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Uncertainty Modelling in Risk-averse Supply Chain Systems Using Multi-objective Pareto Optimization

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Abstract

Risk modelling along with multi-objective optimization problems have been at the epicenter of attention for supply chain managers. In this paper, we introduce a dataset for risk modelling in sophisticated supply chain networks based on formal mathematical models. We have discussed the methodology and simulation tools used to synthesize the dataset. Additionally, the underlying mathematical models are discussed in granular details along with providing directions to conducting statistical analyses or neural machine learning models. The simulation is performed using MATLAB ™Simulink and the models are illustrated as well.

Keywords— Supply Chain Management (SCM); Supply Chain Risk Management (SCRM); risk modelling; time-series analysis; machine learning

1 Summary

The emergence of business intelligence has broadly reinforced the interplay among business entities in the digital realm. These AI tools are undoubtedly powerful in employing self-learning paradigms to facilitate convenient services but such tools still remain inadequate to reduce the impact of inevitable risks involved in business operations. In context to Supply Chain Risk Management (SCRM), it is therefore an open problem to eliminate and more significantly, optimize the impact of such risky operations that have been an evolutionary target for supply chain managers. This dataset is primarily targeted to support self-learning models and evolutionary algorithms for estimating non-linear functions and trends in supply chain systems. The Time-series sequence consists of 6 Lakh timesteps of seven attributes namely, Timestamp, RI_Supplier1, RI_Distributor1, RI_Manufacturer1, RI_Retailer1, Total_Cost, SCMstability_category. The time-series sequence is generated by simulating a multi-echelon supply chain network in MATLAB ™with three suppliers, one distributor, one manufacturer and one retailer. An arbitrary demand is introduced to the supply chain model and selective features such as total cost and risk index are calculated at each time-step. Section 2.2 describes the features and their mathematical formulation extensively. Finally, the obtained results are tabulated and exported as a dataset.

2 Dataset for Modelling Risks in Supply Chain Systems

2.1 Scope of the Dataset

The purpose of this dataset is intended for academic purposes only. The dataset is not claimed to resemble the nature of a real-time supply chain networks. After a careful literature review, a set of succinctly defined mathematical models were selected to formulate the attributes and yield an empirical dataset. Hence, the dataset is generated based on limited assumptions on the underlying principles in supply chain networks.

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This dataset is suitable for training machine learning models for time-series analyses and estimation of non-linear functions in risk-averse supply chain networks. It is thoroughly verified with absolute minimal outliers and could serve as an appropriate source for time-series analysis and evaluating non-linear auto-regressive models. As described in section 2.2, the calculated risk indices of supplier, distributor, manufacturer and retailer are non-linear in nature due to intended disruptions in the supply chain. Considering all the variables as cross-sectional data and performing trend analysis or regression analysis, a broader investigation on the nature of the risks involved in supply chain networks can be carried out.

2.2 Mathematical Modelling

In this section, a deterministic mathematical model for each attribute in the supply chain network is discussed.

For a given supply chain with 4 echelons: Supplier, Distributor, Manufacturer, Retailer and selective activities such as sourcing or supplying raw material to each component, assembling final products and delivering to destination markets, each component has its own cost, lead-time and associated risk.

1. The Risk Index (RI) is derived from the model proposed in [1], and can be mathematically formulated as:

$$RI_{supplier} = \sum_{i=1}^{n} \alpha s_{ij} \;.\; \beta s_{ij} \;.\; (1 - (1 - \prod_{j=1}^{m} P(\tilde{S}_{ij})) \tag{1}$$

   where, αs_{ij} is the consequence to the supply chain if the i^{th} supplier fails,
   βs_{ij} is the percentage of value added to the product by the i^{th} supplier,
   $P(\tilde{S}_{ij})$ denotes the marginal probability that the i^{th} supplier fails for j^{th} demand,

   Similarly, the risk indices for the rest of the components can be calculated as:

$$RI_{distributor} = \alpha d_{risk_i} \;.\; \beta m_i \;.\; (1 - (1 - P(\tilde{M}_j))) \tag{2}$$

$$RI_{manufacturer} = \alpha m_{risk_i} \;.\; \beta m_i \;.\; (1 - (1 - P(\tilde{M}_j))) \tag{3}$$

$$RI_{retailer} = \alpha r_{risk_i} \;.\; \beta r_i \;.\; (1 - (1 - P(\tilde{R}_j))) \tag{4}$$

2. For each set of demand, the cumulative risk index of the supply chain network can be calculated as:

$$TRI = w_1 \;.\; RI_{supplier} + w_2 \;.\; RI_{distributor} + w_3 \;.\; RI_{manufacturer} + w_4 \;.\; RI_{retailer} \tag{5}$$

   where, w_1, w_2, w_3, w_4 are arbitrary weights such that $w_1 + w_2 + w_3 + w_4 = 1$

3. The risk fluctuation subjected to the supply chain network is generated by a sine-wave generator, and is mathematically gives as :

$$\tilde{\delta_r} = A.\; sin(\omega t + \phi) + B_i \tag{6}$$

   where, $\tilde{\delta_r}$ denotes the absolute value of risk fluctuation,
   A denotes the peak amplitude of disruption,
   ω denotes the angular frequency, t denotes time,
   ϕ denotes the phase and B_i denotes a bias

4. The total supply chain cost can be calculated as [2]:

$$TC = \xi \times \sum_{i=1}^{N} (\mu_i \, . \sum_{j=1}^{N_i} C_{ij} y_{ij}) \tag{7}$$

where, N is the number of components,
ξ denotes the period of interest,
μ_i is the average demand per unit time,
C_{ij} is the cost of the j^{th} resource option for the i^{th} component,
y_{ij} is a binary variable denoting whether the i^{th} component is a participant for the j^{th} resource option

5. For each couple of normalized risk index and total cost of the supply chain, the main objective function Z is given as [2]:

$$Z = w_1 \, . \, TC_n \; + \; w_2 \, . \, TRI_n \tag{8}$$

where, TC_n is the normalized total cost,
TRI_n is the normalized total risk index,
w_1, w_2 are the weights ; $w_1 + w_2 = 1$

3 Setup

In Quasi-experimental evaluations, a system is evaluated by intervening the model parameters with reference to variable constraints. Particularly in context to supply chains, a supply chain model is subjected to either risk fluctuations or demand variations and the resiliency of the supply chain network is recorded. For modelling this proposed scenario, we have used MATLAB ™simulink library. The psuedo supply chain models are given below in fig. 1 and fig. 2:

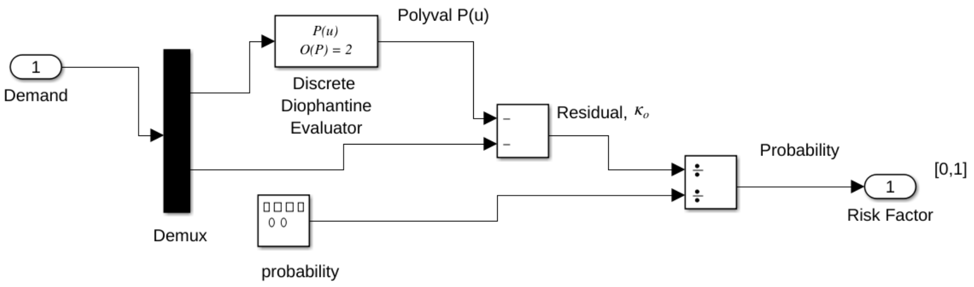

Figure 1: Psuedo Supply Chain Model using linear Diophantine evaluator

In Fig. 1, A linear Diophantine evaluator model is illustrated to emulate simple supply chain networks. The demand is fed to the polynomial evaluator subsystem which determines the suitable coefficients for the Diophantine equation. Consequently, the residual, denoted by κ_0 is determined by subtracting the demand from the real value of the cost function. Additionally, the probability associated with the risk is calculated by dividing the residual with the demand. The output is the risk magnitude.

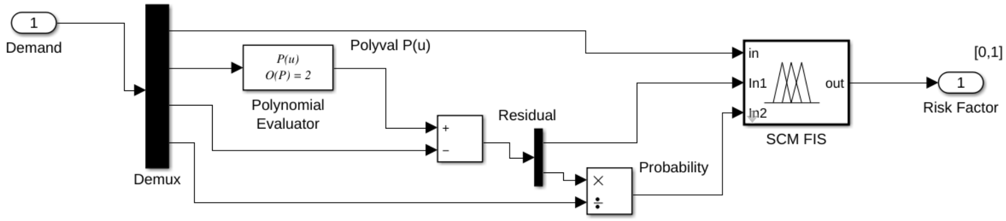
1
Demand
Demux
P(u)
O(P) = 2
Polynomial Evaluator
Polyval P(u)
+
−
Residual
×
÷
Probability
in
In1
In2
out
SCM FIS
[0,1]
1
Risk Factor

Figure 2: Psuedo Supply Chain Model using Fuzzy Inference system

In Fig.2, A Fuzzy Inference System (FIS) is used to evaluate the risk factor. A FIS is a rule-based system that operates on linguistic variables, which represents uncertainty or vagueness in the magnitude of the input variables. The FIS input parameters are demand, residual loss, probability of risk and the output is the risk magnitude.

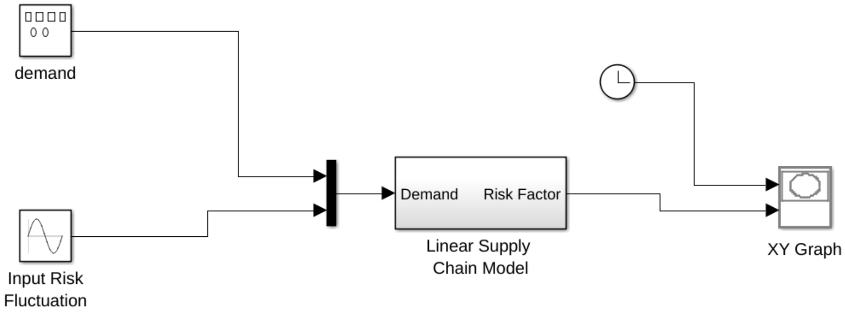
demand
Input Risk Fluctuation
Demand
Risk Factor
Linear Supply Chain Model
XY Graph

Figure 3: Quasi-Experimental setup for Risk Analyses in Supply Chain Networks

As shown in Fig. 3, a sine-wave generator is used to synthesize a sinusuidol waveform expressed in equation 6 with amplitude equal to 'A'. The value 'A' denotes the peak magnitude of disruptions to be introduced to the supply chain system in order to evaluate its resiliency. The demand is generated as a discrete waveform with constant amplitude of value 'd'. Both the input signals are introduced to the pseudo supply chain model, which then evaluates the risk factor.

4 Citing the Dataset

The dataset is available online in Mendeley Data library.
To manually add the dataset in the bibiliography, use the following :
"Banerjee, Heerok; Saparia, Grishma; Ganapathy, Velappa; Garg, Priyanshi; Shenbagaraman, V. M. (2019), "Time Series Dataset for Risk Assessment in Supply Chain Networks", Mendeley Data, v2 http://dx.doi.org/10.17632/gystn6d3r4.2"

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