using an MDP framework where, at every step t, the environment presents a state s_t , the agent acts using action a_t , collects reward r_t and the system progresses to state s_{t+1}. The objective is to identify a policy that maximises the expected cumulative reward, particularly over the long term. The optimal action-value function Q* (s,a) satisfies the Bellman equation, as expressed in equation 2:

$$Q^*(s,a) = \mathbb{E}_{s`}\left[r + \gamma \max_{a`} Q^*\left(s`, a`\right) | s, a\right] \qquad (2)$$

The discount factor γ, which lies within the range [0,1], is employed to balance the significance of immediate rewards against those anticipated in the future. The neural network, parameterised by θ, approximates Q(s,a;θ), enabling the agent to evaluate actions based on complex state representations derived from KG embeddings. Through iterative updates and repeated interactions, DQN progressively identifies optimal strategies for allocating and managing emergency resources in response to evolving conditions [29].

4.3 Hybrid Integration of KGs and DQN

The hybrid CDSS-ER integrates KG and DQN within a single framework to address the complexities of decision-making in emergency response. KG aggregate diverse emergency-related data—including incident categories, resource availability, geographic locations, and temporal information—and organise them within a graph structure that preserves relational connections. This structured representation enables the system to identify significant features and relationships in the data that are difficult to capture using conventional formats [18]. Features derived from the graph are subsequently converted into numerical embeddings, which serve as input for the DQN. The DQN interprets these embeddings to model the environment as a sequence of actions, learning optimal strategies through iterative interaction and feedback, with rewards guiding adjustments. Consequently, the DQN can evaluate long-term outcomes rather than making decisions solely on immediate observations.

The system's functionality fundamentally relies on the integration of KG and DQN, allowing decisions to adapt dynamically to diverse emergency scenarios [20; 37]. KG are employed to encode the semantic relationships of emergency data into embeddings, which define the current system state s_t. This state vector encapsulates key attributes such as the incident type, affected area, available resources, and timing. Based on the updated state, DQN selects the action most likely to maximise future rewards. The policy is refined in practice through the continual update of Q-value estimates, utilising the temporal difference learning method as formalised in equation 3.

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha[r_t + \gamma \max_{a`} Q^*\left(s_{t+1}, a`\right) - Q(s_t, a_t)] \qquad (3)$$

In this context, α denotes the learning rate, r represents the immediate reward, and γ is the discount factor. Through continuous real-time feedback, the hybrid approach enables the model to refine its action selection by leveraging both the semantic insights provided by KG and the decision-making capabilities of DQN. The resulting system demonstrates enhanced reliability and accelerated response times in managing emergency operations compared with conventional standalone solutions.

The integration of KG into the emergency environment follows a structured process: initially, live emergency data are collected to build and continually update the database; subsequently, essential information from the database is transformed into vector representations; finally, these vectors are provided to DQN to inform the selection of appropriate actions. By combining the semantic knowledge from KG with the advanced pattern recognition capabilities of DQN, the system enhances the precision of its decisions. This synergy allows the hybrid CDSS-ER to allocate emergency resources more effectively and make rapid decisions in response to evolving situations [6; 24]. The close interaction between these components improves both the efficiency and reliability of responses during critical emergency events.

5. Results

The performance and practical applicability of the integrated CDSS-ER, utilising KG and DQN, are systematically evaluated. A combination of quantitative metrics, visualisations, and case studies is employed to assess the system's operational effectiveness, adaptability, and decision accuracy. Indicators such as resource allocation efficiency, responsiveness to incidents, and decision-making precision confirm the system's overall efficacy. The outcomes produced by the model are compared with those of conventional rule-based and heuristic approaches, highlighting the improvements afforded by semantic reasoning and reinforcement learning. In the context of urban disaster management, CDSS-ER demonstrates the ability to recommend timely and effective actions in response to rapidly evolving environmental conditions. Furthermore, the model's potential for broader application is considered, including adaptation to sectors such as healthcare, transportation management, and routine safety operations.

5.1 Case Study Dataset Description

Between 2018 and 2024, the Integrated Emergency Response Analytics Dataset (IERAD) compiled detailed information from carefully selected emergency response cases in metropolitan Sydney, Australia [6]. The dataset encompasses emergency operations through contributions from ambulance dispatchers, drone operators, and regional hospitals. By integrating operational procedures, response times, environmental contexts, and logistical details, IERAD provides representations of emergency scenarios that closely reflect real-world conditions. To capture the diverse challenges faced by emergency services in both urban and suburban settings, the dataset incorporates real-time data from aerial drones and ambulances. The inclusion of actual incident records enhances the reliability and value of the dataset for emergency response analysis. IERAD addresses a wide range of emergency situations, considering factors such as traffic conditions, incident severity, and weather, thereby supporting robust and consistent AI-based optimisation of emergency service routing. Collaboration with local partners has ensured that IERAD serves as a practical resource for emergency studies. All sensitive information within the dataset has been anonymised, preserving the integrity and analytical value of the data. Table 2 presents a comparative analysis of performance evaluation metrics between the proposed system and conventional rule-based and heuristic methods.

Table 2
Performance Evaluation

Aspect	Metric	Proposed	Traditional	Heuristic
Performance Comparison	Operational Speed (Seconds)	9.5	15.5	17.0
	Decision Accuracy (%)	92.3	78.6	74.9
	Resource Efficiency (%)	87.5	70.2	68.0
System Evaluation	Resource Management Efficiency (%)	88.0	69.5	65.7
	Average Response Time (Minutes)	7.2	12.8	14.5
	Decision Accuracy (%)	91.5	79.0	75.3
Case Study Application	Average Response Time (Minutes)	6.8	13.2	14.8
	Number of Incidents Handled	150	120	110
	Resource Deployment Efficiency (%)	89.0	71.5	69.0

Figure 2 illustrates the deployment of emergency units to incident locations, with dashed lines and associated timings indicating the planned routes. In the upper-central zone, a single emergency team attends to multiple incidents at 4.0, 4.5, 7.2, and 10.0 minutes, demonstrating efficient handling of simultaneous events. Units on the right manage incidents within their designated area, with the first unit responding to two incidents in 2.0 and 4.5 minutes, while the second unit is dispatched to a more distant incident in 16.1 minutes, ensuring that the closest calls are prioritised. In the lower section of the grid, units are dispatched on missions taking 8.2, 5.7, and 4.5 minutes, respectively. These results highlight the improvement in response selection achieved through DQN learning from real-time information provided by the KG. The KG continuously integrates spatial, temporal, and resource data, maintaining real-time links as emergency situations evolve. Consequently, emergency services are able to make rapid and well-informed decisions. The findings indicate that employing CDSS-ER enhances resource utilisation, accelerates response times, and streamlines overall operational workflow more effectively than conventional rule-based methods.

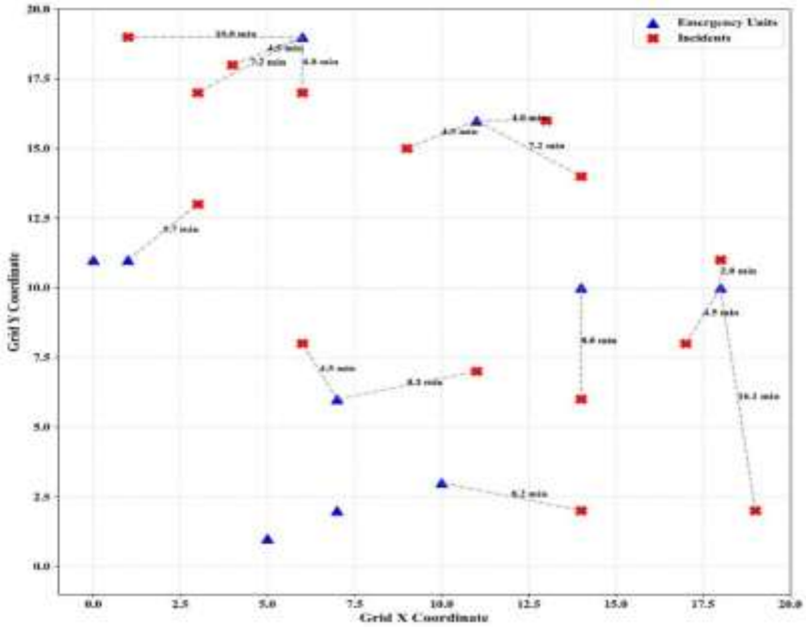

Fig.2: Urban Disaster Response Allocation (Metropolitan Sydney, Australia)

Figure 3 presents a comparison of the accuracy achieved by different approaches over ten simulation runs. The proposed method demonstrates an improvement from approximately 88% accuracy in the initial run to around 95% by the tenth iteration. In contrast, the traditional method begins with an average accuracy of 75%, gradually increasing to just below 80%, while the heuristic approach starts at 70% and reaches roughly 74% by the final run. The integration of KG with DQN within CDSS-ER accounts for the substantially superior performance of the proposed system. This configuration allows the system to progressively refine its decision-making over time. Traditional and heuristic approaches, relying on fixed strategies, lack the adaptability required to achieve comparable improvements. The experimental results confirm that CDSS-ER offers a more efficient, responsive, and scalable solution for managing complex emergency scenarios.

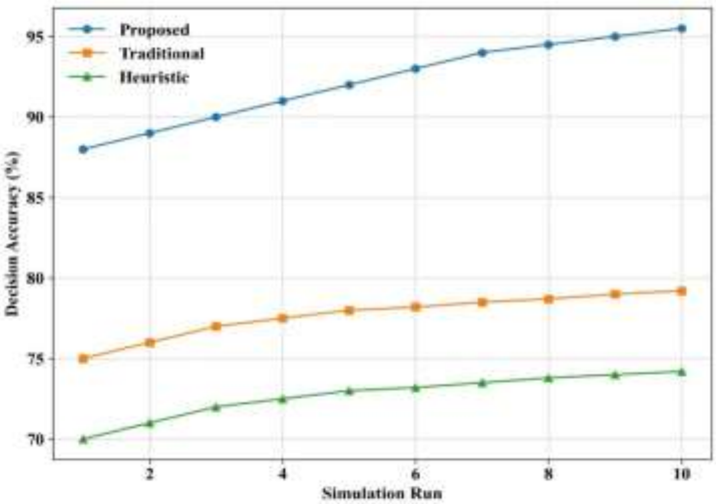

Fig.3: Decision Accuracy

Figure 4 illustrates the superior performance of the proposed method compared with traditional and heuristic approaches after 50 training episodes. Initially, the model achieves approximately 56% accuracy, followed by a consistent upward trend, reaching around 89% accuracy by the final episode. In comparison, the traditional method maintains a static accuracy of 70%, while the heuristic approach remains at 65%. The progressive improvement of the proposed method demonstrates the effective synergy between KG and DQN within CDSS-ER. Its performance increases incrementally as it incorporates feedback from interactions, a capability absent in the conventional approaches. These findings indicate that the proposed CDSS-ER enhances both adaptability and decision accuracy in emergency scenarios, outperforming traditional strategies due to its continuous learning capability.

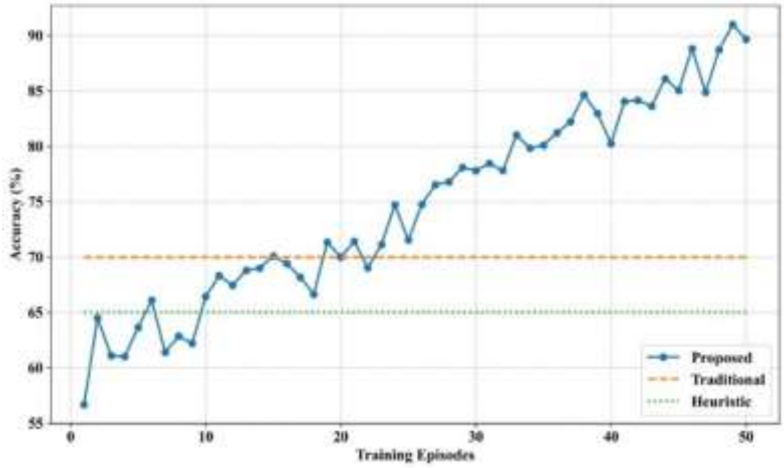

Fig.4: Average Accuracy

Figure 5 depicts the operational speed of the proposed, traditional, and heuristic methods across ten simulation runs. The proposed CDSS-ER consistently outperforms the other approaches, initially completing tasks in 12.5 seconds and subsequently improving to 9.8 seconds. In comparison, the traditional method begins at 18 seconds, decreasing to 15.6 seconds, while the heuristic approach starts around 20 seconds and converges to 17 seconds. The progressive improvement in the proposed method highlights its effectiveness in reducing response times through intelligent decision-making. In contrast, the limited gains observed in traditional and heuristic methods reflect their rigid operational frameworks. These results indicate that the integration of DQN and KG within CDSS-ER enhances both decision accuracy and the speed of responder actions, making it particularly suitable for emergency scenarios requiring rapid intervention.

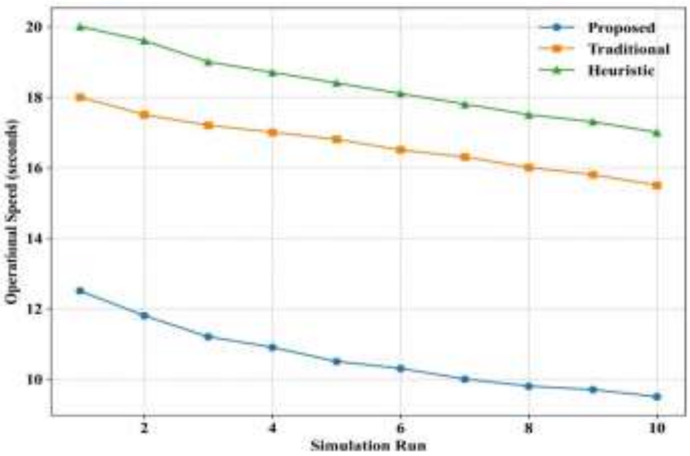

Fig.5: Operational Speed

Figure 6 presents the efficiency metrics of three decision-making approaches—CDSS-ER (92%), traditional methods (75%), and heuristic approaches (68%). These percentages are calculated based on assessments of resource utilisation, response times, and decision accuracy during emergency scenarios. The figure provides a quantitative comparison of each method's ability to process information and adapt to changing conditions, with higher efficiency scores reflecting superior performance in time-critical and resource-limited environments.

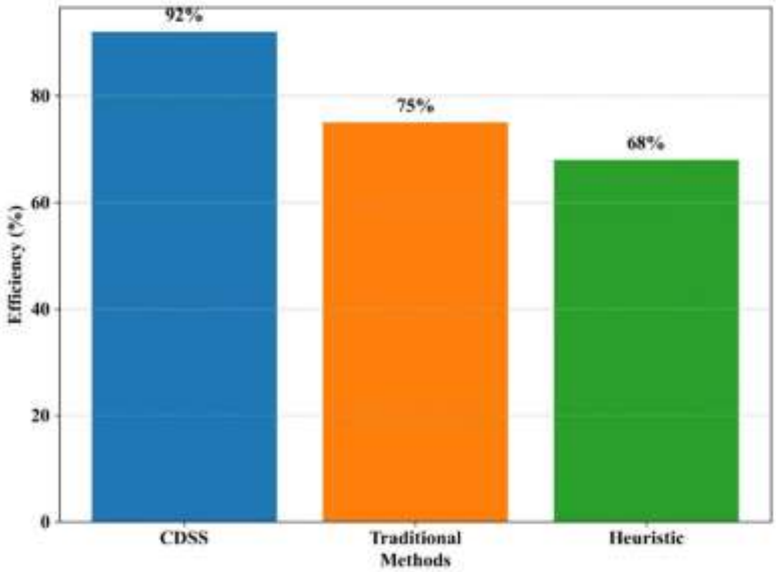

Fig.6: Efficiency

Figure 7 demonstrates that the proposed CDSS-ER substantially outperforms the alternative approaches in terms of resource utilisation across ten simulation runs. In the initial run, CDSS-ER achieves 85% efficiency, which increases to 94.5% by the tenth run. The traditional method exhibits only a modest improvement, rising from 70% to 74.5%, whereas the heuristic approach progresses from 65% to just below 69.5%. These results corroborate that CDSS-ER excels at managing resources effectively and delivering superior responses in rapidly evolving emergency scenarios, as highlighted in the abstract.

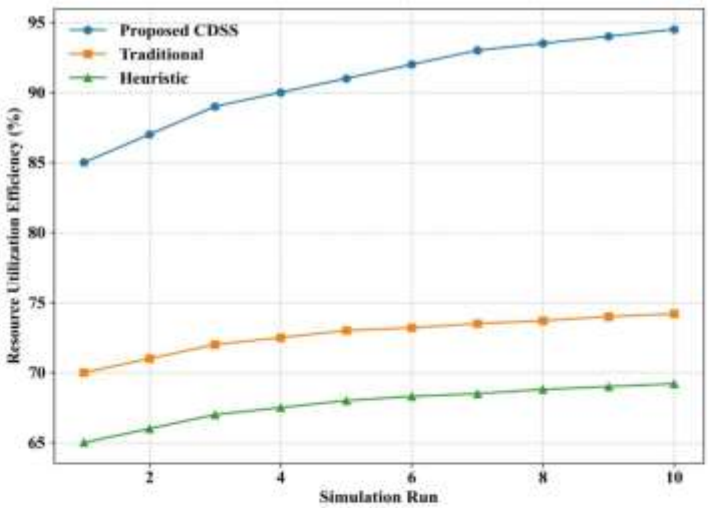

Fig.7: Resource Utilization Efficiency

6. Discussion

The proposed CDSS-ER exhibits significant advantages over conventional and heuristic approaches in dynamic emergency scenarios through the integration of KG and DQN. The system attains a decision accuracy of 92.3%, markedly exceeding that of traditional (78.6%) and heuristic (74.9%) methods, while reducing operational time to 9.5 seconds, thereby enhancing responsiveness. Resource utilisation reaches 87.5%, with resource management efficiency improving to 88.0%, reflecting superior coordination and real-time allocation. Figure 4 highlights the model's learning progression, with accuracy increasing from 56% to 89% over 50 episodes, and Figure 7 demonstrates resource utilisation improving from 85% to 94.5% across ten simulation runs. These results substantiate the claims made in the abstract, confirming that CDSS-ER enhances adaptability, scalability, and decision-making quality in high-pressure emergency environments. Additionally, the system achieves an average response time of 6.8 minutes in real-world case studies and is capable of managing up to 150 incidents, demonstrating operational robustness. Collectively, CDSS-ER provides a reliable and intelligent alternative to static systems, particularly in contexts requiring real-time, context-aware decision-making.

7. Conclusion

In this study, a robust CDSS-ER was developed by integrating KG and DQN to address the complexities inherent in emergency response. The framework enables the construction of a dynamic KG from diverse and rapidly evolving emergency data, supporting context-aware decision-making. Experimental results demonstrate that the CDSS-ER substantially improves resource utilisation, achieving high success rates. These findings confirm that the system continuously evolves through feedback while maintaining comprehensive situational awareness. Its adaptive design allows for faster and more accurate responses in dynamic environments, underscoring its operational value. Overall, the proposed CDSS-ER is both scalable and intelligent, offering a practical solution for emergency response as well as applications in public safety, disaster management, and healthcare logistics. The scalability of CDSS-ER is further validated by consistent performance enhancements across increasing simulation runs. Operational time decreased from 12.5 to 9.8 seconds, decision accuracy improved from 88% to 95%, and resource utilisation efficiency rose from 85% to 94.5%. These outcomes illustrate that the system not only adapts to increasing complexity but also enhances performance over time. This stability under expanding workloads confirms the framework's suitability for large-scale, real-time deployment in emergency management scenarios.

8. Limitations and Future Directions

Despite its advantages, the proposed CDSS-ER faces certain limitations, including challenges in transferring knowledge to previously unseen emergency scenarios and the considerable time required for KG updates and DQN inference. These issues may constrain an organisation's capacity to scale resources effectively in complex situations. Future research should focus on enhancing model flexibility through online learning, developing real-time efficient versions, and extending applications to areas such as epidemic control and smart city logistics to assess broader usability. Additionally, subsequent work will investigate the adaptation of the CDSS-ER framework for manufacturing and industrial automation, emphasising real-time decision-making and resource optimisation within dynamic production environments. This extension seeks to demonstrate the system's versatility and applicability across diverse high-stakes domains.

Acknowledgement

Supported by the Research Program of Yazhou Bay Innovation Research Institute, Hainan Tropical Ocean University,Grant No: 2023CXYZD001

References

[1] Abbas, A. N., Amazu, C. W., Mietkiewicz, J., Briwa, H., Perez, A. A., Baldissone, G., & Leva, M. C. (2024). Analyzing operator states and the impact of ai-enhanced decision support in control rooms: a human-in-the-loop specialized reinforcement learning framework for intervention strategies. *International Journal of Human–Computer Interaction*, 1-35. https://doi.org/10.1080/10447318.2024.2391605

[2] Aboualola, M., Abualsaud, K., Khattab, T., Zorba, N., & Hassanein, H. S. (2023). Edge technologies for disaster management: A survey of social media and artificial intelligence integration. *IEEE Access*, *11*, 73782-73802. https://doi.org/10.1109/ACCESS.2023.3293035

[3] Abu-Rasheed, H., Nadeem, M., Dornhöfer, M., Zenkert, J., Weber, C., & Fathi, M. (2024). Texkg in health domain: The application of knowledge graph based framework for explainable recommendations in the contexts of elderly care, mental health, and emergency responses. In *Integrated Systems: Data Driven Engineering* (pp. 265-285). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-53652-6_16

[4] Arora, S. (2025). Transforming AI Decision Support System with Knowledge Graphs & CAG. *International Journal on Engineering Artificial Intelligence Management, Decision Support, and Policies*, *2*(2), 15-23. https://doi.org/10.63503/j.ijaimd.2025.110

[5] Bajwa, A. (2025). *AI-based emergency response systems: A systematic literature review on smart infrastructure safety*. http://dx.doi.org/10.2139/ssrn.5171521

[6] Cepero, M. T., Montané-Jiménez, L. G., Toledo-Toledo, G., Benítez-Guerrero, E., & Mezura-Godoy, C. (2021). Heuristics for awareness support in groupware systems. *Dyna New Technologies*, *8*(1). https://doi.org/10.6036/NT9980

[7] Chen, M., Tao, Z., Tang, W., Qin, T., Yang, R., & Zhu, C. (2024). Enhancing emergency decision-making with knowledge graphs and large language models. *International Journal of Disaster Risk Reduction*, *113*, 104804. https://doi.org/10.1016/j.ijdrr.2024.104804

[8] Chen, S., Luo, G., & Chen, L. (2024). Intelligent Urban Emergency Response: Integrating Large Language Models, Multi-Objective Optimization, and Reinforcement Learning. 2024 IEEE Smart World Congress (SWC), 1469-1476. https://doi.org/ 10.1109/SWC62898.2024.00226

[9] Fan, J., Chang, X., Mišić, J., Mišić, V. B., & Kang, H. (2022). DHL: Deep reinforcement learning-based approach for emergency supply distribution in humanitarian logistics. *Peer-to-Peer Networking and Applications*, *15*(5), 2376-2389. https://doi.org/10.1007/s12083-022-01353-0

[10] Gerolimos, N., Alevizos, V., Edralin, S., Xu, C., Priniotakis, G., Papakostas, G. A., & Yue, Z. (2025). Autonomous Decision-Making Enhancing Natural Disaster Management through Open World Machine Learning: A Systematic Review. *Human-Centric Intelligent Systems*, 1-16. https://doi.org/10.1007/s44230-025-00098-2

[11] He, F., Bai, W., & Wang, Z. (2025). Investigating the synergistic effects of temporal knowledge graphs and digital twin technologies to enhance situational awareness decision-making in smart cities. *Journal of Computational Methods in Sciences and Engineering*, *25*(2), 1793-1810. https://doi.org/10.1177/14727978241305755

[12] He, L., Li, J., Zhao, M., & Yuan, R. (2022). Research on Emergency Logistics Decision Platform Based on Knowledge Graph. In *International Conference on Logistics, Informatics and Service Sciences* (pp. 199-210). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-2625-1_15

[13] Kyrkou, C., Kolios, P., Theocharides, T., & Polycarpou, M. (2022). Machine learning for emergency management: A survey and future outlook. *Proceedings of the IEEE*, *111*(1), 19-41. https://doi.org/10.1109/JPROC.2022.3223186

[14] Li, D., Zhang, Z., Alizadeh, B., Zhang, Z., Duffield, N., Meyer, M. A., & Behzadan, A. H. (2024). A reinforcement learning-based routing algorithm for large street networks. *International Journal of Geographical Information Science*, *38*(2), 183-215. https://doi.org/10.1080/13658816.2023.2279975

[15] Li, M., Yuan, C., Li, K., Gao, M., Zhang, Y., & Lv, H. (2024). Knowledge Management Model for Urban Flood Emergency Response Based on Multimodal Knowledge Graphs. *Water*, *16*(12), 1676. https://doi.org/10.3390/w16121676

[16] Li, Q., Zhang, M., Shen, Y., Wang, R., Hu, M., Li, Y., & Hao, H. (2023). A hierarchical deep reinforcement learning model with expert prior knowledge for intelligent penetration testing. *Computers & Security*, *132*, 103358. https://doi.org/10.1016/j.cose.2023.103358

[17] Li, W., Wang, S., Chen, X., Tian, Y., Gu, Z., Lopez-Carr, A., & Zhu, R. (2023). Geographvis: a knowledge graph and geovisualization empowered cyberinfrastructure to support disaster response and humanitarian aid. *ISPRS International Journal of Geo-Information*, *12*(3), 112. https://doi.org/10.3390/ijgi12030112

[18] Li, X., Chen, C. H., Zheng, P., Wang, Z., Jiang, Z., & Jiang, Z. (2020). A knowledge graph-aided concept–knowledge approach for evolutionary smart product–service system development. *Journal of Mechanical Design*, *142*(10), 101403. https://doi.org/10.1115/1.4046807

[19] Li, X., Zhao, T., Wen, J., & Cai, X. (2024). Many-objective emergency aided decision making based on knowledge graph. *Applied Intelligence*, *54*(17), 7733-7749. https://doi.org/10.1007/s10489-024-05557-0

[20] Linardos, V., Drakaki, M., Tzionas, P., & Karnavas, Y. L. (2022). Machine learning in disaster management: recent developments in methods and applications. *Machine Learning and Knowledge Extraction*, *4*(2). https://doi.org/10.3390/make4020020

[21] Liu, M., Li, X., Li, J., Liu, Y., Zhou, B., & Bao, J. (2022). A knowledge graph-based data representation approach for IIoT-enabled cognitive manufacturing. *Advanced Engineering Informatics*, *51*, 101515. https://doi.org/10.1016/j.aei.2021.101515

[22] Nussbaumer, A., Pope, A., & Neville, K. (2023). A framework for applying ethics-by-design to decision support systems for emergency management. *Information Systems Journal*, *33*(1), 34-55. https://doi.org/10.1111/isj.12350

[23] Olan, F., Spanaki, K., Ahmed, W., & Zhao, G. (2025). Enabling explainable artificial intelligence capabilities in supply chain decision support making. *Production Planning & Control*, *36*(6), 808-819. https://doi.org/10.1080/09537287.2024.2313514

[24] Peralta-Abadía, J. J., Cuesta-Zabaljauregui, M., & Larrinaga-Barrenechea, F. (2024). Tool condition monitoring in machining using robust residual neural networks. *Dyna*, *99*(5). https://doi.org/10.52152/D11111

[25] Piadeh, F., Behzadian, K., Chen, A. S., Campos, L. C., Rizzuto, J. P., & Kapelan, Z. (2023). Event-based decision support algorithm for real-time flood forecasting in urban drainage systems using machine learning modelling. *Environmental Modelling & Software*, *167*, 105772. https://doi.org/10.1016/j.envsoft.2023.105772

[26] Sasikumar, A., Ravi, L., Devarajan, M., Kotb, H., & Subramaniyaswamy, V. (2024). Cognitive Computing System-Based Dynamic Decision Control for Smart City Using Reinforcement Learning Model. In *Cognitive Analytics and Reinforcement Learning: Theories, Techniques and Applications* (pp. 29-50). https://doi.org/10.1002/9781394214068.ch2

[27] Shan, S., & Li, Y. (2024). Research on the application framework of generative AI in emergency response decision support systems for emergencies. *International Journal of Human–Computer Interaction*, 1-18. https://doi.org/10.1080/10447318.2024.2423335

[28] Soularidis, A., Kotis, K. I., & Vouros, G. A. (2024). Real-Time Semantic Data Integration and

Reasoning in Life-and Time-Critical Decision Support Systems. *Electronics*, *13*(3), 526. https://doi.org/10.3390/electronics13030526

[29] Suárez-Varela Macià, J. R. (2020). *Enabling knowledge-defined networks: deep reinforcement learning, graph neural networks and network analytics*

[30] Vankayalapati, R. K. (2020). *AI-Driven Decision Support Systems: The Role Of High-Speed Storage And Cloud Integration In Business Insights*. http://dx.doi.org/10.2139/ssrn.5103815

[31] Wu, D., Song, J., Bian, Y., Zheng, X., & Zhang, Z. (2021). Risk perception and intelligent decision in complex social information network. *Industrial Management & Data Systems*, *121*(1), 99-110. https://doi.org/10.1108/IMDS-10-2020-0566

[32] Wu, W., Wen, C., Yuan, Q., Chen, Q., & Cao, Y. (2025). Construction and application of knowledge graph for construction accidents based on deep learning. *Engineering, Construction and Architectural Management*, *32*(2), 1097-1121. https://doi.org/10.1108/ECAM-03-2023-0255

[33] Xiao, X., Liang, J., Tong, J., & Wang, H. (2024). Emergency decision support techniques for nuclear power plants: Current state, challenges, and future trends. *Energies*, *17*(10), 2439. https://doi.org/10.3390/en17102439

[34] Yang, S., Zhang, Y., Lu, X., Guo, W., & Miao, H. (2024). Multi-agent deep reinforcement learning based decision support model for resilient community post-hazard recovery. *Reliability Engineering & System Safety*, *242*, 109754. https://doi.org/10.1016/j.ress.2023.109754

[35] Zhang, D., Zhou, L., & Nunamaker Jr, J. F. (2002). A knowledge management framework for the support of decision making in humanitarian assistance/disaster relief. *Knowledge and Information Systems*, *4*, 370-385. https://doi.org/10.1007/s101150200012

[36] Zhao, J., Xu, X., & Xiao, F. (2025). Aegis: A cloud-edge computing based multi-disaster crowd evacuation model using improved deep reinforcement learning. *Computer Communications*, *231*, 108036. https://doi.org/10.1016/j.comcom.2024.108036

[37] Zhao, Z., Zhang, M., Chen, J., Qu, T., & Huang, G. Q. (2022). Digital twin-enabled dynamic spatial-temporal knowledge graph for production logistics resource allocation. *Computers & Industrial Engineering*, *171*, 108454. https://doi.org/10.1016/j.cie.2022.108454