ISSN: 2319-5967
ISO 9001:2008 Certified
International Journal of Engineering Science and Innovative Technology (IJESIT)
Volume 7, Issue 1, January 2018

A Method for Estimating Operational Damage due to a Flood Disaster using Sales Data

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Abstract*—Recently, natural disasters have increased in scale compared to the past and typically cause much damage. In Korea, storm and flood damage cause serious property losses as well as human casualties. For small businesses, disasters often have catastrophic outcomes, and serious damage can result from business interruptions. However, previous studies of disasters focused mainly on direct damage to physical property structures, whereas research on indirect types of damage, such as operational damage, has been insufficient. In particular, there have been no big-data-based studies of indirect damage in Korea. In this paper, we propose an operational damage estimation model that can provide operational damage information in conjunction with flooding predictions. The proposed model uses actual sales data to predict local sales losses in the event of a disaster. Experimental results show that the damage to sales predicted by the proposed model is in very good agreement with actual data, with the correlation exceeding 0.9. The proposed model is expected to reduce damage by providing operational damage predictions to small businesses in disaster situations.

***Index Terms*—big data, flood disaster, operational damage estimation, sales data, disaster prediction.**

I. INTRODUCTION

Recent natural disasters have been stronger than those in the past, and they cause much more damage to urban areas. Flooding caused by torrential rain and typhoons has caused both serious property damage and casualties in urban areas. However, statistical information on flood damage in Korea only amounts to approximately 50% of that in Japan and the USA, and various problems, such as a lack of statistical data on indirect damage at present, have been indicated[1].

According to statistics from Korea for the year 2009, small commercial and industrial entities account for 87.5% of all business entities. Moreover, 38.9% of industrial workers are small commercial and industrial workers. However, most small businesses are tiny, with monthly sales of 10 million won or less. Since the average loss of them is over 30 million won when a wind and flood disaster have occurred, it is difficult for them to recover from damage the disaster [2].

Previous disaster damage research in Korea focused on estimating direct types of damage, such as damage to buildings. However, for small businesses, given that most are tenants, more than half of the damage affects movables (56% in 2009-2010) [2]. Moreover, indirect types of damage, such as discontinuance due to a disaster were not assessed [1]. Despite the popularity and vulnerability of small businesses, due to the opinion that they could reduce disaster prevention efforts due to moral hazard, there has not been enough compensation in flood damage insurance for them [3].

In such a situation, a method capable of mitigating damage to small businesses during a disaster is necessary. We measure quantitatively the damage expected from a disaster before its occurrence, with the result then transferred to small business owners. We believe that predictions of disaster damage can motivate aggressive disaster prevention efforts by small business in potentially affected regions.

In this paper, we propose a method for estimating indirect damage (especially operational damage caused by the suspension of the business), which was not addressed in previous studies in Korea. The operational damage prediction model is intended to reflect the different characteristics of sales by region. The proposed model is designed to estimate operational damage based on actual sales data. Using big data collected by region, the proposed model can show regional characteristics.

II. RELATIVE WORK

The easiest way to estimate the indirect loss from a disaster is to estimate it using the indirect damage rate, which represents the ratio of indirect loss to direct loss [4]. This value is derived through case studies. When the direct

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loss is estimated, the indirect loss is calculated through multiplication with the indirect damage rate considering the attributes of the damaged area. The advantage of using the indirect damage rate is that the result can be derived immediately and simply. However, because the calculations are done in simple proportions, this method cannot reflect regional characteristics. Indirect losses are calculated using the same ratio for metropolitan and rural commercial areas. Therefore, this method is overly simple and less accurate.

The flood control economic survey manual (The Ministry of Land, Infrastructure and Transport of Japan) [5] includes calculations of business interruption losses. In this manual, business interruption losses are calculated by multiplying the number of lost days by the number of employees and the value added per capita. The value added per capita and the number of employees are sourced from the average corresponding values of each industry classification. The number of days for which interruptions and stagnation occurred was estimated from the 1995 Disaster Questionnaire. This method has the advantage of being able to calculate operational damage independently of direct damage. However, the operational damage estimation method in Japan is indirectly calculated using the average value of the added per capita measure depending on the industrial classification. The features of the model do not readily reflect local characteristics.

To overcome the disadvantages of previous studies, we calculate the sales loss due to a disaster through actual sales data. The sales data used to estimate the damage is aggregated in blocks, implying that there are significant differences depending on the region and commercial area. Based on this data, the proposed model can estimate disaster damage according to the characteristics of the damaged area compared to previous models.

III. DISASTER PREDICTION AND DAMAGE ASSESSMENT SYSTEM

DIPDAS (Disaster Prediction and Damage Assessment)[6][7] is a system that predicts damage caused by disasters such as floods, typhoons, and heavy rains. It provides indirect types of damage, such as disruptions and losses of business affected by direct damage to facilities as well as direct damage caused by flooding from events such as typhoons and heavy rains. This method utilizes big data, such as predicted weather information, flood depths, building properties and spatial information, credit card transaction information, news from the Internet, and real estate prices. In addition, the DIPDAS system can use the results of numerical prediction models as input data. With these characteristics, the DIPDAS system can be estimated the direct and indirect damage of future disasters. Fig. 1 shows the structure of the DIPDAS system[7].

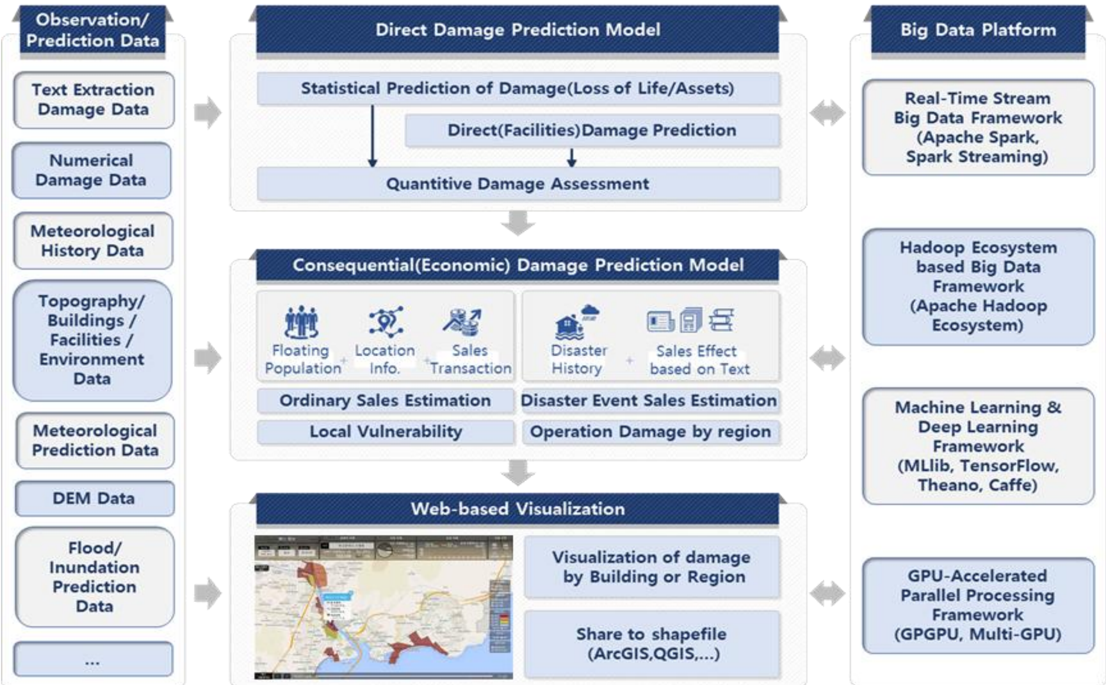

Fig 1.The structure of Disaster Prediction and Damage Assessment system [7]

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ISO 9001:2008 Certified
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DIPDAS mainly includes three functions, as depicted using the labels 1, 2, and 3 in Fig. 1. First, the Direct Damage Prediction Function provides information about direct damage to building units in the form of the damage ratio of the buildings, building damage costs, flood victims, damage costs to the industry, and the costs of casualties[8].The direct damage estimation is performed by using a modified Multi-Dimensional Flood Damage Analysis (MD-FDA) methodology[9]. Second, the Indirect (Operational) Damage Estimation Function indicates the amount of estimated economic damage due to downtime caused by inundation damage. The amount of damage is calculated according to the block or administrative unit. Detail description of the operational damage estimation model is given in section 4. Finally, the Damage Simulation Function visualizes the amount of direct and indirect damage based on spatial information according to the depth of flooding. Even at identical flood depths, the level of damage can vary depending on the business category of the current store/company, the sales amount, and the geographic location. Simulating a disaster can provide valuable information that helps emergency planners modify evacuation plans.

IV. OPERATIONAL DAMAGE ESTIMATION METHOD USING FLOOD DISASTER USING SALES DATA

Much damage can be caused by massive flooding during a disaster. In 2015, the WMO proposed guidelines for measuring the impact of disasters. In the guidelines, the impact risk of a disaster is expressed as a combination of risk, vulnerability and exposure [10].

Applying this concept to operating damage caused by a flood, the hazard can be expressed as the flood depth and the exposure can be expressed as the sales volume. The vulnerability can be expressed as a function of how much sales are affected by the flood depth. Finally, from the perspective of operational damage, the impact of a disaster can be defined as the loss of revenue. This can be summarized as (1).

$$(\text{operational damage}) \cong (\text{ordinary sales}) \qquad (1)$$

where is the flood depth, is the sales volume.

There are various methods, which can be used to predict flood depths depending on the cause of the flood. In this paper, we used the depth of the flood as caused by the height of the surge of the sea[11].

Fig. 2 shows the operating damage estimation model for the flood depth. There are three steps involved in estimating the operational damage of a flooded area. The first is to estimate the ordinary sales during the target time using past sales data. The second step is to calculate the operational damage by applying the vulnerable function of the flood to normal sales. The final step is to estimate the final operational damage by applying the local disaster vulnerability to the calculated operational damage. We estimated ordinary sales using credit sales data for two years. The collected sales data was aggregated by blocks in the form of sufficiently small units [12]. The sales data acquired is data from a credit card company over a specific period in the past. Therefore, to estimate normal sales in the event of a disaster, two conversion processes are required. First, we need a process that translates the sales of the card company into gross sales. The sales data is then converted into total credit card sales using the occupancy rate of the credit card company. Afterwards, the total card sales for the data period is converted into gross sales considering the credit card and cash ratio [13].

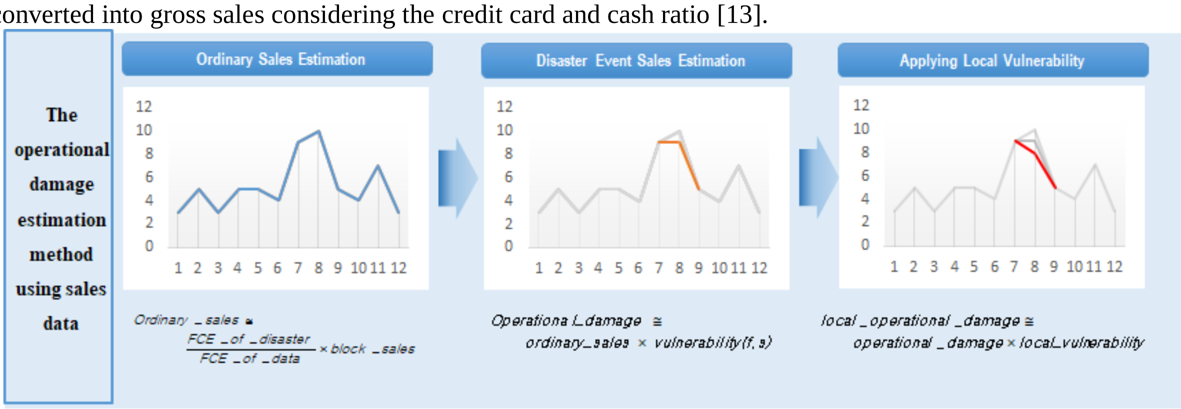

Fig 2. The operational damage estimation method using sales data

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ISO 9001:2008 Certified
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$$block\ sales \cong \frac{1}{card\ rate} \times \frac{}{occ} \qquad (2)$$

Second, sales of the data period should be converted into sales during the disaster period. We perform this transformation using final consumption expenditure data from the Bank of Korea's Economic Statistics System [14]. The sales data is adjusted to the ratio of final consumption during the data period to final consumption during the disaster period. When predicting disaster situations, we use the polynomial trend function to calculate the final consumption expenditure at the time of the disaster.

$$Ordinary\ sales \cong \frac{FCE\ of\ dis}{FCE\ of\ d} \qquad (3)$$

where $F($ is the final consumption expenditure.

The flood vulnerability should be applied to calculate the damage to sales using the calculated ordinary sales. Flood vulnerability can be divided into the flood vulnerability function and local vulnerability. The flood vulnerability feature is a measure of the degree to which sales are affected by flood levels, and local vulnerability refers to how vulnerable the area is to flooding damage.

The flood vulnerability function was calculated using the number of days for which interruptions and stagnation were present according to the flood depth. Here, we used the dates in the Japanese Dimensional Economy Survey Manual, as shown in Table 1 [5].

Table I The number of days of interruption and stagnation according to the flood depth

Flood depth(cm)	floor	~50	50 ~ 99	100 ~ 199	200 ~ 299	300~
Interruption period (days)	3.0	4.4	6.3	10.3	16.8	22.6
Stagnation period (days)	6.0	8.8	12.6	20.6	33.6	45.2

[a.] Dimensional Economy Survey Manual [5], 1995-1996 "Survey on the flood"

The flood vulnerability is influenced by local characteristics as well as by the depth of the flood. For proximate water sources such as seas and rivers, they may cause flooding. The degree of flood vulnerability can be influenced by the local disaster prevention level. We collected regional damage cases using annual disaster reports and calculated the local vulnerability rates. We calculated the local operational damage by reflecting the local vulnerability rate.

$$local\ operational\ damage \cong (operational\ damage) \times (local\ vulnerab \qquad (4)$$

V. EXPERIMENT

To verify the proposed damage estimation model, we used credit card sales data over a course of two years (from June of 2014 to May of 2016). Sales data was aggregated according to the district administration, such as 'eup', 'myeon', and 'dong' in Korea. For the experiment, the flood disaster cases occurred during the data period. These results are shown in Table 2.

Table II. The Number of flood damage cases from 2014 to 2016

Year	Duration(month)	Months	Number of disaster cases	Average disaster cases per month
2014	6 - 12	7	190	27.1
2015	1 - 12	12	64	5.3
2016	1 - 5, 7 - 10	9	428	47.6
Total		28	682	

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We created an ordinary sales estimate model using data from 2015, a year during which relatively few disasters occurred. The data from 2014 and 2016 were used for model verification. We used correlation (5) and the RMSE (Root Mean Squared Error) (6) to measure the performance of the proposed method.

$$Correlation(X,Y) = {}^{\sum(x-\bar{x})(y-\bar{y})}\Big/ \qquad (5)$$

(6)

We measured the correlation to confirm that the explanatory power about actual data increased when the disaster damage was applied. RMSE was used to measure the accuracy of the estimated sales value. If the proposed method is effective, the correlation is expected to increase and the RMSE is predicted to decrease. Table 3 shows the results of the comparison of the actual and estimated sales for 2014 and 2016.

Table III. The results of the comparison of actual and estimated sales

Test year	Method	Correlation	RMSE
2014	Ordinary sales estimation	0.97551	0.04341
	Disaster sales estimation	**0.97555**	**0.04314**
2016	Ordinary sales estimation	0.96643	0.02031
	Disaster sales estimation	**0.96661**	**0.02014**
Average	Disaster sales estimation	0.97108	0.03164

As expected, we confirmed that the correlation increases and that the RMSE decreases when the operating loss is applied in comparison with the estimated ordinary sales.

VI. CONCLUSION AND FUTURE WORK

Operational damage is an important target because it represents a significant portion of the total damage to small business owners who experience a flood-related disaster. However, most studies of such disasters deal with only direct damage, whereas few have investigated operational damage. To resolve this shortcoming, this study proposed a method by which to estimate operational damage for flooding.

The proposed method uses actual sales data to calculate the operational damage of a disaster. This method has the advantage of providing a better reflection of the characteristics of the target area as compared to that by previous methods, which oversimplified this issue.

We undertook validation using sales data for 2014-2016 to validate the proposed model. Disaster damage was reflected in estimated sales, and actual sales and estimated sales were compared. As a result, the correlation increased between actual sales and estimated sales and the RMSE decreased between them. In addition, we obtained meaningful results, with an average correlation of 0.97108.
The proposed method combined with the disaster prediction model will provide disaster damage information in advance. Providing such timely damage information is expected to help small businesses respond more effectively to disasters.
The current model was used as the vulnerable function with information from Japan in the 1990s. Based on sales data, we need to create vulnerable functions according to the current situation in Korea. Additional efforts are needed to collect supplementary data pertaining to disaster damage and to improve the accuracy of the model proposed here.

ACKNOWLEDGMENT

This research was supported by the Korea Institute of Science and Technology Information (KISTI).

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ISO 9001:2008 Certified
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