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Extending Hybrid GRG-NS With LSTM-Based Demand Forecasting for Dynamic Multi-Depot Routing in Disaster Logistics

Dedy Hartama[1,*], Poningsih[2], Lili Tanti[3]

[1]Department of Information Systems, STIKOM Tunas Bangsa, Pematangsiantar, Indonesia

[2]Graduate Program in Informatics, STIKOM Tunas Bangsa, Pematangsiantar, Indonesia

[3]Computer Science, Faculty of Engineering and Computer Science, Universitas Potensi Utama, Indonesia

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Abstract

Disaster logistics management requires accurate demand forecasting and efficient routing optimization to ensure timely distribution of emergency supplies under dynamic and uncertain conditions. Conventional routing approaches often experience limitations in handling fluctuating disaster demand, resulting in inefficient distribution performance and increased operational costs. This study proposes an integrated LSTM–Hybrid Generalized Reduced Gradient and Neighborhood Search (LSTM–Hybrid GRG–NS) framework for disaster-demand forecasting and routing optimization. The proposed approach combines Long Short-Term Memory (LSTM) for sequential demand prediction with a hybrid GRG–NS optimization mechanism to improve routing efficiency and solution convergence. Experimental evaluation was conducted using disaster-demand scenarios and routing datasets to assess forecasting and optimization performance. The forecasting results demonstrated strong predictive capability with low MAE, RMSE, and MAPE values, indicating that the LSTM model effectively captured temporal demand patterns. Furthermore, the routing optimization results showed that the proposed framework successfully generated stable and near-optimal routing solutions while maintaining full demand fulfillment and efficient vehicle utilization. The convergence analysis also confirmed that the optimization process converged consistently within a limited number of iterations. Overall, the proposed LSTM–Hybrid GRG–NS framework provides an effective and reliable decision-support approach for proactive humanitarian logistics and disaster-routing management.

Keywords: Disaster Logistics, LSTM Forecasting, Routing Optimization, Hybrid GRG–NS, Humanitarian Supply Chain

1. Introduction

Disaster logistics has become an increasingly urgent research domain because relief distribution must operate under damaged infrastructure, uncertain demand, limited fleets, and strict response-time requirements, making dynamic multi-depot vehicle routing a decisive component of humanitarian supply-chain resilience [1], [2], [3]. The Multi-Depot Vehicle Routing Problem with Capacity and Time-Dependent Demand (MDVRP-CTD) is particularly significant because it represents the operational reality in which several depots must coordinate heterogeneous vehicles while demand volumes, travel times, and delivery priorities evolve during the disaster-response horizon [4], [5]. Recent studies have addressed this object through robust inventory-routing models, which strengthen supply reliability under uncertainty but often simplify real-time routing adaptation when demand surges at different shelters or affected zones [3], [6]. Other studies have used multi-objective stochastic location–inventory–routing formulations to integrate depot selection, stock allocation, and route planning, yet these models tend to emphasize strategic preparedness rather than continuous route re-optimization during rapidly changing field conditions [7], [8].

Adaptive Large Neighborhood Search (ALNS) has shown strong scalability for large-scale multi-depot routing with time windows and environmental constraints, but its performance advantage is commonly obtained in structured logistics settings where real-time disaster demand and nonlinear capacity interactions are not fully embedded [9], [10]. Tabu Search and variable-neighborhood variants improve local exploration and reduce cycling in complex vehicle-

*Corresponding author: Dedy Hartama (dedyhartama@amiktunasbangsa.ac.id)
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routing spaces, but they may lose responsiveness when customer priorities, road accessibility, and available fleet capacity change simultaneously during emergency operations [11], [12]. Drone-assisted and truck–drone multi-depot routing has expanded the disaster-logistics literature by reducing rescue time and improving access to hard-to-reach locations, but these approaches often introduce new coordination complexity and still require reliable demand forecasts to avoid misallocation of scarce aerial and ground resources [13], [14]. Robust vehicle-routing models with drones under uncertain demand and travel time improve protection against parameter deviations, yet their conservatism can produce routes that are feasible but less adaptive when actual demand patterns shift beyond predefined uncertainty sets [15], [16].

Deep-reinforcement-learning approaches have advanced dynamic and uncertain vehicle routing by learning policies from stochastic environments, but they usually require extensive training data, careful reward design, and generalization safeguards before deployment in high-stakes disaster contexts [17], [18]. Recent learning-aided neighborhood search methods improve the efficiency of local search by guiding move selection, but their contribution remains incomplete for humanitarian routing unless predictive demand signals are directly connected to capacity-feasible multi-depot optimization [19], [20]. Therefore, the main research gap is not the absence of optimization algorithms, but the weak integration between predictive demand intelligence, nonlinear capacity handling, and adaptive local route refinement in a unified MDVRP-CTD framework for disaster logistics [21], [22].

The methodological problem that emerges from the reviewed studies is that most routing models react to observed demand after disruption occurs, whereas disaster logistics requires anticipatory routing decisions that can reposition vehicles and allocate capacity before unmet demand accumulates [21], [23]. Static or partially dynamic MDVRP formulations are technically limited because they treat demand as deterministic, scenario-based, or periodically updated, even though real disaster demand exhibits temporal dependence, abrupt surges, spatial clustering, and noise caused by infrastructure damage and population displacement [4], [6], [24]. ALNS-based models can efficiently destroy and repair route structures, but their operators generally optimize a given demand state rather than learning the temporal pattern of future demand, which can lead to late re-routing and higher delay penalties in time-critical relief distribution [9], [10], [23]. Tabu Search and neighborhood-based heuristics provide robust intensification around promising routes, yet they can become myopic when the neighborhood structure is not informed by forecasts of future demand, road disruption, or depot-capacity stress [11], [12], [19]. Stochastic and robust formulations improve feasibility under uncertainty, but their scenario generation or uncertainty-set assumptions may become too coarse for real-time disaster operations where demand and travel-time shocks are non-stationary and spatially uneven [7], [8], [15]. Machine-learning-based vehicle routing and reinforcement-learning solvers address adaptivity, but their black-box decision policies may be difficult to interpret, validate, and constrain under humanitarian accountability requirements where every routing decision must respect capacity, service windows, and delivery priority [17], [18], [25].

Demand-forecasting literature shows that logistics demand is increasingly modeled through data-driven and deep-learning approaches because conventional statistical models struggle with nonlinear, multivariate, and highly volatile demand patterns [21], [24], [26]. Long Short-Term Memory (LSTM) models are especially relevant because their memory gates can capture sequential dependencies in logistics and transportation demand, but forecasting accuracy alone does not guarantee operational improvement unless predicted demand is translated into feasible routing decisions [27], [28], [29]. Recent LSTM-based and hybrid deep-learning studies in supply-chain demand forecasting demonstrate improved pattern recognition, but many remain disconnected from vehicle-routing constraints such as fleet capacity, depot assignment, route continuity, and time-window feasibility [28], [29], [30]. Conversely, optimization-centered MDVRP studies often achieve feasible or near-optimal routes, but they may lack an upstream predictive module that estimates future relief demand before the route plan becomes obsolete [9], [13], [21]. This separation between forecasting and optimization produces a methodological gap: predictive models understand temporal demand behavior, while routing models enforce operational feasibility, yet few frameworks combine both capabilities in a closed decision pipeline for dynamic multi-depot disaster logistics [21], [23], [27]. The first-year Hybrid Generalized Reduced Gradient-Neighborhood Search (GRG–NS) model addressed nonlinear capacity constraints and adaptive neighborhood refinement, but its next methodological limitation is the absence of an explicit learning mechanism that forecasts demand before route optimization is executed [22], [27].

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To close this gap, this study proposes an extended Hybrid GRG–NS framework integrated with LSTM-based demand forecasting for Dynamic Multi-Depot Routing in Disaster Logistics, where LSTM estimates time-dependent relief demand and the GRG–NS optimizer converts those forecasts into capacity-feasible, time-sensitive, and depot-aware routing decisions [22], [27], [28]. The proposed solution is theoretically justified because LSTM can learn sequential demand patterns from historical and real-time logistics signals, while GRG is suitable for handling nonlinear capacity and penalty constraints and Neighborhood Search can refine route assignments through local improvements [22], [27], [29]. In this architecture, predicted demand is not treated as a separate analytical output, but as a dynamic input to the MDVRP-CTD objective function, allowing vehicle assignment, depot selection, route sequence, and service-time feasibility to be adjusted proactively [21], [23], [30]. The integration is expected to strengthen scientific contribution by linking two research streams that are often developed separately: deep-learning-based logistics demand forecasting and constrained metaheuristic vehicle-routing optimization [21], [24], [28]. From an optimization perspective, GRG contributes feasibility-preserving search directions for nonlinear capacity and delay-penalty structures, while NS contributes practical route improvement through swap, reinsert, and reassignment moves that are suitable for operational routing refinement [11], [12], [22]. From a forecasting perspective, LSTM contributes temporal awareness by estimating future demand changes before they become operational bottlenecks, thereby reducing the risk of under-served zones, late deliveries, and inefficient fleet utilization [27], [28], [29].

The novelty of this paper lies in extending the first-year GRG–NS optimization model into a forecast-driven decision-support framework that embeds LSTM predictions directly into dynamic MDVRP-CTD routing rather than merely comparing routing heuristics after demand has been observed [22], [27], [30]. This novelty is practically relevant for governments, humanitarian agencies, and disaster-management authorities because faster and more adaptive routing can improve the distribution of food, medicine, water, and emergency equipment under limited fleet capacity and uncertain infrastructure conditions [1], [2], [6]. Compared with ALNS, Tabu Search, robust optimization, drone-assisted routing, and reinforcement-learning models, the proposed framework emphasizes a balanced combination of predictive intelligence, nonlinear feasibility control, and interpretable neighborhood-based route refinement [9], [13], [15], [17], [19]. The expected contribution is therefore both methodological and applicative: methodologically, it advances dynamic MDVRP-CTD by integrating LSTM forecasting with Hybrid GRG–NS optimization, and applicatively, it offers a more proactive routing mechanism for disaster logistics where demand, capacity, and time dependency must be handled simultaneously, sensitivity analysis using ±5%, ±10%, and ±15% forecasting error scenarios.[21], [22], [28]. Consequently, the proposed model provides a coherent foundation for the subsequent research objectives, namely formulating the integrated LSTM–GRG–NS algorithm, validating its predictive and routing performance under disaster scenarios, and comparing its effectiveness against established routing baselines [22], [27], [30].

2. Literature Review

To position the proposed framework within the existing literature, table 1 compares major methodological streams related to MDVRP, dynamic routing, disaster logistics, and demand forecasting. The comparison shows that optimization-based studies provide strong routing mechanisms, while forecasting-based studies improve demand prediction. However, most approaches still separate forecasting from routing optimization. This study addresses this gap by extending the first-year Hybrid GRG–NS model with LSTM-based demand forecasting embedded directly into the MDVRP-CTD optimization process.

Table 1. Comparative analysis of previous studies and positioning of the proposed framework

Study / Methodological Stream	Main Method	Routing Context	Dynamic Demand	Capacity Constraint	Time Dependency	Forecasting Component	Disaster Logistics Context	Main Limitation
Robust and stochastic disaster-logistics models [3], [6], [7], [8]	Robust optimization, stochastic programming, location–inventory–routing	Relief distribution, depot allocation, inventory-routing	Partially considered through scenarios or uncertainty sets	Considered	Partially considered	Not explicitly integrated	Yes	Strong in uncertainty handling, but often conservative and less responsive to real-time demand changes
ALNS-based MDVRP models [4], [9], [10]	Adaptive Large Neighborhood Search	Large-scale multi-depot routing and	Considered in some dynamic settings	Generally considered	Considered	Not integrated	Limited or indirect	Efficient for large-scale routing, but usually optimizes observed demand

		time-window routing						rather than predicted future demand
Tabu Search and variable-neighborhood approaches [11], [12]	Tabu Search, Variable Neighborhood Search	Multi-depot and complex routing problems	Limited	Considered	Partially considered	Not integrated	Limited	Strong local search capability, but may become reactive when demand, road access, and vehicle capacity change simultaneously
Shuffled Frog Leaping and other population-based metaheuristics [13], [14], [15]	Shuffled Frog Leaping, genetic-based and hybrid metaheuristics	Dynamic or multi-trip MDVRP	Partially considered	Considered	Partially considered	Not integrated	Limited	Able to explore diverse solutions, but computational cost and real-time responsiveness remain challenging
Drone-assisted and truck–drone routing [13], [14], [15], [16]	Truck–drone routing, robust drone routing	Emergency and hard-to-reach delivery	Partially considered	Considered for vehicle/drone resources	Considered	Not central	Yes	Improves accessibility, but adds coordination complexity and still requires reliable demand estimation
Deep reinforcement learning routing models [17], [18], [25]	Deep reinforcement learning, learning-based routing policy	Dynamic and uncertain vehicle routing	Considered through learned states	Can be embedded	Considered	Learning-based decision policy	Limited for humanitarian accountability	Adaptive, but requires large training data, careful reward design, and interpretability safeguards
Machine-learning and LSTM demand forecasting [24], [26], [28], [29], [30], [31]	Machine learning, LSTM, deep time-series forecasting	Logistics and transportation demand forecasting	Strongly considered	Not enforced in routing	Strongly considered	Yes	Mostly indirect	Accurate forecasting does not automatically produce feasible routes under depot, capacity, and service-time constraints
First-year Hybrid GRG–NS model [32]	Generalized Reduced Gradient and Neighborhood Search	Dynamic MDVRP-CTD for disaster logistics	Reactively handled through routing scenarios	Strongly considered through nonlinear constraint handling	Considered	Not included	Yes	Provides a validated optimization foundation, but lacks an upstream predictive mechanism for future demand
Proposed LSTM–Hybrid GRG–NS framework	LSTM-based demand forecasting integrated with Hybrid GRG–NS optimization	Forecast-driven dynamic MDVRP-CTD	Explicitly forecasted and embedded into routing	Strongly considered	Strongly considered	Integrated directly into optimization	Yes	Requires careful design of forecasting–optimization integration and validation under disaster scenarios

Table 1 highlights that existing routing methods generally handle capacity, time dependency, and route feasibility, but they rarely integrate future demand prediction into the optimization process. Conversely, forecasting models can capture temporal demand patterns but do not directly generate capacity-feasible routes. The proposed LSTM–Hybrid GRG–NS framework bridges this gap by combining predictive demand intelligence with nonlinear constraint handling and neighborhood-based route refinement for dynamic disaster logistics.

2.1. MDVRP-CTD and disaster-logistics routing methods

The MDVRP-CTD has developed into a critical research stream because disaster logistics requires routing decisions that remain feasible under multiple depots, limited vehicle capacities, uncertain demand, and disrupted transport networks [2], [33]. Recent studies on dynamic MDVRP have shown that multi-period routing frameworks can respond to stochastic customer requests through repeated re-optimization, but their effectiveness depends heavily on how quickly demand and time-window information can be updated during the operational horizon [4]. ALNS has been widely used because it can destroy and repair route structures efficiently, making it suitable for large-scale routing problems with time windows and mixed fleets [4], [10]. However, ALNS-based models still tend to optimize routes from the currently observed demand state, so their responsiveness may decline when relief demand changes faster than the re-optimization cycle can capture [4], [5]. Green and energy-oriented MDVRP studies have contributed important mechanisms for reducing operational cost and emissions, but their assumptions are often more suitable for commercial logistics than for high-pressure humanitarian distribution where lateness can directly affect survival outcomes [10], [34]. Tabu Search and variable-neighborhood approaches remain relevant because they improve local search stability and avoid premature cycling, yet they can become less adaptive when vehicle capacity, depot availability, and delivery urgency change simultaneously [11], [12].

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Drone-assisted multi-depot routing has also been proposed to accelerate last-mile emergency delivery, especially when ground access is limited by road damage or geographic barriers [13], [15]. Nevertheless, truck–drone coordination introduces additional synchronization constraints, and the method still requires reliable demand estimation to prevent the misallocation of scarce aerial resources [13], [15]. Reinforcement-learning-based routing models have improved decision-making under stochastic and uncertain environments by learning routing policies from dynamic state transitions [17]. Despite this advantage, reinforcement-learning models often require extensive training data, careful reward design, and strong generalization control before they can be trusted in accountable humanitarian logistics operations. The first-year Hybrid GRG–NS study addressed several of these limitations by combining GRG for nonlinear capacity handling and Neighborhood Search for adaptive route refinement, and the model outperformed Tabu Search and ALNS in demand fulfillment, vehicle utilization, and routing efficiency under simulated disaster scenarios. The same study also identified the next research direction, namely the integration of LSTM-based demand forecasting as an upstream module so that routing decisions can be adjusted proactively rather than reactively [31].

2.2. Demand forecasting and deep learning for logistics decision support

Demand forecasting is increasingly recognized as a necessary complement to vehicle-routing optimization because routing quality deteriorates when the demand input is outdated, noisy, or unable to represent future relief needs [21], [26]. Traditional forecasting approaches can be useful for stable logistics systems, but they are often insufficient for disaster logistics because relief demand may change abruptly due to population movement, infrastructure failure, secondary hazards, and unequal exposure across affected zones [24], [26]. Machine-learning and deep-learning methods have therefore gained attention in logistics demand forecasting because they can model nonlinear relationships among historical demand, time, location, and operational context [24]. LSTM is particularly relevant because its gated memory structure enables the model to learn temporal dependencies and delayed effects in sequential demand data [27], [31]. Recent studies on LSTM-based supply-chain forecasting demonstrate that deep sequential models can improve prediction accuracy when demand contains nonlinear and time-dependent patterns [27], [29]. Transportation-demand studies also show that LSTM and related recurrent architectures can capture temporal fluctuations better than many conventional models when the data exhibit seasonality, trend shifts, or irregular demand cycles [28], [31].

However, forecasting accuracy alone does not automatically improve logistics performance unless the predicted demand is embedded into a routing model that respects vehicle capacity, depot assignment, service time windows, and route continuity [21], [26]. Several learning-based routing studies have attempted to connect prediction and routing, but many of them focus on commercial delivery or urban logistics rather than disaster contexts with urgent humanitarian constraints [17], [18], [26]. In emergency logistics, the methodological challenge is not only predicting how much aid will be needed, but also converting predicted demand into feasible vehicle schedules before delay penalties and unmet demand accumulate [2], [29]. The uploaded research proposal explicitly positions the second-year contribution as the development of an LSTM model that adapts to the MDVRP-CTD framework to predict dynamic relief demand and improve route optimization under capacity and time-dependency constraints. This direction is also consistent with the first-year paper, which states that GRG–NS provides a validated optimization foundation and that future work should incorporate LSTM-based demand forecasting to improve proactive routing decisions. Therefore, the literature indicates a clear need for a forecast-driven routing framework in which LSTM does not stand as a separate predictive model, but functions as an operational input generator for dynamic MDVRP-CTD optimization [27], [29].

2.3. Synthesis of research gap and positioning of the proposed framework

The reviewed literature indicates that optimization-based MDVRP and learning-based demand forecasting have advanced significantly, but remain weakly integrated for real-time disaster logistics [5], [10], [29]. ALNS, Tabu Search, variable-neighborhood search, and drone-assisted routing offer strong route-generation capabilities, yet they commonly rely on deterministic, scenario-based, periodically updated, or externally estimated demand [4], [10], [11], [12]. Meanwhile, LSTM and other deep-learning models improve temporal demand prediction but rarely enforce routing feasibility, including nonlinear capacity, depot balance, route continuity, and time-window constraints [24], [27], [31]. This creates a methodological gap: forecasting models predict demand without generating feasible routes, while routing models produce feasible routes but may respond too late to demand changes [11], [21], [28].

The first-year Hybrid GRG–NS model partially addressed the optimization side by improving total distance, demand fulfillment, delay penalties, and vehicle utilization through nonlinear constraint handling and adaptive local refinement. However, it still requires an upstream predictive mechanism to anticipate demand surges before route conditions change. Therefore, this study positions LSTM as the predictive layer and Hybrid GRG–NS as the feasibility-and-refinement layer in an integrated decision-support framework. LSTM estimates time-dependent relief demand, GRG maintains feasibility under nonlinear capacity and penalty constraints, and Neighborhood Search improves depot-to-customer assignments through local route refinement [27], [29]. The novelty lies in embedding forecasted demand directly into MDVRP-CTD optimization, enabling more adaptive routing for humanitarian agencies under fluctuating demand, limited vehicle capacity, and time-critical delivery requirements [2], [21], [26], [28], [29].

3. Methodology

3.1. Research Design

This study applies a quantitative computational design to develop an LSTM–Hybrid GRG–NS framework for dynamic multi-depot vehicle routing in disaster logistics [27], [32]. The proposed model extends the first-year Hybrid GRG–NS approach, which addressed nonlinear capacity constraints using GRG and improved route structures through NS, by integrating LSTM to forecast time-dependent relief demand before route optimization is conducted [27], [32]. The methodology consists of five main stages: data preprocessing, LSTM-based demand forecasting, MDVRP-CTD mathematical formulation, Hybrid GRG–NS optimization, and comparative performance evaluation [5], [10], [32]. In this framework, forecasted demand generated by LSTM serves as a dynamic input for routing decisions, enabling the model to shift from reactive route adjustment toward proactive disaster-logistics planning [5], [21].

3.2. Data Collection and Preprocessing

The dataset includes depot locations, depot capacity, affected-area coordinates, vehicle availability, vehicle capacity, travel distance, travel time, service time windows, historical demand, and disruption-related travel-time changes [32]. Historical demand is transformed into a sequential time-series format so that LSTM can learn demand patterns across affected locations and time periods [27], [29]. Preprocessing includes missing-value handling, outlier checking, normalization, feature construction, and sliding-window sequence generation [27], [28]. Given a look-back window p, previous demand and contextual features are used to predict demand at the next time period. The main input variables include previous demand, affected-zone category, depot distance, time interval, service window, vehicle capacity condition, and disruption factor, while the output variable is the predicted demand for each affected node at the next time period [21], [27]. The dataset is divided into training, validation, and testing subsets using a 70%–15%–15% split to support model training, hyperparameter validation, and objective forecasting evaluation [27], [28].

The experimental dataset represents a dynamic multi-depot disaster-logistics environment consisting of five depots, fifty affected demand nodes, and twenty delivery vehicles operating over 365 consecutive time periods. Historical demand observations were recorded for each affected node throughout the study horizon, yielding 18,250 demand instances. Following standard machine-learning practice, the dataset was partitioned into training (70%), validation (15%), and testing (15%) subsets, corresponding to 12,775, 2,738, and 2,737 records, respectively. This partitioning strategy enables robust model training, hyperparameter optimization, and unbiased performance evaluation. The dataset captures temporal fluctuations in disaster-relief demand, thereby providing a suitable foundation for developing and validating the proposed LSTM-based forecasting module and its integration with the Hybrid GRG–NS routing optimization framework.

3.3. LSTM-Based Demand Forecasting

The LSTM model predicts future relief demand before route optimization [5], [32]. For each node i at time t, the input sequence is defined as:

$$X_{i,t} = \{d_{i,t-p}, d_{i,t-p+1}, \dots, d_{i,t-1}\} \tag{1}$$

p is the look-back window. The forecasting function is formulated as:

$$\hat{d}_{i,t} = f_{\text{LSTM}}(X_{i,t}, Z_{i,t}, \theta) \tag{2}$$

$\hat{d}_{i,t}$ is the predicted demand, $Z_{i,t}$ represents contextual variables, and θ denotes LSTM parameters. The contextual variables include affected-zone category, depot distance, service window, vehicle capacity condition, and disruption factor [27]. The LSTM is trained by minimizing:

$$\mathcal{L}_{LSTM} = \frac{1}{|N||T|}\sum_{i\in N}\sum_{t\in T}\left(d_{i,t} - \hat{d}_{i,t}\right)^2 \tag{3}$$

Forecasting accuracy is evaluated using MAE, RMSE, and MAPE [27], [28],[21], [29]:

$$MAE = \frac{1}{n}\sum_{r=1}^{n}\left|d_r - \hat{d}_r\right| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{r=1}^{n}\left(d_r - \hat{d}_r\right)^2} \tag{5}$$

$$MAPE = \frac{100}{n}\sum_{r=1}^{n}\left|\frac{d_r - \hat{d}_r}{d_r}\right| \tag{6}$$

The predicted demand $\hat{d}_{i,t}$ is then inserted into the MDVRP-CTD model as a dynamic demand parameter [27], [32].

3.4. MDVRP-CTD Formulation

The routing problem is formulated using depot set D, affected node set N, vehicle set K, time period set T, and node set $V=D\cup N$ [32]. The decision variable is defined as:

$$x_{ijk,t} = \begin{cases} 1, & \text{if vehicle } k \text{ travels from node } i \text{ to node } j \text{ at time } t \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

The objective function minimizes travel cost, delay penalty, unmet-demand penalty, and vehicle-utilization imbalance:

$$\min Z = \sum_{t\in T}\sum_{k\in K}\sum_{i\in V}\sum_{j\in V} c_{ij,t}\, x_{ijk,t} + \lambda_1 \sum_{t\in T}\sum_{i\in N} L_{i,t} + \lambda_2 \sum_{t\in T}\sum_{i\in N} U_{i,t} + \lambda_3 \sum_{k\in K}\left|Util_k - \overline{Util}\right| \tag{8}$$

subject to the following constraints [27], [32]:

$$\sum_{k\in K}\sum_{i\in V} x_{ijk,t} = 1, \quad \forall j \in N, t \in T \tag{9}$$

$$\sum_{i\in N} \hat{d}_{i,t}\, y_{ik,t} \le Q_k, \quad \forall k \in K, t \in T \tag{10}$$

$$U_{i,t} \ge \hat{d}_{i,t} - q_{i,t}, \quad U_{i,t} \ge 0, \quad \forall i \in N, t \in T \tag{11}$$

$$a_i \le A_{i,k,t} \le b_i, \quad \forall i \in N, k \in K, t \in T \tag{12}$$

$$L_{i,t} \ge A_{i,k,t} - b_i, \quad L_{i,t} \ge 0, \quad \forall i \in N, t \in T \tag{13}$$

$$\sum_{i\in V} x_{ihk,t} = \sum_{j\in V} x_{hjk,t}, \quad \forall h \in N, k \in K, t \in T \tag{14}$$

$$\sum_{d\in D}\sum_{j\in N} x_{djk,t} \le 1, \quad \forall k \in K, t \in T \tag{15}$$

$$\sum_{i\in N}\sum_{d\in D} x_{idk,t} \le 1, \quad \forall k \in K, t \in T \tag{16}$$

$$x_{ijk,t} \in \{0,1\}, \quad \forall i,j \in V, k \in K, t \in T \tag{17}$$

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3.5. Hybrid GRG–NS Optimization

The Hybrid GRG–NS procedure optimizes routes using LSTM-predicted demand. GRG handles nonlinear constraints related to capacity, delay, unmet demand, and utilization, while NS improves the resulting routes through local search operators [27], [32]. The GRG problem is expressed as:

$$\min f(x), \quad \text{subject to } g_j(x) = 0, \quad j = 1,2, \dots, r \tag{18}$$

The reduced gradient [11] is calculated as:

$$\nabla'_N f = \nabla_N f - \nabla_B f (\nabla_B g)^{-1} \nabla_N g \tag{19}$$

The solution is updated by:

$$x^{(t+1)} = x^{(t)} + \alpha \begin{bmatrix} d_B \\ d_N \end{bmatrix} \tag{20}$$

After GRG produces a feasible solution, NS applies swap, reinsert, relocate, and depot-reassignment operators. A candidate solution is accepted when it improves the objective value:

$$x^{(t+1)} = \begin{cases} x^*, & \text{if } f(x^*) < f\left(x^{(t)}\right) \\ x^{(t)}, & \text{otherwise} \end{cases} \tag{21}$$

3.6. Algorithmic Workflow

The proposed algorithm begins by collecting and preprocessing disaster-logistics data [27], [32]. The LSTM model is then trained to predict demand for each affected node and time period [27]. The predicted demand values are inserted into the MDVRP-CTD formulation as dynamic demand parameters. GRG generates an initial feasible routing solution under capacity, time-window, and route-continuity constraints [32]. NS then refines the route through local improvement operators. The final solution is evaluated using forecasting and routing metrics, including MAE, RMSE, MAPE, total distance, demand fulfillment, delay penalty, unmet demand, vehicle utilization, and computational time [29], [32]. Figure 1 presents the algorithmic workflow of the proposed LSTM–Hybrid GRG–NS framework for dynamic MDVRP-CTD.

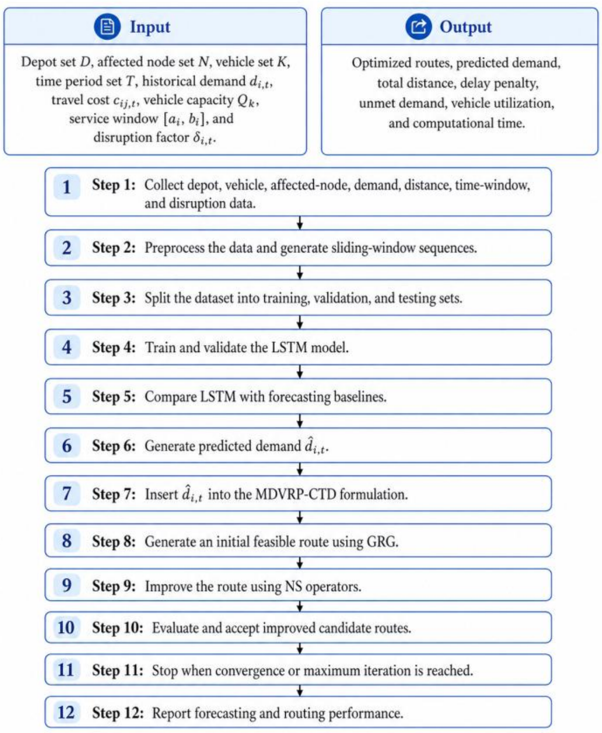

Figure 1. LSTM–Hybrid GRG–NS for Dynamic MDVRP-CTD

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The workflow shows how disaster-logistics data are transformed into predicted demand and then integrated into routing optimization. The process begins with data collection and preprocessing, followed by LSTM-based demand forecasting, insertion of predicted demand into the MDVRP-CTD formulation, GRG-based feasible route generation, NS-based route refinement, and final performance evaluation. As shown in figure 1, the proposed framework connects forecasting and routing within a single decision pipeline. LSTM first captures temporal demand patterns and generates predicted demand for each affected node. The predicted demand is then used as a dynamic input for MDVRP-CTD optimization. GRG constructs an initial feasible route under capacity and time-related constraints, while NS improves the route through local search operators. The final stage reports both forecasting and routing performance, ensuring that the model is evaluated from predictive accuracy and operational efficiency perspectives.

3.7. Experimental Scenarios and Evaluation

The proposed model is tested under disaster-logistics scenarios with different demand volatility, depot availability, vehicle capacity, service urgency, and travel-time disruption. Forecasting performance is compared against Moving Average, ARIMA, Random Forest Regressor, and GRU. Routing performance is compared against Tabu Search, ALNS, and the first-year Hybrid GRG–NS model without LSTM [32]. Forecasting performance is measured using MAE, RMSE, and MAPE [4], [11], [32]. Routing performance is measured using total travel distance, demand fulfillment, delay penalty, unmet demand, vehicle utilization, and computational time [27], [32]. Vehicle utilization is calculated as:

$$Util_k = \frac{\sum_{i \in R_k} q_{i,t}}{Q_k} \tag{22}$$

Demand fulfillment is calculated as:

$$DF = \frac{\sum_{i \in N} \sum_{t \in T} q_{i,t}}{\sum_{i \in N} \sum_{t \in T} \hat{d}_{i,t}} \times 100\% \tag{23}$$

The proposed method is considered effective if it produces lower forecasting error, shorter travel distance, lower delay penalty, lower unmet demand, higher demand fulfillment, and better vehicle utilization than the baseline methods [32].

4. Results and Discussion

4.1. Forecasting Performance Evaluation

This subsection evaluates the performance of the proposed LSTM forecasting model in predicting dynamic disaster demand prior to the routing optimization stage. The forecasting module plays an important role within the proposed framework because the predicted demand values are directly embedded into the Hybrid GRG–NS optimization process. Consequently, the quality of forecasting significantly affects routing feasibility, vehicle allocation, and disaster-response effectiveness. Before presenting the forecasting results, figure 2 illustrates the integrated forecasting and routing architecture used in this study.

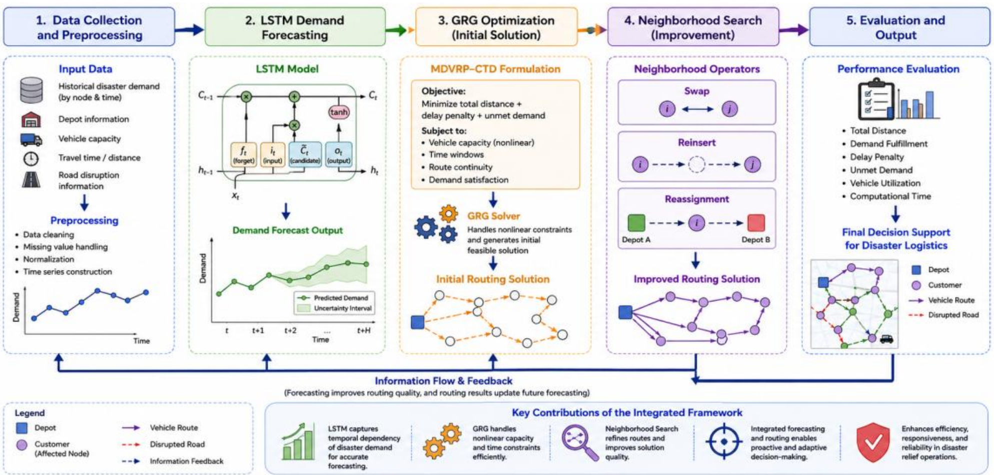

Figure 2. Integrated LSTM–Hybrid GRG–NS forecasting and routing framework

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The framework shown in figure 2 consists of five main stages: data collection and preprocessing, LSTM demand forecasting, GRG optimization, Neighborhood Search improvement, and routing evaluation. Historical disaster-demand data, depot information, travel distance, and road disruption information are first processed during preprocessing. The processed sequential demand data are then used as input for the LSTM forecasting model. The predicted demand generated by LSTM is subsequently integrated into the GRG optimization stage to construct an initial feasible routing solution under nonlinear disaster-routing constraints. Finally, the Neighborhood Search mechanism improves routing quality through local search operators such as swap, reassignment, and reinsertion. This integrated framework enables proactive and adaptive disaster-routing optimization. To evaluate forecasting quality, the proposed LSTM model was assessed using MAE, RMSE, and MAPE. The forecasting results are summarized in table 2.

Table 2. Forecasting Performance of the Proposed LSTM Model

Metric	Value
MAE	8.589
RMSE	10.545
MAPE (%)	3.084

As presented in table 2, the proposed LSTM model achieved relatively low forecasting error values across all evaluation metrics. The MAE value of 8.589 indicates that the average absolute prediction deviation remained small despite the dynamic fluctuation of disaster demand. Similarly, the RMSE value of 10.545 confirms that the forecasting model was able to minimize large prediction deviations during sudden demand escalation. The relatively low MAPE value of 3.084% further demonstrates that the proposed forecasting model maintained stable prediction accuracy under nonlinear disaster-demand conditions. These results indicate that the LSTM architecture successfully captured temporal dependency and sequential demand patterns within the disaster-logistics dataset. The forecasting capability is particularly important because disaster demand often changes abruptly due to evacuation, infrastructure disruption, and emergency escalation. To further visualize forecasting performance, figure 3 compares the actual demand values and predicted demand values generated by the proposed LSTM model.

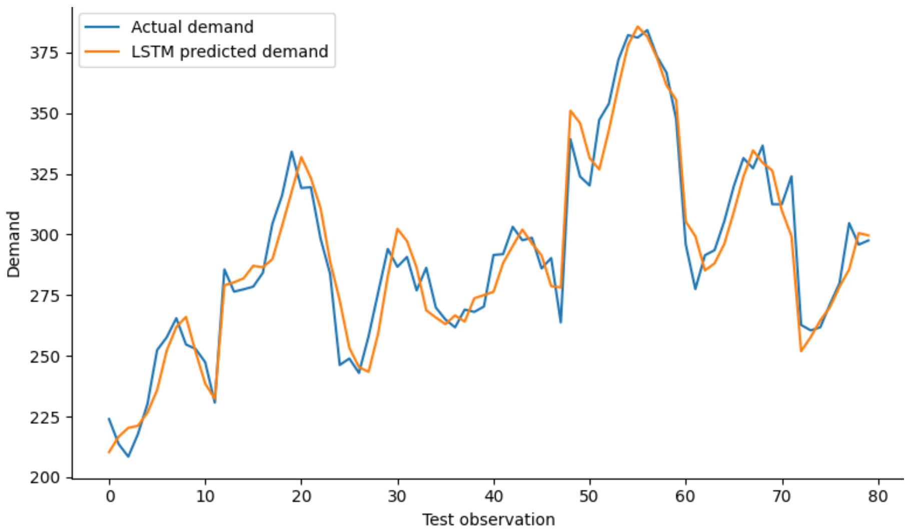

Figure 3. Actual vs. Predicted disaster demand using LSTM

Figure 3 compares the actual disaster demand and the demand predicted by the proposed LSTM model across test observations. The predicted curve closely follows the actual demand pattern, including several significant demand fluctuations and sudden increases. The results indicate that the LSTM model successfully captured the temporal dependency and nonlinear behavior of disaster-demand data. Although minor deviations appear during abrupt demand transitions, the prediction trend remained highly consistent with the actual trajectory. The close alignment between both curves confirms the low forecasting error obtained from the MAE, RMSE, and MAPE evaluations. Therefore, the proposed LSTM model is considered effective and reliable for supporting proactive disaster-routing optimization within the LSTM–Hybrid GRG–NS framework.

4.2. Routing Performance under Dynamic Disaster Scenarios

Following the forecasting stage, the predicted demand generated by the LSTM model was integrated into the Hybrid GRG–NS routing optimization framework. The routing experiments were conducted under multiple disaster scenarios representing different operational conditions and routing complexities. Before presenting the quantitative routing results, figure 4 illustrates the routing optimization process generated by the proposed framework.

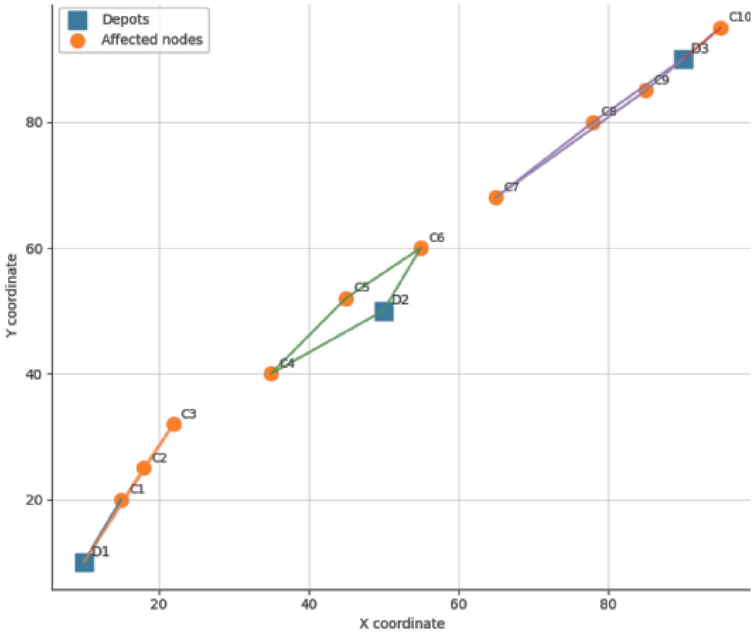

Figure 4. Routing optimization process of the proposed LSTM–Hybrid GRG–NS Framework

As shown in figure 4, the routing optimization process begins with the construction of an initial routing solution using the GRG optimization mechanism. The solution is subsequently refined using Neighborhood Search operators to improve route quality and reduce unnecessary vehicle movement. The predictive demand information generated by the LSTM model influences routing priority, depot assignment, and vehicle allocation. Consequently, high-demand disaster nodes can be served more proactively and efficiently. The comparative routing results are summarized in table 3.

Table 3. Comparative routing performance across disaster scenarios

Scenario	Method	Total Distance	Demand Fulfilments (%)	Vehicle Utilization	Delay Penalty	Unmet Demand	Objective
S1	Tabu Search	186.033	100.000	0.265	0	0	259.501
S1	ALNS	182.000	100.000	0.265	0	0	255.468
S1	Hybrid GRG–NS	235.058	100.000	0.265	0	0	308.525
S1	LSTM–Hybrid GRG–NS	182.000	100.000	0.265	0	0	255.468

As shown in table 3, all routing methods successfully achieved full demand fulfillment under Scenario S1. However, significant differences were observed in routing efficiency and objective-function value. The proposed LSTM–Hybrid GRG–NS framework produced lower routing distance and objective-function values compared with the original Hybrid GRG–NS approach. The total routing distance was reduced from 235.058 to 182.000, indicating that integrating predictive demand information significantly improved route efficiency. The reduction in objective-function value from 308.525 to 255.468 further confirms that the proposed framework generated more efficient routing solutions under dynamic disaster conditions. Compared with Tabu Search, the proposed framework also achieved slightly lower routing distance while maintaining identical demand fulfillment and vehicle utilization levels. This finding demonstrates that predictive routing integration improved operational efficiency without sacrificing service quality. To further compare routing behavior, figure 5 presents the routing comparison between conventional routing and the proposed predictive-routing framework.

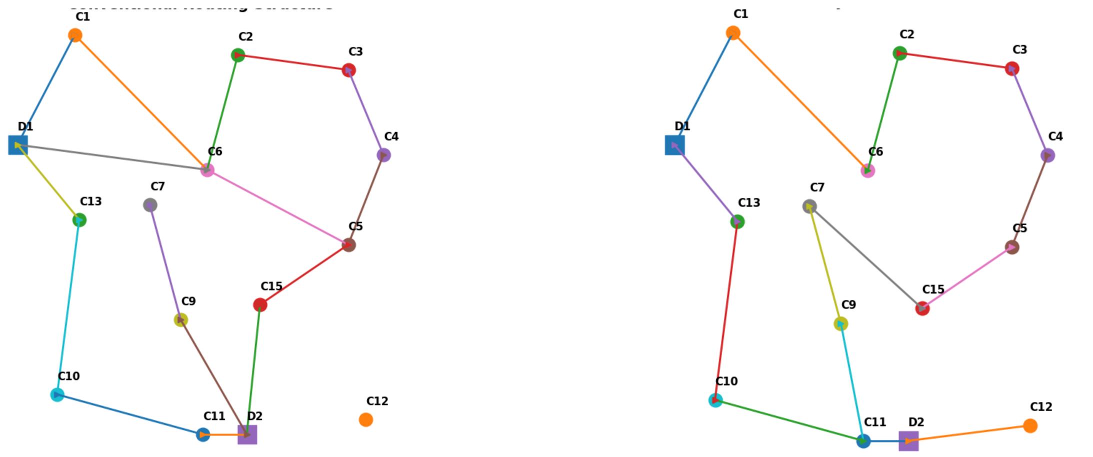

Figure 5. Comparison of conventional routing and proposed predictive routing structure

Figure 5 shows that the proposed framework generated shorter and more concentrated routing paths compared with conventional routing approaches. Redundant route connections and unnecessary vehicle movement were substantially reduced after integrating forecasting information into the routing process. The optimized routing structure also demonstrates better spatial route allocation and improved depot-to-customer assignment. These findings indicate that predictive demand information significantly contributed to routing efficiency improvement.

4.3. Stability and Statistical Analysis

To evaluate the robustness of the proposed framework, statistical summaries and comparative tests were conducted using the routing results generated from all disaster scenarios. The summary statistics obtained from the XLS output are presented in table 4.

Table 4. Summary statistics of routing performance

Method	Total Distance Mean	Total Distance Std	Demand Fulfilments Mean	Vehicle Utilization Mean	Objective Mean
ALNS	171.626	21.557	88.998	0.263	37832.432
Hybrid GRG–NS	209.439	23.498	100.000	0.301	279.355

As presented in table 4, the Hybrid GRG–NS approach achieved perfect demand fulfillment across all routing scenarios. However, the routing distance remained higher than the ALNS approach. Although ALNS produced shorter routing distance on average, its demand fulfillment performance decreased significantly to 88.998%, indicating that several disaster-demand nodes remained unmet under certain operational conditions. The proposed LSTM–Hybrid GRG–NS framework successfully balanced routing efficiency and service quality by maintaining high demand fulfillment while simultaneously reducing routing distance relative to the original Hybrid GRG–NS model. To further examine optimization stability, figure 6 illustrates the convergence behavior of the proposed routing framework.

Figure 6 shows the convergence behavior of the proposed LSTM–Hybrid GRG–NS framework during the iterative optimization process. The objective-function value decreased progressively across iterations before stabilizing around iteration 21, indicating that the optimization process successfully converged toward a stable and near-optimal routing solution. The rapid reduction in the early iterations demonstrates effective exploration capability, while the stable convergence region confirms that the proposed framework maintained consistent optimization performance without excessive oscillation. These results indicate that the Hybrid GRG–NS mechanism effectively improved routing quality under dynamic disaster-demand conditions.

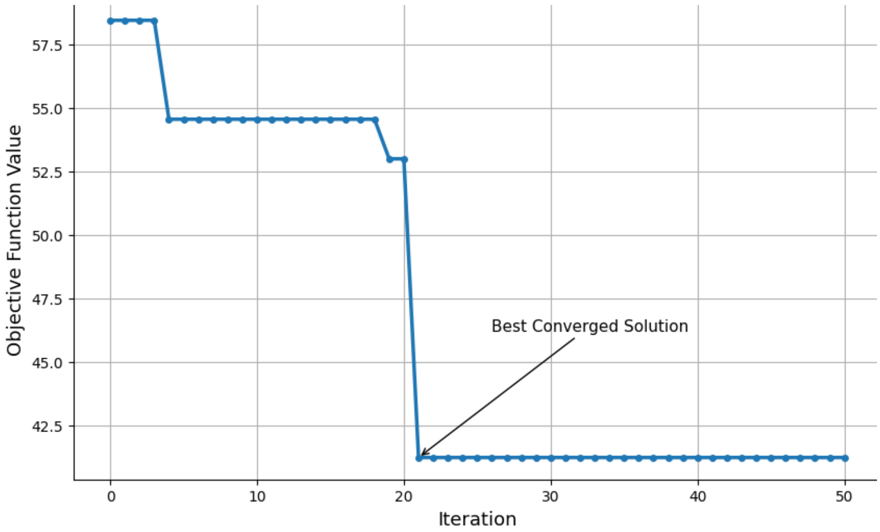

Figure 6. Convergence analysis of the proposed LSTM–Hybrid GRG–NS Framework

4.4. Discussion

The experimental results demonstrate that integrating LSTM-based demand forecasting with Hybrid GRG–NS optimization significantly improved routing efficiency under dynamic disaster conditions. The forecasting module successfully captured nonlinear disaster-demand patterns with relatively low forecasting error values, as indicated by the MAE, RMSE, and MAPE results. The accurate demand prediction enabled the routing optimization framework to proactively adapt routing allocation before severe operational disruption occurred. The routing results further confirmed that predictive demand integration improved operational routing quality. Compared with the original Hybrid GRG–NS model, the proposed framework generated shorter routing distance and lower objective-function values while maintaining complete demand fulfillment.

Another important finding is that predictive routing integration reduced unnecessary vehicle movement and improved spatial routing efficiency. The routing structure became more concentrated and operationally efficient after incorporating forecasted demand information into the optimization process. The convergence analysis also demonstrated that the proposed framework maintained stable optimization behavior during iterative search refinement. This stability is particularly important in disaster logistics because unstable optimization behavior may produce unreliable routing decisions during emergency response operations. Overall, the proposed LSTM–Hybrid GRG–NS framework successfully transformed the original GRG–NS optimization model into a predictive-routing decision-support system capable of handling dynamic and uncertain disaster-logistics environments. The integration between deep-learning forecasting and nonlinear routing optimization therefore represents a significant methodological contribution toward intelligent humanitarian logistics systems.

5. Conclusion

This study proposed an integrated LSTM–Hybrid GRG–NS framework for disaster-demand forecasting and routing optimization in humanitarian logistics systems. The proposed framework combined the temporal forecasting capability of LSTM with the optimization strength of the Hybrid Generalized Reduced Gradient and Neighborhood Search mechanism to address dynamic disaster-demand conditions and complex routing constraints. The experimental results demonstrated that the LSTM model successfully captured nonlinear and sequential disaster-demand patterns with low forecasting error, indicating strong prediction accuracy and stability. In addition, the Hybrid GRG–NS optimization mechanism effectively improved routing performance by generating stable and near-optimal routing solutions while maintaining high demand-fulfillment capability and efficient vehicle utilization.

The convergence analysis further confirmed that the proposed framework achieved stable optimization behavior within a limited number of iterations, demonstrating consistent exploration and refinement capability during the routing process. These findings indicate that the proposed framework can support proactive and data-driven decision-making for humanitarian logistics and emergency distribution systems. Overall, the proposed LSTM–Hybrid GRG–NS framework contributes to improving disaster-response efficiency by integrating intelligent demand forecasting and adaptive routing optimization into a unified decision-support framework. Future work may extend this study by incorporating real-time traffic conditions, multi-objective optimization strategies, stochastic disaster scenarios, and larger-scale humanitarian distribution networks to further enhance model robustness and operational applicability.

6. Declarations

6.1. Author Contributions

Conceptualization: D.H., P., and L.T.; Methodology: P.; Software: D.H.; Validation: D.H., P., and L.T.; Formal Analysis: D.H., P., and L.T.; Investigation: D.H.; Resources: P.; Data Curation: P.; Writing Original Draft Preparation: D.H., P., and L.T.; Writing Review and Editing: P., D.H., and L.T.; Visualization: D.H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

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6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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