Artificial Intelligence Driven Optimized Resource Allocation In Emergencies

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Abstract
In emergency priority situations, efficient resource allocation is vital for a rapid and effective response. Resources such as human , equipment, and information must be dynamically managed to meet urgent demands while upholding operational security. A strategic approach is required to prioritize resources based on the severity of the situation, ensuring critical areas receive timely support. Implementing robust security measures helps protect sensitive information and prevent unauthorized access, preserving the integrity of emergency response efforts. Integrating advanced technologies, including real-time tracking and data analysis, can enhance decision-making, optimize resource distribution, and improve overall preparedness and responsiveness.

1 Introduction

Strategic resource allocation in emergency priority situations is a crucial aspect of disaster management, ensuring that limited resources are distributed efficiently to mitigate the impact of crises. Emergencies, including natural disasters, pandemics, and humanitarian crises, often create unprecedented demands for personnel, medical supplies, food, water, and shelter. Effective resource allocation strategies are necessary to address these urgent needs while maintaining security, efficiency, and adaptability in response efforts (Van de Walle & Comes, 2015).

Emergency resource allocation has evolved from reactive, ad hoc methods to proactive, data-driven approaches. Earlier models primarily relied on pre-positioning resources based on historical data and expert judgment (Altay & Green, 2006)[1]. However, with advancements in technology, modern emergency management incorporates predictive analytics, artificial intelligence, and real-time monitoring systems to enhance decision-making (Kapucu & Garayev, 2016)[4]. The shift toward networked disaster response, involving governments, NGOs, private organizations, and international agencies, has further improved resource distribution efficiency (Kovács & Spens, 2011)[5].

Emergencies are unpredictable, and demand for resources fluctuates rapidly. Sudden surges in cases during a pandemic or after a natural disaster can overwhelm response systems (Tatham et al., 2017)[8].

The limited availability of critical supplies, such as medical equipment or food, necessitates prioritization and optimization of existing stockpiles (Coban & Saydam, 2020)[2].Transporting resources to affected areas, particularly in conflict zones or remote regions, poses significant challenges. Infrastructure damage can further complicate logistics (Devi & Kumar, 2021)[3].

Emergency response involves multiple stakeholders, including government agencies, military forces, humanitarian organizations, and private companies. Inefficiencies in coordination can lead to delays and duplication of efforts (Kovács & Spens, 2011)[5].The risk of theft, fraud, and misallocation of resources can undermine response efforts. Ensuring transparency and accountability through secure tracking mechanisms is critical (Patel et al., 2022).

Strategic resource allocation in emergency priority situations is a continually evolving field that integrates historical lessons, technological innovations, and policy frameworks. The goal remains to enhance preparedness, optimize response efficiency, and ensure equitable distribution of critical resources. By leveraging emerging technologies and strengthening coordination among stakeholders, emergency management can significantly improve its ability to mitigate crises and save lives.

Effective resource allocation in emergency priority situations is critical for minimizing the impact of disasters and ensuring a coordinated response. Rapid decision-making plays a key role in distributing essential resources such as personnel, equipment, and medical supplies to areas of greatest need (Van de Walle & Comes, 2015)[9]. Given the unpredictable nature of emergencies, resource distribution must be both proactive and adaptive, leveraging real-time data analytics and predictive modeling to enhance situational awareness and optimize deployment (Kapucu & Garayev, 2016)[4].

A well-structured emergency response framework involves setting clear priorities based on severity assessments and ensuring a flexible allocation system that can adapt to changing conditions (Coban &

Saydam, 2020)[2]. Advanced planning, including scenario-based simulations and capacity-building initiatives, helps organizations anticipate resource demands and improve readiness (Altay & Green, 2006)[1]. Furthermore, the application of machine learning and artificial intelligence (AI) in emergency logistics can facilitate more efficient decision-making, reducing response time and resource wastage (Devi & Kumar, 2021)[3].

Security in resource allocation is paramount, as the mismanagement or diversion of critical supplies can exacerbate an already dire situation (Tatham et al., 2017)[8]. To prevent misuse, theft, or misappropriation, emergency management systems should incorporate robust security measures, including digital authentication, inventory tracking, and personnel verification protocols (Lodree & Taskin, 2009)[6]. Emerging technologies such as blockchain can enhance transparency and accountability by creating immutable records of transactions, ensuring that resources are distributed equitably and efficiently (Patel et al., 2022)[7].

Ultimately, optimizing resource allocation in emergencies not only enhances response effectiveness but also strengthens resilience by maintaining a secure and well-coordinated supply chain. The integration of data-driven technologies and security protocols can significantly improve emergency preparedness, ensuring that life-saving resources reach those in need promptly while minimizing risks associated with resource misallocation (Kovács & Spens, 2011)[5].

2 LITERATURE REVIEW

Emergencies such as natural disasters, pandemics, and industrial accidents require efficient and dynamic resource allocation to mitigate damage and save lives. Traditional cloud-based resource management systems often struggle with latency, bandwidth limitations, and real-time data processing challenges. Fog computing, combined with artificial intelligence (AI) and machine learning (ML), has emerged as a promising solution to enhance resource allocation in emergency priority situations. This literature review explores existing research on the role of edge computing, AI, and ML in optimizing emergency resource management.

Edge computing extends cloud capabilities to the edge of the network, enabling faster decision-making by processing data closer to the source (Bonomi et al., 2012). It reduces the dependency on centralized cloud servers, minimizing latency and improving response efficiency in time-sensitive emergency scenarios (Chiang & Zhang, 2016). Edge computing provides low latency(Shi et al., 2016) with bandwidth optimization reduces bandwidth congestion, allowing for efficient communication in disaster-prone areas (Yousefpour et al., 2019). It distributes computational tasks across multiple edge nodes, ensuring resilience and fault tolerance (Mahmud et al., 2018). Edge computing application in Disaster Response with IoT-enabled fog nodes can track real-time data from sensors, cameras, and wearable devices to optimize personnel and supply deployment (Deng et al., 2020)[12].In Healthcare Emergencies: Fog-based AI models help prioritize medical resource distribution by analyzing patient vitals and predicting treatment urgency (Rahmani et al., 2018).Smart Transportation in urban emergencies can optimize traffic flow by managing emergency vehicle routing and crowd evacuation (Mukherjee et al., 2021).

AI and ML enhance emergency resource allocation by analyzing vast datasets, identifying patterns, and optimizing decision-making. These technologies play a crucial role in demand prediction, risk assessment, and automated resource allocation (Zhang et al., 2021).ML models use historical data, sensor readings, and social media inputs to predict resource demand during emergencies. Techniques such as deep learning, reinforcement learning, and federated learning are widely applied (Zhou et al., 2019).AI-driven algorithms optimize the distribution of emergency supplies, personnel, and transportation by dynamically adjusting resource allocation based on real-time data (Lu et al., 2020).AI-Based Routing Uses heuristic algorithms to optimize the movement of emergency responders and supplies (Gao et al., 2018)[13].Automated Decision Support Systems**:** AI-powered dashboards provide emergency coordinators with real-time situational analysis (Sun et al., 2021).*Drone-Assisted Resource Delivery:* AI-controlled UAVs (unmanned aerial vehicles) enhance last-mile delivery of medical supplies and relief materials (Jawhar et al., 2020)[14].

Fog-AI Hybrid Systems: Combining fog computing with AI reduces processing time for emergency predictions and decision-making (Wang et al., 2020).**Edge Intelligence:** AI-powered edge computing enables real-time decision-making at disaster sites without relying on remote cloud infrastructure (Xu et al., 2022) and blockchain-based AI-fog architectures ensure data integrity and prevent cyber threats in emergency management systems (Singh et al., 2021).

While edge computing and AI-ML present promising advancements, large-scale emergency response networks requires infrastructure investments (Yousefpour et al., 2019) , sensitive emergency data require secure handling to prevent misuse (McMahan et al., 2017)[16] with existing emergency management frameworks requires standardization efforts (Deng et al., 2020)[12] and optimize power consumption to function reliably in disaster-hit areas with limited energy sources (Mahmud et al., 2018).

3. RESEARCH METHODOLOGY

This literature review identifies key challenges in emergency response network implementation. To address these challenges, the AI-Driven Optimization Model (AIDOM) facilitates a systematic evaluation of their relative significance, offering valuable insights for decision-making. By leveraging this approach, the research aims to quantitatively assess and prioritize the obstacles associated with emergency response systems. This contributes to the development of enhanced strategies for emergency prediction and decision-making, ultimately improving resource allocation and crisis management efficiency.
To address the challenges of emergency resource allocation using Fog Computing with AI/ML, the proposed an AI-driven Optimization Model (AIDOM)**.** This model **i**ntegrate**s** Reinforcement Learning (RL), Federated Learning (FL), and Blockchain to dynamically allocate resources while ensuring security, efficiency, and real-time adaptability.

Fog Nodes Distributed computing real-time decision-making
AI-ML Agent dynamically optimize resource distribution.
Federated Learning improve learning without centralized data
Blockchain Layer **Ensures** secure, transparent, and tamper-proof tracking of allocated resources
IoT Sensors Real-time data collection
Priority Classifier classifier that prioritizes emergency requests

Fig 3.1: Optimized Model of AIDOM

1) *. Optimization Model Framework*

- R={r1,r2,...,rn}R = \{r_1, r_2, ..., r_n\}R={r1,r2,...,rn} be the set of **available resources** (e.g., medical supplies, personnel).
- D={d1,d2,...,dm}D = \{d_1, d_2, ..., d_m\}D={d1,d2,...,dm} be the set of **emergency demand nodes** (e.g., hospitals, disaster zones).
- F={f1,f2,...,fk}F = \{f_1, f_2, ..., f_k\}F={f1,f2,...,fk} be the set of **fog computing nodes** handling real-time data processing.
- P(di)P(d_i)P(di) be the **priority score** of demand node did_idi, computed using AI-based classifiers.

Maximize the efficiency of resource allocation while minimizing response time and network overhead. The optimization function is:
max∑i=1m∑j=1nAij·P(di)−λCij\max \sum_{i=1}^{m} \sum_{j=1}^{n} A_{ij} \cdot P(d_i) - \lambda C_{ij}maxi=1∑mj=1∑nAij·P(di)−λCij
where:

- AijA_{ij}Aij is the allocation decision (1 if resource rjr_jrj is allocated to demand did_idi, else 0).
- P(di)P(d_i)P(di) is the AI-prioritized emergency demand score.
- CijC_{ij}Cij is the **cost** (network latency, energy consumption, transportation delay).
- λ\lambdaλ is the penalty factor for high-cost allocations.

Constraints:

1. Resource Availability:
∑i=1mAij≤Rj,∀j\sum_{i=1}^{m} A_{ij} \leq R_j, \quad \forall ji=1∑mAij≤Rj,∀j
(A resource cannot be allocated beyond availability.)

2. Demand Satisfaction:
∑j=1nAij≥Di,∀i\sum_{j=1}^{n} A_{ij} \geq D_i, \quad \forall ij=1∑nAij≥Di,∀i
(Demand at a priority site should be met.)

3. Fog Node Capacity:
∑i=1mWi≤Cf,∀f\sum_{i=1}^{m} W_{i} \leq C_f, \quad \forall fi=1∑mWi≤Cf,∀f
(Fog nodes should not be overloaded beyond capacity CfC_fCf.)

2) 3. Model Workflow

Step 1: Data Collection (IoT Sensors & Fog Nodes)
- IoT sensors at emergency sites collect real-time environmental data (e.g., patient vitals, crowd density).
- Fog nodes process this data and classify emergency levels using AI-based priority scoring.

Step 2: AI-Based Optimization for Resource Matching
- Reinforcement Learning (RL) optimizes dynamic resource allocation based on real-time demand.
- Federated Learning (FL) ensures continuous model improvement without requiring centralized data.

Step 3: Secure & Transparent Tracking with Blockchain
- All allocations are recorded in a blockchain ledger, preventing fraud and misallocation.
- Smart contracts ensure automatic resource dispatch when predefined emergency conditions are met.

4. Results and discussion

Simulation Procedure for AI-Driven Resource Allocation in a Fog Computing Environment

To validate the proposed AI-driven Optimization Model (AIDOM) for strategic resource allocation in emergency situations, we conducted a simulation using a combination of:
- AI-based Optimization (Reinforcement Learning - RL)
- Fog Computing for Low-Latency Processing
- Blockchain for Secure Allocation Tracking
- Network Simulation (NS3) for Performance Evaluation

Simulation Procedure

4.1 Experimental Setup

Parameter	Value
Simulation Environment	Python (TensorFlow, NumPy), NS3 (Network Simulation), Hyperledger Fabric (Blockchain)
Optimization Algorithm	Deep Q-Learning (Reinforcement Learning)
Fog Nodes	10 - 50 distributed nodes
IoT Devices	500+ emergency sensors
Blockchain Network	5 Hyperledger Fabric Peers
Evaluation Metrics	Response Time, Latency, Resource Utilization, Security
Emergency Scenarios	Earthquake, Flood, Urban Fire

4.1.2 Simulation Phases

Step 1: Data Generation and Preprocessing
- IoT sensors detect emergency events and generate real-time data (e.g., number of injured individuals, location severity).
- AI models classify demand sites based on severity scores (1-10 scale).
- Data is processed at fog nodes to minimize latency before being sent to the cloud.

Step 2: Reinforcement Learning-Based Resource Allocation
- State (S): Current emergency demand, available resources.
- Action (A): Allocate or reallocate resources to emergency nodes.
- Reward Function: Maximizing response time efficiency and resource utilization while minimizing latency.
- Training: RL agent trains for 5000 episodes to optimize decision-making.

Step 3: Network Simulation via NS3
- Fog node-to-cloud communication is modeled to analyze network latency.
- Latency measurements are taken for traditional cloud-based and AI-driven fog-based models.

Step 4: Blockchain Integration for Secure Resource Tracking

- Hyperledger Fabric smart contracts ensure tamper-proof records of resource allocations.
- Unauthorized transactions are blocked, ensuring fraud prevention.

Step 5: Performance Evaluation

- The AIDOM model is compared against:
  - Traditional Cloud-Based Allocation
  - Non-Optimized Fog Allocation
- Metrics analyzed include response time, security, and resource efficiency.

B. 4.2. Results Analysis

4.2.1 Comparison of Response Time (Lower is Better)

Number of Requests	Cloud-Based Model	Non-Optimized Fog	Proposed AIDOM Model
100	8.2 sec	5.5 sec	**3.1 sec**
500	15.6 sec	9.3 sec	**4.5 sec**
1000	22.4 sec	12.7 sec	**6.2 sec**

The AIDOM model reduces response time by up to 72%**,** ensuring faster emergency response.

4.2.2 Resource Utilization Efficiency (Higher is Better)

Metric	Cloud-Based Model	AIDOM Model
Resource Wastage (%)	**38.2%**	**12.5%**
Successful Allocations (%)	**78.6%**	**96.4%**

AIDOM minimizes resource wastage by 25.7%**,** ensuring efficient use of emergency supplies.

4.2.3 Blockchain Security Evaluation

Security Metric	Without Blockchain	With Blockchain (AIDOM)
Unauthorized Transactions	12% risk	0% (Immutable Ledger)
Transaction Time (ms)	22ms	28ms (Slight Overhead)

Blockchain eliminates unauthorized allocations, making emergency response tamper-proof**.**

4.2.4 Network Latency Comparison

Configuration	Average Latency (ms)
Traditional Cloud Model	125 ms
Non-Optimized Fog Model	80 ms
Proposed AIDOM Model	42 ms

AIDOM reduces network latency by 66%**,** ensuring low-latency emergency response.

Discussion & Key Findings

1. **Faster Response Time:** AIDOM improves response time **by up to 72%**.
2. **Higher Resource Utilization: 96.4% successful allocations**, reducing wastage.
3. **Secure Transactions:** Blockchain eliminates **fraudulent resource misallocations**.
4. **Lower Network Latency: 42ms vs. 125ms** (cloud-based) due to fog-layer AI processing.

5. Conclusions and discussion

This research demonstrates that AI-driven fog computing, combined with blockchain, provides a scalable, efficient, and secure solution for emergency resource allocation. The proposed AIDOM model significantly outperforms traditional cloud-based approaches in terms of response time, efficiency, and security. Future work will explore lightweight AI models and multi-layer fog networks for large-scale emergency scenarios.
AIDOM model tried to solve challenges by using adopting digital technology framework.
The most significant challenge in the process of implementing solutions needs the faster response time. This work implemented edge computing which removes the dependency on the cloud which cause the dealy in the responces. This decentralization 72% faster response time with AIDOM model.Resource wastage is a critical concern in emergency resource allocation, as inefficient distribution can lead to shortages in high-priority areas while excess resources remain underutilized elsewhere. In traditional cloud-based systems Reducing resource wastage was challenge . Assesing real time demand and priority resources are allocated which ensuring 12.5% efficient utilization .

unauthorized access, resource mismanagement, and lack of transparency in Traditional systems often suffer from data manipulation, duplication of requests, and resource hoarding, leading to inefficiencies and inequitable distribution .In this the Resource allocations are validated by multiple nodes and predefined conditions for traceable transactions, allowing real-time audits and preventing manipulation.

AIDOM the Proposed Model achieves the lowest latency (42 ms) by leveraging real-time AI decision-making in fog nodes, dynamically optimizing resource distribution, and reducing data transmission to the cloud.

Challenges & Future Improvements

Blockchain Overhead: Implement lightweight blockchain protocols (e.g.,DAG-based systems).

Fog Node Scalability: Use dynamic node clustering for large-scale deployments

AI Model Adaptability: Implement Transfer Learning to generalize across different emergency types.

Future work can focus on lightweight AI models for real-time deployment in disaster-prone regions.

References

[1] Altay, N., & Green, W. G. (2006). OR/MS research in disaster operations management. *European Journal of Operational Research, 175*(1), 475-493.

[2] Coban, M., & Saydam, C. (2020). Optimal resource allocation in disaster response. *International Journal of Disaster Risk Reduction, 42*, 101339.

[3] Devi, R., & Kumar, R. (2021). AI-driven logistics in emergency management. *Journal of Humanitarian Logistics and Supply Chain Management, 11*(3), 415-432.

[4] Kapucu, N., & Garayev, V. (2016). Disaster resilience and adaptive capacity in emergency management. *Journal of Homeland Security and Emergency Management, 13*(3), 395-419.

[5] Kovács, G., & Spens, K. M. (2011). Humanitarian logistics and supply chain management: The start of a new journal. *Journal of Humanitarian Logistics and Supply Chain Management, 1*(1), 5-14.

[6] Lodree, E. J., & Taskin, S. (2009). Supply chain planning for hurricane response with wind speed information updates. *Computers & Operations Research, 36*(1), 2-15.

[7] Patel, R., Jain, S., & Singh, M. (2022). Blockchain for emergency logistics: A systematic review. *IEEE Access, 10*, 65742-65759.

[8] Tatham, P., Wu, Y., Kovács, G., & Butcher, T. (2017). Supply chain management in disaster response: A research agenda. *International Journal of Production Research, 55*(6), 1663-1682.

[10] Van de Walle, B., & Comes, T. (2015). On the nature of information management in complex and natural disasters. *Proceedings of the 48th Hawaii International Conference on System Sciences*.

[11] Bonomi, F., Milito, R., Zhu, J., & Addepalli, S. (2012). Fog computing and its role in the Internet of Things. *Proceedings of the First Edition of the MCC Workshop on Mobile Cloud Computing*, 13-16.

[12] Chiang, M., & Zhang, T. (2016). Fog and IoT: An overview of research opportunities. *IEEE Internet of Things Journal, 3*(6), 854-864.

[13] Deng, S., Zhao, H., Fang, W., Yin, J., Dustdar, S., & Zomaya, A. Y. (2020). Edge intelligence: The confluence of edge computing and artificial intelligence. *IEEE Internet of Things Journal, 7*(8), 7457-7469.

[14] Gao, Y., Wang, X., Li, X., & Chen, X. (2018). AI-based emergency management for smart cities. *IEEE Communications Magazine, 56*(3), 30-36.

[15] Jawhar, I., Mohamed, N., & Zhang, L. (2020). UAV-assisted emergency networks: A review of applications and challenges. *Ad Hoc Networks, 97*, 102015.

[16] Mahmud, R., Kotagiri, R., & Buyya, R. (2018). Fog computing: A taxonomy, survey, and future directions. *Internet of Everything*, 103-130.

[17] McMahan, H. B., Moore, E., Ramage, D., & Hampson, S. (2017). Communication-efficient learning of deep networks from decentralized data. *Proceedings of the 20th International Conference on Artificial Intelligence and Statistics*, 1273-1282.

[18] Mukherjee, M., Shu, L., & Wang, D. (2021). Survey of fog computing: Fundamental, network applications, and research challenges. *IEEE Communications Surveys & Tutorials, 20*(3), 1826-1857.

[19] Rahmani, A. M., Liljeberg, P., & Tenhunen, H. (2018). Fog computing in healthcare—A review and discussion. *Future Generation Computer Systems, 88*, 635-643.

[20] Shi, W., Cao, J., Zhang, Q., Li, Y., & Xu, L. (2016). Edge computing: Vision and challenges. *IEEE Internet of Things Journal, 3*(5), 637-646.

[21] Wang, X., Han, Y., Leung, V. C., Niyato, D., Yan, X., & Chen, X. (2020). Convergence of edge computing and deep learning: A comprehensive survey. *IEEE Communications Surveys & Tutorials, 22*(2), 869-904.