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A Hidden Markov Model Based Extended Case-Based Reasoning Algorithm for Relief Materials Demand Forecasting

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Abstract

In emergency situations, accurate demand forecasting for relief materials such as food, water, and medicine is crucial for effective disaster response. This research is presented a novel algorithm to demand forecasting for relief materials using extended Case-Based Reasoning (CBR) with the best-worst method (BWM) and Hidden Markov Models (HMMs). The proposed algorithm involves training an HMM on historical data to obtain a set of state sequences representing the temporal fluctuations in demand for different relief materials. When a new disaster occurs, the algorithm first determines the current state sequence using the available data and searches the case library for past disasters with similar state sequences. The effectiveness of the proposed algorithm is demonstrated through experiments on real-world disaster data of Iran. Based on the results, the forecasting error index for four relief materials is less than 10%; therefore, the proposed CBR-BWM-HMM is a strong and robust algorithm.

Keywords: Demand forecasting, Emergency relief material, Case-based reasoning, Hidden Markov model.

2020 Mathematics Subject Classification: 62M05, 91B06, 90B06.

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1. Introduction

Natural disasters such as earthquakes, hurricanes, and floods can cause significant damage to lives, homes, and infrastructure. In such emergencies, the demand for relief materials such as food, water, and medicine can rapidly escalate, making it essential to accurately forecast demand to ensure that aid organizations can respond effectively [1]. Since the occurrence and severity of these events are often high, the sudden demand for rescue services and relief for affected people is often unknown [2]. This creates uncertainty for emergency response planners, hampers actions needed for the effective deployment of emergency response resources [3]. Similarly, Iran has the fourth highest rate of rapid on-set natural disasters in Asia countries [4]. It is the sixth highest ranked in the world regarding frequency and occurrence of immediate on-set natural disasters [5]. Because of the unexpected nature of these sudden sudden-onset natural disasters, forecasting relief resources is complex and difficult [6]. It is a severe challenge for emergency and disaster managers worth studying. An urgent task of emergency first responders is to deliver an appropriately calibrated response [7]. Such an important task requires effective forecasting and planning and management control of emergency relief resources [8]. Traditional demand forecasting methods for relief materials often rely on limited data, basic statistical models, and expert judgment, leading to inaccurate forecasting and suboptimal allocation of resources [9–11]. Moreover, these approaches may fail to account for the uniqueness of each disaster situation and the complex interplay of factors. As a result, aid organizations face the challenge of making quick decisions under uncertainty and allocating relief materials in a timely and efficient manner [7, 12]. Therefore, there is a pressing need for innovative and data-driven approaches for demand forecasting of relief materials that account for the specific characteristics of each disaster situation and enable effective disaster response [13]. This paper is based specifically on the demand for the four most important relief items [14]. The relief items include (1) drinking water (2) tents for temporary shelter (3) conserves, and (4) food packages. In demand forecasting for relief items, several published papers have addressed various aspects of the topic. The problem of demand forecasting for relief items revolves around accurately predicting the quantity and timing of required items during emergencies. The timely availability of relief items, such as food, medical supplies, and shelter materials, is crucial for effective disaster response and mitigation of human suffering. While existing papers have made valuable contributions to this field, there may still be specific gaps. Some common issues and gaps in the published papers include:

- **Limited Data Availability:** One of the primary challenges in demand forecasting for relief items is the limited availability of accurate and comprehensive historical data. [7, 13, 15] face difficulty obtaining reliable datasets due to the sporadic nature of disasters, inadequate recording systems, or inconsistent data collection practices.

- **Contextual Factors:** Relief item demand is influenced by various contextual factors, including demographics, geographic location, cultural considerations, and the type of disaster. Furthermore, there are interdependencies between different relief items and their demand patterns. Some published papers such as [13, 16] did not adequately capture the influence of these contextual factors.

- **Evaluation and Comparison of Forecasting Models:** While various forecasting models have been proposed for relief item demand forecasting, there is a need for standardized evaluation methodologies and comparative studies. Published papers provide a limited comparative analysis of different forecasting techniques [17–19].

By addressing these gaps, this research contributes to more accurate, adaptive, and context-specific forecasting approaches that enhance the efficiency and effectiveness of disaster response operations. This paper presented a hybrid approach to demand forecasting for relief materials using extended Case-Based Reasoning (CBR) with Best Worst Method (BWM) and Hidden Markov Models (HMMs). Our algorithm involves training an HMM on historical data to obtain a set of state sequences representing the temporal fluctuations in demand for different relief materials. A case library is then created, consisting of past disasters and their associated demand patterns for different materials. When a new disaster occurs, the algorithm first determines the current state sequence using the available data and searches the case library for past disasters with similar state sequences. It then adapts the demand patterns from past cases to the current situation by adjusting for differences in available data and the specific context of the current situation. Finally, the adapted demand patterns forecast the demand for various relief materials in the recent disaster. We demonstrate the effectiveness of our algorithm through experiments on real-world disaster data, achieving significantly improved demand forecasting accuracy compared to traditional methods.

The remainder of the paper is structured as follows: Section 2 provides a brief overview of relevant literature on demand forecasting in emergency disaster response and conventional approaches to forecasting. Section 3 presents the research methodology. In Section 4, we deploy and demonstrate the proposed method by applying it to the case of Tehran province, region 20. The paper concludes with Section 5.

2. Relevant literature

Affected people are often unable to accurately provide helpful information about the items needed and associated levels of demand because of trauma and shock or because they are in remote, inaccessible areas. In addition, demand information is often very diverse and communicated under chaotic and irregular conditions [18]. In operations research (OR) and related disciplines, time series analysis and CBR have been used to forecast demand [20]. Conventional forecasting methods predict the demand for relief after a disaster are often undertaken based merely on the experience and subjective judgments of emergency and disaster decision-makers. Such subjective judgments take place under many constraints and restrictions.

Because qualitative methods are unable to be used accurately and widely for prediction in volatile and chaotic situations, many researchers present quantitative techniques [6, 18, 20, 21]. With the expansion of emergency relief problems and issues globally, many researchers now adapt and deploy standard statistical demand forecasting methods used in stable, routine, repetitive environments to predict the demand of affected people's needs in the often volatile aftermath of disasters [18]. However, the demand created after disasters is often irregular, volatile, irrational, and ad-hoc. Thus, many statistical methods are invalidated in forecasting and predicting the demand for emergency resources. Table 1, presented the various forecasting methods and feature-based comparative research of these methods. Additionally, CBR is easier for managers to learn and use among

Table 1: Comparison of different relief items forecasting method.

Forecasting approach	Based on historical data	Based on dynamic environmental variables	Need to weight	Reference
Artificial Intelligence	✓	×	×	[9, 11]
Multivariate Regression	×	✓	✓	[22, 23]
Fuzzy Logic	✓	×	×	[24, 25]
Time Series	✓	×	✓	[4, 18, 26]
CBR	✓	×	✓	[12, 13]

Source: Our elaboration summary comparing relief resource forecasting methods

the historical historical-based techniques discussed. It requires practically little or no direct expert knowledge acquisition [27, 28]. Consequently, it is picking up significance over other historical-based forecast techniques. Thus, in this paper, we advocate the CBR approach and further develop it by using BWM and HMM as a more accurate and appropriate method of forecasting and predicting the demand for emergency relief resources in the immediate relief phase of a large sudden-onset disaster. The contribution and novelty of this paper can be outlined as follows:

- Integration of CBR and HMM: The novelty of this research lies in integrating

CBR and HMM specifically for relief material demand forecasting. This integration combines the benefits of both approaches and addresses the unique challenges of demand forecasting in relief operations.

- Extended CBR Algorithm: this research introduces an extended version of the CBR algorithm with BWM tailored for relief material demand forecasting. This extended algorithm includes modifications to the traditional CBR process to improve its effectiveness in the given context. The novel algorithm may incorporate domain-specific features, similarity metrics, case adaptation strategies, and retrieval mechanisms to optimize forecasting accuracy and adaptability.

- Improved Demand Forecasting Accuracy: this research demonstrates improvements in demand forecasting accuracy compared to existing approaches. By combining the strengths of CBR and HMM, the proposed algorithm leverages historical cases, incorporate expert knowledge, capture temporal dynamics, and model hidden states and their transitions.

- Evaluation and Validation: this research includes an assessment of the proposed algorithm using real datasets. The evaluation process aims to assess the performance, robustness, and practical applicability of the extended CBR algorithm integrated with HMM.

3. Methodology

This section describes the methodological steps we took, the data collection and analysis undertaken, and the specifications we applied. In section three, we also argued for deploying HMM and extended case-based reasoning in forecasting emergency relief resource requirements. The paper utilizes the extended CBR method and further develops it using BWM to predict the selected emergency relief resource. The BWM approach is productive for weighting the proposed model factors [29].

The CBR-based HMM Algorithm for forecasting of relief materials demand is a method to predict the demand for relief materials during any disasters or emergencies. It combines the power of HMMs and CBR to achieve better forecasting accuracy. The proposed algorithm works as follows:

1. **HMM state sequences:** The HMM is first trained on historical data to obtain a set of state sequences that represent the temporal fluctuations in demand for various relief materials such as food, medical supplies, water, etc.

2. **Case library creation:** A case library consists of a set of past disaster situations, along with their demand patterns for different relief materials.

3. **Classification of the current situation:** When a new disaster occurs, the algorithm determines the current state sequence based on the available data. Given the current state, this involves estimating the likelihood of the available demand patterns for the different relief materials.

4. **Case retrieval:** It then searches the case library for past situations with similar state sequences to the current situation.

5. **Adaptation:** If a set of past cases is found, the demand patterns for the different relief materials from those situations are retrieved and adapted to the current situation based on the similarity of the state sequence. This adaptation involves adjusting the demand pattern to account for any differences in the available data and the specific context of the current situation.

6. **Forecasting:** Finally, the adapted demand patterns are used to predict the demand for different relief items in the current situation.

Overall, this algorithm leverages the power of both HMM and CBR techniques to improve the accuracy and relevance of demand forecasting for relief materials during emergency situations, enabling aid organizations to respond more effectively to disasters.
The research data was gathered through two sources: (1) archival data, which included documents about Iran's disasters, and (2) interviews with senior emergency response managers in Tehran. In the data collection process, a decision panel of 6 experts was formed, and their backgrounds are shown in Table 2.

Table 2: Background of expert panel.

No.	Specialty	Positions	Experience (year)
E1	Emergency response sector	Chairman of Red Crescent Society of Tehran Province	17
E2	Emergency response sector	Deputy of Red Crescent Society of Tehran Province	13
E3	Emergency response sector	Director of Tehran Disaster Mitigation and Management Organization in Region 20	12
E4	Emergency response sector	Logistic Manager of Medical Equipment in Red Crescent Society of Tehran Province	9
E5	Emergency response sector	Logistic Manager of Food Items in Red Crescent Society of Tehran Province	11
E6	Emergency response sector	Supervisor of Search & Rescue Team in Region 20	14

Source: Our elaboration summary of the backgrounds of expert panel members

The six experts recruited were selected because of their long experience and position within emergency response organizations in Tehran's red crescent society. After finalizing the selection of the expert panel, we began the data collection process. Afterward, the expert responses were collated. The research methodological steps deployed are illustrated in Figure 1.

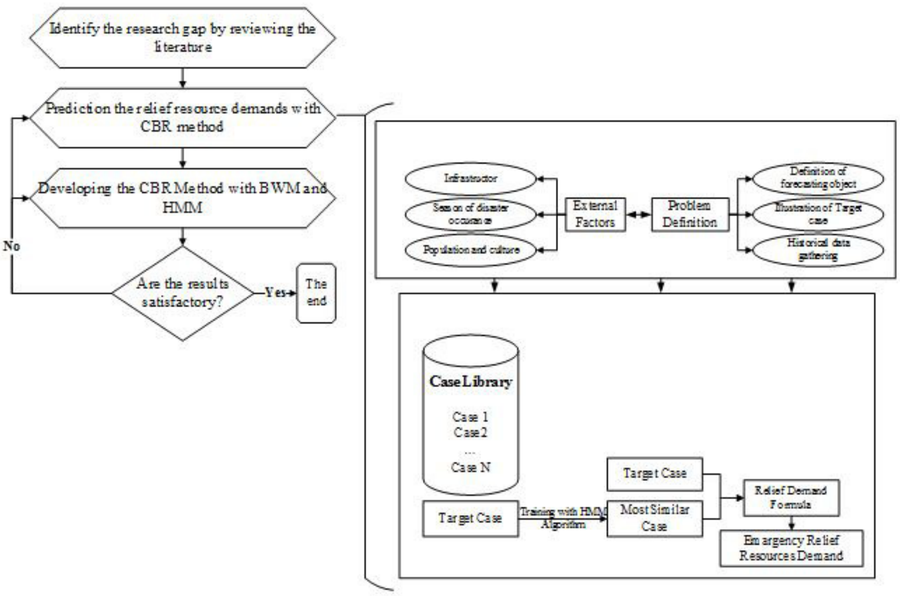

Figure 1: Research framework.

3.1 Case-based reasoning

CBR is a recent approach to problem-solving and learning that has received significant attention over the last few years [30]. CBR models imitate human reasoning, using specific knowledge collected on previously encountered situations to solve new cases [31]. The CBR method was inspired by humans' experiential behavior in dealing with contemporary issues [32].

When a new problem arises, and its conditions compare closely and favorably with the previously addressed issue through similarity comparison mechanisms, then CBR is appropriate for deployment. To provide a solution for new problems, the data and circumstances from the retrieved historical case and the proposed solution are reviewed and prepared. The case generally includes two parts (1) case attribute description and (2) case solution, of which the former one (#1) is the indicator of the structure of cases, and the latter one (#2) is the solution of a case. Therefore, demand forecasting of emergency relief resources of comprises two parts: a characteristic description of emergency response and a description of the nature and features of emergency resource demand.

In the emergency resource demand prediction, the case can be formulated as [33]: $Case\ (F, D)$, that $F = (f_1, f_2, \ldots, f_n)$, f_n is a characteristic attribute of emergency response; D is the demand attribute of emergency resource and n is the number of case. Given that there are n cases in the case library, the case i is expressed as C_i $(i = 1, 2, \ldots, n)$.

Its characteristic factor set $B = \{b_1, b_2, \ldots, b_m\}$. Therefore, the membership function of case C_i to the characteristic factor $b_j (j = 1, 2, \ldots, m)$ is expressed as $n_{Ci}(b_j)$, in which m is the number of characteristic factors, and the characteristic vector corresponding to the case C_i in the case library is as Equation (1):

$$V_{C_i} = \{n_{C_i}(b_1), n_{C_i}(b_2), \ldots, n_{C_i}(b_m)\} = \{n_{C_i}(b_j)|\ j = 1, 2, \ldots, m\}. \tag{1}$$

Given that the characteristic vector set of prediction demand case is T, which can be expressed as Equation (2):

$$V_T = \{n_T(b_1), n_T(b_2), \ldots, n_T(b_m)\} = \{n_T(b_j)|\ j = 1, 2, \ldots, m\}. \tag{2}$$

The nearest neighbor method used to retrieve the case with HMM, namely Equation (3):

$$\frac{\sum_{i=1}^{n} w_i \cdot sim(b_i^I, b_i^R)}{\sum_{i=1}^{n} w_i}. \tag{3}$$

Then the similarity calculated by the Equation (4):

$$sim\,(A, B) = \frac{\sum_{j=1}^{m} w_j \cdot (n_A\,(x_j) \wedge n_B(x_j))}{\sum_{j=1}^{m} w_j \cdot (n_A\,(x_j) \vee n_B\,(x_j))}. \tag{4}$$

Where,
sim : is the similarity function,
b_i^I : is the inputcase value of characteristic factor i,
b_i^R : is the retrieve case value of characteristic factor i,
w_i : is the important weight value of characteristic factor (results of BWM),
$n_A(x_j)$: is the value of characteristic factor x_j in the case A,
$n_B(x_j)$: is the value of characteristic factor x_j in the case B,
$\wedge$: is the maximum lower limit,
$\vee$: is the minimum upper limit.
In the next step, the weight of each characteristic factor can be calculated researchers in this study for this purpose and developing the CBR method used the BWM that described in section 3.2. Then to validate the model, the standard error rate and estimation accuracy must be calculated by using Equations (5)–(6):

$$SER = \frac{\left|\overline{D}_{actual} - D_{CBR-final\ solution}\right|}{\overline{D}_{actual}} * 100\%, \tag{5}$$

$$EA = 100 - SER. \tag{6}$$

$\overline{D}_{actual}$ is the average of actual demand, and $D_{CBR-final/solution}$ is the average of forecasted demand for each relief item. Also, EA is the estimated accuracy of the CBR model. The mean absolute estimate error ($MAEE$) was obtained by using Equation (7):

$$MAEE = \frac{\sum_N \frac{|\overline{D}_{actual} - D_{CBR-final\ solution}|}{\overline{D}_{actual}}}{N} * 100. \tag{7}$$

Here N is the number of cases.

3.2 Best worst method

We describe below the steps of BWM to derive the weight of the criteria [34]:

1. Determine the set of decision criteria $\{c_1, c_2, \ldots, c_n\}$ by decision-makers.

2. Determine the best and the worst criterion to be used for the decision environment.

3. Determine the preference of the best criterion over all the other criteria.

A number between 1 and 9 (1: equally important, 9: extremely more critical) is used to indicate this value. The resulting Best-to-Others vector would be as $A_B = (a_{B1}, a_{B2}, \ldots, a_{Bn})$. Where $a_{B\mathrm{j}}$ indicates the preference of criterion B (best criterion) over criterion j and $a_{\mathrm{BB}} = 1$.

4. Determine the preference of each of the other criteria over the worst criterion.

5. Find the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$.

Solving Equation (8) will result in the optimal weights for the criteria. To determine the optimal weights of the criteria, the maximum absolute differences $\{|w_B - a_{Bj} w_j|, |w_j - a_{jw} w_w|\}$ for all j should be minimized.

$$\begin{aligned} & \min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_w} - a_{jw} \right| \right\}, \\ & \text{s.t.} \\ & \sum_j w_j = 1, \\ & w_j \geq 0, \quad \text{for all } j. \end{aligned} \tag{8}$$

By solving this problem, the optimal weights $(w_1^*, w_2^*, \ldots, w_n^*)$ and the optimal value of the BWM objective function (The first row of Equation (8)) were obtained.

3.3 Hidden Markov model

HMM is a stochastic process at any distinct time instant [35]. This process is presumed in a state, and random functions corresponding to the preset state generate observation. Before applying HMM for a problem, an HMM should be trained. Numerous criteria might be used for problem learning. The one is maximizing the sequence probability of observation, $O = (o_1\ o_2 \dots o_T)$, which is made by HMM λ, i.e.,$P[O|\,\lambda]$. Equations (9)–(10) show the re-estimation equation:

$$\overline{\pi} = \alpha_1(i)\,\beta_1(i)/\sum_{j=1}^{N}\alpha_T(j)\,, \tag{9}$$

$$\overline{a}_{ij} = \sum_{t=1}^{T}\alpha_{t-1}(i)\,a_{ij}b_j(o_t)\,\beta_t(j)/\sum_{t=1}^{T}\alpha_{t-1}(i)\,\beta_{t-1}(i), \tag{10}$$

In which $\overline{\pi}$, $\overline{a}_{ij}$, $\overline{c}_{jk}$, $\overline{\mu}_{jk}$ and $\overline{U}_{ij}$ represent the model parameters of $\overline{\lambda}$, $\gamma_t(j,k)$ which is defined as the probability of being in state j at time t with kth mixture component accounting for o_t of the form (Equation (11)):

$$\gamma_t(j,k) = \left[\frac{\alpha_t(j)\,\beta_t(j)}{\sum_{i=1}^{N}\alpha_t(i)\,\beta_t(i)}\right]\left[\frac{c_{jk}G(o_t,\mu_{jk},U_{jk})}{\sum_{m=1}^{M}c_{jm}G(o_t,\mu_{jm},U_{jm})}\right], \tag{11}$$

and $\alpha_t(i)$ is the forward variable [36] of the form Equation (12):

$$\alpha_t(i) = \begin{cases}\pi_i b_i(o_i)\,, & t=1,\quad 1\le i\le N,\\ \left[\sum_{i=1}^{N}\alpha_{t-1}(i)\,a_{ij}\right]b_j(o_t)\,, & 1<t\le T,\ 1\le i\le N.\end{cases} \tag{12}$$

Also, $\beta_t(i)$ is the backward variable [36] of the form Equation (13):

$$\beta_t(i) = \begin{cases}1, & t=T,\ 1\le i\le N,\\ \sum_{j=1}^{N}a_{ij}b_j(o_{t+1})\,\beta_{t+1}(j), & 1\le t\le T,\ 1\le i\le N.\end{cases} \tag{13}$$

4. Application to a case: region 20 of Tehran

The forecasting process specified above can be applied to forecasting an emergency materials demand. Given the extent of affected peoples' needs, this research focuses on the four most essential needs based on [37]. These include drinking water; tents; conservation; and food packaging. In this research, demand forecasting was undertaken for the four relief items for an earthquake occurring in region 20 of Tehran, Iran's capital city. In Figure 2, we present the map of Tehran and region 20.

After investigating previous earthquakes in Iran in general and Tehran in particular, we collect detailed data about 13 historical earthquakes ($C = C_1 - C_{13}$).

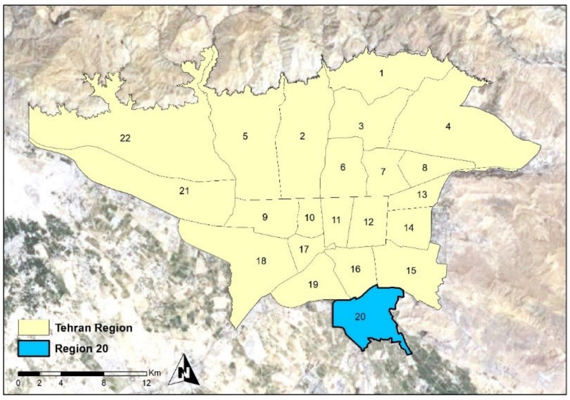

Figure 2: Map of Tehran and Region 20.

The authors extracted and entered the data into the database with each of the 13-case data, including demand information about the quantity demanded for the four selected most important needs tents, drinking water, conserves, and food packages (Table 3).

The standing emergency relief and rescue plans for this type of earthquake emergency relief response in the same municipality (Tehran) are the same. After informal interviews with the 6 experts and a review of standing disaster relief plans for Tehran, six characteristics reflecting the key characteristics of typical Tehran earthquake emergency response are selected. The characteristic factors in set B are composed of:

1. Earthquake magnitude (b_1),
2. Earthquake depth (b_2),
3. Number of affected people (b_3),
4. Number of direct victims (b_4),
5. Number of injured persons (b_5), and
6. Disaster life cycle (b_6).

The relevant data and information on the six characteristics above are drawn from each consecutive earthquake case in the database presented in Table 4. The six attributes of each of the 13 cases are drawn respectively as follows:

4.1 Weighting characteristic factors by using the BWM

As mentioned in Section 5, six characteristic factors were identified. It is impossible to assume that all the identified factors have equal importance. In this

Table 3: Relief items consumed in earthquakes are available at the case library.

Case	Earthquake name	Tents (number)	Drinking water (kg)	Food packages (number)	Conserves (number)
C_1	Dashti	6934	185730	59600	7624
C_2	Khormoj	4600	136475	30000	5740
C_3	Bashagard	2600	10230	560	4000
C_4	Goharan	1849	6730	2921	1267
C_5	Ahar	10515	30248	22260	11592
C_6	Varzaghan	11304	27866	867	13067
C_7	Haris	4470	15435	9460	1000
C_8	Bam	13000	326450	21216	26740
C_9	Manjil	56400	765426	9568	69570
C_{10}	Zahan zirkoh	1678	10334	5283	3000
C_{11}	Hossein abad	1560	98400	3500	2680
C_{12}	Zarand	10000	150000	4000	8654
C_{13}	Ardebil	3248	10560	2000	4860

Source: Our elaboration summary of relief supplies consumed in previous earthquakes

Table 4: Characteristics of each case of previous earthquakes.

Earthquake	Year	Magnitude	Depth (Km)	Affected people	Killed people	Injured people	Disaster life cycle (Day)
Dashti	2013	6.1	12	3500	38	997	4
Khormoj	2013	6.2	12	2400	37	1170	4
Bashagard	2014	6.2	15	1500	1	17	4
Goharan	2014	6.2	15	1200	2	14	5
Ahar	2012	6.2	10	4134	120	854	6
Varzaghan	2012	6	10	6900	132	937	6
Haris	2012	6	10	3472	54	354	6
Bam	2003	6.6	10	65760	26797	30000	10
Manjil	1990	7.4	13.3	120000	40021	105090	9
Zahan zirkoh	2012	5.5	8	1200	6	23	5
Hossein abad	2010	6.5	10	750	11	535	4
Zarand	2005	6.4	11	11526	625	1621	4
Ardebil	1997	6.1	6	16510	14	131	6

Source: Our elaboration summary of each case of previous earthquakes derived from Ghasemian (2015) study, BWM is used to determine the factors' weights. The opinion of Expert 1 is illustrated in Table 5.

Table 5: BO vector for Expert 1.

Best criterion	$\mathbf{b}_1$	$\mathbf{b}_2$	$\mathbf{b}_3$	$\mathbf{b}_4$	$\mathbf{b}_5$	$\mathbf{b}_6$
$\mathbf{b}_1$	1	4	2	8	5	6

Similar to the previous step, a value between 1 and 9 is used. The opinion of Expert 1 is illustrated in Table 6, for instance.

Table 6: OW vector for Expert 1.

Worst criterion	$\mathbf{b}_4$
b_1	8
b_2	5
b_3	6
b_4	1
b_5	3
b_6	2

The weights of factors are determined with a linear model (Equation (9)) of BWM. These results are illustrated in Table 7 and Figure 3. Also, in this table, the summary statistics of this phase are shown.

Table 7: Final factor weights.

Factor	**Weight (mean)**	**Min**	**Max**	**s.d.**
b_1	0.079	0.036	0.101	0.022
b_2	0.111	0.042	0.168	0.036
b_3	0.326	0.183	0.453	0.104
b_4	0.051	0.031	0.085	0.022
b_5	0.126	0.081	0.141	0.022
b_6	0.307	0.168	0.461	0.117
$\boldsymbol{\xi}^*$	0.102			

Source: Our calculation summary of each characteristic factor weight based on BWM

As can be seen from the results, in this case, 'Number of affected people (b_3)', 'Disaster life cycle (b_6)' and 'Number of injured persons (b_5)' are the most critical characteristic factor and 'Earthquake depth (b_2)', 'Earthquake magnitude (b_1)' and 'Number of direct victims (b_4)' are the least essential characteristic factor respectively.

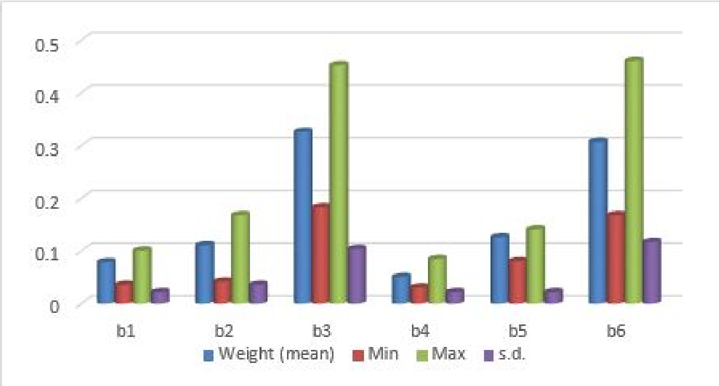

Figure 3: Summary of weighting phase results.

4.2 Case retrieve-similarity calculation

Here are the steps to combine CBR with HMM for emergency items prediction. This approach leverages the strengths of both CBR and HMM [38], allowing aid organizations to accurately forecast demand for resources during emergencies and allocate resources efficiently. Through the previous section, the membership function of 13 cases are as follows respectively:

$$n(C_1\,(b)) = \frac{0.8}{b_1} + \frac{0.7}{b_2} + \frac{0.4}{b_3} + \frac{0.4}{b_4} + \frac{0.6}{b_5} + \frac{0.6}{b_6},$$

$$n(C_2\,(b)) = \frac{0.7}{b_1} + \frac{0.8}{b_2} + \frac{0.6}{b_3} + \frac{0.8}{b_4} + \frac{0.9}{b_5} + \frac{0.6}{b_6},$$

$$n(C_3\,(b)) = \frac{0.6}{b_1} + \frac{0.7}{b_2} + \frac{0.6}{b_3} + \frac{0.6}{b_4} + \frac{0.5}{b_5} + \frac{0.8}{b_6},$$

$$n(C_4\,(b)) = \frac{0.5}{b_1} + \frac{0.6}{b_2} + \frac{0.7}{b_3} + \frac{0.7}{b_4} + \frac{0.8}{b_5} + \frac{0.7}{b_6},$$

$$n(C_5\,(b)) = \frac{0.5}{b_1} + \frac{0.7}{b_2} + \frac{0.8}{b_3} + \frac{0.7}{b_4} + \frac{0.8}{b_5} + \frac{0.8}{b_6},$$

$$n(C_6\,(b)) = \frac{0.7}{b_1} + \frac{0.7}{b_2} + \frac{0.6}{b_3} + \frac{0.6}{b_4} + \frac{0.5}{b_5} + \frac{0.6}{b_6},$$

$$n(C_7\,(b)) = \frac{0.6}{b_1} + \frac{0.5}{b_2} + \frac{0.5}{b_3} + \frac{0.7}{b_4} + \frac{0.8}{b_5} + \frac{0.6}{b_6},$$

$$n(C_8\,(b)) = \frac{0.8}{b_1} + \frac{0.7}{b_2} + \frac{0.4}{b_3} + \frac{0.4}{b_4} + \frac{0.6}{b_5} + \frac{0.6}{b_6},$$

$$n(C_9\,(b)) = \frac{0.9}{b_1} + \frac{0.4}{b_2} + \frac{0.7}{b_3} + \frac{0.6}{b_4} + \frac{0.5}{b_5} + \frac{0.6}{b_6},$$

$$n(C_{10}(b)) = \frac{0.7}{b_1} + \frac{0.6}{b_2} + \frac{0.8}{b_3} + \frac{0.7}{b_4} + \frac{0.6}{b_5} + \frac{0.9}{b_6},$$

$$n(C_{11}(b)) = \frac{0.5}{b_1} + \frac{0.7}{b_2} + \frac{0.9}{b_3} + \frac{0.6}{b_4} + \frac{0.6}{b_5} + \frac{0.7}{b_6},$$

$$n(C_{12}(b)) = \frac{0.7}{b_1} + \frac{0.9}{b_2} + \frac{0.8}{b_3} + \frac{0.8}{b_4} + \frac{0.8}{b_5} + \frac{0.8}{b_6},$$

$$n(C_{13}(b)) = \frac{0.8}{b_1} + \frac{0.7}{b_2} + \frac{0.6}{b_3} + \frac{0.5}{b_4} + \frac{0.6}{b_5} + \frac{0.6}{b_6},$$

Given that an earthquake occurs in region 20 of Tehran and emergency relief response occurs immediately, emergency managers need to conduct a demand forecast and prediction of emergency managers need to conduct a demand forecast and predict emergency resource demands. Given that the relief materials demand prediction is expressed as T, and its membership function is expressed in the following:

$$n(T(b)) = \frac{0.6}{b_1} + \frac{0.6}{b_2} + \frac{0.6}{b_3} + \frac{0.4}{b_4} + \frac{0.6}{b_5} + \frac{0.4}{b_6}.$$

According to the similarity calculation procedure, the similarity of each case is presented as follows:

$$\begin{aligned}
&sim(T, C_1) = 0.602, && sim(T, C_2) = 0.732, && sim(T, C_3) = 0.711,\\
&sim(T, C_4) = 0.722, && sim(T, C_5) = 0.645, && sim(T, C_6) = 0.736,\\
&sim(T, C_7) = 0.744, && sim(T, C_8) = 0.702, && sim(T, C_9) = 0.360,\\
&sim(T, C_{10}) = 0.673, && sim(T, C_{11}) = 0.740, && sim(T, C_{12}) = 0.491,\\
&sim(T, C_{13}) = 0.720.
\end{aligned}$$

In Table 8, the priority of each case due to its similarity to the target case is listed. It can be seen from the calculations above that this emergency response is similar

Table 8: Priority of cases according to their similarities with the target case.

Case	**C$_1$**	**C$_2$**	**C$_3$**	**C$_4$**	**C$_5$**	**C$_6$**	**C$_7$**	**C$_8$**	**C$_9$**	**C$_{10}$**	**C$_{11}$**	**C$_{12}$**	**C$_{13}$**
Priority	11	4	7	5	10	3	1	8	13	9	2	12	6

Source: Our calculation of cases similarity based on CBR

to case C_7 in the case library. Several cases are highly similar to the target case. For this reason, cases in which their similarity is more than 70% (according to experts' panel opinion) are selected for retrieval. In this research, cases C_2, C_3, C_4, C_6, C_7, C_8, C_{11}, and C_{13} are retrieved because they have high similarity. The arithmetic average demand of selected cases was used to retrieve (i.e., cases with similarity above 70%). The amount of emergency relief items for the given target case is as follows in Table 9.

Table 9: Prediction of selected needs for region 20 of Tehran.

Quantity of relief materials / Characteristic Factor in the target case	Tents	Drinking water	Food package	Conserves
Magnitude:6.4 Depth: 12 Affected: 5555 Killed:150 Injured:1000 Life cycle:4day	5329	79018	8591	7419

Source: Our calculation of demand forecasting of selected needs for Tehran region 20

Then, to validate results, the MAEE index was calculated:

$$MAEE_{tents} = \frac{\frac{|6934-5329|}{6934} + \cdots + \frac{|3248-5329|}{3248}}{13} = 6.03\%$$

$$MAEE_{drinking\ water} = \frac{\frac{|185730-79018|}{185730} + \cdots + \frac{|10560-79018|}{10560}}{13} = 8.52\%$$

$$MAEE_{food\ package} = \frac{\frac{|59600-8591|}{59600} + \cdots + \frac{|2000-8591|}{2000}}{13} = 9.27\%$$

$$MAEE_{conserves} = \frac{\frac{|7624-7419|}{7624} + \cdots + \frac{|4860-7419|}{4860}}{13} = 7.84\%$$

MAEE index in the four relief items calculated less than 10%; therefore, the proposed CBR-BWM-HMM algorithm is robust in demand forecasting in the emergency and disaster response.

Our approach of combining CBR and HMMs for demand forecasting of relief materials has several strengths. HMMs allow us to capture the temporal fluctuations in demand for different relief materials over time, while the CBR approach enables us to account for the specific context of a disaster situation and adapt demand patterns from similar past cases to the current situation. As shown in our experiments on real-world disaster data, this combination of HMM and CBR significantly improves demand forecasting accuracy compared to traditional methods. Moreover, our proposed algorithm offers a powerful tool for aid organizations to make data-driven decisions, allocate resources more effectively, and respond more efficiently to disasters. By reliably predicting the demand for various relief materials, our approach can help aid organizations to better plan and prepare for disaster responses and minimize potential logistical constraints and operational bottlenecks.

5. Concluding remarks and further research

In this research, we have presented a hybrid approach to demand forecasting of relief materials using a combination of CBR and HMMs. Our proposed algorithm provides a powerful tool for predicting the demand patterns of different relief materials during a disaster, enabling aid organizations to plan better, allocate resources, and respond more effectively. Our experiments demonstrate that our approach outperforms traditional methods, significantly improving demand forecasting accuracy. CBR has recently attracted enormous scholarly interest in various research fields, and is at the forefront of research in artificial intelligence and machine learning.

The hybrid approach combining CBR and HMM for relief item demand forecasting offers several advantages. CBR allows the system to adapt to the specific context of relief item demand forecasting by considering past cases and their similarities to the current situation. By leveraging CBR, the hybrid approach utilizes historical cases similar to the present forecasting scenario. This consideration of past cases helps capture demand patterns and trends, especially in situations where reliable historical data may be limited or fragmented. The past instances act as valuable references that aid in estimating future demand [38]. CBR integrates expert knowledge and domain expertise through the case base. The HMM component of the hybrid model provides probabilistic outputs, indicating the likelihood of different demand scenarios. Combining probabilistic forecasts from HMM with the retrieved and adapted cases from CBR, the hybrid approach offers a comprehensive prediction that considers both the temporal dynamics and historical patterns, resulting in more robust and reliable forecasts. Hybridization of CBR and HMM for relief item demand forecasting offers a synergistic combination of data-driven modeling, historical case relevance, contextual adaptability, and expert knowledge incorporation. By leveraging the strengths of both approaches, it has the potential to provide enhanced forecast accuracy, adaptability to dynamic environments, and actionable insights for effective relief operations.

However, there are some limitations and challenges associated with our approach. For example, the quality of historical data used for training the HMM models can impact the quality of the demand forecasts. Furthermore, the scalability of our algorithm may be challenging for large-scale disasters or on a global scale, given the computation requirements needed for training HMMs. In future work, we suggest exploring ways to improve scalability and incorporate more data from sources such as social media or mobile phone data to improve demand forecasting accuracy. Overall, our approach represents a promising direction for more effective demand forecasting in disaster response, helping to improve the efficiency and efficacy of disaster relief efforts worldwide. It is also suggested, future researcherdevelop game-theoreticmodels such as cooperative [39] or non-cooperative [40] game that consider the strategic interactions between multiple relief organizations involved in the allocation of relief items.

Conflicts of Interest. The authors declare that they have no conflicts of interest regarding the publication of this article.

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