Development of a knowledge-based intelligent decision support system for operational risk management of global supply chains

Yang-Byung Park, Sung-Joon Yoon* and Jun-Su Yoo

Department of Industrial and Management System Engineering,
Kyung Hee University,
Yongin-si, Gyeonggi-do, South Korea
Email: ybpark@khu.ac.kr
Email: pgenesis@khu.ac.kr
Email: yoojs1231@gmail.com
*Corresponding author

Abstract: This paper proposes a knowledge-based intelligent decision support system for operational risk management of global supply chains (DSSRMG), a full-phase system not yet treated in the literature. DSSRMG predicts the supply chain performance using the enhanced artificial neural network combined with particle swarm optimisation, infers the core risk source using a method based on principle component analysis, and evaluates risk mitigation alternatives using the digraph-matrix approach combined with principle component analysis. A methodology using an adaptive-network-based fuzzy inference system is suggested to construct the knowledge base for mitigation alternatives. An industrial example is used to illustrate the performance of DSSRMG. Computational experiments show that the techniques used for DSSRMG are excellent. Especially, the algorithm for selecting the useful operation indicators improves the performance prediction accuracy by 7.1% on average. DSSRMG provides supply chain managers with a practical tool to accurately predict and effectively control the operational risk. [Received: 9 March 2017; Revised: 22 July 2017; Accepted: 2 October 2017]

Keywords: supply chain operational risk management; knowledge-based decision support system; particle swarm optimisation; PSO; principle component analysis.

Reference to this paper should be made as follows: Park, Y-B., Yoon, S-J. and Yoo, J-S. (2018) ‘Development of a knowledge-based intelligent decision support system for operational risk management of global supply chains’, *European J. Industrial Engineering*, Vol. 12, No. 1, pp.93–115.

Biographical notes: Yang-Byung Park is a Professor of Industrial and Management Systems Engineering at Kyung Hee University, Republic of Korea. He is a former President of the Korean Institute of Industrial Engineers. He received his MS and PhD in Industrial Engineering and Management from Pennsylvania State University and Oklahoma State University, respectively. His research interests include decision support system, supply chain risk management, and artificial intelligence.

Sung-Joon Yoon is a Lecturer in Industrial and Management Systems Engineering at Kyung Hee University, Republic of Korea. He received his BS, MS, and PhD in Industrial Engineering from Kyung Hee University. His research interests include logistics, simulation, and evolutionary algorithm.

Jun-Su Yoo is a PhD candidate in Industrial and Management Systems Engineering at Kyung Hee University, Republic of Korea. He received his BS and MS in Industrial Engineering from Kyung Hee University. His research interests include multi-objective optimisation, sourcing, and logistics.

1 Introduction

During the last two decades, companies have moved toward more outsourcing, offshoring, single sourcing, global trade, and efforts to remove slack. These strategies have provided companies with an opportunity to significantly reduce supply chain costs. However, overexertion of the supply chain efficiency makes the supply chain more vulnerable to serious disturbances arising from risks. Accordingly, one of the most critical issues facing supply chain managers has become how to proactively and systematically address risk that might negatively affect global supply chain performance. Supply chain risk management (SCRM) plays a major role in ensuring sustainable effective supply chain in inscrutable modern business environments, whose whole process includes activities used to measure, assess, evaluate, and mitigate risks that are specific to a supply chain.

A lot of research focusing on SCRM has been reported. Ho et al. (2015) have provided good reviews of recent works on SCRM. In recent years, there has been a significant amount of work, especially concerning operational planning problems with risk. Schmitt and Singh (2012) analysed the inventory placement and back-up methodologies in a supply chain network subject to risk using a discrete-event simulation model. Singh et al. (2012) presented a mathematical model to address the facility location-allocation problem of global supply chain networks that incorporated a set of risk factors expressed as additional costs. Park and Kim (2016) proposed a simulation-based evolutionary algorithm approach for the inventory management problem in global supply chains subject to risk. Some researchers (Han and Wang, 2015; Shishebori et al., 2017) have formulated stochastic mathematical models for operational planning problems with risk. However, those works considered the usual uncertainties as risks and ignored the dynamics of supply chain systems.

The solutions obtained by applying analytical approaches are likely to be impracticable because the type, occurrence, and impact of the risk are highly uncertain in the dynamic system. As supply chain managers have come to recognise the importance of supply chain continuity and resilience, conventional methodology to manage the supply chain risk has given way to risk management using a computer-based decision support system (DSS) which enables to aid complex decision-making and problem solving in a systematic and interactive manner based on the real-time information of supply chain operation. The DSS for SCRM benefit from a holistic approach for managing risks and so is fast becoming an indispensible tool for managing complex supply chains (Lam et al., 2015). A number of researchers have studied the DSS for SCRM. The relevant literature is summarised in the next section.

This paper proposes a multi-phase knowledge-based intelligent DSS for operational risk management of global supply chains, termed to as DSSRMG. Supply chain operational risk refers to the potential for unwanted negative consequences caused by random events or activities related to the supply chain operation which generally result from composite internal and external malfunctions. DSSRMG predicts the supply chain performance, assesses the supply chain risk based on the predicted performance, infers the operational risk sources where improvements are most needed, and evaluates mitigation alternatives for the core operational risk source. DSSRMG employs case-based reasoning for decision support, using intelligent knowledge storage and learning techniques such as artificial neural network (ANN) and adaptive-network-based fuzzy inference system (ANFIS). Twenty three kinds of risk indicators are developed to measure the local operating performances in five functional areas of the global supply chain.

The main contributions of this paper are threefold. First, DSSRMG is the full-phase DSS for operational risk management of global supply chains not yet treated in the literature, which uses various artificial intelligent and analytical techniques for data analysis and decision-making. Second, DSSRMG enables supply chain managers to accurately predict and effectively control the operational risk, which is an awfully complex phenomenon, while contributing to the competitiveness and sustainability of the company. Third, the research approach used for DSSRMG is applicable to the development of DSSs for the intelligent risk management in various fields of industry.

The remainder of this paper is organised as follows. Section 2 reviews previous studies on the DSS for SCRM. Section 3 describes the research method of DSSRMG. Section 4 presents the application of DSSRMG to an industrial example. Section 5 discusses the computational experiments to validate the methodology for performance prediction used in DSSRMG. Finally, conclusions are drawn in Section 6.

2 Literature review

In recent years, many DSSs for SCRM have been studied. Those have mainly focused on the conceptual framework for the whole SCRM process or on approaches to support decision-making for the local problems such as sourcing, logistics, risk assessment, and risk mitigation.

Works on DSS employing the SCRM process are still at a germinal stage. Tummala and Schoenherr (2011) divided the SCRM process into five phases and presented a structured and ready-to-use conceptual framework for managing the complete process by aggregating specific techniques for conducting each process. Xia and Chen (2011) proposed a strategic decision-making framework for the optimal selection of risk management methods based on internal triggering and interactive mechanisms in the SCRM process. Mogre et al. (2016) proposed a two-stage DSS that integrated the SCRM process including probability estimation, measure selection, assessment of interdependence of risks and measures, and selection of mitigation strategies and tactics. A few researchers (Kumar and Havey, 2013) dealt with the partial process of the SCRM, mainly focusing on risk assessment and mitigation.

Sourcing has been the most popular operational problem in the DSS for SCRM due to subjective considerations in the decision-making process. In particular, AHP has been successfully employed to select appropriate suppliers due to its merits of handling multiple criteria systematically and permitting subjective factors to be considered in risk analysis. Samvedi et al. (2013) quantified risks in a supply chain through integration of fuzzy AHP and fuzzy TOPSIS. Hashemian et al. (2014) presented a hybrid fuzzy multi-criteria group decision-making approach for supplier evaluation for a dairy company, integrating the fuzzy AHP and the fuzzy preference ranking. Scott et al. (2015) proposed a DSS for dealing with supplier selection and order allocation problems in stochastic and multi-stakeholder environments. They used an approach that combined AHP, quality function deployment, and a chance-constrained optimisation algorithm. Fashoto et al. (2016) developed a decision support model for evaluating and selecting suppliers in the healthcare service centre using AHP and ANN.

Analytical techniques other than AHP have also been employed in the decision-making process of sourcing with risk. Tse and Tan (2012) proposed a decision support framework based on a marginal incremental analysis justification approach for quality risk management of products purchased in a multi-layer global supply chain. García et al. (2013) proposed a DSS based on fuzzy inference for supplier selection, which analysed both the information about the type of product to be purchased and the risk conditions of each bid. Hong and Lee (2013) proposed a DSS for procurement risk management, utilising a simulation to help managers realise the trade-off between profit and risk. Silbermayr and Minner (2016) proposed a decision support model for sourcing. The model could provide insights on how reliability, cost, and learning ability of potential suppliers impact the buyer’s sourcing decision.

Unlike the sourcing problem, less work has been conducted on DSSs for logistics problems with risk, despite the fact that logistics play a pivotal role in the supply chain and so the risk in this operation is critical to the overall performance. Kengpol et al. (2012) developed a DSS based on 0-1 goal programming that can accommodate evaluation models with risk factors in order to optimise multi-modal transportation routing. Rodger et al. (2014) proposed a decision support tool for supply chain risk trigger inventory decisions in government organisations, utilising the Petri-nets and Pareto charts. Basu and Nair (2014) developed a DSS for risk-reward analysis in multi-period inventory control, which used mean-variance solutions obtained by solving stochastic dynamic programming. Accorsi et al. (2014) presented a DSS based on the top-down approach for the design, management, and control of warehousing systems. Lam et al. (2015) proposed a knowledge-based logistics planning system to facilitate the decision-making process for warehouse operations subject to risks faced by logistics service providers. Li et al. (2016) suggested a decision support framework based on a simulation method to evaluate the dynamic risk effects in chemical supply chain transportation. Othman et al. (2017) proposed a multi-agent-based architecture for a DSS to solve the scheduling problem for the delivery of resources from the supplying zones to the crisis-affected areas.

Risk assessment estimates the risk magnitude of the supply chain. This is a key phase of the SCRM process because it has a direct effect on mitigation measures. Jiang and Chen (2014) proposed a quantitative risk evaluation model based on support vector machines, incorporating the Delphi method as a decision support tool. Stefanovic (2014) introduced a decision support model for risk assessment, which combined process modelling, performance measurement, and data mining. Aqlan and Lam (2015) presented a DSS framework for risk assessment. The system consisted of a survey for identifying the risks, Bow-tie analysis for calculating the risk impact, and a fuzzy inference system for scoring the risks. Kengpol and Tuammee (2016) developed a decision support framework to assess risks in multi-modal green logistics.

Table 1 Summary of DSSs for SCRM mentioned in the literature review

Problem area	*Reference*	*Methodology*							*Case study (industry)*
		Conceptual framework	*AHP*	*Simulation*	*Math. programming*	*AI*	*Optimisation*	*Etc.**	
Management process	Tummala and Schoenherr (2011)	√							-
	Xia and Chen (2011)	√							
	Mogre et al. (2016)	√						Decision tree analysis	Wind power
Sourcing	Tse and Tan (2012)	√						Marginal theory	Toy
	Samvedi et al. (2013)		√					TOPSIS	Textile and steel
	García et al. (2013)					√			Metal construction
	Hong and Lee (2013)			√					Semiconductor
	Hashemian et al. (2014)		√						-
	Scott et al. (2015)		√				√		Bioenergy
	Fashoto et al. (2016)		√			√			-
	Silbermayr and Minner (2016)				√				-
Logistics	Kengpol and Tuammee (2012)		√					FMEA, DEA	Transportation
	Rodger et al. (2014)			√				Petri-net	-
	Basu and Nair (2014)				√				Distribution
	Accorsi et al. (2014)	√		√					Distribution
	Lam et al. (2015)					√		Genetic algorithm	Distribution
	Li et al. (2016)			√					Chemical
	Othman et al. (2017)						√		Healthcare
Risk assessment	Jiang and Chen (2014)					√		Support vector machines	-
	Stefanovic (2014)	√				√			-
	Aqlan and Lam (2015)	√						Bow-tie analysis	Computer
	Kengpol and Tuammee (2016)		√					FMEA, DEA	Transportation

Note: *FMEA: failure mode and effects analysis; TOPSIS: technique for order preference by similarity to ideal solution; DEA: data envelopment analysis.

Table 1 Summary of DSSs for SCRM mentioned in the literature review (continued)

Problem area	*Reference*	*Methodology*							*Case study (industry)*
		Conceptual framework	*AHP*	*Simulation*	*Math. programming*	*AI*	*Optimisation*	*Etc.**	
Risk mitigation	Giannakis and Louis (2011)	√							-
	Talluri et al. (2013)			√				DEA	-
	Micheli et al. (2014)				√				Baby products
	Kırılmaz and Erol (2017)				√				Automotive

Note: *FMEA: failure mode and effects analysis; TOPSIS: technique for order preference by similarity to ideal solution; DEA: data envelopment analysis.

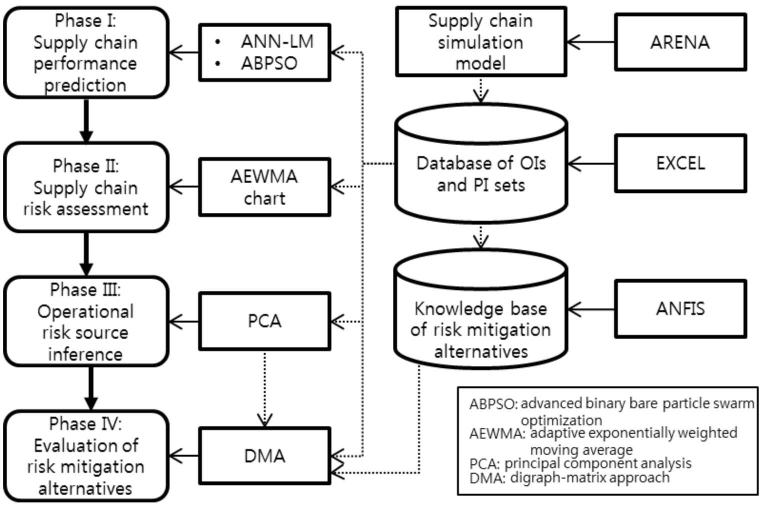
Most studies on risk mitigation have focused on tools that can effectively evaluate the risk profile of a supply chain. However, the selection of effective mitigation measures to minimise such risk profiles has not been optimised. Giannakis and Louis (2011) presented a framework for a DSS that facilitated collaborative disruption risk mitigation in manufacturing supply chains. Talluri et al. (2013) developed a methodology to help managers select the appropriate risk mitigation strategies. They combined simulation technology with DEA and non-parametric statistical methods. Micheli et al. (2014) proposed a DSS to select appropriate mitigation measures for risks within a given budget. The system was formulated as a stochastic linear programming, which elaborated on the manager's judgements by way of fuzzy-extended pairwise comparisons. Kırılmaz and Erol (2017) proposed a decision support model for procurement risk mitigation.

Table 1 shows a summary of DSSs for SCRM mentioned in this section with respect to the methodology and the industry type treated in a case study. No DSS is available in the literatures which treats the operational risk management problem intensively and comprehensively. The research of this paper closes a gap in the literature by incorporating a full process of decision-making for operational risk management of global supply chains into an integrated framework of DSS.

3 Research method for the proposed DSSRMG

DSSRMG consists of four phases and its comprehensive framework is depicted in Figure 1. Acronyms shown in rectangular boxes denote the principle techniques or tools used. In the first phase, the performance index (PI) of a supply chain is predicted with selected operation indicators (OIs). In the second phase, the supply chain risk is assessed based on the predicted performance. In the third phase, operational risk sources are inferred when the supply chain is assessed as risky. In the fourth phase, several feasible mitigation alternatives for the core risk source are evaluated and the best one with the highest net value is presented. Some artificial intelligent techniques such as ANN, particle swarm optimisation (PSO), and ANFIS are used for decision support. The database can be supplemented with artificial datasets created by simulating the supply chain model. The knowledge base is completed by applying a fuzzy inference system with supplemented datasets. The research method is described in the following subsections.

Figure 1 Framework of DSSRMG



3.1 Database construction of the OIs and PI set

Performance measurement relies on a set of metrics. However, developing performance metrics that are the most suitable to an individual supply chain and measuring them accurately are complex undertakings, because the characteristics of the supply chains are different from each other, and the measurement of the metrics is a transversal process that involves several actors cooperating to achieve a common goal. Some researchers (Chan et al., 2014; Stefanovic, 2014) have designed performance measurement systems. However, these systems are mostly backward looking, isolated, and static. Furthermore, they lack the ability to deliver extensive operation information and to reflect the changes that are caused by internal and external risk events. The performance metrics for SCRM should be predictive, comprehensive, dynamic, and risk-sensitive.

Thus, 23 kinds of OIs are developed to measure the operation performance in five functional areas of the global supply chain, as presented Table 2. All of the OIs are expressed as rate so that they can be easily manipulated in data mining. A single PI is used to represent the overall performance of the global supply chain. The PI is computed by summing the performances of the products sold to customers at sales facilities during a specific period with respect to the quality, customer service, cost, and time, as shown in equation (1). The four components are well known as main factors that affect the overall performance of supply chains (Chan et al., 2014). There exists a time lag between the OIs and the corresponding PI due to the supply chain lead time.

$$PI_y = \alpha_1 GR_t + \alpha_2 FR_t + \alpha_3 CE_t + \alpha_4 TE_t \tag{1}$$

where t is a period, GR_t is the good product ratio in t, FR_t is the product fill ratio in t, CE_t is the supply chain cost efficiency in t, TE_t is the supply chain lead time efficiency in t, and α_i is a weight of component i. The efficiency is computed by the equation, (expected maximum value-actual value) / (expected maximum value-expected minimum value). A database is constructed with the historical datasets of the operation parameters, OIs, and PI of the global supply chain that have been collected over previous periods. The operation parameters affect the OIs and PI. Thus, the datasets of the OIs and PI are relevant to each other with a time lag caused by the supply chain lead time.

Table 2 Twenty three kinds of OIs in five functional areas of the global supply chain

Area	*OI*
Supplier	Supply fulfilment rate, defect rate, part price change rate, production lead time delay rate
Plant	Production fulfilment rate, process time delay rate, production cost change rate, defect rate
Sales facility	Demand fulfilment rate, inventory turnover rate, demand forecast error rate, demand variation rate
Distribution centre	Product availability, order process time delay rate, storage utilisation storage excess rate, inventory turnover rate, product damage rate
Transportation	Transportation time variation rate, transportation cost change rate, transport delay rate, customs clearance delay rate, product damage rate

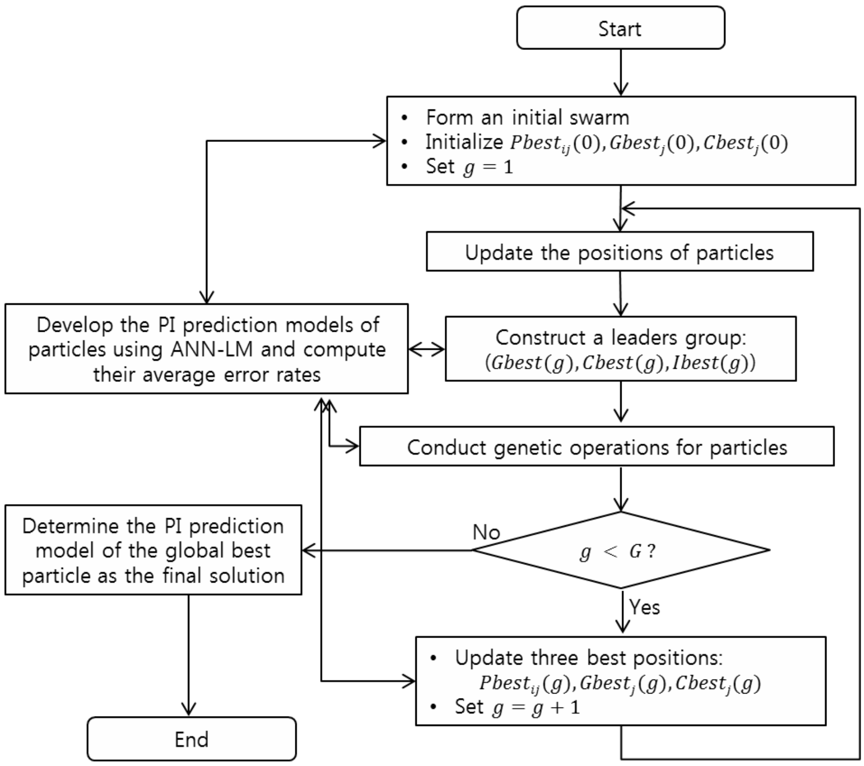
3.2 Development of the PI prediction model

The PI prediction model is developed, along with the effective OI selection algorithm. The OI selection is to remove less useful OIs without sacrificing the predictive accuracy. Predicting the PI with the useful OIs improves the accuracy and shortens the computation time that is required for data mining. PSO, a meta-heuristic search technique that is inspired by the behaviour of bird flocks, finds optimal subsets in the full search space by some global search strategies. Due to its advantages such as simplicity, fast convergence, effectiveness, and population-based feature, recently the attention upon PSO for feature selection problems is much higher than other meta-heuristic methods (Zhang et al., 2015). Ghamisi and Benediktsson (2015) showed the superiority of PSO integrated with genetic algorithm over other evolutionary-based feature selection techniques through computational experiments using the real dataset. An advanced version of the binary bare bones particle swarm optimisation (ABPSO) is proposed for OI selection; these searches for an optimal position using a new Gaussian sampling based on the positions of three excellent particles along with new genetic operations for exploitation and exploration.

When performing ABPSO, an ANN combined with Levenberg-Marquardt's algorithm (ANN-LM) is trained to develop the PI prediction model for each particle, using the historical datasets of the selected OIs of the particle and the corresponding PI. Training consists of exposing the neural network to a set of OIs-PI patterns. Levenberg-Marquardt's algorithm, which is a function optimisation technique to solve nonlinear least square problems, improves the search speed and accuracy in the application of ANN (Lourakis, 2005). For ANN-LM, a two-hidden-layer feed-forward model, which learns by a back-propagation algorithm, is used because it has efficient and effective generalisation capabilities. A general form of the PI prediction model of a particle is described as $PI_{t+1} = \sum_{j=1}^{m} w_j x_{jt} + w_0$, where m is the number of selected OIs, x_{jt} is an observation of OI j in period t, w_{jt} is the weight of OI j such that $0 \le w_{jt} \le 1$, and w_0 is the bias term that is passed to the activation level through a transfer function.

The mean error rate of the predicted PI reflects the fitness of a particle to evaluate the OI subset, which is denoted by the particle. A particle with a lower mean error rate is a better particle with a higher fitness. The PI prediction model of the global best particle is determined to be the optimal prediction model. Figure 2 shows the flowchart of the proposed algorithm used to develop the PI prediction model.

Figure 2 Flowchart of the proposed method used to develop the PI prediction model



3.2.1 Particle representation

In ABPSO, a particle is comprised of multiple elements with real values between 0 and 1, which are equivalent to the number of OIs that represents a candidate solution for OI selection. The encoding element is interpreted as the probability that each OI will be selected in the OI subset. Suppose that there is a dataset with m OIs. Then, particle i is denoted with an m-bit real string as $Z_i = (z_{i1}, z_{i2}, \dots, z_{im})$, $i = 1, 2, \dots, |S|$ where $|S|$ is the swarm size. If $z_{ij} \ge rand$, OI j of particle i is selected into the OI subset, where *rand* denotes a random number on [0, 1]. Otherwise, OI j is not selected for the OI subset. Only the members in the OI subset of a particle are used for training ANN-LM to derive the PI prediction model.

3.2.2 Position update of particles

In order to update the positions of particles in ABPSO, a new parameter that denotes the position of the best particle in the current swarm is considered for tuning in addition to the two parameters suggested by Zhang et al. (2015). The purpose of this parameter addition is to move the particles more precisely and quickly, perhaps toward the optimal position. The new positions of particles at iteration g are computed as follows:

$$z_{ij}(g) = \begin{cases} Norm\left[\dfrac{Pbest_i(p-2) + Gbest_j(p-2) + Cbest_j(p-2)}{2}, \right. \\ \qquad \left|Gbest_j(g-1)\right. \\ \qquad \left. \left. - \min\left(Pbest_{ij}(g-1), Cbest_j(g-1)\right)\right| \right], & rand < 0.5 \\ \dfrac{Pbest_i(p-2) + Gbest_j(p-2) + Cbest_j(p-2)}{2}, & rand \geq 0.5 \end{cases} \quad (2)$$

where $Pbest_j(g)$ is the value of element j at the best position of particle i obtained up to iteration g, $Gbest_j(g)$ is the value of element j of the global best particle obtained up to iteration g, and $Cbest_j(g)$ is the value of element j of the best particle obtained at iteration g. Values of $z_{ij}(g)$ that are below 0 and above 1 are adjusted to 0 and 1, respectively. $Norm[m, S]$ denotes the value that is randomly selected from the Gaussian distribution with mean i and variance S.

3.2.3 Genetic operation

Once the positions of the particles are updated, the probability of conducting the genetic operation is computed using the following equation:

$$p_0 = \begin{cases} \dfrac{0.3}{\{1 + e^{b-rep(g)}\}^2} & \text{if } rep(g) \leq b \\ \dfrac{0.3}{\{1 + e^{b-rep(g)}\}^{0.5}} & \text{otherwise} \end{cases} \quad (3)$$

where $rep(g)$ is the number of stagnation iterations of the swarm until iteration g, and b is the threshold for changing the probability scale. If no improvement occurs on the fitness of the global best particle at iteration g, then $rep(g)$ increases by one; otherwise, reset $rep(g)$ to 0. When $rep(g)$ increases above b, the probability of conducting the genetic operation increases rapidly.

A leader group at iteration g is formed with the global best particle up to iteration g, $Gbest(g)$, the best particle at iteration g, $Cbest(g)$, and the most improved particle from iteration g – 1 to g, $Ibest(g)$. $Ibest(g)$ plays a major role in exploring the new probable solution space. If leaders are duplicated, the original is replaced by the next ranked particle in the order of $Ibest(g)$ and $Cbest(g)$. Two parents are selected for the crossover operation. One is selected from the swarm by applying a roulette wheel method based on the relative fitness of the particles. The other is selected from the leader group, whose vector distance is the greatest from the previously selected parent. Selecting the leader as the other parent that is most different from the previously selected parent regarding the values of the elements reduces the probability of premature convergence while maintaining good schemata. The composition of parents is repeated $N/2$ times, where N is the swarm size. The blend crossover (Yu and Gen, 2010) is conducted for all pairs of parents. The blend crossover has the merit of generating more diverse offspring than the arithmetic crossover which is generally used for real code entities.

A mutation is selectively conducted on the offspring to modify the values of elements, while attempting to prevent the loss of desired genetic traits by varying both the mutation probability for the offspring and also the mutation rate for an element of the offspring. The mutation probability of the offspring is computed by the equation $p_m = \varphi\left(\frac{\theta_i - 1}{N - 1}\right)^2$ where φ is a scale parameter such that $0 < \varphi \leq 1$ and θ_i is the fitness rank of the offspring. The value of p_m is 0 for the first-ranked offspring and increases as the rank of the offspring is increased. Once the offspring is selected on the basis of p_m, its elements are selected for the mutation operation based on the mutation rate of an element, which is computed by equation $p_\theta = 1 - \delta^{\left(1 - \frac{g}{G}\right)}$ where δ is a scale parameter such that $0 < \delta \leq 1$, and g and G are the current and maximum iteration numbers, respectively. The value of p_θ decreases in a nonlinear fashion as the number of iterations increases. This property causes a mutation to search the solution space uniformly in earlier iterations and very locally in later ones. The mutated values of the elements are determined by subtracting the original values from 1.

3.3 Risk assessment

The adaptive exponentially weighted moving average (AEWMA) control chart can be suitably modified to assess the supply chain performance risk over specific periods. Since the predicted PIs over periods are a sequence of independent normal data with a common variance, the AEWMA statistic in period $t + 1$ may be computed as follows.

$$W_{t+1} = \pi(\theta_t)\,\hat{y}_{t+1} + \{1 + \pi(\theta_t)\}\,W_t \tag{4}$$

where $\hat{y}_{t+1}$ is the predicted PI in period $t + 1$, and $\pi(\theta_t)$ is the varying weight of the prediction error in period t, computed as $\pi(\theta_t) = \Phi(\theta_t) / (\theta_t)$, where $\theta_t = y_t - \hat{y}_t$.

$\Phi(\theta_t)$ is the correction value of the prediction error in period t, which is computed using the Huber's (1981) score function:

$$\Phi(\theta_t) = \begin{cases} \theta_t + (1-\gamma)\kappa & \text{if } \theta_t < -\kappa \\ \gamma\theta_t & \text{if } |\theta_t| \leq \kappa \\ \theta_t - (1-\gamma)\kappa & \text{if } \theta_t > \kappa \end{cases} \tag{5}$$

where γ is a suitable constant such that $0 < \gamma \leq 1$, and $\kappa \geq 0$. Small values of γ must be used to quickly detect small shifts of the PI, and large values of γ must be used to efficiently detect large shifts of the PI. In general, κ is set to three times the standard deviation of the PI. The control statistic behaves like an EWMA chart when $|\theta_t| \leq \kappa$ and like a Schewart chart when $|\theta_t| > \kappa$. Thus, the analyst can effectively react to either small or large shifts by varying the values of γ and κ.

The risk warning signal is triggered for the supply chain performance of period $t + 1$ if $W_{t+1} < \mu_0 - 3\sigma\sqrt{\gamma/(2-\gamma)}$, where μ_0 is the average the PI. The root equation in the right-hand side is the formula used to compute the covariance of the AEWMA statistic and the predicted value when sufficient data are available.

3.4 Inference of operational risk sources

Principal component analysis (PCA) (Abdi and Williams, 2010) is probably the most popular multivariate statistical technique that analyses a dataset in which observations are described by several inter-correlated dependent variables just like OIs. PCA computes new variables called principle components (PCs) that account for a large portion of the total variance of dependent variables, which are obtained as linear combinations of orthogonal variables. PCA provides the advantage of extracting the most important information accurately from the dataset and compressing it in a small set of PCs. In particular, the eigenvectors of PCs can be used to compute the weights of OIs which are the essential information needed to infer risk sources and evaluate mitigation alternatives. For these reasons, a methodology based on PCA is suggested. In order to apply PCA to the datasets of the OI subset of the prediction model, the observed values of OIs should be linearly normalised between 0 and 1 based on the minimum and maximum values for each OI. The normalised values of some OIs should be adjusted by subtracting each value from 1 in order for larger values to be better in common.

Let V be the $m \times s$ vector of the observations of m OIs in s periods, C be the covariance matrix of V, and E be the eigenvector matrix of C. Then, PCs are defined as a linear combination of the OI subset, in each of which the coefficients of m OIs are equal to the elements in each row of the transpose of E. The eigenvalues of m PCs are the diagonal elements of the matrix of E^TCE. The ratio of the eigenvalue of each PC to the sum of the eigenvalues of all PCs is computed, which represents a proportion of the variance associated with the corresponding PC. The critical PCs are formed by selecting PCs in descending order of the ratio until the accumulated sum of the ratio reaches an upper limit.

Suppose k critical PCs are selected. Then, the EWMA vector of period t is computed as follows.

$$A_t = \pi(\theta_t) B_t^T R_t + \{1 - \pi(\theta_t)\} A_{t-1} \tag{6}$$

where B_t^T is the transpose of an $m \times k$ matrix with columns equal to the eigenvalues of the critical PCs of period t, and R_t is an $m \times 1$ vector with elements equal to the observations of OIs in period t. At = $(a_{1t}, \ldots, a_{1t}, \ldots, a_{kt})$, where a_{it} is the score (importance) of the critical PC i in t. $\pi(\theta_t)$ is explained in equation (4).

The weights of OIs in a PC are determined by its eigenvectors. Using those weights, the contribution ratio of OI j to the supply chain risk of period $t + 1$ in period t is computed as follows.

$$Q_{jt} = \frac{\sum_{i=1}^{k} \alpha_{it} w_{ijt}}{\sum_{i=1}^{k} \alpha_{it} \sum_{j=1}^{m} w_{ijt}} \quad \forall j \tag{7}$$

where w_{ijt} is the weight of OI j in the critical PC i of period t.

Then, the probability that OI j is a risk source in period t is computed as follows.

$$P_{jt} = \frac{Q_{jt}}{\sum_{j=1}^{m} Q_{jt}} \quad \forall j \tag{8}$$

A larger probability means that the corresponding OI affects the supply chain performance of period $t + 1$ more negatively. The OI with the largest probability is determined as the core risk source.

3.5 Development of a knowledge base for mitigation alternatives

A knowledge base is developed to store the mitigation alternatives with OI information as the rules for potential risk sources. Once the core risk source is identified, risk mitigation alternatives are searched for in the knowledge base. A risk mitigation alternative is defined as a combination of the implementation levels of risk mitigation methods. A risk mitigation method is defined as the action taken on a specific supply chain operation. The level ranges from 1 to 5. A higher level indicates a higher intensity with respect to the improvement effort. The normal condition is set to level 3. Levels lower than 3 are cases in which the mitigation method is rather alleviated (or deteriorated) compared with the normal condition in order to enhance other mitigation methods when the available resources are limited. For each level, the numerical ranges of the relevant operation parameters are pre-assigned by the analyst.

The rules of the knowledge base, stated as if-then propositions, contain actual knowledge about the mitigation alternatives for potential risk sources. A rule has three essential elements: the rule name, rule premise, and rule conclusion. The rule premise, beginning with the keyword ‘If’, is where one or more conditions of the mitigation methods, combined using the logical operator ‘AND’, are stated as a mitigation alternative. The rule conclusion, beginning with the keyword ‘Then’, consists of the sets of expected values and standard deviations of the OIs which are significant to the alternative. The complete form of an if-then rule appears as follows.

Rule of mitigation alternative v for risk source r

$$If\ \left(\theta_1^r = l_1\ AND \ldots AND\ \theta_u^r = l_u\ AND \ldots AND\ \theta_M^r = l_M\right), then\ \left\{E\left(x_j^v\right), s\left(x_j^v\right)\right\}, j \in \Phi$$

where θ_u^r is the mitigation method u for risk source r, l_u is the level of mitigation method u, $E(x_j^v)$ is the expected value of OI j for alternative v, $s(x_j^v)$ is the standard deviation of OI j for alternative v, and Φ is the set of significant OIs. The significant OIs affected by the alternatives of risk source r are selected using the condition $s(x_j^r)/\overline{x}_j^r \geq \rho$, where $\overline{x}_j^r$ and $s(x_j^r)$ are the mean and standard deviation of OI j computed using the observed values for all mitigation alternatives of risk source r, respectively, and ρ is the selection criterion. A higher value of ρ indicates a more rigid setting for the variability of the OI.

It is quite burdensome to develop a complete knowledge base that contains the rules of all mitigation alternatives for all potential risk sources. It is uncommon that the complete datasets of all OIs for all mitigation alternatives are available. Applying ANFIS is suggested to complete the rule construction. ANFIS is a neuro-fuzzy inference system implemented in the framework of adaptive networks with multi-layers. This can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions (MFs) to generate the stipulated input-output pairs. ANFIS has been shown to be superior to ANN in inferring the uncertain variables with respect to the accuracy and learning speed (Amirkhani et al., 2015). A sufficient number of OI datasets for various mitigation alternatives is mandatory in order to obtain reliable outcomes with ANFIS. When the datasets are insufficient for application to ANFIS, artificial datasets can be created by simulating mitigation alternatives.

3.6 Evaluation of mitigation alternatives

The core operational risk source is primarily considered as the target for mitigation because its mitigation can most effectively improve the supply chain performance of period $t + 1$. The digraph-matrix approach combined with PCA is applied to evaluate feasible alternatives for mitigation. The digraph-matrix approach is specifically suited to problems with a strong interdependent relationship framework of attributes. In the permanent procedure of this method, even a small variation in the attributes leads to a significant difference in the selection index; hence, it is easy to rank the alternatives (Rajesh et al., 2015).

The step-by-step procedure is described as follows:

Step 1: Construct the integrated OI relation matrix

First, the relative importance of OIs j over h in the critical PC i of period t is computed:

$$\varsigma_{jht} = \frac{w_{ijt}}{\left(w_{ijt} + w_{iht}\right)} \qquad \forall i, j, h;\ j \neq h \tag{9}$$

where w_{ijt} is the weight of OI j in the critical PC i of period t. Next, the integrated relative importance of OIs j (row) over h (column) is computed with the weights of the critical PCs:

$$\varsigma_{jht} = \frac{\sum_{i=1}^{\kappa} a_{it}\varsigma^{i}_{jht}}{\sum_{i=1}^{k} a_{it}} \qquad \forall j, h;\ j \neq h \tag{10}$$

where k is the number of the critical PCs in period t and a_{it} is the score of the critical PC i in period t.

Step 2: Construct the positive and negative influence matrices of alternatives on OIs

For the OIs which are maximised, the positive and negative effects of alternative v (row) on OI j (column) in period t are computed, respectively:

$$\lambda_{jt}^{v,p} = \max\left[\frac{E\left(x_j^v\right) - x_{jt}}{s\left(x_j\right)}, 0\right] \qquad \forall v, j \tag{11}$$

$$\lambda_{jt}^{v,N} = -\min\left[\frac{E\left(x_j^v\right) - x_{jt}}{s\left(x_j\right)}, 0\right] \qquad \forall v, j \tag{12}$$

where $E(x_j^v)$ is the expected value of OI j for alternative v stored in the knowledge base, x_{jt} is the value of OI j observed in period t, and $s(x_j)$ is the standard deviation of OI j. Division of the difference by the standard deviation is to correct the different scales of the respective OIs. For the OIs which are minimised, the formulas for computing $\lambda_{jt}^{v,p}$ and $\lambda_{jt}^{v,N}$ are switched.

Step 3: Construct the positive and negative permanent function matrices for alternatives

The elements of OIs j (row) and h (column) of the positive and negative permanent function matrices in period t for alternative v are computed, respectively:

$$\tau_{jht}^{v,p} = \begin{cases} \varsigma_{jht} & \text{if } j \neq h \\ \lambda_{jt}^{v,p} & \text{if } j = h \end{cases} \tag{13}$$

$$\tau_{jht}^{v,N} = \begin{cases} \varsigma_{jht} & \text{if } j \neq h \\ \lambda_{jt}^{v,N} & \text{if } j = h \end{cases} \tag{14}$$

Step 4: Compute the net values of alternatives

The net values of alternatives represent their pure influence on the supply chain performance of the next period. The net value of an alternative is computed by subtracting the permanent function value of the negative permanent function matrix for the alternative from that of the positive permanent function matrix for the alternative. The alternatives are ranked based on the decreasing ratings of the net values.

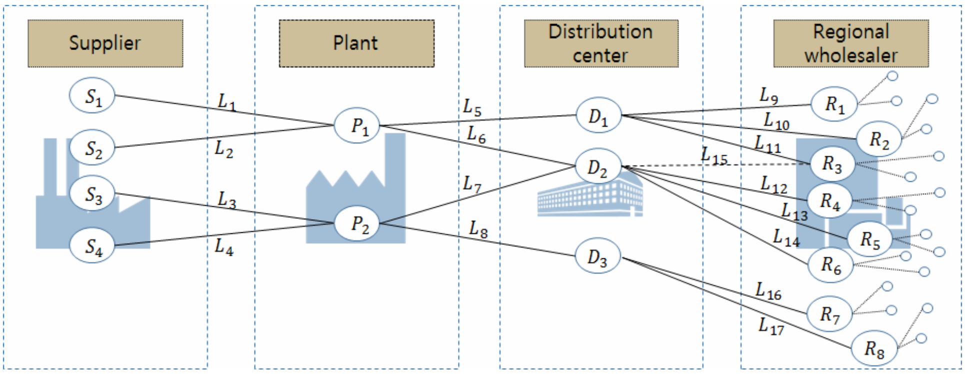
4 Application example

4.1 Global supply chain operation

In order to demonstrate DSSRMG, we construct an example based on the Asian supply chain of an electronics company that manufactures high-end devices in South Korea.

Figure 3 shows the supply chain configuration. The regional market includes numerous retailers who order from regional wholesalers based on proximity. The solid lines represent the sources of supply for facilities in downstream positions. The dotted line between D_2 and R_3 means that D_2 is the supplementary supply source for R_3 when the inventory at D_1 is insufficient. The base time unit of the operation is one day. Suppliers S_1 and S_2 manufacture module A, and suppliers S_2 and S_4 manufacture module B, based on the reorder-point (ROP) inventory policy. These are delivered to dedicated plants nearby every morning. The delivery quantity is equal to the daily production quantity scheduled at the plant, which is constant throughout the planning horizon. At the plant, the products are manufactured on a lot basis by passing through three workstations in sequence. Each workstation consists of multiple identical machine cells. Once the full container load of products is collected at the plant, it is sent to one of the dedicated DCs. The wholesalers order from the assigned DCs based on the ROP inventory policy. The wholesalers generate revenue for the company by fulfilling the retailers' demand. The wholesalers handle defect products that are returned from their customers.

Figure 3 Global supply chain configuration of the example (see online version for colours)



4.2 *Application of the DSSRMG*

We create artificial datasets of the OIs and PI by simulating the supply chain model because sufficient historical data are not available from the company. The simulation model is constructed with Arena (Kelton et al., 2015). Some parameter values are collected from the company and modified upon its request. The rest are reasonably assumed. The input data of parameters used in the example are presented in Table 3. A total of 156 OIs are needed for 17 facilities and 17 links in the global supply chain. For the PI, the weights of the four components are equally set. The simulation is conducted for 135 days with 1000 replications. The OIs are computed using the data collected during the first 90 days (i.e., one period). The PI is computed using the data collected for the last 90 days for the products sold at regional wholesalers. The time lag of 45 days in computing the PI is based on the mean supply chain lead time. The database is constructed with all 1000 datasets of the operation parameters, OIs, and PI.

Table 3 Input data of parameters used in the example

Area	*Input data*
Suppliers	Module A: production lot size = 1,146 K*, ROP = 365 K, production time per lot ~ TRIA(2, 3, 4) days, setup cost = $9 K, daily inventory cost = 0.256%, defective rate ~ NORM(0.02, 0.001)%, unit price = $30
	Module B: production lot size = 1,120 K, ROP = 486 K, production time per lot = TRIA(3, 4, 5) days, setup cost = $17 K, daily inventory cost = 0.256%, defective rate ~ NORM(0.02, 0.001)%, unit price = $50
Plants	Production schedule = 120 K/day, production lot size = 20 K, production time per lot in a cell ~ TRIA(0.5, 1, 1.5) days, defective rate ~ Norm(0.02, 0.001)%
Distribution centres	Daily inventory cost = 0.3%, daily rental cost = 0.4%, storage capacity: D_2 = 150 K, D_2 = 250 K, D_2 = 100 K
Regional wholesalers	Daily customer demand ~ TRIA(2 K, 6 K, 8 K) to TRIA(20 K, 30 K, 40 K), ROP = 31K to 127K, ordering cost = $60 K, sales price = $600, shortage cost = 20%, daily inventory cost = 0.385%, cost for a returned product = 3%
Links	Truck capacity = 20 K, transit time ~ TRIA(1, 1.5, 2) to TRIA(2.5, 3, 3.5) days, customs clearance ~ EXPON(2) days

Note: *K = 1,000.

PCA is applied to the datasets of 72 OIs in order to infer the risk sources. 19 critical PCs are formed, indicating an associated variance of 91.96%. Plant 1's production fulfilment rate (PFR1) is determined as the core operational risk source, whose probability of being a risk source is 10.87%. PFR1 is computed by dividing the actual production quantity by the scheduled production quantity at plant 1. The observed value of PFR1 in this period is 0.45. MATLAB R2014a is used for PCA.

The knowledge base of mitigation alternatives for PFR1 is developed. Six mitigation methods are considered: the change in production capability at machine cells of plant 1 (method 1), change in the number of operating machine cells at workstations of plant 1 (method 2), change in supplier 1's production capability (method 3), change in supplier 1's safety inventory level (method 4), change in supplier 2's production capability (method 5), and change in supplier 2's safety inventory level (method 6). Different numerical ranges of the relevant operation parameters to each mitigation method are set for six levels. A total of 8600 artificial OI datasets are created to apply ANFIS by simulating 860 mitigation alternatives with 10 replications with Arena, respectively. The alternatives are created by randomly assigning one of the five levels to six mitigation methods.

When applying ANFIS, the number of MFs is set to 2, the type of MF is selected to be bell shaped, the type of output MF is constant, and the number of epochs is set to 1,000. 36 significant OIs are selected using ρ = 0.01. The training errors of OIs mostly converge at very low values. For example, the training error of PFR1 converges at 0.0386. Figure 4 shows a portion of the rules for some mitigation alternatives to PFR1. The values under the OI term denote the expected value and standard deviation of that OI for each alternative. MATLAB R2014a is used for applying ANFIS.

Figure 4 A portion of the rules for some mitigation alternatives to PFR1 stored in the knowledge base

Migitation	Level						OI			
alternative	Method1	Method2	Method3	Method4	Method5	Method6	PFR1		SCR1	
3	5	3	3	3	3	5	0.83	0.011	0.68	0.014
5	5	3	3	3	1	5	0.75	0.010	0.60	0.013
7	2	5	3	3	5	3	0.80	0.010	0.68	0.014
8	4	3	3	3	4	4	0.81	0.011	0.68	0.014
12	2	4	3	4	2	4	0.74	0.010	0.76	0.016

Twelve feasible alternatives are suggested to mitigate PFR1. For the matrix computation efficiency, only 13 OIs with high probability of being a risk source among 36 OIs are considered when applying the diagraph-matrix method combined with PCA for evaluation. Alternative 8 appears as the best one, with a net value of 447,996. The positive and negative permanent function values for alternative 8 are 1,054,211 and 606,215, respectively. Although alternative 3 is the best for improving PFR1, it ranks as the ninth best in terms of net value. This outcome is due to the fact that the net value represents the positive and negative effects of an alternative on all of the OIs in an integrated way.

5 Computational experiments

Computational experiments are conducted in order to validate the performance of the methods employed to develop the PI prediction model, using the OIs and PI set stored in the database of the previous example. The input data of the example are used. Two evaluation measures are employed to assess the prediction accuracy: the mean error rate and the correlation coefficient. All of the experiments are executed on an IBM-compatible PC (CPU 2.21 GHz, 2 GB RAM).

The performance of ANN-LM that is used for PI prediction is evaluated by comparing it with the performances of ANN, principle component regression (PCR), and multi-linear regression analysis (MLRA). PCR is a hybrid method which employs PCA along with MLRA. All of the 156 OIs are used for PI prediction in the four methods. ANN-LM shows a superb performance with respect to both evaluation measures, as summarised in Table 4. Especially, it seen that the Levenberg-Marquardt’s algorithm in ANN-LM improves the accuracy and search speed of the classical ANN. PCR shows poor performance because it analyses the relationship of the OIs and PI based on the critical PCs, causing it to lose some of the information related to OIs.

Table 4 Performance comparison of four PI prediction methods

Measure	*ANN-LM*	*ANN*	*PCR*	*MLRA*
Number of OIs	145	145	145	145
Mean error rate	23.6%	23.9%	27.8%	32.5%
Correlation coefficient	0.672	0.664	0.621	0.597
Computation time	21 min.	28 min.	4 min.	2 min.

The performance of PI prediction with selected OIs is evaluated by comparing the results of ANN-LM combined with ABPSO to those of ANN-LM without OI selection. The PI prediction with selected OIs shows a superb performance with respect to both evaluation measures, whereas it takes much longer computation time due to the repetitive execution of ANN-LM, as summarised in Table 5. For instance, the mean error rate is reduced by 7.1% when only the selected OIs are used for prediction.

Table 5 Performance comparison of PI predictions with and without OI selection

Measure	*PI prediction w/ OI selection*	*PI prediction w/o OI selection*
Number of OIs	72	145
Mean error rate	16.5%	23.6%
Correlation coefficient	0.816	0.672
Computation time	8 hr.	21 min.

The performance of ABPSO that is used for OI selection is evaluated by comparing it with the performances of the frequency-based filter method (TFFM) developed by the authors, ABPSO without genetic operation (BPSO), and MLRA. ANN-LM is commonly used for PI prediction in the four methods. In TFFM, the frequency for the OI is defined as the number of cases that the absolute difference of that OI in a pair randomly chosen from the datasets is greater than the standard deviation of that OI. The OIs with a frequency ratio that is greater than 0.9 are selected. In MLRA, the OIs with a correlation to PI that is greater than 0.6 are selected. ABPSO shows a superb performance with respect to both evaluation measures, whereas it takes the longest computation time for selecting OIs among the four methods, as summarised in Table 6. ABPSO owes its superiority over BPSO mostly to the proposed Gaussian sampling method and new genetic operations. In contrast, TFFM and MLRA take a relatively short computation time because they execute ANN-LM only once.

Table 6 Performance comparison of four OI selection methods

Measure	*ABPSO*	*BPSO*	*TFFM*	*MLRA*
Number of OIs	72	60	83	71
Mean error rate	16.5%	21.1%	21.5%	21.8%
Correlation coefficient	0.816	0.758	0.659	0.637
Computation time	8 hr	7.38 hr	1.25 hr	0.6 hr

The performance of the blend crossover (BC) that is used for genetic operation in ABPSO is evaluated by comparing it with the performances of multi-point multi-level crossover (MC), swap crossover mixed with MC (XC), and arithmetic crossover (AC). These methods are widely used in evolutionary algorithms and are explained by Yu and Gen (2010). In XC, the probability of the swap crossover is set to 0.4. ANN-LM is commonly used for PI prediction in the four methods. BC shows a superb performance with respect to both evaluation measures, as summarised in Table 7. BC takes 16 to 32 minutes more computation time, compared to other three methods.

Table 7 Performance comparison of four crossover methods in ABPSO

Measure	*BC*	*MC*	*XC*	*AC*
Number of OIs	72	98	46	70
Mean error rate	16.5%	17.7%	17.6%	17.4%
Correlation coefficient	0.816	0.798	0.801	0.806
Computation time	8 hr	7.56 hr	7.73 hr	7.47 hr

Based on the results of computational experiments, three findings are summarised. First, the accuracy of the PI prediction model is highly improved when only the selected OIs are used for prediction. Second, the mean prediction error rate and the correlation coefficient correlate positively to each other. That is, when one measure is improved, other one is also improved. Third, the OI selection takes about 96% of the computation time required for developing the PI prediction model.

6 Conclusions

This paper proposed a knowledge-based intelligent DSS for operational risk management of global supply chains, termed as DSSRMG, a full-phase system not yet treated in the literature. DSSRMG consists of four phases: risk measurement and prediction, risk assessment, risk source inference, and risk mitigation. For DSSRMG, we developed an index to represent the overall performance of the global supply chain, developed 23 kinds of indicators to measure the local operating performances in five functional areas of the global supply chain, developed a method to predict the supply chain performance using ANN-LM combined with PSO, modified an AEWMA control chart to assess the supply chain risk, developed a methodology based on PCA to infer operational risk sources, and formalised the digraph-matrix approach combined with PCA to evaluate risk mitigation alternatives. A methodology using ANFIS together with simulation was suggested to construct the rule-based knowledge base. DSSRMG was successfully applied to an industrial example, presenting the best mitigation alternative for the core operational risk source identified. Computational experiments showed that the techniques used for DSSRMG were excellent. Especially, the algorithm for selecting the useful OIs improved the PI prediction accuracy by 7.1% on average. However, it took several hours for computation to select the useful OIs. The mean prediction error rate and the correlation coefficient correlated positively to each other.

DSSRMG has the following advantages:

1 operational risk management in a phased manner based on the standard process of SCRM

2 minimal requirement of the decision maker's involvement in the decision process

3 use of a knowledge base with a learning capability based on previous experiences for mitigation alternatives

4 proactive risk management.

However, the long computation time of DSSRMG may restrict its application. A lack of the historical data related to the global supply chain operation can degrade the reliability and accuracy of the decision support using DSSRMG. This problem may be resolved by establishing a comprehensive information system that integrates the ERP systems of the partners involved in the global supply chain. DSSRMG would provide supply chain managers with a practical tool to accurately predict and effectively control the operational risk in a phased manner which is an awfully complex phenomenon, while contributing to the competitiveness and sustainability of the company.

DSSRMG should be improved further to become a more intelligent system by using advanced artificial intelligence techniques and optimisation algorithms, such as genetics based machine learning, which is capable of managing operational risk in an optimal way. The computation time for OI selection should be reduced, for instance, by devising a way to reduce the number of generations in PSO without sacrificing the solution quality.

Acknowledgements

This research was supported by Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Science, ICT, and Future Planning (NRF-2013R1A1A2005302).

References

Abdi, H. and Williams, L.J. (2010) 'Principal component analysis', *Wiley Interdisciplinary Reviews: Computational Statistics*, Vol. 2, No. 4, pp.433–459.

Accorsi, R., Manzini, R. and Maranesi, F. (2014) 'A decision-support system for the design and management of warehousing systems', *Computers in Industry*, Vol. 65, No. 1, pp.175–186.

Amirkhani, S., Nasirivatan, S.H., Kasaeian, A.B. and Hajinezhad, A. (2015) 'ANN and ANFIS models to predict the performance of solar chimney power plants', *Renewable Energy*, Vol. 83, pp.597–607.

Aqlan, F. and Lam, S.S. (2015) 'A fuzzy-based integrated framework for supply chain risk assessment', *International Journal of Production Economics*, Vol. 161, pp.54–63.

Basu, P. and Nair, S.K. (2014) 'A decision support system for mean-variance analysis in multi-period inventory control', *Decision Support Systems*, Vol. 57, pp.285–295.

Chan, F.T.S., Nayak, A., Raj, R., Chong, A.Y.L. and Manoj, T. (2014) 'An innovative supply chain performance measurement system incorporating research and development (R&D) and marketing policy', *Computers and Industrial Engineering*, Vol. 69, pp.64–70.

Fashoto, S.G., Akinnuwesi, B., Owolabi, O. and Adelekan, D. (2016) 'Decision support model for supplier selection in healthcare service delivery using analytical hierarchy process and artificial neural network', *African Journal of Business Management*, Vol. 10, No. 9, pp.209–232.

García, N., Puente, J., Fernández, I. and Priore, P. (2013) 'Supplier selection model for commodities procurement. Optimised assessment using a fuzzy decision support system', *Applied Soft Computing*, Vol. 13, No. 4, pp.1939–1951.

Ghamisi, P. and Benediktsson, J.A. (2015) 'Feature selection based on hybridization of genetic algorithm and particle swarm optimization', *IEEE Geoscience and Remote Sensing Letters*, Vol. 12, No. 2, pp.309–313.

Giannakis, M. and Louis, M. (2011) 'A multi-agent based framework for supply chain risk management', *Journal of Purchasing and Supply Management*, Vol. 17, No. 1, pp.23–31.

Han, W. and Wang, J. (2015) 'The impact of cooperation mechanism on the chaotic behaviours in nonlinear supply chains', *European Journal of Industrial Engineering*, Vol. 9, No. 5, pp.595–612.

Hashemian, S.M., Behzadian, M., Samizadeh, R. and Ignatius, J. (2014) 'A fuzzy hybrid group decision support system approach for the supplier evaluation process', *The International Journal of Advanced Manufacturing Technology*, Vol. 73, No. 5, pp.1105–1117.

Ho, W., Zheng, T., Yildiz, H. and Talluri, S. (2015) 'Supply chain risk management: a literature review', *International Journal of Production Research*, Vol. 53, No. 16, pp.5031–5069.

Hong, Z. and Lee, C.K.M. (2013) 'A decision support system for procurement risk management in the presence of spot market', *Decision Support Systems*, Vol. 55, No. 1, pp.67–78.

Huber, P.J. (1981) *Robust Statistics*, John Wiley & Son, New York.

Jiang, F. and Chen, J. (2014) 'A hybrid support vector machines and two-dimensional risk matrix model for supply chain risk assessment', *Research Journal of Applied Sciences, Engineering and Technology*, Vol. 7, No. 11, pp.2193–2199.

Kelton, W., Sadowski, R.P. and Sturrock, D.T. (2015) *Simulation with Arena*, 6th ed., McGraw-Hill, New York.

Kengpol, A. and Tuammee, S. (2016) 'The development of a decision support framework for a quantitative risk assessment in multimodal green logistics: an empirical study', *International Journal of Production Research*, Vol. 54, No. 4, pp.1020–1038.

Kengpol, A., Meethom, W. and Tuominen, M. (2012) 'The development of a decision support system in multimodal transportation routing within Greater Mekong sub-region countries', *International Journal of Production Economics*, Vol. 140, No. 2, pp.691–701.

Kırılmaz, O. and Erol, S. (2017) 'A proactive approach to supply chain risk management: shifting orders among suppliers to mitigate the supply side risks', *Journal of Purchasing and Supply Management*, Vol. 23, No. 1, pp.54–65.

Kumar, S. and Havey, T. (2013) 'Before and after disaster strikes: a relief supply chain decision support framework', *International Journal of Production Economics*, Vol. 145, No. 2, pp.613–629.

Lam, H.Y., Choy, K.L., Ho, G.T.S., Cheng, S.W.Y. and Lee, C.K.M. (2015) 'A knowledge-based logistics operations planning system for mitigating risk in warehouse order fulfillment', *International Journal of Production Economics*, Vol. 170, pp.763–779.

Li, C., Ren, J. and Wang, H. (2016) 'A system dynamics simulation model of chemical supply chain transportation risk management systems', *Computers and Chemical Engineering*, Vol. 89, pp.71–83.

Lourakis, M.I.A. (2005) 'A brief description of the Levenberg-Marquardt algorithm implemented by Levmar', *Foundation for Research and Technology*, Vol. 4, No. 1, pp.1–6.

Micheli, G.J.L., Mogre, R. and Perego, A. (2014) 'How to choose mitigation measures for supply chain risks', *International Journal of Production Research*, Vol. 52, No. 1, pp.117–129.

Mogre, R., Talluri, S.S. and D'Amico, F. (2016) 'A decision framework to mitigate supply chain risks: an application in the offshore-wind industry', *IEEE Transactions on Engineering Management*, Vol. 63, No. 3, pp.316–325.

Othman, S.B., Zgaya, H., Dotoli, M. and Hammadi, S. (2017) 'An agent-based decision support system for resources' scheduling in emergency supply chains', *Control Engineering Practice*, Vol. 59, pp.27–43.

Park, Y.B. and Kim, H.S. (2016) 'Simulation-based evolutionary algorithm approach for deriving the operational planning of global supply chains from the systematic risk management', *Computers in Industry*, Vol. 83, pp.68–77.

Rajesh, R., Ravi, V. and Rao, R.V. (2015) 'Selection of risk mitigation strategy in electronic supply chains using grey theory and digraph-matrix approaches', *International Journal of Production Research*, Vol. 53, No. 1, pp.238–257.

Rodger, J.A., Pankaj, P. and Nahouraii, A. (2014) 'A Petri net Pareto ISO 31000 workflow process decision making approach for supply chain risk trigger inventory decisions in government organizations', *Intelligent Information Management*, Vol. 6, pp.157–170.

Samvedi, A., Jain, V. and Chan, F.T. (2013) 'Quantifying risks in a supply chain through integration of fuzzy AHP and fuzzy TOPSIS', *International Journal of Production Research*, Vol. 51, No. 8, pp.2433–2442.

Schmitt, A.J. and Singh, M. (2012) 'A quantitative analysis of disruption risk in a multi-echelon supply chain', *International Journal of Production Economics*, Vol. 139, No. 1, pp.22–32.

Scott, J., Ho, W., Dey, P.K. and Talluri, S. (2015) 'A decision support system for supplier selection and order allocation in stochastic, multi-stakeholder and multi-criteria environments', *International Journal of Production Economics*, Vol. 166, pp.226–237.

Shishebori, D., Karimi-Nasab, M. and Snyder, L.V. (2017) 'A two-phase heuristic algorithm for designing reliable capacitated logistics networks under disruptions', *European Journal of Industrial Engineering*, Vol. 11, No. 4, pp.425–468.

Silbermayr, L. and Minner, S. (2016) 'Dual sourcing under disruption risk and cost improvement through learning', *European Journal of Operational Research*, Vol. 250, No. 1, pp.226–238.

Singh, A.R., Mishra, P.K., Jain, R. and Khurana, M.K. (2012) 'Design of global supply chain network with operational risks', *The International Journal of Advanced Manufacturing Technology*, Vol. 60, No. 1, pp.273–290.

Stefanovic, N. (2014) 'Proactive supply chain performance management with predictive analytics', *The Scientific World Journal*, pp.1–17.

Talluri, S.S., Kull, T.J., Yildiz, H. and Yoon, J. (2013) 'Assessing the efficiency of risk mitigation strategies in supply chains', *Journal of Business Logistics*, Vol. 34, No. 4, pp.253–269.

Tse, Y.K. and Tan, K.H. (2012) 'Managing product quality risk and visibility in multi-layer supply chain', *International Journal of Production Economics*, Vol. 139, No. 1, pp.49–57.

Tummala, R. and Schoenherr, T. (2011) 'Assessing and managing risks using the supply chain risk management process (SCRMP)', *Supply Chain Management: An International Journal*, Vol. 16, No. 6, pp.474–483.

Xia, D. and Chen, B. (2011) 'A comprehensive decision-making model for risk management of supply chain', *Expert Systems with Applications*, Vol. 38, No. 5, pp.4957–4966.

Yu, X. and Gen, M. (2010) *Introduction to Evolutionary Algorithms*, Springer, London.

Zhang, Y., Gong, D., Hu, Y. and Zhang, W. (2015) 'Feature selection algorithm based on bare bones particle swarm optimization', *Neurocomputing*, Vol. 148, pp.150–157.