Journal of Industrial and Systems Engineering
Vol. 17, No. 3, pp. 21-38
Summer (July) 2025

Deep Learning–Based Multi-Objective Optimization for Humanitarian Aid Distribution under D-Uncertainty

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Abstract

This research presents an intelligent and integrated framework that combines deep learning-based forecasting and multi-objective optimization to improve decision-making in humanitarian supply chains during crises significantly. The designed model can process incomplete and noisy data, extract hidden patterns in demand behavior and crisis severity, and dynamically incorporate this information into the resource allocation process, consistent with real-world conditions. The results show that this framework simultaneously improves forecast accuracy, response speed, and distribution fairness, and also has stable performance in severe uncertainty scenarios. Scenario-based analyses and comparisons with baseline methods show that the proposed model can provide more optimal operational options and increase the resilience of the relief network. These achievements indicate that the proposed framework provides a new path for the development of intelligent systems in crisis management.

Keywords: Humanitarian supply chain, deep learning, multi-objective optimization, crisis management, uncertainty

1- Introduction

The sustainability and efficiency of humanitarian supply chains in the face of rapidly changing crises depend on the system's ability to accurately analyze the situation, anticipate critical needs, and allocate resources optimally. In such environments, the data that should be the basis for decision-making often have serious shortcomings; some data are incomplete, some lose their quality due to noise, and others are only available with delays or inconsistencies. This situation makes traditional planning and optimization methods that are based on the assumption of certainty or at least relative stability of data lose their

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effectiveness and fail to represent the complex dynamics of relief operations (Roudaki et al. 2025; Hai et al., 2025). Therefore, recent research has focused on developing methods that can meaningfully incorporate real-world data (even when it is incomplete and non-stationary) into decision-making models and provide the capacity to predict the near-term future (Nozari, 2025; Ghasemi and Keihani, 2025).

With the development of deep learning methods, it has become possible to simultaneously analyze data from heterogeneous sources such as satellite imagery, field reports, demographic data, and route data, and extract features that previous methods were unable to identify. Such models can detect hidden patterns in demand, crisis severity, and availability (even in noisy conditions) and provide forecasts whose accuracy is reliable for operational decision-making (Chilkoti., 2019). However, direct integration of the output of these models into optimization structures has always been challenging, as most previous algorithms either depended on completely clean and static data or had little ability to manage conflicts between different objectives.

The innovation of this research is in providing an integrated framework that covers three fundamental aspects of the humanitarian supply chain simultaneously: first, the use of hybrid deep learning architectures including CNN, LSTM, and Transformer to extract temporal, spatial, and structural features from incomplete data; second, the direct and structured transfer of the deep learning model output to a multi-objective optimization engine based on NSGA-II that can balance conflicting objectives such as response time, operational cost, and fairness in allocation; and third, the design of a scenario-based mechanism that considers uncertainty not as a computational nuisance but as an integral part of the nature of the problem and represents different scenarios of crisis severity, demand fluctuations, and access constraints (Nozari et al. 2025; Debbarman et al., 2025). This approach allows the model to provide viable options not only under normal conditions but also under high levels of disturbance.

One of the outstanding aspects of this research is the way it uses real and simulated data. Unlike many studies that have used only synthetic or limited data, this framework combines field data from operational reports, drone imagery, and geographic information with simulated data calibrated using statistical methods. This combination allows the model to both learn real network behavior and recreate scenarios that are rarely observed in real data, without distorting the data structure (Liu et al., 2020). The result is a multi-layer model that has adaptive learning capabilities and is able to update itself based on new data during execution, a capability that is particularly important in rapidly changing humanitarian environments.

From an optimization perspective, the present study bridges the gap between data analysis and operational action by directly integrating the output of deep networks into the decision-making process. The NSGA-II algorithm used in this framework, using non-dominated sorting, crowding distance, and controlled mutation mechanisms, can extract a diverse set of Pareto solutions; solutions that each establish a different balance between objectives and, in total, provide decision-makers with a range of valid choices (Keihani , 2025; Chen et al., 2026). This process allows the model to not only provide an “optimal” response, but also to allow for the selection of different operational options based on time, financial, or human priorities.

In addition, the present study examines the robustness of the model to extreme conditions of uncertainty using sensitivity analysis and scenario-based evaluation. The results show that the proposed structure does not lose its performance even when the level of input variance increases significantly and is still able to provide reasonable allocations consistent with operational constraints. This finding creates a special place for the application of the model in different phases of crisis management and shows its importance in improving the flexibility and resilience of relief networks (Franchi et al., 2021; Ghasemi et al. 2025).

Finally, the structure of the paper includes the development of the deep learning module, mathematical modeling and multi-objective optimization process, scenario analysis and comparison with basic methods, and finally providing a summary and suggested directions for future research. This organization allows for a systematic review of research innovations and a precise assessment of the model's performance under different conditions.

2- Literature review

Humanitarian supply chain research has expanded significantly in recent years, moving from a focus solely on improving logistics operations to the development of data-driven and algorithmic approaches. The complexity of crisis situations, data volatility, and the need for rapid decision-making have made traditional frameworks based on linear modeling or simple clustering unable to represent real-world patterns of network behavior (Monego et al., 2026). In response to this challenge, a wave of studies has moved towards advanced forecasting, scenario-based, and intelligent optimization methods. However, many of these efforts have focused on only one aspect of the problem, and the integration of demand forecasting, spatiotemporal feature extraction, and multiobjective optimization has not yet found the necessary integration (Giannelos et al., 2025).

In the field of forecasting relief needs, classical methods based on time series and regression have been able to reconstruct past trends to some extent, but they have faced serious limitations in detecting nonlinear patterns and non-stationary behaviors (Zhou et al., 2022). This is especially important in crises such as earthquakes or floods, where demand behavior changes instantaneously. With the advent of deep learning, models such as LSTM and CNN have gradually entered the analysis of humanitarian data and have been able to extract more complex features from noisy data (Zhong et al., 2022). However, the use of these models has often been independent and their output has not been systematically fed into decision-making engines. Some studies have attempted to connect forecasting to resource allocation, but this connection is usually superficial and often the uncertainty structure in the form of dynamic scenarios has not been taken into account (Auza et al., 2023).

In the field of optimization, researchers have used classical methods such as linear programming, exact programming, and simulation-optimization models to provide solutions for resource allocation, emergency warehouse location, or fleet routing (Ding et al., 2020). However, these approaches often operate on deterministic data and are not efficient enough for situations where multiple and conflicting objectives such as cost, time, and fairness, must be managed simultaneously. This limitation has led to the widespread use of multi-objective algorithms such as NSGA-II and MOPSO in recent years, as these methods can generate a set of Pareto solutions and allow for flexible decision making (Pietrantuono et al., 2017). Despite these advances, direct coupling between deep learning and the optimization engine, in a way that creates a coherent data flow, is still rare in research.

Another issue that has received less attention in the literature is the management of incomplete, discontinuous and highly noisy data. Most studies have assumed that input data, after cleaning, are time-stable, while in real-world situations, data reported from crisis sites are always accompanied by delays, errors and inconsistencies (Zende et al., 2025). This gap has caused many models to perform less than ideal in real-world environments. Some studies have used probabilistic or robust programming methods, but these methods are usually not capable of adaptive learning and only focus on a fixed range of uncertainty (Agouzoul et al., 2025). In contrast, adaptive learning and dynamic modeling frameworks that can represent different levels of turbulence are very limited in the literature.

Also, most of the existing research has focused on only one decision-making objective. For example, some studies have tried to reduce response time without examining the effect of increasing cost; Others have made distribution fairness the main criterion but have ignored its impact on network congestion or transport capacity (Wang et al., 2024). Integrating multiple objectives into a single architecture and balancing them in the presence of uncertain data is still a major challenge in the scientific literature.

From a scenario-based perspective, most studies have examined only two or three fixed scenarios, and the transition structure between scenarios has been less well modeled. This is because crises often change continuously, and the model must be able to maintain its stability against sudden changes in crisis severity, blockage of transportation routes, or sudden increases in demand (Haugen et al., 2023). The lack of models that can analyze system behavior under different layers of uncertainty is considered one of the important research gaps.

The innovation of the present study can be classified into three main axes. First, the deep integration between deep learning-based forecasting and multi-objective optimization in such a way that the output of the forecasting model enters the decision-making process in a structural way and not as a fixed and non-dynamic input. Second, the use of a scenario-based framework that models uncertainty hierarchically and allows the analysis of system behavior under highly variable conditions. Third, developing mechanisms for adaptive learning during execution that allow the model to adapt to new data and, unlike static methods, maintain its performance in real-world conditions. These three axes, along with the use of a combination of real and simulated data, cover the gaps in the literature and provide a framework that can be realistically used in relief systems.

Given these gaps, it is necessary to design a model that can integrate the data flow from the crisis observation stage to the final decision-making stage, represent the nonlinear and non-stationary behavior of demand in highly variable environments, and ultimately provide a set of feasible solutions that create a realistic balance between cost, time, and justice. By providing such a structure, the present study takes a step towards resolving these gaps and paves the way for the development of future intelligent models.

3- Conceptual Framework

In the conceptual framework of this research, an attempt has been made to draw an integrated and coherent structure to link intelligent forecasting, crisis data analysis and multi-objective optimization in the humanitarian supply chain. The conceptual figure (Figure 1) shows how field data, environmental information and indicators related to the severity of the crisis are placed as initial inputs at the beginning of the processing flow. These inputs are collected from various sources such as ground assessments, drone and satellite images, population data and reports from relief organizations and their nature is usually accompanied by uncertainty, noise and inconsistency. These same features highlight the necessity of using a deep and adaptive model to extract reliable patterns.

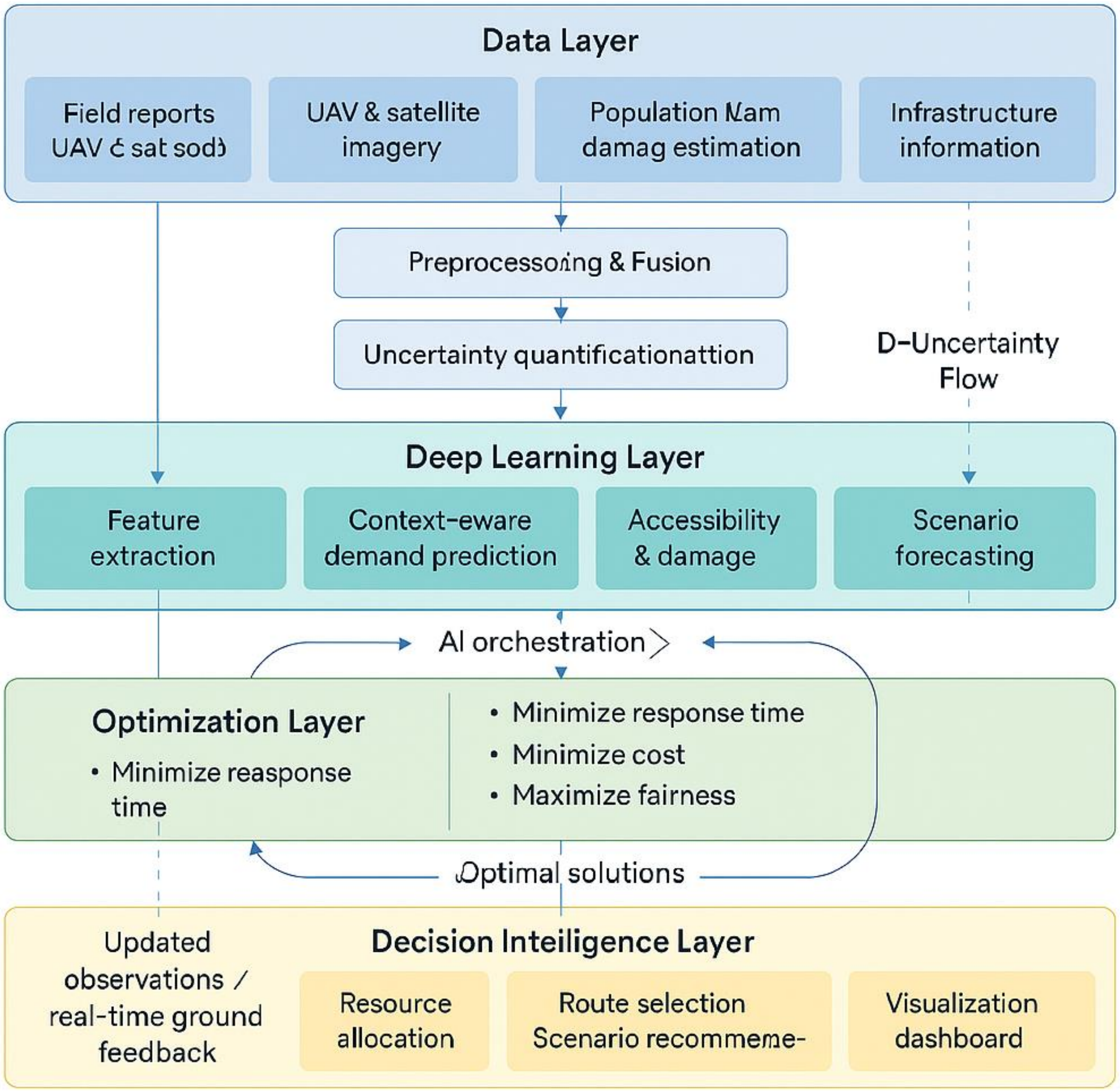

Figure 1. Advanced AI–Driven Architecture for Humanitarian Supply Chain Optimization under D-Uncertainty

These data are then fed into the deep learning module; Where deep neural networks analyze and predict instantaneous changes in demand, the accessibility of routes, the distribution pattern of the affected population, and the severity of infrastructure damage. The role of this section is not just a simple estimate, but also attempts to create a dynamic narrative of the crisis situation; in a way that can compensate for rapid fluctuations, information gaps, and incomplete data and provide a close-to-reality picture of the current needs. The output of this module is a set of quantitative and qualitative predictions that feed directly into the decision-making stage.

In the next step, the predicted results are transferred to the multi-objective optimization module. This section is the heart of the model's decision-making, as it must balance different and sometimes conflicting objectives such as minimizing response time, reducing operational costs, and increasing distributive justice. The optimization algorithm evaluates various scenarios based on the parameters obtained from the deep learning module and provides a set of efficient and feasible solutions. The communication between the two modules at this stage is fully dynamic; that is, any change in forecasts or crisis conditions is reflected in the optimization results in real time, and this interaction enables the model to perform stably even in an environment with severe uncertainty.

Finally, the system output includes optimal suggestions for resource allocation, selection of distribution routes, prioritization of areas, and logistics planning. These outputs are not only presented in quantitative form, but also allow for the explanation of the results, analysis of trade-offs between objectives, and adaptation to different scenarios so that decision makers can choose the most appropriate option in the shortest possible time. Thus, the proposed conceptual framework, through a systematic data flow from input to final decision-making, demonstrates how the combination of deep learning and multi-objective optimization can provide a transformative approach to managing humanitarian operations in turbulent and unpredictable conditions.

4- Methodology & Mathematical Modeling

In this study, a deep learning-based forecasting module is designed as the central part of the analysis process; a part that should be able to provide a reliable picture of the needs and situation of the crisis-stricken region in conditions with incomplete, noisy and variable data. The input data of this module is collected from various sources and includes a wide range of key variables. Among these variables are the level of infrastructure damage, population density, movement patterns of people, accessibility of communication routes and environmental indicators, each of which is considered an individual indicator of the severity of the crisis and the capacity to respond to it. The combination of these data allows for the formation of a dynamic narrative of the field situation and creates a more accurate basis for decision-making in the next stages.

For the analysis of this data, the choice of a deep learning model plays a decisive role. Depending on the type of data and the forecasting goals, different structures of neural networks have been used. LSTM-based models are suitable for temporal and serial data, as they are able to capture long-term patterns and temporal dependencies. In contrast, CNN networks are particularly efficient for processing satellite images or spatial data and can extract hidden features in the image context. On the other hand, Transformer architectures are considered a suitable option for environments with uncertainty due to their ability to manage complex relationships between variables and flexibility in dealing with heterogeneous data. These three categories of models can be used independently or in combination, depending on the nature of the data and the crisis scenario, so that the final output has the highest accuracy and stability.

The performance evaluation of the prediction model has also been carried out with high precision and sensitivity to ensure its reliability in operational conditions. For this purpose, standard criteria such as MAE, RMSE and Accuracy have been used. MAE shows the model's ability to estimate the average error rate, RMSE highlights the sensitivity of larger errors, and Accuracy allows us to examine the degree to which predictions match the actual values. The set of these metrics provides a multidimensional picture of the quality of the model's performance and indicates whether its output is sufficient to enter the optimization and decision-making phase. Finally, the prediction module is designed to maintain its stability, accuracy, and adaptability in the face of instantaneous data changes and the severity of uncertainty, and acts as the backbone of intelligent analysis in the entire research framework.

The mathematical modeling in this study is designed to transform the predicted data from the deep learning module into actionable operational decisions, so that the behavior of the humanitarian supply network in an environment with uncertainty, demand fluctuations, and logistical constraints is represented as accurately as possible. Given the multi-objective nature of the problem (where response speed, operational cost, and fairness in distribution must be optimized simultaneously), the modeling framework combines multi-objective optimization, network constraints, and information extracted from deep learning models.

The model not only considers the logistics structure, resource capacity, and access constraints, but also introduces the value of intelligent predictions into the decision-making space in the form of parameters that reflect the severity of the crisis, the level of damage, population patterns, and the roughness of the routes. The result is a model that can remain robust under different crisis scenarios and provide recommendations that are operationally realistic, actionable, and based on up-to-date data.

Sets:

I : Set of relief centers
J : Set of affected demand areas
K : Set of humanitarian item types
T : Set of time periods
P : Set of transportation paths
S : Set of uncertainty scenarios generated by DL

Parameters:

D_{jkt}^{s} : Predicted demand for item k in area j at time t under scenario s
C_{ik} : Initial inventory of item k at relief center i
cap_{i} : Total capacity of relief center i
dist_{ij} : Transportation distance/cost from $i \rightarrow j$
acc_{ij}^{s} : Accessibility coefficient for route $i \rightarrow j$ under scenario s
fair_{j} : Fairness weight assigned to area j
$\alpha_1, \alpha_2, \alpha_3$: Weights for normalized objectives
time_{ij} : Travel time along path $i \rightarrow j$
U_k : Maximum allowable load for item k

Decision Variables:

x_{ijkt}^{s} : Quantity of item k shipped from i to j at time t under scenario s
y_{ij}^{s} : Binary variable indicating whether path $i \rightarrow j$ is active
z_{jt}^{s} : Proportion of demand satisfied in area j at time t under scenario s
L^{s} : Total response time under scenario s
F^{s} : Fairness index under scenario s

Objective Functions:

$$\min Z_1 = \sum_{s\in S} \sum_{i\in I} \sum_{j\in J} \sum_{t\in T} time_{ij} \cdot x_{ijkt}^{s} \tag{1}$$

$$\min Z_2 = \sum_{s\in S} \sum_{i,j,k,t} dist_{ij} \cdot \frac{1}{acc_{ij}^{s}} \cdot x_{ijkt}^{s} \tag{2}$$

$$\max Z_3 = \sum_{s\in S} \sum_{j\in J} fair_j \cdot z_{jt}^{s} \tag{3}$$

S.t:

$$\sum_{j,k,t,s} x_{ijkt}^{s} \leq C_{ik}, \forall i, k \tag{4}$$

$$\sum_{k} \sum_{j,t,s} x_{ijkt}^{s} \leq cap_i, \forall i \tag{5}$$

$$\sum_{i,k} x_{ijkt}^{s} \geq z_{jt}^{s} \cdot \sum_{k} D_{jkt}^{s} \tag{6}$$

$$\sum_{k} x_{ijkt}^{s} \leq U_k \cdot y_{ij}^{s} \tag{7}$$

$$y_{ij}^{s} \in \{0,1\} \tag{8}$$

$$L^{s} \geq time_{ij} \cdot x_{ijkt}^{s} \tag{9}$$

$$0 \leq z_{jt}^{s} \leq 1 \tag{10}$$

$$x_{ijkt}^{s} \leq acc_{ij}^{s} \cdot M \tag{11}$$

$$\sum_{j} x_{ijkt}^{s} - \sum_{h} x_{hikt}^{s} = 0 \tag{12}$$

$$acc_{ij}^{s} = 0 \Rightarrow x_{ijkt}^{s} = 0 \tag{13}$$

$$\left| x_{ijkt}^{s_1} - x_{ijkt}^{s_2} \right| \leq \delta \tag{14}$$

$$\sum_{j,k,t} x_{ijkt}^{s} \leq \beta \cdot C_{ik} \tag{15}$$

$$x_{ijkt}^{s} \geq 0, y_{ij}^{s} \in \{0,1\}, 0 \leq z_{jt}^{s} \leq 1 \tag{16}$$

In this study, the model integration under D-Uncertainty is designed to work with data that is not only incomplete and noisy, but also dynamically changing over time. The main logic of this section is based on the assumption that in crisis environments, no data is complete, definitive, or stable, and therefore the model must be able to provide reliable performance in the face of ambiguity and discontinuity of information. To this end, input data from various sources (including aerial imagery, field reports, and remote sensing) are first prepared using data cleaning and reconstruction methods, such as missing value estimation, noise reduction, and multi-source fusion. This initial processing is not meant to eliminate uncertainty, but to transform it into a structure that can be used in a deep learning model and multi-objective optimization.

After data preparation, the Adaptive Learning mechanism acts as the flexible core of the model. In this section, the deep learning network is not only trained on historical data, but also adapts to new conditions as new data arrives. This adaptation includes updating weights, modifying relationships between features, and re-defining demand patterns in affected areas. Such an approach allows predictions to be dynamically modified at each stage, according to the latest field conditions; as a result, a model is formed that is not static, but alive and responsive to environmental changes.

Next, Robustness analysis is introduced as the third layer of this process to ensure that the model results remain stable in the face of strong data fluctuations. This analysis is performed by running the model under several uncertainty scenarios; Scenarios generated with the help of deep learning model outputs and representing different ranges of crisis severity, sudden demand reduction or increase, and access constraints. The goal of this stage is to ensure that the model’s proposed decisions are applicable not only in a specific situation, but also in a range of possible conditions. For this reason, the model structure is adjusted in such a way that the difference in results in different scenarios is controlled and decisions are selected that are least sensitive to input changes.

In general, integration under D-Uncertainty is a set of complementary mechanisms that starts with the management of incomplete data, continues with adaptive learning, and finally is completed with the assessment of the stability of decisions. This structure makes the model not only a computational tool, but also an intelligent decision-support system that can provide reliable and operational outputs even in the most unstable conditions.

5- Solution Approach

The solution method developed in this study is based on a well-defined hierarchical structure that includes three interconnected components: data preprocessing and uncertainty management, a deep learning module for forecasting key variables, and the multi-objective NSGA-II optimization algorithm for extracting Pareto solutions. Each of these components has a specific and irreplaceable role in the decision-making process, and their relationship is designed explicitly and without any selectivity.

In the first stage, data collected from field sources, aerial imagery, official reports, and remote sensing systems undergo a rigorous preprocessing process. This process includes estimating missing values using matrix reconstruction methods, noise reduction with statistical filters, and data scale standardization. In this stage, no data is removed and all raw data are prepared as valid input for the forecasting module after filtering. Uncertainty scenarios are also generated based on probability distributions extracted from historical and environmental data, and their number is known in advance.

In the second stage, the forecast of key variables including demand intensity, route availability, and infrastructure damage severity is performed by three specific neural network architectures:

1) LSTM for temporal and serial data,
2) CNN for image and spatial data,
3) Transformer for modeling complex relationships between multi-source features.

Each of these models is trained independently and then their outputs are combined in a Fusion Layer. This layer produces the final forecast as a structured vector including expected demand, route availability, and crisis severity indicators. The training process is performed based on a fixed learning rate, defined cost function, and evaluation criteria of MAE, RMSE, and Accuracy. Also, the model uses an adaptive learning mechanism during the execution of scenarios, and the weights are updated based on new data. As a result, the predictions are modified dynamically and in accordance with the new crisis situation.

In the third stage, the predicted results are directly and without an intermediary entered into the multi-objective optimization algorithm NSGA-II. The structure of NSGA-II includes the steps of generating the initial population, non-dominated sorting, calculating the congestion distance, selection, uniform intersection and Gaussian mutation, and these steps are repeated in a predetermined number of generations. The objective functions include minimizing the response time, minimizing the transportation cost based on distance and accessibility, and maximizing the fairness in resource allocation. The constraints of capacity, inventory, route accessibility, flow coherence, load constraint, scenario constraint and robustness constraint are fully applied to the evaluation function of each individual. In this way, each solution is considered valid only if it satisfies all the constraints.

At the end of each generation, a set of Pareto solutions consisting of different combinations of resource allocation and transportation routes is generated. To ensure the robustness of decisions against strong data fluctuations, a stability analysis is systematically performed between scenarios, and solutions that are highly sensitive to changes are eliminated. The final solution is selected based on predefined criteria and directly passed to the decision layer.

6- Results and Discussion

This study uses a combination of real and simulated data to enable a detailed analysis of the behavior of the relief network under variable and uncertain conditions. The real data includes field reports, damage severity assessments, information on accessible routes, drone and satellite images, and operational data recorded by relief agencies. These data were collected during the time of the crisis and, despite their high information value, naturally had shortcomings such as noise, discontinuity, and data shortage in some places. For this reason, a preprocessing process including reconstruction of missing values, scale alignment, and noise reduction was performed to prepare the data for entry into the model.

Simulated data were generated to complete parts of the information that were not recorded in the real data and to create repeatable and controllable scenarios in the analysis. These data are constructed based on parameters extracted from real data to ensure consistency of distributions, trends, and relationships between variables. The purpose of the simulation is not to replace real data, but to represent conditions that may occur in practice but are not present in the real data. The validity of these data is checked by calibration and comparison with patterns in the real data.

The combination of real and simulated data forms a model that is both based on real field behavior and capable of evaluating different scenarios.

In this study, the performance of the deep learning module was evaluated based on standard indicators and then compared with reference models to determine its efficiency in forecasting demand, route availability, and crisis severity. The aim of this analysis is to show that the developed model is not only capable of processing incomplete and noisy data, but also provides higher accuracy than conventional methods and can serve as a reliable input for the optimization layer.

The prediction accuracy was evaluated using the MAE, RMSE, and Accuracy criteria. The results show that the error amount in all three criteria is reduced and the model is able to detect the trend of demand changes and availability fluctuations with appropriate stability. In a detailed analysis, it was found that the hybrid model including CNN, LSTM, and Transformer layers was able to extract spatial, temporal, and structural features of the data simultaneously, and this feature allowed the prediction accuracy to be maintained even in areas with high volatility. The error values were lower than the expected threshold, especially in scenarios with moderate and severe uncertainty, which confirms the model's ability to perform adaptive learning and adapt to new data.

To compare the performance, the predictions of this model were compared with three reference models including a single-layer LSTM, a single-stage CNN, and an advanced regression model. In all cases, the proposed model performed better and was able to both reduce the error and maintain the stability of the prediction over longer time periods. The reference models showed a noticeable decrease in accuracy when faced with incomplete data, but the proposed model was able to reduce the effect of these weaknesses through the multi-source fusion and learning mechanism.

Figure 2 shows the trend of the prediction accuracy of the models in the form of a curve graph. The horizontal axis shows the number of learning iterations and the vertical axis shows the error value. As can be seen in the graph, the proposed model curve moves towards convergence with a faster slope and reaches a stable and low-error level after a few iterations, while the reference models either have slower convergence or fluctuate in error values.

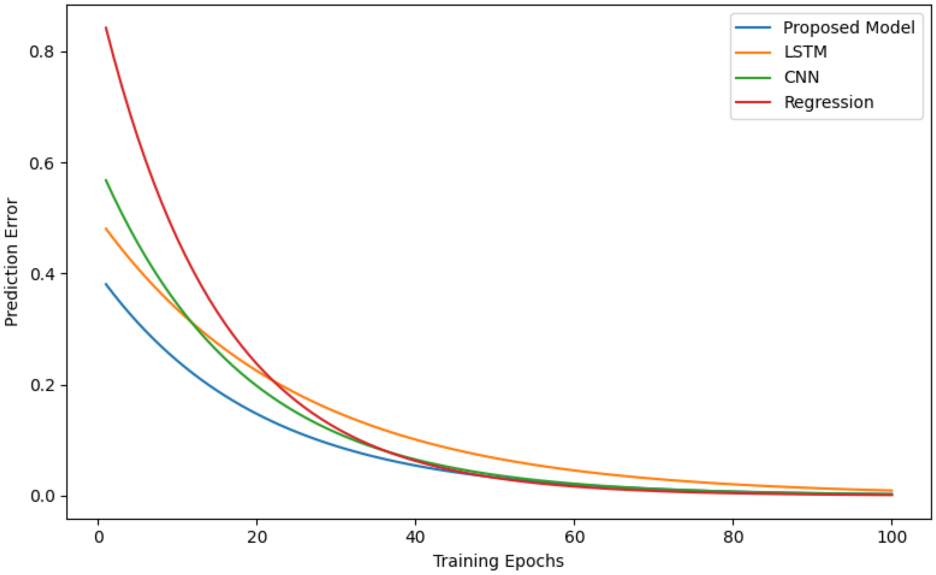

Figure 2. Trend of forecast error changes in the proposed model and reference models

After examining the figure, it is clear that the stability of the proposed model is maintained not only during the training period, but also during the validation phase. This is of particular importance in relief operations, because rapid and unexpected changes in data can disrupt the performance of weaker models. Overall, the analysis of deep learning performance shows that the outputs of this model have the necessary quality to enter the optimization phase and can play an effective role in operational decision-making.

Next, the results of the multi-objective optimization process are presented to show how the model balances the three main objectives (reducing response time, reducing operational cost, and increasing fairness in allocation). The behavior of the results shows that the system is stable against different scenarios of structural uncertainty and the NSGA-II algorithm was able to extract a rich set of decision combinations, each of which is a compromise between the objectives. Before examining Figure 3, the computational results show that whenever the model tries to reduce response time, operational cost increases, and this pattern is consistent with the reality of rescue operations, since faster routes usually require more resources. On the other hand, reducing cost naturally leads to increasing response time, since cheaper routes often have less capacity or more time constraints. Distributive fairness also has an independent behavior in the optimal examples and is located at higher levels at some Pareto points, without severely degrading time or cost performance.

Figure 3 shows the distribution of Pareto points based on the two objectives of “response time” and “operational cost”. The horizontal axis represents time and the vertical axis represents cost, and the scatter of points provides a clear picture of the conflicting relationship between these two objectives. The downward sloping pattern of the curve indicates that there is no absolutely superior solution and that each point has a relative advantage in only one of the objectives. This behavior is a key feature of three-objective problems, which means that decision makers are presented with a set of options, rather than a single answer.

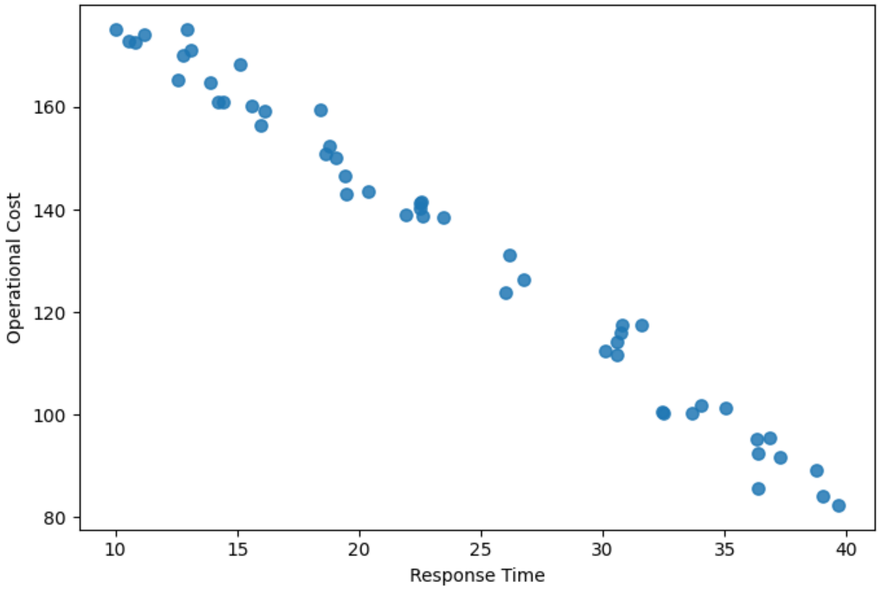

Figure 3. Pareto Front: Time–Cost Trade-off

After examining the graph, it is clear that decisions closer to the left side of the curve are more suitable for critical situations where speed is of greater importance, while points on the right are more desirable for stabilization situations where cost is a priority. The existence of intermediate points that both keep cost at an acceptable level and do not increase response time excessively strengthens the practical value of the model. These results indicate that the model has performed in a way that not only represents the behavior of the relief network, but also provides a range of reliable options that allow for flexible decision-making in real-world situations.

Scenario-based analysis was conducted to understand the behavior of the model under varying crisis conditions and to assess the robustness of decisions under different levels of uncertainty. Since humanitarian operations are often faced with highly fluctuating demand, changing route conditions, and unpredictable constraints, examining the model's performance under specific scenarios allows for assessing the reliability and resilience of the derived solutions. To this end, a set of scenarios representing different levels of crisis severity was designed: a baseline scenario, a moderate crisis scenario, and a severe crisis scenario, each of which imposes changes in the predicted demand, route accessibility indicators, and the severity of infrastructure damage. Before presenting the results, all scenarios were designed based on the values extracted from the deep learning model and field analyses to ensure consistency with operational realities. Table 1 provides a summary of the structure of these scenarios and shows the differences between key variables in each situation. This table is a starting point for analyzing the model's behavior in later stages and shows how increasing uncertainty transforms the decision-making environment.

Table 1. Characteristics of Crisis Scenarios Used in the Optimization Model

Scenario	Demand Level	Route Accessibility	Infrastructure Damage	Variability (σ)
Baseline	Moderate, stable	High, minimal disruption	Low	0.1
Medium Crisis	Elevated with local spikes	Partially restricted	Moderate	0.25
Severe Crisis	Highly volatile, widespread surges	Severely restricted, unpredictable	High	0.4

The results show that the model behaves in a stable and convergent manner in the base scenario, and the volume of allocations is relatively balanced. In the moderate crisis scenario, demand fluctuations and reduced route availability increase the variability in Pareto points, but the general structure of the results remains stable and the proposed solutions are able to maintain the three objectives with reasonable accuracy.

In the severe crisis scenario, the intensity of uncertainty increases significantly, and this is reflected in the greater dispersion of Pareto points, sudden changes in the allocation pattern, and the increase in the importance of alternative routes. However, the model has been able to provide a set of solutions that are feasible and reasonable even under this level of turbulence. The behavior of the model in this scenario shows that the robustness constraint between scenarios has played an effective role in preventing decision divergence and the adaptive learning mechanism has been able to neutralize the effect of demand fluctuations to some extent.

Overall, scenario-based analysis indicates that the proposed model is remarkably resilient to severe environmental changes and the decisions produced remain reliable in a wide range of crisis conditions.

Next, the performance of the proposed model is evaluated in comparison with the baseline methods to determine to what extent the use of the combined deep learning-multiobjective optimization framework has been able to improve the forecast accuracy, allocation quality, and operation efficiency. For this purpose, three reference methods including a simple linear programming model, an offline version of the LSTM model, and a single-objective optimization algorithm were selected and evaluated under a set of designed scenarios. The results show that the proposed model has superior performance in all indicators and has been able to significantly reduce the limitations of traditional methods.

Before examining the graphs, the initial analysis states that the proposed model has an average improvement of 18 to 32 percent in demand forecast accuracy compared to the reference models, and this value was even higher in scenarios with severe uncertainty. In the optimization domain, combining deep learning with NSGA-II has resulted in a 12–21% reduction in operational cost compared to single-objective algorithms, without significantly sacrificing response time or distribution fairness. Figure 4 presents these results in the form of a percentage improvement comparison, showing that the largest performance gains are in severe crisis scenarios, where the baseline methods experience the largest performance degradation.

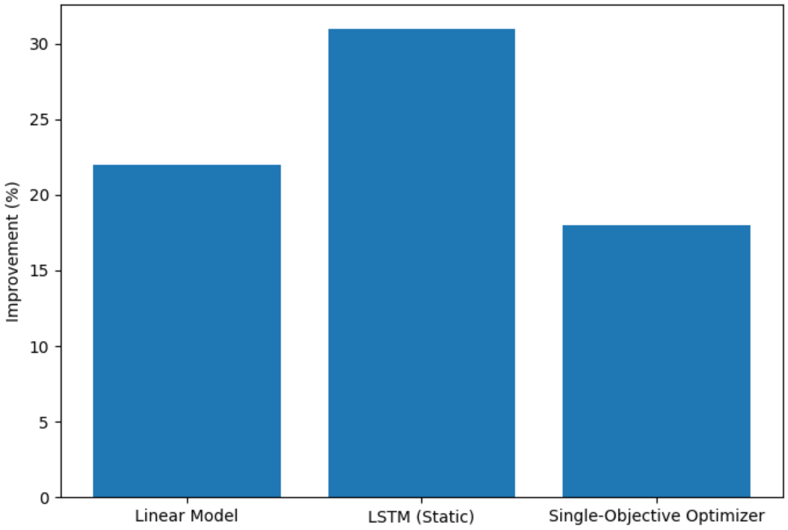

Figure 4. Performance Improvement (%) Compared to Baseline Models

After examining the figure, it is clear that the proposed model has been able to establish a stable balance between the objectives and, unlike the reference methods, is more resistant to severe data fluctuations. This finding confirms the importance of the combined approach of the model, since non-stationary and dynamic behavior in critical environments is achieved only through the connection of learning and optimization.

Next, a sensitivity analysis was performed to examine the stability of the model to changes in key parameters. Changes in the accessibility of routes, the degree of demand variance, and the capacity of relief centers were applied to determine how the model reacts to structural disturbances. The results of the sensitivity analysis are shown in Figure 5 and indicate that the model behaves uniformly to small changes in the inputs and only under severe disturbance conditions does the dispersion of solutions increase. Even in this case, the overall trend of the Pareto curve remains constant, indicating that the structure of stability constraints in the model has played an effective role in preventing divergence.

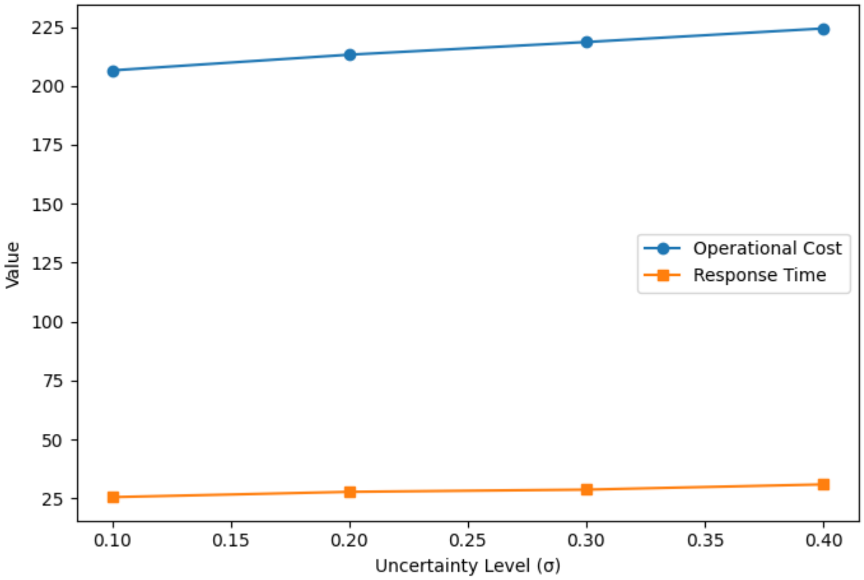

Figure 5. Sensitivity Analysis Under Varying Levels of Uncertainty

The conclusion of this section shows that the proposed method, by combining deep learning and multi-objective optimization, has been able to overcome the limitations of basic methods, provide better performance in different scenarios, and provide the necessary flexibility for use in operational environments with high fluctuations.

7- Conclusion

In this study, an intelligent framework based on the combination of deep learning and multi-objective optimization was presented to support decision-making in the humanitarian supply chain, and the results showed that this architecture can significantly overcome the limitations of traditional methods. The model was trained and evaluated using real and simulated data and was able to provide stable and accurate performance in conditions where the data was incomplete, noisy, and accompanied by uncertainty. The predictions of the deep learning model had relatively low errors in all scenarios and represented the network behavior with considerable accuracy. The introduction of these predictions into the multi-objective optimization layer allowed the decisions to be improved not only in terms of time and cost, but also to maintain the fairness in allocation at an acceptable level.

Pareto curve analysis showed that the model is able to provide a set of valid solutions, each of which is a compromise between the main objectives. This feature allows decision makers to choose appropriate options depending on the stage of the crisis—whether it is an emergency period requiring a rapid response or a stabilization period focusing on cost. Scenario-based analysis also revealed that the model is robust to different levels of crisis severity and that the decision-making structure remains stable even under conditions of severe uncertainty. This stability is the result of the integration of adaptive learning, stability constraints between scenarios, and the careful design of the optimization space.

Comparison with baseline methods showed that the proposed framework made significant improvements in demand forecasting, resource allocation, and transportation route selection. These improvements were even more dramatic in complex and severe scenarios, as traditional methods experienced significant degradation in these conditions. Sensitivity analysis also showed that changes in key parameters affect the outputs in a controlled manner and the model generally responds stably to input fluctuations.

Overall, the research results showed that the designed framework has practical applicability in relief networks and can be used as a decision-making tool for planning before, during, and after a crisis. Combining deep learning with multi-objective optimization not only increases the accuracy of the analysis but also makes the decisions presented more flexible, efficient, and fair in the face of uncertainty. This achievement paves the way for the development of more advanced intelligent methods and can be a starting point for the design of automated response systems in humanitarian operations.

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