Development of Proactive Risk-Predictive Model for 4PL Transaction Center Using PLS Regression and Neural Networks

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Fourth-Party Logistics (4PL) transaction center aggregates trading partner competencies to provide comprehensive supply chain solutions. Since the 4PL transaction center deals with multiple category of trading partners, it offers both opportunities and risks. Especially, estimating risk in 4PL network involves collecting information from different combination of subjective and objective parameters which lacks predictive analytics. Hence, little work is carried out in synchronizing different metric scores to predict risk for managing transaction center effectively. In the first phase, risk assessment was carried out using Cormack's model. By combining individual scaling factors and probability arrived through request for information, risk probability index was estimated. Consequently, supply chain risk was determined considering total financial impact. Subsequently, risk evaluation of all trading partners with respect to high, moderate and low categories was performed utilizing prioritization matrix. In the second phase, predictive model was synthesized using Neural Network (NN) methodology. Moreover, optimal number of predictors was attained through Partial Least Square (PLS) regression. Finally, the NN was evaluated using verification dataset to ensure model adequacy. After achieving significant predictive accuracy, the developed model can be used by the coordinator to estimate risk proactively before conducting cross-segment integration. In addition, the model helps 4PL service provider to reduce supply disruption risks in the distribution network.

Introduction

Globalization led to increase in demand for Fourth-Party Logistics (4PL) which emphasizes on enhancing value proposition compared to cost reduction in Third-Party Logistics (3PL). In particular, 4PL development has been dependent on transaction center which integrates cross-segment (for example: suppliers and logistics service providers) trading partners working towards common goal. As the strength of transaction center lies in selecting and coordinating cross-segment trading partners (Kumar *et al.*, 2013), prior information of risk can help the coordinator to minimize supply disruptions. According to Aberdeen research, 80% of the executives faced supply disruptions to manage their distribution network efficiently (McCormack, 2007). Moreover, disruption risk acts as one of the sources for bullwhip effect in a supply chain. Additionally, individual trading partners synthesize their own metrics and procedures for assessing and predicting risk.

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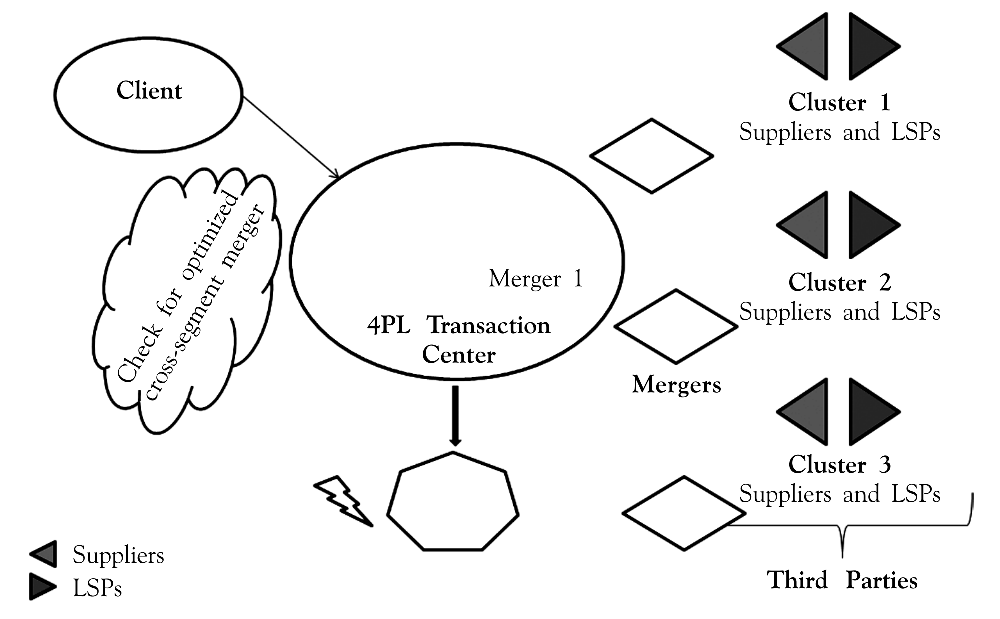
Therefore, the transaction center coordinator needs to assess risk before performing cross-segment integration in order to provide optimal 4PL solutions. Hence, assessment of risk in a proactive manner ensures consistent supply. Taking a cue from this, proactive risk-predictive model using Partial Least Square (PLS) regression and Neural Network (NN) approach was proposed. The NN's ability to model linear and nonlinear relationships, irrespective of the dataset category, was considered as the rationale for application of this methodology. In the process of building NN, datasets were normalized and optimized to match actual and predictive Risk Probability Index (RPI). In particular, this index was estimated by multiplying scaling factors of discrete risk event categories and probability of occurrence. In principle, the model was developed in two phases. Firstly, risk assessment was carried out using Cormack's model with six different risk enablers. In the second phase, predictive model was synthesized using NN methodology. Furthermore, the network was trained till actual and predictive RPI match through feedforward and back propagation techniques (Glenn, 2007). Lastly, viability of the recommended risk model was verified considering casting suppliers of a leading tiller and tractor manufacturing company in India. In summary, estimation of risk in a proactive manner for 4PL transaction center was highlighted.

4PL Transaction Center Working Principles

Prior to risk-predictive modelling for the 4PL transaction center, it becomes necessary to understand its working principles. Alan (2008) reported 4PL concept as independent, singularly accountable, nonasset-based integrator of clients supply and demand chains. Furthermore, 4PL was considered as the next-generation logistics which aims at enhancing value proposition. In principle, 4PL development was dependent on dynamic transaction center operations which integrate cross-segment trading partners. Basically, a transaction center deals with operations process and implementation characteristics for integrating trading partners. More specifically, it acts like a mediator among a constellation of firms. As a result, the service provider has to acquire new competencies for evaluation and selection of trading partners in order to become single point integrator. Thus, a deep understanding of individual chain partner was signified. Figure 1 shows the conceptual framework of 4PL transaction center which consists of suppliers and Logistics Service Providers (LSPs) as trading partners with cluster-wise categorization for instance. The framework suggests that a particular supplier has to be merged with appropriate LSPs to yield maximum operations efficiency by determining standards for integration (Kumar *et al.*, 2013).

More specifically, the transaction center must respond to 4PL requirements in the form of improved process control through consistency and reliability to deliver the product. Additionally, Fulconis *et al.* (2007) reported that transaction centers can manage a large number of complex transactions, nested, staggered in time and space with high customization. Since 4PL deals with many critical activities, multitasking people with expertise have to be selected in order to manage the transaction center. On the other

Figure 1: Conceptual Framework of 4PL Transaction Center



hand, it becomes mandatory to analyze coordination transaction cost in a 4PL transaction center. Transaction cost includes cost of gathering data, contractual agreement and process monitoring cost. Thus, the 4PL transaction center should comprise research-based innovative models to design and implement comprehensive supply chain solutions. Further, the transaction center model presents many extra challenges in the form of implementation characteristics and monitoring cross-segment integration. As the strength of transaction center lies in selection and coordination, prior information of risk can help the coordinator to minimize supply disruptions. Hence, detailed analyses of risks have to be made available to the supply coordinator in planning and management process. Thus, assessment of risk beforehand ensures uninterrupted supply in 4PL network and deemed as vital.

Literature Review

Risk management is becoming one of the critical elements of supply chain and contributes to the decision-making process in cross-functional areas of business (Zsidisin and Ritchie, 2009). Apart from evaluating trading partners with respect to cost, risk parameters have to be viewed critically to ensure uninterrupted supply (Olson and Wu, 2011). Moreover, synthesis of robust analytical tools and new frameworks to capture dynamic risk factors in 4PL network is warranted. More specifically, supply chain risk is dependent on chain partners and has to be effectively mitigated by understanding individual behavior trends of trading partners (Faisal *et al.,* 2006). In addition, quantitative assessment is considered as one of the potential disciplines for managing risk and creating policies to mitigate the same (Cox Jr., 2009). Further, Minahan (2007) documented from supply management forum that apart from yearly cost reduction, procurement team must quantify the risk involved in supply process by linking it to revenue impact savings. Consequently, the impact of not considering risk management in distribution network is critiqued with practical industry examples. Lunsford and Glader (2007) analyzed the root-cause of risk through the Boeing Dreamliner-787 case study. Since Boeing engineers concentrated on developing huge components like wings and fuselage of the aircraft with carbon-fibre plastics; the company faced shortage of nuts and bolts during public launch. Similarly, FedEX temporarily suspended delivery guarantees as Tornados affected the southern part of US (Dentch and Ohnsman, 2008) due to environmental risk. In the same way, auto parts maker Collins and Aikman Corporation stopped supplying instrument panels and interior plastic parts to Ford Motor Company due to misunderstanding over financial issues which led to production stoppage at the Mexico plant (Jeffrey and Neal, 2006). Since 4PL transaction center deals with multiple categories of trading partners, it offers both opportunities and risks. By integrating trading partners, economy of scale is achieved through mergers, while on the other hand, it increases the level of risk. Nevertheless, estimating risk involves collecting information from different combination of subjective and objective parameters of trading partners which lacks predictive analytics. Therefore, little work is carried out in synchronizing different metric scores to predict risk for managing 4PL transaction center. By virtue of this, a predictive model is created to estimate risk proactively before performing cross-segment integration. Conversely, Sreekumar and Mahapatra (2011) illustrated the application of NN methodology for prediction in uncertain situations to ensure transparency.

Proactive Risk-Predictive Model Development

Phase 1: Risk Assessment Model

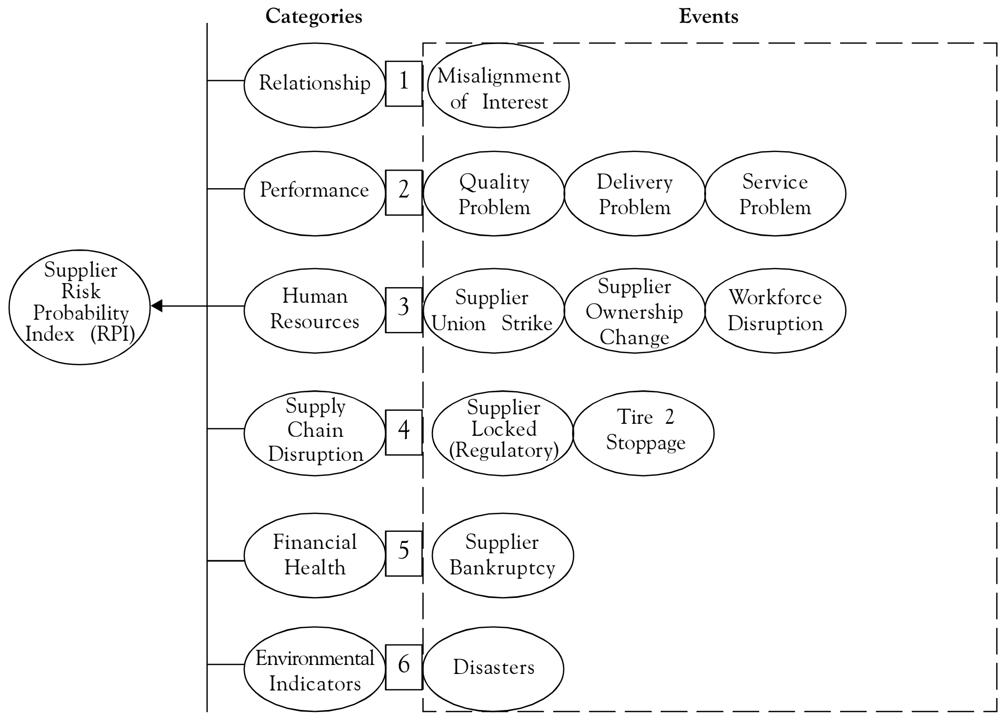
The assessment model considered six categories of risk enablers in a supply chain network based on their industry consulting experience (McCormack, 2007). The six categories were characterized as relationship, performance, human resources, Supply Chain (SC) disruption, financial health and environmental indicators. Figure 2 represents the risk enabler categories along with potential events which have equal likely chance to occur in an SC.

Assumptions

The assumptions include:

- Scaling techniques adopted for Cormack's risk assessment model was mutually agreed between chain partners. Further, corresponding data to estimate marginal probability was available through Request For Information (RFI) for the transaction center coordinator.

Figure 2: Risk Enablers in a Supply Chain



Source: McCormack (2007)

- Learning rate to adjust the weights in NN was assumed as 0.5 in order to train the risk-predictive model to estimate RPI.
- Single hidden layer was considered in the proposed NN to generalize between input descriptors and output response (prediction) variable.

Based on these categories, scaling factors were defined, as shown in Table 1. The description row in Table 1 explains the analogy to select scaling factors. On the other hand, marginal probability technique was implemented using historical data and RFIs to estimate probability of risk occurrence.

By combining individual trading partner's scaling factors and probability, RPI was estimated. Through RPI score, Supply Chain Risk (SCR) was determined considering total financial impact. Nonetheless, optimal merger cost obtained from the transaction center modelled by Kumar *et al.* (2013) was looked as financial impact in USD. Accordingly, the mathematical expression for SCR was depicted as follows:

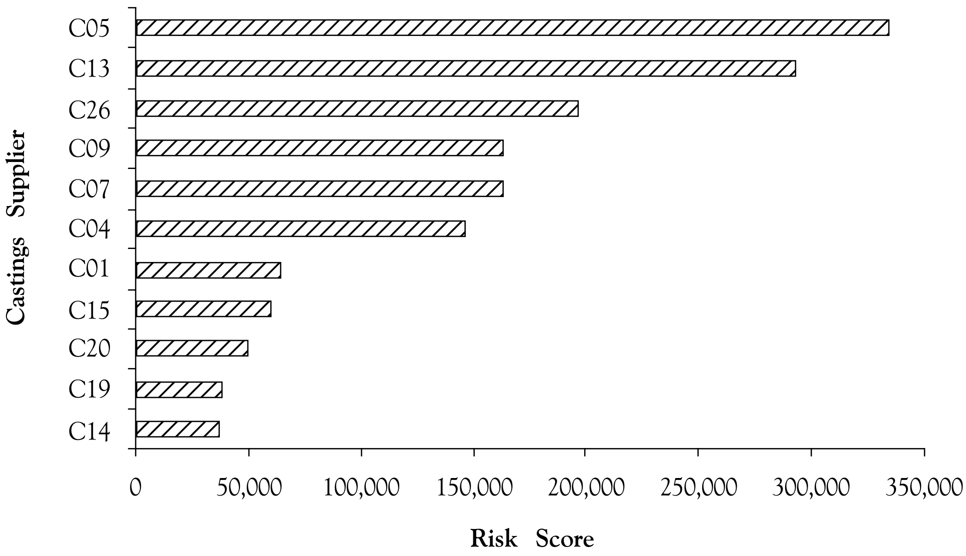
$$\begin{aligned} SCR &= (\text{Likelihood of the Event}) * (\text{Consequences}) \\ &= (\text{Probability of Occurrence}) * (\text{Total Financial Impact}) \\ &= (RPI) * (\text{Total Financial Impact}) \qquad \text{...(1)} \end{aligned}$$

Table 1: Description of Scaling Techniques Adopted

S. No.	Risk Category						
1.	Relationship	**Description**	**% of Production from Supplier Capacity**				
		Scaling Factor	1	2	3	4	5
		Criteria	>90	>65-90	>15-65	>5-15	<5
2.	Performance	**Description**	**% of Materials Accepted from the Deliveries**				
		Scaling Factor	1	2	3	4	5
		Criteria	>99.5	>99 ≤99.5	>98 ≤99	>97 ≤98	≤97
3.	Human Resources	**Description**	**Workforce Disruption**				
		Scaling Factor	1	2	3	4	5
		Criteria	Low	Low to Medium	Medium	Medium to High	High
4.	Supply Chain Disruption	**Description**	**Net Dependence from Kraljic's Matrix**				
		Scaling Factor	1	2	3	4	5
		Criteria	Acquisition	Profit	Security	Critical	To be Marked
5.	Financial Health	**Description**	**% Growth Rate in the Last Five Years**				
		Scaling Factor	1	2	3	4	5
		Criteria	>30	>20-30	>10-20	>5-10	<5
6.	Environmental Risk	**Description**	**Supply Chain Disruption Potential (Natural, Political, Terrorist, etc.)**				
		Scaling Factor	1	2	3	4	5
		Criteria	Low	Low to Medium	Medium	Medium to High	High

For risk assessment, 11 casting suppliers were considered and individual SCR supplier is given in Figure 3. From the secured results, suppliers with high SCR scores were indicated as high risk suppliers which needs to be mitigated on a priority basis before

Figure 3: Individual Supplier SCR Score



performing cross-segment integration. For instance, C05 and C13 suppliers have high SCR scores, which can be mitigated on a priority basis and critically reviewed before carrying out integration in the transaction center.

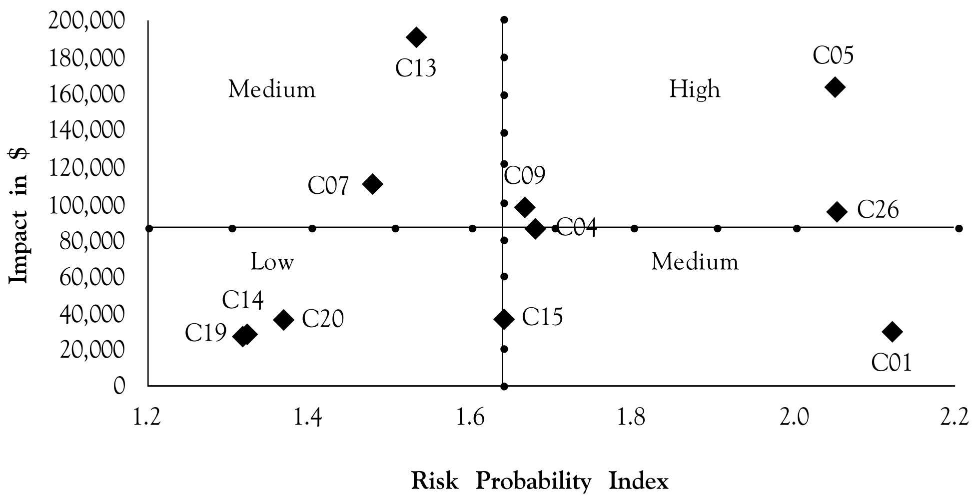
In order to segregate risk with regard to high, moderate and low categories, prioritization matrix was employed to view all trading partners within a commodity group. The matrix was constructed by plotting financial impact versus probability of occurrence. In addition, the matrix acts like a visual sorting mechanism so that trading partners with high risk can be prioritized for mitigation. Figure 4 represents prioritization matrix considering financial impact in USD versus RPI using Kraljic's matrix adopted from the proposed makeshift methodology (Kumar *et al.*, 2012).

The supplier codes, C04, C05, C09 and C26 are regarded as susceptible to high risk and the supplier codes, C14, C19 and C20 are regarded as low risk suppliers. Based on the individual supplier category, a color code (say, Red: High, Yellow: Medium and Green: Low) was assigned and prioritization to carry out risk mitigation was signified. In the next section, an attempt to develop risk model to estimate RPI (response variable) was exhibited by identifying the optimal number of risk enablers (predictors) for the 4PL transaction center.

Phase 2: Synthesizing Risk-Predictive Model

In order to scientifically estimate the optimal number of predictors for the proposed risk model, PLS regression analysis was applied. Moreover, PLS model reduces the number of predictors into uncorrelated variables. Further, cross-validation technique was used to determine the appropriate number of predictors which maximizes the predictive ability.

Figure 4: Risk Matrix of Castings Suppliers



In particular, leave-one-out cross-validation approach was executed for prediction calculations, leaving one observation at a time. The mathematical representation of PLS model was represented as follows:

$$RPI = f\ (Category_i) \qquad \text{...(2)}$$

where i represents the individual category of risk assessment model.

By virtue of PLS regression, the optimal number of predictors for the proposed risk model was formulated considering RPI as response variable and categories from Cormack's risk assessment model as predictors. Nonetheless, environmental indicator was ignored as all the casting suppliers viewed were from the same region. Hence, the model has five predictors and one response variable. After executing PLS regression, the model selection plot signifies four predictors as optimal for the proposed model using fitted and cross-validation data. Additionally, the vertical line validates the optimal number of predictors with the highest coefficient of determination R^2 value, as depicted in Figure 5.

In addition, PLS loading plot exhibits relative influence of predictors on response variable. Figure 6 denotes that performance predictor has least impact on the response variable RPI, thus suggesting to remove the predictor variable from the proposed risk model scientifically.

Therefore, risk model with four predictors (human resources, relationship, financial health and SC disruption) yields adequate predictions with regard to data considered for the study. From the secured PLS regression results, four predictors with one response variable was deemed apt to build the NN risk-predictive model. In general, an NN makes

Figure 5: PLS Model Selection Plot
(Response is Risk Probability Index)

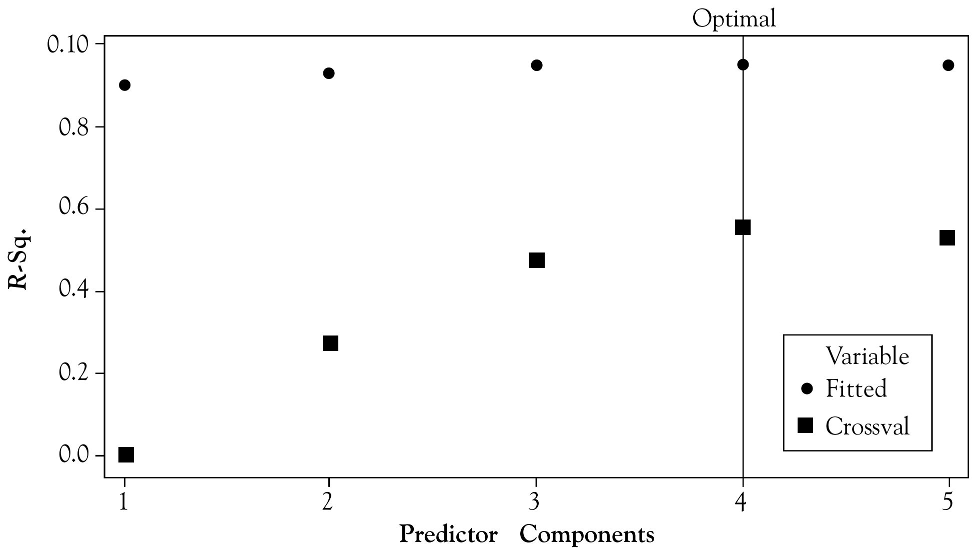
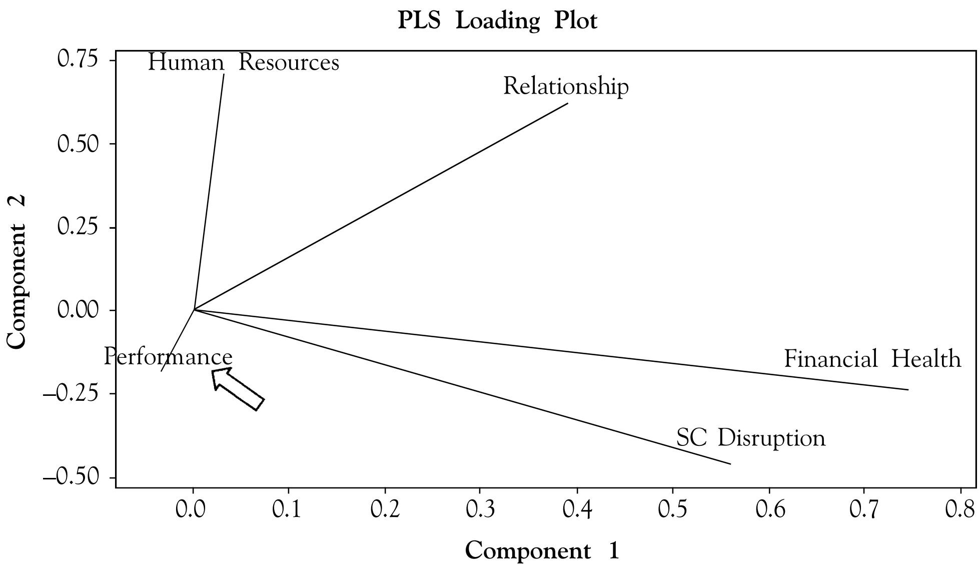
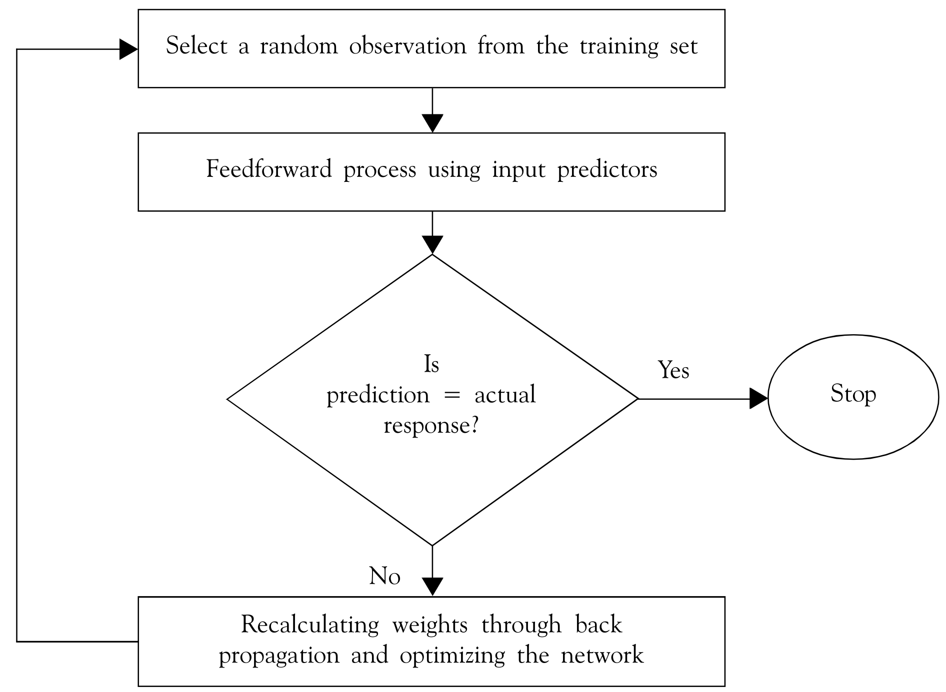


Figure 6: Relative Influence of Predictors on RPI



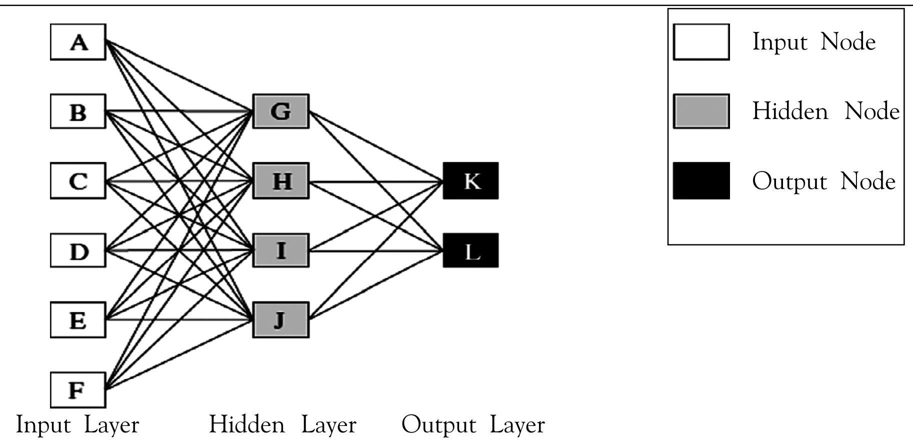
prediction using training dataset of predictors. The training dataset captures the relationship/behavior between input predictors and output responses. Furthermore, proactive estimation of risk for the transaction center can be made in future once the NN model was trained. Figure 7 illustrates the NN building process adopted for proactive risk-predictive modelling.

Figure 7: NN Model-Building Process



The modelling of NN was carried out through feedforward and back propagation technique. Moreover, the topology is given in Figure 8, which consists of input predictors, output responses and hidden layers.

Figure 8: Topology of an NN



Source: Glenn (2007)

Initially, dataset was divided into training and verification sets to assess the developed risk model holistically. Furthermore, demonstration of NN building process was reported by Glenn (2007). Additionally, single hidden layer was regarded with two neurons for synthesizing risk-predictive model as it can approximate any function from one finite space to another (Jeff, 2008). Consequently, each node in the NN was equipped with weights w_{ij} and set of individual input value I_j. Cumulative input X_j for a node j was calculated as follows:

$$X_j = \sum_{j=1}^{n} I_j w_{ij} \qquad \dots(3)$$

Here, n represents the number of training datasets considered for the study. Similarly, individual output of a node $output_i$ was computed by processing X_j through sigmoid activation function, as given in Equation (4).

$$\frac{1}{1+e^{-X_j}} \qquad \dots(4)$$

After carrying out feedforward process for all the nodes in NN, the output response $Output_{1i}$ was predicted and compared with actual response $Actual_i$. Subsequently, weights were adjusted during learning process by estimating error from $Actual_i$ and $Output_{1i}$. More specifically, the learning process of an NN was performed using back propagation technique to enhance the predictive accuracy. Nonetheless, this technique was repeated with different training datasets till generalization between input predictors and output response match. Besides, presenting all training datasets to the network once was regarded as one cycle. Thus the number of cycles was decided considering predictive ability between predicted and actual response value. Output layer response error $Error_{1i}$ was measured as follows:

$$Error_{1i} = Output_{1i} * (1 - Output_{1i}) * (Actual_i - Output_{1i}) \qquad \dots(5)$$

Similarly, error was back propagated to the hidden layer utilizing Equation (6). Here, $Error_{2i}$ represents error resulting from the hidden layer node; $Output_{2i}$ represents value of the output from the hidden layer node and $Error_j$ denotes calculated error for the node j.

$$Error_{2i} = Output_{2i} * \left(1 - Output_{2i}\right) * \sum_{j=1}^{n} Error_j \, w_{ij} \qquad \dots(6)$$

Lastly, the attained error values were utilized to adjust the weights (Adjusted w_{ij}) in the proposed risk model till predicted and actual response values match by employing Equation (7) through predefined number of cycles.

$$Adjusted\ w_{ij} = w_{ij} + (l * Error_j * Output_i) \qquad \dots(7)$$

Risk-predictive model was developed considering five casting suppliers, as shown in Figure 9. Moreover, X_i signifies input predictors and Y represents output response. Further, normalized input-output data matrix is reported in Table 2 for training set suppliers. Figure 10 portrays the initial NN predictive model with random weights for C20 supplier including actual RPI.

Figure 9: Training Set Suppliers Selected for Predictive Modeling

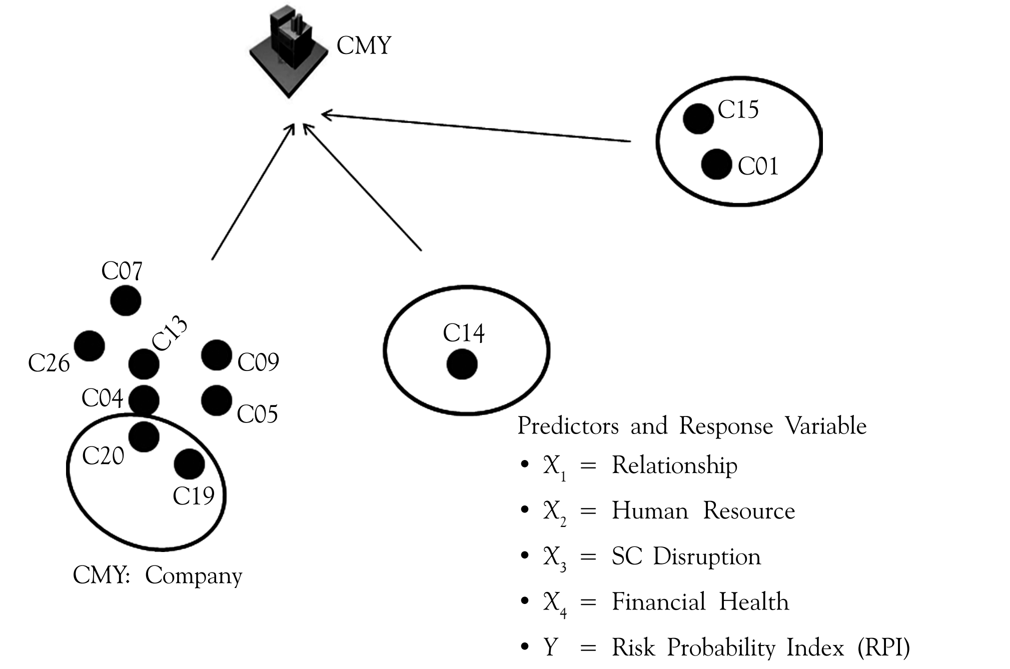
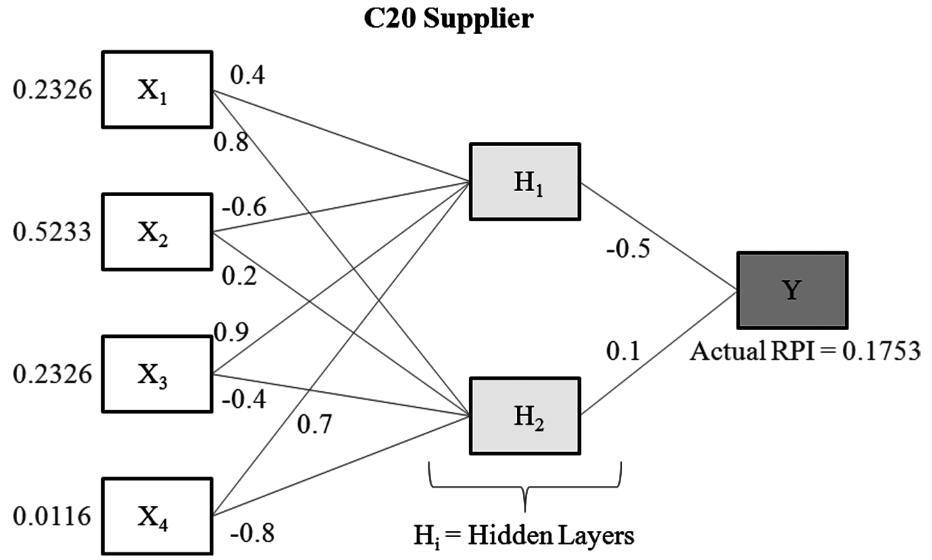


Table 2: Description of Scaling Techniques Adopted

S. No.	Training Set	Input Predictors				Output Response (RPI)
		X_1	X_2	X_3	X_4	Y
1.	C01	0.1290	0.2258	0.5161	0.1290	0.2732
2.	C14	0.2222	0.2222	0.4444	0.1111	0.1701
3.	C15	0.2353	0.4118	0.2353	0.1176	0.2113
4.	C19	0.0430	0.4839	0.4301	0.0430	0.1701
5.	C20	0.2326	0.5233	0.2326	0.0116	0.1753

Subsequently, the error estimates were used with learning rate of 0.5 in order to adjust weights between the connecting nodes. Similarly, this procedure was repeated for 50 cycles to generalize the relationship between input predictors and output response. The

Figure 10: Proposed NN Predictive Model



learning trend of predicted RPI against average actual RPI is given in Figure 11 which reveals that the gap between predicted and actual RPI narrows down at 50^{th} cycle of learning through adjustment of weights. Finally, the NN optimization was stopped after 50 cycles as the network yields significant predictive accuracy, as shown in Figure 12.

Therefore, the final weights attained after learning process can be used for predicting risk in the future by the coordinator. The trained proactive NN risk-predictive model

Figure 11: Learning Trend of the NN Model

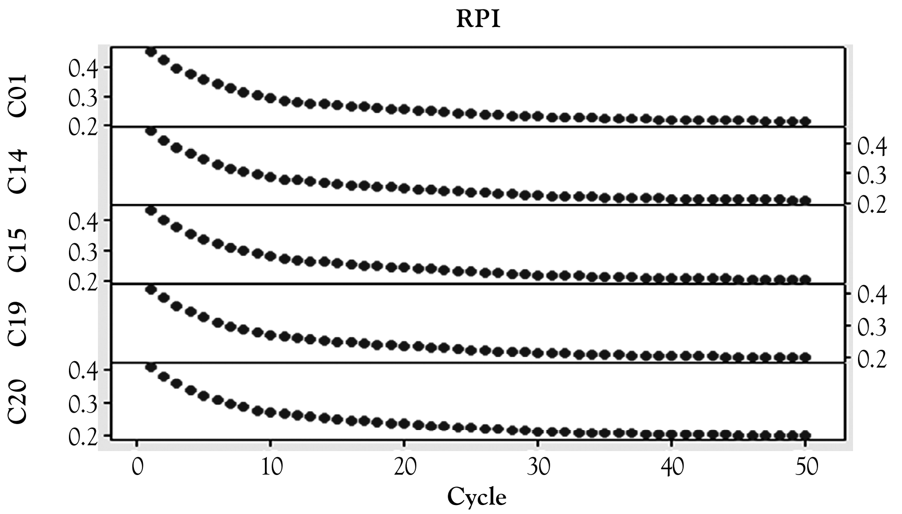
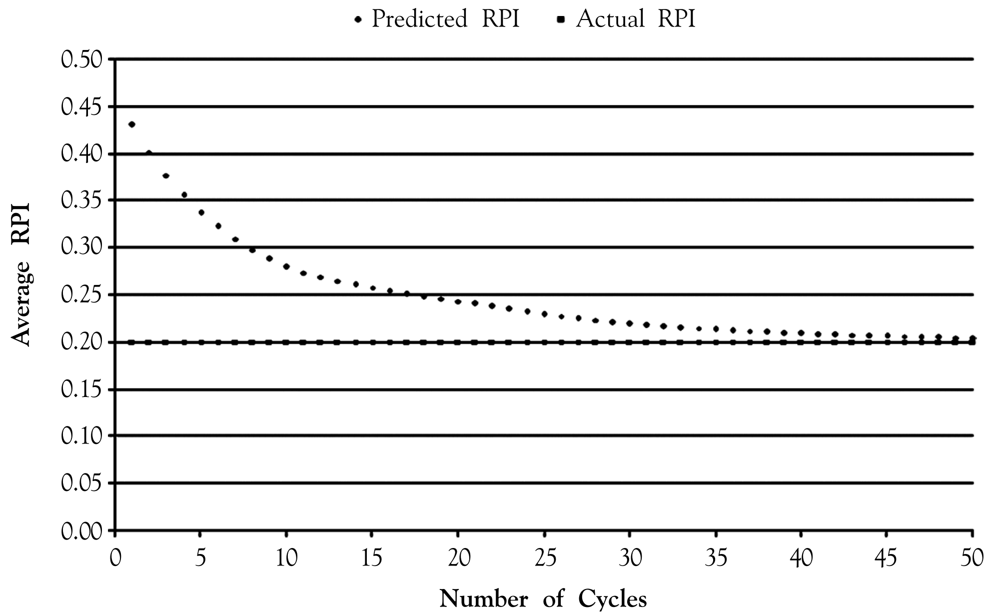


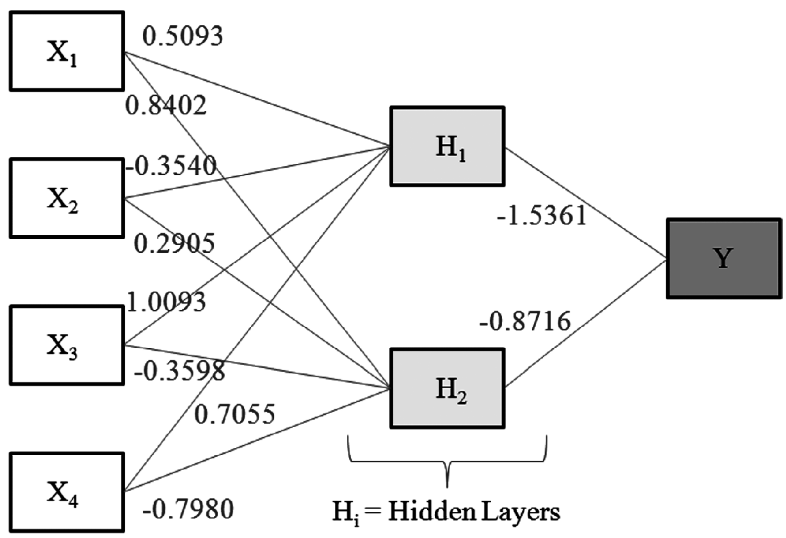
Figure 12: NN Optimization of Predicted RPI



along with weights is reported in Figure 13. Since the coordinator can estimate risk for the future, it has been termed as proactive risk-predictive model.

Conversely, risk-predictive model was evaluated using verification dataset to ensure adequacy of the intended risk model. In particular, the recommended model was evaluated

Figure 13: Optimized NN Predictive Risk Model



by substituting verification dataset to the optimized NN. However, predictive and actual RPI matched with at least 85% predictive accuracy after 50 cycle iterations. Further, the accuracy can be enhanced by enforcing more optimization cycles. In summary, the trained model can be used by the transaction center coordinator to estimate risk proactively with regard to existing trading partners. To put it succinctly, the final weights attained after learning process can be used for predicting risk in the future. Therefore, the intended risk model helps the 4PL service provider to reduce the impact of supply disruption risks on distribution network from well in advance.

Conclusion

Since, 4PL transaction center deals with multiple categories of trading partner, it offers both opportunities and risks. Integrating trading partners ensures economies of scale and contrarily increases risk. To precisely estimate risk, a new predictive model was proposed in two phases for the 4PL transaction center. Besides, the recommended model consists of supply risk information which can help the coordinator to explore merger options proactively by aligning resources in order to manage 4PL operations. In view of the fact that each trading partner synthesizes its own risk metrics, the intended model synchronizes different metric scores through predictive analytics. Thus, proactive risk-predictive model was developed considering RPI as response variable and enablers from Cormack's risk assessment model as predictors. The key message from this study aims at furnishing transaction center coordinator to foresee probable risks proactively before integrating cross-segment trading partners for consistent 4PL operations. Also, the trained NN model can be used as an auxiliary to the transaction center for predicting risk in future and critically review individual trading partner risk. Nonetheless, as and when new trading partners were added to the transaction center pool, the risk model can be trained to generalize the relationship between predictors and response variables. By doing this, supply disruptions can be mitigated and the transaction center can be managed proactively. Thus, an attempt to capture the heterogeneous risk behavior of trading partners and creating proactive risk-predictive model for the 4PL transaction center was considered as an original contribution. From this, the coordinator can foresee supply disruption risk proactively and explore risk mitigation strategies along with contingency planning. ⌘

Acknowledgment: *The authors would like to thank MS Ramaiah School of Advanced Studies, Bangalore, India and Coventry University, UK for allowing them to carry out the research.*

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Reference # 34J-2014-03-03-01