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A Risk Management Framework via Multi-paradigm Simulation for Supply Chain and Business Process Management

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Abstract

With global crises and natural disasters becoming ever more prevalent, the importance of risk management is highlighted more than ever. Furthermore, risk management is often in contrast with more classic objectives of firms such as reaching higher levels of productivity. To add to the difficulty, there are fields that are already plagued with complexity beyond the limits of traditional problem-solving methods. Supply chain and business process management are two such complex fields that will be highly influenced by outside factors beyond a survival point if risk and operations management are treated disjointedly. In the current simulation literature of risk management, discrete event and agent-based simulation methods are mostly used for supply chain and business process management, respectively. In this article, we propose a risk management framework using multi-paradigm modeling and simulation to bring operations and risk under one umbrella. The framework adopts a continuous improvement cycle, quantifies risk as a deliverable, and provides the decision-makers with trade-offs between optimized risk and other management objectives. The framework is validated through the development of a multi-paradigm simulation model for a warehouse supply chain. The case study demonstrates how our framework could be utilized by the decision makers to systematically approach risk management.

Keywords: Multi-paradigm simulation, Risk management, Supply chain management, Business process management

1. Introduction

The concept of risk management has been around since the time of Pharaohs in Egypt storing large quantities of grains to hedge against the risk of famine. However, it was not until the 1990s that large corporations started considering risk management an integral part of their strategies. This was partly due to losses incurred by big companies such as Dresser Industries and Caterpillar in the 1980s as a result of uncertainty in exchange rates, interest rates, and commodity prices (Froot, Scharfstein, & Stein, 1993). With COVID-19 still a live threat and several regions and economies in lockdown, the disruption to supply chains continues to be severe. There is no doubt that this pandemic has tested the creativity, flexibility, and resilience of even the most reliable supply chains worldwide, as they have attempted to maintain essential operations. This has sparked a new interest in risk management and its importance across the globe. As a result, many approaches are being explored worldwide to assist decision-makers in managing risk (Alauddin et al, 2020).

Applications of risk management can range from hedging methods ensuring that a company has the cash available to make value-enhancing investments to suggestions for minimization of COVID-19 disease resurgence when reopening countries.

Supply chain management (SCM) and business process management (BPM) are two such fields that both can benefit from applications of risk management. Supply chain decision-makers operate in a quite complex and continuously evolving environment on a daily basis. This results in tactical, strategic, and operational decisions being made without the ability to completely predict their effects and the consequences. On the same note, analysis of business processes in BPM requires a systematic and reproducible approach to effectively measure the impact of disruptions in a system without compromising its integrity and limiting the scope of the problem. Common complexities plaguing the field of SCM include but are not limited to competing objectives, the need to reduce risks and vulnerability, process robustness, and numerous factors affecting the systems that can show interdependent, non-linear, and uncertain behavior. On the same note, BPM complexities extend beyond business processes capabilities as systems evolve with time in presence of risk. Modeling the behavior of such BPMs with an eye on strategies, management, and operations cannot be achieved by traditional approaches without compromising the comprehensiveness of the system. Mathematical and stochastic models do not give us a sound understanding of these dynamic systems due to the aforementioned reasons. The results of such models hardly support the decision process due to the high number of simplifying assumptions. Therefore, modeling and simulation (M&S) can be used as a decision support tool to investigate these dynamic system behaviors whose complexity is beyond the limits of traditional approaches. This aim is achieved by creating an artificial representation (simulation model) of a real complex system. M&S provides an opportunity to assess the quality of processes "as-is" in presence of risk as the performance of the system will be tested real-time according to the processes' inherent and residual risk. (Tjoa et al., 2010; Longo, 2011a; Safari, 2016).

According to Chen, Ong, Tan, Zhang, and Li (2013), Agent-Based Modeling (ABM) is recognized as the most promising paradigm for analyzing complex real-world supply chains in detail to draw reliable and meaningful insights about them. Jansen-Vullers and Netjes (2006) mention that BPM is mostly simulated with Discrete Event Simulation (DES) to formulate a problem and investigate process capabilities because business processes are event-based, and DES is an excellent tool for supporting operational decisions. In addition, hybrid methods have combined optimization with M&S to capture risk in SCM. A multi-paradigm M&S approach is rarely investigated in SCM literature for risk management. On the same note, BPM risk management literature is mostly focused on modeling risk in a system with either incorporated risk in a DES or static frameworks. Also, the focus is solely on risk in the design phase without investigating dynamic risk exposure. A multi-paradigm M&S risk management framework-agnostic to SCM and BPM domains- that provides a quantitative method to calculate the system's total risk does not exist. Our proposed framework considers a quantified risk value for SCM or BPM besides the objectives defined by stakeholders.

This framework is designed to accommodate a quantitative risk management approach via multi-paradigm M&S in SCM and BPM. Our framework's application in other domains such as financial, quality, human resource, and customer relationship management is not under consideration. However, it might prove practical to adapt this framework to other areas likewise.

The rest of the article is organized as follows. Section 2 provides a literature review that focuses on SCM and BPM risk management with a focus on BPM life cycle. Section 3 describes the framework's methodology and is followed by section 4 which discusses the simulation models and the results for a supply chain case study. Finally, Section 5 presents the conclusions and discusses future work and directions.

2. State of the art

Risk management literature in BPM comprises of modeling risk either in design or execution phase of the BPM life cycle. Most of the literature is focused on the origin of risk in the business process and incorporating it in the design phase of BPM life cycle. Rosemann and Muehlen (2005) describe risk as an inherent part of each process. Event-driven process chains (EPC) are utilized to show the relationship between a given process and the risk in the design phase. They have created a risk taxonomy for future research when simulating a BPM. Tjoa, Jakoubi, and Quirchmayr (2008) propose a risk-oriented process evaluation (ROPE) procedure to combine the advantages of BPM and business continuity management in the design phase. They have introduced a recovery sub-process when the functionality of a process is negatively affected. Betz and Oberweis (2011) model a risk-aware BPM using XML nets to sufficiently capture risks in the design phase. They have integrated risk in a process like Rosemann and Muehlen (2005) and have proposed the utilization of different risk reduction strategies to identify points of failure and instability in the processes. Rotaru, Wilkin, Churilov, Nieger, and Ceglowski (2011) present a value-focused process engineering (VFPE) to sufficiently capture risk in goal-oriented business process models in the design phase. Their work is centered around the idea of combining process-oriented risk management with risk-oriented process management. VFPE is an extended model of EPC which attempts to find process risks and link them with the business process model to provide a hierarchical atomization of risk corresponding to the process flows. Authors do not consider M&S as a tool for their risk management method. Lamine, Thabet, Sienou, Fontanili, Pingaud (2020) consider monitoring the BPM life cycle from design to execution to close the gap between the two phases. They propose a meta-model comprised of four views of business process, risk, risk analysis, and risk context to capture the entire life cycle. In addition, they propose the concept of value created for customers in each business process to model BPM as a value chain. Authors do not incorporate M&S as a tool for their risk management of BPM. Mykoniatis (2015) mentions that the combination and/or integration of M&S approaches presents challenges due to the different criteria and philosophical approaches that satisfy each paradigm based on problem and system perspectives. Prukner and German (2013) applied DES, ABM and System Dynamics approaches to investigate alternative scenarios of electricity generation systems and detect risks and miscalculations under politico-economic constraints. They deployed DES and AB for discrete events and state changes of a gas power plant and SD to capture continuously changing processes such as the electricity demand, the charging or discharging of electricity storages, and other dynamic variables. Satyal, Weber, Paik, Di Ciccio, and Mendling (2019) shine the light on the underlying assumption of processes being incrementally improved in the BPM. BPM projects are said to consist of design and implementation phases. It is then stated that not only the design ideas do not lead to any improvement 75% of the time, but 25% aggravate the situation. To address this faulty assumption, they propose a method called "AB-BPM" that uses ABM to explore alternative designs. Amantea, Di Leva, and Sulis (2018) utilize DES to estimate the risk and intercept it before incurring the costs in a healthcare environment. Their methodology mainly uses DES to assess improvement scenarios.

A review of risk management literature in SCM is presented in the rest of this section based on state-of-the-art surveys. Chen et al. (2013) review the state-of-the-art articles on risk management of supply chains through ABM as the major simulation method in the field. The articles are investigated from three perspectives; (a) supply chains risk management processes; (b) supply chain planning decision levels; and (c) supply chain design goals.

Perspective (a) suggests that there are not many articles in the literature focusing on risk identification. Risk mitigation, in contrast, has been investigated more. Li and Li (2008) use decentralized transshipments between retailers when inventory position does not meet the demand to mitigate risk. Jiron, Jun, Yunhong, and Zongwun (2008) approach risk mitigation by studying lead times and information sharing among the four agent types of retailer, wholesaler, distributor, and manufacturer. Schmitt and Singh (2009) suggest evaluating the trade-off between service level and inventory investment to manage the risk. Longo (2011b) focuses on the process of risk monitoring and evaluation. It is concluded that successful results are dependent on the use of multiple performance measuring indices. Qualitative performance measures such as supply chain resilience and vulnerability are examples of such indices.

Perspective (b) explains that all three levels of decision-making (i.e., strategic, tactical, and operational) have been implemented and investigated through ABM adequately.

In Perspective (c), it is observed that the design goals either have an emphasis on robustness against uncertainty or flexibility towards disruption. Robustness is achieved through fuzzy agents and principles, information sharing and cooperative planning schemes, and simulation-based optimization fused with ABM amongst other approaches. Erol and Ferrell (2003) for example discussed the application of fuzzy set theory to find the supplier with the maximum performance measure as defined by decision-makers. Flexibility towards disruption is achieved through approaches such as transshipment, redundant suppliers, reserving inventories, just to name a few. Jiang and Sheng (2009) utilized reinforcement learning and case-based reasoning to satisfy the target service level in SCM in the event of a disruption. Furthermore, Gao et al. (2020) mention that most of the existing studies have mainly considered a single aspect of risk management (i.e., risk identification, risk assessment, risk warning, risk management, and risk feedback) and propose the use of M&S to tackle this problem. Schlüter, Hetterscheid, and Henke (2019) focused on proactive risk management based on the transparency of real-time risk-related information through different digitalization scenarios. They combined DES with the Monte-Carlo method to evaluate SCM digitalization scenarios. System dynamics (SD) as another simulation approach is said to be applicable here if implemented via the Monte-Carlo method. However, this possibility is not further investigated by the authors. Macdonald, Zobel, Melnyk, and Griffis (2018) state that the researchers' ability to evaluate risk and resilience theories for SCM is restricted by the difficulty of collecting the necessary data. They developed a DES framework to tackle the issue. In addition, Oliveira, Jin, Lima, Kobza, and Montevechi (2019) reviewed 52 articles of SCM risk management and stated that 19% used different M&S methodologies to manage risk while 48% used optimization as their risk management method of choice. Overall, risk mitigation is suggested as the best-investigated risk management strategy by being mentioned in 42 articles. Performance enhancement is the role of choice for models in 28 articles followed by decision support with 12 articles.

To conclude the review of literature, DES and ABM are the most prevalent paradigms used for BPM and SCM risk management, respectively. Several recent articles have deviated from this norm and explored the DES for SCM and ABM for BPM. There are also a few articles like Sulis et al (2019) deploying both methods to a problem and comparing their performances. Even though the exclusivity of simulation paradigms in the risk management of these two fields is decreasing, a multi-paradigm M&S is yet to be devised to manage the risk of SCM and BPM to the best of our knowledge. This article aims to provide a risk management framework to close this literature gap.

3. Risk Management Framework

We are proposing a 4-phase multi-paradigm M&S framework for risk management in BPM and SCM. The framework's four phases are: define, model and measure, improve, and sustain. Figure 1 shows the relationship between these four phases. Sections 3.1 through 3.4 provide more detail about each phase. In

Figure 1. Multi-paradigm M&S Risk Management Framework Phases

the proposed framework and methodology could be applied to both BPM and SCM.

3.1 Phase 1: Define

To provide a robust framework, Phase 1 was developed with the following 8 components:

1-1-Define *m* objectives for the BPM/SCM as the desired outcomes of M&S. Capital utilization, failure rate, and time to deliver are some instances of such objectives O_m.

1-2-Select risk minimization as the objective O_{m+1} of M&S.

1-3-Develop a risk taxonomy to create a holistic view of possible risks. Figure 2 provides an example of high-level risk categories pertinent to most BPM and SCM projects. Two further levels could be explored to get to the root cause of risks (5-why is a practical approach to find root causes). Figure 3 provides an example of expanding the operational category of risk from Figure 2 risk taxonomy. Operational risks might stem from operations, people involved, security breaches, etc. The risks pertinent to people can in turn be rooted in lack of training, employees' not being engaged with mission and vision, etc. Additional examples of risk taxonomy in the literature are provided by Roseman et al (2005); Carr, Konda, Monarch, Ulrich, and Walker (1993); and Jacobi, Hayward, de Zwaan, Kraemer, and Agras (2004).

Figure 2. High-level Risk Taxonomy Example

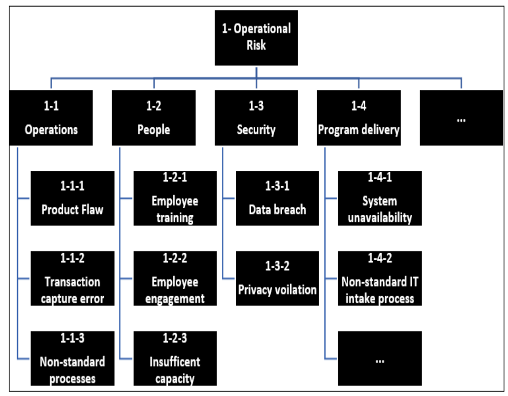

Figure 3. Operational Risk Expansion Example

1-4-Develop a risk severity matrix for the lowest level of risks defined in the risk taxonomy step. To do so, define what constitutes a low, medium, high, and critical severity impact for a given risk (solely from impact perspective and not the frequency of occurrence). Table 1 provides an example of a risk severity matrix in the service industry on a scale of 1 to 10, with 1 being not risky at all and 10 being extremely risky.

Table 1. Risk Factors Severity Matrix Example

Severity	Description	Value
Low	Results in poor business decisions on a limited basis with no to little impact on objective	1
Medium	Results in poor business decisions negatively impacting the objective	3
High	Results in poor business decisions negatively impacting business objective and operations	5
Critical	Results in poor business decisions negatively impacting business viability	10

1-5-Develop a risk frequency matrix (only from a volume perspective and not the impact of the risk) for the lowest level of risks defined in the risk taxonomy step and define what constitutes low, medium, likely, and high frequency. Table 2 provides an example of a risk frequency matrix on a scale of 0% to 100%, with 0% representing no chance of occurrence and 100% representing chance of occurring all the time.

Table 2. Risk Factors Frequency Matrix Example

Frequency	Description	Value
Low	Not expected but there is a slight possibility that the risk event may occur at some point (Less than 10%)	5%
Medium	The risk event might occur at some point due to a history of occasional occurrence (10% to 40%)	25%
Likely	There is a strong possibility that the risk event will occur as there is a history of frequent occurrence (40% to 80%)	60%
High	The risk event is expected (more than 80%)	90%

1-6-Define the project team. For example, a team could be comprised of a subject matter expert to provide in-depth knowledge of the system; a process engineer to accurately map the system; a simulation engineer to model and optimize it; and a project manager to efficiently coordinate the endeavors.

1-7-Define customer requirements that must be satisfied with the BPM/SCM in study. Budget limitation, project's time horizon, and project's outcome reliability are a few examples of such requirements.

1-8-Define quality metrics related to customer requirements. Process time and product specifications variability are examples of such metrics in service and manufacturing industries.

Rest of this section walks through the definitions and process of quantifying risk. Variable R_{ij} is introduced for the process i and the risk j as follows:

$$R_{ij} \begin{cases} 1 & \text{risk } j \text{ is available in process } i \\ 0 & \text{otherwise} \end{cases}$$

Variable C_{ij} is defined to determine whether a risk mitigation or control exists for risk j in process i. Several processes may utilize the same risk control.

$$C_{ij} \begin{cases} 1 & \text{risk } j \text{ has a control in process } i \\ 0 & \text{otherwise} \end{cases}$$

Let RMC_{ij} be the effectiveness of risk mitigation measure for risk j in the process i. RMC_{ij} value could be measured by developing design of experiments in the test environment with sufficient sample sizes.

RIS_{ij} is defined as risk j's inherent severity in the process i collected from the risk severity matrix when no control is in place (even if risk control exists).

RRS_{ij} is defined as risk j's residual severity in the process i collected from the risk severity matrix when risk control is in place. Residual risk is defined as risk present after the application of risk mitigation measure.

Let F_{ij} be the frequency of risk j in the process i according to the risk frequency matrix.

P_i represents the count of related processes existing after process i in BPM's or SCM's flow. The idea is to capture the bullwhip effect. When a risk is present in the initial processes, it has a higher impact on the overall health of BPM or SCM. In other words, the closer the activity to the beginning of the flow, the higher its bullwhip effect and the higher the value of P_i. Let RV_{ij} be the risk value of risk j in the process i that can be calculated as follows:

$$RV_{ij} = R_{ij}(P_i * F_{ij}\left(\left(C_{ij} * RMC_{ij}\right) * RRS_{ij} + \left(1 - \left(C_{ij} * RMC_{ij}\right)\right) * RIS_{ij}\right))$$

RV_{ij} initially checks whether a risk j exists in the process i with R_{ij}, if the risk does exist, then the risk mitigation control availability C_{ij} will reduce its inherent risk to the residual risk RRS_{ij} with proportion to the control's effectiveness. Therefore, the process exposure to residual risk is $(C_{ij} * RMC_{ij}) * RRS_{ij}$. Moving forward, $(1 - C_{ij} * RMC_{ij})$ is the process exposure to the inherent risk severity RIS_{ij} in the presence of a risk control. Considering its effectiveness, the process exposure to inherent risk is calculated in $(1 - C_{ij} * RMC_{ij}) * RIS_{ij}$. Finally, risk severity is multiplied by risk frequency F_{ij} and magnitude of the risk P_i on the entire BPM/SCM's flow.

Hence, the framework's phase 1 is concluded with the calculation of a BPM or SCM *Total Risk* for n processes and J risks following the formula below.

$$Total\ Risk = \sum_{i=1}^{n}\sum_{j=1}^{J} RV_{ij}$$

3.2 Phase 2: Model and Measure

A problem with $m+1$ objectives will be under modeled if all the objectives are treated the same from the modeling perspective. It is reasonable to expect that a BPM/SCM will be more realistically modeled when objectives are evaluated and modeled independently. Therefore, a M&S mechanism that does not assume all the objectives can be modeled with the same approach is best. Mykoniatis (2015); and Mykoniatis and Angelopoulou (2020) developed a multi-paradigm M&S structure that first identifies what M&S approach amongst DES, SD, and ABM works best for a given objective O_m. Then continues with defining sub-objectives and proposing procedures to identify interaction points between different M&S paradigms. This is when the problem and system perspectives require combination/integration of multiple M&S paradigms. In this work, we adopted the Mykoniatis and Angelopoulou (2020) multi-paradigm simulation practice into our framework to select the best modeling approach for the objectives.

A summary of Mykoniatis and Angelopoulou (2020) heuristic is shown in Figure 4. We will go through this heuristic to determine whether objectives should be modeled with the same or different M&S paradigms. If risk and BPM/SCM objectives are satisfied with the same method, construct a model to calculate the BPM/SCM objectives and total risk. If risk and BPM/SCM objectives require different M&S approaches, the project team should identify interaction points and relationship types. Mykoniatis and Angelopoulou (2020) provide a comprehensive approach to identifying interaction points and relationship types.

For: O_m *1* to *m+1*
  Select k criterion that best represent object *m*
  Define variables of interest V_{ct} for criterion *c* and modeling approach *t*
  If: criterion *c* applies to approach *t*
    $V_{ct} = 1$
    Else: $V_{ct} = 0$
  End if
  Assign a weight W_{ct} to V_{ct}
  Calculate $score_t = \sum_{c=1}^{k} V_{ct} W_{ct}$
  Report approach *t* with the highest score as the modeling approach for objective *m*
End for
If: all objectives satisfied with same approach
  Report approach t as the M&S method for the problem
  Else: identify interaction points and relationship types between different approaches

Figure 4. Mykoniatis and Angelopoulou (2020) Heuristic Pseudo-code

3.2 Phase 3: Improve

When M&S is performed and objective values are retrieved, the project team has a chance to refine the system in study and perform what-if scenarios. Sensitivity analysis helps test different levels of risk severity, frequency, and introduction of new risk mitigation measures with higher levels of effectiveness. Being able to quickly observe the impact of possible scenarios is invaluable to devising contingency plans and identifying what processes or chains are the most vulnerable points in the flow. The project team then brainstorms on different solutions that solidify these vulnerable points hoping to reduce the volatility and risk in the system and re-execute the simulation model. Figure 5 shows an example of sensitivity analysis integrated into our framework that the project team could implement to identify which processes are most susceptible to risk and how they can be improved to increase the BPM/SCM robustness in the presence of risk. For example, it can be seen in Figure 5 that P3 almost has the same RV with different levels of risk frequency. Hence, it is inexplicable to invest in analyzing and improving this process' risk frequency while there are other processes such as P4 that are highly correlated with risk frequency. The project team must invest time in testing different combinations of inherent and residual risk severity and risk frequency to find out which processes are highly impacted (correlated) by risk in the BPM/SCM. Then better and more effective risk controls should be worked on for these processes identified as network weak points.

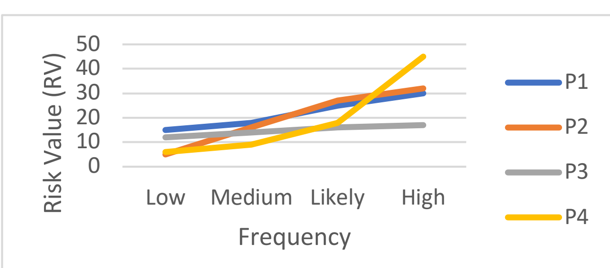

Figure 5. Sensitivity Analysis for different levels of risk frequency

3.2 Phase 4: Sustain

This phase ensures a sustainable mindset is in place to guarantee continuous improvement will take place and contingency plans are developed to respond to unforeseen volatilities created from uncertainties. The project team must clearly inform stakeholders that the simulation results are estimates and real-world scenario no matter how unlikely might drastically differ from the results. Therefore, a sustainable plan to (a) revisit model assumption, (b) update the model, (c) keep data up to date, and (d) design more effective risk mitigation measures should be an integral part of a M&S practice aiming to be sustainably successful.

4. Simulation Model Case Study

A SCM case study was devised via AnyLogic simulation software and its available examples and tutorials to showcase the use of the proposed framework. Phases 3 and 4 are out of the scope of this study and thus were excluded. This is due to the fact that they are heavily dependent on user participation in addition to being used in a variety of disciplines other than M&S. The case study of the supply chain shown in Figure 6 consists of 16 factories in the Northeast, Southeast, and Midwest regions of the United States and a distribution center in Cincinnati, Ohio providing them with their raw materials via trucks.

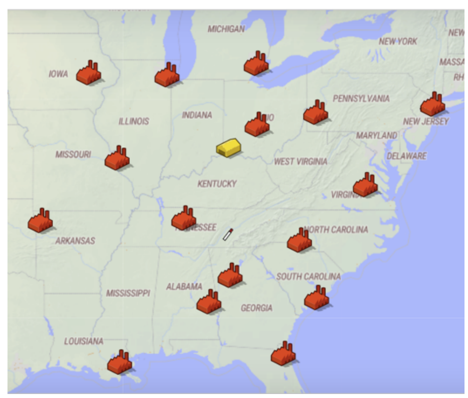

Figure 6. Case Study Supply Chain Map

Starting with step 1-1 of the framework, two objectives of maximum truck utilization (O_1) and customer demand satisfaction (O_2) are defined. Risk minimization is added as the third objective (O_3) in step 1-2. Figure 7 represents the risk taxonomy created following the step 1-3. The risk severity and frequency matrixes utilized for the case study are the same as Tables 1 and 2. Steps 1-6, 1-7, and 1-8 are not applicable in this case study as they need direct user input. For the M&S method selection (Phase 2), the guidelines provided by the multi-paradigm M&S framework of Mykoniatis and Angelopoulou (2020) are followed. Table 3 summarizes the results of the framework and M&S method selection for each sub-objective. DES is selected for the sub-objective of maximum truck utilization as the level of abstraction

Table 3. M&S Method Selection for Objectives

Criterion	Var of Interest	Selection for Obj. (O_1) max. truck utilization	Weight W_1	Selection for Obj. (O_2) Demand Satisfaction	Weight W_2	Selection for Obj. (O_3) Risk	Weight W_3
Scope level	Operational	1	10	0		0	
	Strategic	0		0		0	
	Any	0		1	3	1	10
Required Resolution	Detailed level	0		0		1	3
	Aggregated level	1	7	1	2	0	
	More detailed level	0		0		0	
System process	Discrete	1	5	0		1	4
	Continuous	0		0		0	
	Discrete/ Continuous	0		1	8	0	
Modeling approach	Process centric	1	8	0		1	2
	Top-down	0		0		0	
	Bottom-up	0		1	5	0	
Object	Entity	0		0		1	8
	Feedback	0		0		0	
	Agent	1	4	1	9	0	
Time	Discrete	1	5	1	4	1	4
	Continuous	0		0		0	
M&S method		Discrete Event Simulation		Agent Based Modeling		Discrete Event Simulation	

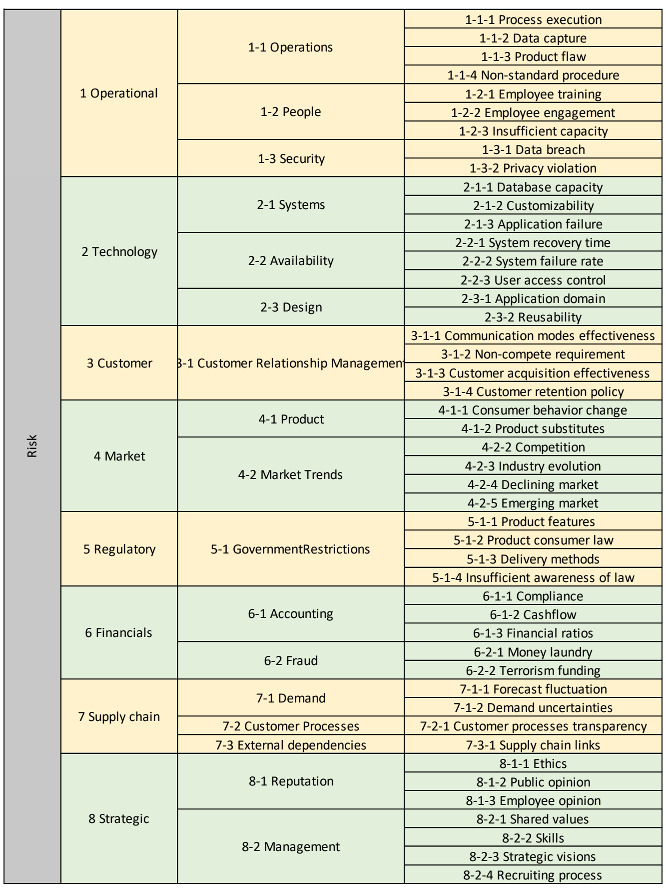

Figure 7. SCM Case Study Risk Taxonomy

is low, trucks are resources of the model, and their behavior is process-centric. ABM is selected for customer demand satisfaction objective as demand behavior is ruled based and factories are individual agents. Finally, risk is modeled with DES since abstraction level is low and risk behavior is entity based and discrete.

As Table 3 displays, this case study uses a multi-paradigm M&S with ABM and DES. The rest of this section is organized as follows. Sub-section 4.1 describes the base model with sub-section 4.1.1 dedicated to the ABM sub-model and 4.1.2 dedicated to the DES

sub-model. Sub-section 4.2 then explains the introduction of risk into the base model with sub-sections 4.2.1 and 4.2.2 dedicated to ABM and DES sub-models, respectively. Sub-section 4.3 follows by illustration of risk controls incorporation into the model. Lastly, sub-section 4.4 discusses the simulation results of sub-sections 4.1 to 4.3 models.

4.1 Base Model

A deterministic model is devised to be used for verification and validation of the proposed framework. This base model will also be used as a reference to compare the results in the presence of risks and risk controls. We made the following assumptions when modeling the SCM case study:

- Orders are delivered with a single truck.
- Demand is defined by a triangular distribution.
- Routes are selected based on time and not distance.
- Trucks assume a constant speed.
- Demand administrative process time is negligible.

4.1.1 Base ABM Sub-Model

The base ABM sub-model is designed to capture how a factory alternates between states of production and waiting for raw materials as shown in Figure 8. A factory transits from "Manufacturing" to

"HasDemand" with a rate and from "HasDemand" to "Manufacturing" instantly once products are delivered to it by sending a message. Triangular distribution is chosen to represent the transition rate. The distribution values are (1,3,5) orders per week.

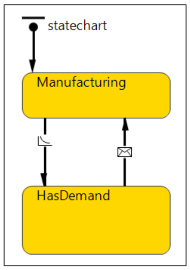

Figure 8 Factory Behavior ABM

4.1.2 Base DES Sub-Model

DES sub-model is designed as a flow of discrete tasks where each activity has a dependency on its previous activity to start and finish as shown in Figure 9. The flow starts with the generation of demand from a factory in the ABM sub-model and the demand which is being received by the distribution hub. Then, products are loaded into trucks and they depart the hub to the destination factory. When the trucks arrive at the factory site, docking, unloading, and undocking processes occur in turn. Lastly, the trucks leave the factory site to the distribution hub, while a message is triggered to alter the factory state from "hasDemand" to "manufacturing" when undocking process is completed. Task names in Figure 9 describes the nature of processes and the connection lines show the flow of service from start to finish. Demand request and products' delivery are the interaction points of DES and ABM sub-models which have causal relationships. Triangular distribution (50,100,150) in minutes is used to represent the loading and unloading delays as not much is known about the processes in lack of empirical data. In presence of data methods like goodness-of-fit test should be used to determine the underlying distribution. If unable to fit a distribution, empirical distributions could be used as mentioned by Reis, Pitombeira-Neto, and Rolim (2017).

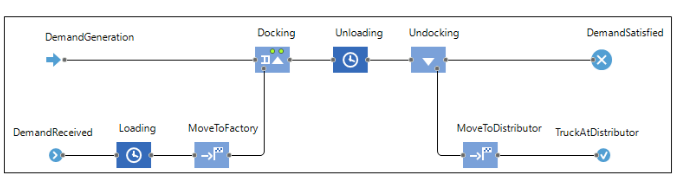

Figure 9. Truck Behavior DES

4.2 Risk Incorporated Model

Once the base model is constructed, we introduce the risk factors and start modeling the risk management element of the model. Four risk factors are introduced to the system for illustration purposes; however, users must go through all the objects (entities, states) to determine whether risk factors exist according to the developed taxonomy. Table 4 represents the risks integrated into the case study. The base model is updated with the risk factors from Table 4 without considering any risk controls first. Risk severity and frequency values are obtained from Table 1 and Table 2, respectively.

4.2.1 Risk Incorporated ABM Sub-Model

The risk factor related to the ABM sub-model is the periods of the year when a factory experiences high demand rate in a week (first risk in Table 4). Factories generate demand with a triangular distribution on a weekly basis. The period of high demand is considered a week when the normal rate is doubled. This is considered a low-frequency risk since it only happens few times a year. The inherent risk severity of this risk is considered high because it has a huge impact on the fulfillment of all three objectives. Figure 10 shows the alteration of a factory from a normal demand state to a high demand state using statechart1. A triangular distribution was used in the transition from "Manufacturing" state to "HasDemand" state in the base ABM-sub-model to incorporate the risk (Figure 10).

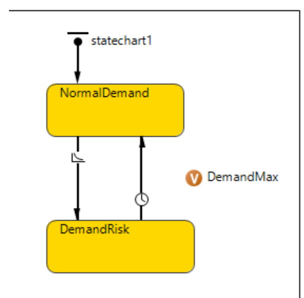

Figure 10 ABM Sub-Model with Risk Factor

4.2.2 Risk Incorporated DES Sub-Model

The DES sub-model risk factors represent lack of sufficient loading workforce, variability in loading time, and variable traffic speed as shown in Figure 11. Insufficient workforce is a medium frequency risk as the distribution hub experiences it few times every month. Inherent risk severity is medium since this risk negatively impacts business decisions related to the risk minimization objective. The second risk related to the loading process is when loading a truck takes more time than expected. Frequency is low because it only happens few times a year and inherent risk severity is low since it minimally impacts business decisions. Loading entity is updated with the aforementioned risks as follows: 73% of the time loading happens as expected; there is not sufficient workforce available 22% of the time; loading lasts unusually longer 4% of the time, and lastly, both risk factors occur simultaneously 1% of the time.

Traffic uncertainty is the third risk related to the DES sub-model. Traffic jams can significantly slowdown the trucks' movement. Frequency is likely since roads regularly go through construction periods. Inherent risk severity is medium since this risk might negatively impact all three objectives. All in all, traffic can slowdown trucks up to 50% of their regular speed of 65 mph.

Table 4. Risk Factors Introduced into the SCM Case Study

Entity/State	Risk Factor	Category	P_i	Frequency	Inherent risk Severity	Inherent Risk Value
Factory "HasDemand"	Demand is significantly incorrect	7-1-2 demand uncertainties	9	Rare	High	2.25
Loading	Insufficient workforce for loading a truck	1-2-3 insufficient capacity	5	Medium	Medium	3.75
	Loading a truck takes more time than expected	1-1-1 process execution	5	Low	Low	0.25
Moving to/from Factory	Traffic slowdowns truck movements	7-3-1 supply chain links	3	Likely	Medium	5.4

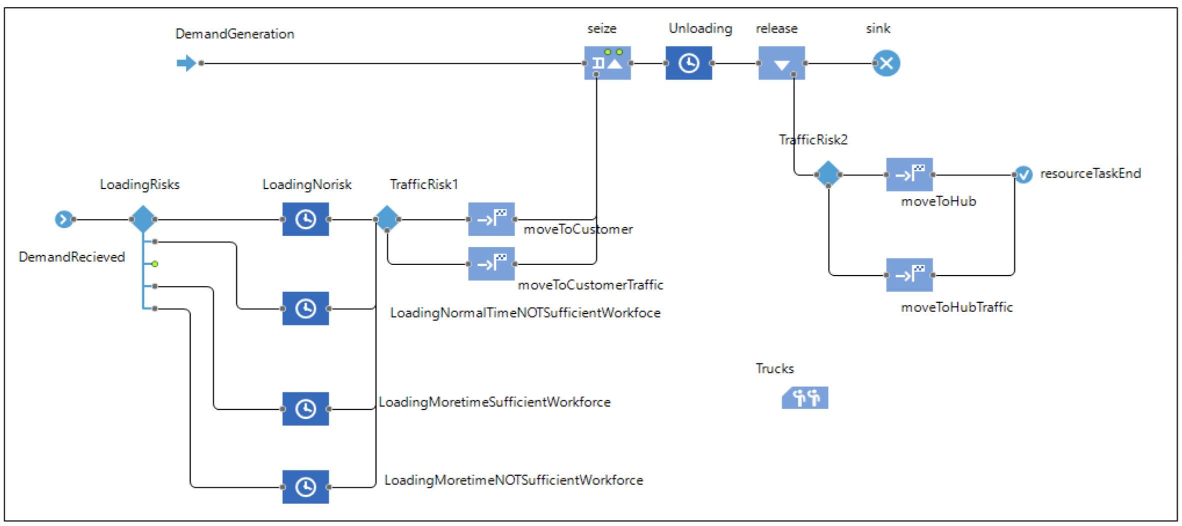

Figure 11. DES Sub-Model with Risk Factors

4.3 Risk Control Incorporated Model

Last step in model construction is introduction of risk controls as the final element of risk management. Controls usually do not reduce the frequency of risks and definitely will not mitigate risks entirely, however, they will reduce their inherent severity. Table 5 shows the proposed risk controls, their effectiveness, and the residual risk when they are applied for risks discussed in the previous section. It is possible for a risk to not have a control. In this case, inherent risk severity and residual risk severity are essentially the same. In our case study, out of the four risks introduced, only two have mitigation measures. For example, a risk that does not have any controls can be found in ABM sub-model when a factory generates high demand rate. Therefore, the ABM sub-model virtually remains the same and does not require any update. The updated DES sub-model from section 4.2.2 that includes risk controls is illustrated in Figure 12. The distribution hub has a contract with local agencies to have on-call workforce whenever necessary. This is used as a control for insufficient workforce risk that has a frequency of occurring few times a month. This control is 90% effective to mitigate the risk and reduces the inherent risk severity from medium to low and *RV* from 3.75 to 1.5. In addition, the distribution hub has an analyst that collects traffic data and schedules trucks' movements to avoid traffic. This control is effective 75% of the time and reduces the inherent risk severity likelihood and *RV* from 5.4 to 1.8.

4.4 Simulation case study results.

Next, the described base model was run several times with varying parameters (i.e., number of trucks, demand frequency, truck speed, etc.) and logically analyzing the changes in model behavior for verification and validation purposes. After the validation step, the base model was optimized to maximize the truck utilization while satisfying demand and not exceeding truck utilization of 85%. The optimization configuration is shown in Table 6. The optimization results of the base model are then inputted in the risk and control incorporated models. The results are shown in Table 7.

Table 5. **Risk Factors and Associated Risk Controls**

Risk Factor	Control	Control Effectivenes s	Residual Severity	Residual Risk Value (RV)
Insufficient workforce for loading a truck	Having on-call contractors when in-house loading capacity is not enough	90%	Low	1.5
Loading a truck takes more time than expected	Does not exist	0%	low	0.25
Demand forecasts upper bound is significantly incorrect resulting in lost opportunity	Does not exist	0%	High	2.25
Traffic slowdowns truck movements	Planning truck moving schedule based on real-time traffic data	75%	Low	1.8

Table 6. Optimization Configuration

Configuration	Value
Number of iterations	70
Number of replications per iterations	5
Model time	356 days
Random seed	Utilized
Parameter variation	Number of trucks (1 to 20)
Requirement	Utilization ≤ 85%

Table 7. Models Results

	Base Model	Risk added model	Risk controls added model without optimizatio n	Risk controls added model with optimizatio n
Min # of trucks	6	6	6	7
Utilizatio n	82%	96%	89%	75%
Total Risk	0	11.65	5.8	5.8

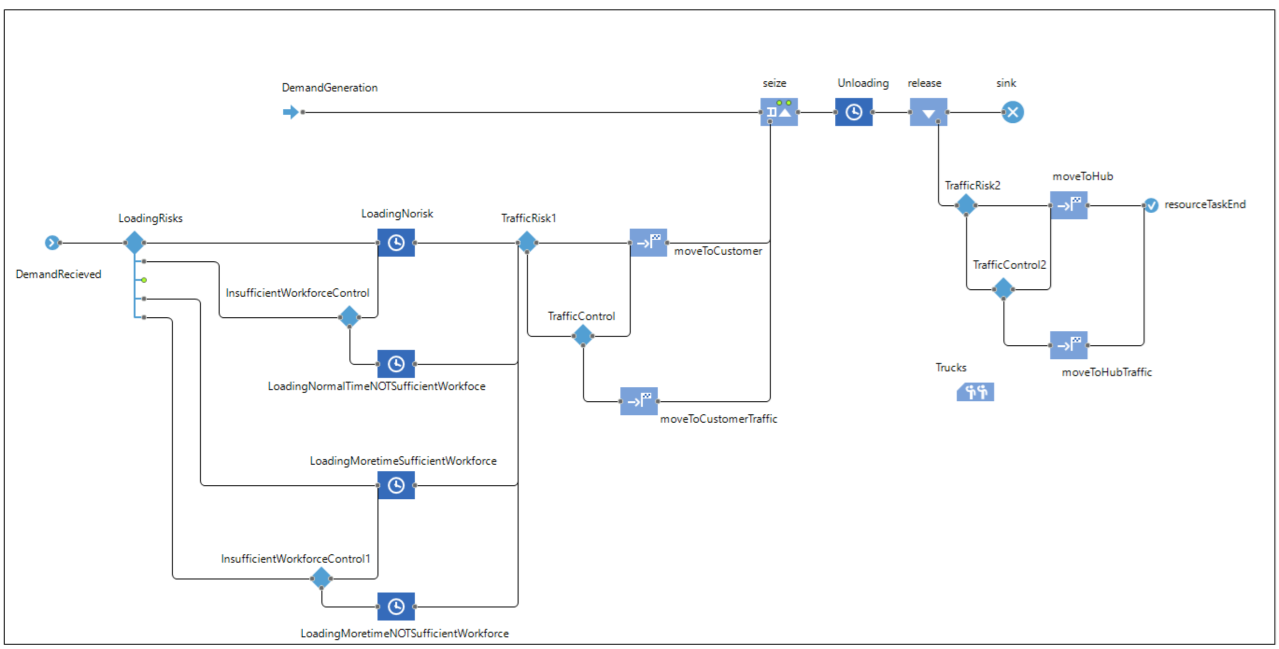

Figure 12. Risks and Controls Integrated into SCM DES Sub-Model

The minimum number of trucks for the base model is 6 resulting in 82% utilization which is only 3% short of the maximum allowable utilization. It is worth noting utilization being less than 85% is violated (96%). The introduction of risk controls improves the performance considerably (from 96% to 89%) and reduces the total risk dramatically (from 11.65 to 5.8). However, the base

that the introduction of risk turns this solution into an infeasible one as the requirement of

model optimal solution still results in violation of the utilization threshold. Therefore, to ensure the optimality of the optimization solution, the updated model illustrated in sub-section 4.3 encompassing the risks and controls is optimized again using the configurations from Table 6. The comparison of the optimization results of the base model (Table 7, column 1) with the sub-section 4.3 model (Table 7, column 4) shows that risk factors reduce the objective of maximum utilization from 82% to 75% in presence of controls. However, this reduction prevents the higher cost of infeasibility (Table 7, columns 2 and 3). Table 7 displays that the optimization results of the base model will at best be suboptimal in presence of risk. These risk factors exist in real- world whether they are modeled in our decision-making or not. Hence, not only should they be considered, but their corresponding risk controls should also be integrated into the M&S design.

Moreover, the fact that the implementation of risk controls to reduce total risk comes with a cost should not be neglected. The process of introducing more risk controls to reduce the total risk is not free of cost itself. This exponentially decreasing trade-off is illustrated in Figure 13. This Pareto frontier needs to be configured by the decision-maker preference of how much cost one is willing to incur for risk reduction. It is also worth mentioning that the risk is quantified to serve as a representation of risks' monetary cost which is quite complex to calculate.

5. Conclusions and Future Work

In conclusion, this article was written in response to the gap identified in the literature where no multi-paradigm M&S approach has been applied to risk management in SCM and BPM to the best of our knowledge. A risk management framework through multi-paradigm M&S for SCM and BPM projects with the following deliverables was devised for both researchers and practitioners to apply in their risk management endeavors:

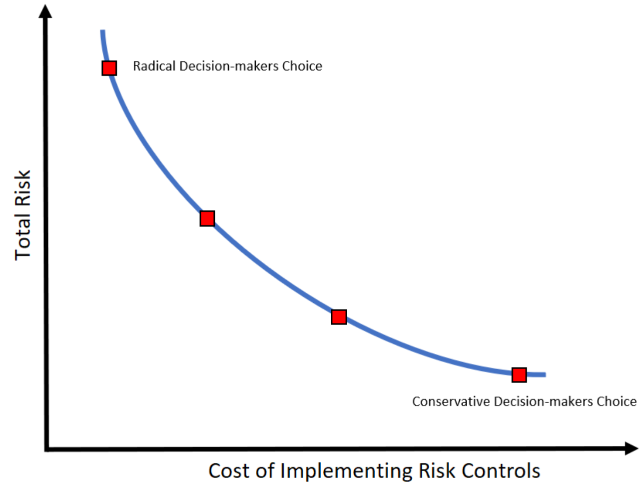

Figure 13. Total Risk and Risk Controls Implementation Cost Pareto Frontier

1- A closed-loop approach to continuously improve the management of risk in BPM and SCM.
2- A quantitative approach to capture risk and its bullwhip effect in a BPM/SCM network.
3- A multi-paradigm M&S approach to risk minimization.

This framework provides the decision-makers with the necessary testing means to finetune risk management improvement ideas. In addition, the multi-paradigm approach provides more flexible and effective improvements as objectives could be optimized using a selection of simulation approaches as opposed to one.

In the future, we plan to further evaluate the proposed framework with more case studies. A real-world case study involving industry decision-makers would help illustrate and verify the phases and steps of the framework that were excluded.

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