



Innovative Applications of O.R.

Multi-criteria robust design of a JIT-based cross-docking distribution center for an auto parts supply chain

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ABSTRACT

We present a solution framework based on discrete-event simulation and enhanced robust design technique to address a multi-response optimization problem inherent in logistics management. The objective is to design a robust configuration for a cross-docking distribution center so that the system is insensitive to the disturbances of supply uncertainty, and provides steady parts supply to downstream assembly plants. In the proposed approach, we first construct a simulation model using factorial design and central composite design (CCD), and then identify the models that best describe the relationship between the simulation responses and system factors. We employ the response surface methodology (RSM) to identify factor levels that would maximize system potential.

To make the system immune to factors that could adversely affect performance, we propose a robust design approach by incorporating Latin hypercube sampling and take the noise factors (disturbances) into account. Due to the need of accommodating multiple performance measures and to ensure all responses stay within the desired targets, we adapt Derringer–Suich's desirability function to determine the optimal operating conditions. Finally, we use bootstrapping to compare the results obtained by the classic RSM and the proposed robust design. The proposed model helps the studied auto parts supply chain to develop insights into the system dynamics, and to identify the operating setting that minimize the impact of supply uncertainty on the performance of the cross-docking facility.

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1. Introduction

1.1. Background

This research was motivated by the need of a third-party logistics provider (3PL) to improve its “Just-In-Time” (JIT) operations. The 3PL is a member of an automobile joint venture between a Chinese and a Japanese car manufacturer with 2500 employees and annual output of 240,000 cars. The supply chain of the joint venture stretches for more than 1000 kilometer between parts suppliers (PSs) and the car assembly plant (AP1) located in Wuhan, central China. A cross-docking distribution center (CDDC), operated by the 3PL, is located near the PSs in Guangzhou, south China. Past success and booming prospect suggest that the Chinese car market will continue to grow at a rate of 10–15% over the next decade (Feng et al., 2010). The joint venture is in anticipation of opening another assembly plant (AP2) to meet the demand. The current capacity at the CDDC is deemed insufficient to fulfill the logistics needs should the new AP2 become operational. However, a new CDDC commercial site in a desired location is hard to come by.

Management at the 3PL decides to expand the existing CDDC so as to keep pace with the growth and minimize the coordination and real estate costs. The leading CDDC concern is how to optimize its internal configuration. Management mandates the revamped distribution center operates optimally and robustly so as to reduce supply chain vulnerability while achieving efficiency.

To successfully reconfigure CDDC, the current and future operations must be understood thoroughly. After repeated communication with the executives, the redesign team narrows the performance measurements down to three categories. Specifically, the multi-criteria design goals are: (1) to minimize parts Dwelling Time in the storage area (DT), (2) to minimize the Number of parts staying Exceeding the threshold time (NE), and (3) to maximize the Number of Throughput (NT). Due to the need to convey our recommendation in animation, we adopt simulation as part of our modeling approach. The comprehensive simulation model serves as a test bed for experimenting alternative configurations and allows us to provide visual insights beyond other design techniques. In short, this research proposes a unified framework that designs a robust CDDC to meet the requirements of the JIT supply chain. It optimizes the operating conditions for the CDDC so that the performance metrics: DT, NE and NT, reach desired targets and are immune to the adverse effects of supply risks.

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1.2. Literature review

1.2.1. Cross-docking

Cross docking (CD) is increasingly gaining ground as a logistics technique that rapidly consolidates shipments from suppliers to realize the scale economy of outbound delivery. Conventional distribution center consists of five basic functions: receiving, sorting, storing, retrieving and shipping. By eliminating the need of storing and retrieving, the most expensive logistics functions (Lee and Ho, 2002), cross-docking essentially reduces inventory holding cost and enhances system efficiency.

Forger (1995), Witt (1998), and Gue (1999) discussed the implementation issues of CD in practice. In the planning level, Jayaraman and Ross (2003) and Ross and Jayaraman (2008) tackle the production, inventory, outbound transportation, and single layer CD problem in a supply chain. Sung and Song (2003) address an integrated service network design to determine the location of CDs and to allocate inbound and outbound trucks. Ma et al. (2011) study a cross-docking distribution network to find the trade-offs between transportation cost, inventory and scheduling requirements. In the operational level, most research is concerned with vehicle routing and scheduling. Yu and Egbelu (2008), Boysen et al. (2008), Chen and Lee (2009), and Chen and Song (2009) regard cross-docking as a two-machine flow shop problem which emphasizes continuous flow with minimum cycle time in CD. Boysen and Bock (2011) propose a new method for scheduling CD's part supply from a central storage center. Vahdani and Zandieh (2010) and Konur and Golias (2013) apply meta-heuristic algorithms to schedule trucks in CD. Although CD is commonly employed in auto industry (Kaneko and Nojiri, 2008), none have addressed its operations with robust design to meet the JIT production needs, and none have considered multi-metric performance optimization (see Table 1a). In today's highly competitive environment, performance measures are often of multiple dimensions (Shang and Tadikamalla, 1998; Shang et al., 2004). Management of the 3PL expects the reconfigured CDDC to maximize its potential, balance the DT, NE and NT objectives, and handle disruptive events in supply with minimal loss.

1.2.2. Simulation optimization

Response surface methodology (RSM) is a sequential method which collects statistical and mathematical techniques to improve and optimize responses of interest (Myers et al., 2008). RSM has many real-world applications in a variety of fields. Table 1b surveyed its integration with simulated systems in which RSM serves as a practical optimization tool to seek the optimal factor setting that maximizes the response variable. Among the researchers who employed RSM for simulation optimization, none have examined the CD design (see Table 1b). Unlike Shang et al. (2004) who use the Taguchi method to deal with Environmental Factors (EFs) in supply chain design, we apply a relative new design of experiment method, i.e. Latin Hypercube Sampling (LHS) technique (Dellino et al., 2010, 2012), to obtain the factor combinations for EFs. Although Taguchi method has been widely used in *real-world (physical) experiments* (Sahoo and Sahoo, 2011), LHS is better suited for risk and uncertainty analysis in *simulation experiments* (Kleijnen, 2008; Dellino et al., 2010, 2012). The comparisons between real-world and simulation experiments can be found in (Kleijnen et al., 2005; Wan et al., 2006; Shen and Wan, 2009). Our study is the first in literature to combine the large scale discrete-event simulation model with RSM and LHS methods to address the robust optimization issue. We consider both the decision factors and the environmental factors in the auto supply chain and demonstrate the superiority of our design. We show that the proposed method offers an effective approach to develop a robust system for real-life application.

Overall, the contributions of our manuscript are fourfold: (i) we formulate a novel cross-docking optimization problem that addresses the *practical* need of a real-life 3PL company. The project meets the practical needs of the 3PL company; (ii) we propose a very useful solution procedure, that includes discrete-event simulation and metamodel-based optimization; (iii) we adapt novel techniques – Latin Hypercube Sampling (LHS) and Bootstrapping, to develop an efficient procedure to search for robust solutions. The proposed approach is relatively new in theory (Dellino et al., 2010, 2012), and we are the first to put these methods to business use, in particular to the supply chain setting. In addition, and (iv) we compare the robust solution approach with the classical RSM solution. The robust approach is frequently neglected by practitioners, but it has *gained increasing attention* given today's volatile, complex and competitive business environments.

The remainder of this paper is organized as follows. In Section 2, we propose an integrated multi-criteria robust design optimization framework. Section 3 develops a comprehensive CDDC simulation model, while Section 4 rationalizes the chosen factors and response measures. The classic design and the proposed robust design are contrasted in Section 5. Section 6 concludes this research and provides future research directions.

2. A multi-criteria robust design for cross docking distribution center

2.1. The proposed framework

We propose a hybrid model that aims to build an agile and resilient system (see outlines in columns 2–3 in Fig. 1), which differs from the classic response surface methodology (see column 1 in Fig. 1). A simulation model is first developed to emulate the supply chain and to estimate the impact of diverse operating conditions on the performance of DT, NE and NT. As simulation itself does not prescribe optimal solutions, an optimization technique is needed to attain the best performance (Nelson, 2004). Metamodels are capable of describing the underlying relations (Kleijnen, 2005; Barton and Meckesheimer, 2006) by establishing the relationship between the independent variables and the simulation outputs. They are subsequently explored by optimization techniques to derive the best system outcome.

Factors that influence the performance of a system can be divided into two types: decision factors (DFs) and environmental factors (EFs). DFs are controllable variables, denoted as d_i , whereas EFs are uncontrollable variables (noises), denoted as e_i . Although EFs are uncontrollable in the real-world, they are estimated and approximately controlled for experimental purpose. The objective is to apply the robust design concept to identify the optimal setting of DFs that maximize the system performance while minimizing the variability transmitted from EFs (the disturbing factors). The robust design concept was pioneered by Taguchi (1987), who believe the 'robustness' can be achieved by reducing variation in design. He divided robust design process into three stages. (1) System design: applying the engineering principles to create a prototype; (2) parameter design: uncovering the settings for the product/process parameters to minimize variation and tolerances; and (3) set tolerances on the control parameters to minimize the loss. Borrowing the structure of Taguchi (1987), our robust design for CDDC incorporates simulation for system design, and employs both DFs and EFs in a model for parameter design. This differs from the classic RSM, which only focuses on DFs.

Montgomery (2007) showed that Taguchi method is inefficient and in many cases ineffective. To avoid the weakness of the Taguchi

Table 1
Literature review.

Cross-docking literature	Research perspective	Multiple objectives	Risk factors	Modeling method	Problem complexity	Research type
<i>(a) Comparison of literature on cross-docking research</i>						
Jayaraman and Ross (2003)	Only external CDDC operation. The CDDC is a simple node in SC	No	No	Mathematical Programming	NP-Complete	Theoretical study
Sung and Song (2003)	–	No	No	–	–	–
Ross and Jayaraman (2008)	–	No	No	–	–	–
Ma et al. (2011)	–	No	No	–	–	–
Yu and Egbelu (2008)	Only consider internal operation, not external one	No	No	–	NP hard	–
Boysen et al. (2008)	–	No	No	–	–	–
Chen and Lee (2009)	–	No	No	–	–	–
Chen and Song (2009)	–	No	No	–	–	–
Vahdani and Zandieh (2010)	–	No	No	–	–	–
Boysen and Bock (2011)	–	No	No	–	–	–
Konur and Golias (2013)	–	No	Yes	–	–	–
This paper	Consider both internal and external operations	Yes	Yes, supply risks	Multicriteria Optimization; Simulation	Simulation model; Large-scale; Realistic problem	Case study with empirical data.
Simulation optimization literature	System type	Multiple responses	Robust optimization	Optimization method	Model validation	Optimum comparison
<i>(b) Comparison of literature on simulation optimization research</i>						
Shang and Tadikamalla (1993)	Manufacturing system	No	No	RSM	ANOVA	Not applicable
Shang (1995)	Manufacturing system	No	Yes	Taguchi; RSM	MO & SO	Not applicable
Shang and Tadikamalla (1998)	Manufacturing system	Yes	Yes	Taguchi; RSM	MO & SO	Not applicable
Kenne and Gharbi (1999)	Manufacturing system	No	No	RSM	MO & SO	Not applicable
Chan and Spedding (2001)	Manufacturing system	Yes	No	RSM; Neural Network	MO & SO	Algorithm comparison
Irizarry et al. (2001a)	Manufacturing system	No	No	RSM	MO & SO	MO & OO
Irizarry et al. (2001b)						
Tsai (2002)	Manufacturing system	No	No	Taguchi	Not applicable	Not applicable
Shang et al. (2004)	Supply chain	Yes	Yes	Taguchi; RSM	ANOVA	Not applicable
Durieux and Pierreval (2004)	Manufacturing system	No	No	Not applicable	MO & SO	Not applicable
Noguera and Watson (2006)	Manufacturing system	No	No	RSM	ANOVA	MO & OO
Kumar and Nottestad (2006)	Manufacturing system	Yes	No	RSM	ANOVA	MO & OO
Reis dos Santos and Porta Nova (2006)	Repair center	No	No	RSM	Rao's test; double cross-validation	Not applicable
Lavoie et al. (2007)	Manufacturing system	No	No	RSM	Graphic; MO & SO	Not applicable
Longo and Mirabelli (2008)	Supply chain	Yes	No	RSM	Graphic; ANOVA	Not applicable
Yalçınkaya and Mirac Bayhan (2009)	Metro line	Yes	No	RSM	ANOVA; MO & SO	MO & OO
Shukla et al. (2010)	Supply chain	Yes	No	Taguchi; Psychoclonal algorithm	MO & SO	Algorithm comparison
This paper	Cross-docking	Yes	Yes	LHS; RSM	ANOVA; MO & SO (Bootstrapping)	Robust & RSM optimum.

Note: “–” Indicates same as above.

Note: “MO”: “model optimum”; “OO”: “original outputs”; and “SO”: “simulated outputs under optimal inputs setting”.

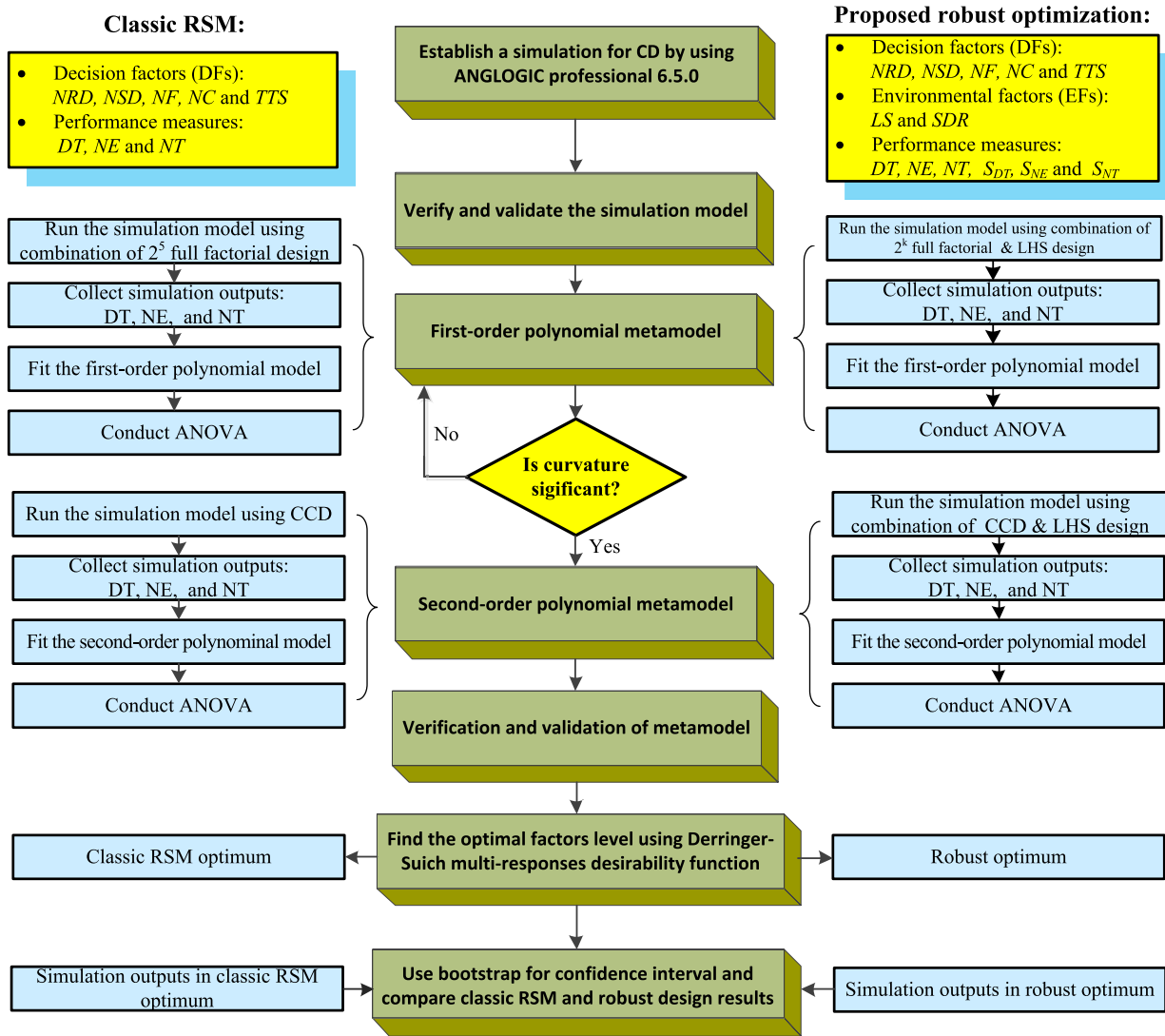


Fig. 1. Logic flow of the proposed model.

chi method, we generate combinations of EFs through Latin Hypercube Sampling (LHS). LHS can create a near orthogonal design (Jin et al., 2005; Kleijnen, 2008). Because the uncontrollable factors involved in our study follow specific probability distributions (see Table 3), rather than the two values (high and low) often seen in Taguchi method for real experiments, the LHS is a better sampling method.

2.2. The response surface under robust design

We define a robust first-order response model as:

$$y_l(d, e) = \beta_0 + \sum_{i=1}^k \beta_i d_i + \sum_{i=1}^k \sum_{i' \neq i}^k \beta_{ii'} d_i d_{i'} + \sum_{j=1}^r \gamma_j e_j + \sum_{i=1}^k \sum_{j=1}^r \gamma_{ij} d_i e_j + \varepsilon \quad (1)$$

where $y_l(d, e)$ denotes the responses while $\{d_i\}$ and $\{e_j\}$ stand for DFs and EFs respectively. The coefficients $\beta = (\beta_0, \beta_i, \beta_{ii'})'$ and $\gamma = (\gamma_j, \gamma_{ij})'$ are determined by the least squares method, and ε is the residual with mean of 0 and constant variances.

Similarly, we define a second-order polynomial model as:

$$y_l(d, e) = \beta_0 + \sum_{i=1}^k \beta_i d_i + \sum_{i=1}^k \sum_{i' \neq i}^k \beta_{ii'} d_i d_{i'} + \sum_{i=1}^k \beta_{ii} d_i^2 + \sum_{j=1}^r \gamma_j e_j + \sum_{i=1}^k \sum_{j=1}^r \gamma_{ij} d_i e_j + \varepsilon \quad (2)$$

Eqs. (1) and (2) can be generalized as:

$$y_l(d, e) = f_1(d) + h_1(d, e) + \varepsilon \quad (3)$$

where $f_1(d)$ stands for DFs, while $h_1(d, e)$ corresponds to EFs and their interactions with DFs. The expected covariance for ε is zero. Since the EFs are expressed in coded values, their expected value is zero. We transform (3) to Eqs. (4) and (5):

$$E_1(d, e) = f_1(d) \quad (4)$$

The variance for the response becomes:

$$V_l(d, e) = \sum_{j=1}^r \left[\frac{\partial y(d, e_j)}{\partial e_j} \right]^2 \sigma_j^2 + \sigma_l^2 \quad (5)$$

Because the standard deviation model $S_l(d, e)$ has the same scale as the simulated outputs, DT, NE and NT, we re-write (5) as:

$$S_i(d, e) = \sqrt{\sum_{j=1}^r \left[\frac{\partial y(d, e_j)}{\partial e_j} \right]^2 \sigma_j^2 + \sigma_i^2} \quad (6)$$

To fit the first-order model in Eq. (1), we use a 2^k full factorial design and the LHS to sample EF combinations. LHS, developed for risk analysis, does not assume a specific model, but focuses on the design space of the k -dimensional unit cube defined by the coded simulation inputs (Kleijnen, 2008). If the first-order is unfit, we explore the second-order models by combining central composite design (CCD) with LHS. In general, CCD contains a 2^k factorial (or fractional factorial) with n_F runs (i.e. 2^k full factorial design), 2^k axial runs (k is the number of DFs), and n_C center runs.

To determine the level of DFs that will optimize DT, NE and NT simultaneously, we adapt the multiple responses optimization concept originated by (Derringer and Suich, 1980) and convert each response into a desirability function, g_i , with $0 \leq g_i \leq 1$. If the response y_i meets its target, then $g_i = 1$; if y_i is outside its target, then $g_i = 0$. The optimal set of DFs maximizes the overall desirability, $D = (g_1 * g_2 * \dots * g_l)^{1/l}$ where l is the number of performance metrics. If the goal of a system is to minimize its response y_i , we have

$$g_i = \begin{cases} 1 & y_i < T_i \\ \left[\frac{U_i - y_i}{U_i - T_i} \right]^r & T_i \leq y_i < U_i \\ 0 & y_i \geq U_i \end{cases} \quad (7)$$

When the weight $r = 1$, the desirability function is linear. If $r > 1$, the importance of being close to the target is emphasized, whereas $0 < r < 1$ indicates being close to the target is less important.

The normality assumption holds for large sample size. However, it is often not clear whether the number of simulation is sufficiently large. Even if the average simulation outputs have a constant variance and are independent, the estimated residuals may not be independent and have constant variance (Kleijnen, 2008; Dellino et al., 2010, 2012). In the studied case, our outputs suffer heteroscedasticity. As a result, we apply the bootstrapping method (Kleijnen and Deflandre, 2006) to construct the confidence interval for comparison. Bootstrapping is a computer-based method for estimating properties of an estimator. It measures system characteristics when resampling with replacement from the original observations.

3. The cross-docking distribution center (CDDC)

The main uncontrollable factors (EFs) of the CDDC design come from the upstream supply and our goal is to minimize their impact

on the operations at the downstream assembly plants (APs). To configure the CDDC so as to smooth the operation at APs, we simulate the three-echelon supply chain network which consists of parts suppliers (PSs), a regional CDDC and two APs (see Fig. 2).

The studied automobile supply network has 60 PSs dispersed over Guangdong province. The PSs are responsible for fabricating over 2000 types of auto components and parts. To achieve economies of scale, a regional CDDC is established in the capital of Guangdong. The joint venture, the PSs and the 3PL have signed a tripartite agreement, which authorizes the 3PL to implement the milk-run pickup and carry out JIT. Five milk-run regions are created based on the geographical location of PSs, parts' replenishment frequencies and quantities. Milk-run operates with routine trip involving stops at those suppliers who have received purchase orders.

The supply chain operates as a pull system. When parts reach the reorder point, APs place purchase orders with the CDDC, which then aggregate orders and places the orders with PSs. Typically, completed purchase orders from a given milk-run region will not fill an entire truckload (TL), i.e., they only form a less-than-truckload (LTL). Therefore, parts collected from individual milk-run suppliers are first transferred to the CDDC, in which parts are sorted in line with the APs and then consolidated and loaded onto large trucks for TL delivery.

The JIT practice mandates that APs maintain only 1–2 days on-hand inventory. To ensure smooth operation in the assembly plants even at a supply glitch, the CDDC must continuously supply auto parts to both APs. Currently the main activities of the CDDC is to sort 2000 plus auto parts made by the 60 local suppliers and ship them out within 20 hours of their arrival to DC.

Fig. 2 shows one side of the CDDC receives parts from PSs, while the other side ships parts out to APs. Doors are a primary portal for receiving and sending off parts, and their numbers in both sides are different. Only one truck at a time is permitted to a door. The LTL truck is also named inbound truck (IBT) in CDDC. As soon as an IBT arrives at CDDC, it is guided to an idle door, or waits until a door becomes free. If more than one door is available, the IBT seizes a free door randomly. The queuing discipline for waiting trucks is first-come-first-serve (FCFS). Meanwhile, workers within CDDC are assigned with the task of unloading IBTs. During the unloading process, forklifts, automated truck loading and unloading system may be used depending on the types of parts. Parts are either loaded onto an outbound truck (OBT) directly to form a full load, or placed on temporary storage area first and then sent to OBT later. If any parts stay at the temporary storage area for more than the threshold time (say 20 hours), they are viewed as late and

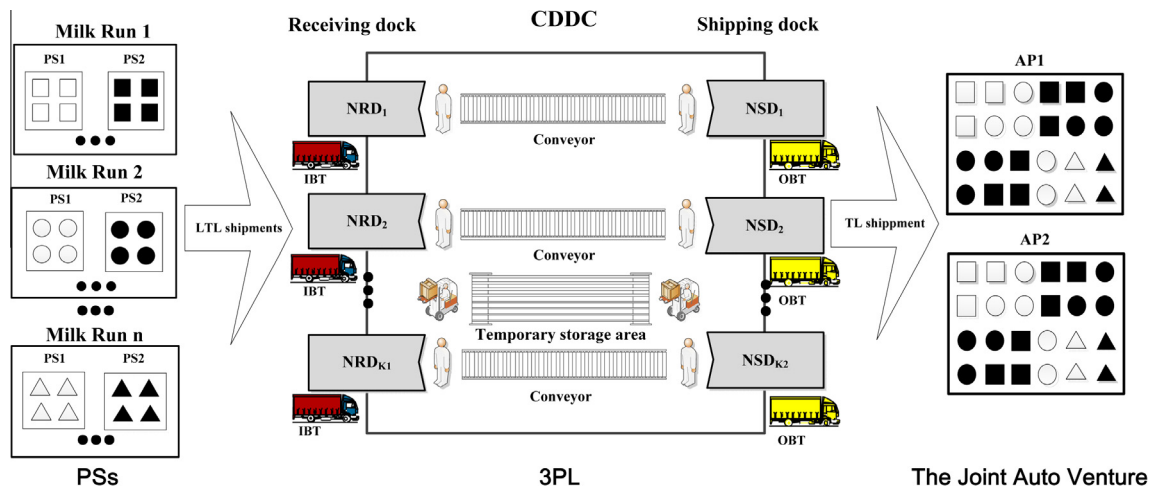


Fig. 2. CDDC supply chain network.

should be sent immediately, often by special delivery arrangement to the corresponding APs.

To simulate this three-echelon supply chain network, we use Anylogic software to support the process-centric modeling paradigm. Through its Enterprise Library, we are able to model the sophisticated system in details, including entities (parts, IBTs, OBTs, pallets), processes (queues, dispatching rules, services, resource utilization), and resources (receiving doors, shipping doors, forklifts, conveyors, operators). Fig. 3 shows the flow of parts and trucks and reflects the 3PL's operations. IBTs are scheduled between milk-run suppliers and CDDC, while OBTs are scheduled between CDDC and plants. Parts begin the trip from a given supplier, unload at a receiving dock, pass through conveyor to the outbound truck or stay in temporary storage area after sorting, then load at a shipping dock and end at an AP.

Randomness in CDDC includes truck arrival times, parts processing times, failure and repair times of scanners, and demand uncertainty at plants. Together, they symbolize the stochastic nature of the CDDC. The data collected from the CDDC system fit the following distributions: (1) The interarrival time between successive LTL is exponentially distributed with mean 0.2 hours. (2) The unloading, sorting and loading times of each part involves labor uncertainty and are found to follow a modified Normal distribution, as $\text{Max}[1, \text{Norm}(2,1)]$ (minutes), $\text{Max}[5, \text{Norm}(10,5)]$ (seconds), and $\text{Max}[1, (3,1)]$ (minutes) respectively. (3) Bar-code scanners may fail due to package orientation or corrupt labels. The time between the scanning device malfunction follows an Exponential distribution with the mean of 8 hours, while the *failure duration* follows a Weibull distribution with shape parameter of 0.6 hour and scale parameter of 0.9 hour. (4) Plants' demands of parts are proportional to their capacity. Currently, AP1's annual production capacity is 240,000 cars, and AP2's is estimated at 360,000, we thus expect 40% parts demand from AP1, while the remainder from AP2.

The DC starts at 08:00 and closes at 24:00. Due to the JIT requisite, the distribution center will dispatch a truck to milk-run at the pre-coordinated pick-up time. Ideally, the lead time for milk-run pickup is 0, i.e. no parts should wait for pickup from suppliers. The initial location for both IBTs and OBTs is the CDDC. IBTs or OBTs leave the CDDC as soon as they are unloaded or loaded. The capacity of an OBT is 40 cubic meters, twice that of an IBT. Workers and machines are needed for unloading and loading the parts. The production cycle of the APs is a month. We follow Sargent (2008) to validate our simulation model. Two engineers from the 3PL have worked closely with the authors throughout the project and verified the model results.

4. The performance metrics and operating conditions

4.1. System performance

The car market in China is a seller's market, in which demand greatly exceeds supply. To maximize their potential to serve the market, auto manufacturers are highly motivated to exploit the supply chain efficiency. Thus, our performance measures are efficiency oriented.

The Dwelling Time, DT, is the average time parts spend at the temporary storage area. Due to JIT requirement, currently parts in our study are not allowed to stay in the DC for more than 20 hours. An extra truck has to be employed to pick up the over-stayed parts. We thus use NE to signify the Number of parts Exceeding the threshold time at the temporary storage area. More NE implies more contingent LTL outbound trucks and extra costs. The Number of Throughput, NT, is also a system measure, which is the sum of the shipments unloaded at the receiving dock and

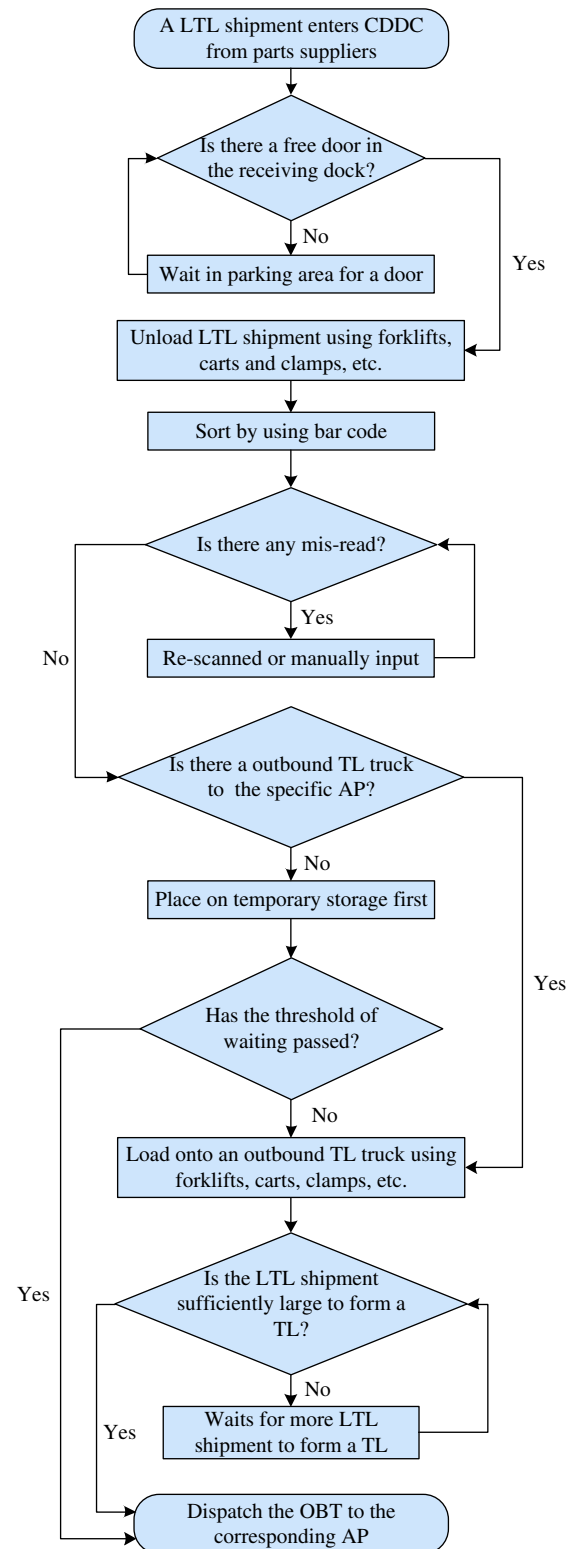


Fig. 3. The flow of parts and trucks, and the operation of the 3PL distribution center.

loaded at the shipping dock within a production cycle (30 days). The minimum shipment volume is specified at 480,000 loads.

The objective is to determine the optimal operating conditions for the CDDC so that DT, NE and NT are as close as possible to their desired targets, while variabilities (S_{DT} , S_{NE} and S_{NT}) of these measures are minimized (see the 3rd column in Table 2).

Table 2

Performance metrics.

Responses of interest	Classic objective	Robust objective
DT (Dwell Time)	[0, 20] h	[0, 20] h
NE (Number Exceeding Threshold Time)	0	Minimum
NT (Number of Throughput)	$\geq 480,000$ loads	$\geq 480,000$ loads
S_{DT}	Not applicable	Minimum
S_{NE}	Not applicable	Minimum
S_{NT}	Not applicable	Minimum

4.2. Controllable decision factors

Five DFs and two EFs affecting the system performances are identified after discussing with management and incorporating the 3PL's experience. The five controllable system factors are:

4.2.1. Number of receiving doors (NRD)

To reduce footprint, doors should be adjacent to each other and equally spaced out while attending to safety concerns (e.g. *back-up collision*). The number of doors is limited by the space of the CDDC (see Table 3). Too few receiving doors causes long queue and lengthen IBTs' waiting time, whereas too many doors (smaller sized doors) congest the receiving dock, increase the crash risk, and decrease throughput.

4.2.2. Number of shipping doors (NSD)

A high-flow CDDC requires multiple doors to provide sufficient "bandwidth" to APs (Bartholdi and Gue, 2004). Lacking shipping doors will force parts to be sent to temporary storage; whereas excessive doors result in low utilization and cause truck collision.

4.2.3. Number of forklifts (NF)

Forklifts are a major warehouse equipment used to lift and transport parts. They are also the most dangerous mobile machinery. The CDDC must be designed to accommodate efficient and safe movement of forklifts by considering their maneuverability. Lacking forklifts increases trucks waiting, whereas excessive forklifts cause injury and damage.

4.2.4. Number of conveyors (NC)

The CDDC has a series of conveyors, which serve as a main mode of parts transfer from receiving door to shipping door. They are much safer but less flexible than forklifts. Too many conveyors promote underutilization and reduce forklifts' maneuver scope, which further increase the risk of the forklifts accident. Likewise, too few conveyors cause gridlock and curtail throughput.

4.2.5. Threshold time allowed to dwell in temporary storage area (TTS)

When parts stay at the warehouse longer than the specified duration, they are sent to the AP through special delivery. Large

TTS allows parts to stay at CDDC longer, which adversely leads to higher DC inventory and fail to realize JIT. Alternatively, small TTS increase LTL shipments to APs, a serious cost concern.

To determine the best setting for DFs that reach the target and minimize the variability in DT, NE and NT performance, we conduct experiments under two types of uncertainties:

4.2.5.1. Load size of LTL shipment (LS). LS is the volume of parts in a LTL shipment. The parts from different milk-run suppliers are often oddly shaped. More accurate account of the LS depends on record precision. However, the vast number of parts makes "exactness" a challenging task. In the "LS" row of Table 3, we assume a complete truck load equals the container's internal dimensions (i.e. the capacity of an IBT is $10 * 2 * 2 = 40$ loads). The actual load size of an IBT follows a normal distribution with a mean of 20 and a standard deviation of 5. The 3PL must wait until the parts reach 5 loads to start the picking-up trip. If the loads reach 40, they are routed directly to the APs since it has formed a truck load (TL).

4.2.5.2. Supply disruption rate (SDR). Although auto industry touts the benefits of maintaining strong relationship with just a few key suppliers, the risk of having limited number of suppliers could outweigh benefits. For example, on May 2011 workers of a gear-box supplier went on strike, which resulted in AP1 a 3-day production disruption. To designate all supply disturbances in one parameter and reflect the collective supply variability, we use Eq. (8) to estimate the mean supply disruption rate:

$$SDR = \left[1 - \frac{\text{Completed orders per month}}{\text{Total orders per month}} \right] \quad (8)$$

We found the system's SDR is normally distributed with mean of $\mu = 0.02$ and $\sigma = 0.012$, i.e. 2% of parts ordered fail to reach the assembly line on time.

5. Experimental design and simulation optimization

5.1. Classic RSM design and model development

Following the logic in the leftmost column of Fig. 1, a 2^k factorial design with central run is first designed to fit first-order regression models. Since ANOVA suggests that the second order polynomial models would fit better, we employ the central composite design (CCD), and replicate the simulation 10 times at each DFs combination. Eqs. (9)–(11) show the models of the simulated responses of DT, NE, and NT:

$$\begin{aligned} \hat{y}_{DT} = & 14.21 + 1.74d_1 + 2.48d_2 + 0.29d_3 + 1.05d_4 + 3.55d_5 \\ & + 2.04d_1d_2 + 0.39d_1d_3 + 0.97d_1d_4 + 0.75d_1d_5 \\ & - 0.11d_2d_3 - 2.00d_2d_4 + 1.92d_2d_5 - 0.11d_3d_4 \\ & - 0.39d_3d_5 + 0.12d_4d_5 - 1.17d_1^2 - 1.23d_2^2 + 0.26d_3^2 \\ & - 1.06d_4^2 - 0.18d_5^2 \end{aligned} \quad (9)$$

$$\begin{aligned} \hat{y}_{NE} = & 64617.61 + 12321.09d_1 + 15187.07d_2 + 455.73d_3 \\ & + 3449.62d_4 - 2130.96d_5 + 10928.69d_1d_2 \\ & - 421.56d_1d_3 - 1980.88d_1d_4 - 595.06d_1d_5 \\ & - 212.69d_2d_3 - 664.87d_2d_4 - 991.06d_2d_5 \\ & + 112.63d_3d_4 - 1612.69d_3d_5 - 2146.87d_4d_5 \\ & - 7243.70d_1^2 - 7271.19d_2^2 - 3057.89d_3^2 - 10638.52d_4^2 \\ & - 4459.73d_5^2 \end{aligned} \quad (10)$$

Table 3

Factors and their associated values.

DFs		Low Actual	Medium	High Actual
Notation	Variables	Level -1	Level 0	Level +1
NRD	d_1	11	16	21
NSD	d_2	12	17	22
NF	d_3	10	15	20
NC	d_4	7	10	13
TTS	d_5	12	18	24
EFs		Distribution		
LS	e_1	Min{40, Max[Norm(20,5), 5]}		
SDR	e_2	Norm(0.02, 0.012)		

$$\begin{aligned}
\hat{y}_{NT} = & 476,600 + 48060.59d_1 + 16715.66d_2 + 27.27d_3 \\
& + 6230.19d_4 - 583.03d_5 + 10509.69d_1d_2 \\
& - 2142.50d_1d_3 + 1.06d_1d_4 + 1518.88d_1d_5 \\
& - 2590.56d_2d_3 - 5021.00d_2d_4 - 8696.06d_2d_5 \\
& - 1152.69d_3d_4 - 3303.62d_3d_5 - 4821.44d_4d_5 \\
& - 20184.74d_1^2 - 6164.05d_2^2 + 8452.28d_3^2 - 2977.65d_4^2 \\
& + 8936.03d_5^2
\end{aligned} \quad (11)$$

For a significance level of 5%, since the coefficients of determination $(R_{DT}^2, R_{NE}^2, R_{NT}^2) = (0.878, 0.965, 0.978)$ and the P -values of lack-of-fit F test for each model are $(0.428, 0.860, 0.978)$, the above models can be used to identify the optimal $\{d_i\}$ setting, so as to achieve the goals established in Table 2 (see the 2nd column). The optimal solutions are obtained by solving the nonlinear constrained problem (NLCP) in:

$$\begin{aligned}
P_{CCDC}(d^*) = & \text{Min}(y_{NE}) \\
\text{Subject to } & \begin{cases} 0 \leq y_{DT} \leq 20 \\ 480,000 \leq y_{NT} \leq \infty \\ L_i \leq d_i \leq U_i \text{ with } i = 1, \dots, 5 \end{cases}
\end{aligned} \quad (12)$$

where $\{d_i\}$ satisfy respective DF constraints set in Table 3, e.g. for NRD, $11 \leq d_1 \leq 21$. In this paper, we use Response Optimizer tool in Design-Expert (version 8.0), which identify the optimum point via a penalty function in a downhill simplex (Nelder–Mead) multi-dimensional pattern search (Press et al., 2007). More solution tools for NLCP can be found in Leyffer and Mahajan (2010). Table 4 summarizes the results of the classic design without taking into account the uncontrollable factors.

5.2. Robust design and model development

In this section we use the robust design technique and allow for consideration of lot size (LS) and supply disruption rate (SDR) when building models. Following the logic in the rightmost column of Fig. 1, we employ full factorial design and 8 replicates at $d = 0$ to sample DFs. For EFs, since they are statistically independent and follow a normal distribution, their joint distribution becomes the product of their marginal distribution. We split LS and SDR into $n_{LHS} = 5$ equal regions. Table 5 shows the five LHS combinations, which in practice are sampled from their joint distribution randomly at five equal probability intervals. Therefore, the total number of runs is the product of n_F (runs of 2^k full factorial design adding central points) and n_{LHS} , i.e. $(2^5 + 8) * 5 = 200$.

At $\alpha = 5\%$, the interaction terms are significant, indicating the response surface may have curves in subregions, which prompt us to fit the second-order models. We use CCD plus LHS to design for the experiment. For EFs, we use the combinations in Table 5. Thus, we augment $10 * 3 * 5 = 150$ (10 axial design

points of DFs, 3 replicates of each design points and 5 combinations of n_{LHS}) axial points to the second-order polynomial model.

The main effects, two-way interactions and quadratic effects are all significant. Hence the second-order polynomial models are significant, in congruence with the ANOVA results, in which $(R_{DT}^2, R_{NE}^2, R_{NT}^2) = (0.953, 0.960, 0.947)$ and the p -values of lack-of-fit F test are $(0.160, 0.528, 0.215)$ for each model. We then apply Eqs. (4) and (5) to derive the mean and variance models for DT, NE and NT:

$$\begin{aligned}
E_{DT} = & 11.43 + 1.20d_1 + 2.04d_2 - 0.17d_3 + 0.78d_4 + 3.30d_5 \\
& - 0.44d_1d_2 + 0.29d_1d_3 - 0.26d_1d_4 + 0.33d_1d_5 \\
& + 0.21d_2d_3 - 0.45d_2d_4 + 0.55d_2d_5 - 0.061d_3d_4 \\
& + 0.062d_3d_5 + 0.35d_4d_5 - 0.63d_1^2 - 1.27d_2^2 - 0.03d_3^2 \\
& - 0.25d_4^2 - 0.11d_5^2
\end{aligned} \quad (13)$$

$$\begin{aligned}
E_{NE} = & 32482.17 + 10256.36d_1 + 9889.72d_2 - 300.42d_3 \\
& + 4379.24d_4 + 52.43d_5 + 5415.96d_1d_2 + 437.38d_1d_3 \\
& + 214.75d_1d_4 + 597.11d_1d_5 - 97.79d_2d_3 \\
& - 1618.36d_2d_4 - 724.67d_2d_5 - 1639.28d_3d_4 \\
& - 1243.25d_3d_5 + 1728.59d_4d_5 - 1188.43d_1^2 \\
& - 1072.35d_2^2 + 226.71d_3^2 - 372.20d_4^2 + 148.91d_5^2
\end{aligned} \quad (14)$$

$$\begin{aligned}
E_{NT} = & 479,700 + 39819.17d_1 + 20253.25d_2 + 41493.43d_3 \\
& + 7339.86d_4 + 339.78d_5 + 7895.49d_1d_2 \\
& + 121.06d_1d_3 + 33.75d_1d_4 - 21.24d_1d_5 + 7.36d_2d_3 \\
& - 649.55d_2d_4 - 1136.31d_2d_5 - 788.40d_3d_4 \\
& - 407.64d_3d_5 + 1101.55d_4d_5 - 34063.49d_1^2 \\
& - 17810.89d_2^2 - 108.13d_3^2 - 10333.23d_4^2 + 1107.72d_5^2
\end{aligned} \quad (15)$$

$$\begin{aligned}
V_{DT} = & 63.37 + 14.04d_1 + 26.32d_2 - 1.62d_3 + 9.13d_4 \\
& + 46.19d_5 + 2.99d_1d_2 - 0.19d_1d_3 + 1.04d_1d_4 \\
& + 5.32d_1d_5 - 0.34d_2d_3 + 2.02d_2d_4 + 6.49d_2d_5 \\
& - 0.12d_3d_4 - 0.611d_3d_5 + 3.46d_4d_5 + 0.82d_1^2 \\
& + 2.90d_2^2 + 0.01d_3^2 + 0.35d_4^2 + 8.77d_5^2
\end{aligned} \quad (16)$$

$$\begin{aligned}
V_{NE} = & (1.49 * 10^9) + (1.03 * 10^9)d_1 + (1.40 * 10^9)d_2 \\
& - (5.79 * 10^7)d_3 + (4.84 * 10^8)d_4 + (4.48 * 10^7)d_5 \\
& + (5.06 * 10^8)d_1d_2 - (2.09 * 10^7)d_1d_3 + (1.75 * 10^8)d_1d_4 \\
& + (1.61 * 10^7)d_1d_5 - (2.85 * 10^7)d_2d_3 + (2.39 * 10^8)d_2d_4 \\
& + (2.26 * 10^7)d_2d_5 - (9.84 * 10^6)d_3d_4 - (9.03 * 10^5)d_3d_5 \\
& + (8.21 * 10^6)d_4d_5 + (1.85 * 10^8)d_1^2 + (1.90 * 10^8)d_2^2 \\
& + (5.90 * 10^5)d_3^2 + (4.16 * 10^7)d_4^2 + (5.35 * 10^5)d_5^2
\end{aligned} \quad (17)$$

$$\begin{aligned}
V_{NT} = & (1.11 * 10^{10}) + (5.04 * 10^9)d_1 + (7.91 * 10^9)d_2 \\
& - (1.96 * 10^8)d_3 + (2.75 * 10^9)d_4 - (3.10 * 10^8)d_5 \\
& + (7.54 * 10^8)d_1d_2 - (2.25 * 10^7)d_1d_3 + (2.67 * 10^8)d_1d_4 \\
& - (2.84 * 10^7)d_1d_5 - (3.94 * 10^7)d_2d_3 + (4.36 * 10^8)d_2d_4 \\
& - (4.49 * 10^7)d_2d_5 - (1.55 * 10^7)d_3d_4 + (1.18 * 10^6)d_3d_5 \\
& - (1.57 * 10^7)d_4d_5 + (2.36 * 10^8)d_1^2 + (6.08 * 10^8)d_2^2 \\
& + (1.10 * 10^6)d_3^2 + (7.93 * 10^7)d_4^2 + (8.70 * 10^5)d_5^2
\end{aligned} \quad (18)$$

Table 4
Optimal DFs setting and responses under the classic RSM design.

Optimal setting	Coded values	Actual values
NRD	1	21 doors
NSD	−1	12 doors
NF	1	20 forklifts
NC	−1	7 conveyors
TTS	1	24 hours
Response variables	Desirability	Results
DT	1	6.34 hours
NE	0.800	14,871 loads
NT	1	486,984 loads

Table 5
LHS value with five combinations of two EFs.

SDRs level	LSs level				
	1	2	3	4	5
1					(26.4433, 0.0087)
2	(10.8959, 0.0167)				
3				(22.8973, 0.0222)	
4			(19.9472, 0.0235)		
5		(18.6327, 0.0488)			

Eqs. (16)–(18) suggest that the estimated V_{DT} , V_{NE} and V_{NT} are *heteroscedastic*, since they vary with $\{d_i\}$. We retain the DFs that have insignificant main effects but have interactions with EFs, i.e. d_3 in V_{DT} , d_3 and d_5 in V_{NE} , because these DFs can be utilized to reduce the variance of outputs.

Based on Eqs. (13)–(18), we proceed to determine the levels of DFs that optimize the responses. Since the goal is to develop a robust CDDC, we include performance variabilities in the objective function. The nonlinear robust optimization problem becomes:

$$P_{CCDC}(d^*) = \arg \max D_{CCDC}[g(E_{NE}) * g(S_{DT}) * g(S_{NE}) * g(S_{NT})]^{1/4}$$

$$\text{Subject to } \begin{cases} 0 \leq E_{DT} \leq 20 \\ 480,000 \leq E_{NT} \leq \infty \\ L_i \leq d_i \leq U_i \text{ with } i = 1, \dots, 5. \end{cases} \quad (19)$$

In Eq. (19), we maximize the composite desirability D , while ensuring E_{DT} and E_{NT} stay within targets. After discussing with 3PL management, we set the upper limit of E_{NE} at 50,000, which is nearly twice of the current level due to the addition of AP2. For the S_{DT} , S_{NE} , and S_{NT} , based on historical data we set limits at 8 hours, 20,000 units and 100,000 units, respectively. Any value better than the target is an improvement and is welcome, otherwise unacceptable. The individual desirability functions are established as follows.

For E_{NE} :

$$g(E_{NE}) = \begin{cases} 1 & E_{NE} < 20,000 \\ \frac{50,000 - E_{NE}}{30,000} & 20,000 \leq E_{NE} \\ 0 & E_{NE} \geq 50,000 \end{cases} \quad (20)$$

For S_{DT} :

$$g(S_{DT}) = \begin{cases} 1 & S_{DT} < 2 \\ \frac{8 - S_{DT}}{6} & 2 \leq S_{DT} < 8 \\ 0 & S_{DT} \geq 8 \end{cases} \quad (21)$$

For S_{NE} :

$$g(S_{NE}) = \begin{cases} 1 & S_{NE} < 10,000 \\ \frac{20,000 - S_{NE}}{10,000} & 10,000 \leq S_{NE} < 20,000 \\ 0 & S_{NE} \geq 20,000 \end{cases} \quad (22)$$

For S_{NT} :

$$g(S_{NT}) = \begin{cases} 1 & S_{NT} < 40,000 \\ \frac{100,000 - S_{NT}}{60,000} & 40,000 \leq S_{NT} < 100,000 \\ 0 & S_{NT} \geq 100,000 \end{cases} \quad (23)$$

The optimal parameter settings, including coded and natural values, are summarized in Table 6, along with the resulting desirability values and system performance measures. In Fig. 4, the predicted desirability level of “0.9055” in the 3D surface plot along the number of the receiving doors (NRD) and number of the shipping doors (NSD)-axes reflects the position that maximize overall desirability (D). Compared with the desirability score of the Classic RSM

Table 6
Optimal DFs setting and responses under robust design.

Factors	Coded values	Actual values
NRD	0	16 doors
NSD	−1	12 doors
NF	1	20 forklifts
NC	−0.499	9 conveyors
TTS	−1	12 hours
Response variables	Desirability	Results
E_{DT}	1	4.3775 hours
E_{NE}	0.9751	20,747 loads
E_{NT}	1	480,002 loads
S_{DT}	0.9098	2.5690 hours
S_{NE}	0.9613	10,832 loads
S_{NT}	0.7882	52,705 loads

(see Table 4), the proposed robust design not only offers a higher overall desirability score but also accounts for system variability to ensure robust performance.

5.3. Performance comparison based on bootstrapped confidence intervals

Confidence intervals are often more satisfactory for statistical inference than hypothesis tests. We use a bootstrap resampling method to derive confidence intervals for performance mean. Bootstrapping gives valid statistical results even if the normality assumption does not hold (Kleijnen and Deflandre, 2006). We use it to construct confidence intervals for the two design methods discussed above, and to check the validity of the models developed. Different pseudorandom number (PRN) streams are used to generate IID samples. This IID assumption is essential for bootstrap techniques; see Efron and Tibshirani (1993, pp. 170–173), Deflandre and Kleijnen (2002), and Kleijnen and Deflandre (2006). The bootstrapping procedures are as follows:

- Using the optimal DF settings given in Tables 4 and 6, we made 100 simulation runs to obtain an original sample of observations $(DT_1, DT_2, \dots, DT_{100})^T$, $(NE_1, NE_2, \dots, NE_{100})^T$ and $(NT_1, NT_2, \dots, NT_{100})^T$.
- From the original sample, we generate a random sample of 100 observations with replacement, denoted by $(DT_1^*, DT_2^*, \dots, DT_{100}^*)^T$, $(NE_1^*, NE_2^*, \dots, NE_{100}^*)^T$, and $(NT_1^*, NT_2^*, \dots, NT_{100}^*)^T$, where the superscript “*” refers to the bootstrapped version of the corresponding ‘original’ data. This bootstrap sample gives the bootstrap estimates \overline{DT}^* , \overline{NE}^* and \overline{NT}^* , and $\overline{s(DT)}^*$, $\overline{s(NE)}^*$ and $\overline{s(NT)}^*$, e.g., $\overline{DT}^* = \sum_{j=1}^{100} DT_j^* / 100$, $\overline{s(DT)}^* = \sqrt{\sum_{j=1}^{100} (DT_j^* - \overline{DT}^*)^2 / 99}$.
- We then replicate this procedure for 1000 times and calculate the means $(\overline{DT}_{(1)}^*, \overline{DT}_{(2)}^*, \dots, \overline{DT}_{(1000)}^*)^T$, $(\overline{NE}_{(1)}^*, \overline{NE}_{(2)}^*, \dots, \overline{NE}_{(1000)}^*)^T$ and $(\overline{NT}_{(1)}^*, \overline{NT}_{(2)}^*, \dots, \overline{NT}_{(1000)}^*)^T$ and the standard deviations $(s(DT_{(1)}^*), s(DT_{(2)}^*), \dots, s(DT_{(1000)}^*))^T$, $(s(NE_{(1)}^*), s(NE_{(2)}^*), \dots,$

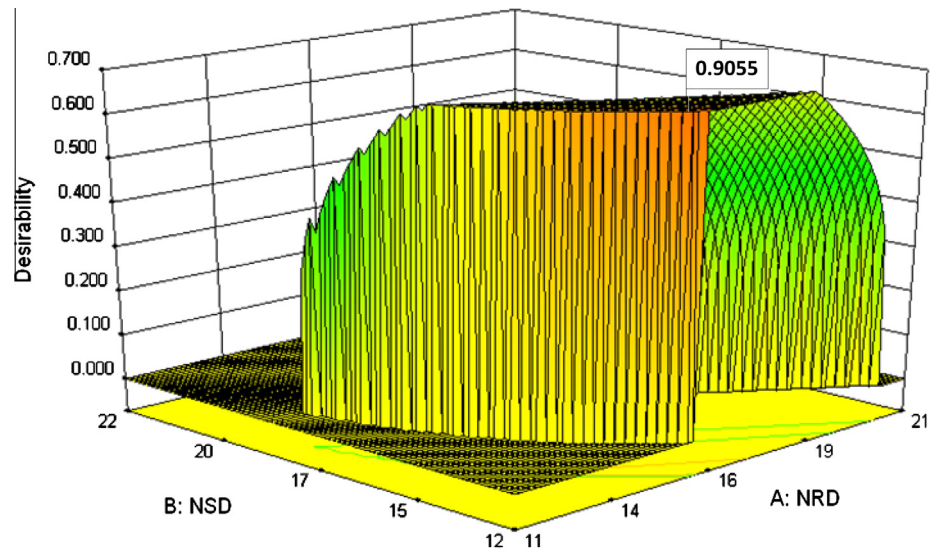


Fig. 4. The 3D plot of NRD, NSD and the composite desirability.

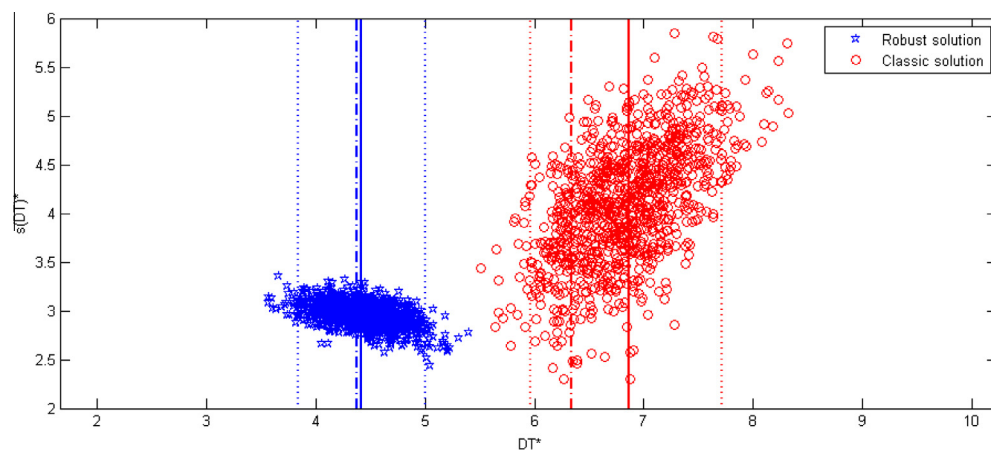


Fig. 5. The model prediction, bootstrap estimated DT, and original estimate. *Note:* The simulation outputs in the optimal settings: the solid vertical lines. The model prediction: the dash-dotted lines. The bootstrapped confidence intervals: intervals of the dotted lines (same color). The bootstrap estimated value: all of the points. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

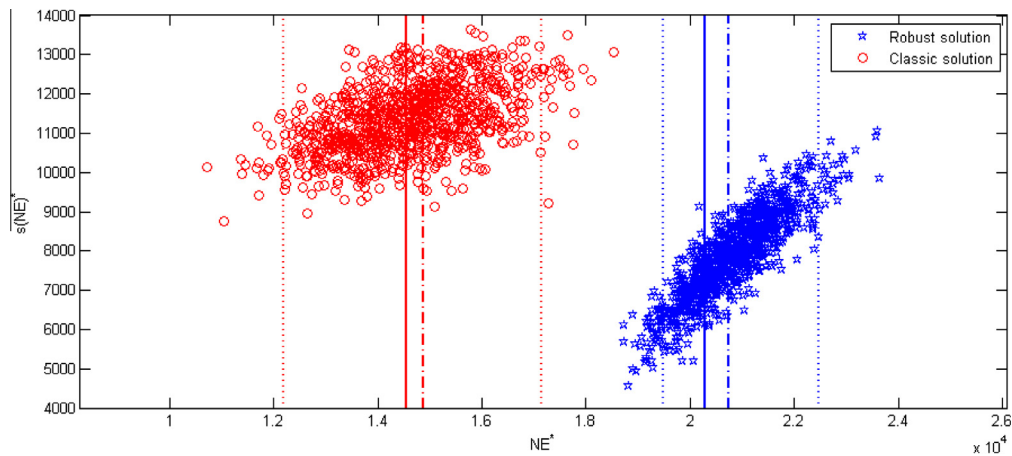


Fig. 6. The model prediction, bootstrap estimated NE, and original estimate.

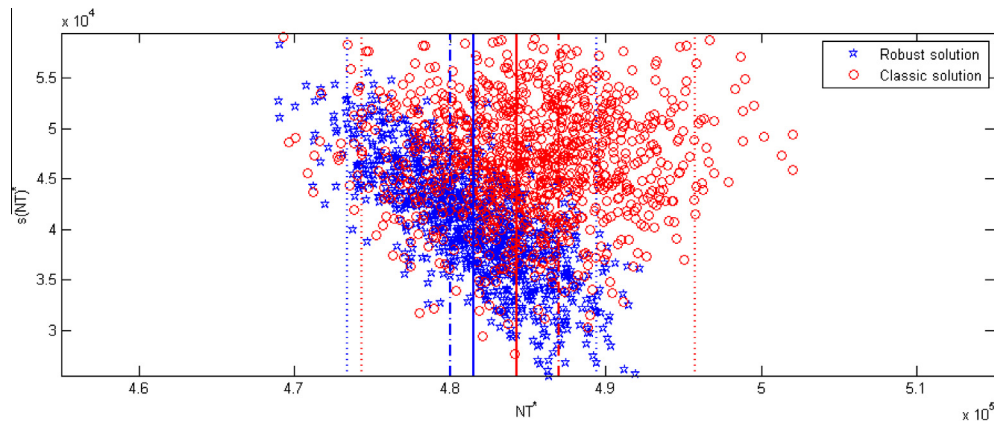


Fig. 7. The model prediction, bootstrap estimated NT, and original estimate.

$s(NE_{(1000)}^*)^T$ and $(s(NT_{(1)}^*), s(NT_{(2)}^*), \dots, s(NT_{(1000)}^*))^T$, for each of the bootstrapped samples. Finally, we sort each of these two statistics – from low to high, to obtain the 95% confidence intervals, e.g. $[\overline{DT}_{(25)}^*, \overline{DT}_{(975)}^*]$.

The bootstrapped estimates as well as the estimates from the original samples are presented in Figs. 5–7. In these figures, the symbols “☆” and “○” represent the 1000 bootstrap results of the robust and classic solution respectively. The solid vertical lines are the averages from the original sample after 100 simulation runs. Intervals between the dotted lines are the estimated confidence intervals from the 1000 bootstrapped samples. The dash-dotted lines are the estimates of the models using the optimal DFs setting (see Tables 4 and 6). The model optimums (dash-dotted line) are enveloped by bootstrapped confidence intervals (dotted lines), and are close to the originally estimated values (solid line). It demonstrates the validity of the proposed method, and verifies that the developed models (Eqs. (9)–(11) and (13)–(18)) are indeed appropriate for studying the performance of the CDDC system.

We found all the outputs from the robust design have smaller variabilities. Given that management at the 3PL prefers robust DT, NE and NT performance, the proposed model did accomplish its mission. In addition, the mean performance of DT and NT from the proposed robust design are also better or comparable to the classic RSM.

However, the mean performance of NE is significantly worse than that of the classic RSM (see Fig. 6). This is because in the NE desirability function, Eq. (20), the undesirability of large NE is not penalized heavily. Namely, the 3PL management chooses to allow for large NE in exchange for lower variability. If the 3PL wants to further reduce E_{NE} (to the level of the classic optimum) in robust design, the target in Eq. (20) has to be revised, say $10,000 \leq E_{NE} \leq 30,000$. But this change will lead to higher S_{DT} , S_{NE} and S_{NT} , which are not desirable to the 3PL.

6. Summary and conclusions

We proposed a hybrid modeling and solution approach that consists of discrete-event system simulation, robust optimization combining LHS and RSM, and bootstrapping validation for a complex problem, which originates from the need of reconfiguring a cross-docking distribution center in a Chinese–Japanese joint venture supply chain. The simulation model is a generic one that can adapt to changes in the number of doors, forklifts and conveyors inside a CDDC, and can address what-if questions to optimize the

system. We identify five decision factors (NRD, NSD, NF, NC, and TTS) and two environmental factors (LS and SDR) that have bearing on system performance. Three different responses: DT, NE and NT are investigated. Using the LHS to sample the combinations of the simulation outputs, whereas applying RSM to post-simulation serves as an optimization tool to search for the best settings of decision factors. The bootstrapping procedure can give good confidence intervals of the optimal response values, even if the responses are not normally distributed.

Due to the popularity of JIT in auto industry, robust design of the supply chain has gained much attention. We innovatively integrated RSM and LHS to design the cross-docking facility for an auto supply chain, a complex dynamic system. The proposed robust design approach is capable of tackling multiple performance metrics, and identifying the best configuration.

To objectively compare between the classic RSM optimum and the robust optimum, we propose the bootstrapping approach. Our numerical studies indicate that the robust approach is less efficient in determining the optimum compared with the classic RSM approach because the robust approach takes environmental factors into account, requires more factor combinations (input combinations or design points) and more simulated runs. However, the classic RSM can only pursue better average performance of responses, while the robust approach could obtain robust solutions that have smaller variability and stable outputs. The parallel results – much like the classic RSM optimum – can also be achieved by relaxing the constraints in the standard deviation models. Given today's increasingly complex and uncertain business environment, we conclude that the robust design approach is a more flexible and versatile approach that allows decision makers to better implement company's policy and deal with risks. In the studied case, the robust solution meets the need of the supply chain and thus wins the approval of the 3PL, while the classic RSM solution did not satisfy management's need. Despite extra experimental efforts are called for in the robust design, we believe that the additional time required is justifiable relative to the savings that can be derived by this better suited approach.

Although we have identified the robust operating conditions of a practical CDDC, we believe future research in this domain could include the following extensions: (i) compare our approach with the Taguchi method; (ii) extend the proposed robust optimization procedure to different industries and different supply chains. (iii) Compare it with the Kriging approach (Kleijnen, 2008; Dellino et al., 2012), since it also involves using the interpolation and extrapolation techniques for complex and flexible global models. Finally, one can (iv) combine our approach with novel algorithms

for NLCs, since the metamodels constructed via our RSM including environmental factors is often too complicated to search for the global optimum.

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