International Journal of Progressive Sciences and Technologies (IJPSAT)
ISSN: 2509-0119.

http://ijpsat.ijsht-journals.org
Vol. 22 No. 2 September 2020, pp. 194-200

Probabilistic Modeling and Risk Analysis of Flood Disruptions on Regional Industry Sector

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Abstract – In this research work, a probabilistic model is developed for regional marble industry sector. Three cases are studied on the basis of flood intensity. Data is acquired by conducting survey of multiple regional facilities. Based on this model, a probabilistic relation is developed by integrating workforce unavailability in the aftermath of flood with the inoperability of the sector. For this purpose, full day equivalent lost is integrated with dynamic inoperability input output model. On the basis of this inoperability at different time intervals, economic losses are measured.

Keywords – Floods, Inoperability, Economic Loss, Probabilistic Modeling

I. Introduction

Disasters are the events that have unfortunate consequences on the lives, infrastructure, property and economy [1]. Disasters may be natural, caused by men or hybrid [2]. All kinds of disasters have adverse effect on industries. Disasters cause damage to infrastructure as well as to lives of employees. They cause injuries and deaths of the employees and hence results in disruption of workforce. Some natural disasters of recent era are; earthquake in Pakistan in October 2005, Tsunami in Indonesia on December 26, 2004, flood in Pakistan in 2010 etc. All these had adverse effect on work force absenteeism and hence on economy of the respective regions.

Flood is one of the natural disasters that have a great impact on the work force disruption. Severe injuries and deaths occur and infrastructures are destroyed. Due to this damage usually the absenteeism of workers occurs in industry sectors and industry sectors become inoperable. Due to inoperability there is reduction in production output of industry sectors which results in economic losses. As different industries are linked with each other, the output of one industry is usually the input of another industry so the whole economic network becomes unstable which results in inoperability and economic losses of almost all industry sectors in an area.

II. Literature Review

In early stages some other methods were used for risk assessment. HAZOP is a method which means hazard and operability [3]. It is a qualitative method in which a team of experts identifies the hazards and risks which causes the industry to be inoperable and human injury. Due to their high impact on economy, natural disasters have motivated the researchers to focus their research on risk analysis studies. The basic Leontief Input Output (I-O) model [4] have been extended to handle the unfortunate impacts of disasters. The I-O model and its disaster-related extensions, for example the Inoperability Input-Output Model (IIM) [5], have been widely used in analysis of interdependent sectors. Olsen et. al., (1997) [6] established a method for the risk analysis related to flood protection. Cho et. al., (2001) [7] worked on the I-O model for determining the losses due to earthquakes to transportation sector in city areas. Okuyama and Chang (2004) [8] introduced other different methods for estimation of economic losses due to disasters. Velazquez (2006) [9] combined the basic I-O model with the Proops model (1984) [10] to shape an extended input output based model for sector-specific analysis of water consumption. Qin et. al., (2011) [11] conducted a study highlighting the workforce absenteeism as a result of disaster. Other applications of these models to disasters include Santos et. al., [12] on cyber security, Anderson et. al., [13] on the Northeast Blackout in 2003. Crowther et al [14] on Hurricane Katrina. A shift-share analysis was implemented by Mehregan et. al., [15]to estimate the disruptions of the earthquake 2003 on employment. Krista et. al., (2013) [16] used Inoperability input output model for inoperability and economic losses estimation of flooding in Manila. Akhtar et. al., (2013) [17] conducted a risk based input output analysis of hurricane impacts on interdependent industry sectors. Santos et. al., (2013) [18] conducted a risk based analysis for widespread impacts of influenza on interdependent industry sectors. Niknejad et. al.,(2016) [19] used a novel Fuzzy Dynamic Inoperability Input Output Model to propose a risk evaluation method for Global Production Networks.

Yasuhide Okuyama used input output model with Miyazawa extension for Hanshin earthquake to find spatial impacts of the disaster [1]. This model was also used to find economic losses and inoperability of interdependent sectors by Crowther [2]. Yaseen ranked regional industrial sectors of Budhni Nalla by utilizing input output economic model [3].

III. Parameters

Inoperability parameters that will be used to measure the economic losses are discussed below.

3.1 Leontief Input Output Model: Input-output model was presented by Leontief [20] for which he was awarded with the Nobel Prize. Input-output model shows interdependency between different industry sectors in a region. The output of an industry sector in a region can be estimated from the final demand and regional technical coefficient matrix using the following relation.

$$\boldsymbol{x} = (\boldsymbol{I} - \boldsymbol{A}_{\boldsymbol{reg}})^{-1}\boldsymbol{c}$$

Where $x = output\ vector$

A_{reg}
$= Regional\ technical\ coefficient\ matrix$

$c = Final\ demand\ vector$

Output vector has production outputs in monetary values for different industry sectors. Regional technical coefficient matrix is obtained from national technical coefficient matrix which is explained in coming topics. Final demand vector has final demands in monetary values for different industry sectors. In this ten sectors have been selected so final demand vector has final demands of ten different industry sectors.

3.2 Inoperability Input Output Model: Inoperability Input Output model is an extension of the basic I-O model. It includes the effect of a disaster on the interdependent industries. Initially, the IIM was used to model a system consists of numerous subsystems. Santos and Haimes (2004) extended IIM to determine the economic losses to industries in an economic area triggered by a disaster. Crowther et al. (2007) used IIM to study the impacts on several critical interrelated industry sectors after being interrupted by a hurricane in Katrina. The mathematical form of the IIM is as follow.

$$q = (I - A^*)^{-1}C^* \qquad (2)$$

Where $q = Inoperability\ vector$

$A^* = Interdependency\ matrix$

$C^* = Perturbation\ vector$

3.3 Dynamic Inoperability Input Output Model: Dynamic inoperability input-output model (DIIM) is an extension of the Inoperability Input-output model which has the capability used to find time variant inoperability. Whenever an industry sector is hit by a disaster then just after the disaster the inoperability is maximum, but with the passage of time (e.g. days) the inoperability decreases. So, the inoperability does not remain constant. Therefore, there should be a model like DIIM which is capable of calculating this time variant inoperability. DIIM can be used to find inoperability at different time (days) after a disaster using iterations. DIIM is given as;

$$q(t+1) = q(t) + K[A^*q(t) + c^*(t) - q(t)] \qquad (3)$$

Where,

$q(t+1) = inoperability\ vector\ at\ time\ t+1$

$q(t) = Inoperability\ vector\ at\ time\ t$

$c^*(t)$
$= Reduction\ in\ fianl\ demand\ or\ perturbation\ vector$

IV. Analysis

In this proposed research methodology, the data obtained through surveys is used to develop workforce perturbation model to measure the economic losses caused by workforce absentee in the aftermath of floods. This model is then integrated with risk-based framework to answer three questions of risk assessment and three questions of risk management. Industrial surveys were conducted to gather the required values of data for regional Marble industrial sector. Data of multiple facilities of marble located in Shabqaddar (Charsadda), Warsak road and Nowshera were gathered. Each facility owner or supervisor was asked questions related to previous flood disasters and his facility workforce and revenue. The productivity of an industry is dependent on its workforce availability. When there is shortage of workforce, the production process is slowed down, resulting in economic losses. The industrial sectors are dependent to each other, and low production of one sector results in low production of goods. Because of this, those sectors which are utilizing these goods as input for their production also suffers economic losses. That is why it is important for an economic region to recover from inoperability in the aftermath of flood disaster as soon as possible. Statistical analysis is performed to estimate the dependency of the surveyed marble facilities on its workforce. The production operations of marble are completely performed by manpower, which makes this industrial sector highly dependent on workforce.

Local area personal income (LAPI) is the ratio of sum of income of the workforce of a region by total number of workforce of that region. It is given by:

$$\text{LAPI} = \frac{\sum workforceincome}{totalworkforce}$$

To measure the effects of reduced workforce on the production of marble sectors, ratio between LAPI and total production output (x) for each sector is computed. A proportionality relation is established to link initial inoperability (q_0) of a sector with this labor dependency ratio. It is given by the following equation:

$$q_0 \;\alpha\; \frac{LAPI}{x} \qquad (11)$$

Table 1: Probabilistic FDEL Computed

Probabilistic FDEL										
8.855336	8.633976	8.628174	8.540248	8.480046	8.472834	8.437024	8.436884	8.418393	8.400254	8
11.82709	11.56252	11.55558	11.45049	11.37854	11.36992	11.32712	11.32695	11.30485	11.28317	1
15.70428	15.25179	15.23993	15.06019	14.93713	14.92239	14.84919	14.8489	14.8111	14.77403	1
11.86607	11.66113	11.65576	11.57435	11.51862	11.51194	11.47879	11.47866	11.46154	11.44474	
8.822823	8.551714	8.544608	8.436921	8.363188	8.354356	8.310498	8.310326	8.28768	8.265464	
8.83826	8.590773	8.584286	8.485981	8.418673	8.41061	8.370574	8.370417	8.349744	8.329463	8
23.56343	22.89541	22.8779	22.61256	22.43088	22.40912	22.30105	22.30063	22.24482	22.19008	2
11.82709	11.56252	11.55558	11.45049	11.37854	11.36992	11.32712	11.32695	11.30485	11.28317	1
8.88401	8.706528	8.701876	8.631378	8.583109	8.577327	8.548615	8.548502	8.533677	8.519133	8
132.5156	127.1839	127.0441	124.9263	123.4763	123.3026	122.4401	122.4367	121.9913	121.5544	1
39.18532	37.93872	37.90605	37.41089	37.07185	37.03124	36.82958	36.82879	36.72465	36.6225	3

From this probabilistic FDEL table, workforce disruption ratio is computed. In each iteration the workforce disruption constant is varied, which affects the workforce availability. For each sector it is multiplied with labor dependency ratio to compute initial inoperability of that sector, and because of iterations we get inoperability for each iteration. The workforce disruption constant, w is computed by the equation:

$$w = \frac{AvgFDEL}{Max\left[\frac{1}{n}FDEL\right]} \qquad (13)$$

Cumulative economic losses can be measured at each time interval for a sector by summing up losses of previous inoperable days. Total economic loss is the sum of losses at time interval t of each sector for any intensity flood. Economic loss equation is given below:

$$\text{Economic loss} = \frac{q(t).x}{ProductionTime}$$

At flood water depth less than 0.2 meters the inoperability and economic losses recovery curve is shown in figure 18 and figure 19. Facilities having critical losses are also identified with highest cumulative economic losses. The economic losses are flattened after 11th day. Combined economic losses are 0.23 million PKR for only the selected facilities. The peak inoperability in this case is 45.6%. It is flattened out after 11th day showing that sector is entered in normal state of operation. Each sector reaches to 1% of initial inoperability after 11 days which is assumed as acceptable inoperability.

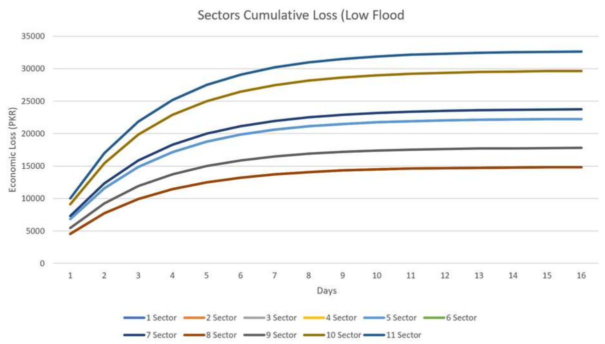

Figure 1: Low Flood Economic Losses

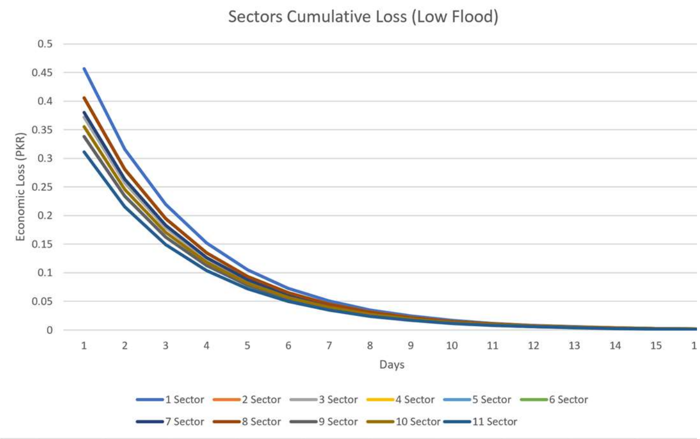

Figure 2: Low Flood Inoperability

For medium intensity flood when water depth is in between 0.2 to 1.0 meter, the inoperability and economic losses recovery curve is shown in figure 21 and figure 22. Facilities having critical losses are identified with highest cumulative economic losses. The economic losses are flattened after 32nd day. Combined economic losses are 0.61 million PKR for only the selected facilities. The peak inoperability in this case is 45.6%. It is flattened out after 36th day showing that sector is entered in normal state of operation. Each sector reaches to 1% of initial inoperability after 36 days which is assumed as acceptable inoperability.

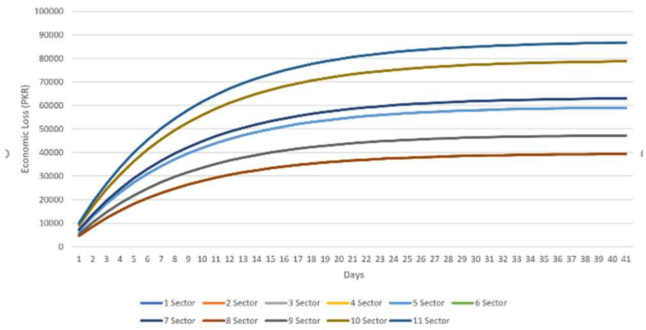

Figure 3: Medium Flood Economic Loss

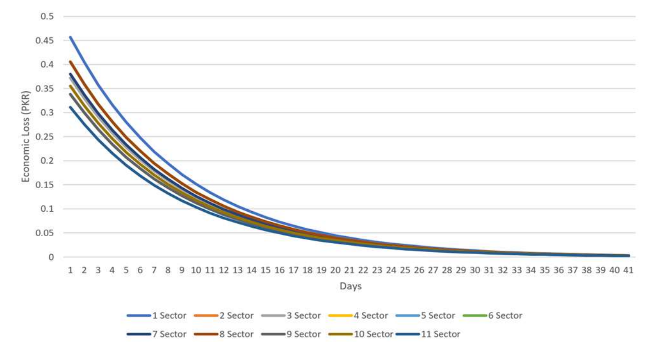

Figure 4: Medium Flood Inoperability

For high intensity flood when depth of water is above 1 meter, the inoperability and economic losses recovery curve is shown in figure 24 and figure 25. The economic losses are flattened after 125th day. Combined economic losses are 2.28 million PKR for only the selected facilities. The inoperability is flattened out after 130th day showing that sector is entered in normal state of operation. Each sector reaches to 1% of initial inoperability after 130 days which is assumed as acceptable inoperability.

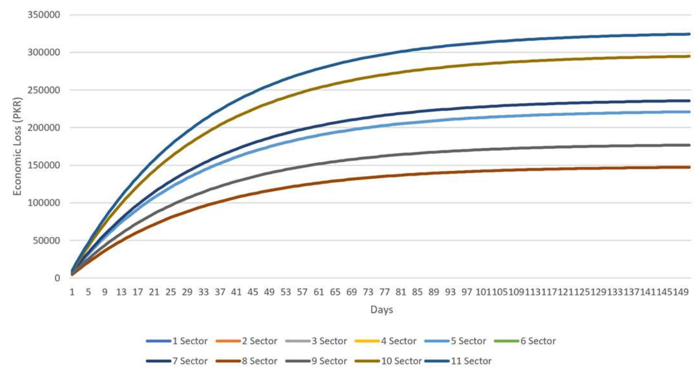

Figure 5: High Flood Economic Losses

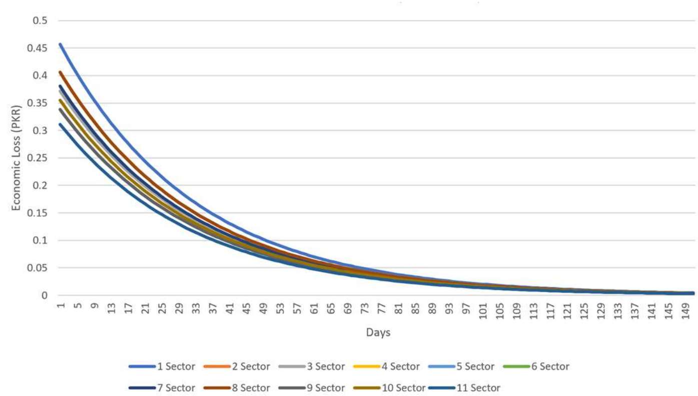

Figure 6: High Flood Inoperability

Table 2: [5] Regional Industries Ranking

Sector	Economic losses		Inoperability	
	Rank	Value (Rs. M)	Rank	Value (10^{-2})
Agriculture	1	1.005	2	7.38
Marble industry	2	0.988	3	7.22
Electricity supply	3	0.802	1	8.90
Flour mills	4	0.655	4	5.21
Wood industry	5	0.588	8	2.91
Education	6	0.335	6	4.61
Health	7	0.276	5	4.91
Telecom	8	0.275	9	2.36
Construction	9	0.273	10	1.82
Storage	10	0.133	7	4.49

V. CONCLUSION

In this research, workforce disruption uncertainty affects is integrated to dynamic inoperability of its sector and economic losses by incorporating full day equivalent lost model. The perturbation of workforce uncertainty was measured by linking workforce recovery time period with intensities of flood impacts. Risk factors associated with unavailability of workforce is discussed. By enhancing the mobility of workforce availability in the aftermath of flood reduces the economic losses for marble industrial sector.

Inoperability and its time period vary for each intensity of flood, due to which the total economic losses of selected marble facilities in case of low intensity floods are 0.28 million PKR and inoperability is encountered for 11 days. For medium intensity floods it is 0.61 million PKR and lasts for 36 days. For high intensity floods economic losses are 2.28 million PKR and industry remains dynamic inoperability is for 130 days.

Since this research focuses on estimation of inoperability and economic losses, it can be extended in several different directions. Risk analysis can also be integrated with this research to help the industries how to prepare for disasters and what strategy should in the aftermath of a disaster. A decision making tool e.g., cross prioritization can be used to select critical sectors in different situations on the basis of inoperability and economic losses. In this research DIIM is used to estimate impacts of flood, similarly this methodology can also be used to determine the impacts due to other disasters e.g., rain, earthquake, hurricane etc. This research focuses on a local area Peshawar similarly it can be used to determine impact estimations due to disasters in other areas.

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