Mustafa Jan[1,*], M. Saeed Khalid[1], Akber Ali Awan[2], Salman Nisar[1]

Proposing Probabilistic Operational Risk Assessment Model for Textile Industry Using Bayesian Approach

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[1] **National University of Science & Technology, Department of Industrial & Manufacturing Engineering,**
PNEC, Karachi, Pakistan
* E-mail: mattari.26@gmail.com

[2] **National University of Science & Technology, Department of Management & Information System,**
PNEC, Karachi, Pakistan

Abstract
Accidents, operational failures and losses prompt authorities to highlight the importance of adequate systems and controls to deal with operational risk (OR). Therefore risk assessment methodology has become a dire need of major industries for undertaking valuable measures in production and operation's research. The paper describes methodology for conducting the risk assessment of the textile operational domain in general i.e. developing a conceptual risk assessment framework and conducting the methodological implementation of the selected operational risk element using the approach proposed. The risk assessment model proposed embraces the concept of probabilistic risk assessment structural modeling using the Bayesian Approach in its generalised form that may be applied to specific textile operational settings with the definition of dimensions and scales for a specific textile environment. The generalised model proposed can also be applied to different textile industries with the insertion of real data for testing and validation. The OR prediction model proposed is GUI-based, scalable, expandable and can be tested for any textile operations with little modification in parent/end nodes under the specific risk element. The paper is helpful to ensure safety and a pro-active approach in textile risk management and also contributes towards the sustainable development of industry operations in the future.

Key words: *operational risk, probabilistic risk assessment model, probability, impacts, Bayesian approach.*

Introduction & background

The textile industry is one of the industries earning substantial gains for national economies. Because of the massive balance of textile export trade in the nation's favour, this industry has become an important tool for enhancing foreign exchange and building up funds. Because of the above, the textile industry has occupied an important position in the national economy, especially in the Asian business environment. In today's textile business environment, many uncertainties and fears are affecting the business operations environment of a textile organization. For this reason, risk management in industries has come to be a paramount step in the project management chain. Indeed the risks are unpredictable and can occur suddenly, closely linked to uncertainty. It includes financial and operational crises, terrorist attacks and natural disasters. These uncertainties and hazardous risks, specifically in textiles, can have a significant impact on both the short and long-term performance of a business organisation and on economic growth. In addition to operational and business risk, the pollution in textile processing may be in the form of air, water or noise, and is considered critical to employees' health and surroundings. Therefore environmental pollution risk analysis in the textile industry is deemed vital in order to prevent a chemical disaster, which may lead to appalling results [15].

Major organisations can suffer catastrophic damage as a result of a single accidental event or a slow accretion of such events over time. Failures and losses in the industrial environment as regular features prompt regulatory authorities to highlight the importance of adequate systems and controls to deal with organisational risk. This has given the industry an impetus to develop methods for measuring and modelling organisational risk. Therefore nowadays, risk assessment methodologies in general and for the textile industry have become a standard step in the project management process in order to achieve objectives in terms of time, cost, quality, safety and security. In terms of operational risk assessment, the majority of research and studies address the operational risk of financial institutions, especially banks and insurance companies [25]. The structural modeling of banking operational risk via Bayesian inference was conducted by Pavel V. Shevchenko, in 2006 [9]. The method allowed structural modelling of expert opinions incorporated into probabilistic analysis via specifying distributions for operational risk model parameters. Hence operational risk estimation for textile industrial application in general has not been addressed. However, this study attempted to achieve this.

This paper aims to present a probabilistic risk analysis for the quantification of textile operational risk in a generalised form using the Bayesian approach. The study is meant to show operational risk estimation as a reference where the operational risk can be defined as resulting from inadequate or failed internal processes, people and systems, or from external events [37]. The universal and generalised model proposed can take account of operational risk measures in textiles to produce a unified prediction of an organization's operational vulnerability. The objective of this study is to present a probabilistic risk analysis model that combines the Bayesian probability approach and PRA based structural diagrams into a single generalised form that may be easily scaled for any specific textile operational scenario with little or some modification. The paper also provides a soft computational environment in the form of java-based, user-friendly GUI. Hence the model is scalable and expandable for application in any specific textile industrial set up.

Literature review

A great variety of tools and different methodologies have been proposed to develop solutions for assessing risk. Based on a literature review, we can find several methods for risk assessment/management mainly classified into two categories, namely the deterministic approach and stochastic approach. The stochastic approach includes statistical methods and accidental forecasting modelling. Numerous risk assessment models have been developed over the years, especially in the nuclear, financial, and medical fields.

Keeping in view the stochastic nature of complex operational risk uncertainties and scenarios in the industry and the need for incorporating management decisions, competencies and preferences for effective risk management decision support, the stochastic based risk event forecasting model will be applied. Some of the risk prediction non-linear model includes a fuzzy logic model, regression method, neural networks and Bayesian networks. Fuzzy logic uses a multivariate logical set that recognises human decisions by allowing gradations in its formulations. The brief case studies on how fuzzy logic is utilized in a bank for operational risk management has been presented by Hoffman in 2002 [33]. Sofyalioglu C. in 2012 [7] proposed the fuzzy analytical hierarchy process approach to determine the critical supply chain and operational risks for a Turkish company operating in the iron and steel industry. Although the fuzzy method has ease-of-understanding, in itself it cannot substitute robust statistical methods in measuring operational risk in a capital-at-risk sense.

Neural networks are useful for modelling complex relationships between variables that would be difficult to do using linear methods. In statistical pattern recognition modeling, several ANN designs (MLNN/RBFN) have been experimented upon under a variety of conditions. A NN utilises a training set to train the network with the help of large data sets and validates its authenticity using a validation/test set. Vincenzo Pacelli and Michele Azzollini in 2011 developed a neural network based model to forecast the credit risk of a panel of Italian manufacturing companies. N. Chauhan in 2009 [17] and E. Angelini in 2008 [19] proposed the application of an ANN based system for the classification and discrimination of economic phenomena, with particularly focus on the management of credit risk. Ryszard Pukała in 2016 [22] presented a study using artificial neural networks in quantifying the activity related risks of an innovative enterprise for optimising probable financial losses. A weakness of this NN based approach is its heavy dependency on large data sets, and the routines of training for the network require a huge amount of data to ensure statistically precised result. The non linear nature of ANN hinders the application of statistical tests for parameters significance classification.

When data-driven approaches to risk assessment are not possible, such situations can easily be successfully addressed using the Bayesian approach. Analyses of risk assessment using the Bayesian approach have been conducted by several researchers from various fields. Applications of Bayesian networks for modelling operational risks in banking and finance were described by Alexander (2001) [11]. Probability updating is one of the benefits of BN that enable dynamism in the risk assessment model, which quickly scales itself to new input in a mathematically traceable manner. The Bayesian approach estimates the frequency distribution of future risk variables "Xn" conditional on all available data regarding observation X = (x1, x2 ,..., xn)There is broad literature covering Bayesian inference and its applications in industrial areas.

Numerous risk assessment models have been developed over the years, especially in the nuclear, financial, and medical fields with the application of probabilistic risk assessment methodology [30]. Additionally analyses using the Bayesian approach to probabilistic risk assessment and model simulations were also developed by Kalantarnia [20]. Zhao L. in 2012 [26] used a Bayesian network to predict factors related to the risk of hazardous material transportation accidents in China, in which the authors analysed 94 cases of transportation accidents. The study evaluated the most influential factors in hazardous material transportation accidents, which are human factors, the transport vehicle, facilities, as well as the packing and loading of the hazardous material. Han-Ki Jang in 2011 [24] conducted probabilistic risk analysis for radiation risk associated with the field radiography using gamma sources. In this study, the Bayesian probability model was employed for data processing to improve Delphi. Minto Basuki in 2014 [23] conducted probabilistic risk analysis on the construction of new vessels using the Bayesian network approach, and risk assessment was carried out using the probabilistic value at risk (VaR).

In terms of operational risk assessment, the majority of existing literature addresses the operational risk of financial institutions, with a strong focus on banks. Indeed insurance companies have also been discussed [25]. The structural modeling of banking operational risk via Bayesian inference was conducted by Pavel V. Shevchenko in 2006 [9]. The method enabled structural modelling of expert opinions incorporated into probabilistic analysis via specifying distributions for operational risk model parameters. The author proposed the Bayesian method for quantification of probability distributions of banks' operational risks based on prior distributions for the parameters of data held.

The review concludes upon several strategies and approaches developed in quantitative risk assessment, although they have been limited by one or more factors. In terms of operational risk estimation, there has been focus on financial based applications using different approaches. However, textile operational risk estimations have not been addressed through probabilistic risk analysis using the Bayesian approach; however, this paper attempts to achieve this. In this study, a risk analysis was conducted on the main risk elements in the operational risk factor for the textile industry in a generalised form, and subsequently the PRA bottom-p process based approach was used to construct a risk structural model with risk elements divided into parents and end nodes. In this study the major risk elements were proposed by surveying the textile industry of Pakistan, India and Singapore to make it more generalised and universal. A case study of Singapore's textile industry was also kept in mind while making an HRBS of textile operational risks [3].

Textile operational risk assessment – problem formulation

The problem formulation step is used to establish the context for the assessment of operational risk of the textile industry. To fulfill the requirement of problem formulation for operational risk assessment, the following need to be defined and determined:

- Purpose of study,
- Risk node assessment objectives,
- Scope of assessment

Purpose & objectives

The motive of this research is to develop an appropriate risk prediction model

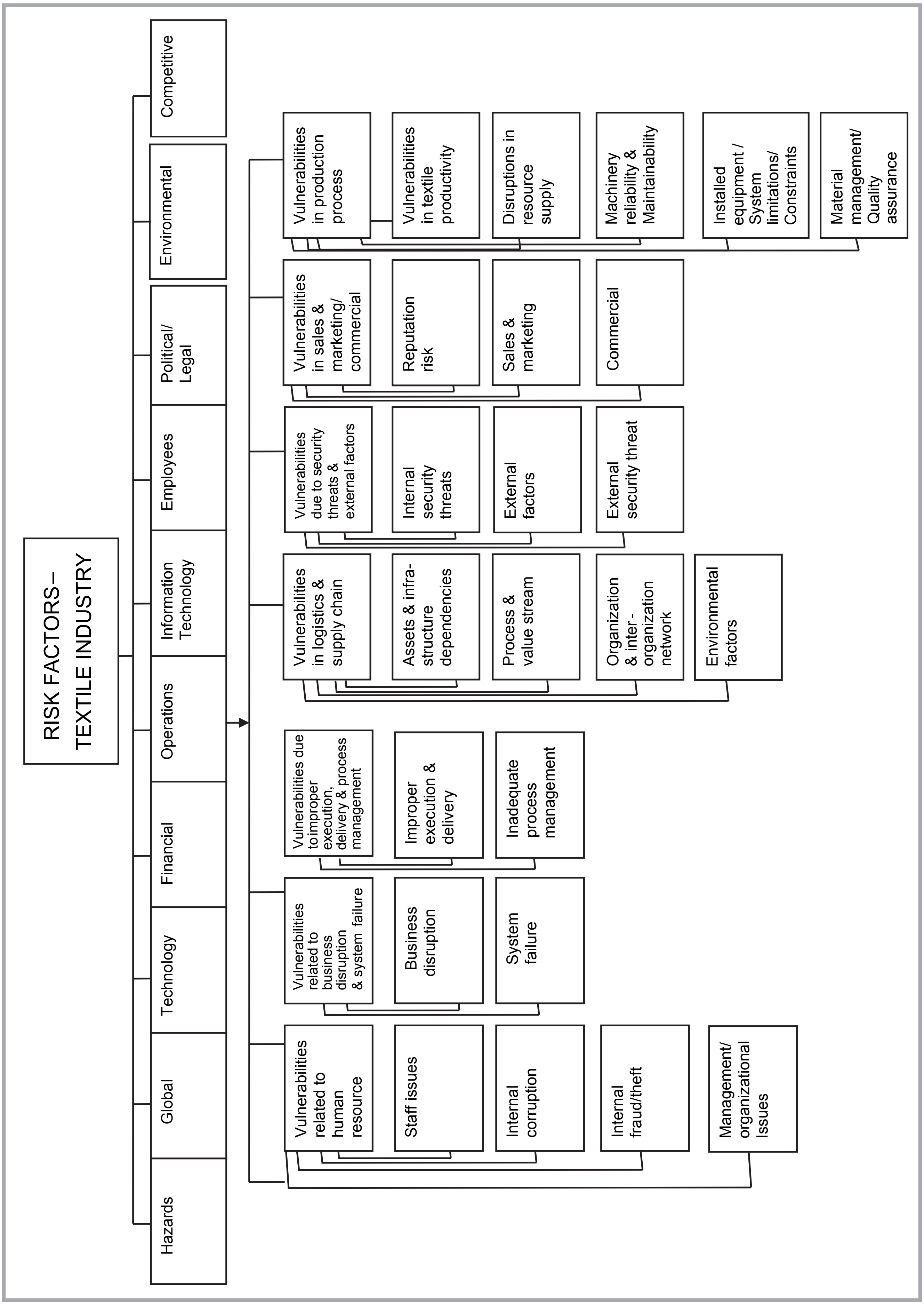

Figure 1. *HRBS model for textile operational risk.*

covering the operational context of the textile industry in general. The paper uses a quantitative approach to analyse current business operations of the textile sector. The objective includes the construction of a PRA structural model for quantification of operational risk related to large/medium textile industry. In model proposed, the PRA based risk structural model and Bayesian approach will take account of all of these risk measures to produce a unified prediction of an organization's operational vulnerability. In general the specific objectives include identification of a collective list of operational risks that may affect textile operations generally and developing a risk assessment model that will be used by decision makers to trigger the risk mitigation step and consequently the level of control to be placed. The core objective of the study is to develop a generalised and universal textile OR assessment model as a proprietary tool that may be applicable to any textile or other industrial set up outside Pakistan.

End assessment objectives

The assessment's endpoint is the overt expression of the operational vulnerability value related to textile operations that are to be protected, operationally defined by their attributes. Accordingly the risk endpoints considered in textile operations will be

- Human resource vulnerabilities
- Vulnerabilities due to business disruption and system failures
- Vulnerabilities due to security threats & external factors
- Vulnerabilities in the production process
- Vulnerabilities due to improper execution, delivery & process arrangement
- Vulnerabilities in logistics & supply chain stream
- Vulnerabilities in sales/marketing & commerce

Scope of operational risk assessment

Operational risk is defined as the risk of loss or reputational damage resulting from inadequate or failed internal processes, people and systems or from external events. For effective risk analysis and management regarding any industry set up, the identification of risks covering major operational aspects is a very important step to be carefully prepared such that no important factor is left which can negatively affect an industry's operations. Risk identification & classification is the primary step for proceeding further. For this purpose, as per standard regulations, operational losses were categorised into multiple dimensions covering business and productions lines as well as internal/external event types. Each of these dimensions is defined at multiple levels depending on the number of probable losses and the need for further bifurcations.

At a minimum, a total number of 07 risk elements were considered under the heading of textile operational risk factors, and further risk elements were divided into parent and end nodes. Risk elements related to business dynamics, production processes, human resources, logistics and the supply chain, business disruption and failure, sales & marketing/commerce, execution delivery, process arrangement, and security threats/external factors were also included. It should also be stated that risk factors under OR have been described on three levels and every factor at each level has its own scale of risk as per real time scenarios. The three levels are as follows:

i. 07 risk elements under OR factor
ii. Each risk element has been bifurcated into its own factors, named as "Parent Nodes"
iii. Each specific parent node under any risk element has its own factors, named as "End Nodes"

The levels above have been transformed into a PRA based structural model for mathematical modelling of the structure. Every factor has its own dimensions and scales depending on the specific textile OR scenario. The dimensions or scales will be determined as per specific textile OR domains. Details of the dimensions and scales have not been covered by this paper and left as limitations for future works on the subject. The hierarchical risk break down structure covering textile operations' major risk elements up to the parent node level is shown in ***Figure 1***.

Methodology

Model methodology developed

Building an operational risk model addressing all textile organisations encompassing all business sectors is clearly an unattainable task. Building a customised operational risk model as a second option for specific textile businesses is equally over burdening. A generalized PRA structural model using the Bayesian approach can tackle this challenge by developing a generic operational risk model that produces a local risk module for specific textile business areas. Once developed, this modifiable PRA structural module may be applicable for any textile organisation with minimal or medium tailoring.

This study concerns the operational risk domain, thus risk elements related to the production process, human resources, logistics and the supply chain, business disruption and failure, sales & marketing/commerce, execution delivery and process arrangement, security threats and all external factors were included. The broad categorisation and classification of risk factors into parent/end nodes as well as the relationships between risk factors and events are mainly based on previous studies and expert opinion. This methodology combines the operational risk causation theory approach with a PRA structural model to quantify risk probability based on the Bayesian probability model. Thus we have utilised the probabilistic risk assessment concept in conjunction with the application of the Bayesian method. ***Figure 2*** shows the breakdown of methodology for undertaking quantitative operational risk analysis for textiles in general.

Textile operational risk elements

In principle, risk always results as a consequence of activities or non-activities. For industries like textile, engaged in a variety of manufacturing activities, there is a critical need to keep all operations running efficiently. Effective textile operations require full and complete knowledge of the factors that can impact the ability to continue such production operations. Implementing a quantifiable based risk assessment and the way the risks are managed is widely recognised as the key step towards the success of a project. Keeping in mind the aspect above, we have divided the operational risk into seven major risk elements, as shown in ***Figure 3***. Furthermore these risk elements will be broken down into parent nodes until the end nodes are exposed in the PRA structural model.

Figure 5 shows the number of vulnerabilities of an organisation's operational side, encompassing internal and external factors, the production process, logistics & the supply chain, sales marketing/

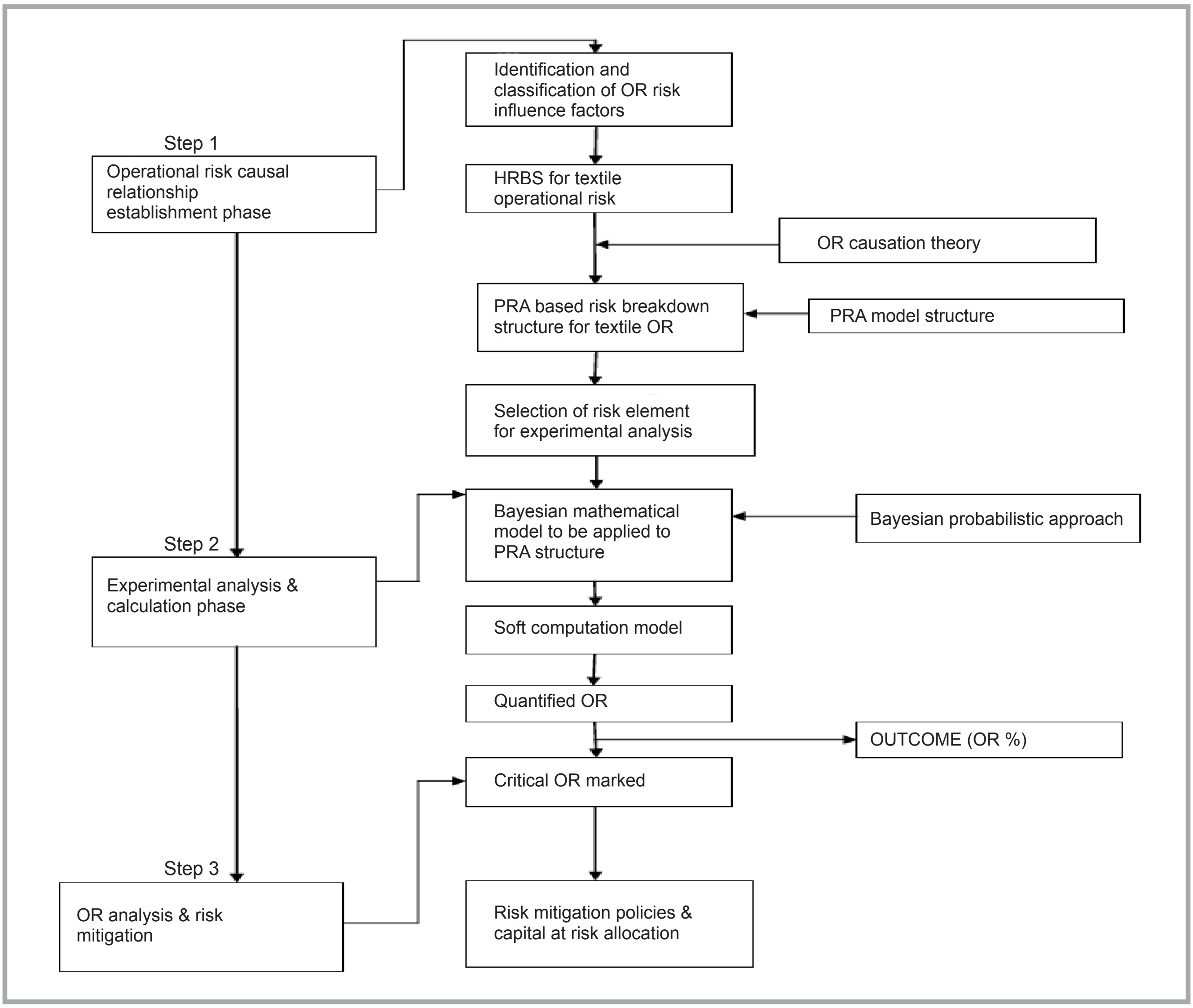

Figure 2. *Methodology for quantitative operational risk analysis.*

commercial losses, and vulnerability to natural disasters and security/terrorist threats. A brief description of major areas covered by each risk element under the textile operational risk factor is appended below:

- Human Resource: The major areas included under this element are employee integrity, which could lead to fraud or pilferage; industrial unrest, which could lead to disruptions in operational activities; shortage of skilled manpower or high skill turnover, which could affect the continuity and growth of the business; risk related to management and staff skills, which could affect textile operation dynamics.
- Logistics & Supply Chain: The few sub areas under this element are non-optimal inventories, which could lead to the blockage of working capital, obsolescence of material, and risk of under-stocking, leading to loss of sales; discontinuity of supplies, which could affect the smooth production process and result into loss of orders; SC process risk relates to factors that cause disruptions to a smooth supply chain; control risk relates to the risks arising from the application or misapplication of governing rules in supply chain processes and demand/supply risks relate to potential or actual disturbances to the flow of the product network, upstream/downstream.
- Production Process: The major risk areas in production include risk of rejections, which could result in business and reputation loss; disruptions in resource supply i.e inadequate resource supply like power, water and fuel, which could affect the continuity of manufacturing lines; shop floor hazards, as failure to take adequate safety precautions may lead to accidents in manufacturing facilities and disruption of the production process; Physical hazards to employees, as failure to follow adequate safety precautions and procedures by workers may lead to accidents in manufacturing facilities and disruption of the production process, and sales and marketing include two risk sub-areas, namely incorrect pricing and a high number of customers claims.
- Security Threats and Other External Factors: The major sub areas under this element include internal/external security threats and any adverse change in the security environment of the city, which can impact the growth strategies of the company. External factors also include actions by outsiders, such as the theft or embezzlement of assets or data, as well as catastrophic or natural disasters, which cause damage to textile assets.

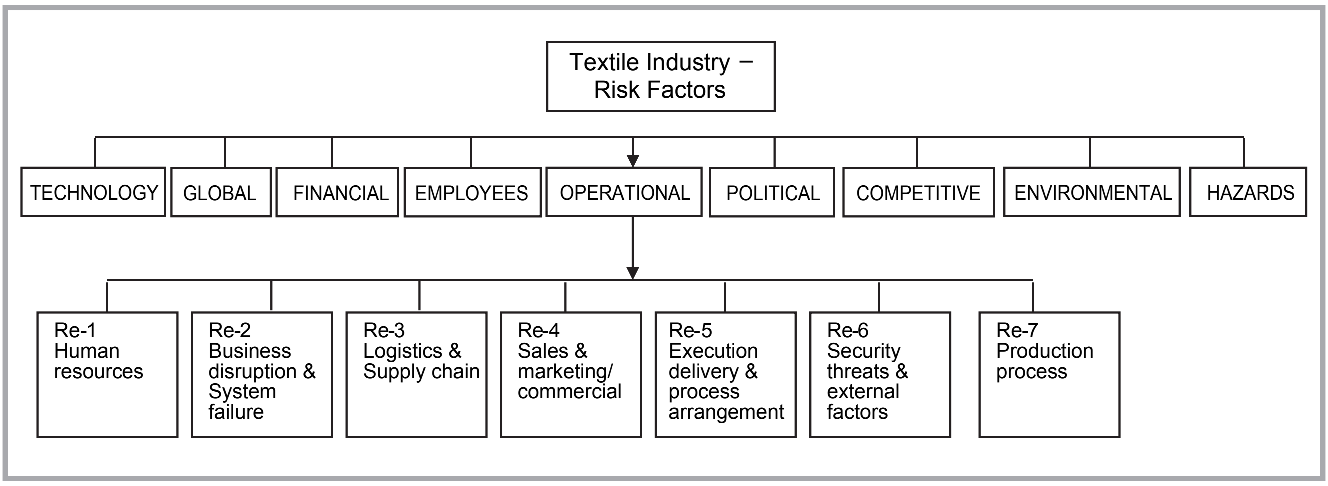

Figure 3. *Breakdown of textile operational risk up to risk elements.*

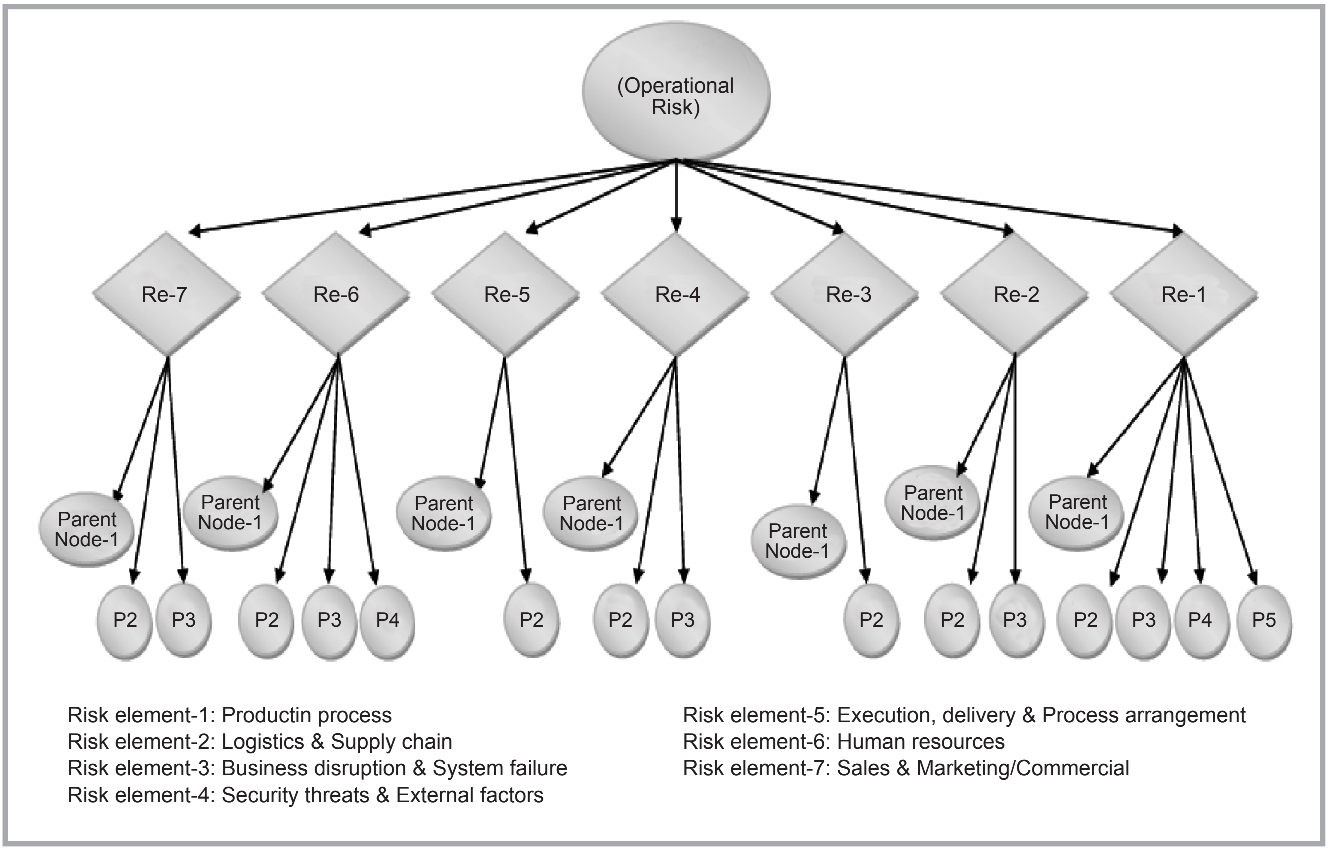

Figure 4. *PRA Structural model for operational risk estimation.*

- Execution Delivery & Process Arrangement: It includes the risk of unexpected financial or reputational loss as a result of poor execution of regular business tasks, which includes those related to the execution and maintenance of transactions, as well as the various aspects of running a textile business, like data entry and accounting errors, failed mandatory reporting and loss of assets. The risks above could lead to data entry and loading errors, modelling of inappropriate operations, entity attribution errors and delivery failures etc; risk related to revenue account management could lead to incorrect account records, as well as financial damage to assets. Inadequate or weak process management across any functional level depending on the specific textile OR. It may include inadequate or weak internal control of any process lying in the textile OR domain. As an example, the non-availability of regular audit or weak internal audit would lead any process to inadequacy. The dimensions or scales will be determined as per the specific textile OR domain.
- Business Disruption & System Failure: The major sub areas under this element are utility disruption as well as software and hardware failure, which includes risk related to system/equipment hardware/software failure due to natural disasters, theft of data/modules and equipment etc. The risks above could lead to disruption in business and affect productivity performance.

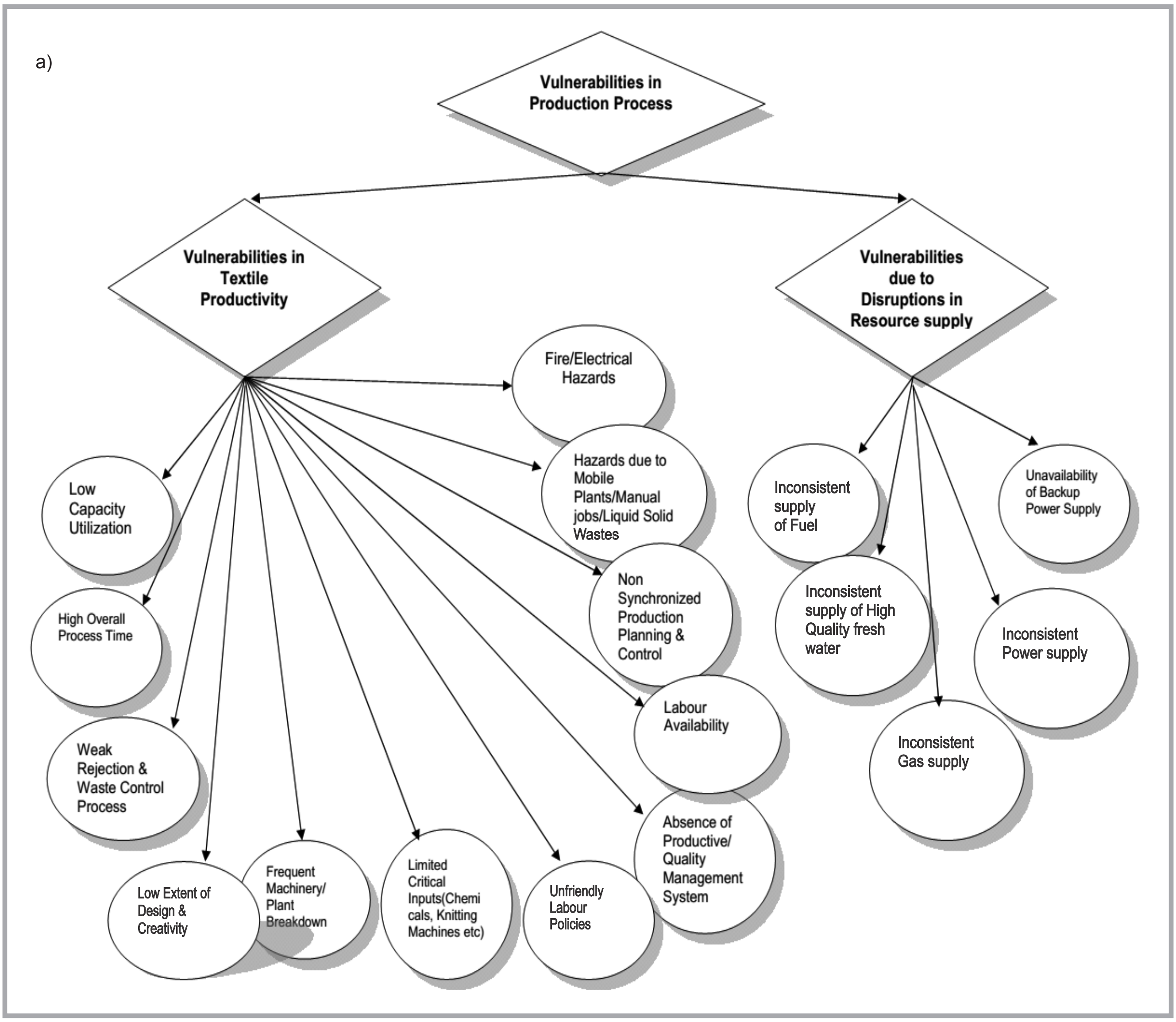

Figure 5.a. *PRA structural model for risk element of production process.*

- Sales&Marketing/Commerce: The major sub areas under these elements are risks related to inadequate market analysis, incorrect pricing, a high number of customer claims, loss of benefits, damage to property and assets. business partner risk etc. The risks above could lead to loss of market benefits and loss of reputations.

PRA structural model

The model involves the mapping of operational risk factors/risk elements up to the macro/micro level in a PRA based risk structural model, which provides a framework for assessing the risks posed by textile operations. The PRA aims to facilitate risk analysis in the research and assessment of micro-prudential risk covering entire operations. The PRA model works on the basis of Baye's probabilistic principle. The PRA model moves in the upward direction from the bottom, starting from end nodes. The specific PRA structural breakdown model applied for operational risk analytics in our study is shown in ***Figure 4***. On the basis of the operational risk PRA structural model shown in ***Figure 4***, the PRA structural model for each risk element in a discrete form is shown in Appendix 'A'[1)].

Mathematical model

The PRA model works on the basis of Baye's probabilistic principle. The basic Bayesian probabilistic model is shown as ***Equation (1)***. The PRA structural model enumerated in ***Figure 4*** moves in an upward direction from the bottom. As shown in ***Figure 4***, the risk of the end node (X) is quantified and aggregated to the parent node. Similarly the risk of parent (P) nodes are aggregated to the risk element (Re), and similarly all risk elements are simply accumulated, and the process moves in an upward direction until the operational risk factor (Rf) is finally obtained. Calculation of the risk factor starts from the quantification of risk at each end node, and then the risk factor at each end node is calculated by ***Equation (1)***, as mentioned below:

$$P(Xk|Pk = \frac{P\left(P\acute{k}Xk\right) * P(Xk)}{P(Xk)} \quad (1)$$

The distribution P (Pk|Xk) is a likelihood function of risk observations. Here P(Xk) normalises the prior probability data, and thus the posterior distribution (Xk|Pk) is directly proportional to the prior knowledge and likelihood function of data observed. The probability approach of Bayesian directs towards optimal predictions in a way that the mean square error

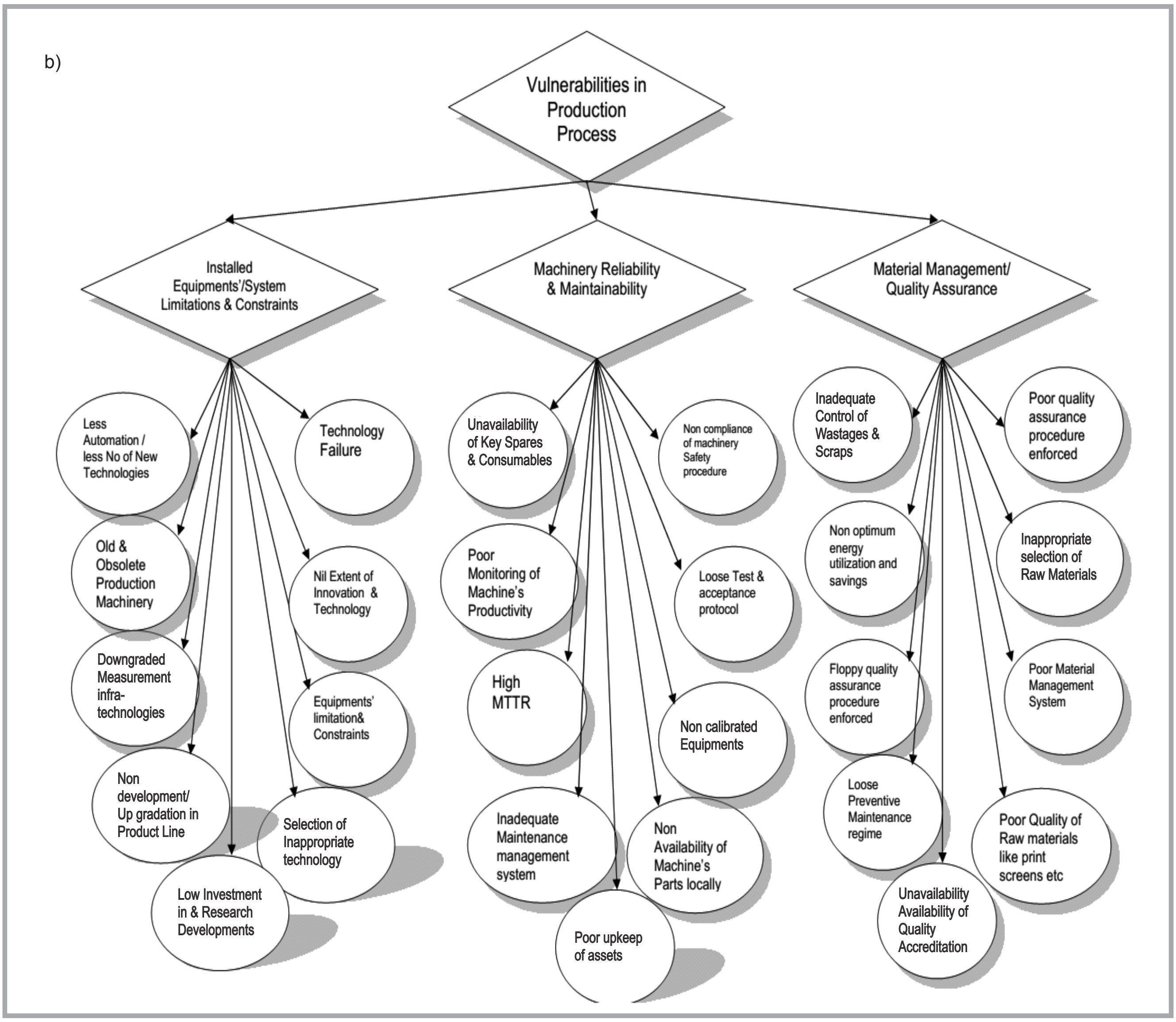

Figure 5.b. *PRA Structural model for risk element of production process*

of prediction is minimised. **(**Pavel V. et al, 2006)

Risk at nth end node (Xn)

The risk is the product of the probability of occurrence for the specific event and its impact, as shown in ***Equation (2)***. The posterior probability of end node 'X' is calculated using the prior probability of the node normalised by the respective end node. The impact is calculated in terms of the financial value of the node affecting the total financial value of the respective node. The posterior probability of end node '*Xn*' is calculated using the prior probability of the node normalised by the respective end node using ***Equation (3)***. Finaly the risk at end node '*Xn*' is calculated by ***Equation (4)***.

$$R(Xn) = \frac{I(Xn)}{I(Pn)} * P\ (Xn \mid Pn) \quad (2)$$

Where, n = 1, 2, 3…...k (number of end/parent nodes), *I(Xn)* = financial impact of end node '*Xn*', *I(Pn)* = financial impact of parend node '*Xn*', n = nth node.

$$P(Xn \mid Pn) = \frac{P\big((Pn \mid Xn\big) * P(Xn)}{P(Pn)} = \frac{P((Pn \mid Xn) * P(Xn)}{\sum_{i=1}^{n} P\ (Pn \mid Xi) * P(Xi)} \quad (3)$$

So,

$$R(Xn) = \frac{I(Xn)}{I(Pn)} * \\ * \frac{P\big((Pn \mid Xn\big) * P(Xn)}{\sum_{i=1}^{n} P\ (Pn \mid Xi) * P(Xi)} \quad (4)$$

Risk at nth parent node (Pn)

Similarly the risk at the nth parent node is given by ***Equation (5)***. The posterior probability of the parent node '*Pn*' is calculated using the prior probability of the node normalised by the respective end node using ***Equation (6)***. Finally the risk at the parent node '*Pn*' is calculated by ***Equation (7)***.

$$R(Pn) = \sum_{i=1}^{k} Ixi * P\big((Xi|Pn\big) * \\ * P(Pn \mid Ren) \quad (5)$$

Where, n = 1, 2, 3…...k, Pn = nth parent node, Ren = nth risk element.

$$\mathrm{P\ (Pn \mid Ren)} = \frac{P(Ren \mid Pn) * P(Pn)}{\mathrm{P(Ren)}} = \frac{P(Ren \mid Pn) * P(Pn)}{\sum_{i=1}^{n} P(Ren \mid Pi) * P(Pi)} \quad (6)$$

$$R(Pn) = [\sum_{i=1}^{n} \mathrm{Ixi} * P\big((Xi \mid Pn\big) * \\ * \frac{P(Ren|Pn) * P(Pn)}{\sum_{i=1}^{k} P(Ren|Pi) * P(Pi)} \quad (7)$$

Model evaluation & analysis

The proposed model evaluation & OR analysis using the Bayesian probability approach is performed on a specific operational risk element to evaluate the PRA structural model proposed. The model evaluation proposed is performed for any one of the risk elements i.e the production process under the textile operational risk factor, as enumerated in the ***Figures 5 a, b***. ***Figures 5.a*** and ***5.b*** show the factorisation of the risk element related to the production process into five different parent nodes. Furthermore these have been decomposed into end nodes for causal based risk assessment. It has been clarified that due to the unavailability of real time OR data, the model evaluation conducted for the production process risk element is based on dummy probability data; the application of the Bayesian mathematical model along with soft computational intelligence is presented in the form of scalable GUI. The same can be validated if true OR data is made available for risk estimation and compared with the impacts of OR in a real textile scenario. However, the experimental analysis of real empirical data has been left as future research work, in which case, the validity will be checked by comparing the results of OR outcomes from the model and the actual risk impact in real time scenario with absolute financial effects.

Quantification of risk element

As shown in ***Figures 5.a*** and ***5.b***, risk factors related to the production process are divided into four major parent nodes as follows:

- Vulnerabilities in textile productivity
- Vulnerabilities due to disruptions in resource supply
- Vulnerabilities due to installed equipment/system constraints & limitations
- Vulnerabilities due to fragile machine reliability & low maintainability
- Vulnerabilities due to poor material management and quality assurance

The major risk sub areas under the production include disruptions in resource supply i.e. inadequate resource supply like power, fresh water and fuel, which could affect the continuity of manufacturing lines; textile manufacturing hazards, which means safety failure, which may lead to accidents/employee injuries and illness, which will cause deviations in manufacturing through-put. The textile production equipment and system installed, its production efficacy at efficiency, equipment's operational availability and its maintainability through material management and quality assurance system enforced, are directly related to production through-put. As shown in the PRA mathematical model, the calculation of risk elements starts from calculating risk factors at each end node (*Xk*) using ***Equation (8)*** below:

$$R(Xn) = \frac{I(Xn)}{I(Pn)} * \frac{P\big((Pn \mid Xn\big) * P(Xn)}{\sum_{i=1}^{n} P\ (Pn\ |Xi) * P(Xi)} \tag{8}$$

The PRA model moves in an upward direction after calculating the risk at the end node (X), and the end node risk is then aggregated to the parent node. The calculation at the parent node is performed using ***Equation (9)*** below:

$$R(Pn) = [\sum_{i=1}^{n} \text{Ixi} * P\big((Xi \mid Pn\big) * \frac{P(Ren\ |Pn) * P(Pn)}{\sum_{i=1}^{n} P(Ren\ |Pi) * P(Pi)}\ ] \tag{9}$$

Similarly the risk of parent (P) nodes is aggregated to the risk element (Re) and parent nodes are removed. The quantified risk for the risk element of the production process is given by ***Equation (10)*** below:

$$\text{Re (Production Process)} = [\text{R (P1)} + \text{R (P2)} + \text{R (P3)} + \text{R (P4)}] + \text{R(P5)} \tag{10}$$

Similar to the production process, the quantified risk value for each risk element mentioned below under operational risk will be calculated. The process moves in an upward direction until the operational risk factor (Rf) is obtained. Similarly the risk at all risk elements of the operational risk will be calculated and finally accumulated to calculate the operational risk factor. Details of other risk elements and the formula for operational risk factor calculation as a cumulative are appended below:

- Risk Element-2: Logistics & Supply chain
- Risk Element-3: Human Resources
- Risk Element-4: Security Threats and External Factors
- Risk Element-5: Execution, Delivery & Process Arrangement
- Risk Element-6: Business Disruption & System Failure
- Risk Element-7: Sales & Marketing/ Commerce

$$\text{Risk Factor (Operational Risk)} = \text{Re1} + \text{Re2} + \text{Re3} + \text{Re4} + \text{Re5} + \text{Re6} + \text{Re7} \tag{11}$$

Soft computational model for PRA structure

To estimate the risk accurately, soft computational methods offer high-accuracy of prediction, which additionally creates no constraints in the complexity of the probability models proposed. With the integration of soft computational intelligence with the PRA structural model, the risk assessment methodology will become more power full in terms of scalability and expandability for real time commercial scenarios. In this paper, Eclipse/Net Beans IDE has been used for implementing the PRA structural model proposed in a JAVA environment. It also provides users with a friendly interface (GUI) to aid in the development of a scalable and expandable textile operational risk assessment model. The user can input probability data for end nodes and parent nodes to calculate risk probabilities. Finally the software will generate the total value of the risk element, and similarly all risk elements will be accumulated to obtain an operational risk factor value. In order to assist the user with respect to input to the model, a graphical user interface (GUI) and post-processing risk estimation module have been made available. ***Figures 6*** and ***7*** demonstrate the user interfaces made for giving input to the model proposed.

The software model developed is a user friendly software interface that can be applied for evaluating risk assessment model output if true probability data for operational vulnerabilities are available. The major components include the user input area and the result demonstration area. The software employs PRA risk breakdown structural modelling with the Bayesian probability approach, which are less subject to approximation errors found in traditional analysis techniques. Although the soft model above is initially developed for the textile operational domain, the features of this software allow it to be applied to a range of other applications suitable for PRA based modeling. ***Figure 6*** includes input by the user regarding the total number of risk elements under the textile operational risk factor for any specific industrial scenario as a first step, and then number of parent nodes under each risk element will be defined

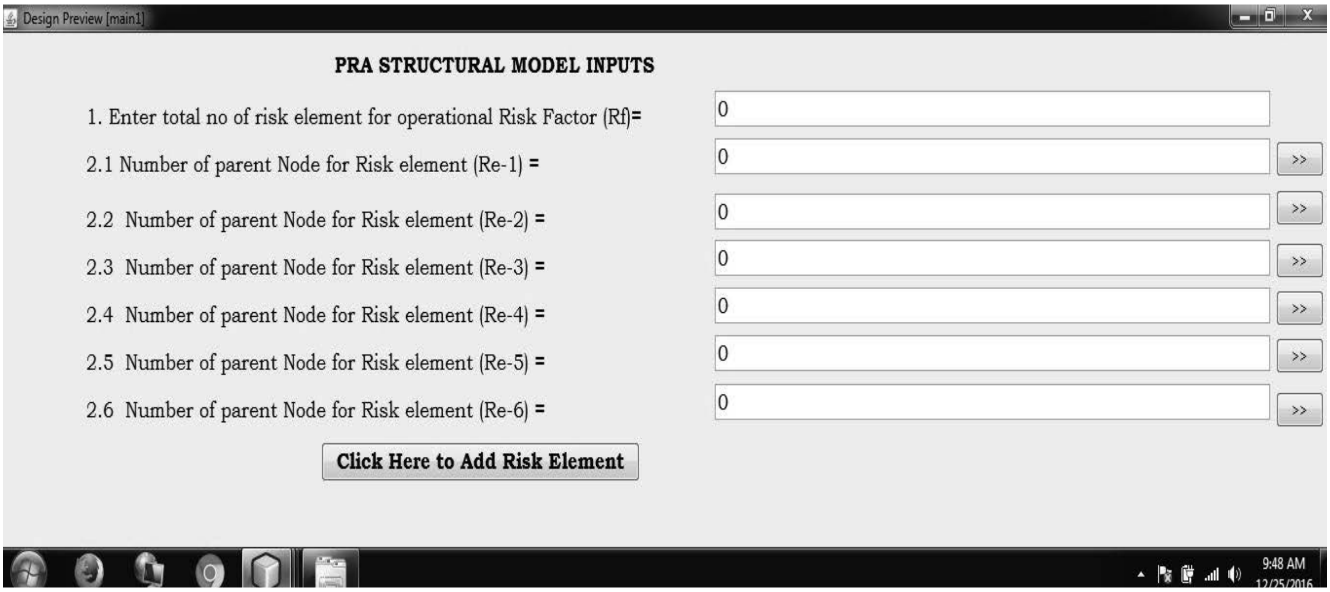

Figure 6. *GUI input model for PRA structure input.*

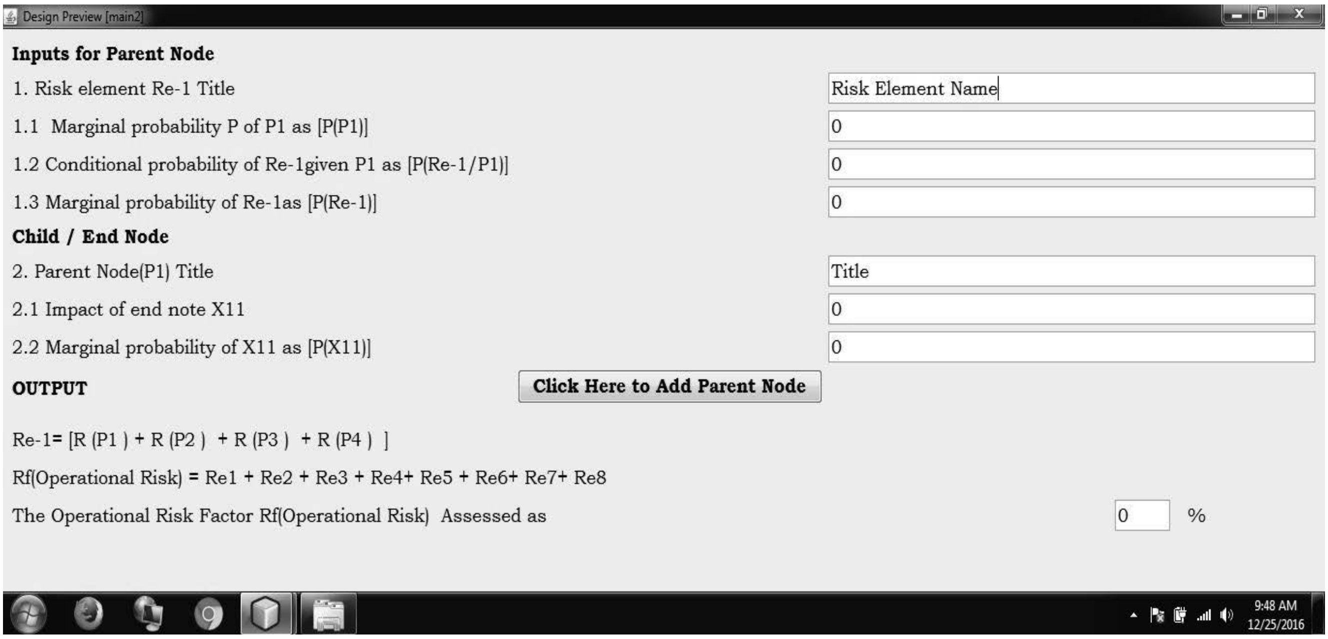

Figure 7. *GUI input model for parent/end node input.*

through a given interface. The arrow in front of pointer 2.1 in ***Figure 6*** will take the user to the user interface for calculation of the posterior probability of the parent and end node ‘’ using the prior probability of the node normalised by respective end nodes using ***Equations (8)*** and ***(9)***. In this interface, the number of risk elements in the model is expandable, and similarly the number of parent/end nodes under any specific risk element can be adjusted as per the specific textile environment.

Conslusions

The paper introduces probabilistic risk structure based Bayesian methodology in a generalised form for predicting textile operational risk distribution. The model proposed has elaborated the utility of the probabilistic risk assessment structure with the application of the Bayesian probability approach for operational risk assessment. The model provides a risk analysis proprietary tool utilising a bottom-up process based approach for developing the probabilistic structure of textile operational risks and its causal flow. The bottom-up approach performs analyses of OR at the unit level and then builds up to form a firm-wide evaluation of OR. Major risk elements that relate to textile operation in the general context have been identified by this model, and triggers have also been marked through PRA based risk causal flow diagrams. By this method operational risk posterior distributions can be derived, from which appropriate mitigation steps can be undertaken and the expected deficit can be derived. Keeping in mind the generalised and universal type OR assessment approach, the model proposed can be tested on a real OR database related to any textile industry. The real type application of proprietary tool proposed and its experimental analysis based on corporate data have been left as future work.

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[1)] 'Appendix A' available upon request. Please contact author Mustafa Jan e-mail: mattavi.26@gmail.com.

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