A Rapid Decision Model of Disaster Relief Logistic, based on Internet of Things (IoT) Data Analytics and Case-Based Reasoning

M. Dachyar[1], Yadrifil1[2], Maulana Ihsan Al Ghifari[3]
Industrial Engineering Department
Universitas Indonesia, Indonesia
[1]mdachyar@yahoo.com, [2]yadrifil@yahoo.com, [3]maulana.ihsan1911@gmail.com

Abstract

The biggest challenge in earthquake emergency logistics lies in determining the demand for emergency logistics support. To forecast the need for emergency logistics support plays a vital role in optimal disaster logistics management. An accurate demand forecasting can prevent an out-of-stock, can save time, and ensure a proper allocation of emergency logistical relief to overcome the long-suffering of victims. This paper aims to design a model for estimating emergency logistical assistance requests after an earthquake. The methodology of Case-based Reasoning (CBR) is applied to build the model. At the same time, the implementation of the Internet of Things (IoT) able to supports retrieving data to the model to produce the forecasting results quickly. The research results show that the error forecast for relief logistics includes blankets, tents, food are respectively 16.78%, 15.99%, and 10.48%. All errors forecast in the range of 10% -20%; thus, the results indicate that the forecast output model is valid to use for predicting emergency logistical assistance requests immediately after an earthquake occurs.

Keywords
logistics management, demand forecasting, Case-based Reasoning (CBR), Internet of Things (IoT), disaster

1. Introduction

Earthquake is the most lethal natural disaster that brings destructive impact for living creatures (Cao et al. 2018; Jin 2014). For the last decade, several earthquakes that occurred in Indonesia resulted in a large number of deaths, damaged infrastructure, and great economic losses. The highest earthquake occurrence that afflicts Indonesia happened in 2018 with 35 destructive earthquake incidents, the greatest number compared to previous years. According to Indonesia disaster management agency, a series of earthquakes in 2018 caused 4,814 deaths (increase 597% from 2017), 21,083 injured victims (increase 1923% from 2017), 322,864 property damaged (increase 522% from 2017), and the economic loss to swiftly increase 233% from 2017. While the earthquake incidents might be unavoidable, the effective response operation should be carried out to reduce the devastating impact on the lives of those who affected (Loree and Aros-Vera 2018).

One of activity that is considered as the key success for effective response operation is emergency logistic (EL) (D'Haene, Verlinde, and Macharis 2012), (Y. Liu et al. 2018). The main purpose of EL is to distribute the logistic reliefs to those who affected as quickly as possible to reduce their suffering and loss of life after the earthquake (Clay Whybark 2007). The greatest challenge in earthquake emergency logistics lies in determining emergency logistic relief demand. (Song, Chen, and Lei 2018). The chaos situation after earthquake makes it difficult to obtain demand-related information e.g affected areas, the damage level of the affected area, number of displaced population, etc. (Sheu 2007), whereas the forecasting number of total emergency logistic relief demand is a premise and basis to distribute emergency logistic relief optimally. (X. Wang et al. 2016), (W. Liu, Hu, and Li 2012). Emergency logistic relief must always be ready whenever the victims need it. The lack of amount of emergency logistic relief will potentially increase the number of death (Loree and Aros-Vera 2018). In order to reduce victim suffering and prevent additional deaths, disaster management agency strongly requires the method to forecast emergency logistic relief demand after earthquake so they can determine how many emergency logistic relief must be procured, stored and distributed to the victims. Accurate and efficient demand forecasting will prevent stock-out, save time, and ensure appropriate allocation of logistic relief to alleviate the suffering of affected victims (van der Laan et al. 2019).

This paper proposes the model to forecast the demand of emergency logistic relief to help disaster management agency make the strategic decision of how many emergency logistic relief must be procured, stored, and distributed after earthquake using the CBR method, which is supported by IoT. IoT will give real-time data and information about earthquake events as well as its destructive impact to be used as an input for CBR, so the forecasting result can be obtained quickly.

1. Literature Review

2.1 Emergency Supplies Demand Forecasting

The research of emergency logistic relief demand forecast has been becoming a hot spot of researchers and practitioner to study (Yang, Jiangyuan, and Yuan 2016). Emergency logistic relief demand forecasting possesses an important role in EL, as an activity which really determines the success and effectiveness of response operation after disaster (Clay Whybark 2007), (H. Zhang and Xu 2010). Demand forecasting acts as a precondition of the storage and distribution of emergency logistic relief (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014; van der Laan et al. 2019). Accurate forecasting result will drive the response operation to become more effective. (Tang 2012; X. Wang et al. 2016).

2.2 Case-Based Reasoning

Case-based Reasoning (CBR) is a problem-solving method that reuses the solution from previous similar problem to find the solution for a problem encountered (W. Liu, Hu, and Li 2012). The main principle of CBR is retrieving the most similar historical case based on the similarity analysis with the target case, so to solve the problem occurs on the target case, the solution from similar historical case can be used and adapted (Zhu, Sun, and Jin 2016). CBR is mainly comprised of 4 phases which are case retrieval, case reuse or case revision, dan case retain (W. Liu, Hu, and Li 2012). Case retrieval is a phase to retrieve the most similar case from the stored historical case based on certain attributes (Lamalewa et al. 2018). Nearest neighbor method has been widely used to determine the similarity of historical case and the target case (van der Laan et al. 2019; Lo et al. 2015; Wu 2010; Zhong et al. 2010). Case reuse and case revision phase will reuse and adapt the solution based on the most similar historical case (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014), (Case 2017), then case retain phase will store the target case on case database once it has been successfully solved (Lamalewa et al. 2018).

CBR application in forecasting the number of emergency logistic relief has drawn much attention from researchers (W. Liu, Hu, and Li 2012). CBR has been applied to forecast emergency logistic relief on earthquake disaster (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014; W. Liu, Hu, and Li 2012; X. Wang et al. 2016), typhoon disaster (H. Zhang and Xu 2010; Zhong et al. 2010), and flood disaster (Wu 2010). CBR is chosen because it successfully provides an accurate forecasting result without enough emergency information, one advantage that is not possessed by another forecasting method (X. Wang et al. 2016). Besides, CBR also has the capability of incremental learning without time-consuming training, so its ability of learning and solving problem is growing quickly as the time goes by (Taylor, Kim, and Kim 2013; X. Wang et al. 2016).

2.3 IoT Implementation in Earthquake Disaster Management

In the context of earthquake disaster management, IoT enables the creation of affordable, flexible, and effective system for notification, early warning, data analytic, victim localization, and remote monitoring (Ray, Mukherjee, and Shu 2017), (Greco et al. 2018). Telecommunication company innovation is indispensable for this IoT to succeed (Dachyar and Hananto 2014)

IoT implementation in earthquake disaster management can detect earthquake incidents in real time to send early warning notification for the population around affected area through smartphone (Alphonsa and Ravi 2016), enable distribution emergency information service to find victim location based on their smartphone (Hidayanti and Supangkat 2018) (Dachyar and Risky 2014), and acquire earthquake magnitude, epicenter coordinate, and ground surface acceleration data short after incident using seismograph and accelerator sensor (Chen et al. 2011; Spalazzi, Taccari, and Bernardini 2014). The data then be sent to remote monitor center through a gateway which will process, compute, and analyze the data as well as store the results into a database server.

IoT implementation in earthquake disaster management provides real-time information about earthquake event, its destructive impact, condition in the affected area, and victim location. Those information are highly needed by disaster management agency to perform quick response operation to mitigate additional impact of those who affected (Greco et al. 2018) (Dachyar, Zagloel, and Saragih 2019).

2. Methods

In conducting emergency logistic relief demand forecasting, this paper follows RADIUS rules which are discussed in (Mazumder and Salman 2019; Oktarina et al. 2013). RADIUS has been used as tools to estimate the seismic damage short after earthquake which was launched by the United Nations Office for Disaster Risk Reduction (UNISDR) in 1996 (Mazumder and Salman 2019). According to the rules, to forecast the number of emergency logistic relief demand, the estimated number of the victim should be carried out first (Oktarina et al. 2013), so the CBR method in this paper will result to the estimated number of post-earthquake victims which is used to forecast the number emergency logistic relief demand.

Based on CBR method, the steps to conduct this research are as follow: (1) Selecting factor/attributes, (2) Assigning weight for each attribute, (3) Retrieving the most similar historical case as target case, (4) Estimating the number of post-earthquake victims, (5) Forecasting the number of emergency logistic relief demand based on estimated number of post-earthquake victims.

3.1 Selection of Attributes

Literature review from previous researches has been conducted to obtains attributes that affect the number of post-earthquake victims. Based on the literature review, six attributes have been selected, which are: earthquake magnitude (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014; Tang 2012); depth of hypocentre (H. xia Wang, Niu, and Wu 2011; Zhu, Sun, and Jin 2016); epicenter distance (Oktarina et al. 2013; X. Wang et al. 2016); affected population (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014; X. Wang et al. 2016); duration of response phase (W. Liu, Hu, and Li 2012; Y. Zhang 2014); and Modified Marcelli Intensity (MMI) (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014; Oktarina et al. 2013).

3.2 Attributes weighting

The six predetermined attributes have a different relative important level in affecting the number of post-earthquake victims, so each attribute should be weighted. The proper weight will increase the precision and accuracy of case retrieval (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014). This paper uses Integrated Determination of Variable Weight (IDVW) which was proposed by Ha, Wang, & Liu (2017). IDVW is a method that combines analytical hierarchy process (AHP) as one of subjective weighting method and mean square difference (MSD) as one of objective weighting method, which has been proved to increase the efficiency and precision of case retrieval (Y. Wang 2017).

3.2.1 AHP-based attribute weighting

In order to obtain AHP-based weight of each attribute, seven experts from disaster management agency were asked to evaluate attribute importance by filling Likert 9-scale measurement pairwise comparison questionnaire. The scale represents the weight of importance of one attribute to another attribute. For example, we have two elements, a and b. If the expert filled attribute a in 2, this means that element a is two times more important than element b. If the questionnaire was filled in with the value of ½, then element b is two times more important than element a. The result was converted into a pairwise comparison matrix to calculate the inconsistency ratio. The inconsistency ratio of each is less than 0.1, meaning all expert inputs are validated and acceptable. AHP-based attribute weight is shown in Table I.

Table 1: Attribute weight based on AHP

Attributes	Weight

Magnitude	0.08
Depth of hypocentre	0.05
Epicenter distance	0.05
Total affected population	0.44
Duration of response phase (day)	0.22
Modified Mercalli Intensity (MMI)	0.17

3.2.2 MSD-based attribute weighting

MSD is an objective weighting method that has been widely used in similar studies such as in (W. Liu, Hu, and Li 2012; Sahebi and Jafarnejad 2018; X. Wang et al. 2016; Wu 2010). Different from the subjective weighting method, the weight results from MSD really depends on attributes value, so data processing and analysis should be conducted. According to (Y. Wang 2017), the steps in using MSD are as follow:

1) Apply the dimensionless method to each attribute of the historical case using (1)

$$Rt_{(i,j)} = \frac{R(i,j) - \min(Rj)}{\max(Rj) - \min(Rj)} \quad (1)$$

where Rt(i,j) is value of attribute j on historical case i after dimensionless method, R(i,j) is value of attribute j on historical case i before dimensionless method, min (Rj) is the minimum value of attribute j, dan max (Rj) is the maximum value of attribute j.

2) Calculate the mean of Rt(i,j) using (2)

$$Z_j = n^{-1} \sum_{i=1}^{n} Rt_{(i,j)} \quad (2)$$

where Zj is mean for attribute j and n is the total historical case used.

3) Calculate the mean square deviation for each attributes using (3)

$$\sigma_j = \sqrt{\sum_{j=1}^{b} (Rt_{(i,j)} - Z_j)^2} \quad (3)$$

where σ_i is mean square deviation for attribute j dan b is the total attribute used.

4) Calculate the weight based on (4)

$$W_{MSD(j)} = \frac{\sigma_j}{\sum_{j=1}^{b} \sigma_j} \quad (4)$$

where WMSD(j) is MSD-based weight for attribute j.

To acquire MSD-based weight, we use 39 earthquake incidents that occurred in Indonesia during 2006-2019 as historical cases. Table VI shows the representation of historical cases based on six predetermined attributes. Using the attribute value from 39 earthquake historical cases on (1)-(4), the weight of each attribute can be obtained. Table II shows MSD-based attribute weight.

Table I. Attribute weight based on msd

Attributes	**Weight**
Magnitude	0.17
Depth of hypocentre	0.17
Epicenter distance	0.19
Total affected population	0.14
Duration of response phase (day)	0.18

Modified Mercalli Intensity (MMI)	0.15

3.2.3 Final attribute weight

The final attribute weight can be calculated using (5) since AHP-based and MSD-based attribute weight have been obtained.

$$Wj = 0.4 \times WAHP(j) + 0.6 \times WMSD(j) \quad (5)$$

where Wj is final weight of attribute j, WAHP(j) is the AHP-based weight of attribute j, and WMSD(j) is MSD-based weight of attribute j. MSD-based attribute weight is given the higher percentage since it is obtained through data processing and analysis, so it has higher credibility compared to AHP-based attribute weight which largely depends on expert opinion. (Y. Wang 2017). Table III shows the final weight for each attribute.

3.3 Case Retrieval

The next step of CBR method is to retrieve the most similar historical case as target case. Historical cases are represented by earthquake incidents that affect a regency in Indonesia during 2006-2019 (See Table VI). The data are collected from Indonesia disaster management agency and meteorological, climatological, and geophysical agency.

The target used in this research is the North Lombok earthquake which occurred on 5 August 2018. It was the most devastating earthquake in Indonesia for the last decade. The earthquake caused at least, 464 people died, 829 people injured, 101,236 people displaced, and 40,795 property damage. Table IV shows the attribute value of North Lombok earthquake which will be used further to retrieve the most similar historical cases.

Table II. Final attribute weight

Attributes	Weight
Magnitude	0.13
Depth of hypocentre	0.12
Epicenter distance	0.14
Total affected population	0.26
Duration of response phase (day)	0.20
Modified Mercalli Intensity (MMI)	0.16

The attribute's value can be obtained in real-time so the demand forecasting can be performed quickly. By leveraging seismograph and accelerator sensors that are connected through a specific network, the value of earthquake magnitude, depth of hypocentre, epicenter distance, and MMI can be captured in real-time then is transmitted to remote monitor center owned by disaster management agency. According to United States Geological Survey (USGS), the exact value of those four attributes can be obtained within 10 minutes after earthquake occurs. The value for number of affected population is assumed as the total population in the affected regency which is collected from central bureau of statistic database. The value for duration of response phase is determined by the disaster management agency as quickly as possible after earthquake occurs to decide the demand forecasting horizon time.

Nearest neighbor method is used to analyze similarity between the target case and each historical cases. It is started by calculating local similarity between each attribute value of the two cases. Equation (6) shows the formula to calculate local similarity (Lamalewa et al. 2018).

$$\mathrm{Sim}(Q_j, C_{i,j}) = 1 - \frac{|q_j - c_{ij}|}{fmax - fmin} \quad (6)$$

where $\mathrm{Sim}(Q_j, C_{i,j})$ is local similarity between target case and historical case i, cij is the value of attribute j in historical case i, fmax is the maximum value of attribute j that is used in the calculation, and fmin is the minimum value of attribute j that is used in the calculation.

Table III: Attribute value of target case

Attributes	Value
Magnitude (M)	7.0
Depth of hypocentre (Km)	32
Epicenter distance (Km)	233,691
Total affected population	22
Duration of response phase (day)	25
Modified Mercalli Intensity (MMI)	9

After obtaining the local similarity, global similarity calculation between two cases is conducted. The higher global similarity means the two cases are more similar. Using (7), global similarity can be acquired (He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014; Taylor, Kim, and Kim 2013).

$$SI\,(Q, C_i) = \sum_{j=1}^{n} [Wj\ x\ \mathrm{Sim}(Q_j, C_{i,j})] \tag{7}$$

where SI (Q,Ci) is global similarity between target case and historical case i and Wj is the final weight of attribute j Using steps (6)-(7) between target case and every historical case that are used in this research, the global similarity can be obtained, as shown in Table V.

3.4 Number of post-earthquake victims estimation (case reuse or case revision)

In this section, the number of post-earthquake victims estimation for the target case is carried out If the result shows only one historical case whose global similarity exceeds the threshold then the number of post-earthquake victims in the most similar historical case can be directly used as an estimated number of post-earthquake victims in target case (case reuse), whereas if there are more than one or none of historical case whose global similarity exceeds the threshold, then the number of post-earthquake victims of three historical cases with the highest similarity will be calculated using weighted similarity method (Case 2017; He Ding-Yang, Jiang Da-Li, Wang Yi-Sheng 2014) to estimate the number of post-earthquake victims on the target case. Based on the experts, this research uses the threshold of 0.860. As can be seen in Table V, the result shows that there are more than one historical case whose global similarity exceeds the threshold, so weighted similarity method is conducted. Equation (8) shows the formula for weighted similarity.

$$P' = \frac{\sum_{i=1}^{3} SI\,(Q,C_i)\ x\ P_i}{\sum_{i=1}^{3} SI\,(Q,C_i)} \tag{8}$$

where P' is the forecasting number of post-earthquake victims after earthquake, SI (Q, Ci) is global similarity between the target case and historical case i, and Pi is the actual number of victim from historical case i. Based on Table V, the three most similar historical case to the target case are Lombok Timur (C1) with global similarity of 0.932, Lombok Barat (C2) with global similarity of 0.884, and Kota Mataram (C4) with global similarity of 0.879. According to Indonesia disaster management agency, the actual number of post-earthquake victims in C1, C2, dan C4 are 104,171 people (P1), 86,852 people (P2), and 62,957 people (P3) respectively. Equation (9) shows the result for number of post-earthquake victims estimation for the target case.

D' = 85,047

$$D' = \frac{(0.932\ x\ 104{,}171) + (0.884\ x\ 86{,}852) + (0.879\ x\ 62{,}957)}{0.932 + 0.884 + 0.879} \tag{9}$$

Table IV. Global similarity of historical case to target case

i	Regency	Global similarity	i	Regency	Global similarity
1	Lombok timur	0.932	21	Kerinci	0.736
2	Lombok barat	0.884	22	Padang	0.811

i	Regency	Global similarity	i	Regency	Global similarity
3	Lombok tengah	0.819	23	Agam	0.783
4	Kota Mataram	0.879	24	Bandung	0.616
5	Sumbawa barat	0.855	25	Tasikmalaya	0.711
6	Pidie	0.805	26	Cianjur	0.708
7	Pidie Jaya	0.844	27	Tanah datar	0.774
8	Bireun	0.810	28	Padang panjang	0.778
9	Bogor	0.408	29	Solok	0.829
10	Parigi	0.757	30	Bantul	0.773
11	Mamasa	0.734	31	Sleman	0.768
12	Morotai	0.614	32	Kulon progo	0.763
13	Banjarnegara	0.655	33	Garut	0.619
14	Lembata	0.723	34	Ciamis 1	0.612
15	Poso	0.736	35	Manokwari	0.726
16	Buru	0.702	36	Sorong	0.825
17	Halmahera barat	0.634	37	Pangandaran	0.677
18	Aceh tengah	0.785	38	Ciamis 2	0.609
19	Bener meriah	0.779	39	Solok Selatan	0.746
20	Biak numfor	0.696			

The result shows that during the 25 days of response phase in North Lombok regency, the estimated number of post-disaster victims reach 85,047 people.

3.5 Emergency logistic relief demand forecasting

In this section, an emergency logistic relief demand forecasting is conducted based on the formula that we propose. This paper uses food, tent, and blanket as a sample of logistic relief commodities to be forecasted for the target case. Food was chosen since it is a primary need of human to survive after earthquake, while tent and blanket were chosen because both of it are the most frequently complained commodity by post-earthquake victims due to its lack of availability when the victims need. According to Indonesia disaster management agency, the minimum standard needs for food is 2 packages per person per day, for the blanket is 1 blanket per person per incident, while for the tent, 1 tent can accommodate 16 victims. According to the provision, equation (10) shows the formula to forecast the number of food package needed by the post-earthquake victims.

Table V/ Earthquake historical case database

i	Regency	Attributes					
		Magni - tude	Depth (Km)	Epicenter distance from Regency	Total affected population	Duration of response phase (day)	MMI
1	Lombok timur	7.0	32	18	1,289,907	25	9
2	Lombok barat	7.0	32	51	713,848	20	8
3	Lombok tengah	7.0	32	42	1,035,355	20	6
4	Kota Mataram	7.0	32	46	419,506	20	7
5	Sumbawa	7.0	32	77	135,031	20	7

i	Regency	Attributes					
		Magni - tude	**Depth (Km)**	**Epicenter distance from Regency**	**Total affected population**	**Duration of response phase (day)**	**MMI**
	barat						
…		.	.	.	.	.	.
36	Sorong	6.8	10	31	225,558	21	5
37	Pangandaran	6.9	107	45	405,683	7	6
38	Ciamis	6.9	107	53	1,401,423	7	6
39	Solok Selatan	5.3	10	51	162,724	14	6

$$DF' = P' \times T \times Mf \tag{10}$$

where Df' is the number of food package forecasted, P' is the number of post-earthquake victims estimated, T is duration of response phase in units of day, and Mf is minimum standard need of food package. To forecast the number of blankets needed, equation (11) is used.

$$DB' = P' \times MB \qquad 1 \tag{11}$$

where DB' is the number of blankets forecasted, P'is the number of post-earthquake victims estimated and MB is minimum standard need of blanket. To forecast the demand for tent, equation (12) is used.

$$DT' = P' \times {}^{1}/_{16} \tag{12}$$

where DT' is the number of tents forecasted, P'is the number of post-earthquake victims estimated, dan ${}^{1}/_{16}$ is constant variable which is used since 1 tent can accommodate 16 victims. Table VII shows the demand forecasting result for each emergency logistic relief commodity based on (10), (11), and (12).

Table VIII. Demand forecasting result of food, blanket, and tent for target case

Commodity	Forecasting result
Food	4,252,365
Blanket	85,047
Tent	5,315

In order to measure the forecasting result error, mean absolute percentage error (MAPE) parameter is used. The smaller MAPE means the result is more accurate. MAPE parameter has been used by (Jin 2014) to measure forecasting accuracy. MAPE calculation is shown in (13).

$$MAPE = \left(\frac{|D' - D|}{D}\right) \times 100\% \tag{13}$$

where D' is demand forecasting result and D is the actual demand. Using (20), MAPE of food, blanket, and tent for target case is obtained, as shown in Table VIII.

Table VIII. Forecasting result accuracy based on mape

Commodity	Forecasting result	Actual demand	MAPE
Food	4,252,365	4,750,200	10.48%
Blanket	85,047	102,190	16.78%

Tent	5,315	6,327	15.99%

3. Results And Discussion

Based on Table VIII, MAPE value for food, blanket, and tent are 10.48%, 16.78%, and 15.99% respectively. All of MAPE value is less than 20%, meaning that the forecasting result is valid (W. Liu, Hu, and Li 2012). Besides, based on Lewis classified model (Lewis 1982), the forecasting result is also considered having a good accuracy since all of MAPE value lies in the range of 10%-20%.

The accurate forecasting result in this research is driven by few reasons: first, this paper uses precise attributes to determine case similarity. Four attributes which are magnitude, depth of hypocentre, epicenter distance, and MMI, are the factors which really affect the extensive damage of earthquake. The greater the damage, the number of emergency logistic demand will increase (Tang 2012). Other attributes are total population affected and duration of response phase. The more affected population, the more demand for emergency logistic relief (Tang 2012). The longer duration of response phase will result in increasing number of victims since during response phase, the risk of earthquake damage might be still threatening and the victims should not be allowed to leave the evacuee shelter. Therefore, the number of emergency logistic relief demand will increase if duration of response phase is longer. Second, this paper uses the appropriate attribute weighting method, which is IDVW, that is proven can increase the precision and accuracy in case retrieval. Third, the formula we proposed to forecast emergency logistic relief demand is based on number of post-earthquake victims estimation and logistic relief minimum standard needs, which reflects the real circumstances.

IoT implementation proposed in this research supports the CBR model to obtain the value of magnitude, depth, epicenter distance, and MMI short after earthquake occur, so demand forecasting process can be conducted as quick as possible to increase the agility of EL.

4. Conclusion

This paper establishes an empirical model to forecast emergency logistic relief demand in the aftermath of earthquake disaster based on the most similar historical case. The similarity is assessed by six attributes which are determined based on literature review and expert validation. Using IoT implementation, the model will estimate the number of post-earthquake victims quickly which is used as variable to forecast the number of food, blanket, and tent demand based on the formula we proposed in this research. The forecasting result is considered as valid and accurate since the MAPE value lies in the range of 10%-20%.

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Biographies

M. Dachyar is a Professor, and Head of Management Information System and Decision Support (MISDS) Laboratory, Industrial Engineering Dept., Universitas Indonesia. His research on management information system, decision support system, operations management, and business process reengineering.

Yadrifil is a senior lecturer at Industrial Engineering Dept., Universitas Indonesia. His research focuses on supply operation management, lean production, and innovation management.

Maulana Ihsan Al Ghifari is a research assistant at Laboratory of Management Information System and Decision Support (MISDS), Industrial Engineering Dept., Universitas Indonesia. His research focused on the information system and decision support system.