International Journal of Computer Applications Technology and Research
Volume 2– Issue 3, 237 - 244, 2013, ISSN: 2319–8656

Risk Prediction for Production of an Enterprise

Kumar Ravi
Department of Computer Science
School of Engineering, Pondicherry University
Pondicherry, India

Sheopujan Singh
Department of Mathematics and Computer Application
S. Sinha College
Aurangabad, Bihar, India

Abstract: Despite all preventive measures, there is so much possibility of risks in any project development as well as in enterprise management. There is no any standard mechanism or methodology available to assess the risks in any project or production management. Using some precautionary steps, the manager can only avoid the risks as much as he can. To address this issue, this paper presents a probabilistic risk assessment model for the production of an enterprise. For this, Multi-Entity Bayesian Network (MEBN) has been used to represent the requirements for production management as well as to assess the risks adherence in production management, where MEBN combines expressivity of first-order logic and probabilistic feature of Bayesian network. Bayesian network provides the feature to represent the probabilistic uncertainty and reasoning about probabilistic knowledge base, which is used here to represent the probable risks behind each causes of a risk. The proposed probabilistic model is discussed with the help of a case study, which is used to predict risks inherent in the production of an enterprise, which depends upon various measures like labour availability, power backup, transport availability etc.

Keywords: Bayesian network, UnBBayes, MEBN, PR-OWL

1. INTRODUCTION

Risk management is particularly important for the supply chain management because of the inherent uncertainties in the various stages of it. It occurs due to loosely defined requirements, under or over estimation of time and resources required for product development, dependence on individual skills, and requirements changes due to changes in customer needs. The manager of an enterprise should be aware of the impact of these risks on the project, the product and the business in advance, and should have some contingency plans so that, if the risks do occur, those can be managed effectively [7]. Although several steps for risk management are needed to address as shown in Fig. 1, but here risk assessment have been considered mainly.

There is no standard mechanism to handle the risk, so it can be minimized using some preplanned strategies. Risk is quite uncertain with respect to various attributes like time, schedule, requirements, human resource, raw material etc. So, a probabilistic approach has been used to represent these attributes as well as its effects on the incurred risks in this literature, which is based on Bayesian network.

Bayesian network is a graphical representation of random variables and their conditional dependencies in the form directed acyclic graph (DAG), which is widely used in the field of Semantic web to represent probabilistic relationship among components of knowledge base, where probabilistic dependence between components of knowledge base has been used for the situation awareness, recommender system, sentiment analysis, and data mining. Currently well known Semantic Web (SW) languages like Resource Description Framework (RDF), Resource Description Framework Schema (RDF/S), Web Ontology Language (OWL) etc and their constructs have been used to construct the Bayesian network. One of them is Probabilistic Web Ontology Language (PR-OWL) based on MEBN to represent the uncertainty incurred within any knowledge base system.

Modeling of uncertainty has been widely done using MEBN [2], [9], [14], which can be used to determine the probability of events that are influenced by various variables. Using it, the degree of belief can be specified to determine the favorable and contradicting outcomes for given evidences. It can be used as dynamic Bayesian network, using which degree of belief can be modified time to time according to likeness of the situation or to observe the effect of different evidences for propositions. To model the domain, we need to represent them in the form of Bayesian network, which is a major task to have a well defined probabilistic model. The generation of Bayesian network needed following 3 major steps [1].
-First, identification of propositions and evidences.
-Second, identification of random variables for nodes and creation of dependence graph using them.
-Third, assignment of Conditional Probability Table (CPT) for each node.

To do this, in addition to above listed tasks, incorporation of existing knowledge can be done with the help of domain ontology.

This paper is arranged in following manner. The section 2 will present the survey on risk prediction in various fields like network security, water management, power supply, health risks etc. Some milestones in creation of Bayesian network from semantic web languages is discussed in section 3, out of that MEBN is used in this paper to create a probabilistic model. Section 4 describes a case study for modeling and prediction of causes and effects of risks for an enterprise production. Conclusion has been drawn in section 5.

2. LITERATURE SURVEY

This paper is mainly motivated from [14], which has used MEBN and PR-OWL for risk assessment in the process of Security Certification and Accreditation (C&A). Due to diverse uncertainties in the field of software performance, major security requirements and their causal relationship has been represented using MEBN, which provides probabilistic model driven risk assessment on security requirements.

Bayesian network and Monte Carlo simulation have been used to predict the thermal overload risk for the next hour on the current weather conditions and power system operating conditions [3]. According to [15], an electricity supply industry faces sort of risks like risk of load forecast error, risk of equipment, risk of transmission constraints, risk of financial return, risk within contracts etc. So, some of these risks will also be considered as a part of proposed model in the form of power backup. Nevertheless Bayesian network, this literature has used auto-regressive integrated moving average (ARIMA) models and artificial neural network (ANN) structures.

Caruso (2006) has analyzed the supplier and consumer risk for daily market-price of power uncertainties and it aggregates risk measures for the power supply. Monte Carlo algorithm has been used to verify the simulated results by the OPF-based problem [16].
Fuzzy dominance and similarity analysis have been considered to represent a framework to integrate probabilistic health risk assessment into a comprehensive, yet simple, cost-based multi-criteria decision analysis framework [4]. It has been done for the management of contaminated ground water resources using health risk assessment and economic analysis through a multi-criteria decision analysis framework. These are the trade-off between

population risk and individual risk, the trade-off between the residual risk and the cost of risk reduction, and cost-effectiveness as a justification for remediation.

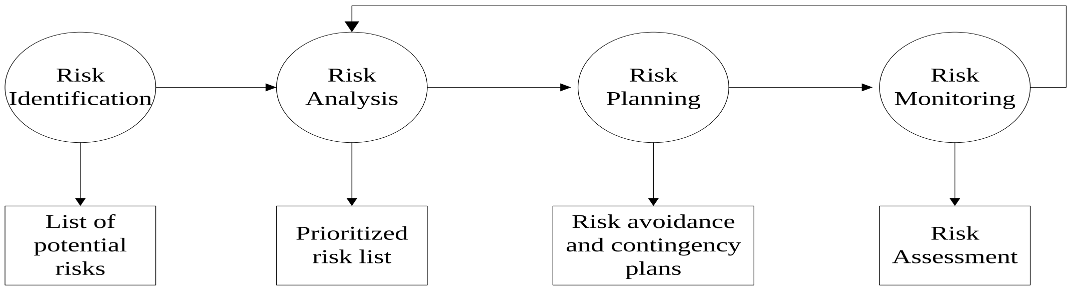

Figure 1 Phases of risk management [7]

Fuzzy-probabilistic modeling process has been adopted for power system risk assessment which can capture both randomness and fuzziness of loads and component outage parameters. This is based on a hybrid method of fuzzy set and Monte Carlo simulation. An actual example using a regional system at the British Columbia Transmission Corporation has been given to demonstrate the application of the presented fuzzy-probabilistic model [5].

Risk assessment is done for information security domain, where Bayesian network has been used as Attack graphs and attack trees to assess the cause-consequence relationships between various network states [6]. Security risk assessment and mitigation have been considered as two major steps of risk management to manage IT infrastructure. Genetic algorithm has been used to refine the outcomes resulted for risk mitigation.

3. BAYESIAN NETWORK AND SEMANTIC WEB FOR UNCERTAINTY REPRESENTATION

Four major works to represent uncertainty on the basis of Bayesian network has been discussed in further sub-sections, which can be used risk prediction. These proposed models will be co-related with following three steps

1. Propositions and evidences identification
2. Identification of random variables for nodes and representation of them in the form of dependence graph.
3. Assignment of Conditional Probability Table (CPT) for each node.

3.1 BayesOWL

This is one of the first successful approaches to create Bayesian network using terminologies of OWL [11]. For the identification of evidences and propositions, it has used the concept of the ontology, which is represented as nodes in the underlying network and for the logical relation between concepts viz. union, intersection, complementation, disjoint, equivalence, and inheritance, it introduces link node, which works as the bridge between given nodes.

The node representing degree of truth in fractional form will be considered as random variable.

For the creation of conditional probability table, some propositional formulas have been given for each logical relations, where CPT will be created for both types of node representing concepts of taxonomies as well as for link nodes.

It considers only terminologies or vocabularies of the knowledge base and it is unable to represent assertions of the knowledge base.

3.2 OntoBayes [12]

Instead of creating single graph, it creates two graphs, one for the Bayesian network i.e. Bayesian graph and other for the ontology constructs i.e. OWL graph. It considers triple form of OWL like subject, predicate, and objects (s, p, o). While both graph will have three constructs of OWL, Bayesian graph will consider only one predicate of the RDF language. Predicate of the OWL will represent dependence of successor nodes on predecessor nodes, which is represented in OWL as <rdfs:dependsOn>.

So, similar to BayesOWL, subject and object will be used as propositions and evidences for the Bayesian graph. Predecessor node will be represented as random variables and CPT will be created according to specification of random variable. It can represent only discrete random variable but not Boolean random variable.

3.3 Using Netica API[1]

Fenz (2012) has used Netica API and Jena API[2] to create a security ontology, where Netica API is used as plugin with Protege[3] to select components and attributes representing uncertain features of the ontology. It has been followed three basic steps given below to create Bayesian Network from ontology.

(i) The determination of relevant influence factors,
(ii) The determination of relationships between the identified influence factors, and
(iii) The calculation of the conditional probability tables for each node in the Bayesian network.

In general, two different methods or a combination of both are used to construct a Bayesian network: (i) automated construction of Bayesian networks from existing data, and (ii) the domain expert-based construction of Bayesian networks covering complex knowledge domains with insufficient or non-existing empirical data regarding relevant variables.

This proposal is mainly based on second approach and it involves both manual and automatic operations. The proposal proposed a generic method for the ontology-based Bayesian network construction by (i) using ontology classes/individuals to create the nodes of the Bayesian network, (ii) using ontology properties to link the Bayesian network nodes, (iii) utilizing the ontological knowledge base to support the conditional probability table calculation for each node, and (iv) enriching the Bayesian network with concrete findings from existing domain knowledge. The developed method enables the semiautomatic construction and modification of Bayesian networks based on existing ontologies. The method is demonstrated on the example of threat probability determination, which uses a security ontology as its underlying formal knowledge base.

It is based on mainly four phases, out of them first step will be done manually and remaining steps will be done automatically using Netica API:

1. Selection of relevant classes, individuals, and properties: Domain expert has to select classes, individuals, and properties which are relevant to the problem and needed to represent in Bayesian network.

---

[1] http://www.norsys.com/netica_api.html
[2] http://jena.apache.org/
[3] http://protege.stanford.edu/

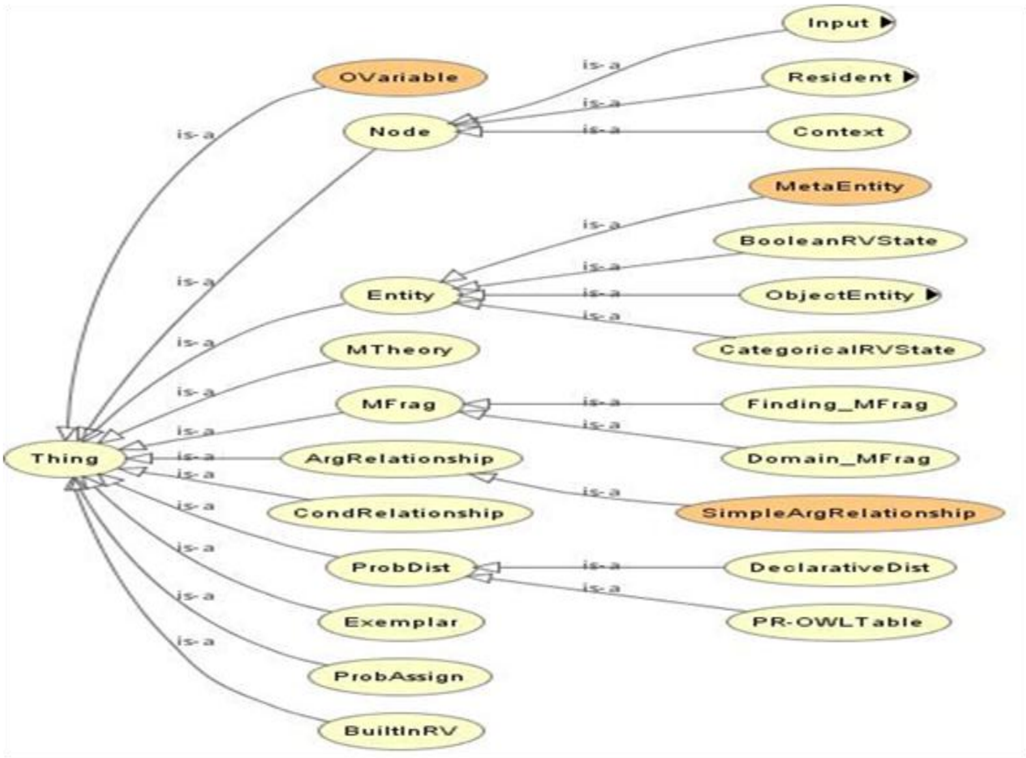

Figure 2. PR-OWL classes in detail [10]

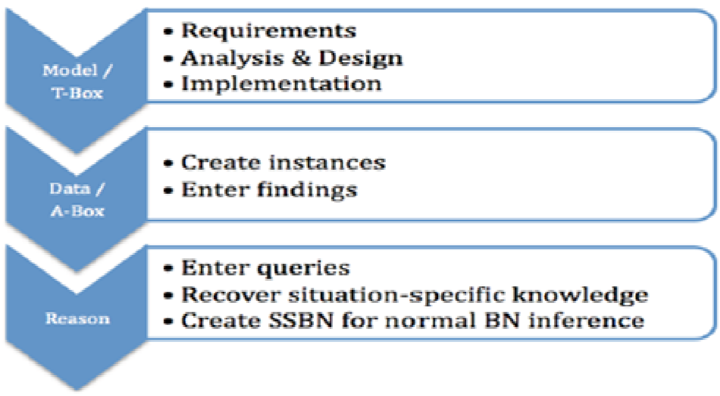

Figure 3. Uncertainty Reasoning Process for Semantic Technologies

2. Creation of the Bayesian network structure
3. Construction of the CPTs
4. Incorporation of existing knowledge facts

3.4 Multi-Entity Bayesian Network (MEBN) [2]

MEBN uses first order logic along with Bayesian network to create dynamic Bayesian network, which can represent uncertainty for complex situations and for different purposes like situation awareness, prediction, weather forecasting, battlefield strategy management etc. MEBN can be used to create multiple instances of whole Bayesian graph. MEBN can generate dynamic Bayesian network and it is able to represent different type of uncertainty like structural uncertainty, attribute uncertainty, number uncertainty, type uncertainty, referential uncertainty etc.

Components of MEBN are MEBN Theory (*MTheory*), MEBN Fragments (*MFrags*), context node, resident node, input node, and probability distribution table as shown in Fig. 2.

Here, MTheory will combine a set of MFrags and represent a whole probabilistic ontology. Each MFrag will contain different types of nodes like context, resident, input and ordinary variable. Each MFrag will represent a Bayesian network and nodes of one MFrag can be re-used as input nodes into other MFrag as well.

For propositions and evidences, it uses uncertain feature of the model, which can have different states either in binary or discrete form.

Instead of having nodes for random variable only in one form, it uses mainly 3 forms of nodes, where first node is known as *context node*, which can specify constraints using first-order logic formula on the used random variable for reasoning or decision purposes in complex situations. Second node is the most important node i.e. *resident node*, which will have different states of random variable and it will be associated with a Conditional Probability Table (CPT), and last one is the *input node*, which is the resident node of other MFrag. Context nodes and input nodes will be connected using edges to form directed acyclic graph (DAG) and each edge will represent the dependence of one node to other.

For CPT, at first it is required to specify probability for each states of random variable, which will be used for the creation of joint probability distribution table for the resident node or random variable. For the decision purposes, it will use the joint probability distribution table.

MEBN is realized in Probabilistic-Web Ontology Language (PR-OWL) [13] to create the probabilistic ontology. Modeling of uncertain situation can be done using MEBN and PR-OWL, which is efficient for the expression of complex situations. UnBBayes is a graphical user interface developed in Java, which implements PR-OWL to create a probabilistic ontology [9]. It provides facilities to create and save a knowledge base as well as to generate the Situation-Specific Bayesian Network (SSBN). Bayesian inference and SSBN inference algorithm are used to find out the inconsistencies in the ontology and to estimate the probability of an event.

PR-OWL 1.0 cannot support continuous random variable, so, PR-OWL 2.0 [10] is proposed to overcome the major disadvantages of PR-OWL 1.0 1) it cannot provide mapping to properties of OWL and 2) although it provides concept of meta-entities for the definition of complex types, it does not have type compatibility with OWL. Major classes of PR-OWL 1.0 are shown in Fig. 2.

4. A CASE STUDY FOR RISK PREDICTION FOR PRODUCTION OF AN ENTERPRISE

Prediction of risk has been done using different techniques [3] [4] [5] [6] [14][15]. Prediction is quite uncertain so, we have come up with a new model using Uncertainty Reasoning Process for Semantic Technologies (URP-ST) [10] to predict the production of an enterprise. Production of an enterprise depends upon various causes, which are listed in following sub-sections.

4.1 Modeling of System

Modeling of system includes 3 steps as shown in Fig. 3.

4.1.1 Identifying Requirements

Production of an enterprise will depend upon several factors some of them are listed below, which can be seen as basic requirements. These requirements will be considered to build the probabilistic model to estimate the probability of affect on the production rate.

4.1.1.1 Labour availability

Most important requirement for production is human resource, which is very uncertain feature for any manufacturing enterprise due to dependence on following attributes.

4.1.1.1.1 Probability of strike by labour

Strike by labour will severely affect the production rate. To avoid this, there should be proper management of their requirements.

4.1.1.1.2 Contractual state of staff

Completion of contract of major technical staffs will affect the project because new staff cannot be trained in short period to take over the running project.

4.1.1.1.3 Variability of staff joining and resigning

If there is lack of constant support of staff then it will result poor quality of product as well as time delay.

4.1.1.1.4 Labour Health Situation

Water and clean accommodation area are major concerns for good health, but every enterprise cannot ensure this, because this will increase the expenditure [4].

4.1.1.1.5 Labour Union Support

Labour union leader may mitigate the labours for unnecessary demands.

4.1.1.2 Power backup

Possibility of power backup will depend upon governmental supply and enterprise's own power availability.

4.1.1.2.1 Oldness of power generator

If power generator is so old, it will often need some rest and repairing as well as it should not have extra overload.

4.1.1.2.2 Power grid availability

Availability of power grid and duration of supply should be considered for scheduling management [15].

4.1.1.2 Transport availability

For transportation of raw materials and produced items, enterprise needs transport. In transportation some difficulties may also occur, which are listed below and these factors also have a bit of uncertainty to affect the production rate.

4.1.1.3.1 Possibility of owned vehicles

Number of more owned vehicles will surely have less probability to affect the transportation facility.

4.1.1.3.2 Rented vehicles availability

This is more susceptible to the means of communication.

4.1.1.3.3 Public transport availability

Easy reach abilities to public cargo will be cost effective.

4.1.1.4. Legal impacts

Legal activities may also hamper the production which may include consumer's claim, copyright conflicts etc.

4.1.1.4.1 License from pollution control board

Periodical renewal of license will decrease the possibility of disturbance.

4.1.1.4.2 License from manufacturing governing bodies

4.1.1.4.3 Enterprise and personnel legal issues

Legal issues may obstruct the production.

4.1.1.4.4 Transportation permit

Permit should be available according to requirement of communication.

4.1.1.5. Raw material availability

Raw material should be available according to demand of supply, but it will depend upon the suppliers' capacities as well as on financial relationship with suppliers.

4.1.1.5.1 Raw Material Suppliers (RMS) availability

Easy availability of RMS will have less effect on production.

4.1.1.5.2 Communication facility between production unit and suppliers or warehouse

This should be trouble-free for less effect on production rate.

4.1.1.5.3 Goodwill of enterprise with RMS

Loss of goodwill is the loss of everything, so trust should be maintained between raw material supplier and enterprise.

4.1.1.5.4 Alternatives of RMS

Limited number of RMS will affect the production severely.

4.1.1.6. Market demand

The second most important aspect is demand of commodities in market, without it production of items is obviously useless.

4.1.1.6.1 Share market situation

The volume of production will be regulated according to share market situation.

4.1.1.6.2 Market agents' performance and dealers' interest Production will be affected by the interest of dealers and performance of market agents.

4.1.1.6.3 Enterprise competitors' production quantity, quality, and rate

For an enterprise it is one of the most influential measures to consider the market availabilities, qualities and rate.

4.1.1.7. Some other factors

These factors can also affect the output of an enterprise.

4.1.1.7.1 Social impact

In some enterprise social impact should also be considered, which depends upon the type of waste generated by production unit and the location of enterprise like in dense or sparse population.

4.1.1.7.2 Share market situation

Share market situation will affect the cost and product of product.

4.1.1.7.3 Inflation rate

It is obvious condition for share market situations.

4.1.1.7.4. Arrangement schedules of machine and labour

The efficient scheduling of machine and labour will increase the production rate.

4.1.1.7.5. Machineries availability

According to demand of production, the enterprise should have enough tools and machineries for good production rate.

4.1.1.7.6 Machine fault rate

It will depend upon the age of machineries' and load on machineries.

4.1.2 Analysis and Design

The proposed model should be able to identify the total probable risk upon specifying probabilities of various factors listed in the requirements section. The relationship among these factors can be seen in the implementation section. The proposed model should be able to achieve following objectives…

- Calculating probability of risk of unavailability of labours and its effect on final production.
- Calculating probability of risk of unavailability of power backup.
- Calculating probability of risk of unavailability of enough transport facilities.
- Calculating probability of affect of legal issues.
- Calculating probability of risk of unavailability of raw materials etc.

4.1.3 Implementation

For implementation, UnBBayes [9] have been used which provides graphical user interface to create complete probabilistic ontology on the basis of Multi-Entity Bayesian Logic. It provides graphical interface for each component of MEBN like Entities, MFrag, Context node, Resident node, input node, MTheory etc. which can be used as dragged and dropped on MFrag area. Identified entities have been shown in Fig. 4.

For each of the requirements, separate MFrag has been created but due to space constraints, only few of them are shown in Fig. 5 and these MFrags can be classified into two categories …

a) MFrag without dependence on other
 i) Strike
 ii) StaffContracts
 iii) LabourHealth
 iv) Variability of Staff

b) MFrags with dependence on other MFrag
 i) Labour Availability
 ii) riskonRawMaterialAvailability
 iii) Transport Availability
 iv) Legal Impacts
 v) PowerBackup
 vi) Market Demand

4.2 Creating instances, findings, and defining probability distribution table for each resident node

Fig. 6 shows the instances of Person entity, findings of RawMaterialAvailabilities, findings of EasyCommunication, and GoodwillStatus horizontally. These findings will be used as knowledge bases. The probability distribution table will be specified for each resident node, where probability for each state will represent the expected degree of risks for each factor. Probability distribution table can be manipulated using first order logic formula as shown in the last snapshot of Fig. 6.

4.3 Reasoning with knowledge base

Reasoning will be performed to predict the risk, which will generate the situation-specific Bayesian network as shown in Fig. 7.

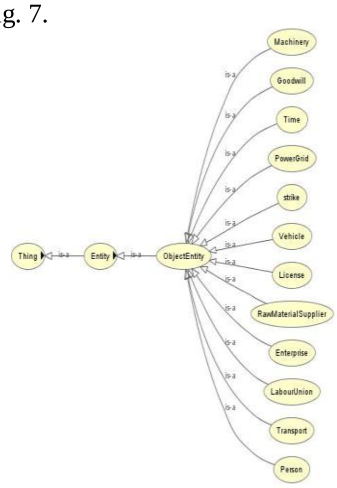

Figure 4 Identified Entities in proposed model

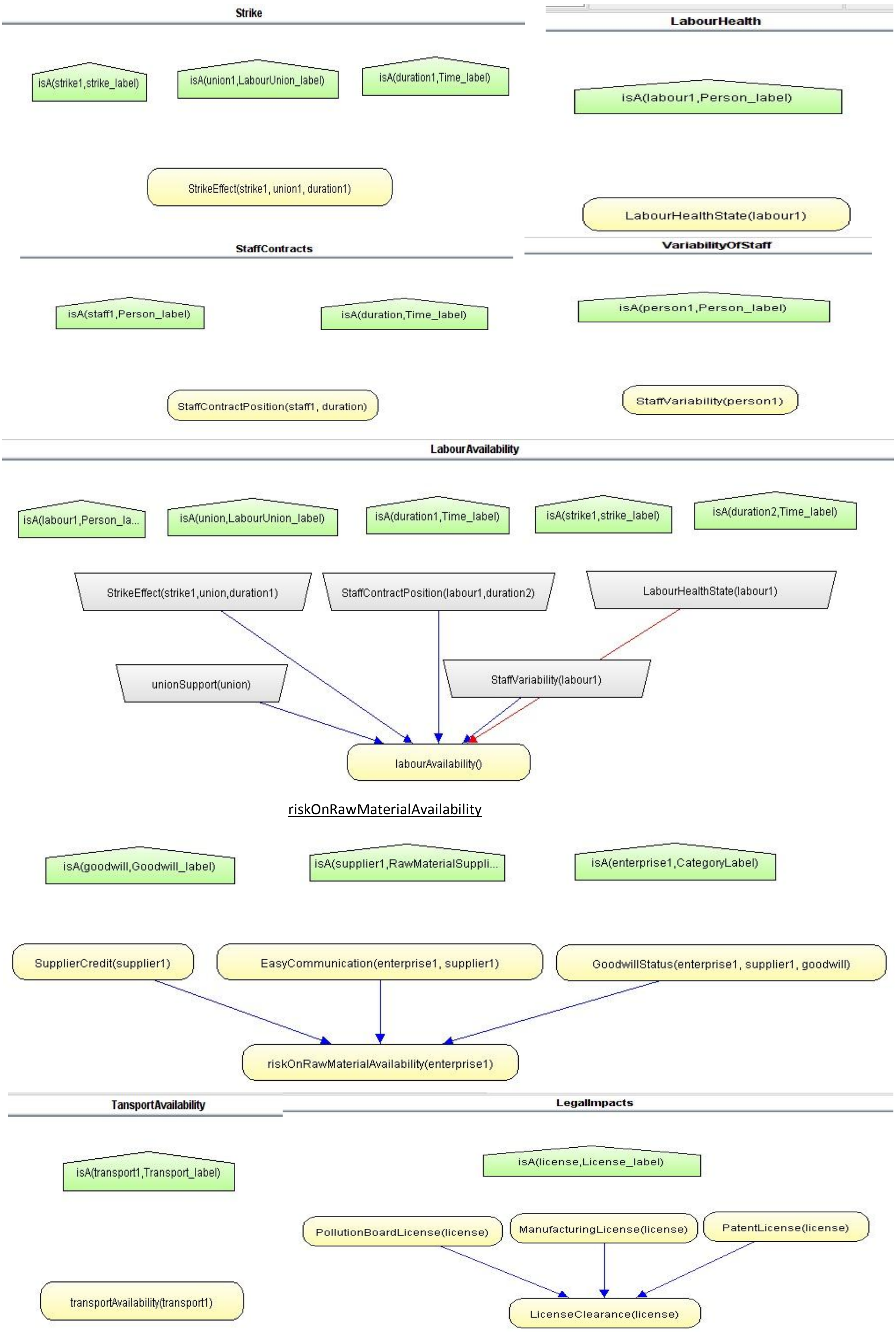

Figure 5. Probabilistic Ontology

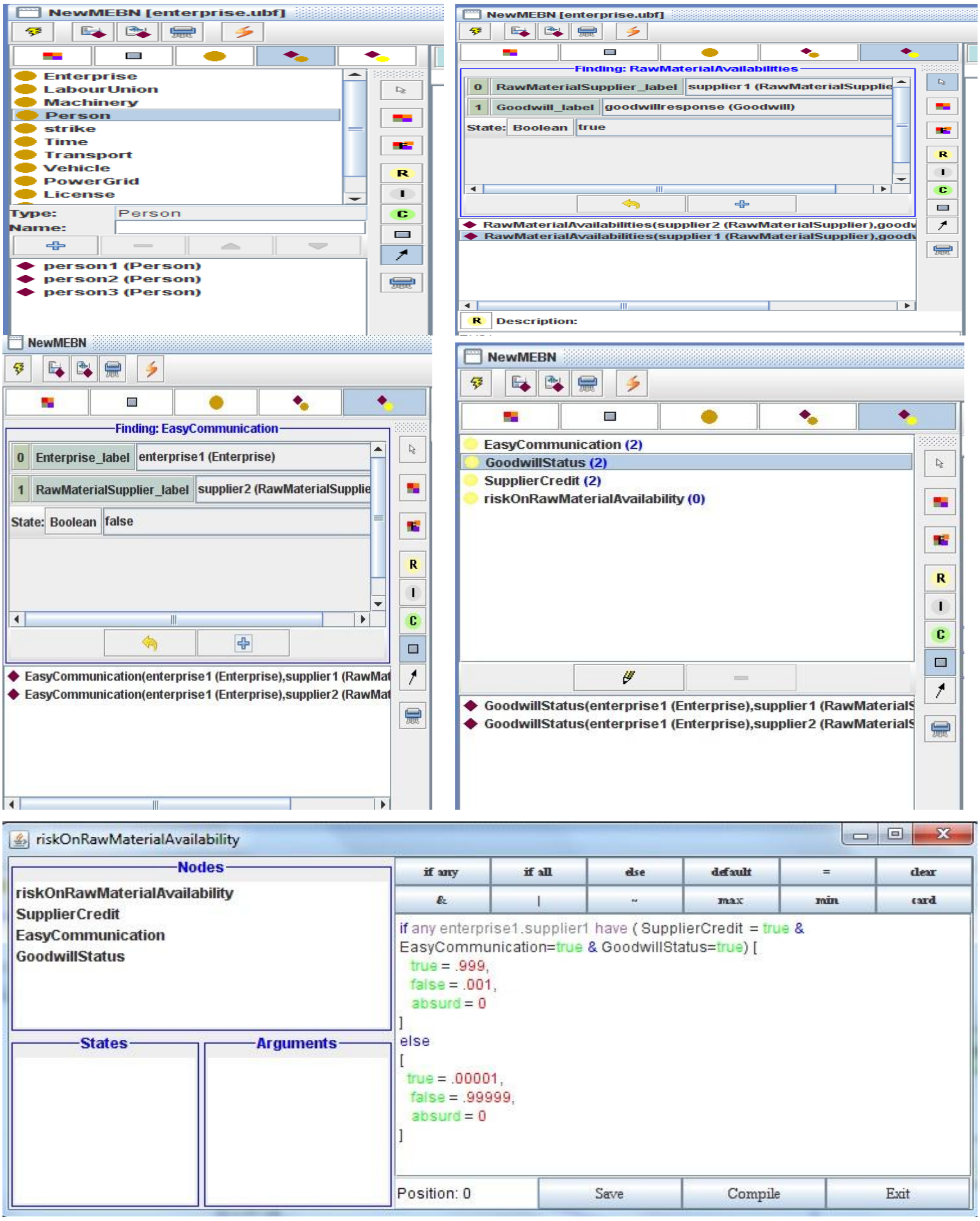

Figure 6. Entity Instances, Knowledge Base and CPT with First-Order Logic formula

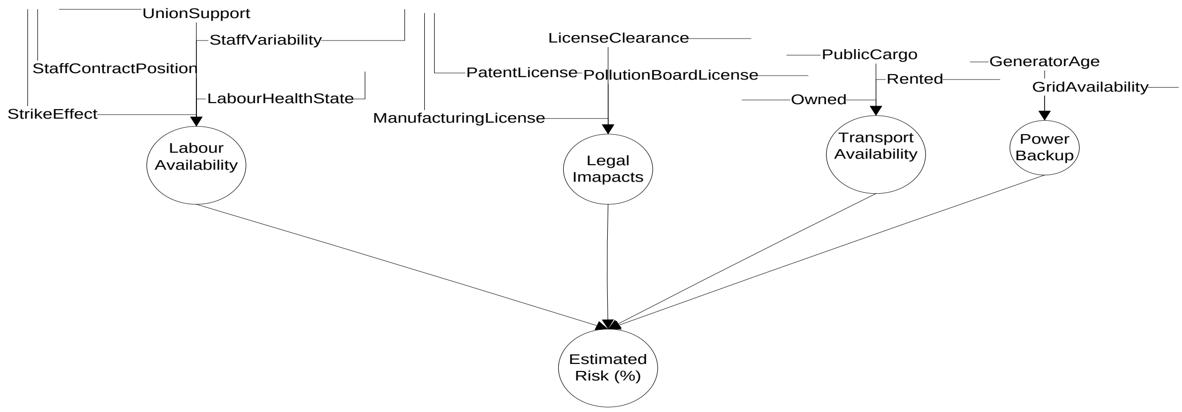

Figure 7. Situation-Specific Bayesian Network

5. CONCLUSION

This paper has presented a probabilistic model to represent the probable risk inherent in major causes for the production of an enterprise. The model can also be applied in other domain as well. MEBN and PR-OWL have been used to realize the model which is embedded in Java open source software UnBBayes.

6. ACKNOWLEDGMENTS

We would like to thank Dr. Rommel N. Carvalho and Dr. Paulo Cesar G. da Costa for giving permissions to use any contents from their Ph. D. theses and papers.

7. REFERENCES

Journal Papers:

[1] S. Fenz, An ontology-based approach for constructing Bayesian networks, Data & Knowledge Engineering, 73, 2012, 73–88

[2] K. B. Laskey, MEBN: A language for first-order Bayesian knowledge bases, Artificial Intelligence 172 (2008) 140–178

[3] Jun Zhang, Jian Pu James D. McCalley Hal Stern, and William A. Gallus, Jr. A Bayesian Approach for Short-Term Transmission Line Thermal Overload Risk Assessment, IEEE TRANSACTIONS ON POWER DELIVERY, VOL. 17, NO. 3, JULY 2002

[4] Ibrahim M. Khadam, Jagath J. Kaluarachchi, Multi-criteria decision analysis with probabilistic risk assessment for the management of contaminated ground water, Environmental Impact Assessment Review 23 (2003) 683–721

[5] Wenyuan Li, Jiaqi Zhou, Kaigui Xie, and Xiaofu Xiong, Power System Risk Assessment Using a Hybrid Method of Fuzzy Set and Monte Carlo Simulation, IEEE TRANSACTIONS ON POWER SYSTEMS, VOL. 23, NO. 2, MAY 2008

[6] Nayot Poolsappasit, Rinku Dewri, and Indrajit Ray, Dynamic Security Risk Management Using Bayesian Attack Graphs, IEEE TRANSACTIONS ON DEPENDABLE AND SECURE COMPUTING, VOL. 9, NO. 1, JANUARY/FEBRUARY 2012

Books:

[7] Ian Sommerville, Software Engineering, 8th Ed., Pearson Education, 2009, pp. 129

Chapters in Books:

[8] Stuart J. Russell and Peter Norvig (2003) Artificial Intelligence – A Modern Approach, Second Edition, Pearson Education, Inc., Chapter 13

[9] Rommel Carvalho, Kathryn Laskey, Paulo Costa, Marcelo Ladeira, Laecio Santos and Shou Matsumoto (2010). UnBBayes: Modeling Uncertainty for Plausible Reasoning in the Semantic Web, Semantic Web, Gang Wu (Ed.), ISBN: 978-953-7619-54-1, InTech, Available from: http://www.intechopen.com/books/semanticweb/unbbayes-modeling-uncertainty-for-plausible-reasoning-in-the-semantic-web

Theses:

[10] Rommel N. Carvalho, (2011). Probabilistic Ontology: Representation and Modeling Methodology. Ph. D. thesis; George Mason University, Brazil

[11] Ding, Z. (2005). BayesOWL: A Probabilistic Framework for Semantic Web. Doctoral dissertation. Computer Science and Electrical Engineering. 2005, University of Maryland, Baltimore County: Baltimore, MD, USA. p. 168

[12] Y. Yi, (2007). A framework for decision support systems adapted to uncertain knowledge. Ph.D. thesis; Fakultat fur Informatik der Universitat Fridericiana zu Karlsruhe.

[13] Costa P. C. G., (2005) Bayesian Semantics for the Semantic Web, Ph. D. thesis; George Mason University.

Proceedings Papers:

[14] Seok-Won Lee, Probabilistic Risk Assessment for Security Requirements: A Preliminary Study, Fifth International Conference on Secure Software Integration and Reliability Improvement, 2011

[15] K.L. Lo and Y.K. Wu, Risk assessment due to local demand forecast uncertainty in the competitive supply industry, IEE Proc.-Gener. Transm. Distrib., Vol. 150, No. 5, September 2003

[16] E. Caruso, M. Dicorato, A. Minoia and M. Trovato, Supplier risk analysis in the day-ahead electricity market, IEE Proc.-Gener. Transm. Distrib., Vol. 153, No. 3, May 2006