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MINIMIZING RECALL RISK BY COLLABORATIVE DIGITIZED INFORMATION SHARING BETWEEN OEM AND SUPPLIERS: A SIMULATION BASED INVESTIGATION

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ABSTRACT

Many Original Equipment Manufacturers (OEMs) and their suppliers face recall and warranty risks due to complex supply chains and products. OEMs and suppliers can hardly take appropriate actions for mitigating these quality risks due to lack of product history data and understanding of their probability. In this work, the product consists of two components delivered by two Tier II suppliers. Probabilities of OEM's acceptance, rework and rejection of the assembled product by a Tier I supplier and probabilities of acceptance, warranty and recall are calculated combining Bayesian Belief Network and simulation of a digitized supply chain. Results show that sharing of incoming quality information between an OEM and Tier I supplier and decision models to estimate warranty and recall probabilities can help in assessing quality improvement benefits to minimize recall risks. Suitable quality improvement contracts between an OEM and Tier I supplier can be designed using embedded product quality data.

1 INTRODUCTION

Multi-tier globally dispersed supply chains coupled with complexity of the products have made those products increasingly vulnerable to failures while in use (Tse et al. 2011). This results in warranties and sometimes recalls which have severe implications on financial performance as well as reputation of the concerned companies (Tse et al. 2011). Tightening product specifications may be a possible means to reduce such instances of warranties or recalls. But, the above approach alone may not help in reducing warranties or recalls until the OEM and its different tiers of suppliers stringently monitor quality of each batch of product and share batch quality related information. OEM and the Tier I suppliers in particular have to decide threshold quality of batches of incoming components which will minimize probabilities of warranty and recall. Determining such threshold levels of quality and continuously monitoring quality may add some additional costs of quality assurance but such costs are expected to be less than the cost of eventual failures in the market.

Companies need to adopt a proactive approach for preventing recalls (Kumar and Schmitz 2011). One such proactive approach can be (*i*) analyzing the impact of supplier quality and quality assurance by Tier I supplier and OEM on probabilities of warranty and recall and (*ii*) sharing such information with partners.

High level of supply chain visibility with information sharing between supply chain partners reduces product- and performance-related errors, thereby reducing the number of defects and enhancing quality, as well as the responsiveness when a risk incident occurs (Paulraj, Lado, and Chen 2008). Tse et al. (2011) empirically validated that supply chain visibility in a multi-tiered supply network can reduce and alleviate the negative impact of supply-chain product quality risk.

Wan, Xu, and Ni (2013) developed game theoretical models and showed that the firm's acceptance sampling plan and the supplier's quality effort level are sensitive to both the recall loss sharing ratio and whether the supplier and customer simultaneously decide the acceptance sampling plan and the quality management efforts or not.

Though the above literature provides useful theoretical justification about collaborative risk management in the context of product recalls, there is limited understanding of the impact of OEM's and Tier I supplier's own quality assurance on warranty and recall. Moreover, there is lack of decision support to aid the OEM and Tier I suppliers in decision making related to incoming batch quality which will minimize the probability of recall and how such information can help to develop contracts between OEM and suppliers to minimize recall risk. Therefore, this work presents a new approach to collaborative analysis and decision-making processes for quality management in a multi-tier supply chain in order to minimize the negative impact of recall and warranty risks. The approach is based on a modeling and analysis framework built upon probabilistic and simulation models. The objectives of the research are:

- To analyze the impact of OEM's quality control on probabilities of acceptance, warranty and recall in the market.
- To analyze the impact of Tier I supplier's quality control on probabilities of acceptance, rework and rejection by OEM.
- To estimate the probabilities of acceptance, warranty and recall in the market based on OEM's sharing of quality control information with a Tier I supplier.
- To utilize the recall probabilities under different scenarios to perform cost-benefit analysis and develop contracts to improve quality and minimize recall risks.

To achieve these objectives, timely collection and sharing of relevant data and information of products and components have to be enabled across companies and linked to physical items across the supply chain. This can be realized by digitizing the supply chain through Internet-of-Things (IoT) technologies, which are here assumed to be deployed.

2 LITERATURE REVIEW

Supply risk is defined as the probability of an incident associated with inbound supply from individual supplier failures in which its outcomes result in the inability of the purchasing firm to meet customer demand or cause threats to customer life and safety (Zsidisin 2003a). Also, supply risk often involves second-tier suppliers which are the companies providing products to an organization's immediate suppliers (Zsidisin 2003b). A global supply chain spread over multiple tiers of suppliers increases the uncertainty and adds extra quality variances to the final products. Product recalls as consequences of quality failures across the supply chain can be very costly and detrimental to firms as illustrated by the catastrophic consequences (Heerde, Helsen, and Dekimpe 2007). Improving end product quality in a multi-tier supply chain will require efforts beyond the boundaries of the firms' in-house capabilities (Chao, Iravani, and Savaskan 2009). Multiple authors have addressed supply chain threats in the context of Supply Chain Quality Management (SCQM) through SCQM frameworks integrated with strategic supply management (Lin et al. 2005; Lo and Yeung 2006). However, the large number of product recalls across industries indicates the need for different approaches to manage quality risk in global sourcing. In a multi-tiered supply chain, managers fail to anticipate the cascading effect that occurs throughout their supply chain operations. As risks get transmitted across the supply chain, firms have to adopt not only internal mitigation practices but also relevant inter-firm practices (Colicchia and Strozzi 2012) to mitigate the effects of such risks. However, there is no easily available approach for anticipating the way that quality risk cascades through a supply chain, which may result in costly warranties or even recalls of the products from the market. This in turn results in lack of understanding for the need to collaborate and share information for mitigating quality risks across the supply chain.

Chao, Iravani, and Savaskan (2009) developed different multiple recall cost sharing contracts between buyer and suppliers to induce quality improvement efforts and showed that knowing the supplier's failure rate information can significantly decrease the manufacturer's costs. The value of such information sharing increases when the difference in failure rates between the high and low quality suppliers increases, the unit recall cost is high compared to the unit cost of root cause analysis, and the initial failure rate of the manufacturer is less than the initial failure rate of the supplier. But, to design such contracts, it is important that the manufacturer and the suppliers are able to jointly estimate the recall probabilities using outcomes of their own quality assurance processes and use those to determine expected costs of recall which can potentially be shared between the manufacturer and the suppliers. However, there is limited research on how an OEM and a Tier I supplier can collectively estimate the probabilities of warranty and recall of the end product in the market by sharing the outcomes of their own incoming inspection processes. In this research, we address the above gap by using a combination of Bayesian Belief Network (BBN) and Discrete Event Simulation (DES) to demonstrate how incoming inspection outcomes of a Tier I supplier and OEM can be used to estimate probabilities of acceptance, warranty and recall of the end product in the market. From the standpoint of enabling technologies to precisely retrieve and timely use the necessary data, the recent developments of IoT technologies based on Radio Frequency Identification technologies (RFId), sensors and wireless communications offer huge potentials in the near future, with applications already reported in logistics and transportation (Xu, He, and Li 2014). A few years ago, RFId applications in supply chain management were already available (Sarac, Absi, and Dauzere-Peres 2010). Nowadays, however, the novel IoT and Cyber Physical Systems concepts can potentially revolutionize production, logistics and business processes across digitized supply chains in which items may communicate and cooperate (Hermann, Pentek, and Otto 2015). These enablers are highly relevant for quality assurance as information on quality of products can be embedded in the product.

3 METHODOLOGY

The methodology is grounded on two basic components, BBN and DES, in order to combine static and dynamic analysis, generate and elaborate on additional data to enhance the estimate and decision making process. The two components produce results further analyzed and elaborated to estimate the probabilities of acceptance, warranty and recall occurrences of end products in the market, establish thresholds of their acceptance, and define quality improvement programmes based on cost-benefit analysis. The two basic components are hereinafter presented. The overall modeling and analysis framework is presented in Section 3.3.

3.1 Bayesian Belief Networks

BBN is a directed acyclic graph with nodes labeled by random variables. It connects the variables with arcs and such a connection expresses the conditional dependence by conditional probability tables between the nodes (Pearl 1988). BBN can be used for problems which can be modeled in a network structure. It can also represent experts' knowledge in domains where such knowledge is probabilistic. Thus, BBN has been used for applications in supply chain risk assessment (Pai et al. 2003; Lockamy and McCormack 2010; Lockamy 2011), engineering project or new product development risk assessment (Lee, Park, and Shin 2009; Chin et al. 2009), etc.

Conditional probabilities can be generated by using pairwise comparisons (Monti and Carenini 2000). In such an approach, experts provide judgments about the probabilities of two states at a time instead of all states of a node at a time. Thus, biases can be reduced significantly and consistency of judgments could be maintained. But, Monti and Carenini (2000) generated conditional probabilities of nodes with a single parent whereas in a BBN, a node can have multiple parents. Chin et al. (2009) developed a method for generating conditional probabilities for nodes with multiple parents in BBN and applied it for assessing risks in a new product development project.

The structure of the analyzed supply chain is shown in Figure 1. Thus, the Tier I supplier (supplier 3) has two parent nodes – supplier1 and supplier 2. Hence, the method developed by Chin et al. (2009) is suitable for generation of conditional probabilities for acceptance, rework and rejection by OEM of an assembled product supplied by Tier I supplier given prior probabilities of acceptance, rework and rejection by Tier I supplier of parts supplied by multiple Tier II suppliers. In turn, conditional probabilities for acceptance, warranty and recall of the product in the market can be generated using the probabilities for acceptance, rework and rejection by OEM of the assembled product.

Based on such insights, cost-benefit analysis of stringent in-process control and incoming inspection can be conducted and eventually coordinating contracts between OEM and supplier 3 and between supplier 1, 2 and 3 can be designed.

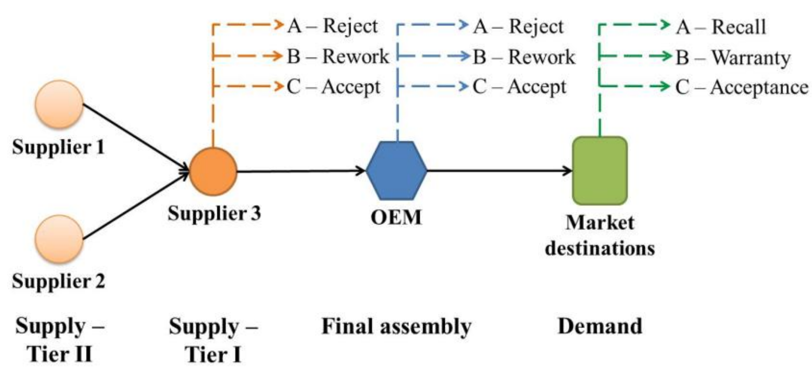

Figure 1: The supply chain structure.

3.2 Simulation

The DES model mimics the supply chain described in Figure 1. The model reproduces the generation of orders of the end product, the generation of orders of components batches at Tier II suppliers according to the Bill-of-Materials, and subsequently the processing and delivery of components, semi-finished products batches at the Tier 1 and OEM (Final assembly) levels. End products are delivered to the market.

The probabilities of OEM incoming inspection and market states presented in Table 1, 2 and 3 are used as input in each relevant stage of the modeled supply chain. The market demand is represented by orders of the end product that are released following an exponential distribution of the interarrival time (mean = 2 days). Processing times at Tier II, Tier I suppliers and OEM are randomly distributed and follow normal probability density functions with different values of the parameters at each supply chain stage (mean = 5-10 min., standard deviation = 0.15-0.6 min.). Reworked components and products undergo a shorter reprocessing time (mean = 2.5-4 min, standard deviation = 0.1-0.25 min.). Components and products are assigned with properties (attributes) related to their quality inspection outcomes according to the a priori probabilities of the BBN. The simulation model combines the components flows so as to dynamically recalculate the actual realization of occurrences of rejection, rework, and acceptance at Tier I supplier and OEM, including the reprocessing flows of components/products to be reworked. Reworked entities again undergo a random labeling process of rejection, rework, and acceptance. The same approach is followed at the market (demand) stage of the supply chain where dedicated flows are devoted to the management of recall, warranty and accepted end products. The simulation length is 360 days. Fifteen replications (95% confidence interval) are carried out for each experiment. The simulation model has been developed following a modular approach where dedicated parts represent the orders generation, the stages of the supply chain including reprocessing or destroying processes of components/products, management of product recalls and warranties, and statistics computation. Dedicated logics have been purposively designed and implemented in order to trace the history of each component and product traversing the supply chain. Therefore, also after assembly processes both semi-finished and finished products keep the data of the various status occurrences and related combinations (e.g., components accepted/reworked at supplier 1 and/or supplier 2, OEM, etc.). This information is then kept and also associated at the final stage of the supply chain for each end product that is recalled or retaken under warranty. Associated statistics are calculated in aggregated and disaggregated forms for all the possible occurrences related to components and product. This data storage, visibility and communication of components/product histories is envisioned to be enabled by devices such as RFId or other technologies within the field of the Cyber-Physical Systems and, more widely, the IoT (Xu, He, and Li 2014; Hermann, Pentek, and Otto 2015). The DES model aims to contribute to the overall estimates of product recall, warranty and acceptance probabilities in the market and acceptance thresholds at the different supply chain stages by dynamically considering more supply chain complexities and random events. Moreover, such simulations can support the assessment of digitized supply-chain projects, their benefits, costs, and limitations (Sarac, Absi, and Dauzere-Peres 2010). The simulation model has been implemented in Simio Version 8.132. A screenshot of the model animation is presented in Figure 2.

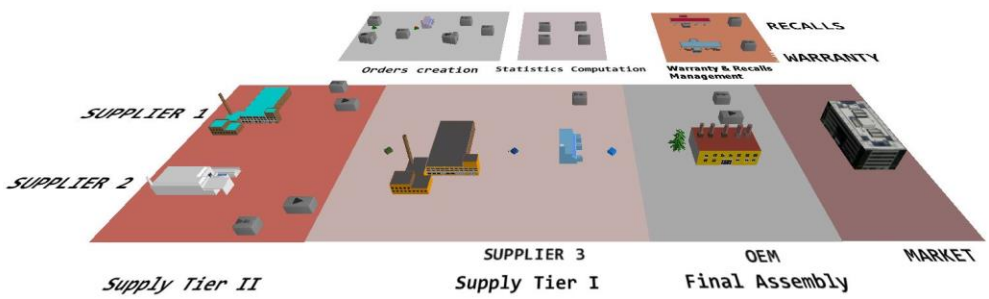

Figure 2: A screenshot of the DES model.

3.3 Modeling and Analysis Framework

The overall modeling and analysis framework is presented in Figure 3, which explains the four steps with related input and output of the methodological approach.

First, a BBN-based group decision model consists of the: (*i*) OEM's decision process to determine the probabilities of acceptance, warranty and recall in the market based on OEM's incoming inspection outcomes; (*ii*) Tier I supplier's decision process to determine probabilities of acceptance, rework and reject by OEM based on Tier I supplier's incoming inspection outcomes of Tier II suppliers' output. BBN is used to generate conditional probabilities of market outcomes based on incoming inspection outcomes at OEM and to generate conditional probabilities of outcomes of incoming inspection by OEM based on outcomes at the Tier I supplier. As explained in Section 3.1, these conditional probabilities are calculated based on pairwise comparisons provided by experts in the respective companies.

Second, simulations of batch productions at Tier II, Tier I suppliers and OEM are carried out. The DES model of the production by the two Tier II suppliers, one Tier I supplier and one OEM to generate incoming inspection outcomes at Tier I supplier and OEM is run. The simulations generate the actual outcomes of the incoming inspection process at the OEM and Tier I supplier by assuming distributions for the production processes taking input from the static calculations of BBN conditional probabilities as reference.

Third, the overall estimation of probabilities of acceptance, warranty and recall in the market based on Tier I supplier's incoming inspection outcomes of Tier II suppliers' output is carried out by combining the output of BBN and DES.

Fourth, a cost-benefit analysis of quality improvement programmes at Tier II suppliers to reduce recall and warranty rates in the market is carried out by relying on information sharing between OEM and

Tier I supplier. Such cost-benefit analysis is used to develop contracts between OEM and Tier I supplier to ensure improvement of quality and minimization of recall risks.

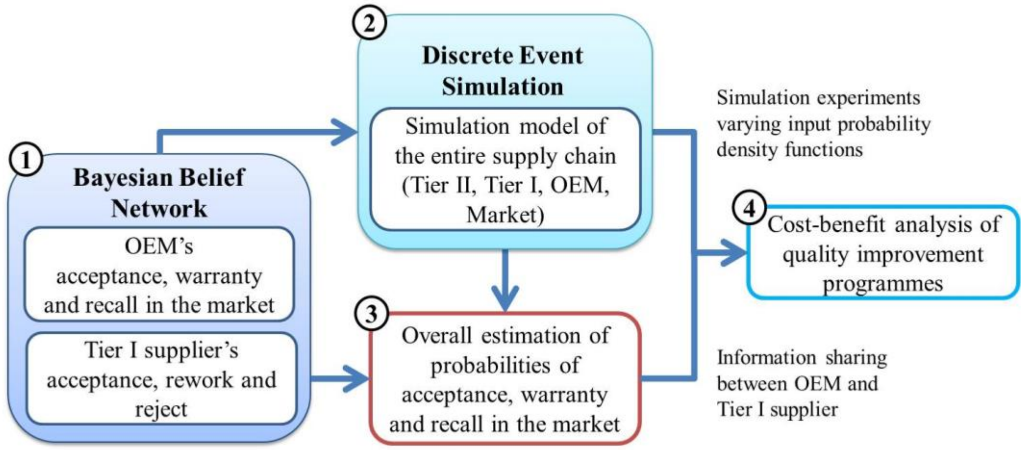

Figure 3: The complete modeling and analysis framework.

4 BAYESIAN BELIEF NETWORK BASED DECISION MAKING PROCESS AT OEM AND TIER I SUPPLIER

4.1 OEM's Decision Process to Estimate Acceptance, Warranty and Recall in the Market

The process involves the determination of prior probabilities for each state S_i, i.e., $P(S_i)$. Traditionally, $P(S_i)$ is specified directly by experts, using their knowledge and experiences. With the increase of states of a node, estimating probabilities directly for all states at a time may create biases and inaccuracies. An alternative way is to perform pair-wise comparisons between states for generating their probabilities. In the context of our problem, an expert in the OEM may provide judgment on, for example, "given that the OEM's incoming inspection process accepts the assembled product supplied by Tier I supplier, how likely is that the finished product will face warranties with respect to being accepted in the market and having no quality problems". This judgment may be expressed as a ratio or percentage. Using the above pairwise comparisons, and by following a process similar to Saaty's Analytical Hierarchy Process (AHP), $P(S_i)$ for each state can be determined and the consistencies of the pairwise comparison matrix ascertained by calculating the consistency ratio CR = CI/RI, where CI is the consistency index, which is defined by $(\lambda_{max}-n)/(n-1)$ (where λ_{max} is the maximum eigenvalue corresponding to the maximum eigenvector $\acute{\omega}$ and n is the size of the comparison matrix). Using this approach, we obtain the prior probabilities of acceptance, warranty and recall of the product in the market for each state, i.e., acceptance, rework and rejection during the first incoming inspection by OEM of the assembled product supplied by Tier I supplier.

It is assumed that the OEM has developed specifications for the components received from the suppliers as well as for the finished product. It undertakes incoming inspection of the parts received from Tier I supplier while the Tier I supplier undertakes incoming inspection of the parts received from Tier II suppliers. The Tier I supplier inspects the parts delivered by the two Tier II suppliers and either accepts, sends for rework or reject them. Parts which are reworked are again delivered and inspected, where they may be accepted, reworked or rejected. A similar process is followed by the OEM for incoming inspection of the subassembly delivered by the Tier I supplier.

It is also assumed that parts from suppliers are accepted when their parameters are within specification limits. Even though such processes are followed, some finished products may fail in the market resulting in recalls while some will have some malfunctions resulting in warranties while the majority of products will perform as per expectation without any quality problems. Such outcomes can happen for multiple reasons. First, incoming inspection is usually carried out using samples and not by inspecting 100 percent of the parts. Though the OEM will create a sampling plan to minimize probability of accepting a part not meeting specifications, there is a finite probability that parts not meeting specifications can be accepted. Second, some parts which are within specification limits may be closer to the limits and may exceed the limits and fail while in use. Third, some parts which are reworked and then accepted may be susceptible to failure in use and finally, some parts may fail due to extreme usage conditions. The OEM is aware of the actual market acceptance without any warranty or recall, warranty without recall, and recall percentages of its product in the market. It also has data from its incoming inspection process. Using those as references, OEM develops a decision model which can link its incoming inspection outcomes to market acceptance, warranty and recall of the product in the market. Such probabilities are shown in Table 1.When the actual proportion of acceptance, rework and rejection by OEM are 0.906, 0.077 and 0.017 respectively, the proportion of acceptances without any quality problems, warranty and recall of the product in the market will be 93.5, 4.7 and 1.8, respectively (e.g., the first calculation is: 0.94×0.906+0.88×0.077+0.87×0.017 = 93.5).

Table 1: Probabilities of market states based on OEM incoming inspection*.

Acceptance of Tier I Supplier Product by OEM	**Market Acceptance**	**Market Warranty**	**Market Recall**	**ώ**
Market Acceptance	1	25	50	0.94
Market Warranty	0.04	1	2.86	0.043
Market Recall	0.02	0.35	1	0.017
	CR=0.0326	CI= 0.0189	λ_{max} =3.037	RI=0.58
Rework of Tier I Supplier Product by OEM	**Market Acceptance**	**Market Warranty**	**Market Recall**	**ώ**
Market Acceptance	1	11.76	28.57	0.88
Market Warranty	0.085	1	3.57	0.087
Market Recall	0.035	0.28	1	0.027
	CR=0.034	CI= 0.0197	λ_{max} =3.039	RI=0.58
Rejection of Tier I Supplier Product by OEM	**Market Acceptance**	**Market Warranty**	**Market Recall**	**ώ**
Market Acceptance	1	10	25	0.87
Market Warranty	0.1	1	3.125	0.094
Market Recall	0.04	0.32	1	0.032
	CR=0.011	CI= 0.006	λ_{max} =3.012	RI=0.58

*CR = Consistency ratio, CI = Consistency index, RI = Random consistency index.

4.2 Tier I Supplier's Decision Process to Estimate Acceptance, Rework and Reject Probabilities by OEM

Similarly, supplier 3 develops a decision model to determine the probabilities of OEM's acceptance, rework and rejection based on its acceptance, rework and rejection of two Tier II suppliers' (supplier 1 and supplier 2) parts. These probabilities are shown in Table 2.

As advocated by Kim and Pearl (1983), when a node *A* in a Bayesian network has two parents, i.e., *B* and *C*, its probability conditional on *B* and *C* can be approximated as follows:

$$P(A/B,C) = \alpha\, P(A/B)\, P(A/C) \tag{1}$$

where α is a normalization factor which is used to ensure that:

$$\sum_{\alpha \in A} P(\alpha/B,C) = 1 \tag{2}$$

The above result can be generalized as follows:

$$P(A/X_1,X_2,\ldots,X_n) = \alpha\, P(A/X_1)\, P(A/X_2)\ldots P(A/X_n) \tag{3}$$

We illustrate using an example of how probabilities of acceptance, rework and rejection by OEM are calculated when parts from supplier 1 and supplier 2 are both accepted by supplier 3:

α = (1/k), where k = P(*OEM acceptance/supplier 1 acceptance*) P(*OEM acceptance/supplier 2 acceptance*) + P(*OEM rework/supplier 1 acceptance*) P(*OEM rework/supplier 2 acceptance*) + P(*OEM rejection/supplier 1 acceptance*) P(*OEM rejection/ supplier 2 acceptance*) = 0.531.

Table 2: Probabilities of OEM incoming inspection states based on Tier I supplier's incoming inspection.

OEM's Incoming Inspection States	**Acceptance of Supplier 1's Parts by Supplier 3**	**Rework of Supplier 1's Parts by Supplier 3**	**Rejection of Supplier 1's Parts by Supplier 3**
Acceptance	0.805	0.556	0.554
Rework	0.152	0.332	0.162
Rejection	0.043	0.112	0.284
OEM's Incoming Inspection States	**Acceptance of Supplier 2's Parts by Supplier 3**	**Rework of Supplier 2's Parts by Supplier 3**	**Rejection of Supplier 2's Parts by Supplier 3**
Acceptance	0.605	0.636	0.663
Rework	0.245	0.295	0.125
Rejection	0.149	0.069	0.212

Table 3 shows all the values of 'k' obtained for the different conditions and the actual proportions of jobs satisfying those conditions. Thus, the probability of acceptance of the product supplied by supplier 3 by OEM when parts supplied by supplier 1 and 2 are both accepted can be calculated as follows: 0.805×0.605×(1/0.531)×0.84 = 0.770. Similarly, the other probabilities can be calculated and the supplier 3 will be able to estimate the probabilities of acceptance, rework and rejection of its product by OEM based on the 9 states shown in Table 3. Note that the actual proportion of parts satisfying the conditions shown in Table 3 (for example, 0.84 is assumed to be the actual proportion of parts when supplier 3 accepts parts from both supplier 1 and supplier 2) are used for illustrative purpose. The actual proportions are determined by simulation explained in the next section. It is important to note here that if the OEM shares its own estimates of conditional probabilities of acceptance, warranty and recall of the end product based on its own incoming inspection outcomes, supplier 3 will also be able to estimate the percentages of acceptance, warranty and recall of the product. This will help supplier 3 to fix minimal thresholds of acceptance for both supplier 1 and supplier 2 which will be needed to minimize or possibly eliminate recall. Based on such insights, cost-benefit analysis of stringent in-process control and incoming inspection can be conducted and eventually coordinating contracts between OEM and supplier 3 and between supplier 1, 2, and 3 can be designed.

Table 3: *k* values and proportions of parts satisfying nine possible conditions.

Conditions	*k*	Proportions of Parts Satisfying the Conditions in a Batch
Parts of supplier 1 and 2 are both accepted by supplier 3	0.531	0.84
Parts of supplier 1 are accepted and supplier 2 are reworked	0.539	0.036
Parts of supplier 1 are accepted and supplier 2 are rejected	0.562	0.019
Parts of supplier 1 are reworked and supplier 2 are accepted	0.435	0.033
Parts of both supplier 1 and supplier 2 are reworked	0.459	0.013
Parts of supplier 1 are reworked and supplier 2 are rejected	0.434	0.009
Parts of supplier 1 are rejected and supplier 2 are accepted	0.417	0.027
Parts of supplier 1 are rejected and supplier 2 are reworked	0.419	0.015
Parts of both supplier 1 and supplier 2 are rejected	0.447	0.008

5 SIMULATION EXPERIMENTS FOR INCOMING INSPECTION AT TIER I SUPPLIER AND OEM

The simulation experiments have been conducted in order to test the combinations of the baseline (base), best and worst scenarios in terms of combined input probabilities of rejection, rework and acceptance at Tier II level for suppliers 1 (S1) and 2 (S2). The base scenario simultaneously combines "base" probabilities of rejection, rework and acceptance for the suppliers 1 and 2 at the supplier 3 stage. The best and worst scenarios simultaneously make use of the "best" probabilities (lower probabilities of rejection and rework) and "worst" probabilities (higher probabilities of rejection and rework), respectively.

Table 4: Computational results of the simulation experiments.

Acceptance Sampling Outcomes at Supplier 3	BASE (S1) - BASE (S2) Cases Average Probabilities	BEST (S1) - BEST (S2) Cases Average Probabilities	WORST (S1) - WORST (S2) Cases Average Probabilities
Accept S1 - Accept S2	0.805	0.922	0.743
Accept S1 - Reject S2	0.032	0.009	0.049
Accept S1 - Rework S2	0.058	0.019	0.058
Reject S1 - Accept S2	0.045	0.014	0.052
Reject S1 - Reject S2	0.002	0.000	0.004
Reject S1 - Rework S1	0.003	0.000	0.004
Rework S1 - Accept S2	0.049	0.034	0.078
Rework S1 - Reject S2	0.002	0.000	0.005
Rework S1 - Rework S2	0.004	0.001	0.006

The results (average probabilities) of these experimental combinations are presented in Table 4. Half width values are equal to 0.001 or lower.

Using the above realization of the simulation results and using its own and OEM's decision model which was virtually shared by the OEM, supplier 3 could estimate the probabilities of acceptance, warranty and recall of the product in the market. Interestingly, the results show that the probabilities of acceptance, warranty and recall of the product in the market remain virtually the same, i.e., 0.935, 0.047 and 0.018 irrespective of scenarios. This shows that the estimation of the performance of the product is dependent to a large extent on OEM's and supplier 3's decision model. This provides insight to the OEM that it needs to update its decision model based on base, best and worst scenarios reported by supplier 3 so that revised estimates of the performance of the product in the market can be generated. Such estimates can be used to develop recall and warranty cost sharing contracts with supplier 3.

6 REVISION OF OEM'S DECISION MODEL FOR DIFFERENT SCENARIOS

Based on the above insight, the OEM updates its decision model for best-best and worst-worst scenarios compared to the earlier base-base scenario. This results in 96.5 percentage for acceptance, 2.9 percent for warranty and 0.6 percent for recall in the best-best scenario and 92.4 percentage for acceptance, 5.4 percent for warranty and 2.2 percent for recall in the worst-worst scenario. Thus, compared to the base-base scenario of 93.5 percent for acceptance, 4.7 percent for warranty and 1.8 percent for recall, warranty percentages drop by 1.8 percent for best-best scenario and increased by 0.7 percent in the worst-worst case. More importantly, recall percentages drop by 1.2 percent in the best-best scenario and increase by 0.4 percent in the worst-worst scenario. Though these estimates are dependent on OEM and supplier 3's expert judgments, these can be used to generate coordinating contracts between the two.

7 COST-BENEFIT ANALYSIS AND QUALITY IMPROVEMENT PROGRAMMES

For the cost benefit analysis, sales volume of 2 million is assumed with warranty costs of 600 USD/unit and recall costs of 5,000 USD/unit. This results in warranty costs of 564,000 USD (0.935×2,000,000×600), 348,000 USD and 648,000 USD, and recall costs of 180 million USD (0.018×2,000,000×5,000), 60 million USD and 220 million USD respectively for base-base, best-best and worst-worst scenarios. Thus, with respect to the base-base case, in the best-best case, the combined savings for OEM and supplier 3 in warranty and recall costs will be 141.6 million USD while loss in the worst-worst case will be 48.4 million USD. In the currently envisioned scenario, the OEM and the supplier 3 do not have any contract to share the savings and losses due to actual batch quality.

Using the proposed approach, if the OEM and the supplier decide to have a 50-50 reward/loss sharing contract, the supplier 3 can potentially save 70.8 million USD (141.6/2) with best quality of parts from suppliers 1 and 2 and lose 24.2 million USD for worst quality of parts from suppliers 1 and 2. Assuming product life of 5 years and a discounting rate of 2 percent, supplier 3's net present value of gains will be 64.12 million USD and 21.9 million USD of losses for best-best and worst-worst scenarios. Thus, suppliers will be encouraged to improve quality and avoid recall and warranty costs using suitable risk and reward sharing contracts which can be designed using the analysis outlined in this paper.

8 DISCUSSION AND CONCLUDING REMARKS

The implementation of our analysis and consequent enforcement of reward and risk sharing contracts will require a digitized supply chain wherein batch quality related information has to be embedded for each batch to avoid any tampering with the results. This will ensure that OEM will have access to supplier 3's incoming inspection results which will be embedded in the product supplied by supplier 3. Thus, at the end of each quarter or each year, OEM and supplier 3 will know what were the quality of the batches and accordingly rewards and losses can be estimated. For example, if 40 percent of batches supplied by supplier 3 have best-best quality, 40 percent have base-base quality and 20 percent have worst-worst quality, OEM can accordingly determine the reward/loss it needs to share with supplier 3. Though such costs may seem to be high, the end result will be a significant improvement of quality and minimization of warranty and recall which have huge cost implications across the supply chain. Without OEM's sharing of its decision model, supplier 3 will not be able to estimate market probabilities of acceptance, warranty and recall. Without such information, supplier 3 will not be able to initiate quality improvement efforts with its suppliers to minimize recall and warranty risks. Similarly, OEM also need to know the outcomes of the incoming inspection process of supplier 3 and embedded batch quality information will ensure that accurate data is available to OEM for every incoming batch. Such cooperation and information sharing will help in designing and enforcing suitable contracts between OEM and supplier 3 providing suitable incentives to supplier 3 to jointly improve quality with its own suppliers.

This research contributes to new analytical approaches for quality management and minimization of recall and warranty risks in supply chains, which are highly relevant due to several critical situations faced by global companies in various sectors in the last years. A digitized supply chain is the key enabler for the proposed approach. Depending on the application sector, digitized production, logistics and distribution chains may confer intelligence to products and enable more proactive approaches for problems detection and communication in the supply chain. Future research can focus on investigating further synergies based on probabilistic models and simulation in the supply chain, and on developing of optimal contracts to minimize recall risks using embedded quality information in products.

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