

Effect of Information Sharing and Capacity Adjustment on Healthcare Service Supply Chain: The Case of Flood Disaster

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Abstract—In recent years, flood has becoming disastrous events in Malaysia causing loss of lives and properties. The damages brought by flood is partly due to lack of appropriate preparedness and effective responses toward such events. Several researchers have reported studies on flood preparedness and response. However, their studies lack of holistic views. This research attempted to holistically analyze the evacuation planning and flood preparedness. A system dynamic model consisting of an evacuation sub-model and a medical service supply sub-model were developed based on historical hydrological data for Kelantan River basin in Malaysia. Decisions on evacuation can be made based on river level and flood risk information. The efficiency of the medical service supply model is showed through the Bullwhip Effect. The effect of information sharing together with capacity adjustment on the bullwhip effect were studied. The results of this research indicates that reducing delay time to provide medical resources to evacuees need and sharing demand information in the upstream medical supply model yields better performance.

Keywords— *Service supply chain; Bullwhip; System dynamics modeling; Evacuation planning*

I. INTRODUCTION

In Malaysia, flood is one of the most critical natural disaster in terms of property, infrastructural and socio-economic damage [1]. The Department of Irrigation and Drainage (DID) of Malaysia stated that 9% of the total land area (29,800 km²) in Malaysia is prone to the flood occurrence and the estimated damages are around USD 0.3 billion yearly [2]. The occurrence of this disaster is expected to rise due to augment unplanned development and urbanization, increased deforestation and continued precipitation as an effect of climatic change in susceptible regions [3]. However, flooding is inevitable and the local authorities must be prepared to respond effectively no matter what have been the causes of flooding.

Flood preparedness is a dynamic and continuous process whereby the overall trend should be maintained over time. Several researchers have confirmed the good fit of system dynamics modeling for the field of disaster management. Altay and Green [4] found that the social and political nature of disaster operations management makes this field suitable for research approaches such as system dynamics, which can integrate soft factors into operations analysis. In Malaysia, although several studies investigated flooding response and preparedness issues, system dynamic modeling approach is not used. Past researchers have explored the causes of flooding and the role of government in flood management and prevention [5-9]. Although, several studies have investigated flood preparedness and response strategies, and the result of their work is beneficial, the flood management in Malaysia is still an open area of research. The recent flood in Kelantan provides clear evidence that the government lacks strategies for better flood response and preparedness and overall flood management.

The focus of this paper is on the response phase of flood management in Malaysia. We address evacuation planning and the process of humanitarian assistance in the form of medicine to areas affected by flooding. A system dynamic model for flood evacuation is developed and integrated with a medical supply model to respond to the evacuees needs. The ability of healthcare systems to quickly adapt to the surge of patient arrivals and flow through their systems is vital to the overall success of healthcare delivery system during disaster. Therefore, impacts of key factors on the overall performance of healthcare service supply chain model are studied. We will use secondary data, so that the operationalization of the model should be based on the availability of data from empirical studies or databases. The rest of the paper is organized as follows; Section 2 provides overview of literature related to flood management and more specific to humanitarian relief operations research and issues. Section 3 describes the base model development. Flood evacuation scenarios is presented in Section 4. Section 5 provides simulation results. Discussion is presented in Section 6. Conclusion is presented in Section 7.

II. LITERATURE REVIEW

While the literature for management of flooding using other engineering approach and techniques is abundant, very few researchers developed system dynamics models to explore issues related to the management of flooding. For instance, Ahmad et al (2005) [10] developed a system dynamic model to describe human behaviour during flood emergency evacuation. The model captures the overall process of evacuation, including total evacuees' population and the time to access shelter. The focus of their study was more on social and mental factors that determined human behaviour before and during the flood evacuation

[11]. Their system dynamics model was capable of simulating the effect of different flood evacuation policies. The model guided emergency managers through most optimistic, most pessimistic, and in-between scenarios. Deegan [12] developed a system dynamics model for flood policy analysis in United States. The dynamic hypothesis for a flood hazard community was presented to illustrate potential leverage points in the system and important feedback structures affecting policy outcomes. The model provides insights to the causal structures which produce outcome behaviour in the policy space. In a follow-up study [12] the author presents a framework for analyzing flood mitigation policies and policy design challenges in the United States.

Other researchers take holistic views where the focuses of their research were more on organizations capabilities to tackle disaster relief operations rather than a specific case of a disaster. Research on this area more focused on humanitarian supply chain management. For instance, Gonçalves [13] modeled the development of organizational capabilities and the efficiency of the relief efforts of humanitarian organizations. Based on his study, enhancing the disaster relief operations can reduce the long term efficiency of relief organization. He suggested that focusing more on capacity building is a better alternative. In a follow-up study, the author analyzed the trade-off between providing relief assistance and building capacity in relief organizations [14]. Besiou et al. (2011) [15] used system dynamic methodology to evaluate different scenarios of vehicle fleet management in humanitarian operations. Using system dynamic modeling they evaluate the long-term costs of different scenarios and discovered the best case scenario that satisfied the needs of a particular organization over several years. However, the limitation of their work was lack of empirical data for their model. This limitation were addressed in Kunz et al. (2013) [16] study by explicitly integrating empirical data gathered through previous case study research into the system dynamics modeling approach.

Kunz et al. (2013) modeled the delivery process of ready-to-use therapeutic food (RUTF) items during the immediate response phase of a disaster. They analyzed how the performance of this delivery process can be improved by investing in disaster management capabilities rather than pre-positioning of supplies. Pre-positioning of inventory supplies satisfy the overwhelmed after disaster demand, but at a very high costs. The disaster management capabilities emphasize on preparing and harmonizing importation processes, training staff, and negotiating customs agreements with the government prior to the disaster. They suggest that a mix strategy of pre-positioning of emergency supply together with improved disaster management capabilities produce better overall performance with a tight budget. Peng et al. (2014) [17] used SD to model disaster relief supply chain with dynamic road conditions and information delay. Their model was conceptualized around inventory planning strategies and forecasting methods in disaster supply chain management. In their model three inventory planning strategies and four forecasting methods used to evaluate the effect of response decisions on the dynamic circumstances of post-seismic supply chain. Furthermore, the author also used the SD results to propose a decision tree to help the decision-makers to select the stocking strategies according quantified risks after a disaster. Cohen et al. (2013) [18] developed two SD models to evaluate the effects of relieve on the overall satisfaction. The author assessed different delivery methods and measured the aid delivery impact on the overall satisfaction of the local population.

However, in this research we chose the healthcare service delivery system because in the larger field of supply chain management, the study of healthcare service delivery and patient logistics is very new, and while it has a few exemplary initiatives, still lacks much academic research [19]. The research on service supply chain management particularly in a healthcare area is a new field and few studies addressed challenges that are unique in this area [20]. Specifically, research on operational aspect of service delivery integration and coordination of care systems regarding patient flows and resource management are a relatively unexplored area of service supply chain management. Most service supply chain management research is still theoretical or conceptually-focused as opposed to operational in nature [21]. Therefore, the research area provides little operational plans to help healthcare managers facing surge of demand after a disaster. There are very limited practical guidelines of identified best-practices for designing and implementing demand responsive healthcare delivery systems. Healthcare managers face a significant gap in knowledge around the optimal design and management of complex care delivery systems and handling surge of demand volatile after math of a disaster to ensure efficient service delivery.

The system dynamic model developed in this study is a generic service delivery system that captures the main features common to most healthcare service delivery chains rather than perfectly simulating one particular service. The healthcare service chain depicted is thus a theoretical depiction of a broad spectrum of possible healthcare services. The aim of this study is to draw generalizable conclusions on the effectiveness of the proposed strategy to improve healthcare delivery through changing management response to the surge of demand.

III. BASE MODEL DEVELOPMENT

In this study, the application of system dynamics is applied to establishing different scenarios to understand behaviour of a medical service supply for flood evacuation preparedness. The model was built using STELLA® simulation software. The system dynamic model consists of two sub-models: evacuation sub-model and service supply chain consisting of three echelons. A commonly used modelling approach involves several models working in a series. The output from one model is fed as input into the other model. In this research the output from the evacuation model generates the surge demand for the service supply chain sub model. The high level model setup for the calculation of flood risk and evacuation planning is shown in Fig 1. The information on river level is used to calculate flood risk and evacuation rate. In the next section we provide a brief overview of

flood evacuation planning and the underlying assumption that used as a basis to develop the evacuation sub-model with regard to the flood risk.

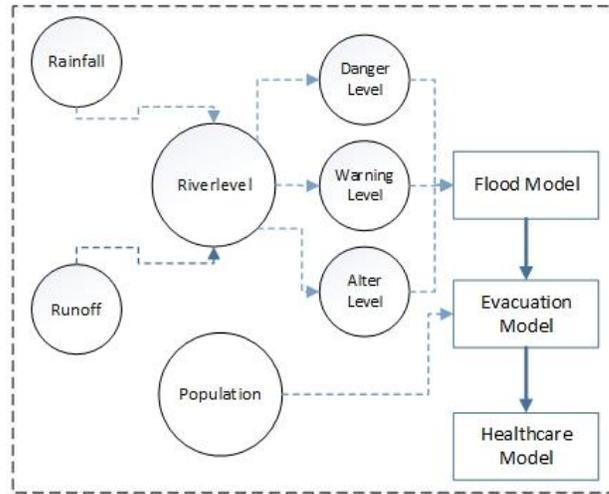


Figure 1: The high-level model setup

A. Flood Evacuation Planning

First, To model the flood risk, on-line historical hydrological data was taken from the official portal for Department of Irrigation and Drainage (DID) (www.water.gov.my/). The hydrologic data is updated at regular intervals (hourly to daily) from over 300 Remote Telemetry Units (RTUs) located at strategic points nationwide. Data is transmitted by various means such as UHF, VHF, telephone or satellite. The Master Telemetry Unit (MTU) in each state DID office receives and displays the data for local use. An automatic mailer program in each state DID office sends all the data through the internet to the Hydrology and Water Resources Division of DID in Kuala Lumpur that operates a Centralized Flood Monitoring System.

The Department of Irrigation and Drainage designated the river level into four main categories: Normal, Alter, Warning and Danger (See Fig 2). The alter level implies that the river level is significantly above normal level and therefore the DID flood operation room is activates. The warning level indicates 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.

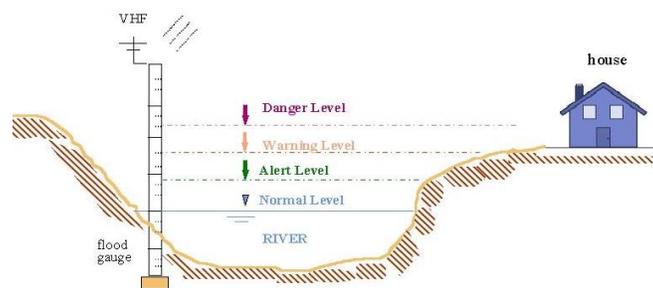


Figure 2: Designated critical levels at a flood warning system

The hydrological data for Kelantan river basin is used since the recent sever flood occurred in this area. The associated river levels for the categorized risk level are shown in Table 1. River levels are either measured against a local datum or ordnance datum. Ordnance datum (mAOD) is based on the mean sea level in Malaysia and is used as the reference point to calculate height above sea level in the Malaysia.

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

B. Evacuation Sub-Model

To calculate the flood risk, the river level is divided by the normal level. The result from this division provides a rate that change from 1 to 2 depending on the time of the year and monsoon season. The stock and flow diagram related to evacuation sub-model is presented in Fig 3.

$$Flood Risk = (River Level)/(Normal Level)$$

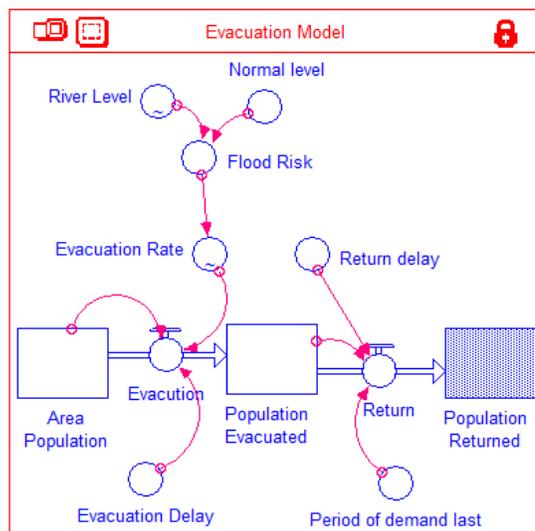


Figure 3: Evacuation Sub-Model

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 flood happens. The evacuation rate is governed according to the following expression:

$$Evacuation Rate = Lookup(Flood Risk) \tag{1}$$

To drive the values of graphical function we have used a reference mode as described in the next section. The result of flood model reproduces the reference mode behaviour. The reference mode defines the behaviour of population during evacuation.

C. Evacuation Reference Mode

System dynamics modeling typically uses reference modes from actual events as checks on model outputs. The reference modes demonstrate behaviour of a model input over time. Several researchers have explored the evacuation process and it is generally agreed that the cumulative percentage of population evacuating by time period follows “S” shape curve [22-25]. The evacuation rate starts gradually, then accelerates sharply, and finally slows down again. The evacuation response curve represents the proportion of total evacuation demand over time during evacuation.

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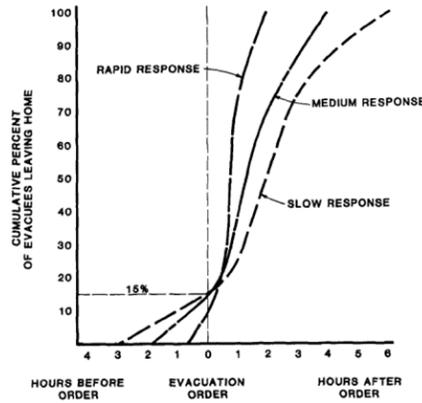


Figure 4: Evacuation behaviour response curves
 (Source: Li et al. (2013))

Therefore, based on the available literature the Evacuation behaviour response curve is used as a reference mode for population evacuation over time. The total probabilities of evacuating increases when the residences are under flood risk. To calculate the number of evacuees choosing to leave over time the population is multiplied by the evacuation rate. Thus, the evacuation can be represented as follows;

$$Evacuation = Evacuation\ Rate * Population \tag{2}$$

D. Medical Supply Sub-Model

The medical supply model is built based on a study by Anderson et al., 2000 [26], who were the first to use system dynamics to simulate a multi-stage service system with their model of the mortgage service industry. Other dynamic serial service models have followed, including publications by [27] and [28]. The models used in all of these studies are based on the same underlying assumptions and no clear criticism or alternative structure has emerged in the system dynamics or service supply chain literatures. We extend the original model to include multiple, serial stages in the service chain. These stages can represent individual clinics or individual hospital departments. They represent any discrete stage of a patient care process with its own locally controlled staff that is linked in series to provide patient care. Each clinic in our model operates in an identical manner, has identical performance standards and parameters, and is autonomous, with capacity decisions based only on the information available at each clinic. Each clinic is linked and the output of clinic forms the demand to the next clinic. However, each clinic requires a separate resource to serve its patient backlog, which could either be from requiring a different set of skills to complete the tasks in each clinic, or that an organizational structure prevents sharing resources between clinics.

The model developed in this paper includes three service stage clinics in sequence. Each stage has three main parameters which include capacity, processing rate, and backlog. At each stage, demand feeds backlog and capacity processes backlog to create demand for the next stage. Backlogs show the number of patients which are in the queue to be processed. Backlogs will be decreased by the processing rates. A complete order considered as when the patients passed through all three stages. The model holds no finished goods inventory, rather only customer order backlogs. Therefore, the main assumption is the availability of enough resources to meet the surge demand aftermath of a flood scenario. All three stages operate identically and have the same structure. As the applications for the first stage of medical supply chain 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) in the new position. The target capacity is the desired number of resources required in each stage. The average service delay is the average nominal delay required to complete a backlogged order. Fig 5 demonstrates the first two stages of service supply chain model.

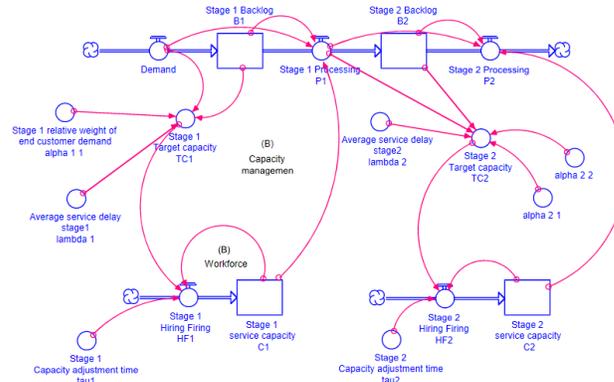


Figure 5 Medical supply model structure

The model includes two main controls loop which are fundamental to the medical service management. The first loop represents manager's decisions to add or remove providers from the clinic schedule to balance workforce with demand and we refer to this loop as the capacity management loop. The second loop is the workforce management loop that compares the current workforce with desired workforce to achieve desired service capacity. In our model each clinic has sole responsibility for operational performance and control over the finite service capacity in the clinic. Management uses the local information available on the order backlog and current service capacity to determine any changes to that service capacity. While this structure is far from optimal, it is a realistic representation of how real managers make decisions in similar settings [29]. This structure follows the common 'staff to demand' heuristic found currently in most hospitals and healthcare centers [30]. The model notations are;

- $B_i(t)$ = stage i backlog at time t . We assume that $B_i(t) \geq 0$ for $t \geq 0$.
- $C_i(t)$ = stage i capacity in job at time t . We assume 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 . We will refer to τ_i as the capacity adjustment time. We assume that $\tau_i > 0$.
- λ_i = the average nominal delay required to complete a backlogged order at stage i . We will refer to λ_i as the average service delay. We assume $\lambda_i > 0$.
- $\alpha_{i,1}$ = the relative weight of end-customer demand in the target capacity decision of stage i . We assume 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. We assume that $0 \leq \alpha_{i,i} \leq 1$.

The service rate in each stage is calculated based on the available capacity at time t divided by the time that takes to serve the patients. Therefore, the service rate is governed according to the following expression;

$$\text{Service rate} = \text{Capacity} / (\text{Time to serve customer}) \quad (3)$$

The capacity is a stock variable and is controlled by the hiring/ firing rate and can be represented as follows;

$$HF_i = (\text{Target capacity} - C_i) / (\text{Capacity adjustment time}) \quad (4)$$

The target capacity is changed based on the available backlog at each stage. Therefore, each stage's capacity will move by the gap unit from its current value toward its target each day. The capacity discrepancy can be modeled by the following expressions;

The Target Capacity is set to be equal to each stage backlog. The target capacity is the desired number of workforce required in each stage. Therefore, the Target capacity can be represented as follows;

$$\text{Target capacity} = \text{Registration Backlog} \tag{5}$$

E. Performance Measure Of Medical Supply Sub-Model

1) Bullwhip Effect Measure

To evaluate the performance of our model the bullwhip effect is measured. 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. Most of the research on amplification effects has focused on manufacturing (or inventory) supply chains. However, with the increasing importance of services in the past 10 years, the research of service supply chains has found a significant role. The ‘bullwhip effect’ in healthcare service 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 labor costs, increased operating costs, and lower healthcare profits. These consequences are parallel to the effects identified in industrial supply chain, where the bullwhip effect has been suggested as a source of stock-outs and higher costs. Therefore, considering bullwhip effect as a performance measure, we studied different strategies to reduce the bullwhip effect inside the patient care and consequently improving overall performance of our healthcare service supply chain model.

The most recent case study of internally-created demand variability in healthcare setting, was in India, which identified the bullwhip effect [31]. The bullwhip effect was similarly identified in a study of one UK hospital [32]. The bullwhip effect in this study was a source of performance degradation, as downstream services reported reduced resource availability and greater probability of exceeding desired utilization and occupancy rates. Research on inventory supply chain models has quantified bullwhip effect as the variance of order and demand ratio [28, 33]. However, in service supply chain model this measure translates to the variance of backlog and capacity. Recent research on quantifying bullwhip effect in healthcare service supply chain model [31], calculated the service rate and patient arrival rate standard deviation ratio as the quantitative measure of bullwhip effect. To calculate this ratio a system dynamic mode must be developed. The system dynamics structure that measures the bullwhip effect is adopted from [31]. The structure and variables for bullwhip effect measure are depicted in Fig 6.

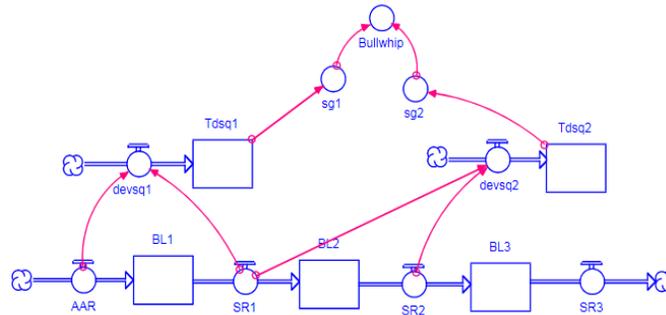


Figure 6 Bullwhip measure flow diagram

The patient arrival rate is accumulated in a level variable denoted as backlog 1. Depending on the stage 2 processing rate, the patient backlog is accumulated in the next level variable denoted as backlog 2. The squares of deviations of the two processing rates are accumulated in specified level variable denoted as TDSQ1 for stage 1 and TDSQ 2 for stage 2. The following formulas are for square of deviations of stage 1 and stage 2:

$$\text{Square Deviation stage 1} = (\text{arrival rate} - \text{Service rate1})^2 \tag{6}$$

$$\text{Square Deviation stage 2} = (\text{Service rate1} - \text{Service rate2})^2 \tag{7}$$

The standard deviation is defined by an auxiliary variable and is denoted by a variable Sg1. This variable is calculated as the ratio of TDSQ1 and DT square root. Similarly, the standard deviation of second stage of model follows the same formulas;

$$\text{Standard deviation stage} = \sqrt{(TDSQ1 / (\text{TIME STEP}))}$$

The bullwhip effect measure is the standard deviation ratio in the last two stage of service supply chain model; therefore, the bullwhip factor can be calculated as the following formulas;

$$BE = (\text{Standard deviation 2}) / (\text{Standard deviation1}) \tag{8}$$

F. Model Parameters

The model was simulated for 60 days with a time step of 0.25. The river level is defined as a graphical function. For the beginning of time the river level is considered to be at 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 normal level. The simulation parameters are shown in Table 2.

Table 2: Parameters used in model with values

Parameter	Value	Reference
Target Service Time (λ 1)	2 days	[34]
Time to Adjust Workforce (τ 1)	2 days	[34]
Minimum Delivery Delay	0.011 day	[34]
Hydrological data	--	[35]
Normal level	62 m	[35]
Alter level	67 m	[35]
Warning level	71 m	[35]
Danger level	75 m	[35]

G. Flood evacuation scenario

To generate flood scenarios, the actual river level is defined to reach the danger level (75m). The flood risk is the ratio of actual river level over normal river level. As the flood risk increases the evacuation rate is also increases. The evacuation rate is defined by a graphical function and follows an S-shape growth for population evacuation over time as described in pervious section. Therefore, as flood risk raises the evacuation rate increases. Once the river level surpassed the warning level the evacuation order is initiated. The ratio of warning level (71m) to the normal river level (62m) is used as a starting point where the evacuation process initiated. Therefore, once the flood risk ratio reaches to the value of 1.14 the S-shape growth function of evacuation process starts. Based on the available hydrological data for SG Kelantan river basin, the danger level is defined as (75m, above mean Sea Level). Therefore, the highest value of flood risk ratio is $75m/62m=1.21$. The S-shape growth graphical function is shown in Fig 7.

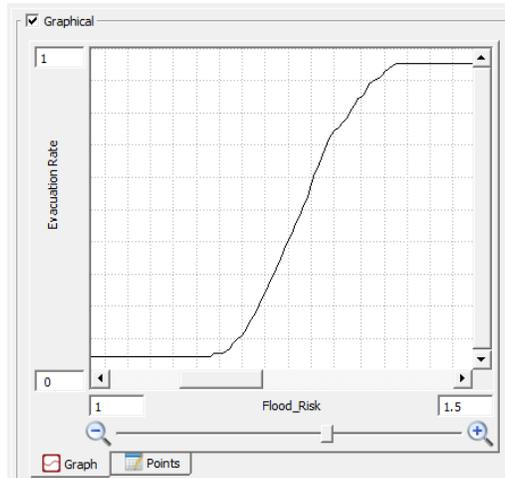


Figure 8 Graphical function of flood risk ratio and evacuation rate

The evacuation scenario is shown in Fig 8. The area population is slowly depleted once the evacuation initiated. There is a delay for evacuation process and return delay specified for population return. The number of evacuated population is fed into the service supply chain model. The red line in Fig 8 represents the surge of demand as an input to the service supply chain model.

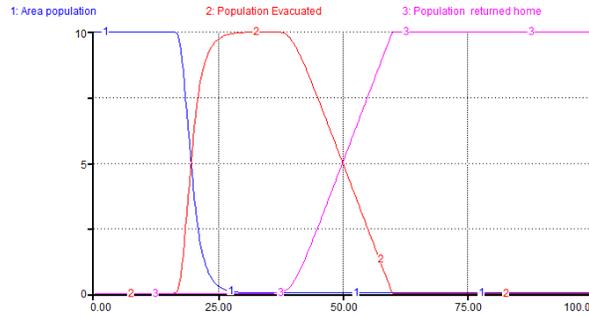


Figure 9: Population evacuation scenario

IV. SIMULATION RESULTS AND ANALYSIS

We studied the bullwhip effect at the third echelon since the dynamics of backlog and processing rate in this echelon present the ‘worst-case’ scenario. In the model developed here, there are two control or design parameters at each echelon:

- i) Capacity adjustment time
- ii) Information sharing

These parameters are the most important ones in the variations of processing times and backlogs. We performed a sensitivity analysis to measure the impact of these parameters on the bullwhip effect. The sensitivity analysis addresses the effect of increasing the speed of capacity adjustment decision making. In the model developed here, this strategy achieved by reducing the workforce adjustment delay (τ).

A. Analysis of Capacity Adjustment Delay

The first strategy addressed in this study focus on the delay inherited in capacity adjustment time. Delays are a key cause of amplification effects and reducing delay is often cited as a strategy to mitigate the amplification effect. The base model is compared with three consecutive declines (25%, 50%, and 75%) in the workforce adjustment delays. The policy comparison is shown in the Table 3.

Table 3: Policy comparisons for delay in adjusting workforce

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

Based on the result of sensitivity analysis when an increase in required capacity occurs (surge of demand after a disaster that lead to more required capacity) if the workforce capacity can be adjusted quickly at each stage of the chain in order to balance workforce with surge demand the values of bullwhip effect decreases. In healthcare setting the reduction in capacity adjustment time is an operations-level strategy. This strategy can be achieved through;

- 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) Reduce the training time for new hires,
- v) Improving coordination between managers and employees over clinic schedule changes

These operational level strategies decrease capacity adjustment time in individual service chain and consequently improve the overall performance of healthcare service supply chain model. However, these strategies cause model to be more sensitive to changes in demand volume.

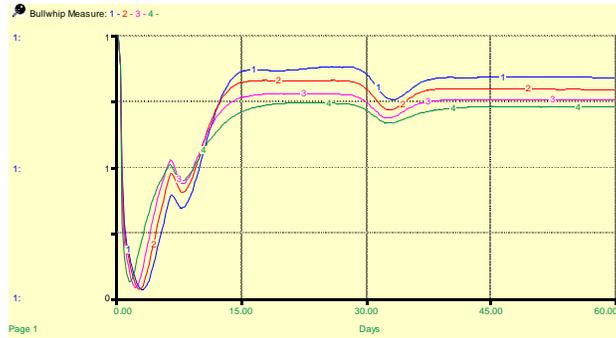


Figure 10: Bullwhip effect measure for capacity adjustment

(Policy 1 - Base case

reduction in capacity adjustment time),
 (Policy 2 - 25% reduction in capacity adjustment time),
 (Policy 3 - 50% reduction in capacity adjustment time),
 (Policy 4 - 75% reduction in capacity adjustment time)

B. The Impact of Information Sharing on the Bullwhip Effect

The second strategy addressed in this study focuses on the centralized demand information and information sharing. Information sharing strategy is frequently suggested for mitigating the amplification effect [26, 28, 36, 37]. This strategy aims to provide actual demand information for each stage of the supply chain. In the centralized demand information supply chain each stage of supply chain can use the actual customer demand data to create more accurate forecasts, while in decentralized supply chain each stage of supply chain rely on the orders received from previous stage which can vary significantly more than the actual customer demand data. Therefore, lack of appropriate information on backlogs and/or management failure to use it is a cause of bullwhip effects. Better information on management of backlogs and its use may be able to prevent, or at least mitigate, many of these problems.

In this research the information sharing strategy is defined through establishing specific weights given to the local or global demand at each stage of service supply chain. The $\alpha_{i,1}$ is the relative weight of end-customer demand (global demand) in the target capacity decision. The $\alpha_{i,i}$ is the relative weight of local demand in the target capacity decision. Increasing these weights means providing each stage of supply chain with additional demand information in the capacity adjustment decision. Since the sum of all the weights for a given stage should be less than or equal to 1, the increase should be made in way to keep the sum of all the weights less than or equal to 1. The result is that incorporating additional demand information in the capacity change decision (increasing $\alpha_{1,1}, \alpha_{2,1}, \dots$) reduces the bullwhip effect (See Fig 10). In other words, providing each stage in the supply chain more information from earlier stages reduces the bullwhip effect [28].

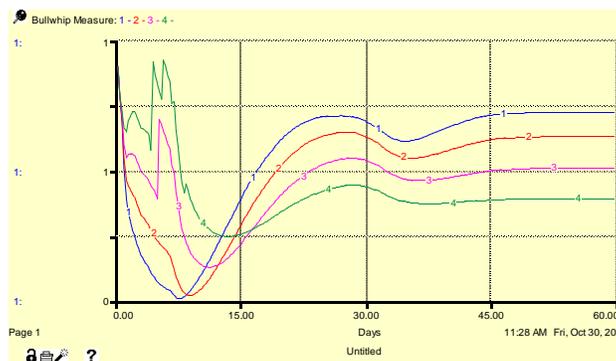


Figure 10: Bullwhip effect measure for information sharing

(Policy 1= Base case, $\alpha_{2,1}=0.2$ Bullwhip Effect= 0.82),
 (Policy 2 = $\alpha_{2,1}=0.3$ Bullwhip Effect= 0.73),
 (Policy 3 = $\alpha_{2,1}=0.4$ Bullwhip Effect= 0.61),
 (Policy 4 = $\alpha_{2,1}=0.5$ Bullwhip Effect= 0.49)

V. DISCUSSION

The medical service supply model developed in this research is a simplified, serial stage model builds on a research by Anderson and Morrice (1999, 2000), who were the first to use system dynamics to simulate a multi-stage service system with their model of the mortgage service industry. Subsequent dynamic serial service models, including publications by Akkermans et al., (2003) and Anderson et al. (2005, 2006), are all based on similar underlying assumptions. Our model represents the patient care chains where each stage lasts only an hour; for example, a trip to the emergency department might last a total of four hours, with each stage patient intake, triage, clinical interview, and discharge with prescription taking one hour each. However, our model can also apply to patient chain where each stages lasts a few months, for instance an elective surgery chain, that starts with a visit to a primary care provider, then next to a specialist, then to an out-patient surgery clinic. Although, in these chains a patient moves across multiple organizations and locations, where each clinic has a desired service time measured in months, the key point is that these service chains must have similar desired service times. Therefore, our results and recommendations are not applicable to care process with very dissimilar desired service times. For instance, the care process of patients suffering heart attack have a broad range of waiting time starting for only a few minutes in emergency department and finishing in physical therapy with a desired time of months.

The Bullwhip Effect is considered as the performance measure of our model. Similar to the Bullwhip Effect in manufacturing supply chain, research on service supply chains and in particular healthcare service supply chain has revealed structural tendencies toward demand amplification [31, 32, 38]. The 'bullwhip effect' in healthcare service supply chain has often cited as an important source of supply chain stress, reduced resource availability, reduced access to services, increasing employee fatigue and stress, degradations in service quality, higher labor costs, higher operating costs, and lower hospital revenues. These effects are comparable to negative consequences of bullwhip effect in manufacturing supply chain such as increasing stock-outs and higher costs. However, unlike manufacturing supply chain, increase in demand variation in healthcare supply chain leads to more medication errors and adverse patient outcomes.

Therefore, controlling demand amplification can greatly increase performance of healthcare systems. This research incorporated system dynamics modelling to study the effects of design parameter related to capacity adjustment delay and information sharing in controlling the bullwhip effect. Previous studies have paid little attention to measuring the impact of causes of the bullwhip effect. Information sharing is often cited as the key to reducing this effect, but there has been little research into the value of information sharing in a medical service supply chain model. This research has addressed this gap by analyzing the effects of the design parameters in a service based medical supply chain model.

Several studies in manufacturing supply chains frequently have confirmed that sharing end-customer demand data improves performance. However, few researchers have investigated the effect centralized demand information in service supply chain context. Our finding is similar with Anderson et al., (2000), integrating actual and local demand information results in better performance in individual service unit. We conclude 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 less variation in service times, enhanced service quality, and consequently better handling of surge of demand. However, implementing centralized demand information system in the real situation involves several expensive modifications in processes such as: installation of IT infrastructure to cluster and transfer the data in real time, and training managers on how to incorporate these new data into their decision heuristics. Hence, results of this study indicate that investing in truly reliable information technology infrastructures to incorporate actual demand data with local demand data across individual chains of healthcare delivery system is a possible strategy to manage the surge of demand during disasters. The research results are in line with the common belief on the benefits of information sharing strategies in healthcare, as summed up by Baltacioglu et al., (2007) [39] as "effective management of healthcare supply chain is only possible via the implementation of effective information and technology management systems." The use of actual demand data had a positive impact on the overall performance of medical service supply chain.

VI. CONCLUSION

This study focused on evacuation planning and how to address surge of demand after a flood scenario. The results of this research indicates that reducing capacity adjustment delay and better information sharing in a medical service chain can produce better performance. Therefore, centralized demand information in healthcare system is a promising approach for better management of surge of demand after a disaster. The main limitation of this research is that equality of service chain parameters. Chains of identical individual service chain, where desired service times, capacity adjustment practices, and service quality are all equivalent, are simply not a realistic representation of healthcare delivery system. The stages, clinics, or departments in any healthcare service chain are more likely to be different in all of these characteristics than they are to be the same. Therefore, identical desired service delivery times in our model results in over-estimation of bullwhip effect. Relaxing this assumption to represent more specific, real-world healthcare delivery chains is the subject of future work. Our suggestion for future work is to examine the validity of this research results under the constraints inherent to Malaysian healthcare delivery system.

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