

Reliability-based Robust Design Optimization of Dynamic Supply Chain Network

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Abstract—Rough oppositions in today's global supply chain have forced business enterprises to focus attention on their supply chains. These issues have guided this research to introduce a qualitative measure to evaluate the reliability of any Supply chain network and develop a novel reliability-based robust design optimization approach to guarantee reliability requirements and minimize uncertainty impacts. A supply chain network design must maintain its efficiency over time while coping with the uncertainty in production and transportation. Analytical models for the determination of the risk involved in a supply chain network design are difficult to derive when uncertainty impacts are integrated. In this paper, a model of evaluating SCN is detailed first. Then, the methodology for the Reliability-based robust design optimization approach is provided. A case study is performed to demonstrate the effectiveness of the proposed Reliability measure and the developed Reliability-based robust design optimization model. Results from the case study have shown that by implementing the developed optimization approach, a SCN is able to achieve a 90% of required reliability while minimizing uncertainty impact.

Keywords— *Supply Chain Network, Reliability Measure, Optimization*

I. INTRODUCTION

The development of global manufacturing centers has increased the need for efficient and reliable Supply Chain Networks (SCN's). Several parameters have been used to quantify the efficiency of a SCN, such as cost of delivery, ability to meet due dates and damages during shipping, which can be considered as important factors for SCN efficiency improvement. Studies have also been reported in the literature to develop the most efficient distribution network for a SCN [1- 3], which focuses mostly on minimizing distance and identifying best distribution routes. Chabrier developed a solution strategy for the Vehicle Routing Problem (VRP) with elementary shortest path based column generations to find a set of routes that cover all nodes with minimum traveling distances [4]. Bräysy and Gendreau also proposed a meta-heuristic algorithm to solve VRP with Time Windows that aims to identify the least costly routes from one depot to others [5]. In [6] Azad and Davoudpour compared Tabu search algorithm and simulated annealing for minimizing total expected costs while considering fixed cost to open distribution centers, transportation cost from distribution centers to customers, and expected cost due to disruption situations. Wen-sheng and Li developed a model of lead-time-contingent pricing model that illustrates how product price is sensitive to delivery time [7]. The study showed that product cost decreases when scheduled delivery time increases, indicating that it is vital to keep the availability of products on time. However, in their research they considered disruptions in the location and the capacity while opening new distribution centers, but did not consider the cause of disruption and how the impact of disruptions can be minimized.

Research in supply chain have also focused on effectively dealing with natural disasters such as tsunami and earthquakes [8, 9]. In [10], researchers introduced a value-at-risk (VaR) model to measure the risk of supply chain disruptions caused by natural disaster events. Jabbarzadeh, Jalali Naini, Davoudpour, and Azad introduced a mixed-integer nonlinear programming has been formulated based on risk disruption at facilities to maximize total profit, wherein the facilities can be disrupted by natural disaster, machine breakdowns, terrorism, and wars [11]. The probability of occurrence of natural disaster events are low, as a result of which, their cost implication cannot be fully understood. In SCN structure, most of the reported studies have focused on a single factory or production network that supplies products to multiple retailers. The upstream SCN in which several manufacturers, either in parallel or in series, supply to a final manufacturer poses a different set of constraints and issues. A complex upstream manufacturing SCN

is shown in Figure 1, where P represents factories, R represent routes, I represent entities, J represents the levels number in the network.

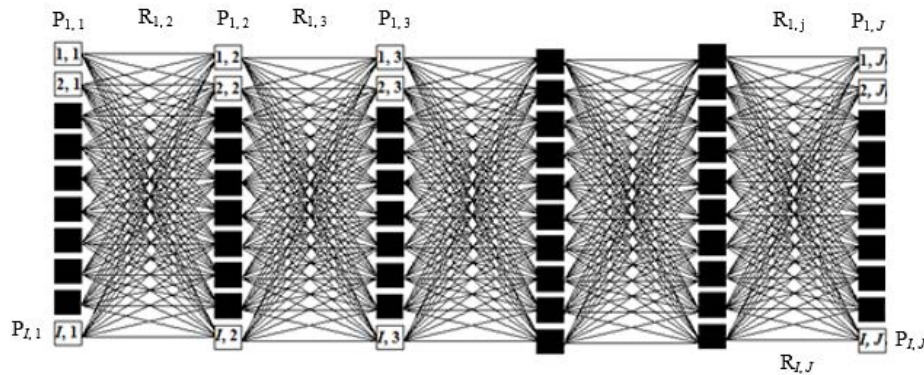


Fig. 1. Complex Upstream SCN

In the route determination problem, the performance of one route can be determined by performance parameters such as cost of distribution and distance traveled. The focus of this paper is to develop a generic measure that able to evaluate entities and overall network reliability rate and then the allocation of optimal reliability rates between suppliers and transportation to ensure overall SCN Reliability. For optimal planning of final product delivery, it is important to achieve a desired reliability rate while maintaining uncertainty impacts of the supply chain. Our contributions in this research is the development of Reliability Rate and a Design Optimization approach that will help to identify the entities (such as factory and/or route) that should be improved in order to satisfy the overall SCN reliability rate requirements while considering uncertainty. The remainder of this paper is organized as follows. Section two introduces a novel SCN reliability measure. Section three illustrates a new optimization algorithm that is able to design in such a way that the entities reliability rate will allow the overall network reliability rate to be achieved while minimizing uncertainty impact. Then, a case study is performed to illustrate the effectiveness of the proposed methodology. Lastly, the paper ends with a brief conclusion and some suggestions for future work.

II. MODEL FOR EVALUATING RELIABILITY OF SCN

In this section, the developed supply chain network reliability measure is explained. Consider the case of a company that manufactures different types of products and purchases its parts from a supplier that could be another manufacturing plant. Supplier S_i can supply up to x number of the demand p for factory F_i (Figure 2) to produce product z . Supplier S_i spends t_i time to produce x number of the demand p for factory F_i . And factory F_i spends time t_i to complete the production of the required product z , where the company spends a total of T_i time to produce product z . Also, the company must manufacture the product z by the due date T^T .

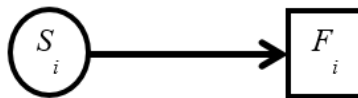


Fig. 2. Typical upstream supply chain network

This interaction between the supplier and the factory can be expressed mathematically as $x = p$, where the output x of supplier S_i must be equal to the quantity p that factory F_i ordered to produce product z . And T_i is the total time that the company spent to manufacture product z . The reliability rate (Ω) can be statistically expressed as the probability of producing product z before the due time (T^T), as shown in equation (1).

$$\Omega = Pr(T_i \leq T^T) \quad (1)$$

Mathematically, the supply chain reliability rate of an entity in the SCN is calculated as shown in equation (2).

$$\Omega_{X(i,j)} = \left(T^T - \left(f_{X(i,j)} \sum_{j=1}^J \sum_{i=1}^I \sigma_{X(i,j)} + f_{X(i,j)} \sum_{j=1}^J \sum_{i=1}^I \varepsilon_{X(i,j)} \right) \right) \times \frac{1}{T^T}$$

$$\text{when } T^T \leq \left(f_{X(i,j)} \sum_{j=1}^J \sum_{i=1}^I \sigma_{X(i,j)} + f_{X(i,j)} \sum_{j=1}^J \sum_{i=1}^I \varepsilon_{X(i,j)} \right), \Omega_{X(i,j)} = 0 \quad (2)$$

where

$$\varepsilon_{X(i,j)} = \begin{cases} \text{if } f_{\mu_{X(i,j-1)}} > f_{\mu_{X(i,j)}}, & f_{\mu_{X(i,j-1)}} - f_{\mu_{X(i,j)}} \\ 0 & \text{otherwise} \end{cases}$$

where $\Omega_{X(i,j)}$ represents the reliability rate of entity type X number i in level number j to complete the required job, T^T represents the due time, and $\sigma_{X(i,j)}$ is the standard deviation (uncertainty) of entity distribution functions for type X number i in level number j . Refrance [12] provides an example that shows how the convolutions of two distribution functions can be calculated, where $\varepsilon_{X(i,j)}$ is the delay waiting time that type X number i in level number j spent waiting for products from a previous entity type X number i at level number $j-1$, and $\mu_{X(i,j)}$ is the mean time to complete a required job at entity type X number i in level number j . When the sum of the delay ($\varepsilon_{X(i,j)}$) and uncertainty ($\sigma_{X(i,j)}$) are longer than the due time (T^T), the reliability rate ($\Omega_{X(i,j)}$) is equal zero, where X represents the type of entity, which can be either the route (R), factory (F), or supplier (S), i represents the entity number, and j represents the level number.

III. RELIABILITY-BASED ROBUST DESIGN OPTIMIZATION OF SCN

It is well known that traditional deterministic optimization has been successfully applied to many engineering designs in order to systematically enhance system quality and reduce life-cycle cost [13]. However, variation and variability in manufacturing processes, material properties, system performance quality, and cost are acquired because of uncertainties. The existence of uncertainty in engineering system and design is initiated by the nature and complexity of processes, which raise the need for robust design optimization (RDO) in order to reduce system cost, control quality, and reduce the impact of associated uncertainty. RDO outperforms existing deterministic discrete optimization tools when dynamic conditions or uncertainty is involved in optimization problems.

RDO is a cost-efficient optimization technique used to minimize the functional variation of a system without eliminating the sources of variation. A robustness technique was first introduced by Taguchi [14 -16]. The Taguchi technique helps to find a robust solution that is less sensitive to unknown variations. In general, RDO can be categorized into three approaches [17]: Taguchi's experimental design [18], optimization procedures based on the Taylor series expansion, and a robust design technique based on response surface methodology [19, 20]. The main goals of all RDO approaches are to reduce the impact of performance uncertainties (variance) about the mean values without eliminating the cause of uncertainties in order to satisfy performance targets, as shown in Figure 3. The objective function of RDO comes from Taguchi's definition of robust design, which minimizes variation around the mean and is constrained by the required quality or performance function.

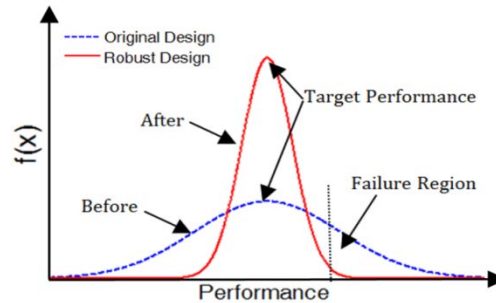


Fig. 3. Robust design optimization concept

Recently, robust design optimization has been widely applied to many engineering problems. For example, Kang and Bai in [21] investigated RDO of truss structures with uncertain-but-bounded parameters and loads. Researchers in [22] designed a robust configuration for a cross-docking distribution center to minimize uncertainties due to disturbances of supply. Reference [23] considered a robust concept in designing a robust servo system of a hard disk drive. Researchers in [24] applied RDO to optimize vibrational characteristics and weights of optical structures of aircraft. In [25], RDO is used to produce new retroaldolase catalysts from a large variety of scaffolds. RDO is also applied to optimize supercritical carbon dioxide anti-solvent process for the preparation of 2,4,6,8,10,12-hexanitro-2,4,6,8,10,12-hexaazaisowurtzitane nanoparticles [26].

Numerous studies in SCN have aimed to reduce uncertainty in order to improve SCN robustness. For example, reference [27] addressed the problem of socially responsible supply chain network design under uncertain conditions. Pan and Nagi presented a robust SC design under uncertain demand in agile manufacturing [28]. a study in increasing SC robustness through process flexibility and strategic inventory is presented in [29]. Paper in [30] modeled a SCN under interval data uncertainty for perishable goods in agile manufacturing. A robust optimization model for agile and build-to-order SC planning is developed in [31]. Amin and Zhang proposed a three-stage model for a closed-loop SC configuration under uncertainty [32].

From the literature, it is clear that there is an urgent need to study the interaction between a connected facilities of an upstream SCN and its impact on the overall SCN performance. Thus, the main goal of using RDO is to design a SCN with inherent robustness. A robust SCN can be obtained by implementing RDO and considering all entities and activity.

The main aim of this paper is to develop an optimization algorithm that help to design a reliable supply chain network with inherent robustness. The developed Reliability-based Robust Design Optimization model is shown in equation (3). The objective function of this optimization algorithm is to minimize delay and variability between network entities. While constraints are required, reliability rates of each entity and overall network. In this research, objective function components are considered to be equally important. However, in different cases, different weightings can be assigned to each of the objective function components. Many research studies have emphasized that multiple objectives can be combined into a single objective function by adding the weighted sum of all [33 - 36]. The weight can be assigned based on the importance of the component on the objective function. More details on determining the optimal weights in multiple objective function optimization can be found in the work of [37].

Minimize

$$\omega_1 * \sum_{j=1}^J \sum_{i=1}^I \sigma_{X(i,j)} + \omega_2 * \sum_{j=1}^J \sum_{i=1}^I \varepsilon_{X(i,j)}$$

Subject to

$$\begin{aligned} \Omega_{X(i,j)} &\geq \Omega_{X(i,j)}^T \\ f_{\mu_{X(i,j)}}^l &\leq f_{\mu_{X(i,j)}} \leq f_{\mu_{X(i,j)}}^u \\ T^T &\leq \left(\sum_{j=1}^J \sum_{i=1}^I \sigma_{X(i,j)} + \sum_{j=1}^J \sum_{i=1}^I \varepsilon_{X(i,j)} \right), \quad i = 1, 2, \dots, I \\ f_{\mu_{X(i,j)}} &\geq 0, \quad j = 1, 2, \dots, J \\ \sum_{n=1}^N \omega_n &= 1, \quad n = 1, 2, \dots, N \end{aligned} \quad (3)$$

where $\sigma_{X(i,j)}$ represents the standard deviations (delay due to internal uncertainty) of the total cycle time function of entity type X number i in level number j , $\varepsilon_{X(i,j)}$ is the delay function of entity type X number i in level number j (delay due time that entity type X , number i in level number j spent waiting for products from the previous entity type X number i in level number $j-1$), ω_n is the weight attached as per the decision-maker preference, $\Omega_{X(i,j)}$ is the reliability rate function of the i th entity type X on level j , $\Omega_{X(i,j)}^T$ is the target reliability rate value for the i th entity Type X on level j , $\mu_{X(i,j)}$ is the design variable for the mean time to complete the required job at entity type X number i in level number j , $\mu_{X(i,j)}^l$ and $\mu_{X(i,j)}^u$ are the lower and upper limits of the $X(i,j)$ design variable, respectively, T^T represents the network total target cycle time, and X represents the type of entity, which can be route (R), factory (F), or supplier (S).

IV. DESIGN CASE STUDY

This case study, considers the case of a company that operates a complex SCN consisting of connected parallel and series suppliers, factories, distribution center, and retailer. This case study is performed to test the efficacy of developed models for evaluating and optimizing reliability rate of all entities in SCN. This SCN consist of 4 stages for different type of operation which are suppliers' stage, factories' stage, distribution centers' stage, and retailers' stage. And has 5 phases that contains 26 entities. It consist of four suppliers, six factories, one distribution center, one retailer, and 14 routs. The required reliability rate in this case study is 90%.

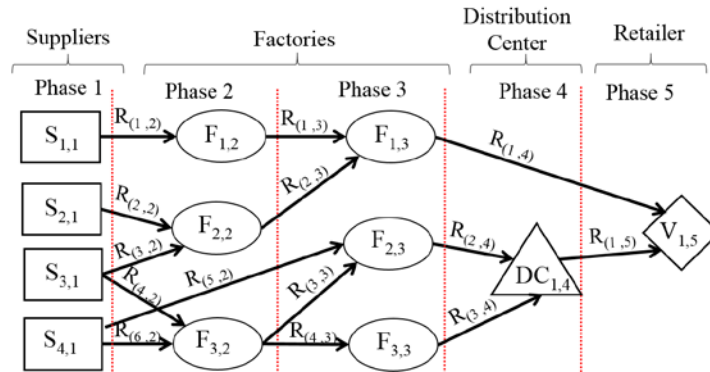


Fig. 4. Case study - complex SCN

The SCN for the company can be divided into four major stages and five phases:

- **Stage 1 (phase 1):** Suppliers of raw materials used in different products.
- **Stage 2:** Consist of two phases. **Phase 2** Factories produce material to be used in producing multiple products, and **phase 3** factories produce final products.
- **Stage 3 (phase 4):** Distribution centers.
- **Stage 4 (phase 5):** Retailer.

Figure 4 represents the case study complex supply chain network, where S_{ij} denotes supplier number i at level number j , F_{ij} denotes factory number i at level number j , DC_{ij} denotes distribution center number i at level number j , V_{ij} denotes retailer number i at level number j , and R_{ij} denotes route number i at level number j . In this SCN it is assumed that factories cannot start the required job until receiving all required parts. For example, factory $F_{1,3}$ will not start until it receives the required parts from factory $F_{1,2}$ and factory $F_{2,2}$. For the purpose of this case study, the collected data (design parameters) were assumed to be normally distributed and their means and standard deviations are shown in Tables 1 – 4. Where Table 1 displays supplier design parameters, Table 2 displays factories design parameters, Table 3 shows distribution center and retailer design parameters, and Table 4 shows routs design parameters. To solve this case study, the SCN was modeled in MATLAB R2013a.

TABLE1. SUPPLIER DESIGN PARAMETERS

SCN Supplier	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Supplier 1 ($S_{1,1}$)	180	22
Supplier 2 ($S_{2,1}$)	300	80
Supplier 3 ($S_{3,1}$)	480	41
Supplier 4 ($S_{4,1}$)	180	60

TABLE 2. FACTORIES DESIGN PARAMETERS

SCN Factories	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Factory 1 ($F_{1,2}$)	120	15
Factory 2 ($F_{2,2}$)	220	30
Factory 3 ($F_{3,2}$)	180	33
Factory 4 ($F_{1,3}$)	280	44
Factory 5 ($F_{2,3}$)	350	56
Factory 6 ($F_{3,3}$)	250	29

TABLE 3. DISTRIBUTION CENTER AND RETAILER DESIGN PARAMETERS

SCN Distribution Center and Retailer	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Distribution Center 1 (DC _{1,4})	180	44
Retailer 1 (V _{1,5})	290	33

TABLE 4. ROUTES DESIGN PARAMETERS

SCN Routes	Mean Time (μ) (hr/batch)	Time Variation (σ) (hr/batch)
Route 1 (R _(1,2))	195	20
Route 2 (R _(2,2))	80	44
Route 3 (R _(3,2))	140	33
Route 4 (R _(4,2))	220	22
Route 5 (R _(5,2))	303	19
Route 6 (R _(6,2))	240	15
Route 7 (R _(1,3))	233	23
Route 8 (R _(2,3))	450	26
Route 9 (R _(3,3))	149	17
Route 10 (R _(4,3))	122	14
Route 11 (R _(1,4))	230	11
Route 12 (R _(2,4))	320	27
Route 13 (R _(3,4))	211	30
Route 14 (R _(1,5))	178	50

First, the SCN mathematical model was implemented in MATLAB to measure the initial network performance using equation (2). Then the developed optimization model equation (3) is applied. Results of this case study are shown in Tables 5 – 10. Table 5 shows suppliers' objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 6 illustrates factories' objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 7 illustrates distribution center and retailer objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 8 illustrates routs' objective optimal mean time, calculated initial reliability rate, and optimal reliability rate. Table 9 illustrates objective optimal reliability rate of SCN phases, initial design reliability rate, initial design delay, and optimal design delay. Table 10 presents objective values obtained at each iteration.

TABLE 5. OBJECTIVE OPTIMAL SUPPLIER RELIABILITY RATE

SCN Supplier	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Supplier 1 (S _{1,1})	245.7292	99.05	98.96
Supplier 2 (S _{2,1})	181.1038	96.68	98.07
Supplier 3 (S _{3,1})	214.6045	98.22	99.05
Supplier 4 (S _{4,1})	209.265	97.32	98.69

TABLE 6. RELIABILITY RATE OF FACTORIES FOR OPTIMAL OBJECTIVES

SCN Factories	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Factory 1 (F _{1,2})	247.5583	95.36	96.89
Factory 2 (F _{2,2})	263.2087	82.83	98.66
Factory 3 (F _{3,2})	197.3271	84.71	96.14
Factory 4 (F _{1,3})	311.0315	74.74	95.59
Factory 5 (F _{2,3})	281.0424	80.92	94.72
Factory 6 (F _{3,3})	227.7399	82.84	92.20

TABLE 7. DISTRIBUTION CENTER AND RETAILER RELIABILITY RATE FOR OPTIMAL OBJECTIVE

SCN Distribution Center and Retailer	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Distribution Center 1 (DC _{1,4})	212.456	73.01	90.84
Retailer 1 (V _{1,5})	265.097	72.17	90.44

TABLE 8. RELIABILITY RATE OF ROUTES FOR OPTIMAL OBJECTIVE

SCN Routes	Optimal Mean Time (μ) (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Route 1 ($R_{(1,2)}$)	319.3426	98.70	98.86
Route 2 ($R_{(2,2)}$)	202.4697	87.14	98.02
Route 3 ($R_{(3,2)}$)	251.581	83.20	99.01
Route 4 ($R_{(4,2)}$)	245.8746	86.85	99.02
Route 5 ($R_{(5,2)}$)	232.8306	97.22	98.66
Route 6 ($R_{(6,2)}$)	257.5559	97.22	98.65
Route 7 ($R_{(1,3)}$)	208.9099	95.06	96.83
Route 8 ($R_{(2,3)}$)	268.7244	82.79	98.66
Route 9 ($R_{(3,3)}$)	299.6555	83.20	96.14
Route 10 ($R_{(4,3)}$)	296.1654	81.95	96.10
Route 11 ($R_{(1,4)}$)	262.0642	72.57	93.81
Route 12 ($R_{(2,4)}$)	267.5808	79.44	94.11
Route 13 ($R_{(3,4)}$)	192.9557	80.29	90.35
Route 14 ($R_{(1,5)}$)	218.1367	72.38	90.77

TABLE 9. RELIABILITY RATE OF SCN PHASES FOR OPTIMAL OBJECTIVE

SCN Phases	Initial Delay (hr/batch)	Design Delay (hr/batch)	Initial Reliability Rate (Ω) (%)	Optimal Reliability Rate (Ω) (%)
Phase 1	76.9171	42.423	96.68	98.07
Phase 2	107.4372	29.4048	82.83	96.89
Phase 3	585.8251	171.7222	74.74	92.20
Phase 4	626.0413	201.6248	73.01	90.84
Phase 5	645.5253	210.4331	72.17	90.44

TABLE 10. OBJECTIVE VALUES OBTAINED AT EACH ITERATION

Iteration	Objective (hr/batch)	Iteration	Objective (hr/batch)	Iteration	Objective (hr/batch)
0	0	7	274.346	14	279.136
1	305.871	8	270.871	15	226.178
2	289.857	9	273.07	16	223.169
3	298.012	10	276.933	17	217.106
4	382.771	11	271.199	18	211.314
5	275.645	12	364.081	19	210.8725
6	275.62	13	274.465	20	210.4331

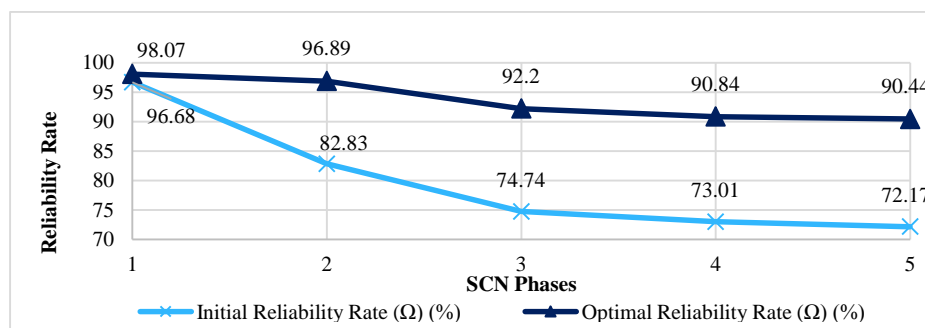


Fig. 5. Reliability rate of all phases

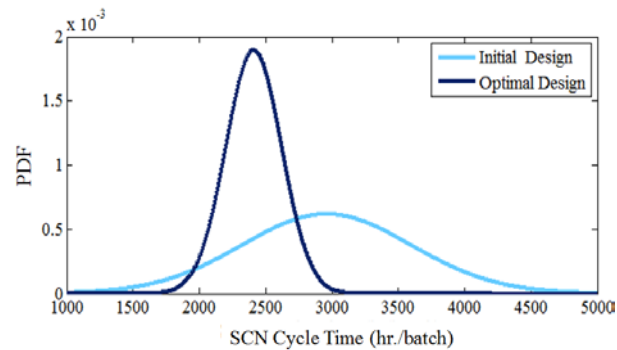


Fig. 6. Distributions of SCN mean cycle time

By applying developed optimization model, the required reliability rate was achieved and delay was minimized. From Table 9, it is clear that SCN delay and uncertainties were decreased from 645.5253 hours per batch in the first initial design to 210.4331 hours per batch in the final iteration in the optimal design. Also, all constraints were satisfied, as shown in Tables 5 – 10, the highest reliability rate for the optimal design is at level one with 99.05%. In contrast, the lowest reliability rate is 90.04% which represents the overall SCN reliability rate.

In Figure 5, it can be easily seen that the reliability rate of the SCN decreases from the first phase to the fifth phase in the network. For example, the reliability rate in the initial SCN design for phase 1 is 96.68%, whereas in phase 2 the reliability rate is decreased by 13.85% to 82.83%. This decrease is caused by uncertainties and different processing and transportation times between entities. The overall reliability rate of the initial SCN design is low (72.17%). In order to reduce total cycle time and satisfy a 90% reliability rate, the developed optimization model is applied.

Figure 6 compares the initial and final probability density functions of the network. By comparing distributions of the mean cycle time of optimal design and initial SCN design, the time variation is significantly reduced because the total delay in the network was reduced by 435.0922 hours. The developed optimization model resulted in a lower mean cycle time where the mean cycle time of the SCN is reduced by 553.3183 hours from 2,965.5253 hours to 2,412.2076 hours. When comparing initial network design and optimal design, it is clear that developed network design has less cycle time and delay, and satisfies the required reliability rate. This optimization helps to determine the entities that should be improved and the level of improvement that should be attained to satisfy the network's reliability rate.

V. CONCLUSION

This paper introduced a novel measure to quantify the reliability of the overall supply chain network and the reliability of each member involved in the network. It also studied the effects of uncertainty and delays introduced by production and transportation on the reliability of the overall SCN. The paper adds more value by introducing an optimization approach to design a reliability rate of each entity in the SCN such that the reliability requirement of the overall SCN is ensured. As more and more companies are involved in outsourcing and building factory supply chains, there is an urgent need to develop the concept of a supply chain network reliability rate for a factory-to-factory SCN. In summary, what has been presented here is a novel Reliability-based Robust design optimization methodology to derive reliability rates of factories and the reliability rates of routes in order to satisfy overall network reliability requirement. As future work, the cost of improving the reliability rate of each entity will be added to the optimization techniques so that the required reliability rate can be satisfied with the lowest cost possible.

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