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Effect of Information Sharing and Capacity Adjustment on the Healthcare Supply Chain: A Case of Flood Disaster

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ABSTRACT

In recent years, flood has become a tragic disaster in Malaysia causing loss of lives and properties. The damages brought by the flood are partly due to lack of preparedness and responses. Researchers have reported studies on the flood preparedness and response. Nevertheless, limited studies have provided a holistic perspective on the flood response operations. This paper attempts to analyze the flood preparedness holistically through system dynamics modelling approach. A system dynamic model consisting of a flood evacuation sub-model and a healthcare supply chain sub-model is developed. The hydrological data for the Kelantan River basin in Malaysia is used to populate the model. Decisions on the evacuation are based on the river level and flood risk information. Bullwhip Effect is formulated as a performance indicator to evaluate the efficiency of the healthcare supply chain model. The effects of information sharing and the capacity adjustment delay on the bullwhip effect were investigated. The findings suggest that reducing the capacity adjustment time and sharing demand information to the upstream healthcare supply chain yields a better overall performance for the health care supply chain.
KEYWORDS: Service Supply Chain, Bullwhip, System Dynamics Modelling, Evacuation Planning.

INTRODUCTION

In Malaysia, floodhas contributed to the property, infrastructural and socio-economic damage [1, 2]. It was estimated that 9% of the total land area in Malaysia is prone to the flood occurrence and the estimated damages are around USD 0.3 billion yearly [3, 4]. It is predicted that flood will continue to occur due to ineffective planning, urbanization, increased deforestation and climatic change [5]. As flood is generally inevitable, authorities, humanitarian organizations, healthcare providers and local governments need to be prepared to respond effectively to flood victims.

Flood preparedness and response is a dynamic and continuous process whereby the overall readiness should be maintained over time. System dynamics modelling approach can be particularly useful to captures a dynamic and holistic perspective of such complex systems over time. Several researchers have highlighted the applicability of the system dynamics modelling in investigating issues related to the disaster management response [6-8]. Although a number of studies investigated flood response and preparedness issues in Malaysia [9-15], limited research have focused on system dynamic modelling approach for flood response [16-18]. This paper investigates flood evacuation planning in a healthcare supply chain. The data from Malaysian Kelantan river is used for simulating flood scenarios.

The rest of this paper is organized into five sections. Section 2 provides a literature review on the flood management issues. Section 3 describes the base model development. Section 4 provides simulation results. The discussion and conclusion are presented in section 5.

LITERATURE REVIEW

Researchers are increasingly paying attention to the implementation of disaster preparedness methods and approaches for enhancing disaster relief assistance and improving aid effectiveness [8, 19-21]. Disaster preparedness is related to the activities that aim at reducing the impact of disaster before it strikes[22]. Researchers have used system dynamics modelling approach to focus on the improvement policies for organizations that are responsible for disaster relief operations. System dynamics is an approach for understanding the behaviour of complex systems using causal loop diagraming [23]. Unlike discrete event simulation that focuses on the operational and tactical problems involving linear processes [24-27], system dynamics enables a holistic perspective on problems related to strategic issues [26, 27].

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In [28] analyzed the trade-off between providing relief assistance and building capacity in the humanitarian organizations. In [6] used system dynamic methodology to evaluate different scenarios of vehicle fleet management in the humanitarian organizations. They evaluated the long-term costs for different fleet management scenarios and proposed a best-case scenario that satisfied the needs of a particular organization over several years. In [8]modelled the delivery process of ready-to-use therapeutic food items during the immediate response phase of a disaster. They analyzed how the humanitarian organization's performance can be improved by investing in the disaster management capabilities and pre-positioning of relief supplies. They suggested that a jointed strategy of pre-positioning of relief supplies and improving disaster management capabilities result in better humanitarian organizations performance. In [29] developed a system dynamic model to evaluate the effects of different delivery methods on the satisfaction of the local population.

Researchers such as [16-18] have used system dynamics tool to study issues related to flood management. In [18] developed a system dynamic model to describe the human response behaviourduring a flood evacuation. They modelled the evacuation process and focused on the social factors that determined human behaviour during the flood evacuation. They investigated the effect of different flood evacuation policies which guided emergency managers through most optimistic, most pessimistic and in-between scenarios. In[30] developed a system dynamics model for the United States flood policy analysis. It investigated potential leverage points and important feedback structures affecting policy outcomes for better flood management. In [16] presented a training model for better decision-making in times of floods.

Although the above researchers have investigated flood response using system dynamics, they are limited to a high level of abstractions. They considered limited influencing variables on the flood preparedness and response. This limitation can be studied by incorporating operational variables when modelling flood events. For instance, after a flood disaster, the healthcare system need to be prepared to respond to the surge of patients related to the drowning, trauma injury, communicable diseases [31]. Limited literature reported on system dynamics modelling on disaster preparedness in the healthcare system [32-34]. Specifically, research on the coordination of healthcare systems and managing surge capacity and resource management during a disaster are still lacking [35, 36].

METHODOLOGY

Base Model Development

This paper investigates the effectiveness of healthcare delivery strategies in response to the surge of demand after flood. A generic healthcare delivery system is modelled using system dynamics approach. It captures the main features commonly found in the healthcare systems.

The model was built using STELLA® simulation software. The system dynamic model encompasses two sub-models: (i) evacuation sub-model and (ii) healthcare supply sub-model. The evacuation model generates the patient'sdemand. A high-level view of the subsystems and the relationships among them are shown in Figure 1. The river level information was used to calculate the flood risk and evacuation rate. The evacuation model presents the population behaviour during a flood. The healthcare model was used to respond to the evacuee's needs. The following sections elaborate on the sub-models.

Evacuation Sub-Model

To simulate the flood risk and population evacuation, the hydrological data for Kelantan river was used. The data was obtained from the Malaysian Department of Irrigation and Drainage (DID) (www.water.gov.my). This hydrologic data is recorded at hourly intervals from over 300 remote telemetry units located at strategic points. The master telemetry unit in each state DID office receives and displays the data. An automatic mailer program sends all the data via the internet to the hydrology and Water Resources Division of DID in Kuala Lumpur that operates as a centralized flood monitoring system.

The DID designated the river levels into 4 main categories: (i) normal, (ii)alter, (iii) warning, and (iv) danger. Figure 2 shows the corresponding river levels. The alter level implies that the river level is significantly above the normal level and the DID flood operation room is activated. The warning level shows that the river level is near the flooding level, and therefore the district flood operation room is activated. The danger level is the ultimate danger recognized and the evacuation process will be initiated if the water level surpasses this level.

The hydrological data for Kelantan River was used since a recent 2014 flood has occurred in this area. The river level categories for Kelantan are shown in Table 1. Ordnance datum which is based on the mean sea level is used as the reference point to calculate the water level height in Malaysia.

Table 1: Actual values of water level for Kelantan river

River level categories	Designated water level
Normal	62m
Alter	67m
Warning	71m
Danger	75m

The stock and flow diagram for the evacuation sub-model is shown in Figure 3. To estimate the flood risk, the river level is divided by the normal river level (62m) as shown in the Equation (1). It provides a rate for flood risk that fluctuates from 1 to 2, depending on the time of the year and monsoon season.

$$\text{Flood Risk} = \frac{\text{River Level}}{\text{Normal Level}} \tag{1}$$

A graphical function is defined to show the relationship between flood risk and evacuation rate. Therefore, the flood risk is converted to a rate that defines the probability of evacuation when a flood happens. The evacuation rate is governed according to the Equation (2).

$$\text{Evacuation Rate} = \text{Lookup(Flood Risk)} \tag{2}$$

The values of the graphical function for evacuation rate and flood risk were based on a reference mode. System dynamics uses reference mode from actual events for verification on model outputs. The result of flood model produces the reference modebehaviour over time [37]. In this paper, the reference mode shows the population behaviour during a flood evacuation. Several researchers have explored the evacuation process and it is commonly known that the cumulative percentage of population evacuating over time follows an "S" shape curve as shown in Figure 4 [38-41]. The evacuation response curve shows the proportion of total evacuation demand over time.

The total probabilities of evacuating increases when the population are under flood risk. Equation (3) shows the evacuees population behaviour over time.

$$\text{Evacuation} = \text{Evacuation Rate} * \text{Population} \tag{3}$$

Healthcare Supply Sub-Model

The healthcare supply sub-model was developed with reference to [42] model. They developed a generic multi-stage service supply chain model. Several researchershave adopted their model as a basis to develop serial service supply chain models for different applications areas [43, 44]. The original model is modified in this research to represent a three-echelon healthcare supply chain model. These echelons can represent individual clinics or individual hospital departments. The model considers discrete stage of a patient care process that are connected in series to provide a patient care chain. Each echelon operates identically and the capacity decisions are based on the information available at each echelon. The output of each echelon forms the demand to the next echelon. Each echelon has resources for processing the backlog.

Each echelon has three main parameters, which are: (i) capacity, (ii) processing rate, and (iii) backlog. Backlogs show the number of flood evacuees in needs of medical supply, which are in the queue to be processed. Backlogs are decreased by the processing rates. A complete process of evacuees orders need to pass through all the three echelons. As the demand arrive, they accumulate in the processing backlog. The service capacity adjustment time is the average nominal delay required to adjust workforce (doctors, nurses, pharmacist and providers). The target capacity is the desired number of resources required in each echelon. The average service delay is the average nominal delay required to complete a backlogged order. Figure 5 demonstrates the first two echelons of the healthcare supply chain model. The model notations are;

- B_i (t) = stage i backlog at time t. It is assumed that $B_i (t) \geq 0$ for $t \geq 0$.
- C_i (t) = stage i capacity in job at time t. It is assumed that $C_i (t) \geq 0$ for $t \geq 0$.
- C_0 (t) equals end-customer demand at time t.
- P_i (t) = the processing rate at stage i at time t.
- TC_i (t) = target capacity of stage i at time t.
- HF_i (t) = turn around rate of the employees in stage i at time t.
- τ_i= the average nominal delay required to adjust capacity at stage i.τ_i refers to the capacity adjustment time. It is assumed that $\tau_i > 0$.
- λ_i = the average nominal delay required to complete a backlogged order at stage i. λ_i refers to the average service delay. It is assumed $\lambda_i > 0$.
- $\alpha_{i,1}$= the relative weight of end-customer demand in the target capacity decision of stage i. It is assumed that $0 \leq \alpha_{i,1} \leq 1$.
- $\alpha_{i,I}$ = the relative weight of local demand of stage i in the target capacity decision of the same stage. It is assumed that $0 \leq \alpha_{i,i} \leq 1$.

The model includes two main loops which are essential to the healthcare service management: (i) the capacity management loop, and (ii) the workforce management loop. The capacity management loop represents manager's decisions to add or remove providers from the clinic schedule to balance workforce with demand.

The workforce management loop compares the current workforce with the desired workforce to achieve desired service capacity. Each echelon has control over the service capacity using information on the order backlog and service capacity to determine changes to the service capacity. This structure shows a simplified perspective of managers' decision-making similar to the 'staff to demand' heuristic as practiced in the healthcare systems [45]. The reset of this section explains selected equations, namely processing rate, hirig and firing rate and target capacity.

The processing rate Pi (t) in each echelon is calculated based on the available capacity at time t as shown in Equation (4).

$$\mathrm{Pi}\,(\mathrm{t}) = \mathrm{IF}\,([(\mathrm{Bi}\,(\mathrm{t}) > 0), Ci\,(t)], Else\,[min\,(\mathrm{P_{i-1}}(\mathrm{t})]) \quad (4)$$

The capacity is changed based on hiring and firing rate as shown in Equation (5).

$$\mathrm{HF_i} = \frac{\mathrm{TC_i(t)} - \mathrm{C_i}}{\tau_\mathrm{i}} \quad (5)$$

The target capacity (TC) is adjusted based on the available backlog at each echelon. The target capacity is the desired number of workforce required in each echelon as given in Equation (6).

$$\mathrm{TC_i(t)} = \alpha_{\mathrm{i1}} \times \mathrm{C}_0(\mathrm{t}) \times \alpha_{\mathrm{ii}} \times \mathrm{P_{i-1}}(\mathrm{t}) + (1\text{-}\alpha_{\mathrm{i1}}\text{-}\alpha_{\mathrm{ii}}) \times (\mathrm{B_i}(\mathrm{t}) / \lambda_{\mathrm{i}}) \quad (6)$$

Bullwhip Effect as a Performance Measure of the Healthcare Supply Sub-Model

To evaluate the performance of our model, the bullwhip effect is formulated. Upstream amplification of inventory and demand in a supply chain has been a well-known phenomenon for supply chain managers for several decades. This phenomenon is called "Bullwhip Effect" in which fluctuations in orders increase as one moves up the supply chain from retailers to wholesalers to manufacturers and to suppliers. The Bullwhip Effect in the healthcare supply chain is identified as an important factor that causes reduced resource availability, fewer access to services, greater employee fatigue and stress, degradations in service quality, higher labour costs, increased operating costs and lower healthcare profits. These consequences are similar to the effects identified in the business supply chain, where the bullwhip effect identified as a source of stock-outs and higher costs. Therefore, considering bullwhip effect as the performance measure of the model, different strategies were investigated to reduce the bullwhip effect to improve the overall performance model. In the business supply chain, researchers quantified the bullwhip effect as the variance of order and demand ratio [44, 46]. In healthcare domain, in [47] formulated the bullwhip effect as the service rate and patient arrival rate standard deviation ratio.

Model Parameters

The simulation parameters are shown in Table 2. The model was simulated for 60 days with a time step of 0.25. Initially, the river level was set to the normal level (62m). Gradually, the river level surpassed the normal level and continues to exceed the danger level (75m). The water level remains above the danger level for 20 days and eventually reaches to a normal level.

Table 2: Parameters used in model

Parameter	Value	Reference
Target Service Time (λ1)	2 days	[48]
Time to Adjust Workforce (τ1)	2 days	[48]
Minimum Delivery Delay	0.011 day	[48]
Hydrological data		
-Normal river level	62 m	[49]
-Alter river level	67 m	[49]
-Warning river level	71 m	[49]
-Danger river level	75 m	[49]

RESULTS AND DISCUSSION

Flood Evacuation Scenario

To generate a flood scenario, the actual river level surpasses the danger level (75m). The evacuation rate is defined by a graphical function and follows an S-shape growth for population evacuation over time. As the flood risk increases, the evacuation rate increases. Once the river level surpassed the Warning level, the evacuation order is initiated. The population evacuation scenario is shown in Figure 7. The area population is depleted once the evacuation initiated. The number of evacuated population generates the demand for the healthcare supply chain model.

The bullwhip effect at the third echelon was investigated since the dynamics of backlog and processing rate in this echelon represent the 'worst-case' scenario. There are two controls or design parameters at each echelon:

i. Capacity adjustment delay
ii. Information sharing

These parameters are important in the variations of the processing times and backlogs. A sensitivity analysis is performed to see the impact of these parameters on the bullwhip effect. The sensitivity analysis addresses the effect of increasing the speed of capacity adjustment. This is achieved by reducing the workforce adjustment delay (τ).

Analysis of Capacity Adjustment Delay

Delays are a key cause of amplification effects in the healthcare supply chain and reducing delay is often cited as a strategy to mitigate the amplification effect [43]. In our analysis, the base model is compared with three consecutive declines in the workforce adjustment delays (25%, 50% and 75%). In the healthcare setting, the reduction in the capacity adjustment time can be achieved through various strategies:

i. Increasing the frequency of information gathering and analysis on the current patient backlog level
ii. Streamlining the human resource process for hiring and firing
iii. Improving the quality of training
iv. Reducing the training time for new hires
v. Improving the coordination between managers and employees over clinic schedule changes

These operational level strategies decrease capacity adjustment time in the individual healthcare chain and consequently improve the overall performance of the healthcare supply chain model. The policy comparisons for delay in adjusting workforce are shown in Table 3. Reduction in the workforce capacity adjustment delay decreases the values of bullwhip effect.

Table 3: Policy comparisons for delay in adjusting workforce (τ)

No.	Policy	Reduction in τ	BE
1	Base Model	--	0.85
2	Policy 1	25 %	0.81
3	Policy 2	50 %	0.78
4	Policy 3	75 %	0.75

The Impact of Information Sharing on the Bullwhip Effect

Information sharing is frequently highlighted for mitigating the amplification effect [42, 44, 50, 51]. It aims to provide the actual demand information to each echelon of the healthcare supply chain. In the centralized demand system, each echelon of the supply chain can use the actual demand data to create accurate forecasts. However, in the decentralized healthcare supply chain, each echelon relies on the orders received from the previous echelon of the supply chain. Lack of appropriate information on demand and backlogs can lead to the bullwhip effects.

In this paper, the information sharing strategy is achieved through establishing specific weights for the local or global demand at each echelon of healthcare supply chain. The $\alpha_{i,1}$ is the relative weight of end-customer demand (global demand) in the target capacity decision. Increasing these weights means providing each echelon of the supply chain with additional demand information in the capacity adjustment decision. By incorporating additional demand information in the capacity change decision (increasing $\alpha_{1,1}$, $\alpha_{2,1}$, ..) the bullwhip effect reduced. In other words, providing each echelon in the supply chain more information from earlier echelons reduces the bullwhip effect [44]. Table 4 shows that increasing the weight of sharing global demand information in echelon two ($\alpha_{2,1}$), reduces the values of bullwhip effect.

Table 4: Policy comparisons for information sharing

No.	Policy	α_{21} Values	BE
1	Base Model	α_{21} =0.2	0.82
2	Policy 1	α_{21} =0.3	0.73
3	Policy 2	α_{21} =0.4	0.61
4	Policy 3	α_{21} =0.5	0.49

CONCLUSION

The healthcare supply model developed in this paper is a simplified, serial stage model built upon the generic structure of service supply chain proposed by[42]. Bullwhip effect is used as a performance measure to study the effect of capacity adjustment delay and information sharing strategies.

The bullwhip effect in the healthcare supply chain has often cited as an important factor for reduced resource availability, reduced access to services, increasing employee fatigue and stress, degradations in service quality, higher labor, operating costs and lower hospital revenues. These effects are comparable to the negative consequences of the bullwhip effect in the manufacturing supply chain such as increasing stock-outs and higher costs. However, unlike manufacturing supply chain, an increase in demand variation in the healthcare supply chain leads to more medication errors and increases the adverse patient outcomes. In general, controlling demand amplification can greatly increase the performance of the medical systems. There has been little research into the capacity adjustment delays and value of information sharing in a healthcare supply chain model.

Based on the results, reduction in the capacity adjustment delay decreases the values of bullwhip effect, which consequently improves the overall performance of the healthcare supply chain model after a flood event. Results for Information sharing indicated that integrating actual and local demand information results in better performance in the individual service unit. It can be concluded that sharing end-customer demand and flexible capacity adjustment strategies are valuable strategies for increasing system flexibility and mitigating the bullwhip effect. Theoretically, centralized demand information has the potential to reduce variation in service times, enhanced service quality, and consequently better handling of the surge of demand. However, implementing centralized demand information system in the real situation involves several expensive modifications such as the installation of new IT infrastructure to cluster and transfer the data in real time. The results are in accordance with the common belief on the benefits of information sharing strategies in healthcare, as noted by [52] where "effective management of healthcare supply chain is only possible via the implementation of effective information and technology management systems."

The findings indicate that investing on strategies that reduces the capacity adjustment delay and establishing centralized demand information is a promising approach for better management of surge of demand after a disaster. The main limitation of this study is the generalization of healthcare service chain parameters used in the model. Relaxing some of the assumptions in the model to represent a specific real-world healthcare delivery system is a valuable future work. This can be done by modifying the model parameter and structure to represents a specific case study or an individual healthcare department.

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