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PREDICTING CONSTRUCTION LABOR PRODUCTIVITY WITH BAYESIAN BELIEF NETWORKS

by

Ayoub Hazrati

A DISSERTATION

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PREDICTING CONSTRUCTION LABOR PRODUCTIVITY WITH BAYESIAN BELIEF NETWORKS

Ayoub Hazrati, Ph.D.

University of Nebraska, 2016

Advisors: Terence Foster and Eddy M. Rojas

Construction labor productivity plays an important role in labor intensive projects. Therefore, increasing construction labor productivity is a vital task to decrease a project's cost (time). The primary goal of this research is to investigate the feasibility of developing a comprehensive causal model that can predict construction labor productivity for various project's situations, such as existence of "Adverse Weather," "Changes," "Working Overtime," etc., while considering uncertainty. It is found that Bayesian Belief Networks (BBNs) is the best approach that can model causal relationships among different factors while considering uncertainty, simultaneously.

Developing a BBNs model requires to extract its structure and, for each node in the network, set up a "Conditional Probability Table." Extensive review of other scholars' publications, regarding factors affecting construction labor productivity, allow us to extract cause-effect diagrams for each factor. These cause-effect networks are independent sub models that by applying various structures and parameters methodologies become a separate BBN. The final step of building the comprehensive model is to combine different sub models, which after 12 iterations and combining

different sub models, the primary contribution of this research to the body of knowledge, which is developing the comprehensive model, is obtained.

The model can do a variety of queries about the effects of a single variable, or a subset of variables, on a hypothesis variable. The findings from these queries is another contribution of this research. In this research, the hypothesis variable is the probability of “High productivity.” Various sensitivity analyses on the hypothesis variable reveals that for different network’s instantiations, the effects of similar variables are not the same. Also, it shows that the “Adverse Management Systems” can decline the probability of “High productivity,” whenever a project is in its perfect conditions, more than 70%. However, when a project is in its worst conditions, it can increase the probability of “High productivity” for less than 10%. From the main variables, “Stacking of Trades” has similar effects on the hypothesis variable with less severity. This research has wonderful applicability for project managers, cost estimators, and schedulers in their decision making process regarding costs and time of projects.

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To:

My parents

My family and fiends

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I want to express my appreciation to the many people that contributed to the completion of this dissertation. My sincere gratitude to my supervisors, Professors Terence Foster and Eddy Rojas, for their support, continuous encouragement, and thoughtful feedback throughout my Ph.D. study. I appreciated the opportunity to assist in teaching and research at the Durham School during the last four years.

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Chapter 1

Introduction

This chapter defines productivity, and examines the significance of predicting construction labor productivity in the construction industry. It will also introduce research objectives, limitations, and describes the dissertation organization.

1.1 Productivity Definitions

The U.S. Bureau of Labor Statistics (BLS) defines productivity as output per hour of one resource. According to BLS, Labor Based Productivity (LBP) is defined as (Bureau of Labor Statistics 2012):

$$LBP = \frac{Number\ of\ Value\ Add\ Units\ Produced}{Number\ of\ Laborers\ Utilized\ \times Hours\ Worked} \tag{1.1}$$

Similarly, Equipment Based Productivity (EBP) is defined as:

$$EBP = \frac{Number\ of\ Value\ Add\ Units\ Produced}{Number\ of\ Equipment\ Utilized\ \times Hours\ Worked} \tag{1.2}$$

Another definition for productivity is Total Factor Productivity (TFP) which is defined as:

$$TFP = \frac{Total\ Output}{Labor + Materials + Equipment + Energy + Captital} \tag{1.3}$$

Or

$$TFP = \frac{Dollars\ of\ Output}{Dollars\ of\ Input} \tag{1.4}$$

"The Baseline Productivity" and "Loss of Productivity" are two important terms in this research and defined as follows:

"The Baseline Productivity" represents the best performance that a contractor can achieve on a particular project (Thomas and Završki 1999). "Loss of Productivity" is defined as the reduction in productivity caused by unanticipated conditions (Thomas and Završki 1999).

1.2 Significance of Predicting Construction Labor Productivity

Productivity plays an important role in predicting time and cost of a project's activities. Predicting cost and time of activities in construction projects is an essential part of each scheduling program. The more accurate the prediction, the more probable the project success. Labor is one of the main resources that have direct effect on the time and cost of each activity, and labors' cost is a function of its productivity. Many researchers have described why predicting labor productivity in an accurate manner is important in construction projects. Construction labor productivity plays key role in predicting time and cost of construction's activities.

Clark and Lorenzoni said, "Estimating or predicting the cost of labor for a given project is, like estimating piping costs, a difficult task that has frustrated both cost estimators and field supervisors. The cost of labor is determined by multiplying man-hours (sometimes called workhours) by the applicable wage rates (i.e., multiplying quantities by unit costs). Establishing the workhours can be accomplished only after establishing or predicting the workhour rate (or productivity) that will be achieved on the project (an average of 15%, with a fairly wide range, depending on the type of project and location). Because this cost and the associated schedule are affected directly by labor productivity achieved, it is of vital importance to cost estimators and to the accuracy of their estimates that the correct labor productivity value be used in the estimate. Unfortunately, field labor productivity is the single greatest variable in any estimate and is extremely difficult to estimate. Often, estimators will not try to do more than use the simplest approach because they feel there is no real science to predicting labor productivity. As a result, many estimates of labor workhours are overrun in the field, often with a disastrous impact on the project. Not only does the final cost of the project exceed the appropriated amount but, because of the close relationship that exists between erection workhours and project schedule, more than likely, the completion date of the project is extended or delayed, with associated debits of not meeting the project objectives in the area of production and marketing" (1996).

Radosavljević and Horner said, "Realistic project scheduling is one of the vital issues for successful completion of construction projects and this can only be achieved if schedules are based on realistic man-hour values. Yet, determination of realistic man-hour values has been a complicated issue due to the complex variability of construction labor productivity" (2002).

Muqeem said, "During the project planning and scheduling, estimators mostly rely on the past project information, their personal judgment and their experience due to the absence of adequate information about the production rates value, and the factors that influence the production rates of labor at site is the reason identified behind the declination of labor productivity. Thus, the construction projects are estimated using the inadequate information of the estimators which results in cost overruns and time overruns of projects (Song et al. 2008). Consequently, reliable and accurate estimation of projects is required to be done through use of modeling techniques to predict the production rates of a project" (2011).

One of the main issues in construction claims is "lost productivity," which is very common in the industry. Hanna and Sullivan stated, "Contractors and owners alike need the ability to quantitatively calculate the impacts of conditions affecting labor efficiency for use in management and claims negotiation and litigation" (2004). Therefore, measuring loss of productivity resulting from the impacts of other factors is important in claim resolution.

In summary, construction labor productivity is an essential element of time and cost prediction of construction projects; therefore, predicting it accurately is important for planning and control of the activities and eventually of the project. Improved methods for predicting work hour requirements for construction activities will enable project managers to make more efficient use of a project's resources.

1.3 Challenges of Predicting Construction Labor Productivity

According to Song and AbouRizk the current practice of estimating and scheduling relies on several sources to get productivity values, including an estimator's personal judgments, published productivity data, and historical project data (2008). Predicting productivity of construction activities due to the dynamic and stochastic nature of variables that affect construction labor productivity is a challenging task. In terms of labor intensive construction activities, the challenge of estimating and predicting construction labor productivity is more critical because there are multiple factors that affect productivity, and these factors affect each other stochastically. The quantitative impact of one factor on labor productivity for numerous factors has been investigated by different researchers, but in a construction site all factors may occur simultaneously. Since the goal is predicting labor productivity, it is necessary to consider the effects of all factors that have a possibility of happening. The need for a system that not only depicts cause-effect relationships among different factors, but also visualizes the stochastic interactions among factors and productivity is crucial for predicting construction labor productivity. Also, there are situations where estimators use linguistic variables like "poor management skills" in their evaluation of productivity. In these situations, causal relationships among variables, randomness, and vagueness cause predicting construction labor productivity a challenging task.

1.4 Objective

The objective of this study is to develop a comprehensive model to predict construction labor productivity while considering the causal relationships and randomness that exist among variables. For achieving this purpose, a "Bayesian Belief Networks Model" for each variable that affects construction labor productivity has been developed, then by combining these models with each other, the comprehensive causal model for predicting construction labor productivity is obtained. Additional objectives of this research are as follows:

- Identify factors that affect construction labor productivity through an extensive literature review.
- Create a comprehensive map of cause-effect relationships among factors that affect labor productivity from literature and expert knowledge with a “mosaic approach.”
- Provide a decision support system for construction managers and project managers to identify controllable variables that affect construction labor productivity and gain higher productivity by managing those variables in a better way.

A comprehensive sensitivity analysis of the model is discussed to show the accuracy of the model and how the model can help project managers in their decision-making process when uncertainty exists.

1.5 Research Scope and Limitations

In this research, the important factors that affect labor productivity have been investigated. The criterion for identifying these factors is the amount of literature that exists about a specific factor. For example, “work overtime” is considered as a main factor that affects productivity. There is extensive research about the effects of this factor on labor productivity. Numerous other factors that affect labor productivity such as “sexual harassment” won’t be investigated in this research because the research in the construction industry is sparse about them, although there exists research about these factors in the industrial engineering domain.

1.6 Dissertation Organization

This dissertation consists of seven chapters. After this introductory chapter, a comprehensive literature reviews about factors that affect construction labor productivity, models and methodologies that have been applied to predict construction labor productivity from professional journals and texts is presented in chapter 2. Chapter 3 is a short introduction to “Probabilistic Graphical Modeling,” “Bayesian Networks,” and different types of “Bayesian Networks.” In this chapter essential concepts that are necessary to understand chapter 5, 6, and 7 are explained. In chapter 4, the structure of the network is extracted from other scholars’ publications and findings. Various methodologies that are employed to find the structure of each subnetworks are also discussed. In chapter 5, the network parameters are obtained. It means that for each node a “Conditional Probability Table” (CPT) is extracted. Various methodologies are used in this chapter to obtain the model CPTs and then by comparing the errors of each method with the actual base network, the best CPTs are chosen. In chapter 6, various approached are used to validate the model. In addition, in this chapter different sensitivity analyses are done to show how the model can be used is the decision-making process and which factors have the highest impact on labor productivity. In chapter 7 and 8, the dissertation is summarized and some areas that can be investigated in the future are discussed.

In the figure 1.1, the flowchart of the dissertation chapters with its major contents and logical structure are summarized.

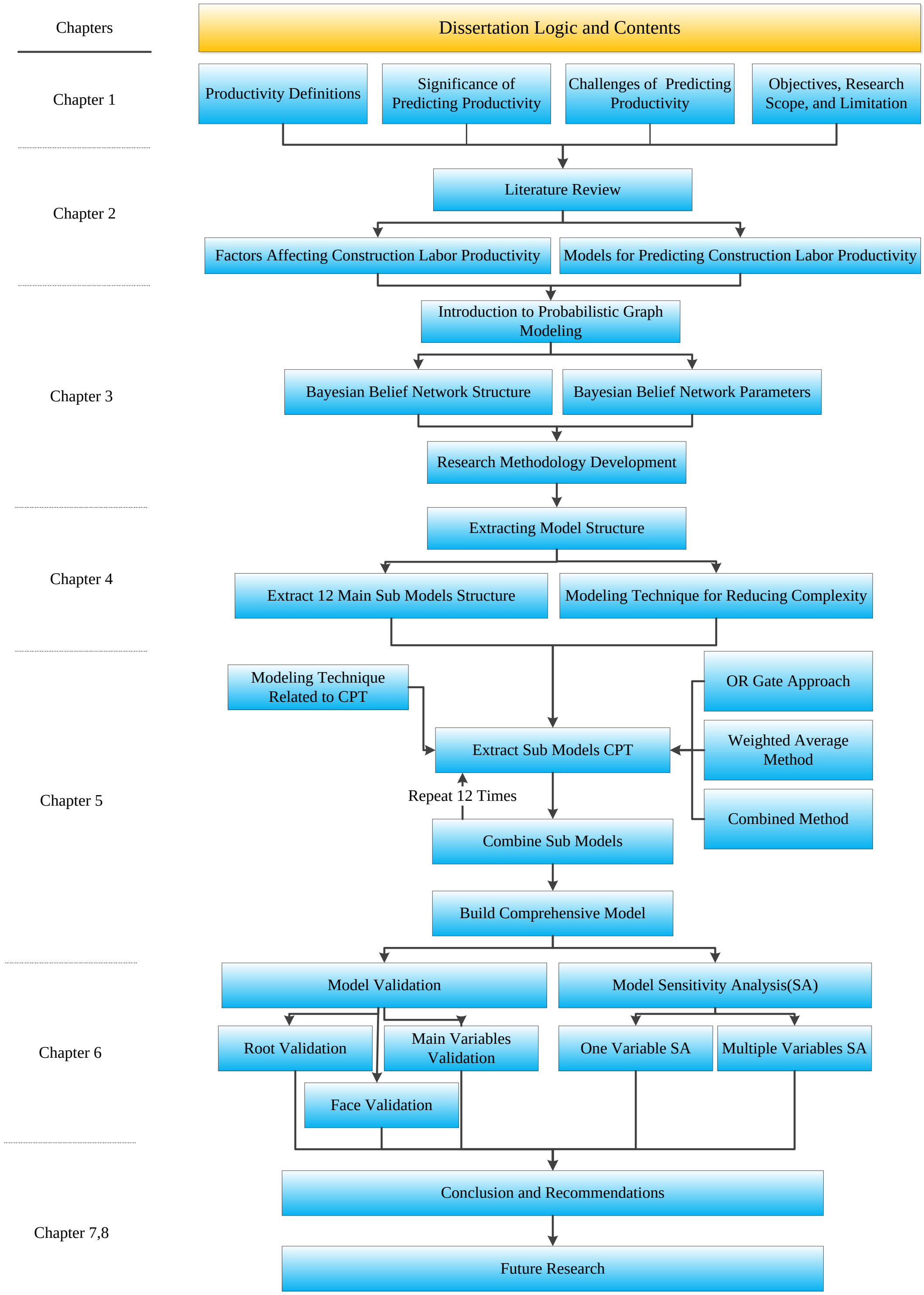


Figure 1. 1: Structural Logic of the Dissertation

Chapter 2

Literature Review

The field of research in construction labor productivity is complex and versatile in nature; therefore, different methods must be implemented to explore different perspectives for measuring or predicting construction labor productivity. Research in construction labor productivity has centered on the identification of factors that affect productivity, and quantifying the impact of such factors on productivity. As a result, various qualitative and quantitative factors have been discovered, and various methods for predicting construction labor productivity have been presented. The literature is divided in two parts. The first part describes methods and models that have been used for predicting construction labor productivity. The second part describes factors that affect construction labor productivity.

2.1 Models for Predicting Construction Labor Productivity

Panas and Pantouvakis have done comprehensive reviews of the construction labor productivity literature from 1999 to 2009. In that investigation, 89 papers were selected from top quality journals and the “qualitative content analysis technique” was implemented to investigate different methodologies that have been used in construction labor productivity research areas (2010). According to Panas and Pantouvakis, different methodologies that exist in construction labor productivity research area are (1) qualitative research methods, (2) quantitative research methods, and (3) mixed method approaches, which is a combination of qualitative and quantitative approaches (2010). Furthermore, another classification of construction labor productivity is based on research focus of each study, which can be: (1) archival study, (2) empirical research and (3) simulation methodology. Archival studies are based on analysis of documentary data while empirical research refers to the creation of models based on observation regarding the responses of a system under investigation (Flood and Issa 2010). The aim of empirical research is development of mathematical models that represent abstraction of construction systems aiming at delineating the effects of a pre-selected set of variables or factors on construction productivity (Panas and Pantouvakis 2010). In the field of construction productivity, the application of quantitative research dominates (60.7%), followed by the application of mixed-method (29.2%), and the application of qualitative approaches (10.1%) (Panas and Pantouvakis 2010).

Thomas et al. applied a generic analytical framework for modeling the impact of weather and material delivery method on construction productivity (1999).Ng et al., by objectively quantifying the negative effects of de-motivators developed a model to predict construction productivity (2004). Choy and Ruwanpura applied situation–based simulation models for predicting construction productivity (2006). They stated that to improve the performance of construction operation, they need to model the impact of different triggering situations that affect productivity. Hanna et al. applied stepwise regression model to estimate impact of changes on labor productivity in mechanical projects (1999a). The Hanna's model input variables are the original estimated labor hours, impact classification, total estimated change hours, number of change orders, and timing of changes. The result of this research showed that impacted projects have a larger decrease in labor productivity than un-impacted projects (1999a). In a similar research, Hanna et.al applied linear regression model to estimate loss of efficiency due to change orders based on number of independent variables in electrical construction (1999b). The independent variables used in this model was qualitative and quantitative criteria used to determine whether projects are impacted by changes, the estimate of change hours for projects, and total number of years that the project manager had worked in the construction industry. Fayek and Oduba applied the fuzzy expert system for predicting construction labor productivity (2005). They stated that using the fuzzy expert system, it is possible to effectively model industrial construction labor productivity, given the realistic constraints of subjective assessments, multiple contributing factors, and limited data sets (Fayek and Oduba, Predicting Industrial Construction Labor Productivity Using Fuzzy Expert Systems 2005). Graham and Smith gathered past productivity data regarding the concrete supply and onsite delivery and created a predictive model by applying Case-Based Reasoning (CBR) principles (2004). Song and AbouRizk, using historical data, predicted construction productivity using techniques such as artificial neural network and discrete-event simulation (2008). Thomas and Zarvski by studying numerical project databases, which consist of labor productivity measurement of masonry, concrete formwork, and structural steel activities, conducted statistical analysis to calculate specific productivity metrics to identify the best and worst performing projects (1999). Zayed and Halpin applied regression technique for the estimating of pile construction productivity. In this study seven regression linear models have been designed and validated to assess productivity (2005). Tam et al. used artificial neural networks (ANNs) to predict excavator productivity. The results of their model show that ANN model is appropriate for mapping non-linear relationship between excavation activities and the performance of excavators (Tam, Tong and Tse 2002). Mosehli et al. by utilizing ANNs investigated the impact of change orders on construction productivity. In this research the field investigation has been carried out for 6-month period to gather required data (Moselhi, Assem and El-Rayes 2005). El-Rayes and Mosehli created a database of climatic historical data and combined it with knowledge-based rules to create an expert system known a WEATHER, which could estimate the lost productivity due to rainfall on highway construction. The model was validated with actual data from contractors and public agencies (2001). Hanna et al. used statistical analysis techniques such as multiple regression, p-value tests, and analysis of variance to find the impacts of extended duration overtime on construction labor productivity (Hanna, Taylor and Sullivan 2005). Zayed and Halpin applied artificial neural networks (ANNs) for assessing productivity in pile construction projects. In this research, three-layer, feed forward, and fully connected ANNs were trained with an architecture of seven input neurons, five output neurons, and different hidden layer neurons (2005). Huang et al. used the CYCLONE modeling methodology to estimate productivity of formwork operations (Huang, Chen and Sun 2004).

2.2 Impact of Different Factors on Construction Labor Productivity

Various factors affect construction labor productivity directly and indirectly. In this section, previous research about the most important factors are reviewed.

Adverse weather conditions is probably one of the most commonly cited causes of construction labor productivity losses in the literature (Christian and Hachey 1995, Halligan, et al. 1994, Thomas, Riley and Sanvido 1999). Clapp described how labor efficiency losses could occur when adverse weather conditions exist in construction sites (1966). National Electrical Contractors Association examined the effects of temperature and humidity on construction labor productivity (NECA 2004). Thomas et al. studied the impact of weather and material delivery methods on labor-intensive productivity for three steel erection projects by proposing a generic analytical framework that could be applied independently of the project actors. They have demonstrated that weather can account for as much as a 30% decline in productivity (Thomas, Riley and Sanvido 1999). Rojas and Aramvareekul did a survey and ranked adverse weather conditions as a productivity driver by placing it as the most important driver in the industry environment category (2003).

Numerous articles exist in the literature about changes and change order factors. Ibbs defined changes as any variation to the original project scope. Change can be physical, such as adding more work, or less tangible, such as change in sequence of works. Also, it can be the responsibility of the owner, the contractor, the designer, or a third party (2005). Change orders have long been identified to have a negative impact on construction productivity, leading to a decline in labor efficiency and, in some cases, sizeable loss of man hours (Barrie and Paulson 1996, O. Moselhi

1998). Although change orders provide a mechanism for satisfying the owner's construction needs throughout the project delivery process and responding effectively to errors and omissions in the design, construction methods, and contract documents, they frequently pose serious problems to owners and contractors, leading to cost overrun and costly disputes (Yitmen, et al. 2006). Moselhi et al. have examined the impact of time of change orders on labor productivity. They also developed a neural network model to evaluate the effects of change order on labor productivity (Moselhi, Assem and El-Rayes 2005). Ibbs has examined the likelihood, severity, and impact of change order on labor productivity (2012). Lee compiled a comprehensive review of the many published articles that measure how a change impacts productivity (2007). The Mechanical Contractors Association of America has published reports on discrete change factors and their impacts on productivity on the basis of member experiences (MCAA, Change Orders, Productivity, Overtime 2014). Other prominent papers that deal with change and its impact on labor productivity are by Leonard (1988), Ibbs (1997, 2005), Thomas (1995), and Hanna et al. (1999a, 1999b). Leonard's thesis is one of earliest and most widely cited publications on the subject of quantitative impact of change (1988). Two key findings were that large amounts of change create large amounts of productivity loss, and change orders can cause productivity loss on both the change work and the base contract work. Thomas and Napolitan reviewed 522 days' work on three different projects. This analysis showed that on many days (though fewer than half) it was possible to incorporate change orders into the project without hurting labor productivity. However, the average impact for all changes was a 30% loss of productivity, indicating that when the impact is negative, it is substantial. The analysis concluded that the timing of a change was a key variable affecting productivity (1995). Ibbs has published curves that further substantiate that timing is crucial, sometimes doubling the consequences that change has on productivity (2005).

Overstaffing (Overmanning) is another factor that has an impact on construction labor productivity. Hanna et al. defined Overstaffing as “an increase of the peak number of workers of the same trade over the actual average manpower used throughout the project” (Hanna, Chang and Lackney, et al. 2007). Given the fact that labor costs for labor intensive mechanical and sheet metal contractors typically range from 33 to 50% of the total construction cost, understanding how and how much Overstaffing affects labor productivity is crucial for a construction manager (Hanna, Chang and Lackney, et al. 2007). Waldron studied the relation between percent overstaffing and percent productivity losses (1968). O’Conner conducted a study on productivity loss resulting from overtime and Overstaffing. His study was based on data from the 1963 through 1968 project records of five fossil fuel power stations located in the Ohio Valley. For situations in which the number of workers on the site were 100, 200, and 300, loss of efficiency was calculated in percent of total hours worked. The study concluded that Overstaffing could result in a productivity loss of up to 30% (1969). The U.S. Army Corps of Engineers released a “Modification Impact Evaluation Guide” in 1979, introducing the effect of Overstaffing on labor productivity. Overstaffing was defined in terms of percent crew size above optimum in that report (Corps 1979). Borcherding and Sebastian defined overcrowding as “those conditions that inhibit an individual from performing as efficiently as possible because of either the high density of workers working in that location or the inherent interferences caused by the physical components of the plant itself." The study found that overcrowded working conditions appeared to affect productivity adversely (1980). Thomas and Jansma defined percent overmanned as the "planned peak manpower divided by the actual peak manpower." They reported Overstaffing affected productivity loss up to 300% (1985). However, this report mistakenly analyzed the project size factor, instead of Overstaffing effects (Hanna, Chang and Lackney, et al. 2007). Hanna et al. examined the impact of Overstaffing on mechanical and sheet metal labor productivity. The results indicate a 0–41 percent loss of productivity, depending on the level of Overstaffing and the peak project manpower (Hanna, Chang and Lackney, et al. 2007). Lyneis and Ford stated that a larger workforce can increase congestion and brings problems related to communication, which can increase errors and decrease labor productivity (2007).

Several researchers have investigated effects of <u>overtime</u> on construction labor productivity. Overtime is defined as "the hours worked beyond the typical 40 hours scheduled per week" (Hanna, Taylor and Sullivan 2005). The Business Roundtable (BRT) published a paper to investigate effects of scheduled overtime on construction projects. The research examined the effect of overtime for a period of 12 weeks on projects which operated on a basis of 50 hours per week and 60 hours per week. The overall conclusion of that research revealed a decline in construction labor productivity when extended overtime existed in a project (BRT 1974). As a schedule compression technique, overtime is often preferred because it can produce a higher rate of progress without the coordination problems that exist in shift work and the additional craftsmen needed for Overstaffing. However, overtime introduces additional problems including: fatigue, low morale, a higher cost per unit, and a higher accident rate (Chang, et al. 2005). Some argue that scheduled overtime can be used without losing labor efficiency (CII 1988) , and others argue that when an overtime schedule is applied, labor efficiency automatically suffers (Thomas and Raynar 1997). Thomas believed that extended overtime, an overtime schedule that lasts longer than several weeks, has a negative effect on construction labor productivity, while Spot overtime, which is intermittent, has a minor negative relative effect to the job as a whole (1992). O'Connor described the experiences of Foster Wheeler in constructing five large fossil boilers in the Ohio Valley between 1963 and 1968. The paper reported an average productivity decline of 7.9 percent per year during that period because of a variety of factors, including overtime, Overstaffing, and labor strikes (1969).

Workforce management is another critical factor that has impacts on construction labor productivity. In a study by Thomas et al., the researchers found that on three bridge construction projects more than half of the inefficient work hours resulted from ineffective workforce management practices (Thomas, Horman and Minchin, et al. 2003). Thomas et al. also showed that symbiotic crew relationships are more difficult to manage than sequential relationships (Thomas, Horman and de Souza 2004). Also, Thomas and Horman described how construction labor productivity can be increased by applying fundamental principles of workforce management (2006). Rojas and Aramvareekul did a survey among owners, consultants, general contractors, electrical contractors, and mechanical contractors regarding different factors that affect construction labor productivity. They found that management system and strategies -which includes management skills, scheduling, material and equipment management, and quality control- is the most important factor that can have highest impact on construction labor productivity (2003).

Absenteeism is another factor that causes decline in labor productivity. Construction operations, especially in labor–intensive activities, depend on labor activity; therefore, absenteeism on a job site can damage project performance in different ways. Hinze et al. stated that absenteeism on a job site can impact project performance in many ways, including interrupting workflow and impeding productivity, and may result in serious revenue loss when the required schedule is not met (Hinze, Ugwa and Hubbard 1985). Hanna et al. examined electrical construction projects and found that productivity decreased by 24.4% when the absence rate on a job site was between 6 and 10%, whereas productivity increased by 3.8% when the absence rate was between 0 and 5% (Hanna, Menches, et al. 2005). Ahn et al. found that "construction workers who perceive salient social norms in their team are less likely to be absent from their job site." Also, they suggested that investing in promoting social cohesion and creating positive prototype in teams can cause lower level of absenteeism in job site (Ahn, Lee and Stell 2014). They also found that "high social adaptation can work as a force to either increase or decrease workers' absence rates," or "when high social adaptation reinforces formal rules, this occurrence reduces the need for additional formal controls on worker behavior" (Ahn, Lee and Steel 2013). Absence rates larger than 6% are not uncommon in electrical construction projects (Hanna, Menches, et al. 2005). Sichani et al. reported that the worker absence rates in Canada's construction sector were 8.6%, 9.3%, and 8.5% in 2006, 2007, and 2008, respectively. It was also reported, in particular, that large industrial projects in Canada recently experienced productivity loss associated with absenteeism (Sichani, Lee and Fayek 2011).

Stacking of trades is one the most important factors that affect labor productivity. Hanna and Sullivan defined stacking of trades as "the total number of craftsmen from all trades working in a given area" (2004). Mechanical Contractors Association of America (MCAA) defined stacking of trades as "operations that take place within physically limited space with other contractors" (MCAA 2011). Stacking of trades relates the number of different trades (pipefitters, electricians, etc.) within a measured work area to labor productivity. Stacking of trades causes operations to take place within physically limited space with other contractors which results in congestion of personnel, inability to locate tools conveniently, increased loss of tools, additional safety hazards, and increased visitors which causes optimum crew size cannot be utilized when stacking of trades exists (MCAA 2011). Riley and Sanvido specified 12 unique characteristics of construction activities-which includes layout area, unloading area, material path, staging area, personnel path, storage area, prefabrication area, work area, tool and equipment area, debris path, hazard area, and protected area - that require space and techniques to avoid congestion and stacking of trades between multiple trades through planning activities , material storage, definition of work flow between trades, and equipment management (1995). Smith reported losses of productivity due to congestion and stacking of trades. He reported that maximum productivity occurred when craftsmen had at least 320 ft2 (99 m2) per person in an offshore work on oil drilling platforms (1987). Logcher and Collins studied the setting of floor tile on five projects in New York and Boston. They found that while more open area was allowed, the productivity was affected only slightly by changes in the floor area (1978). Horner and Talhouni stated that for obtaining maximum labor productivity, craftsmen need 250–300 ft2 (77–92 m2) per person (1993). McDonald and Zack stated that "To achieve a good productivity each member of crew must have sufficient working space to perform their work without being interfered with by other craftsmen. When more labor is assigned to work in a fixed amount of space it is probable that interference may occur, thus decreasing productivity. Additionally, when multiple trades are assigned to work in the same area, the probability of interferences rises and productivity may decline" (AACE International 2004). Thomas et al. investigated the effects of congested working area on labor productivity. They concluded that congestion can be very expensive and may cause up to 30% loss in labor productivity (Thomas, Riley and Sinha 2006).

One of the major field factors that causes losses in construction labor productivity is beneficial occupancy. Hanna and Sullivan defined beneficial occupancy as the situation in which a contractor must work in close proximity to an owner's production equipment or personnel. Therefore, contractors must adjust to environmental circumstances including extra safety precautions, concern regarding dust or noise, and the reduction or absence of a convenient material laydown area (Hanna and Sullivan 2004). MCAA quantified the effect of beneficial occupancy on construction labor productivity. The estimated productivity losses of this factor are 15%, 25%, and 40% for minor, moderate, and severe conditions, respectively

(MCAA 2011). In a similar research, Ovararin investigated the effect of beneficial occupancy on loss of productivity in masonry construction. He found that the estimated productivity losses due to this factor are 7%, 14%, and 25% for minor, moderate, and severe conditions, respectively (2001).

Joint occupancy is an important factor that causes decline in construction labor productivity. Joint occupancy occurs when work is scheduled utilizing the same facility or work area that must be shared or occupied by more than one craft, and not anticipated in the original bid or plan (MCAA 2011). According to the MCAA loss of labor productivity due to joint occupancy has been estimated 5%, 12%, and 20% for minor, average, and severe conditions, respectively (2011). Ovararin showed higher losses of productivity due to joint occupancy in comparison with MCAA. The average loss increases up to 14% when a facility is partly occupied and two or three trades are working in the same area. Even more severely, there is an average productivity loss of 25% when a facility is in full operation and masonry work is on limited shifts (2001).

Shift work is one of the options that contractors usually use to accelerate a construction schedule. Although shift work is very effective at reducing project duration, it has disadvantages and one of them is loss of labor productivity. Also, shift work introduces other additional costs including additional administration, supervision, quality control, safety, and lighting, as well as shift differential (Hanna, Chang and Sullivan, et al. 2008). The cost of shift work to American industry was estimated in excess of $77 billion (Coburn 1997). Also, 84% of total cost of shift work is due to loss of labor productivity at work (Coburn 1997). Penkala described some of common problems associate with shift work; the problems like little cooperation between shifts, inconsistent operating procedures across shifts, inefficient communication between crews, and absence of regular business hours for management (1997). Hung reported problems like harmful health conditions, high personnel turnover, absenteeism, resentment, poor job performance, and unfit mental and physical conditions, or other situations that translate to loss of productivity, quality, and even safety as results of shift work (1992). Waldron estimated the productivity loss due to shift work to be 10% (1968). Hanna stated that Safety may be negatively impacted during the second shift because of increased fatigue, a reduction of support groups, and potentially poor lighting conditions when working at night (2003). Costa found that shift workers generate more errors and accidents, and may have problems in maintaining proper relationships at the family and social levels (1996). Haneiko and Henry found that double shifting has an impact on productivity. They stated that double shifting caused a gradual initial decrease in the unit production rates, followed by a recovery period. They found this results in electric work during one year period (1991). Not all researches concluded that shift work has negative effects on worker performance. Hildebrandt et al. found that shift work had better performance than day-time operation (Hilderbrandt, Rohmert and Rutenfranz 1974). Cook by analyzing of data collected from 36 industries, such as electrical and general engineering, found that shift work has no significant effect on reductions in labor productivity (1954). Cook also stated that shift work greatly affects neither absenteeism nor safety (1954). Horner and Talhouni found that the competition between shifts might actually cause an increase in overall productivity (1993). Smith based on his company experience stated that well-planned second shift with work completely separate from the first could have a productivity rate greater than the first shift (1987). He believed that shift work avoids congestion of trades, allows for the optimization of crew size, and improves motivation (1987).

Morale and attitude is one of the factors that affect labor productivity in the construction industry. According to Merriam-Webster dictionary, morale is defined as “The confidence, enthusiasm, and discipline of a person or group with regard to the function or task at hand” or “A sense of common purpose with respect to a group” (Merriam-Webster n.d.). Warhoe stated that worker morale in the construction industry is an important aspect of maintaining good productivity and reducing error. He also stated that measuring worker morale is difficult (2012). Gould and Joyce stated that workers often take their morale cues from those that lead the projects; therefore, it is essential for project managers to be aware of project policies (2013). Ovararin stated that workers perform the construction job and they have direct control on productivity; therefore, worker morale can have a significant impact on productivity (2001). Warhoe stated that morale can be positively impacted through establishing a sense of achievement amongst construction workers by different methods such as providing safer working condition (2012). Lyneis and Ford stated that fatigue and rework can create a sense of ‘hopelessness’ that increases errors, reduce productivity and increase turnover (2007).

Motivation in construction industry is an important phenomena to energize workers toward a specific goal. In construction industry, motivation has been defined as providing a drive to act to satisfy needs or desires and then stimulate and energize workers with the aim of getting work done on time and within budget (Cox, Issa and Koblegard 2005). Bredillet et al. stated that motivation directly affects project success (Bredillet, Dwivedula and Ruiz 2009). Warhoe stated that appropriate motivation is what workers need to have in order to work at a normal and acceptable productivity rate (2012). Osterloh and Frey stated that two types of motivation exist, namely extrinsic and intrinsic. Extrinsic motivation occurs when managers can satisfy worker's needs especially through monetary compensation, while intrinsic motivation is obtained through self-satisfaction. They also stated that obtaining high productivity rate is achievable through satisfactory and fulfilling incentives (2000). Mackenzie and Harris stated that extrinsic motivation is what primarily dominates workers minds (1984). The Business Roundtable established a set of actions that motivates construction workers and invents a specific program that can help managers to enhance on site construction labor productivity (BRT 1982). Borcherding and Oglesby investigated the effects of job satisfaction and motivation on labor productivity. They found well-planning and smooth work flows two important factors affecting job satisfaction and motivation (1974). Maloney and McFillen stated that contractors need to improve worker satisfaction to increase labor productivity (1986).

<u>Fatigue</u> is one of the factors that is usually stated as a main cause of decline in labor productivity. Hallowel defined fatigue as exhaustion of mental and physical ability caused by over exertion (2010). Akhter et al. stated fatigue reduces workers' capabilities to an extent that may impair their strength, speed, reaction time, coordination, decision making, or balance (2011). American Association of Cost Engineering International (AACE International) stated that fatigue can decrease

productivity through slowing down work, increasing the number of mistakes, accidents, and injuries (2004). Akerstedt stated that measuring fatigue is possible through objective measures such as reaction times or number of errors (1990). Amble did research about fatigue amongst workforce and he found that 38% of workers experience fatigue related problems. He also found that 10% of workers reported unproductive time and stated that fatigue reduced performance by interrupting their concentration and increasing the time needed to accomplish tasks (2007). Warhoe stated that fatigue negatively affects labor productivity on a construction project. He stated that fatigue not only decreases productivity, but also can lead to lapses in safety which could cause fatal accidents (2012).

Previous factors are the most important factors that affect construction labor productivity, and most of the literature is about those factors. Other factors that affect construction labor productivity according to the literature are concurrent operations, errors and omissions, reassignment of manpower, late crew build-up, crew size inefficiency, site access , logistics , learning curve, ripple effect, confined space, hazardous work area , holidays, dilution of supervision , working in operating area , tools and equipment shortages, proximity to work, and alternating work schedules. Thomas and Napolitan stated that scheduling work out-of-sequence can produce loss of momentum because crews need to stop working on their present jobs and reorganize for the new work (1995). Thomas et al. investigated the effects of adverse material management on construction labor productivity (Thomas, Sanvido and Sanders 1989). Makulsawatudom and Emsley investigated the effects of 23 factors on the construction labor productivity in Thailand. They found that lack of material, incomplete drawings, incompetent supervisors, lack of tools and equipment, labor absenteeism, poor communication, instruction time, poor site layout, inspection delay, and rework as the most important factors that affect construction labor productivity (2003). Abdul Kadir et al. surveyed the effects of 50 productivity factors on Malaysian residential projects and identified material shortages, change orders, incapability of site management, late issuance of construction drawings by consultant, and late or no payment to suppliers which causes stoppage of materials delivery to sites as the most important factors that causes loss of labor productivity (2005). Alinaitwe et al. ranked incompetent supervisors, lack of skills, rework, lack of tools/equipment, and poor construction methods as the most important causes of loss of labor productivity (Alinaitwe, Mwakali and Hansson 2007). Enshassi et al. surveyed 45 factors affecting labor productivity on building projects in Gaza Strip. They found that the main factors negatively affecting labor productivity as follows: material shortage, lack of labor experience, lack of labor surveillance, misunderstandings between labor and superintendent, and drawings and specification alteration during execution (2007). The impact of material management and delivery methods on construction productivity has been investigated by several researchers such as Thomas et al. (Thomas, Sanvido and Sanders 1989) , (Thomas, Riley and Sanvido 1999). Also, Horman and Thomas investigated the role of inventory buffers in construction labor performance. They found that some buffer helps achieve the best labor performance in the construction operations (2005). Lamm et al. stated that “there is an increasing and compelling evidence that providing a healthy and safe working environment has the potential to increase labor productivity.” On the other hand, they found that efforts to increase productivity through occupational safety and health can have contradictory results (2006). Greef and Broek stated that research findings support the existence of an important link between a good working environment and the performance of a company (2004).

Chapter 3

Introduction to Probabilistic Graph Modeling and Bayesian Networks

This chapter is a brief introduction to Probabilistic Graphical Modeling (PGM) and Bayesian Belief Networks (BBNs). For deeper understanding of the capabilities of Bayesian Belief Networks and Probabilistic Graphical Models the author suggests “Modeling and Reasoning with Bayesian Networks” by Adnan Darwiche (2009), “Probabilistic Reasoning in Intelligent Systems” by Judea Pearl (1988), and “ Probabilistic Graphical Models Principles and Techniques” by Daphne Koller and Nir Friedman (2009). Most parts of this chapter are from the content of these books.

3.1 Uncertainty

Most tasks require a person or an automated system to reason, which is to take the available information and reach a conclusion, both about what might be true in the world and about how to act. For example, a doctor needs to take information about a patient – his/her symptoms, test results, personal characteristics (gender, weight) - and reach conclusions about what diseases he or she may have and what course of treatment to undertake. An inherent component of this kind of reasoning is a significant amount of uncertainty. Uncertainty defined as the lack of certainty, a state of having limited knowledge in which it is impossible to precisely describe existing state or future outcome (Hubbard 2014). Uncertainty is consequence of several factors such as partial observation, which only some aspects of the world are observed, and noisy observation which includes some errors. To summarize, uncertainty arises because of limitation in our ability to observe the world, limitation in our ability to model it, and possibly even because of non-determinism (Hubbard 2014). Therefore to model this kind of uncertain situation, we need to reason not just about what is possible, but also about what is probable.

3.2 Probabilistic Graphical Models

Koller and Friedman described Probabilistic Graphical Models (PGM) as a mechanism for exploiting structure in complex distributions to describe them compactly in a way that allows them to be constructed and utilized effectively (2009). Probabilistic graphical models use a graph-based representation as the basis for compactly encoding a complex distribution over a high-dimensional space (2009). Jordan (1998) described the PGM as follows:

> An integral part in the idea a graphical model is the notion of modularity -- a complex system is built by combining simpler parts. Probability theory provides the glue whereby the parts are combined, ensuring that the system as a whole is consistent, and providing ways to interface models to data. The graph theoretic side of graphical models provides both an intuitively appealing interface by which humans can model highly-interacting sets of variables as well as a data structure that lends itself naturally to the design of efficient general-purpose algorithms. Many of the classical multivariate probabilistic systems studied in fields such as statistics, systems engineering, information theory, pattern recognition and

statistical mechanics are special cases of the general graphical model formalism – examples include mixture models, factor analysis, hidden Markov models, Kalman filters and Ising models. The graphical model framework provides a way to view all of these systems as instances of a common underlying formalism. This view has many advantages -- in particular, specialized techniques that have been developed in one field can be transferred between research communities and exploited more widely. Moreover, the graphical model formalism provides a natural framework for the design of new systems.

PGM has many advantages. It allows the distribution to be written down tractably, even in cases where explicit representation of the joint distribution is astronomically large. The type of representation provided by this framework is transparent, in that a human expert can understand and evaluate its semantics and properties. Also, the same structure allows the distribution to be used effectively for inference. In particular, computing posterior probability of some variables given evidence on others. We can construct these models not only with using human knowledge and expertise, but by learning from data. A model based on our past experiences can be constructed. Three components- representation, inference, and learning – are critical component in constructing an intelligent system. It is essential to be able to use this representation effectively to answer a broad range of questions that are of our own interest. We need to be able to acquire this distribution, combining expert knowledge and accumulated data. Probabilistic graphical models are one of the small handful of frameworks that support all three capabilities for a broad range of problems (Koller and Friedman 2009).

3.3 Bayesian Belief Networks

Bayesian Belief Network (BBN) or shortly Bayesian Networks is one of the most effective and prevalent probabilistic graphical models which has been developed by Judea Pearl in Probabilistic Reasoning in Intelligent Systems in 1988. The goal is to represent a joint distribution P over some set of random variables $X = \{X_1, X_2, \ldots, X_n\}$. In the smallest case where these variables are binary-valued, a joint distribution requires the specification of $2^n - 1$ numbers (Koller and Friedman 2009). Therefore, the explicit representation of the joint distribution in unmanageable from every perspective. Computationally, it is very expensive to manipulate and generally too large to store in memory. Cognitively, it is impossible to acquire so many numbers from human experts; moreover, the numbers are very small and do not correspond to events that people can reasonably contemplate. These problems were the main barrier of probabilistic methods for expert systems until the development of PGM (Koller and Friedman 2009). Bayesian Networks (BNs) are graphical models for reasoning under uncertainty, where the nodes represent variables and arcs represent direct connections between them. These direct connections are often causal connections. Bayesian Networks model the quantitative strength of the connections between variables by conditional probability distributions of each node. BNs are Directed Acyclic Graph (DAG) models which means no directed cycle exist in the graph. In the figure 3.1 a Directed Acyclic Graph (DAG) and in figure 3.2 a Directed Non-Acyclic Graph is shown.

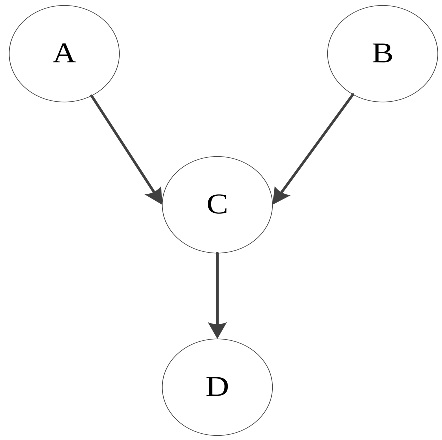


Figure 3.1: Directed Acyclic Graph

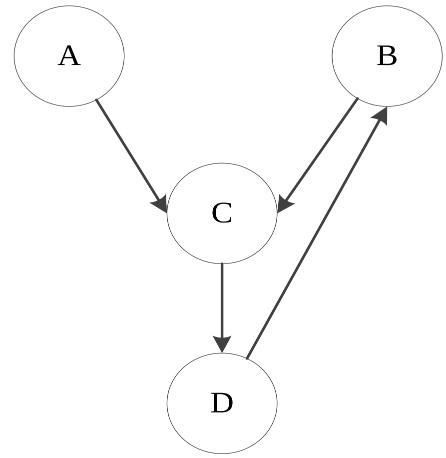


Figure 3.2: Directed Non-Acyclic Graph

Consider the DAG in figure 3.3, where nodes represent propositional variables and edges in the graph represent “direct causal influences” among these variables. Given a causal structure, one would expect the dynamics of belief changes to satisfy some properties. For example, we would expect our beliefs in C to be influenced by evidence on R. If we get a radio report that an earthquake took place in our neighborhood, our belief in the alarm triggering would probably increase, which would also increase our belief in receiving a call from our neighbor. However, we would not change this belief if we knew for sure that the alarm did not trigger ($\neg$A: not A) (Pearl 1988). In this DAG, C is independent of R given A.

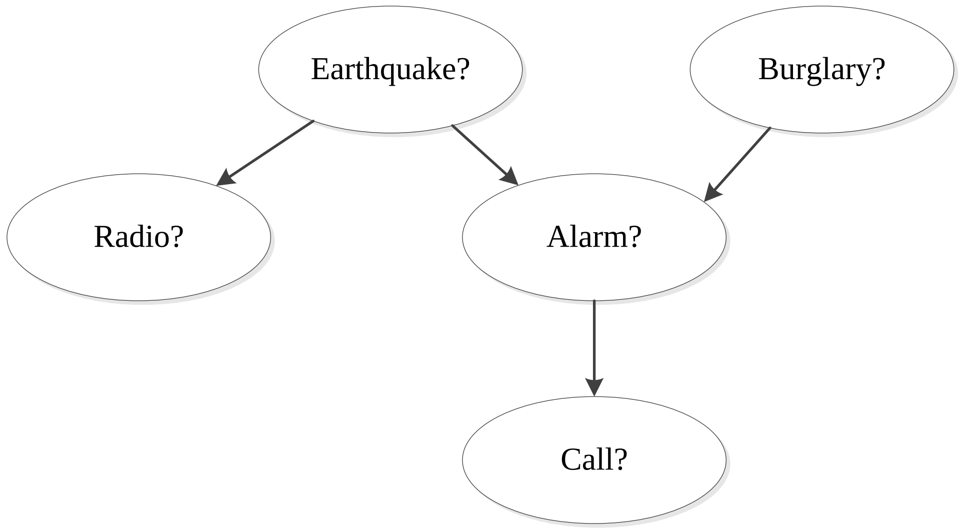


Figure 3.3: A DAG That Captures Independence among Five Propositional Variables

The previous example of independence is implied by a formal interpretation of DAG as set of conditional independence statements. To Phrase this interpretation formally, we need following notation. Given a variable V in a DAG G:

- Parents (V) are the parents of V in DAG G, that is, the set of variables N with an edge from N to V. For example, the parents of variable A in Figure 3.3 are E and B.

- Descendants (V) are the descendants of V in DAG G, that is, the set of variables N with a directed path from V to N (we also say that V is an ancestor of N in this case). For example, the descendants of variable B in Figure 3.3 are A and C.

- Non- Descendants (V) are all variables in DAG G other than V, Parents (V), and Descendants (V). We will call these variables the non-descendants of V in

DAG G. For example, the non-descendants of variable B in Figure 3.3 are E and R.

Given this notation, we will then formally interpret each DAG G as a compact representation of the following independence statements:

$$\mathrm{I}\left(\mathrm{V}, \mathrm{Parents}\ (\mathrm{V}), \mathrm{Non}-\mathrm{Descendants}\ (\mathrm{V})\right) \text{ for all variables V in DAG G} \quad (3.1)$$

That is, every variable is conditionally independent of its non-descendent given its parents. This independence assumption is known as Markovian assumptions of DAG and denote by Markov (G). We can read the statement (3.1) as follows: Given the direct causes of a variable, our beliefs in that variable will no longer be influenced by any other variable except possibly by its effects (Darwiche 2009). Following are all the statements represented by the DAG in Figure 3.3:

$$I\ (C, A, \{B, E, R\})$$

$$I\ (R, E, \{A, B, C\})$$

$$I\ (A, \{B, E\}, R)$$

$$I\ (B, \emptyset, \{E, R\})$$

$$I\ (E, \emptyset, B)$$

The additional set of conditional probabilities that we need are as follows: for every variable X in DAG G and its parents U we need to provide the probability Pr(x|u) for every value x of variable X and every instantiation of parents U. For example, for the DAG in Figure 3.3 we need to provide the following conditional probabilities:

Pr(c|a), Pr(r|e), Pr(a|b, e), Pr(e), Pr(b)

where a, b, c, e, and r are values of variables A, B, C, E, and R. For example, the conditional probabilities required for variable C:

Table 3.1: Sample CPT of Variable C from the Network in Figure 3.1

A	C	Pr(c|a)
True	True	0.8
True	False	0.2
False	True	0.001
False	False	0.999

This table is known as a *conditional probability table (CPT)* for variable C. The set of CPTs, one for each variable, is called the network parameterization. While the directed acyclic graph over variables is called network structure (Darwiche 2009).

3.3.1 Network Factorization

Definition: Let G be a BN graph over the variables $X_1, X_2, \ldots, X_n$. We say that a distribution P over the same space factorizes according to G if P can be expressed as a product:

$$P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P\left(X_i \mid Pa_{X_i}^{G}\right) \tag{3.2}$$

This equation is called the chain rule for Bayesian networks (Koller and Friedman 2009). The individual factors $P\ (X_i|\ Pa_{X_i}^{G})$ are called conditional probability distributions (CPDs) or local probabilistic models. According to factorization, formal definition of Bayesian networks is as follows:

> A Bayesian network is a pair $B = (G, P)$ where P factorizes over G, and where P is specified as a set of CPDs associated with G's nodes.

3.3.2 D-Separation

If $\boldsymbol{X}, \boldsymbol{Y}$ and $\boldsymbol{Z}$ are three disjoint sets of variables, to test whether $\boldsymbol{X}$ and $\boldsymbol{Y}$ are d-separated by $\boldsymbol{Z}$ in DAG G, written $dsep_G(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{Y})$, it is necessary to consider every path between a node in $\boldsymbol{X}$ and a node in $\boldsymbol{Y}$ that is blocked by $\boldsymbol{Z}$. Therefore, the definition of d-separation relies on the notion of blocking a path by a set of variables. Note that $dsep_G(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{Y})$ implies $I_{pr}(\boldsymbol{X}, \boldsymbol{Z}, \boldsymbol{Y})$ for every probability distribution Pr induced by G. To understand the notion of blocking, we need first to describe types of connections in Bayesian networks. First type of connection between variables is serial connection. In Figure 3.4 a serial connection is shown. A has influence on B and B has influence on C. When there is evidence given about B, the communication between A and C is blocked or $dsep_G(\boldsymbol{A}, \boldsymbol{B}, \boldsymbol{C})$. A sequential connection arises when $\boldsymbol{B}$ is a parent of one of its neighbors and a child of the other (Darwiche 2009).

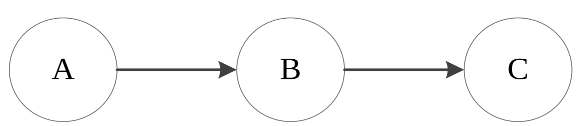


Figure 3.4: Sequential Connection

The second type of connection is divergent connection. In figure 3.5 a divergent connection is shown. In this connection A is parent node and B and C are the child nodes. If evidence is given about A, then communication between child nodes is blocked.

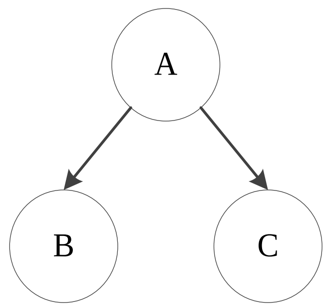


Figure 3.5: Divergent Connection

The third type of connection is convergent connection. In figure 3.6 a convergent connection is shown. In this connection A and B are parent nodes and C is the child node. If no evidence is given about C, then communication between parent nodes is blocked.

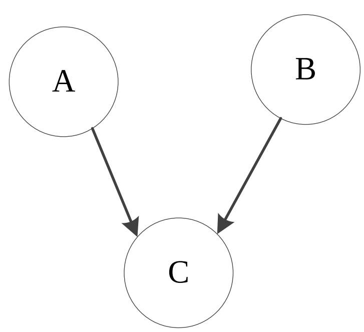


Figure 3.6: Convergent Connection

Based on the concept of d-separation we can identify an active trail in the network. If $X_1 \rightleftarrows X_2 \rightleftarrows X_3 \rightleftarrows \ldots \rightleftarrows X_n$ is a trail in $\boldsymbol{G}$ and $\boldsymbol{Z}$ is a subset of observed variables, the trail $X_1 \rightleftarrows X_2 \rightleftarrows X_3 \rightleftarrows \ldots \rightleftarrows X_n$ is active given $\boldsymbol{Z}$ if whenever we have a convergent connection (V-structure) $X_{i-1} \rightarrow X_i \leftarrow X_{i+1}$ then X_i or one of its descendants are in $\boldsymbol{Z}$ and no other node along the trail is in $\boldsymbol{Z}$. Therefore, if $\boldsymbol{X}$ and $\boldsymbol{Y}$ are not d-separated given $\boldsymbol{Z}$, then $\boldsymbol{X}$ and $\boldsymbol{Y}$ are dependent given $\boldsymbol{Z}$ in some distribution $\boldsymbol{Z}$ that factorizes over the network. D-separation test is sound, this means we can safely use the d-separation test to derive independence statements about probability distributions induced by Bayesian networks (Koller and Friedman 2009).

The final definition in this section is Markov blanket for a variable $\boldsymbol{X}$. A Markov blanket for $\boldsymbol{X}$ is a set of variables that, when known, will render every other variable irrelevant to it. Therefore, if Pr is a distribution induced by DAG G, then a Markov blanket for variable $\boldsymbol{X}$ with respect to distribution Pr can be constructed using its parents, children, and spouses in DAG G. Here variable $\boldsymbol{Y}$ is a spouse of $\boldsymbol{X}$ if the two variables have a common child in DAG G.

3.4 Reasoning with Bayesian Networks

The construction of a Bayesian network consists of three major steps. First, identification of the set of relevant variables and their possible values. Next, building the network structure by connecting variables into a DAG. Finally, defining the conditional probability table or distribution (CPT or CPD) for each variable in the network. After constructing the Bayesian network we can execute several types of queries with respect to a Bayesian network. In this section, different kinds of queries are explained. Since Bayesian networks provide full representation of probability distributions over their variables, they can be conditioned upon any subset of their variables, and therefore produce different kinds of reasoning. Diagnostic reasoning is reasoning from symptoms to causes occurs in the opposite direction to the network arcs. For example, consider a simple network with three variables known as shift work, weather and productivity. Shift work and weather have direct effect on productivity. In figure 3.7 network with related marginal distribution is shown. If we put a condition on productivity, for example, high, the network variables' marginal distribution will change. In figure 3.8 this change in shown. This kind of reasoning which occurs in opposite direction of network is known as diagnostic reasoning. In order to understand this kind of reasoning we need to describe Bayes rule briefly. Bayes rule is as follows:

$$P(B|A) = \frac{P(A|B)P(B)}{P(A)} \tag{3.3}$$

$P(B)$ is prior probability of B , which represents our belief about B before observing any evidence. $P(A)$ represents the probability of evidence A that has been observed and $P(A|B)$ is the conditional probability of seeing A if the event B occurred and is known as likelihood function. $P(B|A)$ is the posterior probability of B given A and is the new estimate of probability distribution of random variable A considering the evidence A . In figure 3.8, the posterior probability distribution of shift work and weather random variable has been computed with regard to the evidence about the productivity random variable.

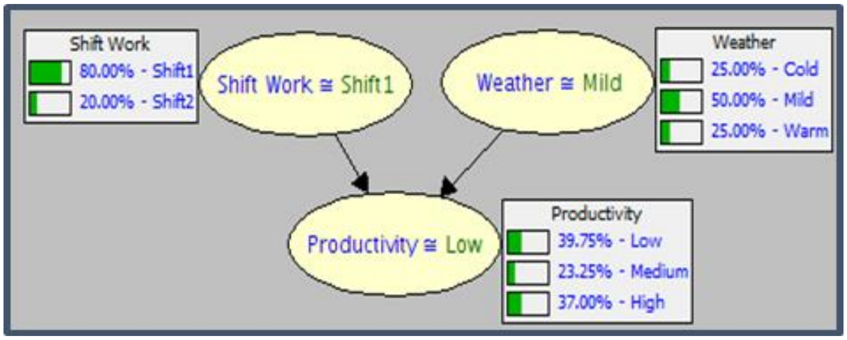


Figure 3.7: A Simple Network with Prior Marginal Distributions

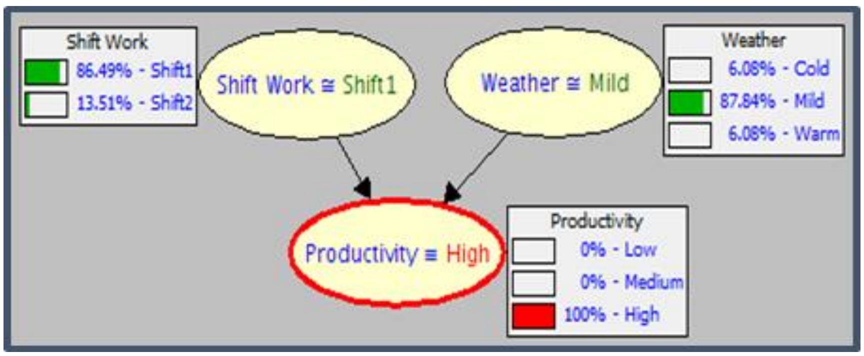


Figure 3.8: Diagnostic Reasoning in Network (Posterior Marginal Distributions)

Another type of reasoning with Bayesian networks is predictive reasoning. This kind of reasoning is reasoning from new information about causes to new beliefs about effects. Predictive reasoning is on the direction of network arcs. For example, in figure 3.9, we put some evidence on shift work, our posterior distribution over productivity random variable has changed.

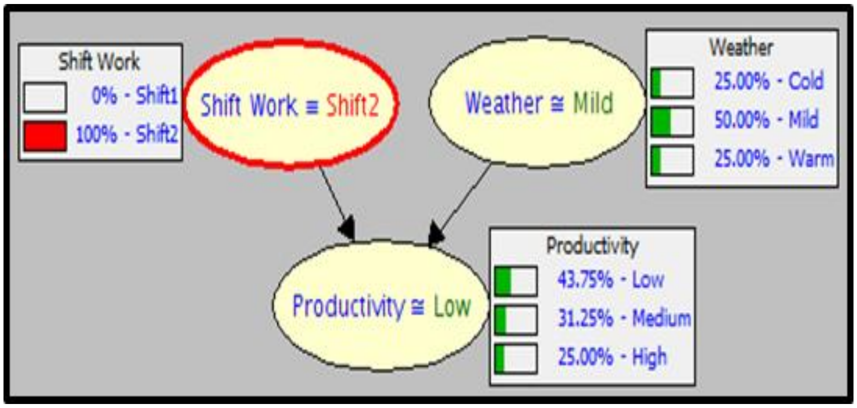


Figure 3.9: Predictive Reasoning in Bayesian Networks

The third type of reasoning is **intercausal reasoning**, which involves reasoning about the mutual causes of a common effect. For example, in figure 3.10, we have some evidence about weather and productivity and show how our belief about shift work has changed. In this situation, evidence on weather increases the probability of working on shift 1, while these two random variables are independent. This situation is known as **explaining away**, that is, even though the two causes are initially independent, with knowledge of the effect, the presence of knowledge about one cause gives knowledge about the alternative cause.

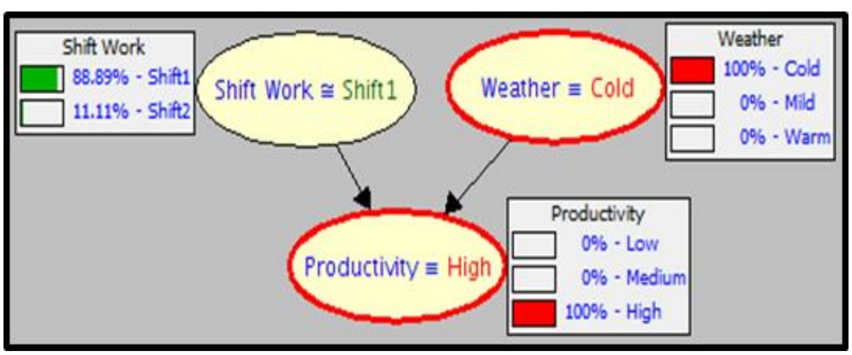


Figure 3.10: Intercausal Reasoning and Explaining Away

There are several types of queries with respect to Bayesian networks. The most probable explanation (MPE). The goal of MPE query is to identify the most probable instantiation of network variables given some evidence. Specifically, if $X_1, X_2, \dots, X_n$ are all network variables and if e is the given evidence, the goal of MPE is to identify an instantiation $x_1, x_2, \dots, x_n$ for which the probability $\Pr(x_1, x_2, \dots, x_n | e)$ is maximal. Such an instantiation $x_1, x_2, \dots, x_n$ is called most probable explanation given evidence e. For example in our example network, if we have observed that productivity is high, the MPE correspond to this evidence is weather to be mild and working on shift 1. Note that the probability of happening this instantiation is 0.7567. In figure 11 MPE is shown.

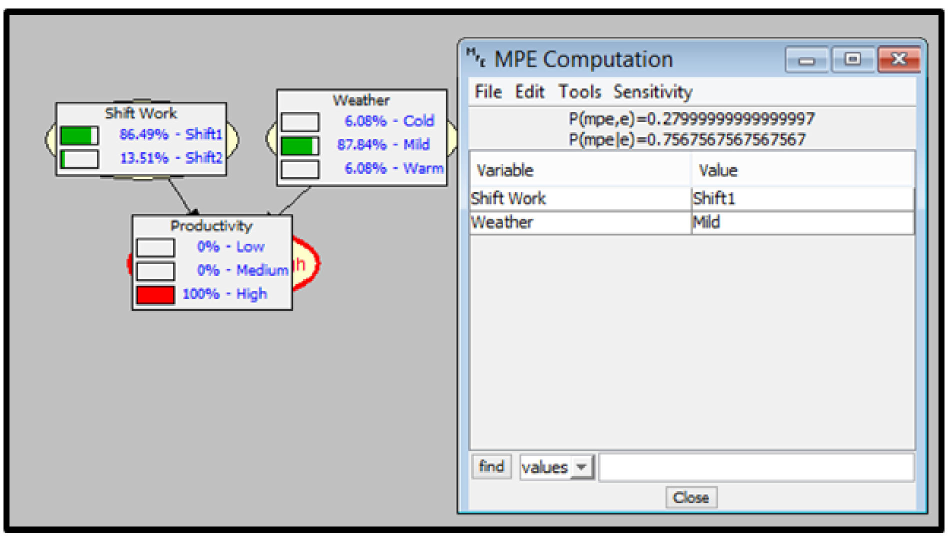


Figure 3.11: MPE of Network for Observing High Productivity

MPE is a special case of a more general class of queries for finding the most probable instantiation of a subset of network variables. These kinds of queries is known as *Maximum a posteriori hypothesis (MAP).* In MAP query if we choose all network variables it becomes an MPE query.

3.5 Types of Bayesian Networks

In this section, different kinds of Bayesian networks are introduced briefly. Each kind of network has specific applications in some area such as classification, diagnosis and prediction. The most cited types of Bayesian networks are: Naïve Bayes, Dynamic Bayesian networks, object oriented Bayesian networks, Gaussian Bayesian networks, and Fuzzy Bayesian networks. All of these networks are subsets of general-type Bayesian networks which have additional restrictions either on their structure or parameters. Adding this kind of restriction can facilitate learning and reasoning with Bayesian networks in specific domains. In this section, the structure of these networks are introduced briefly with some of their applications.

3.5.1 Naïve Bayesian Networks

The structure of Naïve Bayes model (also known as Idiot Bayes model) is shown in figure 3.12 (Koller and Friedman 2009). In this network none of the variables are marginally independent. The naïve Bayes model assumes that instances fall into one of a number of mutually exclusive and exhaustive classes. Thus, we have a class variable C that takes one of the values in set $\{c_1, c_2, \ldots, c_k\}$. The model also includes some number of features $X_1, X_2, \ldots, X_n$ whose values are the children of parent node. Naïve Bayes has been used as an effective classifier because it is easy to construct it and the classification process is very efficient. In naïve Bayes model we have (Koller and Friedman 2009):

$$\{X_i \perp X_{-i} \mid \mathrm{C}\} \text{ for all } i \text{ , where } X_{-i} = \{X_1, X_2, \dots, X_n\} - \{X_i\}\ .$$

Based on independence assumption between features the naïve Bayes model factorizes as follows:

$$P(C, X_1, X_2, \dots, X_n) = P(C) \prod_{i=1}^{n} P(X_i \mid C) \tag{3.4}$$

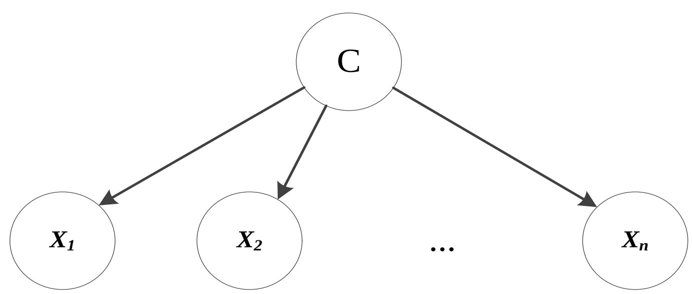


Figure 3.12: Naïve Bayes Model

3.5.2 Dynamic Bayesian Network (DBN)

A Dynamic Bayesian Network is a Bayesian network for modeling time serious data. In a DBN, the state at time t is represented by a set of random variables $X_t = \{X_{1,t}, X_{2,t}, \dots, X_{n,t}\}$. The state t depends on its previous step. In figure 3.13 a simple DBN is shown. The network has two variables: X and Y are network variables at different time slices. In a DBN we have a prior network which represents the prior probabilities for all of the network variables in time slice t=0 and the transition network shows how probabilities for each variables in network in time slices$t = 1,2, \dots, n$ are related to the previous time slice (Koller and Friedman 2009). Therefore, the independence assumption for DBN is as follows:

$$\{X^{(t+1)} \perp X^{(0:(t+1))} | X^{(t)}\} \tag{3.5}$$

This assumption says that variables $X^{(t+1)}$ are independent of variables $X^{(0:(t-1))}$ (variables from time slice t=0 to t=t-1) given variables in time slice $X^{(t)}$. Therefore, the joint probability distribution for this kind of networks is as follow (Koller and Friedman 2009):

$$P\left(X^{(0)}, X^{(1)}, \dots, X^{(T)}\right) = \prod_{t=0}^{T-1} P(X^{(t+1)} \mid X^{(t)}) \tag{3.6}$$

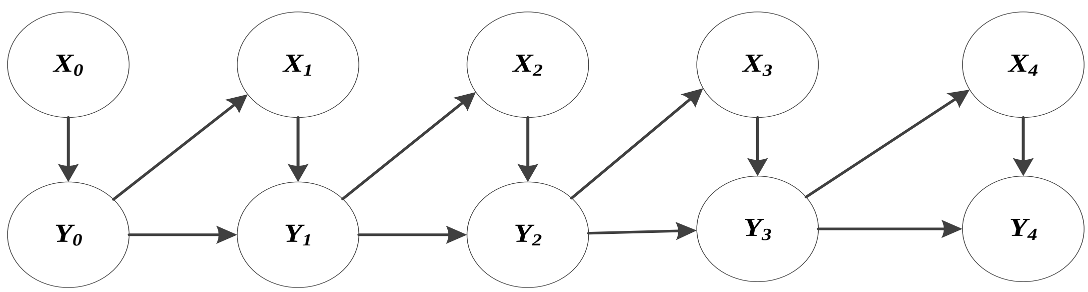


Figure 3.13: A Simple Dynamic Bayesian Network

3.5.3 Gaussian Bayesian Network (GBN)

In the GBN model, the conditional distribution of a node given its parents is given by a Gaussian distribution with expectation that it is linear in the value of its parent nodes, and variance independent of its parent nodes. For example, consider the network in figure 3.12, node X , has a normal distribution or rotationally $X \sim$

$N(\mu_X, \sigma_X^2)$; therefore, the distribution of variable Y is as follows (Koller and Friedman 2009):

$$Y \sim N(\mu_Y + \alpha X, \sigma_Y^2) \tag{3.7}$$

Where μ_Y , α and σ_Y^2 are constants. For node Z this pattern will repeat with constants μ_Z , β and σ_Z^2 .

In general, if node X has parents $\{Y_1, Y_2, \dots, Y_n\}$ then the probability density function of X is as follows:

$$X \sim N(\mu_X + \sum_i \alpha_i y_i, \sigma_X^2) \tag{3.8}$$

Therefore, for obtaining the joint probability distribution of all variables we have to multiply the probability density functions of all variables and the results is a multivariate Gaussian distribution. These kinds of models can only model linear relations between continuous variables and do not allow discrete nodes to have continuous parents (Koller and Friedman 2009).

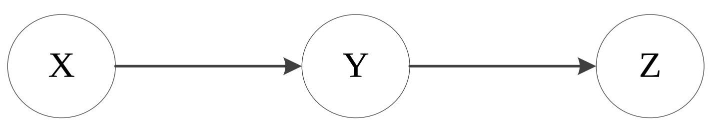


Figure 3.14: Network with Gaussian Variables

3.5.4 Object Oriented Bayesian Network (OOBN)

Koller described the objective of OOBN and why we need OOBN. One of the challenge of Bayesian networks is to create and maintain very large models. OOBN allows complex domains to be described in terms of interrelated objects. OOBN in addition to usual nodes has some instance nodes, which is a node representing an instance of another network. Instance nodes are similar to a subnet that connect with the remaining network through interfaces. The basic element in an OOBN is an object and the most basic object is a standard random variable. OOBN uses concepts of OO programming such as class, inheritance, interface and instantiation for developing the network (2009).

3.5.5 Fuzzy Bayesian Network (FBN)

This kind of network deals with vagueness and uncertainty simultaneously. FBN are BN with fuzzy variables. Fogelberg et al. developed the FBN and belief propagation in FBN (2008). Fuzzy sets are generalizations of set theory that were introduced by Zadeh in 1965 as a mathematical way to represent vagueness. In fuzzy set theory the membership degree can be a value between 0 and 1 although in the classical set theory membership degree can be taken only as 0 or 1. Therefore, in fuzzy set theory we have the notion of "membership function" which represent the degree that a situation belongs to a specific set. For example, in figure 3.14, a trapezoidal fuzzy number $\tilde{A}$ is shown. As shown in the figure, the membership degree of any x value which is shown by $\mu_{\tilde{A}}(x)$ belongs to [0, 1] range.

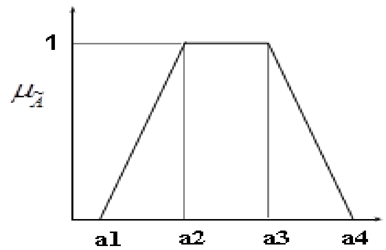


Figure 3.15: Trapezoidal Fuzzy Number

The first thing in FBN that we need to know is Fuzzy probability distribution (FPD). FPD is a probability distribution that has a fuzzy state associated with it. For example if X is a FPD as follows:

$$X = [\{high_{0.6}\ , low_{0.4}\}_{0.7}\ , \{high_{0.4}\ , low_{0.6}\}_{0.3}\ ]$$

This means that the probability distribution $\{high_{0.6}\ , low_{0.4}\}$ has a fuzzy membership value of 0.7 and the probability distribution $\{high_{0.4}\ , low_{0.6}\}$ has a fuzzy membership value of 0.3. Another interpretation of FPD $\{high_{0.6}\ , low_{0.4}\}_{0.7}$ is as follows: $\mu_{high} = 0.7$ will be drawn as a sample from this FPD 60% of the time and $\mu_{low} = 0.7$ will be drawn 40% of the time.

Chapter 4

Extracting Model Structure

This chapter extracts the model structure. After identification of the model's variables, the cause-effect relationships are extracted. The model is divided into several sub-models, then for each sub model based on research that has been done by other scholars and with various modeling techniques related to the model structure, the model structure is extracted. This chapter consists of two sections; in the first section, different "Structure-Related Techniques" are reviewed and in second section, structure of each sub-model, which is used to construct the model comprehensive structure, are extracted.

4.1 Modeling Techniques Related to Structure

There are five modeling techniques that are used to extract the model structure. These modeling techniques are parent divorcing, temporal transformation, undirected dependence link, bidirectional relations, and the representation of structural and functional uncertainty (Kjærulff and Madsen 2013).

4.1.1 Parent Divorcing

This modeling technique is useful for reducing the complexity of a model by adjusting the structure of the graph of a probabilistic network. When there are several cause variables such as $X_1, X_2, \dots, X_n$ that has effect on a single variable Y, as shown in figure 4.1, obtaining CPT of the effect variable becomes complex. In parent divorcing technique, layers of intermediate variables are introduced between effect variable Y and its causes $X_1, X_2, \ldots, X_n$ such that each intermediate variable I captures the impacts of its parents on the child variable (Kjærulff and Madsen 2013). For example, in figure 4.2 by introducing intermediate variable I and combining the effects of X_1 and X_2 onto I and then combining the effects of I and X_3, extracting a model CPT becomes easier. In figure 4.2 X_1, X_2 are divorced from the remaining parents of Y (Kjærulff and Madsen 2013).

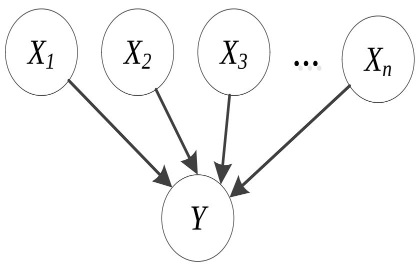


Figure 4.1: Several Cause Variables Affecting Effect Variable

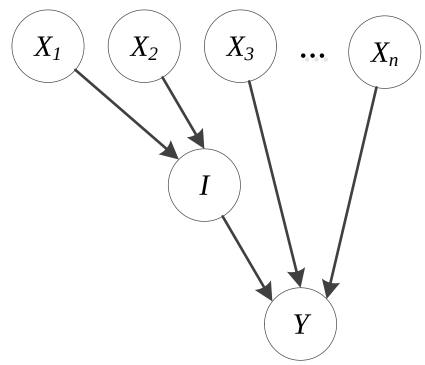


Figure 4.2: Applying Parent Divorcing Technique to X_1 *and* X_2

4.1.2 Temporal Transformation

In this method, instead of combining causes pairwise, the influence of causes on the effect variable is taken into account one cause at a time in their causal or temporal order (Kjærulff and Madsen 2013). In figure 4.3, a network with four cause variables X_1, X_2, X_3, X_4 and one effect variable Y is shown. By using temporal transformation technique, the network shown in figure 4.4 is obtained. Note that in temporal transformation techniques, variable Y_1 and Y_2 have the same state space as Y. This method can be used as an alternative to parent divorcing approach (Kjærulff and Madsen 2013).

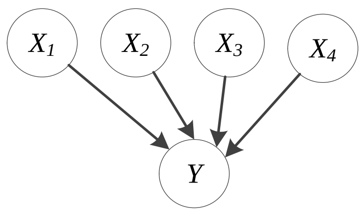


Figure 4.3: Four Variables Affecting Effect Variable Y

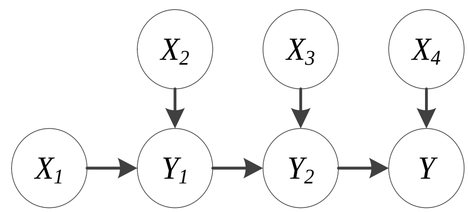


Figure 4.4: Applying Temporal Transformation Technique to X_1 ... X_4 (from Kjærulff & Madsen, 2013)

4.1.3 Structural Uncertainty

This approach is useful when it is difficult to specify the dependence and independence in a DAG. If two variables X_1 and X_2 affect effect variable Y, but not simultaneously, then there exist structural uncertainty in the model. The proposed approach for solving structural uncertainty is to add a selector variable S to the model and an intermediate variable with the same state space as X_1 and X_2. Therefore, selector variable acts like OR gate in the model and select either X_1 or X_2. For example, in figure 4.5 we know that variables X_1 and X_2 affect Y but not simultaneously. According to the proposed approach, we can build the network shown in figure 4.6 to remove structural uncertainty (Kjærulff and Madsen 2013).

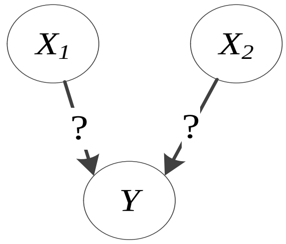


Figure 4.5: Structural Uncertainty in Model

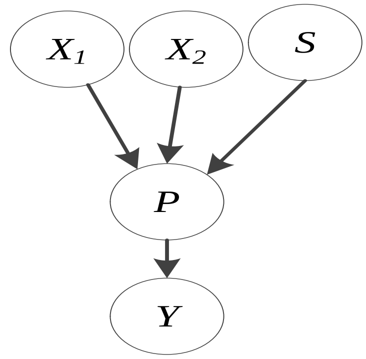


Figure 4.6: Removing Structural Uncertainty from Model

4.1.4 Undirected Dependence Relation

During building a BBN, it is possible that some variables have undirected relationship with each other. According to definition of DAG, this undirected relation between variables violates acyclic property of BBN. The proposed approach for solving this situation is to introduce an auxiliary variable known as the constraint variable as the child of variables whose have undirected relation (Kjærulff and Madsen 2013). For example, in figure 4.7 variables X_1 and X_2 have undirected relation and in figure 4.8 by introducing constraint variable C , the graph has been changed to DAG.

Figure 4.7: Undirected Relation between Two Variables

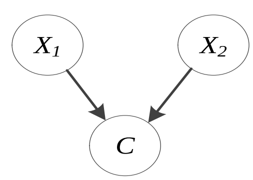


Figure 4.8: Solving Undirected Relation Problem by Introducing Common Child

4.1.5 Bidirectional Relations

Bidirectional relation happens when there exist two variable that direction of causal relation among them is not certain. In figure 4.9 this kind of relation is shown. The proposed approach for solving this problem is by introducing a new variable that is parents of both X_1 and X_2. In figure 4.10 this is shown (Kjærulff and Madsen 2013).

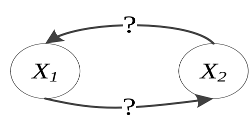


Figure 4.9: Bidirectional Relation between Two Variables

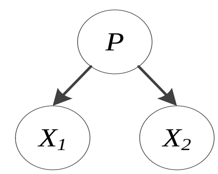


Figure 4.10: Solving Bidirectional Relation Problem by Introducing Common Parent

4.2 Extracting Sub Models' Structure

In this section, causal structure for different factors that affect construction labor productivity has been extracted from other researchers' papers, publications, and reports. This section, as one of the most labor-intensive part of this dissertation, requires to go all over publications that exist related to a certain factor that affect construction labor productivity, and then extract cause-effect relationship between that specific factor, other factors, and construction labor productivity. In some situations, other scholars have said directly or have obtained the causal map between variables. There are several situations that we need to inference cause-effect relationships between factors from other scholars' statements. This kind of methodology for obtaining causal map between variables causes an increase in complexity of the cause-effect map which by using the methodologies that explained in previous section we can solve model's complexity and ambiguity. Factors that have been investigated in this section are those that have the most number of publications related to them. List of factors that we have extracted their cause-effect structure are as follows:

- Change
- Overtime
- Overstaffing
- Shift Work
- Stacking of Trades
- Weather
- Absenteeism and Turnover
- Workforce Management
- Fatigue
- Morale and Attitude
- Motivation
- Rework

4.2.1 Changes

Ibbs and Allen defined changes as "addition, deletions, or other revisions within the general scope of a contract that cause an adjustment to the contract price or contract time" (1995). Lee defined changes as "any action, incidence, or condition that makes differences to an original plan or what the original plan is reasonably based on" (2007). Hanna et al. defined changes as "any event that results in a modification of the original scope, execution time, or cost of work, is inevitable on most construction projects due to the uniqueness of each project and the limited resources of time and money available for planning" (Hanna, Camlic, et al. 2002). Changes usually cause numerous disruption in the original sequence of work such as rework, increased waiting time, and many other things that may reduce labor productivity. Also, changes in most cases generate loss of momentum, reassignment of manpower to other tasks, learning curve effects, and ripple effects on other activities which cause loss of productivity (Leonard 1988, Borcherding and Alarcón 1991). Our goal here is to extract the causal relationship between changes, factors that affect changes, and variables that changes affect productivity through them. Ovararin summarized the cause-effect relationship between changes and productivity factors (2001) . In the same way, Hanna and Russell identified factors affecting changes with their severity degree (2001). In figure 4.11 is the cause-effect diagram of changes according to these research is shown.

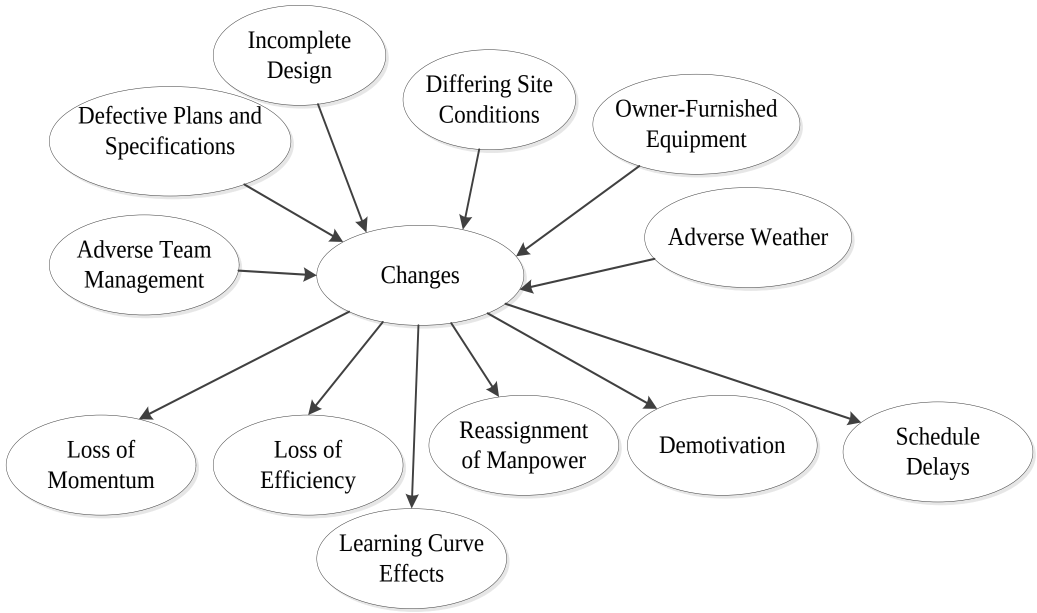


Figure 4.11: Cause –Effect Diagram of Factors Associated with Changes

Thomas and Napolitan investigated effects of changes and change orders on construction labor productivity and efficiency. They gathered a total of 522 workdays of data from three industrial projects constructed in the 1989-1992 time frame. They applied various analysis techniques such as data sorts and averages, analysis of variance tests, and multiple regression technique to the data sets. Finally, they concluded that the average effects of all changes was 30% loss of efficiency (1995). The most common effects of changes that cause loss of efficiency according to this study are lack of materials, lack of information, and performing works out-of-sequence (1995). These disruptions cause a decline in productivity in the range of 25-50%. According to this study we can extract the causal diagram of changes' effects which is shown in figure 4.12.

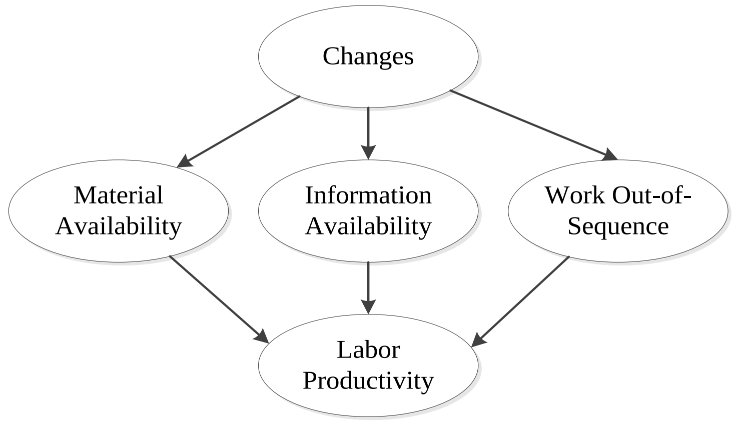


Figure 4.12: Changes' Causal Diagram Extracted from Thomas and Napolitan Study

4.2.2 Schedule Acceleration

According to Borcherding and Alarcon, schedule acceleration occurs when it is required to perform a work in a shorter time than what is included in contract or to accomplish a greater amount of work within the original schedule (1991). Schwartzkopf described the causes of schedule acceleration as follows: owner's request, delay in design, additional work added to the original work through changes, and contractor's actions (1995). Schedule acceleration can be accomplished through different methods such as overtime, Overstaffing, and shift work. In general, schedule acceleration can cause loss of efficiency in variety of ways such as lack of materials, tools, equipment, and inspection (Borcherding & Alarcón, 1991). In this section, the most popular types of schedule acceleration which are overtime, Overstaffing and shift work are investigated and causal relationship between them, other factors, and labor productivity is extracted from other scholars' research.

4.2.2.1 Overtime

Overtime is defined as the application of labor at a rate of more than eight-hours a day, five-days a week (Hanna and Taylor 2004). Thomas defined overtime as "overtime schedule that lasts longer than several weeks" (1992). In the same way, Thomas defined "Extended Overtime" as "a work schedule that extends over more than 40 hours of work per week. The schedule is planned in advance and lasts for at least three consecutive weeks, and typically longer" (1992) Numerous researchers have investigated effects of overtime (extended overtime) on construction labor productivity and they have found that overtime not only is costly due to increased payment rate, but it also decreases construction labor productivity. Lee stated that physical fatigue is the main reason in productivity loss during overtime operation (2007). Also, he stated that fatigue de-motivates workers and it leads to increased error and poorer quality of work, which causes rework later (2007). Kossoris stated that working overtime causes an increase in absenteeism rate because workers need time off to take care of personal things (1944). Futhermore, overtime causes loss of productivity through inability to provide materials, tools, equipment, and information in a timely manner which causes workers to work without accurate information and lack of tools (Thomas and Raynar 1997). Lee, by evaluating all previous literature about overtime, extract the causal relationship among overtime and related factors and showed how overtime can cause loss of productivity. This network has 14 variables and it can be used as a complete model that shows how overtime affect labor productivity (2007). The proposed network is shown in figure 4.13.

Kossoris did a research for Bureau of labor statistics (BLS) about the effects of overtime on labor productivity. Based on this research, which has been done during World War II, Kossoris investigated 78 industrial plants and he concluded that fatigue is the major limiting factor under working overtime schedule. He noted that fatigue causes an increase in absenteeism and work injuries which causes a decline in labor productivity (1944). Therefore, we can extract the causal diagram that shown in figure 4. 14 according to Kossoris findings.

Based on MCAA, overtime decreases work output and efficiency through fatigue and poor mental attitude. MCAA defined three conditions known as minor, average and severe and provided some percentage about the effect of each situation on labor efficiency (2014). According to MCAA we can derive a causal network between overtime, fatigue, attitude and productivity. This causal network is shown in figure 4.15.

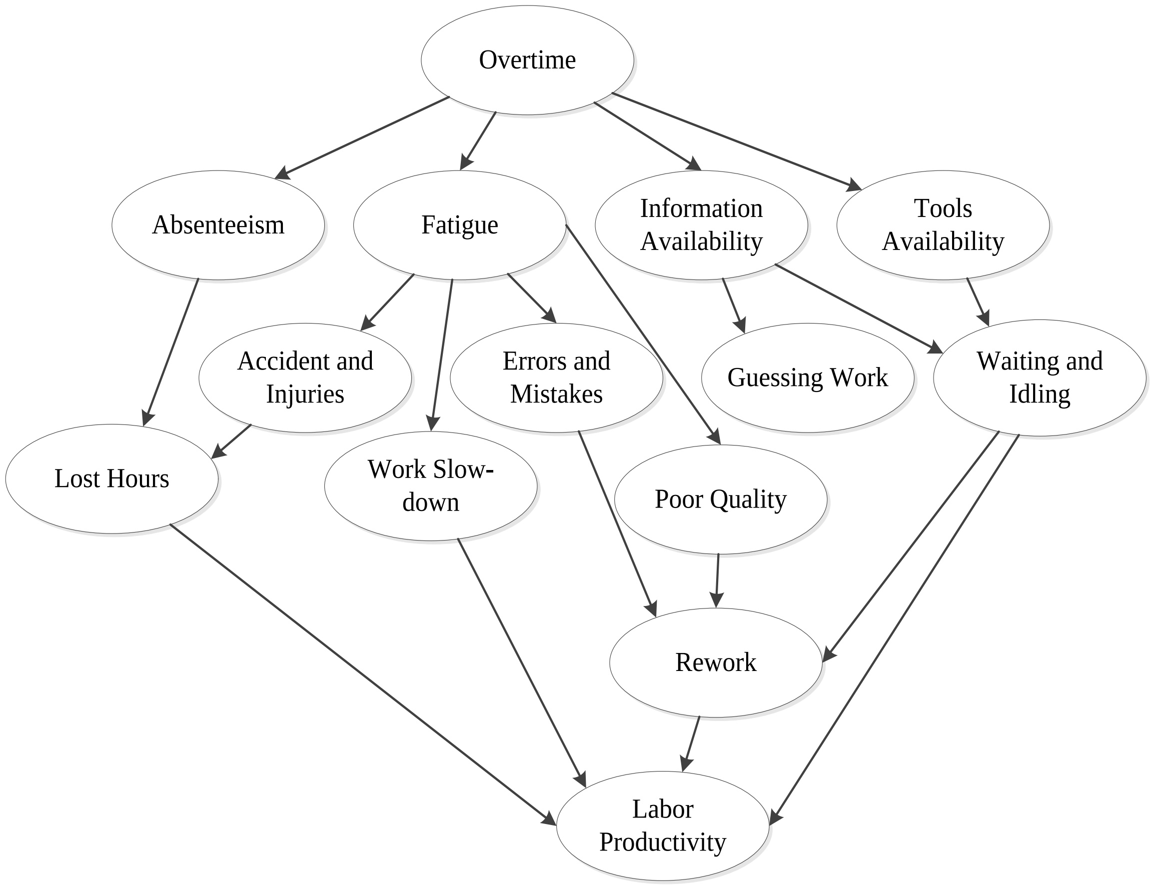


Figure 4.13: Causal Diagram between Overtime and Productivity (Source: (Lee 2007))

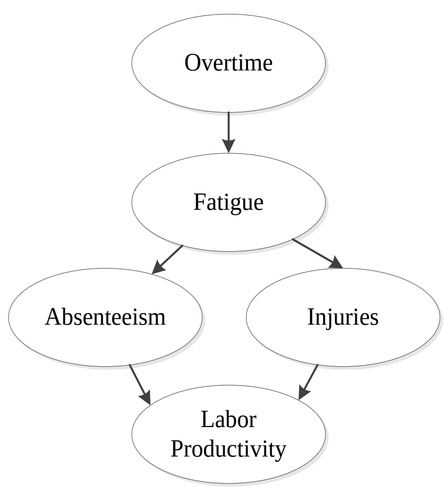


Figure 4.14: Causal Diagram between Overtime and Productivity According to Kossoris Research

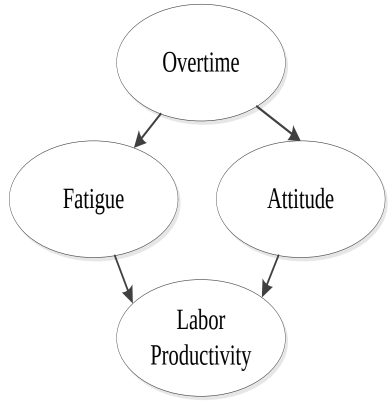


Figure 4. 15: Causal Diagram between Overtime and Productivity According to MCAA (2014)

4.2.2.2 Overstaffing (Overmanning)

Lee defined overstaffing or overmanning as “adding more workers to a jobsite than is optimum or typical for that type of work” (2007). Hanna et.al defined Overstaffing as an “increase of the peak number of workers of the same trade over the actual average manpower used throughout the project” (Hanna, Chang and Lackney, et al. 2007). According to the US Army Corps of Engineers, optimum crew size is “the minimum number of workers that is required to perform a job within the allocated time frame” (Corps 1979). Also, they stated that “As more workers are added to the optimum crew, each worker will increase crew productivity less than the previously added worker. Carried to the extreme, adding more workers will contribute nothing to overall crew productivity” (Corps 1979).

Hanna et.al stated that there exist two ways to increase the total number of workers for a task on a jobsite. First, by adding workers to an existing typical or optimum crew size which results in a bigger crew size. The second approach is through increasing the number of crews. Increasing the number of workers within a crew is an easier way although the proportion of journeymen to workers becomes less than optimal (Hanna, Chang and Lackney, et al. 2007). On the other hand, Overstaffing through adding a new crew is possible when the task is big enough to accommodate multiple crews. Hanna et al. stated Overstaffing is a popular method for schedule acceleration and it doesn't have numerous problems associated with overtime and shift work such as coordination problems realized within shift work and physical fatigue related with overtime and so on (Hanna, Chang and Lackney, et al. 2007).

Hanna et.al stated that although Overstaffing has some advantage over overtime and shift work, there exist some problems with Overstaffing. Overstaffing causes delusion of supervision and material and equipment shortage due to the increased number of workers which causes decline in labor productivity (Hanna, Chang and Lackney, et al. 2007). Base on this statement, we can extract the causal network related to Overstaffing and productivity. In figure 4.16 the causal diagram between Overstaffing and productivity based on this research is shown.

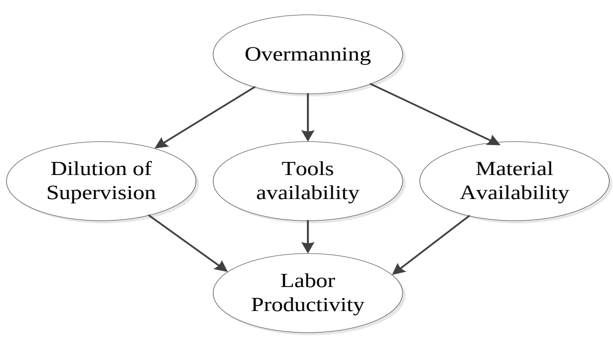


Figure 4.16: Causal Diagram between Overstaffing and Productivity (Hanna, Chang and Lackney, et al. 2007)

Gunduz investigated the negative impacts of Overstaffing on electrical and mechanical projects through quantitative approach. He stated that although the most common response by contractors to an schedule acceleration is the implementation of Overstaffing due to several reasons such as higher rate of progress, it introduces additional problems including site congestion, stacking of trades, dilution of supervision, higher accident rate, and supply chain inefficiencies due to consuming materials and tools at a faster rate (Gunduz 2004). Based on this statement, we can extract the causal network shown in figure 4.17 between Overstaffing and labor productivity.

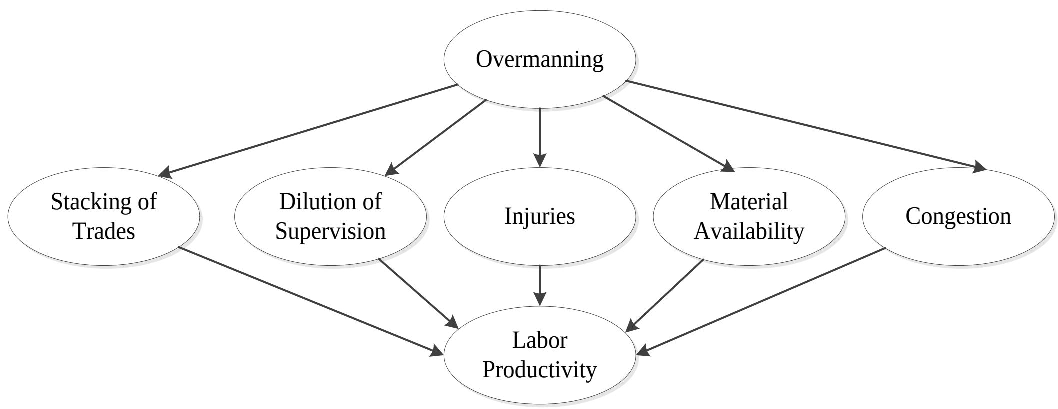


Figure 4.17: Causal Network between Overstaffing and Productivity (Gunduz 2004)

Lee stated that “congestion and dilution of supervision are the reasons most commonly blamed for productivity losses when a project is overmanned” (2007). Also, he proposed a causal network about how Overstaffing affects labor productivity. The proposed causal diagram by Lee is shown in figure 4.18. For the justification of his proposed causal network, he stated that:

Congestion does not occur automatically whenever there is Overstaffing. Rather, it is a function of the number of workers in a limited work space. The problem related to 'coordination, supervision, and management' indicated the importance of management's role in reducing the negative impact of Overstaffing. As the number of workers increase, supervisors and supporting /coordinating activities should increase proportionally. Decrease in learning curve effects should be expected since more workers performing the same amount of work means reduced repetitious per worker, thus limiting the learning curve effect.

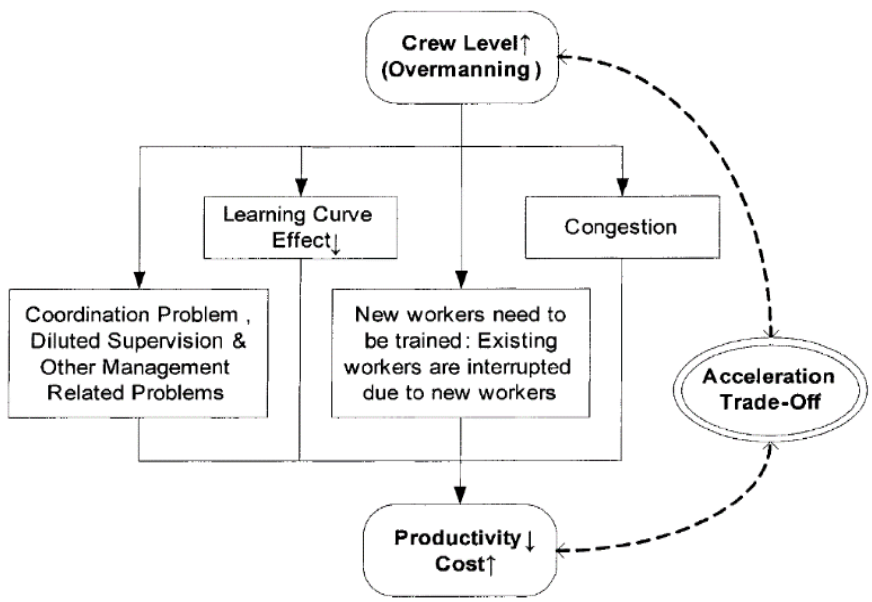


Figure 4.18: Effects of Overstaffing on Productivity (Source: (Lee 2007))

By adding causes of Overstaffing, which actually are causes of schedule acceleration, we can create a complete causal network for Overstaffing. According to Hanna et.al causes of Overstaffing are late start work, delays from weather or prior work crew, changes or added works necessary to complete the project, and poor management (Hanna, Chang and Lackney, et al. 2007). Therefore, we can extract the causal network shown in figure 4.19 between Overstaffing and factors that affect Overstaffing.

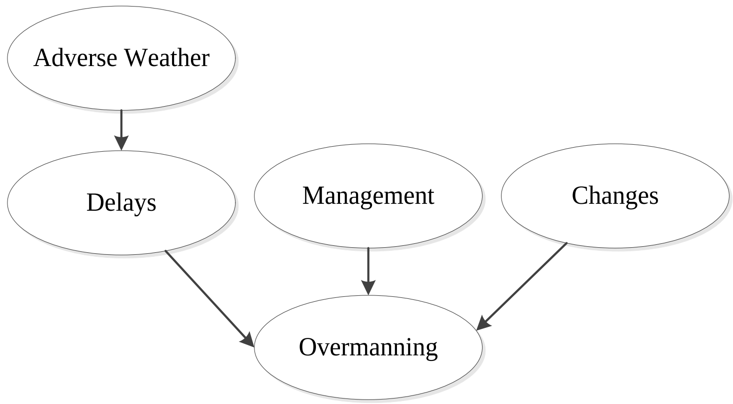


Figure 4.19: Causes of Overstaffing

4.2.2.3 Shift Work

Hanna and Sullivan defined shift work as “The hours worked by a second group of craftsmen whose work on a project is performed after the first, or primary, workforce of the same trade has retired for the day” (2004). They also stated that reasons that managers sometimes prefer to use shift work instead of overtime and Overstaffing is that “shift work can produce a higher rate of progress without the immediate fatigue problems of overtime and the congestion problems of Overstaffing. In addition, premium payment to a second shift is substantially lower than that of overtime.” (2004). They believed that shift work for short period of time can increase labor productivity, but if contractors use shift work for long time, it can decrease labor productivity up to 15% (2004) .

MCAA (2011) has identified problems and factors that are related to shift work which cause loss in labor productivity. The factors are as follows:

1. Additional needs in comparison with day shifts. For example, additional lighting is needed during the second or the third shift. Also, additional heating may be required during the second shift.
2. Inefficiency in the transition from the first shift to the second shift. In comparison with overtime, it takes time for the second shift to go through the learning curve.
3. Tools and equipment may not be on appropriate places when the second shift starts working.
4. Night shift usually result in work force fatigue more than daytime shift.
5. Supervisory problems: shift work causes dilution in supervision because the company's supervisors have to spread over several shifts.
6. Inefficiency due to shorter work hours: usually the second shift is shorter than the first shift, but the amount of time workers spend in starting, stopping, eating and drinking is constant which causes greater portion of work lost in comparison with the daytime shift. Also, being idle in this shift occurs more than during the first shift.
7. Psychological aspects of worker: when only one trade is working, they may not be motivated enough to finish the task. Also, in the second shift, there is an increased consumption of alcohol before coming to work by shift workers.
8. Absenteeism is usually higher in the second shift in comparison with the first shift.

9. Morale and attitudes in the second shift are poorer than the first shift.
10. During bodily adjustment period, which usually takes between 1-2 months, a considerable amount of loss of productivity occurs.

Based on this MCAA bulletin, then we can extract a causal network for effects of shift work on construction labor productivity. This causal network is shown in figure 4.20.

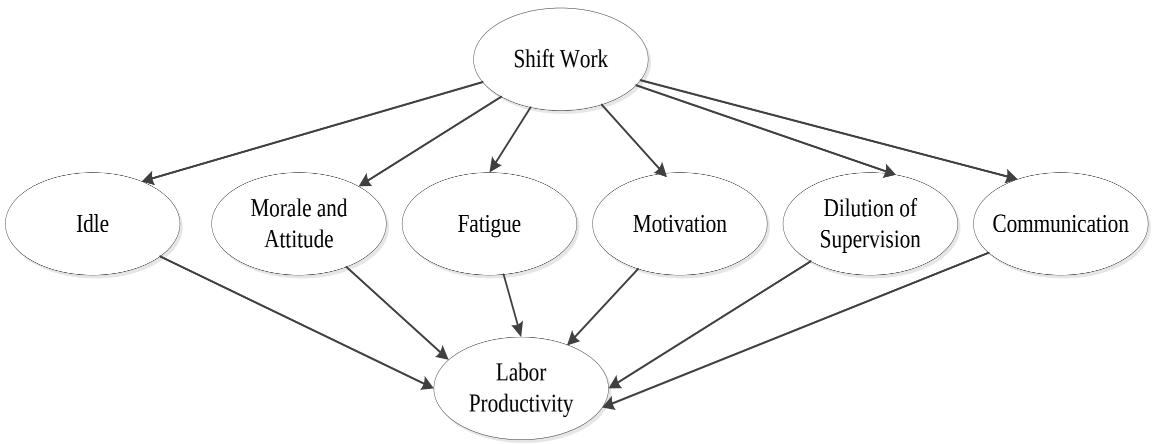


Figure 4.20: Causal Network of Effects of Shift Work on Productivity According to MCAA (2011)

Hanna et al. after investigating literature about how shift work causes loss of labor productivity, proposed a causal network that is shown in figure 4.21. According to this model, numerous factors stimulate contractors to use shift work. These factors are mandated acceleration, delay, changes, unavailability of labor and equipment, and project conditions. Also, shift work has effects on factors like accident rate or safety, coordination and communication which can be causes of loss of labor productivity (Hanna, Chang and Sullivan, et al. 2008). They also provide a productivity multiplier for shift work which is very useful for extracting model's CPT. According to this table, when shift work is less than 5%, productivity can increase up to 6%. For the range of 6-18%, productivity loss is between 0-10%. When shift work is between 20-50%, the loss of productivity is between 10-18% (Hanna, Chang and Sullivan, et al. 2008). They also suggest numerous ways such as “overlapping management,” “selection of work assigned to a second shift,” “being selective on the work assigned to a second shift,” “avoid congestion,” “sufficient amount of artificial lighting,” and “material requirements” to reduce the effects of shift work on labor productivity. However, Lee stated that shift work can have an increase in labor productivity for areas with high temperatures (2007).

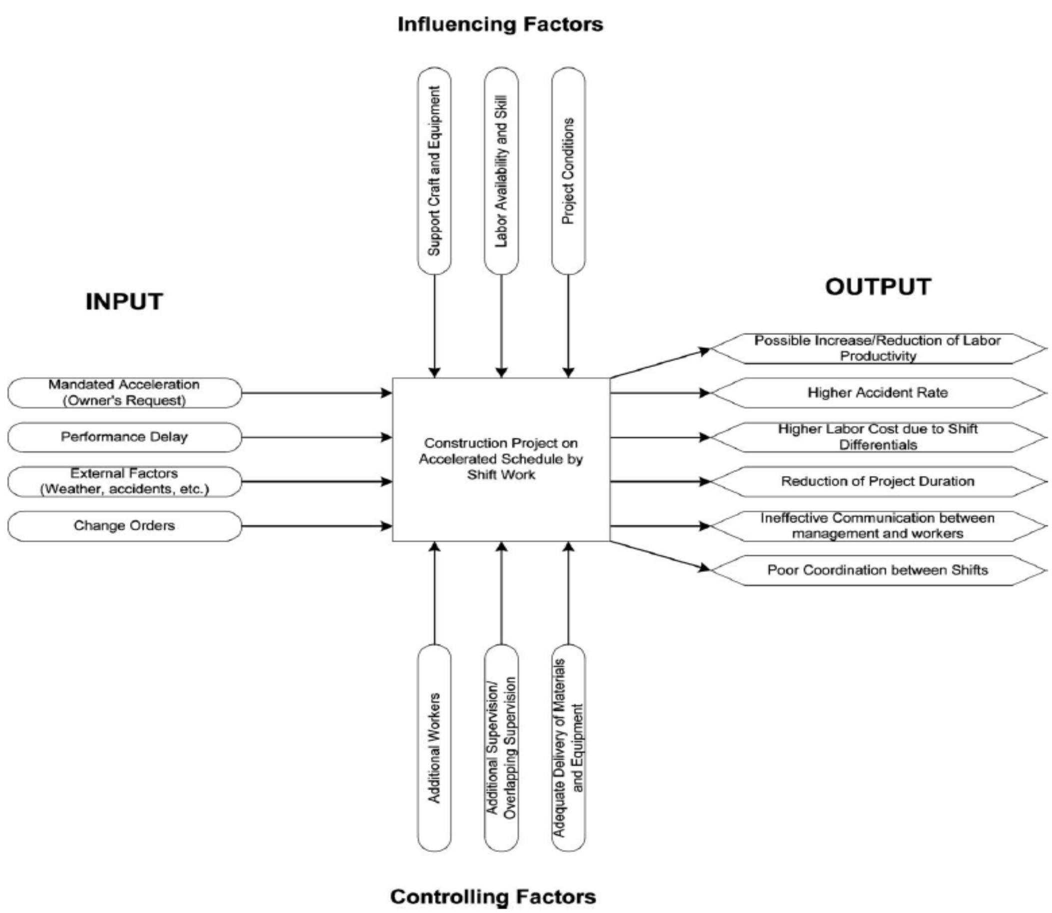


Figure 4. 21: Schematic Structure of Shift Work (Hanna, Chang and Sullivan, et al. 2008)

4.2.3 Stacking of Trades

Based on MCAA manual about factors affecting labor productivity, stacking of trades is “operations that take place within physically limited space with other contractors. Results in congestion of personnel, inability to locate tools conveniently, increased loss of tools, additional safety hazards and increased visitors. Optimum crew size cannot be utilized” (2011). This manual shows that labor productivity decreases by 10, 20, or 30 % when stacking of trades is minor, average, or severe, respectively. Based on MCAA manual, we can extract the causal network that is shown in figure 4.22 for stacking of trades.

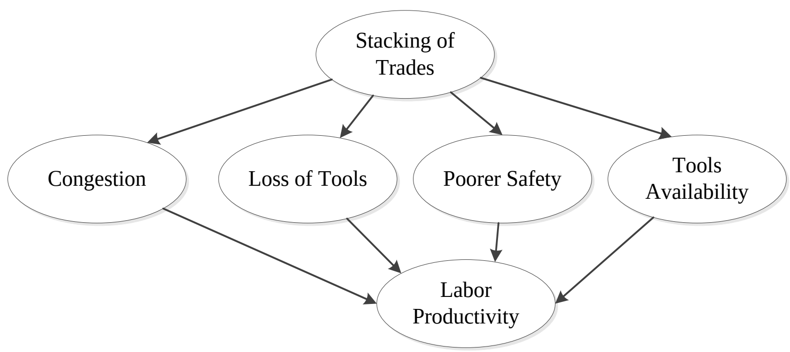


Figure 4.22: The Causal Network of Stacking of Trades Based on MCAA (2011)

Hanna et al. investigated the effects of stacking of trades in electrical works. In that report, they mentioned that “stacking of trades relates a number of different trades (pipefitters, electricians, etc) within a measured work area to labor productivity” (Hanna, Russell and Emerson 2002). Stacking of trades differs from Overstaffing. As mentioned in previous section, Overstaffing is related to changes in size of a specific crew, while stacking of trades is an increase in the number of trades in a specific work area. Another definition that is useful during investigation of stacking of trades is “site density.” Site density is defined as work area divided by the number of people in the measured work area (Hanna, Russell and Emerson 2002). Work area in this definition based on the authors description is “the total amount of project area minus the area for storage areas, crane areas and area taken by owner’s equipment or facilities” (Hanna, Russell and Emerson 2002). According to the definition of stacking of trades, the components of stacking of trades are the number of trades within a work area and the size of the work area. Therefore, for evaluating the effects of stacking of trades on labor productivity, researchers mostly concentrated on these component and obtained numerous results that relates the labor productivity to site density and stacking of trades. Research about the causal relationship between stacking of trades, other factors, and labor productivity is scarce. One of the most prominent research is this area is “Stacking of Trades for Electrical Contractors” by Hanna et al (2002). If we assume that the findings of these research is valid for other areas of construction industry, such as commercial, mechanical and so on, then we can extract some causal relationship between stacking of trades, other factors, and labor productivity. The results of this research are divided into two parts. The first part describes the causes of stacking of trades and the second part describes what consequences stacking of trades has on other factors, and how it affects labor productivity.

For investigating causes of stacking of trades, the authors developed a qualitative survey among members of the National Electrical Contractors Association (NECA) and asked them to rank seven possible causes of stacking of trades on a construction site. These seven indicators are as follows (Hanna, Russell and Emerson 2002):

- Rework
- scope changes
- change orders
- project acceleration
- complexity of work
- poor planning (Management)
- delay in preceding activity (Delay)

These factors have a severity degrees effect on stacking of trades. The severity degrees of different factors based on this research is shown in table 4.1.

Table 4.1: Average Scores of Causes of Stacking of Trades (source: Hanna et al. (2002))

Causes of Stacking of Trades	**Average Score (1=Very important, 5=Not Significant)**
Project acceleration	1.13
Project delay	1.52
Change orders	1.84
Poor Planning	1.87
Change in scope of work	2.03
Complexity of work	1.87
Rework	2.97

In a similar way, the authors did a survey about the effects of stacking of trades which causes contractors to experience loss in labor productivity. Based on this report, respondents identified several factors which are consequence of stacking of trades and which cause a decline in construction labor productivity. These factors are as follows (Hanna, Russell and Emerson 2002):

- Performing work in confined space (Working in restricted area)
- Additional resources are needed, such as tools, equipment, and manpower
- Performing work out-of-sequence or disruption in work sequence
- An increases in the amount of overtime to finish the same amount of work
- An increase in the supervision or dilution of supervision
- An increase in idle and waiting time
- An increase in material handling
- An increase in the amount of rework

We can extract the causal network shown in figure 4.23 for stacking of trades according to these research results.

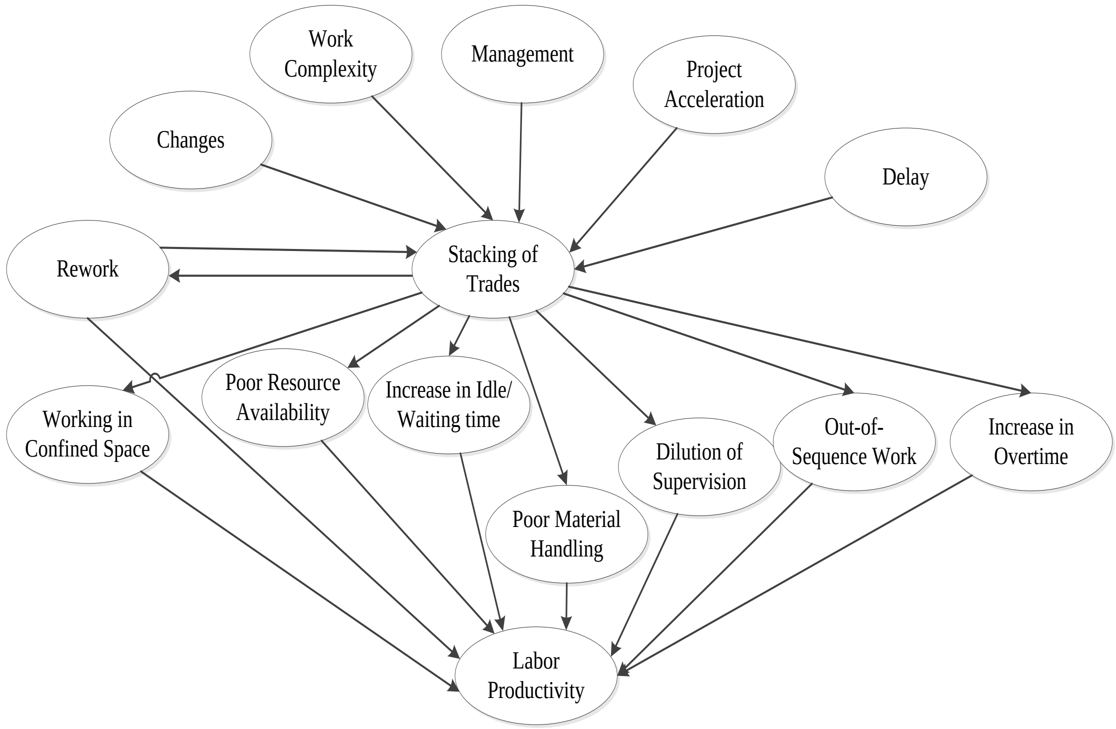


Figure 4.23: Causal Network of Stacking of Trades According to Hanna et al. (2002)

Ovararin investigated the effects of congestion on labor productivity in masonry construction. Congestion refers to situations that causes physically limited space due to stacking of trades or Overstaffing (2001). The US Army of Corps of Engineers stated that congestion in one of the problems that is a consequence of project acceleration and it causes many problems such as change in optimum crew size, difficulty in material handling, more hazards, which ultimately causes a decrease in labor productivity (Corps 1979). If we combine these statement with each other, we can extract a causal network for factors such as project acceleration, Overstaffing, stacking of trades, safety, material management and handling, and labor productivity. The causal network for these statements is shown in figure 4.24.

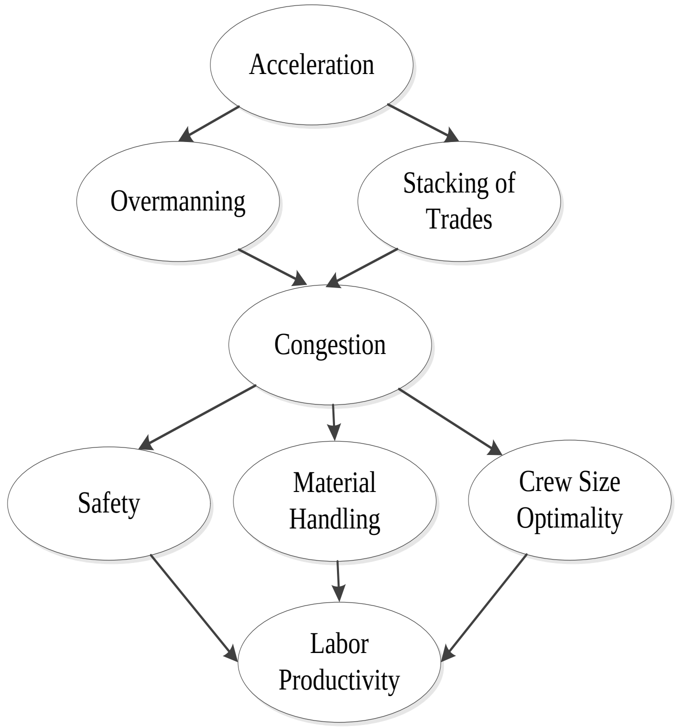


Figure 4.24: The Causal Network Extracted from Corps (1979) and Ovararin (2001) for Stacking of Trades

4.2.4 Weather (Adverse Weather Conditions)

It is the responsibility of contractors to work in unfavorable weather. Adverse weather, which is categorized as one of the external factors that affects labor productivity, causes loss of efficiency. Weather has direct and indirect effects on labor productivity. Direct effects means it affects workers' physical conditions and mobility, while indirect influences on labor productivity is through numerous factors such as lack of material, absenteeism , fatigue, and so on (Thomas and Ellis 2009). Most researchers evaluate the direct effect of adverse weather on labor productivity;

however, in this research we need both direct and indirect effects of adverse weather on construction labor productivity. In this section, first the results of different research about direct effect(s) of adverse weather on labor productivity is summarized, then we investigate the indirect effects of weather on labor productivity. After that, by combing direct and indirect effects, extract the causal network between weather, other factors, and labor productivity.

Lee explained reasons of productivity loss due to cold and hot weather. Cold weather needs protections which takes time to put on and off. Also, cumbersome protective cloths cause less mobility. Cold weather also causes some threats to human health such as hypothermia, depression, heart attacks, colds, and flu which cause loss of dexterity (2007). Hot weather, as an instance of adverse weather, needs frequent cool-off and it usually causes exhaustion, difficulty in breathing, dizziness, and sunstroke (Lee 2007). There exist several quantitative studies that have evaluated the direct impact of weather on labor productivity such as El-Rayes and Moselhi (2001), Thomas and Yiakoumis (1987) (1987), Clapp (1966), NECA (2004)(1974; 2004), and many other scholars.

Clapp determined the effects of adverse weather conditions on labor productivity in five housing projects in the United Kingdom (1966). He summarized the effects of adverse weather conditions on labor productivity. He stated that adverse weather causes loss of labor productivity through the temporarily prevention of craftsmen from working, reduction of working hours, and repeated work resulting from damages. This is one of the few research that explains the indirect effects of adverse weather on labor productivity. Lee stated that the adverse weather can cause loss of efficiency through loss of momentum or learning curve (2007). If we combine these statements, we can extract the causal relationship between adverse weather conditions, other factors, and labor productivity. This causal network is shown in figure 4.25.

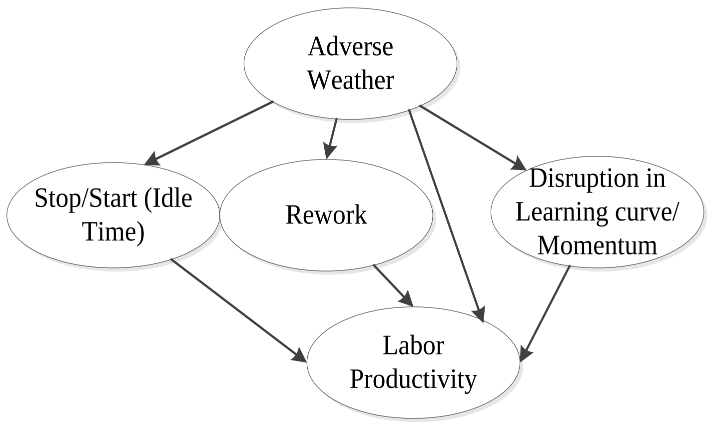


Figure 4.25: The Causal Network Extracted from Clapp (1966) and Lee (2007)

Wittrock investigated the effects of cold weather on labor productivity in road building projects in Sweden (1967). He finally concluded that optimal productivity is achievable at +5oC in Sweden. The construction projects that he investigated experienced 26 percent loss of productivity at temperature of (+30oC) and 10 percent loss of productivity at a temperature of (-10oC) (Wittrock 1967). He also stated that the amount of loss depends on severity of bad weather in the winter and the types of operation that is going to be done (Indoor or outdoor operation) (Wittrock 1967). Grimm and Wagner investigated the effect of weather and humidity on labor productivity. In a 9 month period, temperature and humidity were measured in a masonry project and they found that whenever temperature and humidity deviated from 75oF and 60%, loss of efficiency occurs (Grimm and Wagner 1974). Thomas and Ellis summarize the effects of adverse weather on labor productivity for the purpose of mitigating the effects of adverse weather on labor productivity. According to this study, the adverse weather can cause loss of efficiency not only directly, but also through various indirect ways. The most obvious ways that weather can affects productivity indirectly is through material delivery and availability, fatigue, rework, absenteeism and site access (2009). Therefore, we can extract the causal relationships between adverse weather, other factors, and labor productivity according to Thomas and Ellis which is shown in figure 4.26.

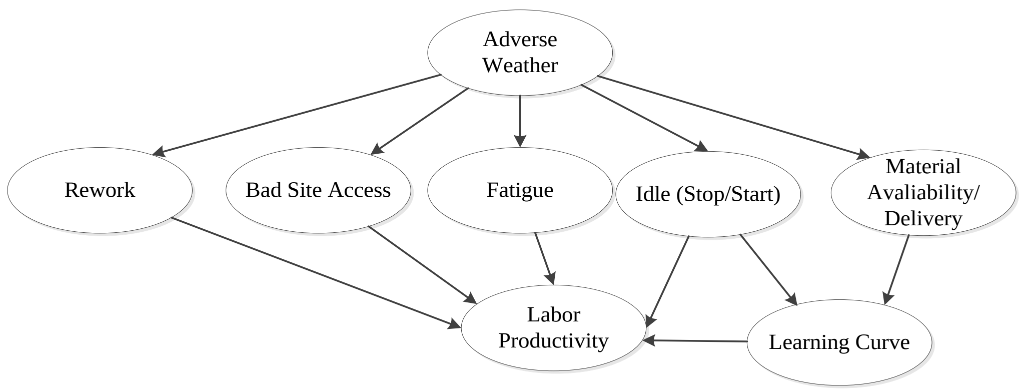


Figure 4.26: The Causal Network Extracted from Thomas and Ellis (2009) for Adverse Weather

Ovararin categorized weather as one of the external factors that affect labor productivity. In this research, the author proposes a general cause and effect relationship between external factors and labor productivity (2001). External factors in this research consists of weather, economy, and project location. In figure 4.27 the causal network extracted from this research is shown.

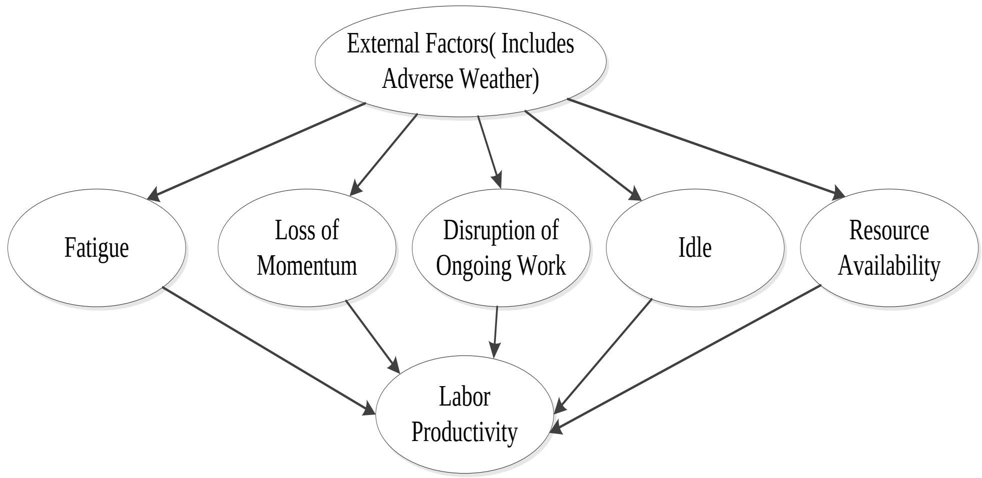


Figure 4.27: The Causal Network Extracted from Ovararin (2001) for External Factors Including Weather

4.2.5 Absenteeism and Turnover

The Merriam-Webster dictionary defines absenteeism as “a tendency to be away from work or school without a good reason or the practice or habit of being absent from work or school,” and turnover is defined as “the rate at which people leave a place, company, etc., and are replaced by others” (Merriam-Webster 2015). Hinze et al. investigated the effects of absenteeism in construction industry and they found that team cohesiveness and management have direct effects on absenteeism. They stated that “absenteeism is lower in work units that have strong team spirit or when the group is cohesive,” and “when management stresses its displeasure of worker absenteeism.” They also stated that distance that workers must travel to a job site also has some negative effects on absenteeism. They believed that management has a central role in controlling absenteeism and can reduce absenteeism by monitoring workforce and working conditions. There are other factors that the authors specified that have some effects on absenteeism, like age and crew cohesion, but they stated that these factors are controllable by managers (Hinze, Ugwa and Hubbard 1985). The causal network that is shown in figure 4.28 is extracted based on this research. Note that in this research we do not investigate involuntary absenteeism, in which workers have little control over being absent.

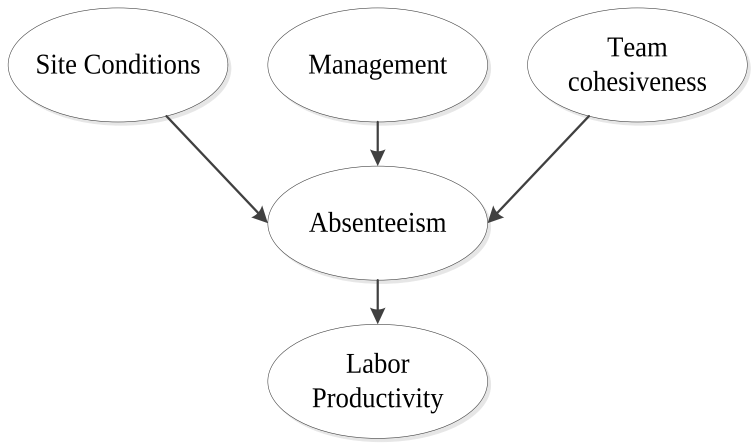


Figure 4.28: The Causal Network of Absenteeism Based on Hinze et al. (1985)

Kim and Philips investigated the determinants of quits and dismissals on industrial construction projects and they found that labor-market conditions, remuneration, personal and worksite characteristics all affected the probability of a worker to quit or be fired before a reduction in force (2012). In this research, labor-market conditions consist of monthly unemployment rate and monthly percentage change in construction employment, which we can categorize them as an external factor. Remuneration consist of straight-time weekly earnings, overtime weekly earnings, and travel-based weekly subsistence incentive. They categorized worksite characteristics as crew size and Overstaffing. The results show that crew size has no effect on the probability of being fired, but as crew sizes shrink, workers anticipate reduction in force (RIF) and some quitting happens. They also found that overmanned crews experienced more quitting and absenteeism. Overall, we can construct a causal network based on this research which is shown in figure 4.29. They provide a useful table about the probability of quitting or firing in different situations which we will use from these results in chapter 5 (Kim and Philips 2012). The mentioned table is shown in figure 4.30.

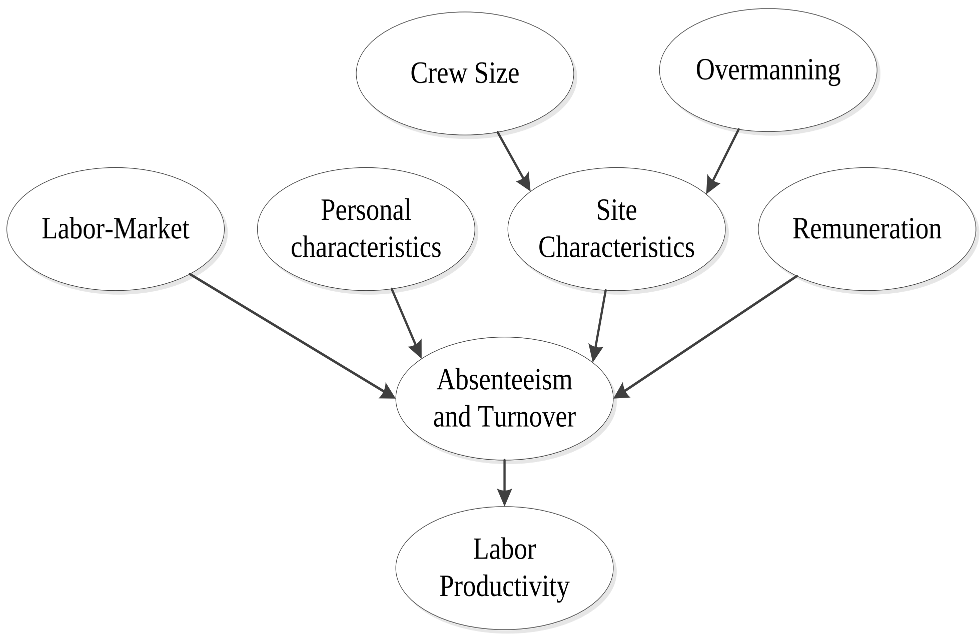


Figure 4.29: The Causal Network of Absenteeism and Turnover Based on Kim and Philips (2012)

Variables	Quitting or fired before layoff	Fired before layoff	Quitting or fired before layoff
Labor-market factors:			
Rise in unemployment rate	*Less likely*	*Less likely*	*Less likely*
Growth in construction employment	*More likely*	*More likely*	*More likely*
Remuneration:			
Increase in hourly wage rate			
Increase in weekly straight-time earnings	*Less likely*	*Less likely*	*Less likely*
Increase in weekly overtime earnings	*Less likely*	*Less likely*	*Less likely*
Increase in travel incentives	*More likely*		*More likely*
Personal characteristics:			
Increase in distance from work		**Less likely**	
Increase in age	*Less likely*	*Less likely*	*Less likely*
Apprentice	*Less likely*	*Less likely*	*Less likely*
Worksite characteristics:			
Increase in crew-size(force curve)			*Less likely*
Increase in overmanning	**More likely**	More likely	More likely

Figure 4.30: Effects of Different Variables on Turnover (Source: Kim and Philips (2012)

One of the first publication about absenteeism and turnover is Business Roundtable (BRT) report (Absenteeism and Turnover 1982). Based on this report, workers mentioned relationship between workers and boss, overtime available somewhere else, unsafe working conditions, excessive rework, and commute time to the site as the main reasons of absenteeism and quitting work (Absenteeism and Turnover 1982). In this report, job dissatisfaction has been identified as a strong factor that affects absenteeism and turnover. We can extract the causal network that is shown in figure 4.31 for absenteeism and turnover based on this research.

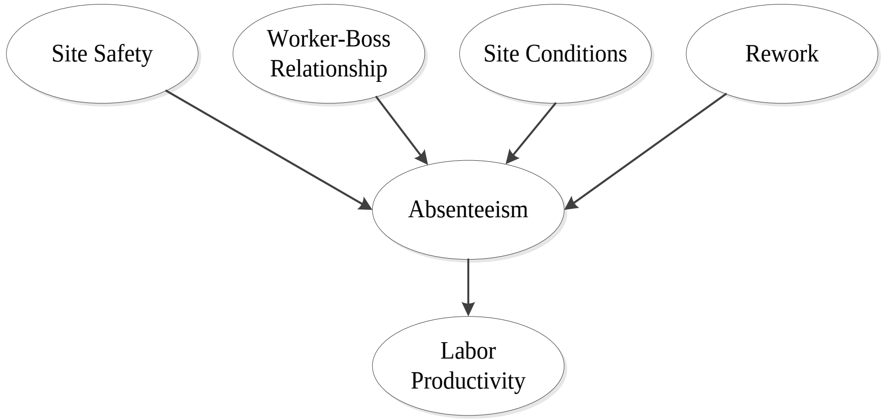


Figure 4.31: The Causal Network of Absenteeism and Turnover Based on BRT Report

The most comprehensive investigation of the effects of absenteeism and turnover on labor productivity has been done by Hanna. Hanna investigated the effects of absenteeism and turnover on labor productivity for electrical contractors (2005). In this report, the author found the following factors as the main causes of absenteeism and turnover (A. Hanna 2005):

- Personal and family illness
- Injury
- Incentive programs
- Drug and alcohol
- Lack of responsibility
- Worker experience
- Distance to work
- Poor planning on the job site
- Safer site elsewhere
- Recognition

- Inadequate tools and equipment

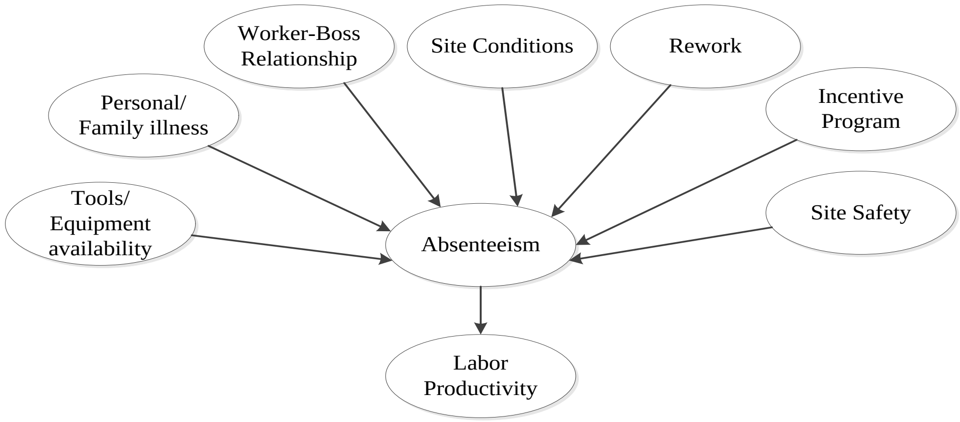


Figure 4. 32: The Causal Network of Absenteeism Based on Hanna (2005)

4.2.6 Management (Workforce, material, and equipment management)

Workforce management is one of the most important factors that affects labor productivity. Halligan et al. did a comprehensive research about the effects of workforce management on construction labor productivity (Halligan, et al. 1994). They showed graphically how productivity loss occurs in construction, which kinds of factors exist in this process, and how crews are influenced by those factors. Then, they explained how crew management can mitigate, eliminate, initiate, or exacerbate any particular loss of labor productivity (Halligan, et al. 1994). According to the proposed model, workforce management plays a central role in construction labor productivity. In this model, the authors found that the consequences of management's actions can be an increase in workload, crowding of workers, stacking of trades, out-of-sequence-work, rework, and dilution of supervision. Crews' responses to these actions are fatigue, low motivation, slowed pace of work, turnover, idle time, and poor quality. We can extract a causal relationship according to this research. This causal relationship is shown in figure 4.33. Based on this model, we can see that workforce management, if not the most important, is one the most important factors that affects construction labor productivity. Managers with proper planning, training, proper responses to other events, and proper coordination can eliminate or decrease the negative effects of different factors that affect labor productivity.

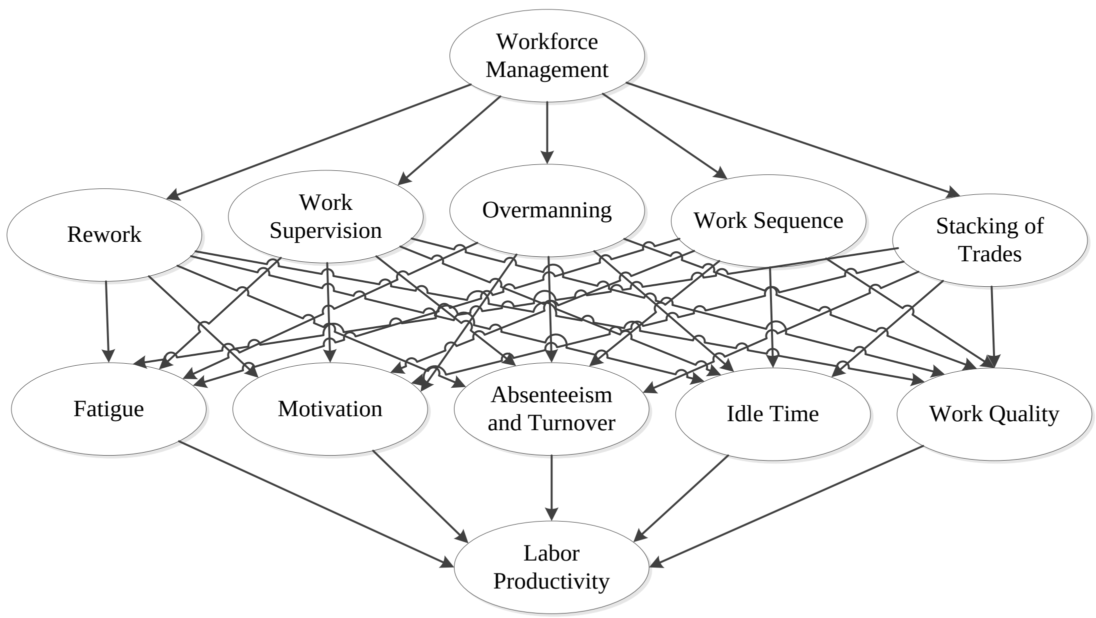


Figure 4.33: The Causal Network of Workforce Management Based on Halligan et al. (1994)

Thomas et al. stated that workforce management strategies can improve labor utilization which lead to better labor performance (Thomas, Horman and Minchin, et al. 2003). They concluded that improving workflow and labor flow can increase labor productivity. In this research, workflow encompasses the material, information, and equipment resources to complete tasks. Labor flow means reliable and timely availability of labors. According to this research, managements have direct effects on material, information, equipment, and labor flow. Further, the authors investigated the loss of efficiency due to these factors, and they found that the most significant cause of loss of labor productivity relates to labor flow. Also, they stated that 58% of total inefficient workhours are related to ineffective labor flow. Overall, we can extract a simple causal relationship based on this research which is shown in figure 4.34.

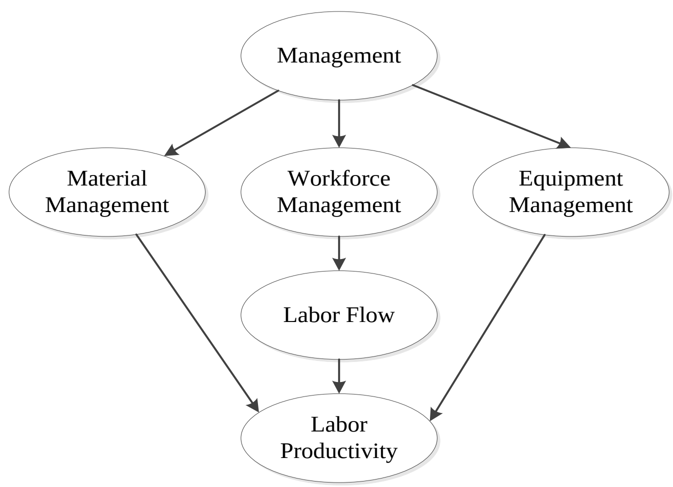


Figure 4.34: The Causal Network of Workforce Management
Based on Thomas et al. (2003)

Ovararin investigated the effects of site management on construction labor productivity. He stated that poor site management can significantly impact productivity because construction crews need resources to perform work in an efficient way. The author proposed a cause-effect diagram among the factors related with site management. According to this research, site management can affect equipment and material availability, material handling in the construction site, site maintenance, construction methods, and hazardous conditions. These factors can in turn affect idle time, labor morale, material flow, labor rhythm, interruption, limited space, and increasing waiting time (2001). Based on this research, we can extract a causal relationship between site management and productivity, which is mostly similar to Halligan et al. This causal relationship is shown in figure 4.35.

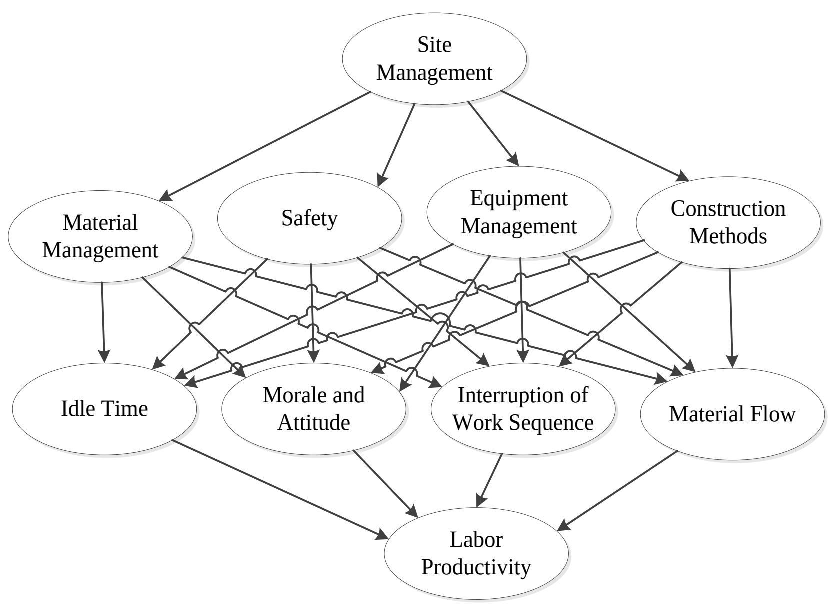


Figure 4.35: The Causal Network of Workforce Management Based on Ovararin (2001)

There exist other research that also investigated the effects of management on labor productivity. For example, the papers that investigated the effects of foremen on labor productivity. The causal relationship that we can extract from these papers is somehow a subset of Halligan et al. and Ovararin's network, so we skip the investigation of those papers and related causal network in this section.

4.2.7 Fatigue

Hallowell categorized "fatigue" as "cognitive fatigue" and "localized muscular fatigue" (2010). Based on this research "cognitive fatigue is the lassitude of thought and decision processes" and "localized muscular fatigue is the reduction in peak tension of a specific muscle group due to prolonged or excessive use" (Hallowell 2010). In this study, Hallowell did a comprehensive literature review about the causes of fatigue; its immediate and long-term effects of it. In the figure 4.36, this comprehensive causal map is shown.

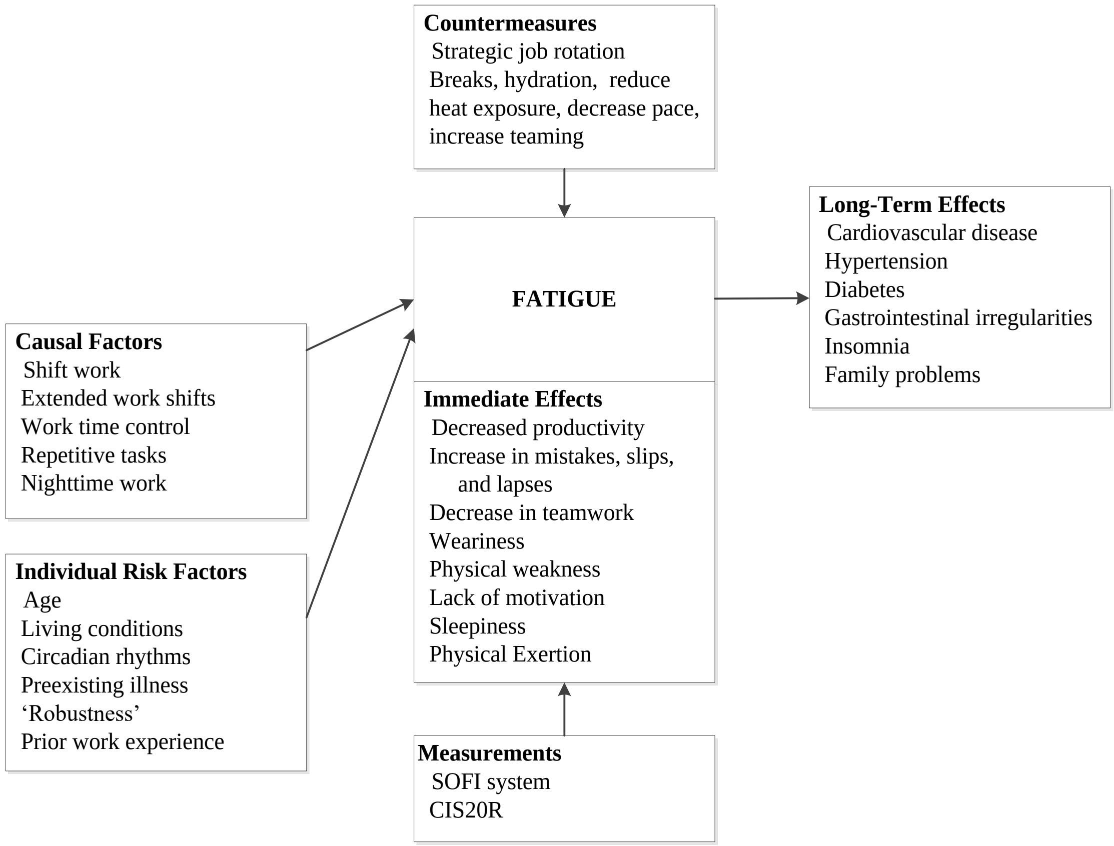


Figure 4.36: The Cause-Effect Diagram of Fatigue (Source: Hallowell (2010))

In this research, slips is defined as "unintended erroneous actions that results from mental distractions in familiar work environments" and lapses is defined as "unintended erroneous actions result from temporary memory failure" (Hallowell 2010).

Lerman et al. investigated the causes of fatigue in the workplace. They identified the following factors as causes of fatigue (Lerman, et al. 2012).

- Sleep deprivation (Fatigue is related to duration of sleep)
- Circadian variability (Fatigue is related to timing of sleep)

- Time awake (Various shift work schedules can affect both the duration and timing of sleep)
- Health factors (sleep disorders, medications)
- Environmental issues (light, noise)
- Workload

They stated that fatigue can have several safety-related consequences such as a reduction in reaction time, poor judgment and decision-making ability, loss of awareness, etc. (Lerman, et al. 2012). The authors proposed a list of actions that can mitigate fatigue. These actions are fatigue management policy, a fatigue reporting system for employees, sleep disorder management, balancing workload, etc. (Lerman, et al. 2012). Based on this research, the causal network in the figure 4.37 is extracted.

O'Neill and Panuwatwanich investigated the impact of fatigue on labor productivity in dam construction projects (2013). Their survey results show that most workers in the projects that they investigated suffered from fatigue. They found that heat, repetitive tasks, and lack of sleep as the main causes of fatigue in the crew (O'Neill and Panuwatwanich 2013). They also stated that a "higher level of fatigue is associated with lower productivity" (O'Neill and Panuwatwanich 2013). The causal network in the figure 4.38 is extracted from this research.

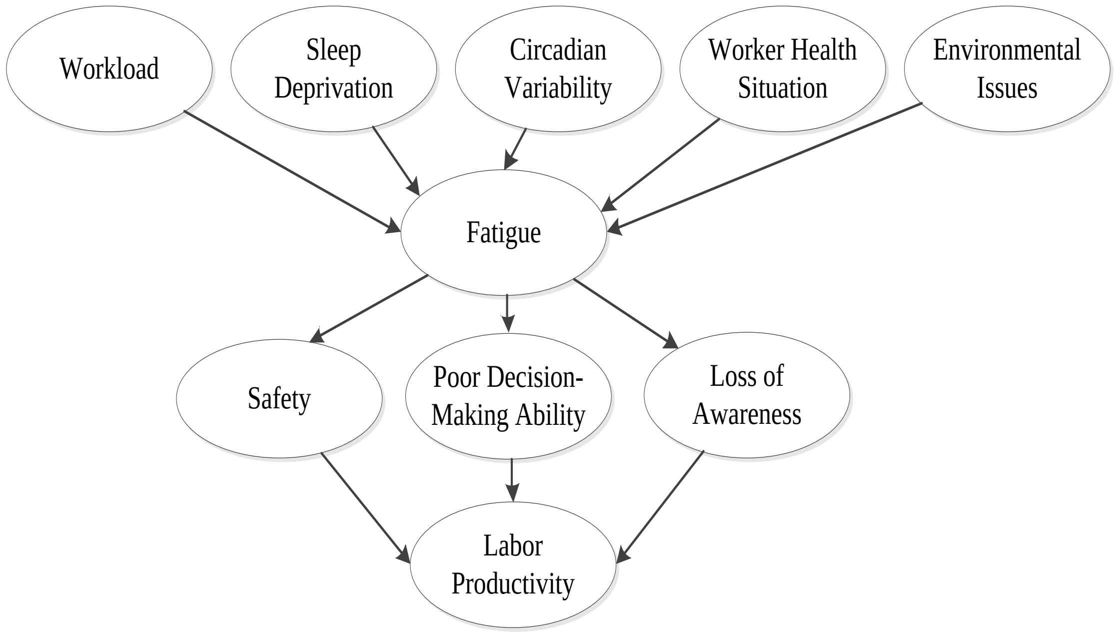


Figure 4.37: The Causal Network of Fatigue Based on Lerman et al. (2012)

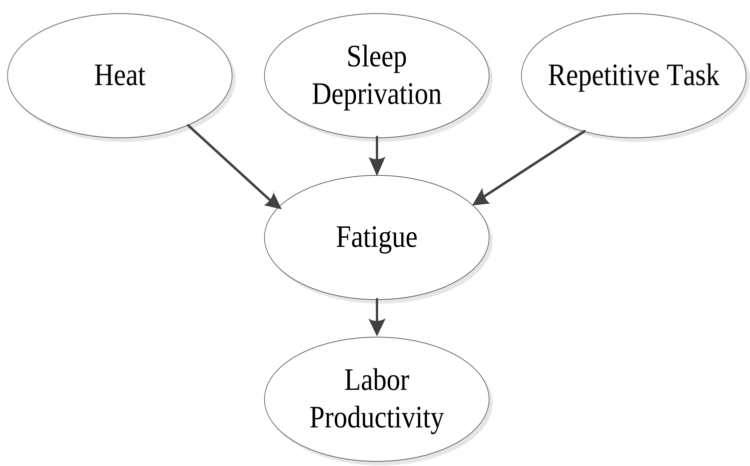


Figure 4.38: The Causal Network of Fatigue Based on O'Neill and Panuwatwanich (2013)

4.2.8 Morale and Attitude

Hull and Azumi investigated effects of different factors on labor morale and productivity in Japanese factories (1988). They stated that employee-oriented management, worker participation in the decision-making process, and the worker-boss relationship affects morale. Also, they believed that whenever the workers' autonomy declines, it causes a decrease in their morale. The causal network in figure 4.39 is extracted based on this research.

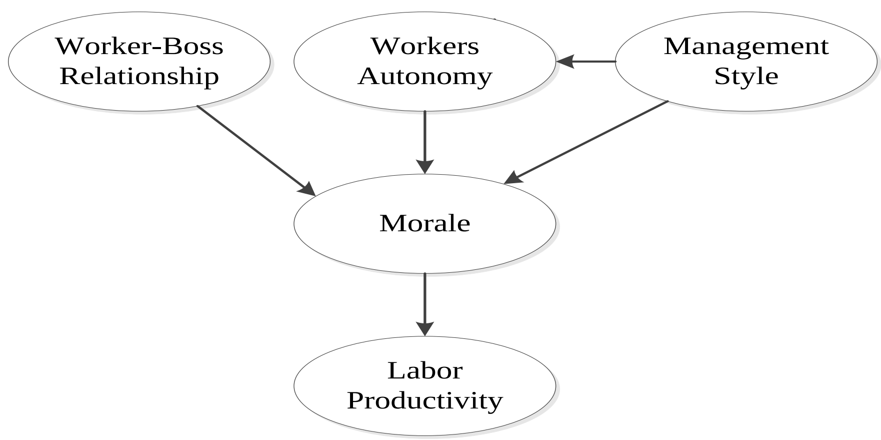


Figure 4.39: The Causal Network of Morale Based on Hull and Azumi (1988)

Weakliem and Frenkel defined morale as "a general orientation that may influence intentions and ultimately behavior" (2006). They provided a set of circumstances which cause low morale and a set of paths in which low morale causes loss in labor productivity. The set of factors that affects morale based on the authors are as follows (Weakliem and Frenkel 2006):

- Organization’s general approach to management: If an organization creates a sense that workers and management are part of the same team, then workers will have a higher level of morale (Sense of commitment).

- Existence or history of poor labor relationship is a cause of lower morale among laborers.

- Autonomy has a direct effect on workers’ morale. The authors stated that “The effect of morale on productivity can be expected to increase with degree of autonomy” (Weakliem and Frenkel 2006).

- Unionization affects morale. They believed that “Unionization may enhance autonomy by giving workers protection against dismissal and other forms of discipline” (Weakliem and Frenkel 2006).

- Workers’ skill increases workers’ autonomy.

- Size of project (organization) affects morale. They stated that “Large workplaces tend to have a more bureaucratic organization, with standardized systems of measurement, reward, and punishment. To the extent that such systems are effective, workers will have less autonomy in larger workplaces” (Weakliem and Frenkel 2006).

- Workers orientation toward authority has effects on morale. They stated that “If workers have a strong general sense of obligation to follow orders, their work effort will be less dependent on morale” (Weakliem and Frenkel 2006).

In the same way, the authors provided a set of paths in which high morale causes an increase in the labor productivity and vice versa. These paths are as follows: (Weakliem and Frenkel 2006):

- High morale causes workers to put in more effort to finish a job; therefore, it increases productivity.
- High morale increases job satisfaction and it causes workers to feel more determined to carry out a job.
- High morale causes the organization to work more smoothly; therefore, it increases productivity.
- High morale causes workers to give good advice to their co-workers and managers which causes a decrease in rework, errors, and mistakes.

Based on this research, the causal network that is shown in figure 4.40 is extracted. The causal diagram that is possible to extract from other scholars' research such as Wahroe (2012), Ovararin (2001), and Lyneis and Ford (2007) is similar or a subset of the network in figure 4.40. Therefore, it is not necessary to investigate those papers further.

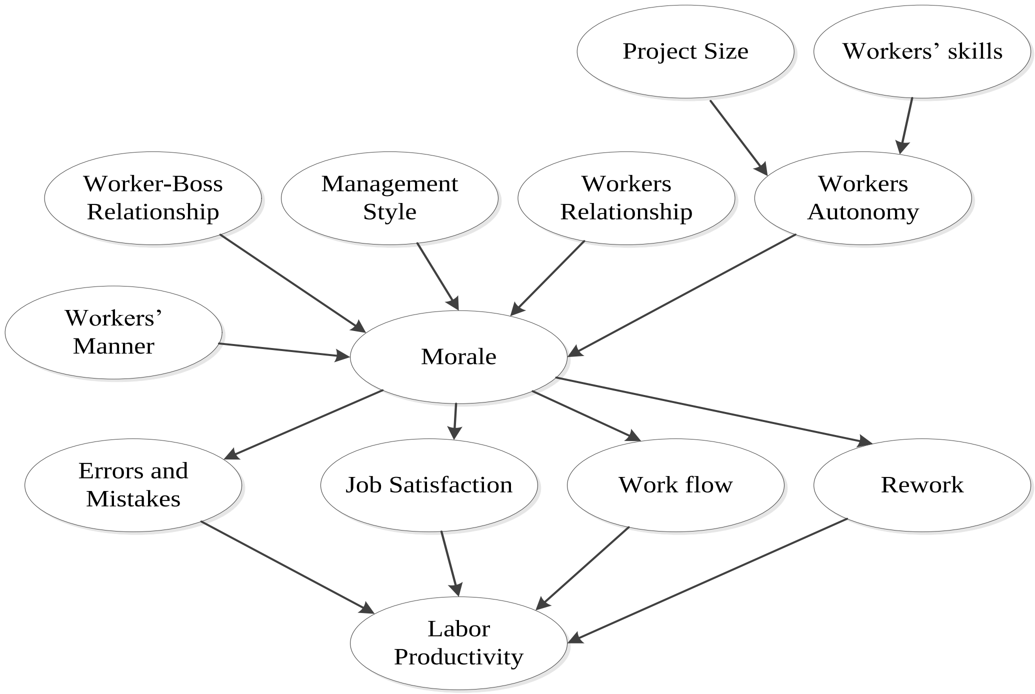


Figure 4.40: The Causal Network of Morale Based on Weakliem and Frenkel (2006)

4.2.9 Motivation

Motivation is a major factor that affects construction labor productivity and many other variables. It has been investigated by numerous researchers in construction industry over the past three decades. Motivation is defined as "the condition of being eager to act or work" or "a force or influence that causes someone to do something" (Merriam-Webster 2015).

Maloney investigated causes of motivation in the construction industry (1986). He identified the following factors as causes that increase motivation (W. F. Maloney 1986):

- More job autonomy

- Feeling of accomplishment
- Increasing payment to workers (Benefits)
- Increasing job security
- Management style
- Workers relationship
- Recognition
- Supervision
- Incentives
- Experienced meaningfulness
- Knowledge of results experienced by workers

Maloney defined the “Experienced meaningfulness” as “the worker must see the work as something that counts within his own set of values” (1986). Also, the “Knowledge of results” is defined as “the availability of information from the job itself that allows the worker to judge his level of performance” (W. F. Maloney 1986). Based on this research, the causal network that is shown in figure 4.41 is extracted.

Ng et al. investigated prominent demotivates and their effects on construction labor productivity (S. T. Ng, et al. 2004). Based on the authors the following factors cause loss in labor productivity because of lack of motivation:

- Unsatisfactory work environment

- Poor interpersonal relationship
- Poor work attitude
- Rework
- Overcrowded work area (Overstaffing)
- Crew interfacing (Stacking of Trades)
- Poor tools availability
- Inspection delays

They stated that rework causes workers to feel little sense of accomplishment, an overcrowded work area causes workers to feel frustrated, crew interfacing causes lack of communication which causes workers to feel demotivated, and inspection delay causes workers to become dissatisfied. Based on this research, the causal network that is shown in figure 4.42 is extracted.

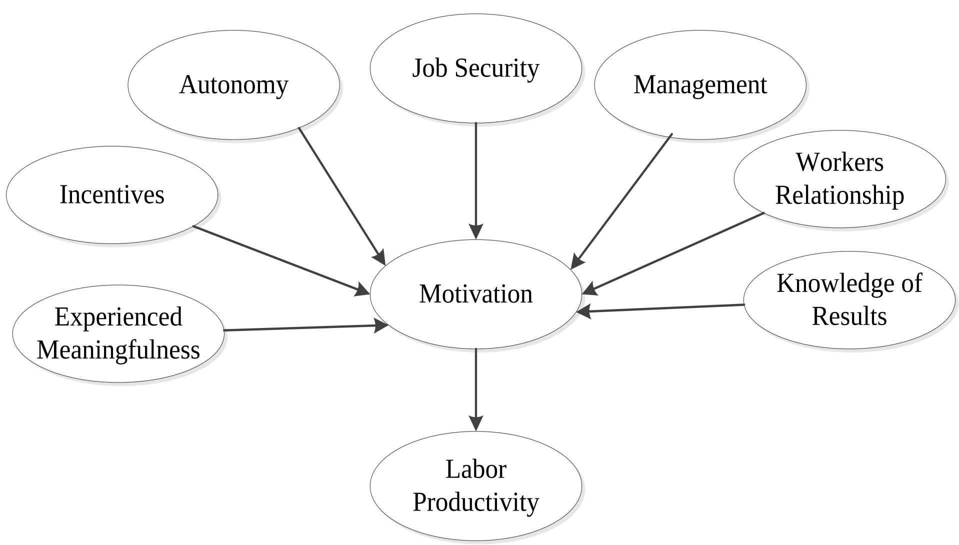


Figure 4.41: The Causal Network of Motivation Based on Maloney *(1986)*

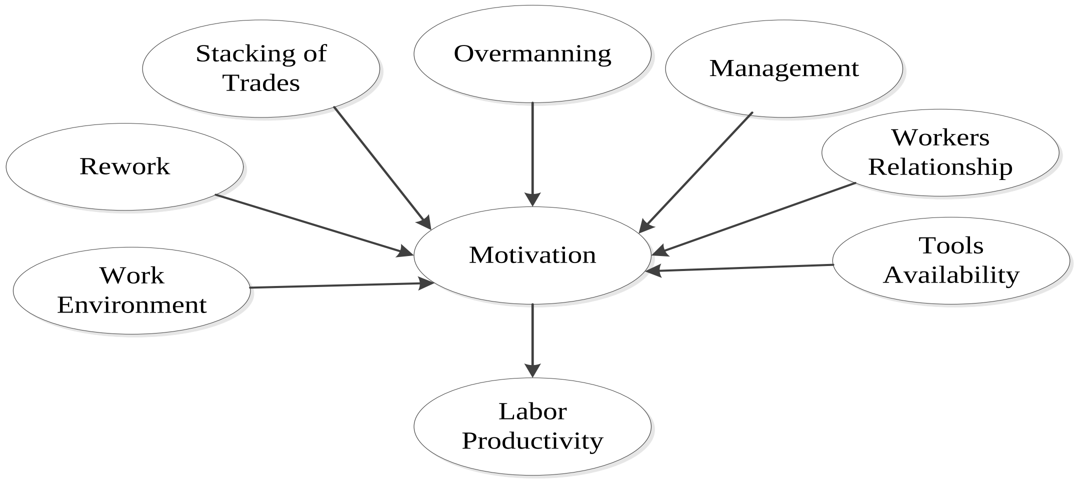


Figure 4.42: The Causal Network of Motivation Based on Ng et al. *(2004)*

4.2.10 Rework

Love and Edwards defined rework as "the unnecessary effort of redoing a process or activity that is incorrectly implemented the first time" (2004). They investigated rework in Australian industry and provided a comprehensive causal network for rework. Based on this research, three main categories of causes of rework are project characteristics, organizational management practices, and project management practices. Each category consists of several other factors which causes rework directly or indirectly. Also, they found that rework causes lower morale level, dilution of supervision, conflict between different crews and even subcontractors, absenteeism, and fatigue. They proposed a comprehensive causal network which is shown in figure 4.43.

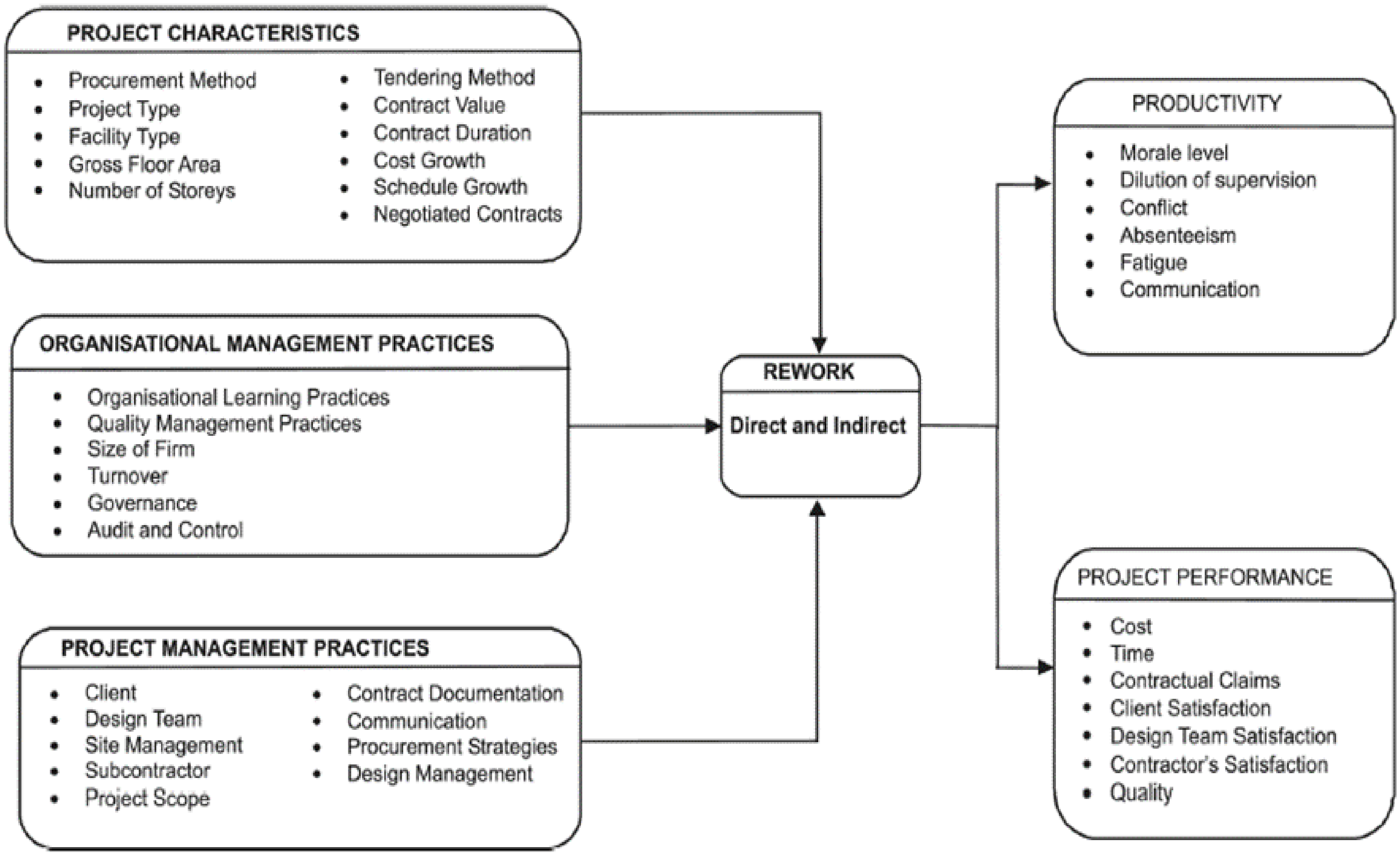


Figure 4.43: The Proposed Causal Network for Rework by Love and Edwards (2004) (Source : Love and Edwards (2004))

Fayek et al. investigated the causes of rework in the Canadian construction industry. They identified five major areas as the main causes of rework in the construction industry. These five major causes of rework are: (1) human resource capability,(2) leadership and communication, (3) engineering and design review, (4) scheduling and planning , and (5) material and equipment supply (2004). They also represented their causal model in a fishbone network which is shown in figure 4.44.

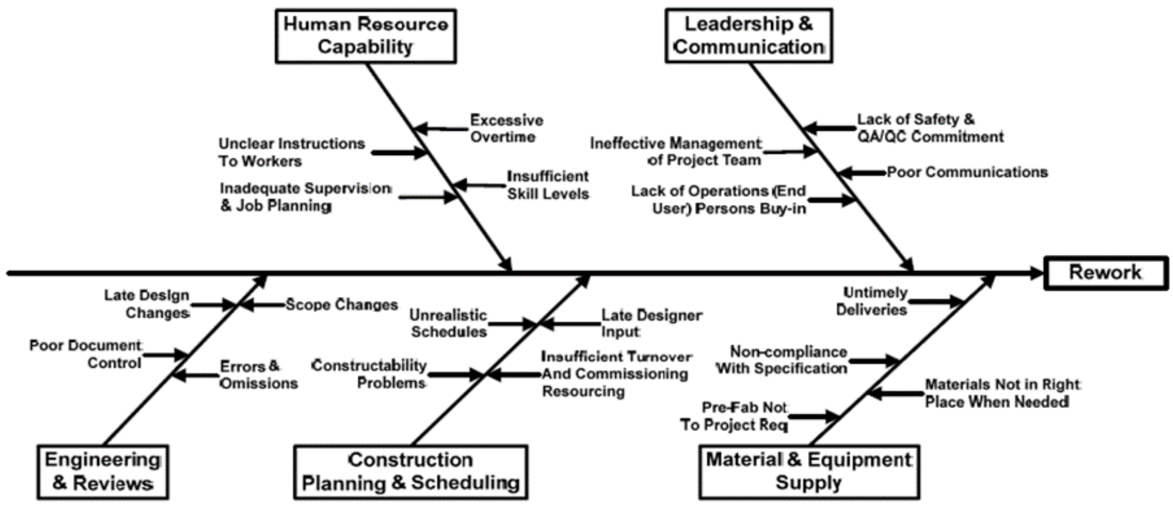


Figure 4.44: The Proposed Causal Network for Rework by Fayek et al. (2004)

(Source: Fayek et al. (2004))

The authors provided a reasoning behind each cause and why it causes rework in the construction industry. For example, for engineering and design review, they stated that poor document control, errors and omission, changes in design (especially late changes), and changes in scope can disrupt information flow and decision-making process which cause rework (Fayek, Dissanayake and Campero 2004).

Errors and mistakes have been identified as one of the main causes of rework in the construction industry. Shimbun identified several major causes of errors and mistakes as follows (1989):

- Forgetfulness errors (workers lose their concentration)
- Errors due to misunderstanding
- Errors occurred by untrained workers
- Ignoring rules by individuals
- Errors because of lack of standards
- Intentional errors occur when workers make mistakes on purpose

Josephson et al. investigated the causes of rework in Swedish industry. They found that costs of rework for the projects that they investigated were 4.4% of the construction values and the time needed to correct errors (rework time) was 7.1% of the total work time (Josephson, Larsson and Li 2002). They found several factors as the causes of rework. They graphically showed causes of rework and their contributions to the overall rework costs. The figure 4.45 is from this research which shows the major causes of rework with their relative importance.

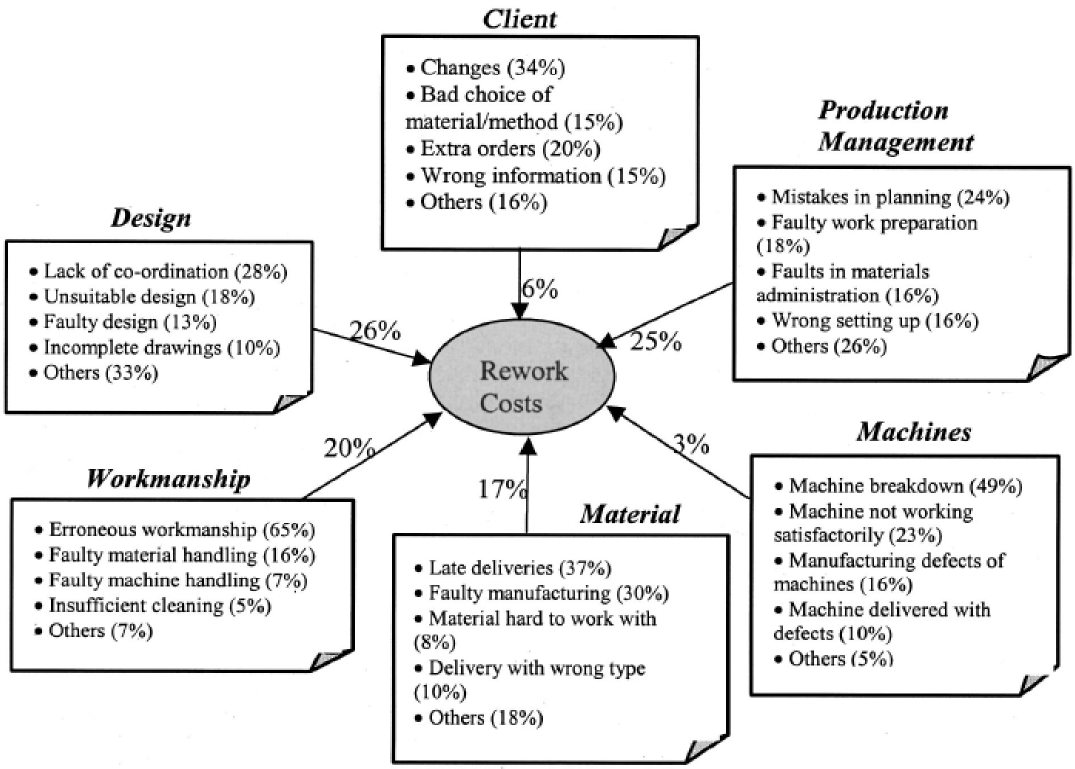


Figure 4. 45: The Proposed Causal Network for Rework by Josephson et al. (2002)(Source: Josephson et al. (2002))

4.2.11 Other Factors

There exist numerous factors in the model that in chapter 2 and this chapter do not define. For clarity of the model, the definition of these factors are as follows:

<u>Dilution of Supervision: “</u>Applies to both basic contract and proposed change. Supervision must be diverted to (a) analyze and plan change, (b) stop and re plan affected work, (c) take-off, order and expedite material and equipment, (d) incorporate change in schedule, (e) instruct foreman and journeyman, (f) supervise work in progress, and (g) revise punch lists, testing and start-up requirements” (MCAA 2011).

Learning Curve: "Period of orientation in order to become familiar with changed condition. If new men are added to project, effects more severe as they learn tool locations, work procedure, etc." (MCAA 2011).

Logistic (Tools and Material Availability): "Insufficient or poor material handling, owner-furnished material, procurement practices, or a lack of controls can cause procurement or delivery problems, as well as other issues. This then prevents, delays, or disrupts the normal material workflow to a work area, warehouse, or laydown yard. This can also be a result from the additional replacement or substitution of material due to contract changes, defects, or delays at the work site" (MCAA 2011).

Availability of skilled labor (Labor Market): "To be productive, a contractor must have sufficient skilled labor in the field. To the extent that skilled labor is unavailable and a contractor is required to construct a project with less skilled labor it is probable that productivity will be impacted" (AACE International 2004).

Defective Specification: "When drawings or specifications are erroneous, ambiguous, unclear, etc., productivity is likely to decline because crews in the field are uncertain as to what needs to be done. As a consequence, crews may slow down or pace their work, or have to stop all together while they wait for clear instruction" (AACE International 2004).

Out of sequence work: "When work does not proceed in a logical, orderly fashion productivity is likely to be negatively impacted as crews are moved around the site haphazardly, for example" (AACE International 2004).

Incentives: “something that encourages a person to do something or to work harder” (Merriam-Webster). There are two types of incentives: extrinsic incentives and intrinsic incentives and both of them have can increase motivation.

Personal/Physical Characteristics: Physical characteristics include age, health situation, and other physical appearances that can be seen with naked eye. Personal characteristics include behaviors that people possess such as intelligence, preciseness, obedience, laziness and so on. These characteristics can affect the work and productivity (Hallowell 2010).

Project Size: There are different approaches that are used to categorize projects based on size. Effort hours is one of the most well-known ones. Based on this approach whenever the effort hours that is required to complete a project is between a certain ranges, then that range specifies the project size.

Chapter 5

Extracting Model Parameters

This chapter extracts the model parameters. It means that for each variable a "Conditional Probability Table" or CPT is obtained. In the first section, different methodologies regarding model's parameters identification are discussed. These methodologies help to extract the model's parameters. In the second section, the methodology for obtaining CPTs of variables are discussed. For this purpose, the procedure for "Changes" sub model is discussed thoroughly and all "Changes" sub model's CPTs are shown in this chapter. In the next step, the procedure for combining different sub models are explained. Similarly, the procedure for combining "Changes" and "Overtime" sub models is discussed thoroughly and their CPTs after combination are shown in this chapter. We continue this procedure for all sub models and by adding each sub model to what we obtained before that, we extract our final model's CPTs. Since there are several CPTs, it is not possible to put all CPTs in this chapter; therefore, they are shown in appendix B.

5.1 Modeling Techniques Related to CPTs

There exist six modeling techniques related to model's CPTs. These modeling techniques are measurement errors, expert opinions, node absorption, setting a value by intervention, and independence of causal influence (Kjærulff and Madsen 2013). Since we use these approaches for obtaining CPTs, we briefly introduce these methodology in this section.

5.1.1 Measurement Errors (Uncertainty)

This approach is useful whenever there are either uncertainty in measurement or noisy observation. Kjærulff and Madsen proposed a modeling technique to capture this uncertainty. An algorithm for implementation of measurement uncertainty technique based on Kjærulff and Madsen is as follows (2013):

1. Define variable “Value” as the actual value of phenomenon that is needed to be measured.
2. Create two variables “Observed” and “Accuracy” which represent the observed value and the accuracy with which observations are made. Put these two variable as the parents of the “Value.”
3. Define the prior probability of “Accuracy” in such a way that it encodes relative frequency.
4. Define CPT of *P(Observation | Accuracy, Value)* in such a way that it encodes relative frequency.

5.1.2 Expert Opinions

When model’s parameters elicitation is based on experts’ opinions, it is usual that experts have different opinions about the CPT of a variable. In this situation, by adding a conditioning or auxiliary variable as the parent of the desired variable we can select among the opinions of different experts (Kjærulff and Madsen 2013). The procedure to implement this methodology is as follows (Kjærulff and Madsen 2013):

1. Let *P(X| par(X))* be the CPT obtained from a group of experts. Then create a variable "Expert" with one state for each expert as the parent of desired variable.
2. Define prior probability distribution of "Expert" is such a way that it encodes the reliability of experts.
3. Define *P(X| par(X),Experts)* such that it encodes assessment of *P(X| par(X))* given by the corresponding expert.

5.1.3 Node Absorption

Node absorption is the process of eliminating a variable from a model. The procedure for eliminating a variable from the model is known as "Arc Reversals." If efficiency of a PGM is of high priority, it may be useful to eliminate variables from the model that neither observed nor are target variables (Kjærulff and Madsen 2013). Since we don't use node absorption approach, we are skipping the explanation of this algorithm.

5.1.4 Set Value by Intervention

This approach is used extensively in this research for obtaining sub model's CPTs and combining sub models to each other. Set by intervention is an active action that force a variable to be in a certain state (Kjærulff and Madsen 2013). The proposed algorithm to implement this approach is as follows (Kjærulff and Madsen 2013):

1. Let X be a variable that we want to set by intervention. Then create a random variable I with $domain\ (I) = domain(X) \cup \{no\ intervention\}$.
2. Set I as the parent of X and define prior CPT of I such that it encodes the relative frequency of setting each state of X and no intervention.
3. Define $P(X|par(X), I)$.

5.1.5 Independence of Causal Influence

In this approach, the parent variable of a common child are considered independent. It means that parent variables are causally independent and the model acts like Noisy-OR model (Kjærulff and Madsen 2013). In this kind of modeling, each cause variable has a no impact state on the effect variable which is useful for combining the effects of all cause variables. Since this model acts like Noisy-OR model, each cause variable is a Boolean variable, which means variable with two states, and its causal impact is independence of other variables (Kjærulff and Madsen 2013). The algorithm for implementing this approach is as follows (Kjærulff and Madsen 2013):

1. Let $\{C_1, \dots, C_n\}$ be the set of causes of effect variable E. Note that the impact of $C_1, \dots, C_n$ on E can be modeled with *Noisy-OR* model which means $\mathrm{C}_1, \dots, \mathrm{C}_\mathrm{n}$ are Boolean variables.
2. For each variable C_i define a variable E_i as the child of it and parent of effect variable E. Then for each C_i define CPT of $P(E_i|C_i)$ such that $P(E_i =$

$true|C_i = true)$ is probability of $E = true$ given $C_i = true$ and $P(E_i = false|C_i = false) = 1$

3. Define CPT of $P(E|E_1, \dots, E_n)$ as disjunction.

5.2 Extracting Sub Model's CPTs- Change Sub Model Example

In this section, the procedure for obtaining model's CPTs are discussed. We first obtain sub models' CPTs, then by combining sub models with each other, the comprehensive cause-effect model with related CPTs are obtained. Once we have finalized the structure of the network, the next step is to obtain the network's CPTs. This procedure for change sub model is explained thoroughly here with corresponding CPTs. This procedure is repeated several times to extract CPTs of other sub models, which we skip explanation of all of them and only in appendix B, the model's final CPTs are documented.

Based on chapter 4, the "changes" has the cause-effect diagram that is shown in figure 5.1. Our goal is to obtain (extract) CPTs of the network based on data, statistics, and other scholars and experts opinions. The network is splitted into two networks, the first network is from changes to labor productivity, and the second network is from causes of changes to changes. These sub networks are shown in figures 5.2 and 5.3.

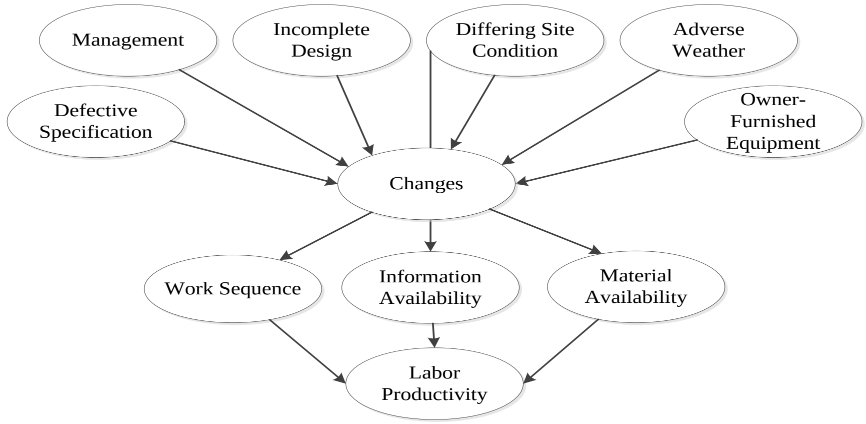


Figure 5.1: The Change Sub Model's Structure

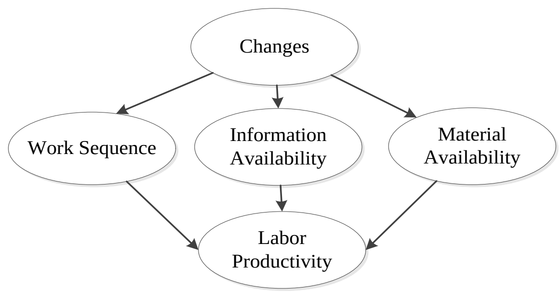


Figure 5.2: The Sub Network from Changes to Labor Productivity

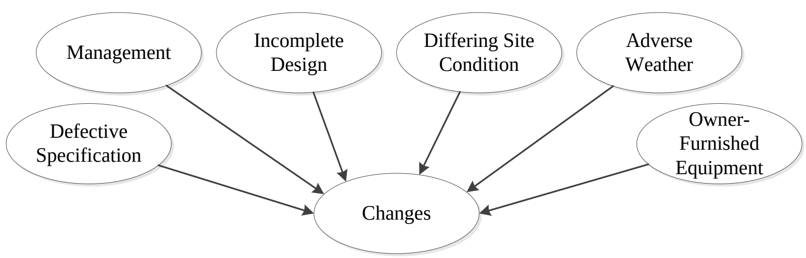


Figure 5.3: The Sub Network from Causes to Changes

In the section 5.2.1 the procedure for extracting CPTs of the network in the figure 5.2 is explained and in section 5.2.2 the procedure for obtaining CPTs of the network in the figure 5.3 is explained.

5.2.1 The Procedure for Extracting CPTs of the Network in Figure 5.2

The procedure for obtaining CPTs of the sub network shown in figure 5.2 is as follows:

Based on MCAA research we know that changes has following effects on labor productivity (2011):

Table 5. 1: Effects of Changes on Labor Productivity (Source MCAA (2011)

Factor	Percent of Loss Per Factor		
	Minor	Average	Severe
Ripple: Changes in other trades' work affecting our work such as alteration of our schedule. A solution is to request, at first job meeting, that all change notices/ bulletins be send to our contract manager	10%	15%	20%

Thomas and Napolitan found the average effect of all changes on labor productivity about 30% loss of productivity. Also, a regression analysis showed a 25-50% loss of efficiency depending on the type of disruption (1995). There exist several similar statements about the quantitative effect of changes on labor productivity. Our focus is on MCAA and Thomas and Napolitan statement about loss of labor productivity because of changes. We know that changes affect productivity. Therefore, the causal network that is shown in figure 5.4 is an obvious cause-effect network.

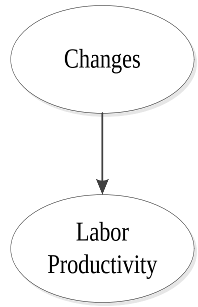
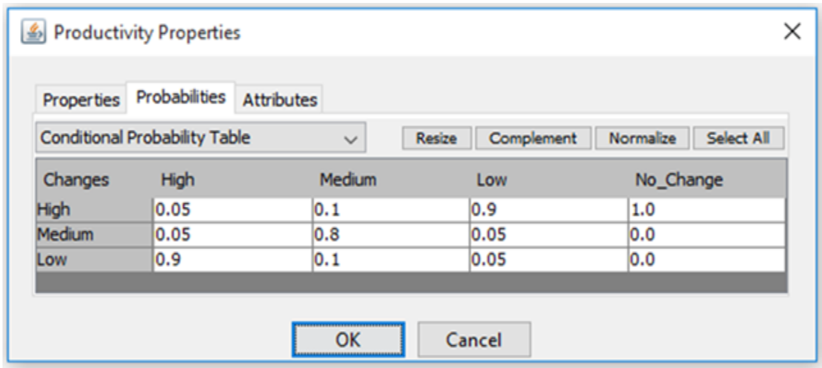


Figure 5.4: The Base Network

Changes have four states: high, medium, low, and no change. In minor, average, and high states, productivity loss is 10, 15, and 20%, respectively. In the "no change" state, productivity loss is 0%. If productivity is high when it is between 0.9-1, medium when it is between 0.8-0.9, and low when it is below 0.8 (Typically since loss of productivity in severe situation is usually around 30%, we consider it between 0.7-0.8). For calculating expected value of productivity, we can consider the average of each boundary as an indicator of that boundary, except for no change situation that we consider high productivity as 1. Therefore, in our model and calculation, when we need calculation, productivity high means 0.95 (except for no change), medium means 0.85, and low means 0.75. So, we have to setup CPTs of the network in such a way that they map minor or low change to 5% loss of productivity or productivity equals to 95%, medium changes to 15% loss of productivity or productivity equals to 85%, high changes to 25% loss of productivity or productivity equals to 75%, and probability of high productivity be 100% in the "no change" state. The goal of adding "no change" state is to combine different sub models with each other and we will use this state extensively in the coming sections of this chapter. Therefore, if we construct the CPT shown in figure 5.5 for changes node, then expected values of productivity for different states of changes can be computed. Note that, in this dissertation we use SamIam (Sensitivity Analysis, Modeling, Inference, and More) package for modeling purposes.



Changes	High	Medium	Low	No_Change
High	0.05	0.1	0.9	1.0
Medium	0.05	0.8	0.05	0.0
Low	0.9	0.1	0.05	0.0

Figure 5.5: The Conditional Probability Table of Productivity of the Network in Figure 5.4

The marginal distribution of different states is shown in the figure 5.6.

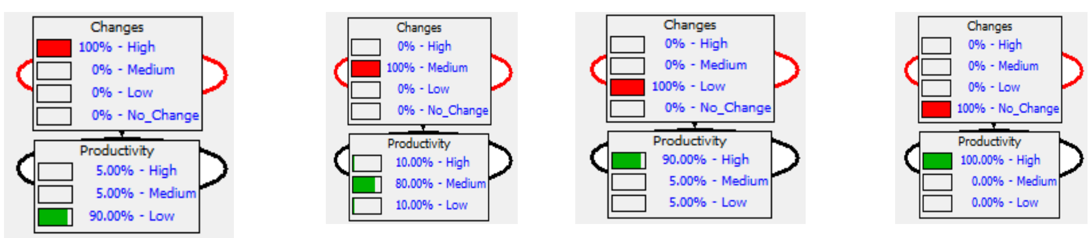


Figure 5.6: Marginal Distribution of the Network in Figure 5.4 for Different Situations

Then we can calculate expected value of productivity for different situations. Note that this calculation is a kind of verification that CPT of productivity is correct or errors are negligible.

$$E[\text{productivity}|\ \text{Changes} = \text{High}] = 0.05 \times 0.95 + 0.05 \times 0.85 + 0.90 \times 0.75 = 0.765$$

$$E[\text{productivity}|\ \text{Changes} = \text{Medium}] = 0.10 \times 0.95 + 0.8 \times 0.85 + 0.10 \times 0.75 = 0.85$$

$$E[\text{productivity}|\ \text{Changes} = \text{Low}] = 0.90 \times 0.95 + 0.05 \times 0.85 + 0.05 \times 0.75 = 0.935$$

For “no change” state, probability of high productivity is 100% which means that we don’t have productivity loss for this state. In the next step, we add one variable to the base network. For this purpose, we add work sequence which has four states. The resulting network is shown in figure 5.7.

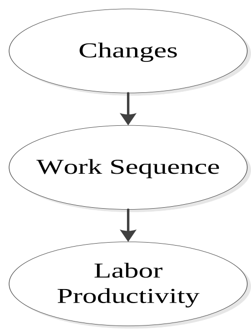
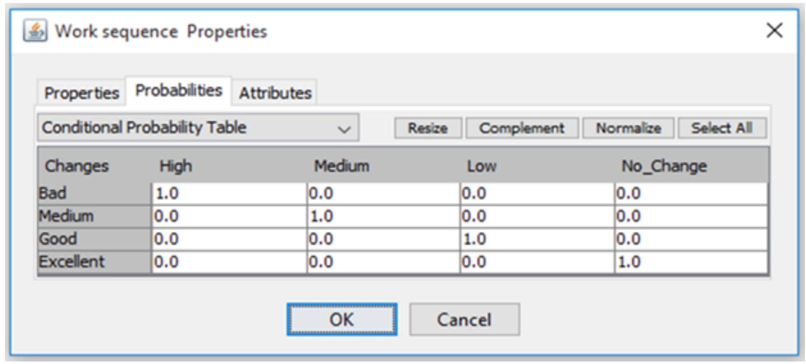


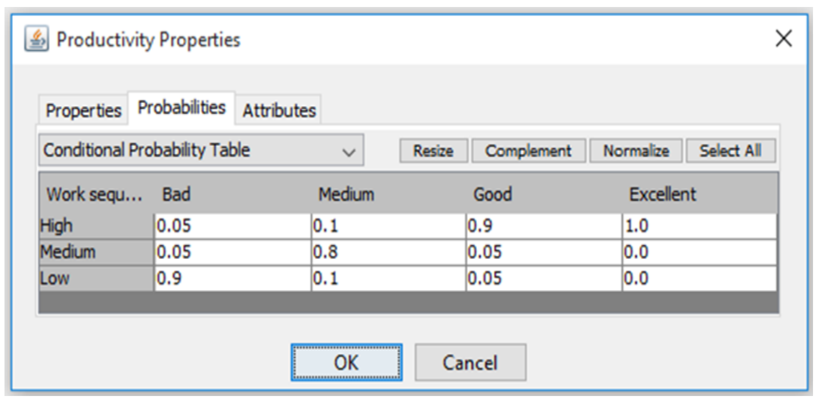
Figure 5.7: Adding Work Sequence to Base Network

The goal is to adjust CPT of work sequence and productivity in such a way that it has the least deviation in comparison with the original network (Network of the figure 5.4). For achieving this goal, the CPTs that are shown in figures 5.8 and 5.9 are set up for the “Work sequence” and “productivity.” Then, for checking the correctness of these CPTs, the marginal distribution of network 5.7 for different scenarios are shown in figure 5.10.



Changes	High	Medium	Low	No_Change
Bad	1.0	0.0	0.0	0.0
Medium	0.0	1.0	0.0	0.0
Good	0.0	0.0	1.0	0.0
Excellent	0.0	0.0	0.0	1.0

Figure 5.8: CPT of the “Work Sequence”



Work sequ…	Bad	Medium	Good	Excellent
High	0.05	0.1	0.9	1.0
Medium	0.05	0.8	0.05	0.0
Low	0.9	0.1	0.05	0.0

Figure 5.9: CPT of “Productivity”

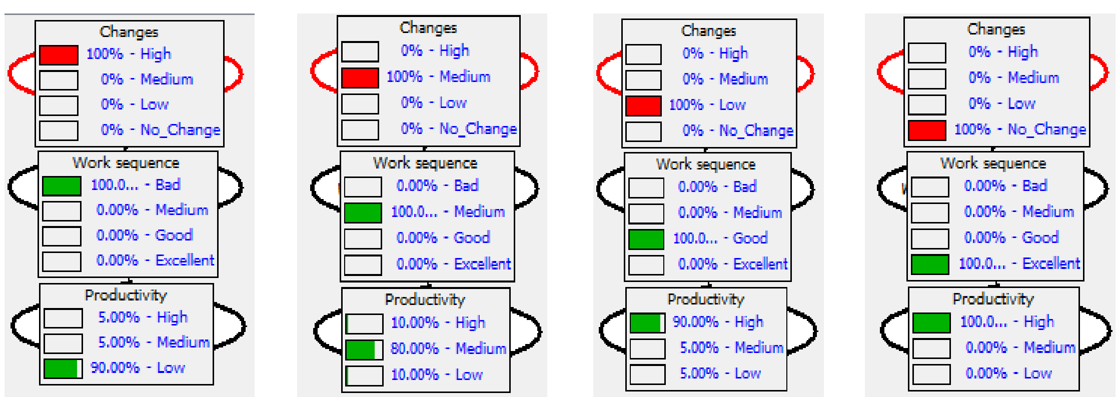
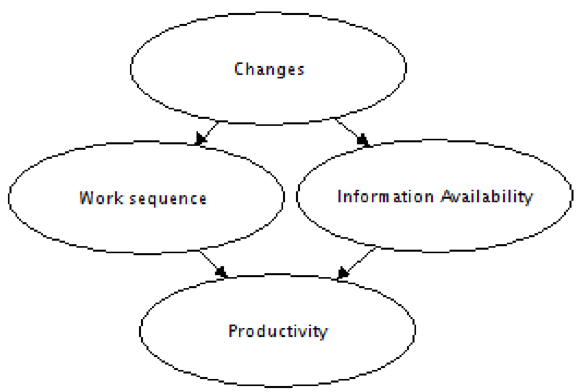
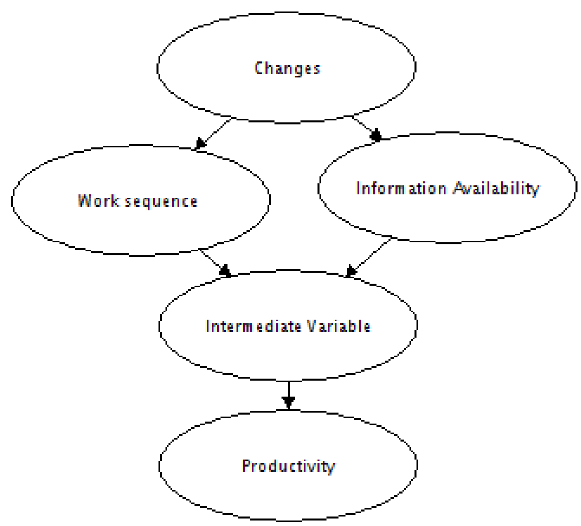


Figure 5.10: Marginal Distribution of Network 5.7 for Different States

The comparison of figure 5.10 with 5.6 shows that with the CPTs that are shown in figures 5.8 and 5.9, the same input maps to the same output. It means that regardless of the intermediate variable that exists between changes and productivity, the same state of the "changes" variable maps to the same state of the "productivity" variable, which proves that our CPTs are accurate. The same procedure is applied for the "information availability" and the "material availability" variables too. Since combining the effects of these three variables needs large CPT (table with 192=4*4*4*3 entries), it is not practical to extract CPT directly. Here the techniques that have been explained in section 4.1 and 5.1 are very helpful for extracting CPTs and refining the model's structure. The "parent divorcing" technique is used to combine the effects of "work sequence" and "information availability." A sequence of networks that is required to build the network that is shown in figure 5.2, is shown in figure 5.11.

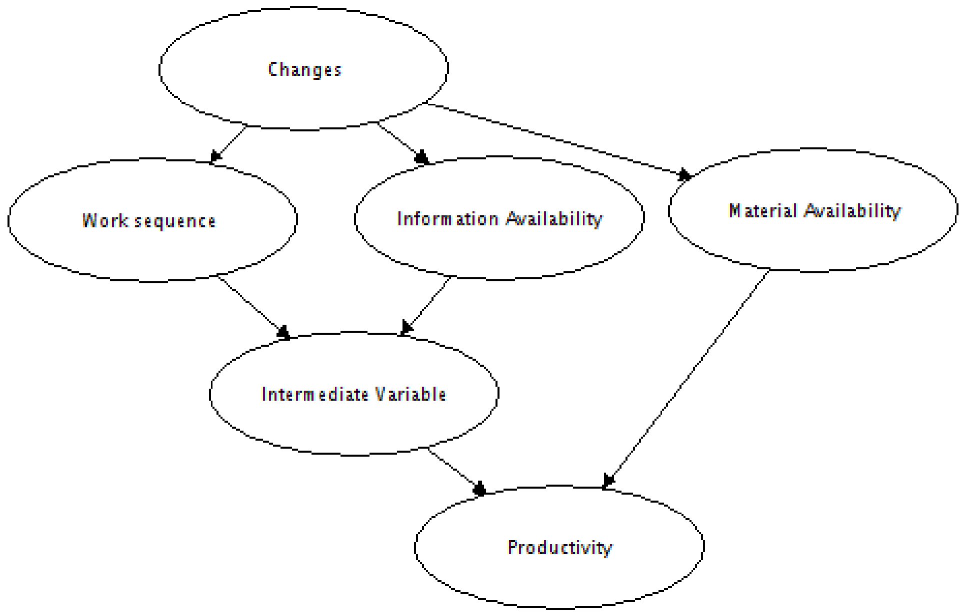


(a)



(b)

Figure 5.11: The Sequence of Networks Used to Build the Network of Figure 5.2

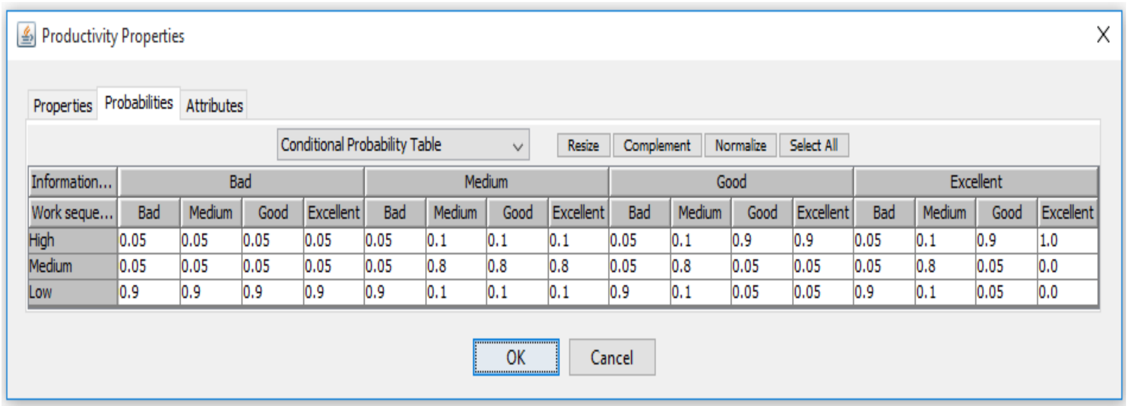


(c)

Figure 5.11: The Sequence of Networks Used to Build the Network of Figure 5.2 (Continuation)

The network that is shown in figure 5.11(a), combines the effects of "work sequence" and "information availability" on construction labor productivity. For obtaining CPT of productivity in this network, *"OR gate," "weighted average*," or *"combined*" method can be used. Comparing these methods with each other, the one that has the least deviance from the base network is chosen.

In the *"OR gate"* method, the worst condition of the two states is selected. For example, when "information availability" is in "Bad" state and "Work sequence" is in "Excellent" state, the state of "information availability" is selected because it has the worst state. The CPT of productivity based on this approach is shown in figure 5.12.



Information...	Bad				Medium				Good				Excellent			
Work seque...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	0.05	0.05	0.05	0.05	0.05	0.1	0.1	0.1	0.05	0.1	0.9	0.9	0.05	0.1	0.9	1.0
Medium	0.05	0.05	0.05	0.05	0.05	0.8	0.8	0.8	0.05	0.8	0.05	0.05	0.05	0.8	0.05	0.0
Low	0.9	0.9	0.9	0.9	0.9	0.1	0.1	0.1	0.9	0.1	0.05	0.05	0.9	0.1	0.05	0.0

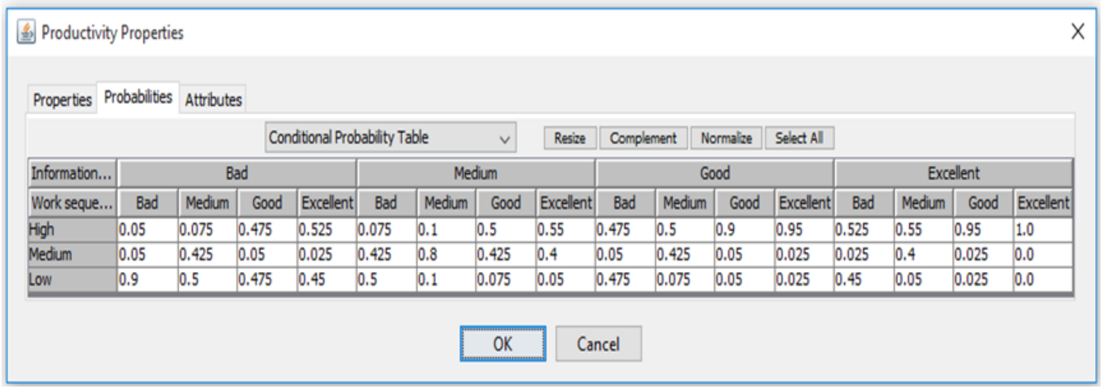
Figure 5.12: The CPT of Productivity figure 5.11(a)'s Network Based on "OR gate" Method

In the *"weighted average"* method, it is assumed that "Information Availability" and "Work sequence" have the same weight or importance. Therefore, for different combination of "Information Availability" and "Work sequence," the effect matrices of the variables are added to each other. For example, when "Information availability" is in "Bad" state and "Work Sequence" is in "Excellent" state, the calculation is as follows:

$$\frac{1}{2} \times \begin{bmatrix} 0.05 \\ .0.05 \\ 0.9 \end{bmatrix} + \frac{1}{2} \times \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix} = \begin{bmatrix} 0.525 \\ 0.025 \\ 0.45 \end{bmatrix}$$

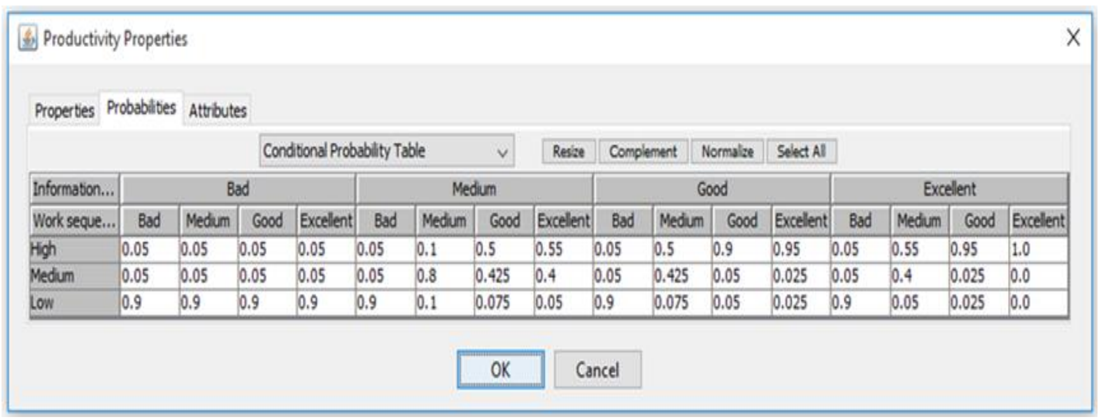
The CPT of productivity based on this approach is shown in figure 5.13.

In the *"combined"* method, The CPT of productivity based on this approach is shown in figure 5.14.



Information...	Bad				Medium				Good				Excellent			
Work seque...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	0.05	0.075	0.475	0.525	0.075	0.1	0.5	0.55	0.475	0.5	0.9	0.95	0.525	0.55	0.95	1.0
Medium	0.05	0.425	0.05	0.025	0.425	0.8	0.425	0.4	0.05	0.425	0.05	0.025	0.025	0.4	0.025	0.0
Low	0.9	0.5	0.475	0.45	0.5	0.1	0.075	0.05	0.475	0.075	0.05	0.025	0.45	0.05	0.025	0.0

Figure 5.13: The CPT of Productivity of Figure 5.11(a)'s Network Based on "weighted average" Method



Information...	Bad				Medium				Good				Excellent			
Work seque...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	0.05	0.05	0.05	0.05	0.05	0.1	0.5	0.55	0.05	0.5	0.9	0.95	0.05	0.55	0.95	1.0
Medium	0.05	0.05	0.05	0.05	0.05	0.8	0.425	0.4	0.05	0.425	0.05	0.025	0.05	0.4	0.025	0.0
Low	0.9	0.9	0.9	0.9	0.9	0.1	0.075	0.05	0.9	0.075	0.05	0.025	0.9	0.05	0.025	0.0

Figure 5.14: The CPT of Productivity of Figure 5.11(a)'s Network Based on "combined" Method

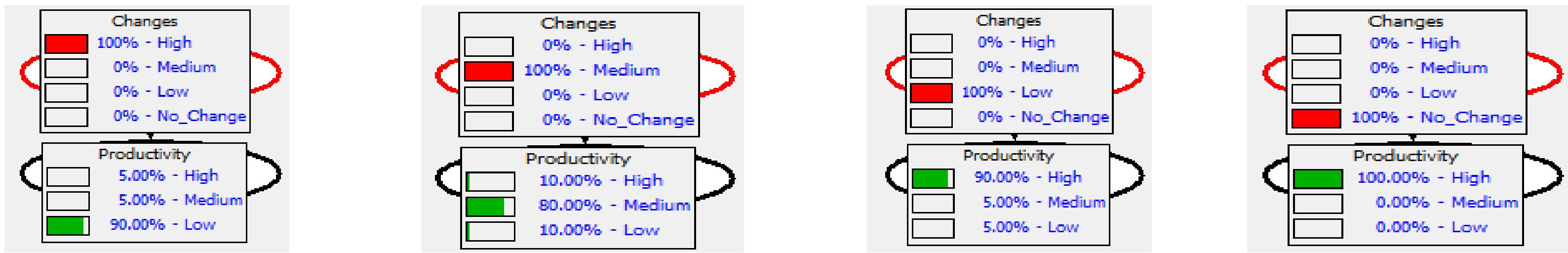
For selecting the best approach, it is necessary to compare these approaches with the base model and see which one has the least deviance. For this purpose, we first check four boundary states, it means that we use the "set by intervention" approach to check which approach is the best one. If we can't distinguish the best approach with this method, it is necessary to calculate the expected value of productivity for a wide range of combination of “changes” states and compare the expected value of productivity for these combinations. In the figure 5.15, this comparison for boundary states is shown.

We can easily understand from figure 5.15 that for all four different states of the “changes” variable, the marginal distribution of the “productivity” variable for different approaches of obtaining the CPT of productivity is the same. There exist situations that we can easily distinguish between different approaches; however, for this specific sub model, we need to investigate more to choose the best approach. For this purpose, ten combination of changes’ probability are selected randomly and we run the model to see marginal probability distribution of productivity for different approaches. Then, the expected value of productivity for each approach is calculated and compared with each other. In the table 5.2, these 10 cases are shown.

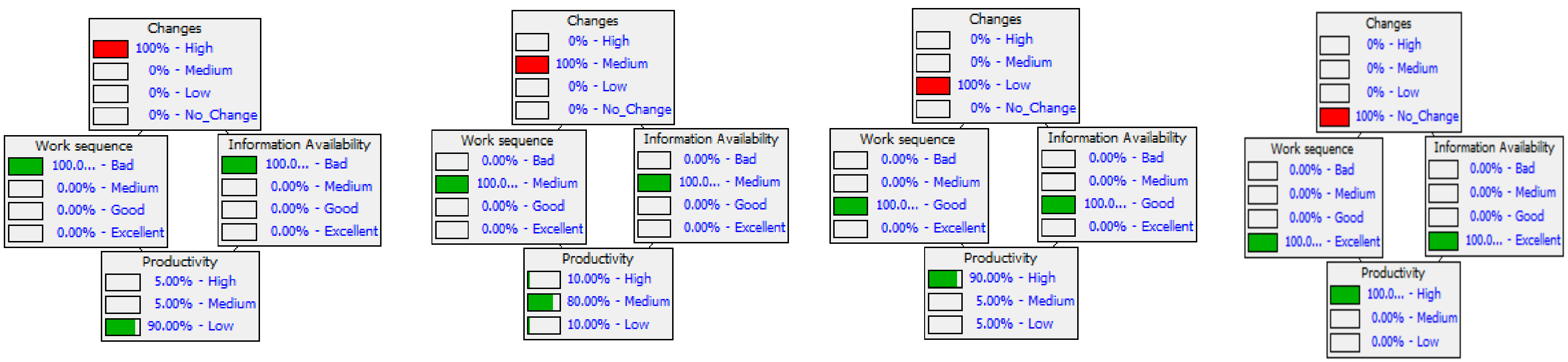
Table 5.2: Ten cases That Are Used for Model Checking

Case Number / Changes	1	2	3	4	5	6	7	8	9	10
High	*10*	*10*	*20*	*30*	*50*	*60*	*30*	*80*	*60*	*20*
Medium	*10*	*20*	*20*	*30*	*30*	*30*	*60*	*10*	*20*	*60*
Low	*10*	*20*	*30*	*20*	*10*	*10*	*0*	*10*	*10*	*10*
No Change	*70*	*50*	*30*	*20*	*10*	*0*	*10*	*0*	*10*	*10*

In the tables 5.3, 5.4, 5.5, and 5.6 the marginal distribution and expected values of productivity for the base network, *“OR gate,”” weighted average,”* and *“combined”* methods are shown, respectively.

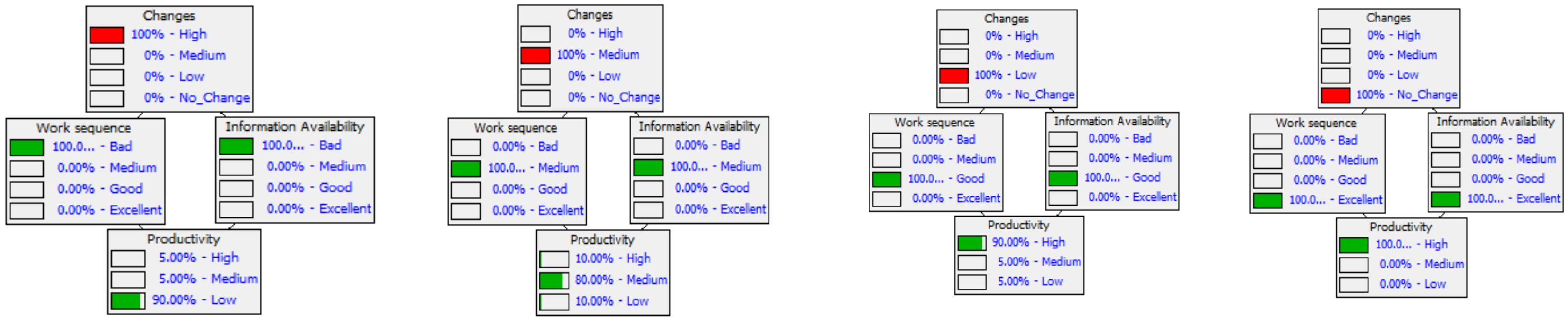


The Marginal Distribution of the Base Network for Different Situations

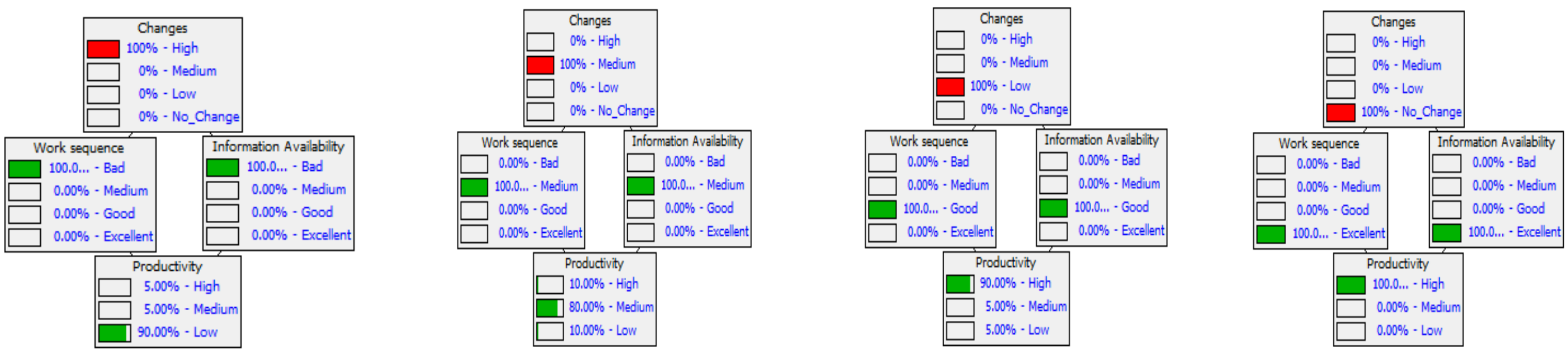


The Marginal Distribution Based on *"OR gate"* for Different Situations

Figure 5.15: Comparison of the Marginal Distribution of Base Network and Network in Figure 5.11(a) for Different Methods of Obtaining Productivity's CPT



The Marginal Distribution Based on *"weighted average"* for Different Situations



The Marginal Distribution Based on *"combined"* method for Different Situations

Figure 5.15: Comparison of the Marginal Distribution of Base Network and Network in Figure 5.11(a) for Different Methods of Obtaining Productivity's CPT (Continuation)

Table 5.3: The Marginal and Expected Values of Productivity of the Base Network

Case Number / Productivity	1	2	3	4	5	6	7	8	9	10
High	*80.5*	*70.5*	*60*	*42.5*	*24.5*	*15*	*17.5*	*14*	*24*	*26*
Medium	*9*	*17.5*	*18.5*	*26.5*	*27*	*27.5*	*49.5*	*12.5*	*19.5*	*49.5*
Low	*10.5*	*12*	*21.5*	*31*	*48.5*	*57.5*	*33*	*73.5*	*56.5*	*24.5*
Expected Value of Productivity	*92*	*90.85*	*88.85*	*86.15*	*82.6*	*80.75*	*83.45*	*79.05*	*81.75*	*85.15*

Table 5.4: The Marginal and Expected Values of Productivity of the Figure 5.11(a) Based on "OR gate" Method

Case Number / Productivity	1	2	3	4	5	6	7	8	9	10
High	*65.15*	*50.75*	*37.9*	*20.65*	*9.55*	*6.6*	*8.35*	*6*	*9.1*	*11.5*
Medium	*15.3*	*27.75*	*25.55*	*29.55*	*20.7*	*16.25*	*40.95*	*7.25*	*13.95*	*49.95*
Low	*19.55*	*21.5*	*36.55*	*49.8*	*69.75*	*77.15*	*50.7*	*86.75*	*76.95*	*38.55*
Expected Value of Productivity	*89.56*	*87.93*	*85.14*	*82.09*	*78.98*	*77.95*	*80.77*	*76.93*	*78.22*	*82.30*

Table 5.5: The Marginal and Expected Values of Productivity of the Figure 5.11(a) Based on "weighted average" Method

Case Number / Productivity	1	2	3	4	5	6	7	8	9	10
High	*80.5*	*70.5*	*60*	*42.5*	*24.5*	*15*	*17.5*	*14*	*24*	*26*
Medium	*9*	*17.5*	*18.5*	*26.5*	*27*	*27*	*49.5*	*12.5*	*19.5*	*49.5*
Low	*10.5*	*12*	*21.5*	*31*	*48.5*	*57.5*	*33*	*73.5*	*56.5*	*24.5*
Expected Value of Productivity	*92*	*90.85*	*88.85*	*86.15*	*82.6*	*80.33*	*83.45*	*79.05*	*81.75*	*85.15*

Table 5.6: The Marginal and Expected Values of Productivity of the Figure 5.11(a) Based on "combined" Method

Case Number / Productivity	1	2	3	4	5	6	7	8	9	10
High	*72.95*	*63.95*	*49*	*31.25*	*14.75*	*9*	*13.75*	*6.8*	*12.6*	*21.8*
Medium	*8.6*	*16.25*	*15.8*	*20.05*	*16*	*14*	*36.15*	*6.5*	*10.8*	*40.6*
Low	*18.45*	*19.8*	*35.2*	*48.7*	*69.25*	*77*	*50.1*	*86.7*	*76.8*	*37.6*
Expected Value of Productivity	*90.45*	*89.42*	*86.38*	*83.26*	*79.55*	*78.2*	*81.37*	*77.01*	*78.75*	*83.42*

By plotting these numbers and comparison of these scenarios with each other, we can understand these methods effects in a better way. In the figure 5.16, this plot is shown. From the figure, several facts about different methods can be understood. These facts are as follows:

1. The *"weighted average"* method has the least amount of errors.
2. The "OR gate" has the highest amount errors.
3. The "combined" method is between "weighted average" and "OR gate" in term of errors.
4. Although "OR gate" has the highest level of errors, in the worst case it has less than 5% of errors. This level of error (errors between 0-5%) is acceptable for this kind of probabilistic prediction.

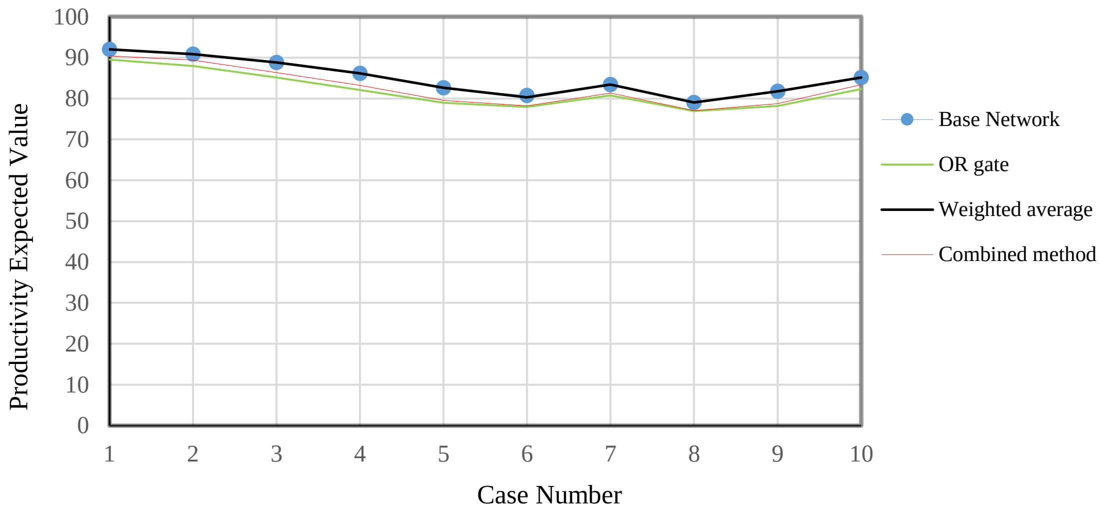
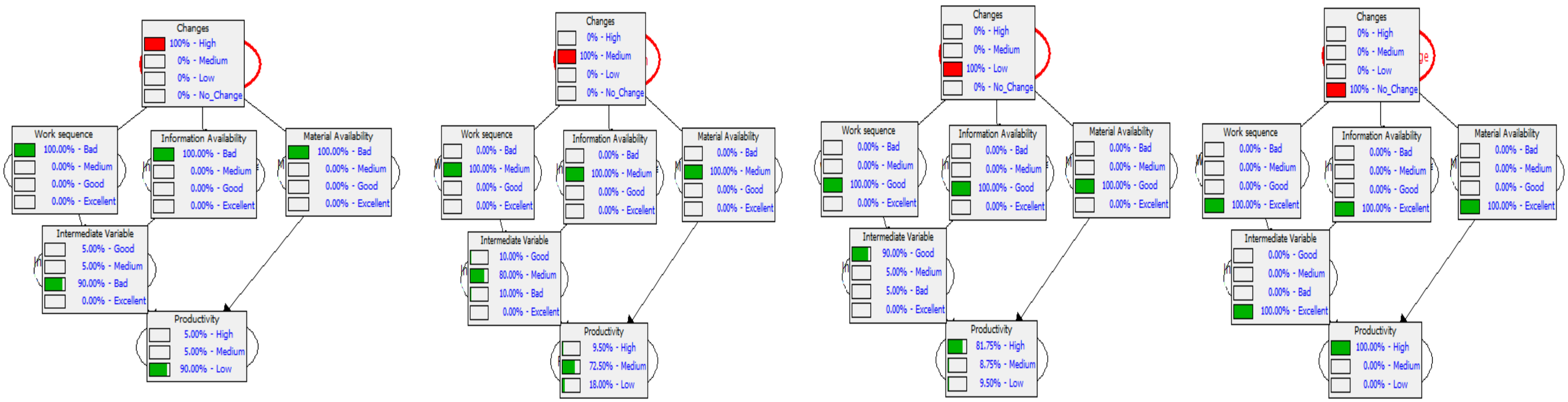


Figure 5.16: The Comparison of Different Approaches

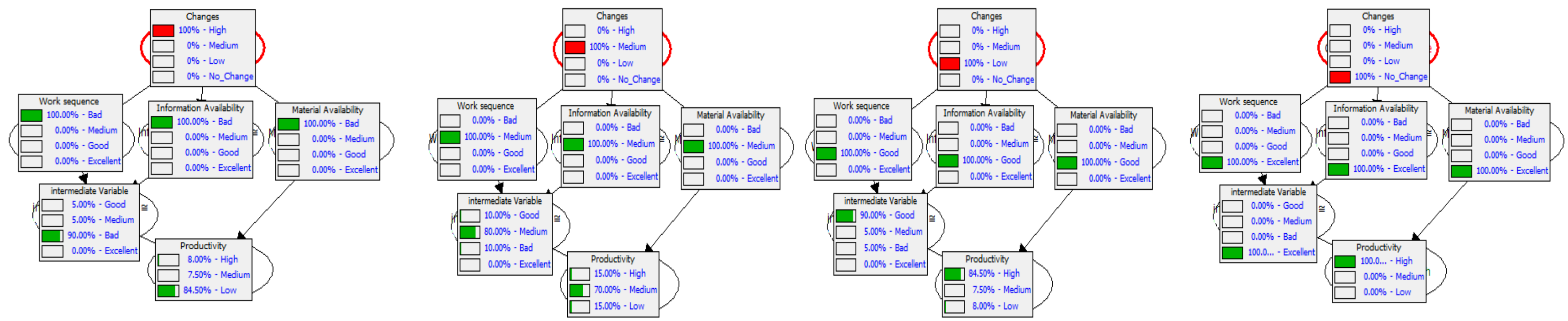
In the next step, by adding an intermediate variable with the same state space as its parents, the network that is shown in figure 5.11(b) is built. In the last step, the “material availability” is added to the 5.11(b) network to build 5.11(c) network. Then, the previous process similar to previous is repeated to choose the appropriate approach among the three different methods to combine the effects of “Intermediate variable” and “material availability” on the “Productivity” with three approaches. For comparing the performance of the networks, the same previous process repeat again. In figure 5.17, the comparison of these models with the “base network” for boundary states is shown.

The Marginal Distribution of the Base Network for Different Situations

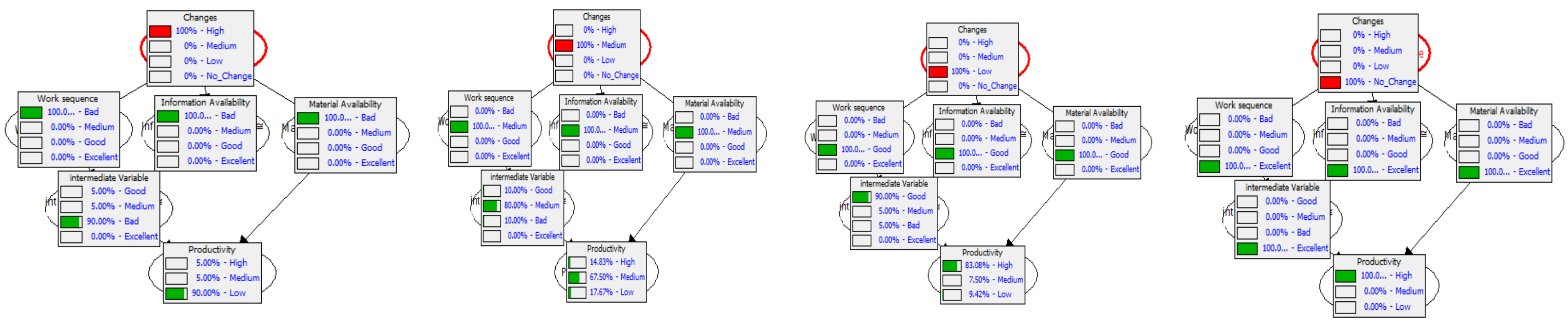


The Marginal Distribution Based on *"OR gate"* method for Different Situations

Figure 5.17: The Comparison of the Marginal Distribution of Base Network and Network in Figure 5.11(c) for Different Methods of Obtaining Productivity's CPT



The Marginal Distribution Based on *“Weighted average”* method for Different Situations



The Marginal Distribution Based on *“combined”* method for Different Situations

Figure 5.17: The Comparison of the Marginal Distribution of Base Network and Network in Figure 5.11(c) for Different Methods of Obtaining Productivity’s CPT (Continuation)

From these marginal distribution for different states of the "changes," the following facts can be understood:

1. Whenever the "changes" is in the "High" state, the *"OR gate"* and *"Combined"* methods have better performance than *"weighted average"* method. However, the difference between all three methods is negligible.

2. In the "no change" state, all three methods are the same.

3. In the "medium" state, the *"OR gate"* and *"weighted average"* have better performance than the *"combined"* method.

The same cases as shown in the table 5.1 are used to investigate more deeply these three approaches and select the best one. We ignore putting all related tables here and just show the diagram in the figure 5.18.

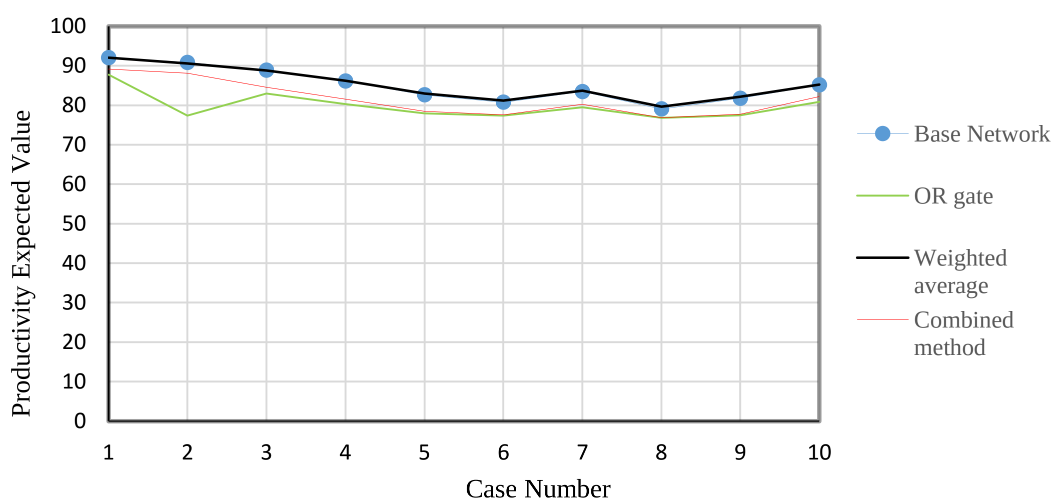


Figure 5.18 The Comparison of Different Approaches for the Network in Figure 5.11(c)

It is obvious from figure 5.18 that the “weighted average” has the best performance and, except for one case, the errors of the other two methods are also negligible. The marginal values of productivity for these cases and for the “weighted average” method is shown in table 5.7. Note that the comparison of table 5.7 and table 5.3 shows that marginal distribution of the “base network” and the network in figure 5.11(c) are very close to each other.

Table 5.7: The Marginal and Expected Values of Productivity of Figure 5.11(c) Based on “Weighted average” Method

Case Number Productivity	1	2	3	4	5	6	7	8	9	10
High	*80.75*	*70.5*	*59.95*	*43.8*	*26.95*	*17.75*	*21.4*	*16.35*	*26.25*	*29.05*
Medium	*8.5*	*16.25*	*17.75*	*24.75*	*25.5*	*26.25*	*44.25*	*13.75*	*19.25*	*44.25*
Low	*10.75*	*13.05*	*22.3*	*31.45*	*47.55*	*56*	*34.35*	*69.9*	*54.5*	*26.7*
Expected Value of Productivity	*92*	*90.575*	*88.765*	*86.235*	*82.94*	*81.175*	*83.705*	*79.645*	*82.175*	*85.235*

For the completeness, all the CPTs of the network in the figure 5.11(c), except “changes,” are showed here. Note that the CPT of the “change” will be obtained in the next section.

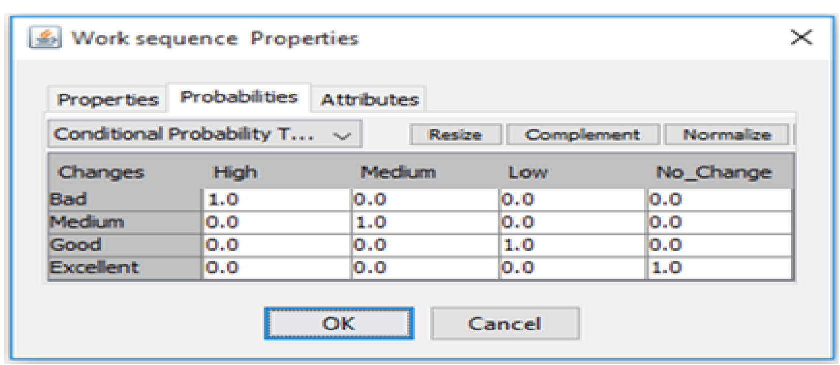
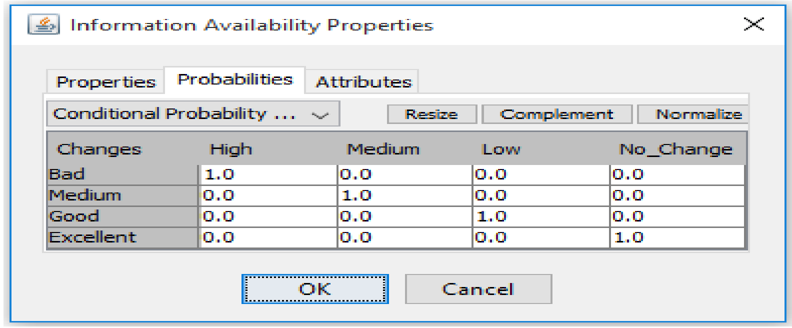


Figure 5.19: CPT of “Work sequence”



Information Availability Properties

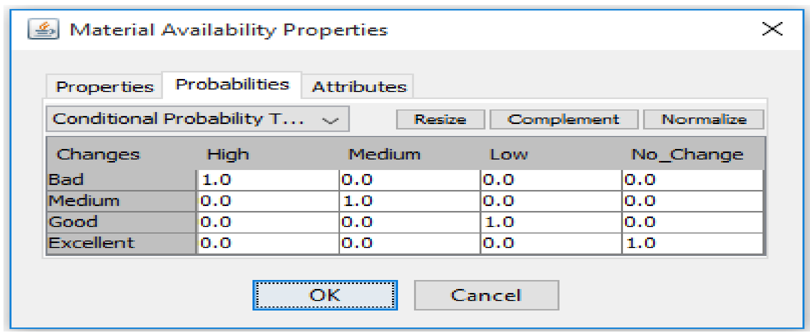
Properties | Probabilities | Attributes

Conditional Probability ... | Resize | Complement | Normalize

Changes	High	Medium	Low	No_Change
Bad	1.0	0.0	0.0	0.0
Medium	0.0	1.0	0.0	0.0
Good	0.0	0.0	1.0	0.0
Excellent	0.0	0.0	0.0	1.0

OK | Cancel

Figure 5.20: CPT of “Information Availability”



Material Availability Properties

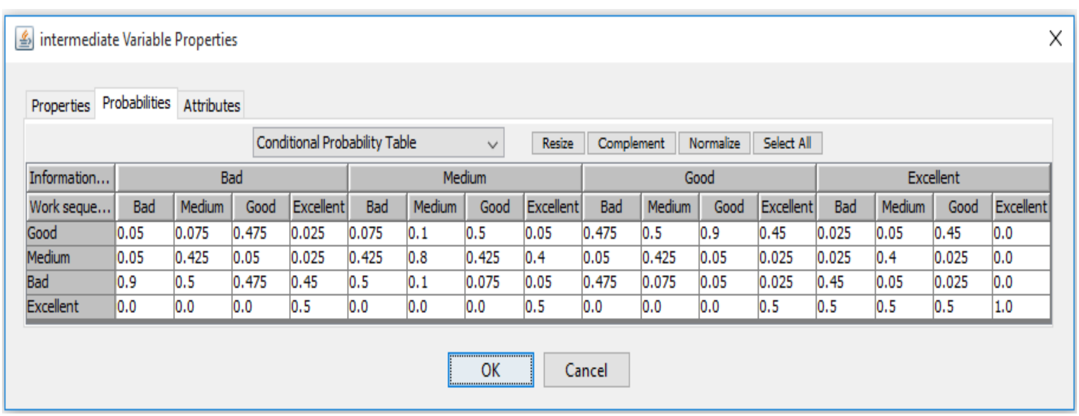
Properties | Probabilities | Attributes

Conditional Probability T... | Resize | Complement | Normalize

Changes	High	Medium	Low	No_Change
Bad	1.0	0.0	0.0	0.0
Medium	0.0	1.0	0.0	0.0
Good	0.0	0.0	1.0	0.0
Excellent	0.0	0.0	0.0	1.0

OK | Cancel

Figure 5.21: CPT of “Material Availability”



intermediate Variable Properties

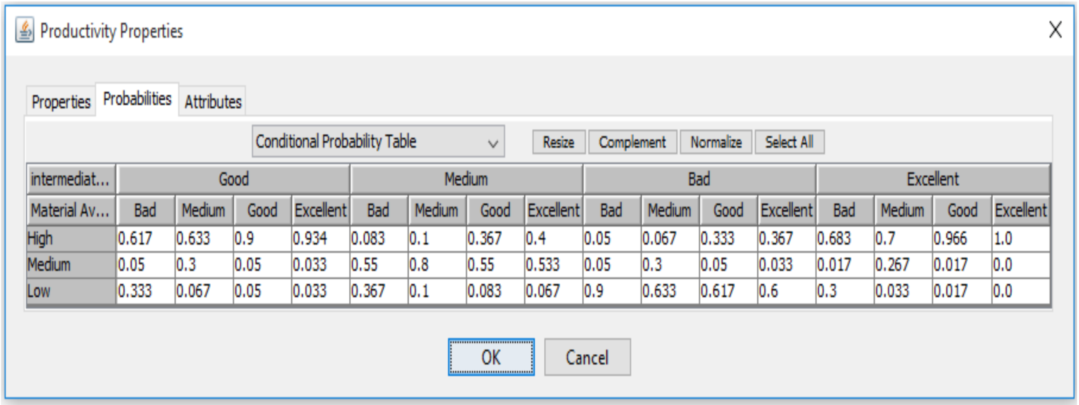
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Information...	Bad				Medium				Good				Excellent			
Work seque...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
Good	0.05	0.075	0.475	0.025	0.075	0.1	0.5	0.05	0.475	0.5	0.9	0.45	0.025	0.05	0.45	0.0
Medium	0.05	0.425	0.05	0.025	0.425	0.8	0.425	0.4	0.05	0.425	0.05	0.025	0.025	0.4	0.025	0.0
Bad	0.9	0.5	0.475	0.45	0.5	0.1	0.075	0.05	0.475	0.075	0.05	0.025	0.45	0.05	0.025	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

OK | Cancel

Figure 5.22: CPT of “Intermediate Variable”



intermediat...	Good				Medium				Bad				Excellent			
Material Av...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	0.617	0.633	0.9	0.934	0.083	0.1	0.367	0.4	0.05	0.067	0.333	0.367	0.683	0.7	0.966	1.0
Medium	0.05	0.3	0.05	0.033	0.55	0.8	0.55	0.533	0.05	0.3	0.05	0.033	0.017	0.267	0.017	0.0
Low	0.333	0.067	0.05	0.033	0.367	0.1	0.083	0.067	0.9	0.633	0.617	0.6	0.3	0.033	0.017	0.0

Figure 5.23: CPT of "Productivity"

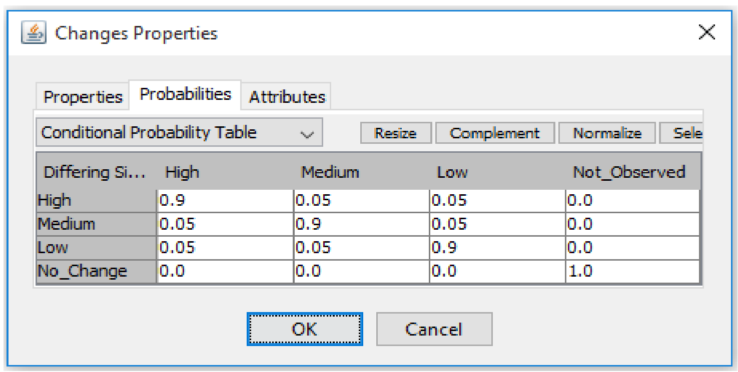
5.2.2 The Procedure for Extracting CPTs of the Network in Figure 5.3

The "Changes" variable in the network that is shown in figure 5.3 has six parents. Each parent variable in this network has four states; therefore, for extracting CPT of the "changes," we need to build a table with $4^7 = 16384$ entries. Extracting this table directly is impossible and causes numerous problems in inference algorithms behind BBN. We use the "Temporal Transformation" and "Parent Divorcing" approaches to modify the structure of the network and extract the CPTs of the network in an easier way. Also, the "Independence of Causal Influence" and "Set value by Intervention" are used to help us extract the network's CPTs. In the first step, it is necessary to understand the effects of these variables individually on the "Changes" variable. Hanna and Russel investigated the severity degree of different factors that influence changes (change order) (2001). Based on this research, the following statements can be concluded (Hanna and Russell 2001):

- Differing site conditions has "severe" effects on changes.
- Adverse weather conditions has "mild" effects on changes

- Incomplete design has “severe” effects on labor productivity.
- Adverse team management has “severe” effects on changes.
- Owner-furnished equipment has mild (medium) impact on changes.
- Defective specification has “severe” effects on changes.

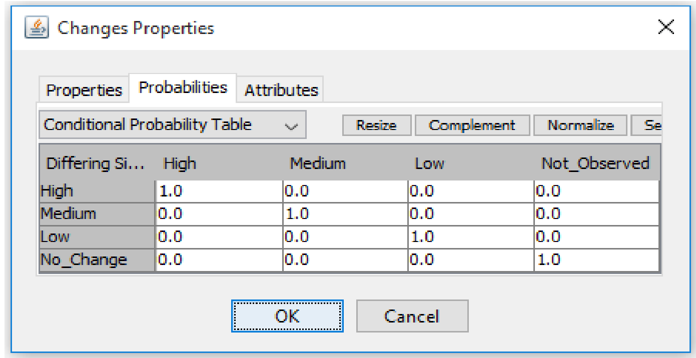
Based on these statements, for variables that have “severe” effects such as “Differing Site Conditions,” we can set up the CPT that is shown in the figure 5.24.



Differing Si...	High	Medium	Low	Not_Observed
High	0.9	0.05	0.05	0.0
Medium	0.05	0.9	0.05	0.0
Low	0.05	0.05	0.9	0.0
No_Change	0.0	0.0	0.0	1.0

Figure 5.24: CPT of the “ Change” When the “Differing Site Condition” Is Its Parent

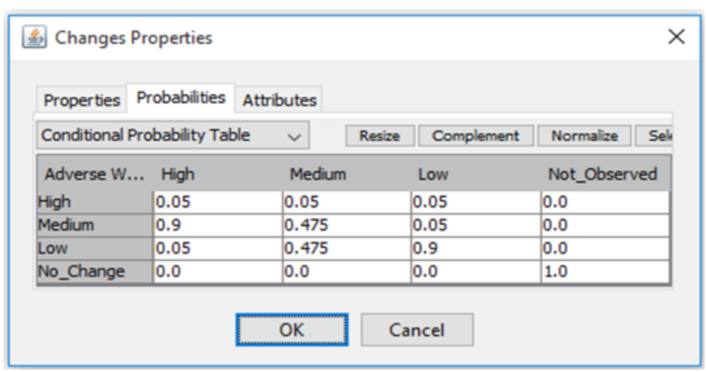
In this CPT, we have to put 1 instead of 0.9 and 0 instead of 0.05, but since 1 is reserved for “Not observed” state, we use 0.9 and distribute 0.1 between the other two states. If we replace the above CPT with the CPT that is shown in the figure 5.25, the overall difference in the model is negligible. We continue the model construction with the CPT that is shown in the figure 5.24 and use 1 for other purposes such as combining the cause variables effects.



Differing Si...	High	Medium	Low	Not_Observed
High	1.0	0.0	0.0	0.0
Medium	0.0	1.0	0.0	0.0
Low	0.0	0.0	1.0	0.0
No_Change	0.0	0.0	0.0	1.0

Figure 5.25: Another Option of the CPT of the “ Change” When the “Differing Site Condition” Is Its Parent

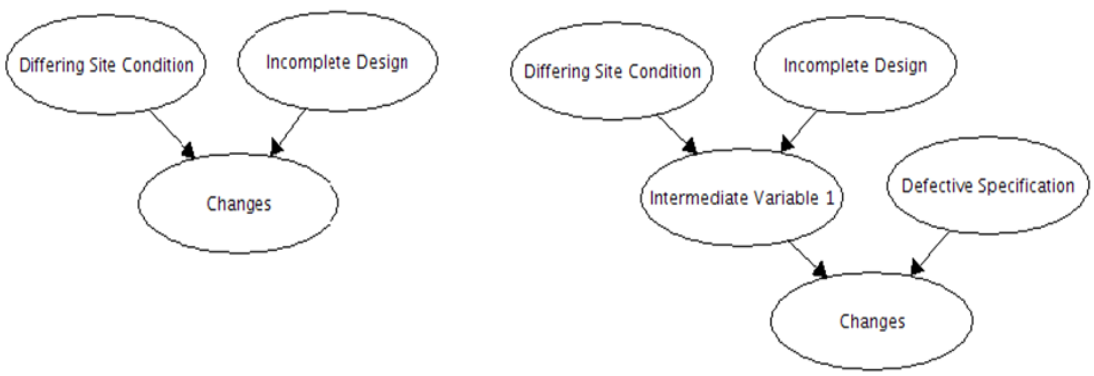
For variables that have “mild” effects on the “change,” we decrease the impact level by one in the CPT of the “change” and then by using the same logic as explained above, we can extract the CPT of those variables. For example, the CPT of the “changes” under the effects of the “Adverse Weather” variable is shown in the figure 5.26.



Adverse W...	High	Medium	Low	Not_Observed
High	0.05	0.05	0.05	0.0
Medium	0.9	0.475	0.05	0.0
Low	0.05	0.475	0.9	0.0
No_Change	0.0	0.0	0.0	1.0

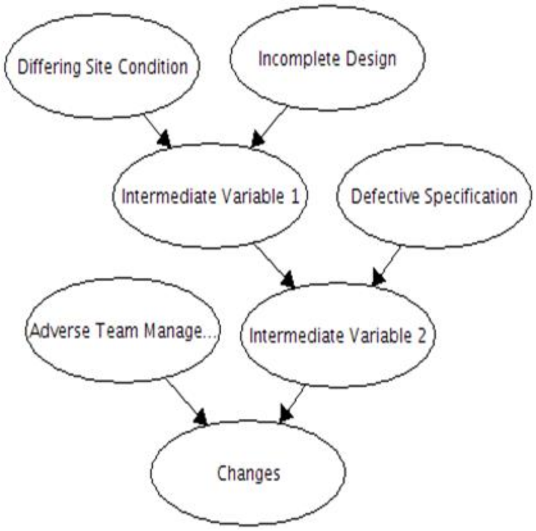
Figure 5.26: CPT of the “ Change” When the “Adverse Weather” Is Its Parent

In the next step, the effects of different variables using “Temporal Transformation” approach should be combined. We start with variables that have "severe" effects on "changes," then, at the end, we add the effects of variables with "mild" effects. For the variable with "severe" effects on "changes", the best approach for combining their effects on "changes" is "combined" approach. The reason for selecting "combined" approach is that whenever a variable with "severe" effects on the "change" is in its worst state, other variable(s) state(s) cannot prevent the state of the "change" from being "high." For building the network that is shown in figure 5.3, we need to build a sequence of networks. This sequence of networks is shown in the figure 5.27.

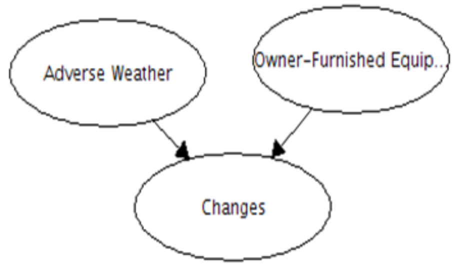


(a) (b)

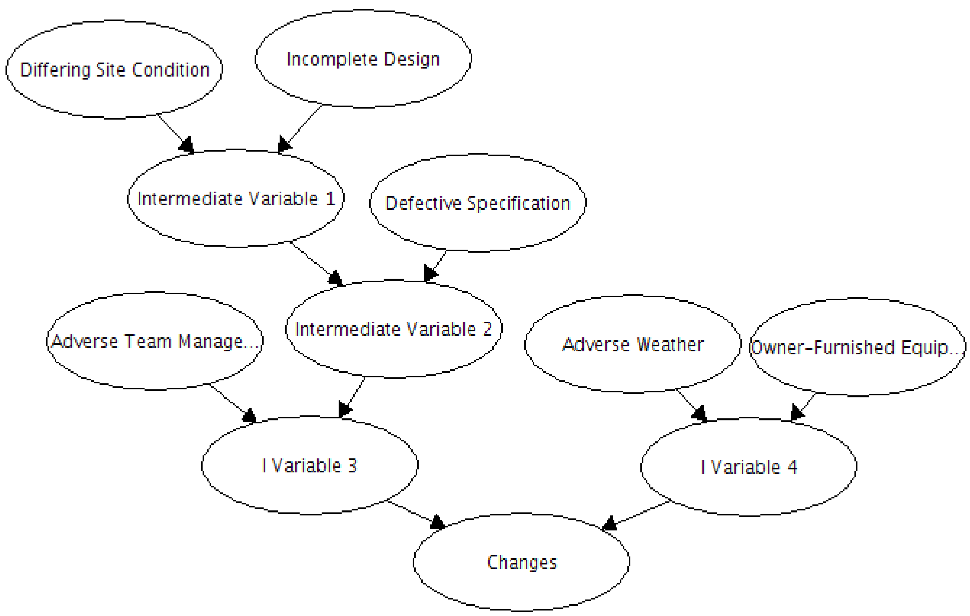
Figure 5.27: The Sequence of Networks Used to Build the Network of Figure 5.3



(c)



(d)



(e)

Figure 5.27: The Sequence of Networks Used to Build the Network of Figure 5.3

(Continuation)

Note that for combining the effects of variable that have "severe" effects on changes, the "Temporal Transformation" method is used to combine the effects of them, as shown in figure 5.27(a), (b), and (c). For combining the effects of "Adverse Weather" and "Owner-Furnished Equipment," because these variables have "mild" effects on "changes" then the "weighted average" method is a better way to combine the effects of these variables. Also, for the purpose of showing the effects of "severe" situations of multiple factors, instead of 0.9 in that state, higher values such as 0.925, 0.95 or 0.975 are used, although this slight variation does not affect the model. With respect to this discussion, CPTs of the network that is shown in the figure 5.27(e) are obtained. For the completeness, all CPTs of the network in the figure 5.27(e) are shown here. Note that it is not necessary to obtain root variables CPTs and they can be observed.

Intermediate Variable 1 Properties

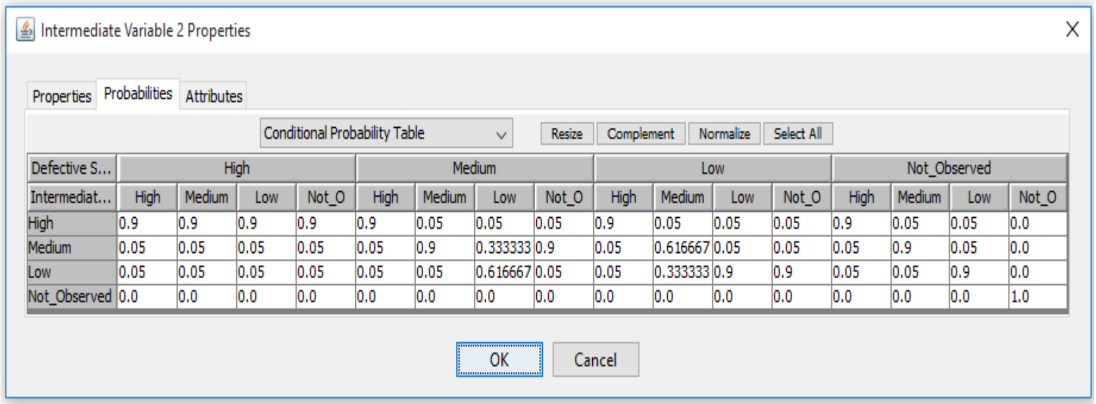
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Differing Sit...	High				Medium				Low				Not_Observed			
Incomplete ...	High	Medium	Low	Not_O	High	Medium	Low	Not_O	High	Medium	Low	Not_O	High	Medium	Low	Not_O
High	0.925	0.9	0.9	0.9	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.0
Medium	0.05	0.05	0.05	0.05	0.05	0.9	0.475	0.9	0.05	0.475	0.05	0.05	0.05	0.9	0.05	0.0
Low	0.025	0.05	0.05	0.05	0.05	0.05	0.475	0.05	0.05	0.475	0.9	0.9	0.05	0.05	0.9	0.0
Not_O	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

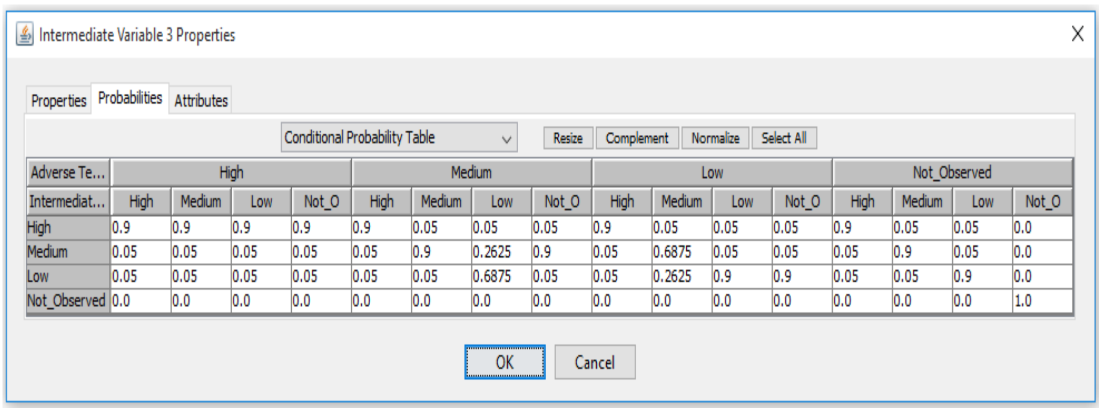
OK | Cancel

Figure 5.28: CPT of "Intermediate Variable 1"



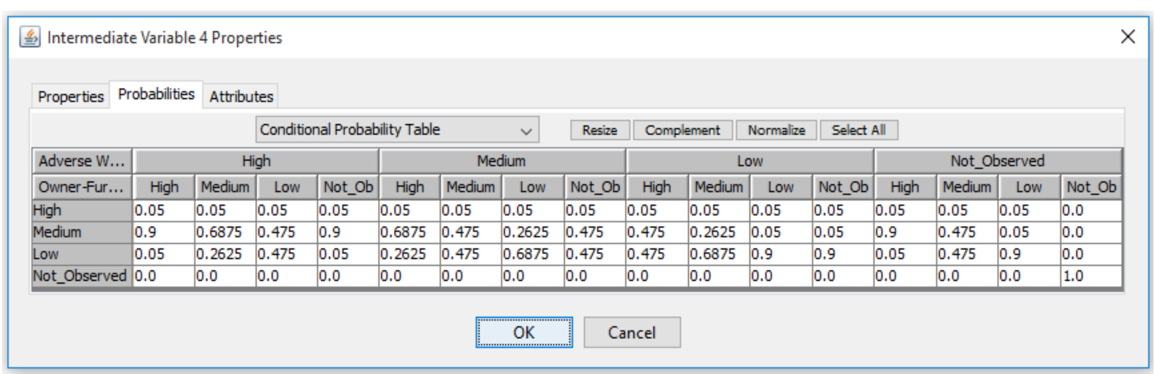
Defective S...	High				Medium				Low				Not_Observed			
Intermediat...	High	Medium	Low	Not_O	High	Medium	Low	Not_O	High	Medium	Low	Not_O	High	Medium	Low	Not_O
High	0.9	0.9	0.9	0.9	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.0
Medium	0.05	0.05	0.05	0.05	0.05	0.9	0.333333	0.9	0.05	0.616667	0.05	0.05	0.05	0.9	0.05	0.0
Low	0.05	0.05	0.05	0.05	0.05	0.05	0.616667	0.05	0.05	0.333333	0.9	0.9	0.05	0.05	0.9	0.0
Not_Observed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure 5.29: CPT of “Intermediate Variable 2”



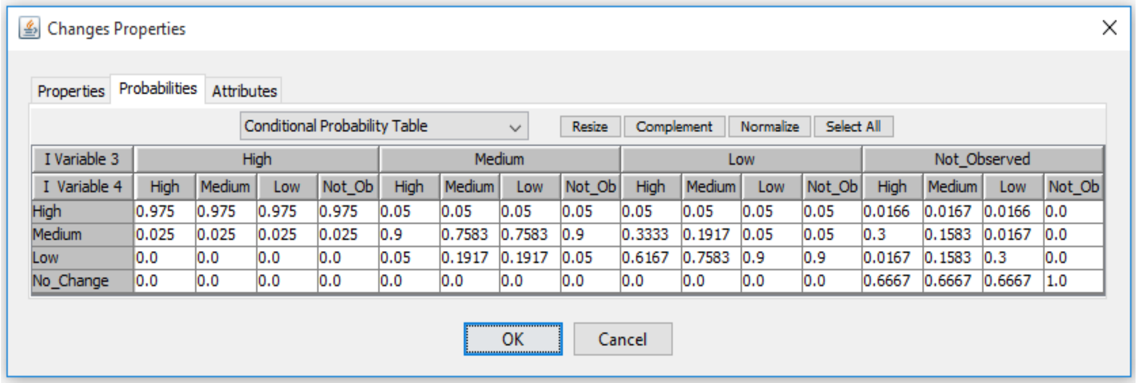
Adverse Te...	High				Medium				Low				Not_Observed			
Intermediat...	High	Medium	Low	Not_O	High	Medium	Low	Not_O	High	Medium	Low	Not_O	High	Medium	Low	Not_O
High	0.9	0.9	0.9	0.9	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.0
Medium	0.05	0.05	0.05	0.05	0.05	0.9	0.2625	0.9	0.05	0.6875	0.05	0.05	0.05	0.9	0.05	0.0
Low	0.05	0.05	0.05	0.05	0.05	0.05	0.6875	0.05	0.05	0.2625	0.9	0.9	0.05	0.05	0.9	0.0
Not_Observed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure 5.30: CPT of “Intermediate Variable 3”



Adverse W...	High				Medium				Low				Not_Observed			
Owner-Fur...	High	Medium	Low	Not_Ob	High	Medium	Low	Not_Ob	High	Medium	Low	Not_Ob	High	Medium	Low	Not_Ob
High	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.0
Medium	0.9	0.6875	0.475	0.9	0.6875	0.475	0.2625	0.475	0.475	0.2625	0.05	0.05	0.9	0.475	0.05	0.0
Low	0.05	0.2625	0.475	0.05	0.2625	0.475	0.6875	0.475	0.475	0.6875	0.9	0.9	0.05	0.475	0.9	0.0
Not_Observed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure 5.31: CPT of “Intermediate Variable 4”



I Variable 3	High				Medium				Low				Not_Observed			
I Variable 4	High	Medium	Low	Not_Ob	High	Medium	Low	Not_Ob	High	Medium	Low	Not_Ob	High	Medium	Low	Not_Ob
High	0.975	0.975	0.975	0.975	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.0166	0.0167	0.0166	0.0
Medium	0.025	0.025	0.025	0.025	0.9	0.7583	0.7583	0.9	0.3333	0.1917	0.05	0.05	0.3	0.1583	0.0167	0.0
Low	0.0	0.0	0.0	0.0	0.05	0.1917	0.1917	0.05	0.6167	0.7583	0.9	0.9	0.0167	0.1583	0.3	0.0
No_Change	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6667	0.6667	0.6667	1.0

Figure 5.32: CPT of “Changes” (I variable is Intermediate variable)

5.3 Combining Sub Models’ Structures and CPTs

After building each sub model’s network with its relevant CPTs, these sub models should be combined to each other to build the comprehensive causal network. For this purpose, by combining the “changes” and “overtime” sub models and then adding the other sub models to this network, the comprehensive causal model is constructed. For constructing the causal network of “overtime,” a sequence of networks are necessary to build. These networks are shown in figure 5.33. We can read variables’ name from figure 5.33 (10).

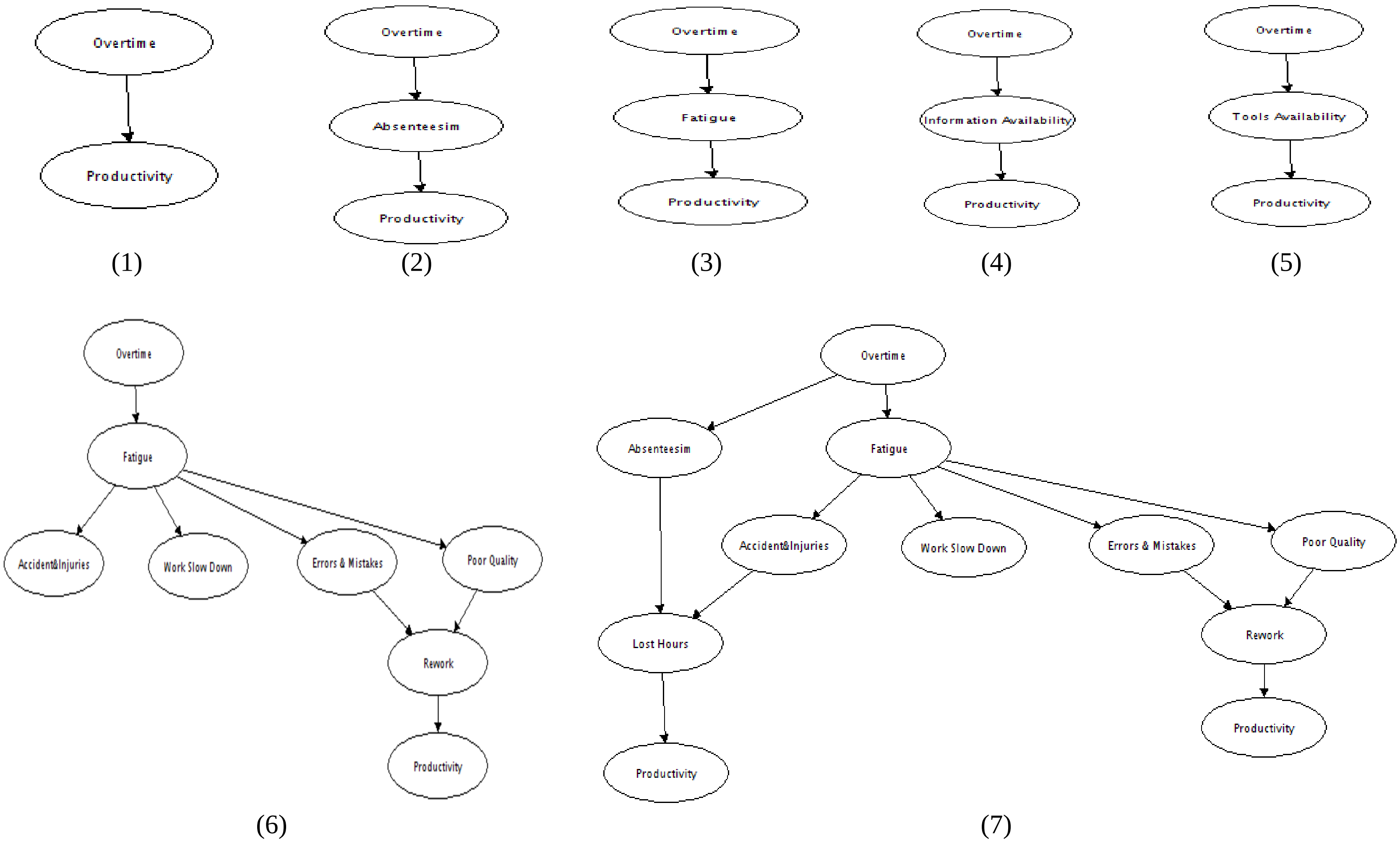
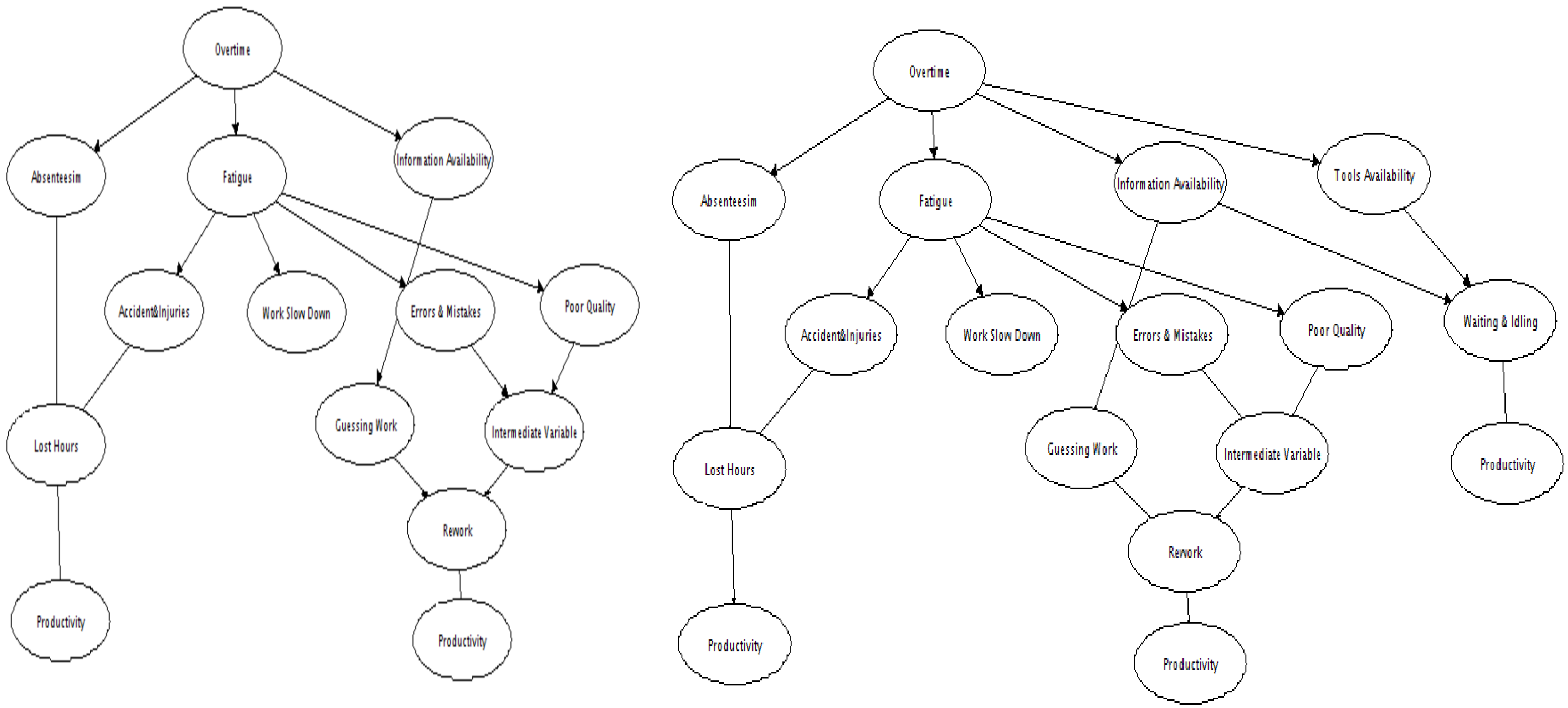
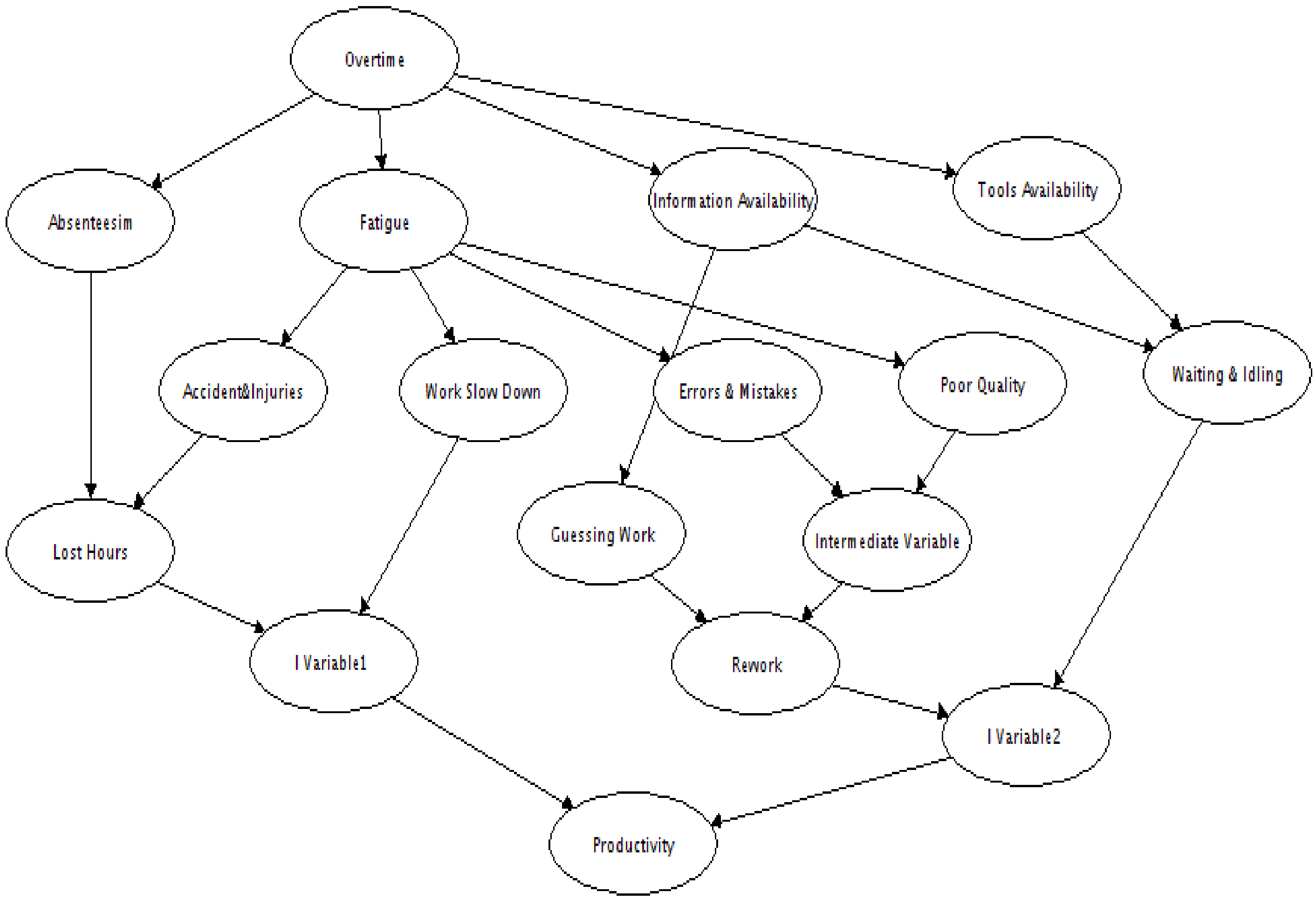


Figure 5.33: The Sequence of Networks That Are Used to Build the “Overtime” Causal Network



(8) (9)

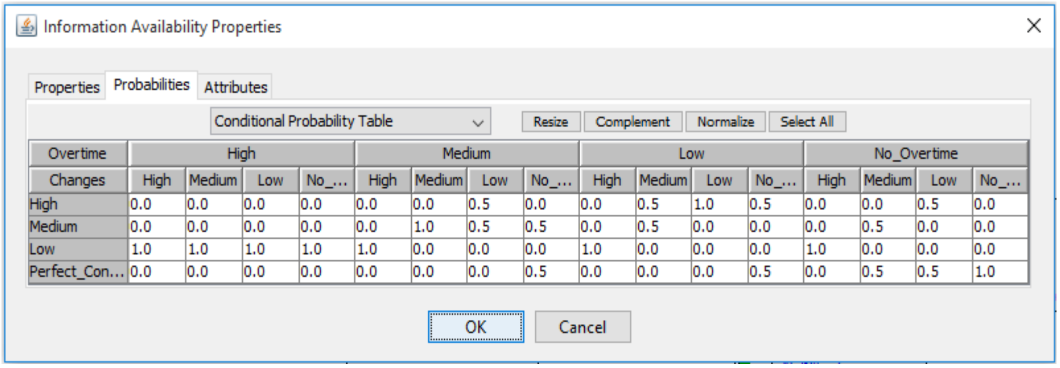
Figure 5.33: The Sequence of Networks That Are Used to Build the “Overtime” Causal Network (Continuation)



(10)

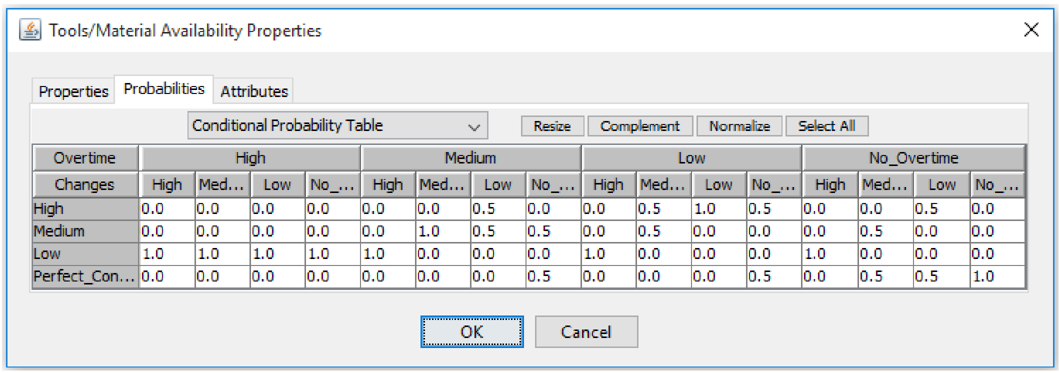
Figure 5.33: The Sequence of Networks That Are Used to Build the “Overtime” Causal Network (Continuation)

In the first iteration for building the comprehensive model, the network in the figure 5.27 (e) and the one in the figure 5.33 (10) must be combined. The combined network is shown in the figure 5.37. There exist three nodes that their CPTs need some modifications. These nodes are “Information Availability,” “Tools/Material Availability” and “Productivity.” For combining these two variable, both “combined” and “weighted average” methods are used. The results of both approach for most combinations of “changes” and “overtime” probability distributions are the same. Since in the worst situation of the “changes” or “overtime,” the state of the other variable is irrelevant, it is better to use the “combined” approach. To make sure the model works correctly, setting the “change” and “overtime” to “No change” and “No Overtime” states, the probability of high “productivity” should be 100%. This fact is shown in figure 5.38. For obtaining CPT of “productivity,” the “weighted average” method is used. Two edges come into “productivity,” one from the “I Variable 3” and one from “Work Sequence.” There are seven edges the come out from “Overtime” and “Changes,” out of this, six of them merges into “I Variable 3” and one of them goes into “Work Sequence.” By assuming equal weight for each edge, “I Variable 3” weight is $\frac{6}{7}$ and “Work Sequence” is $\frac{1}{7}$. New CPTs of “Information Availability,” “Tools/Material Availability” and “Productivity” are shown in figures 5.34, 5.35, and 5.36 respectively. In the figures 5.37 and 5.38 the structure of combined network and its marginal distribution when change and overtime are in “no change” and “no overtime” are shown respectively.



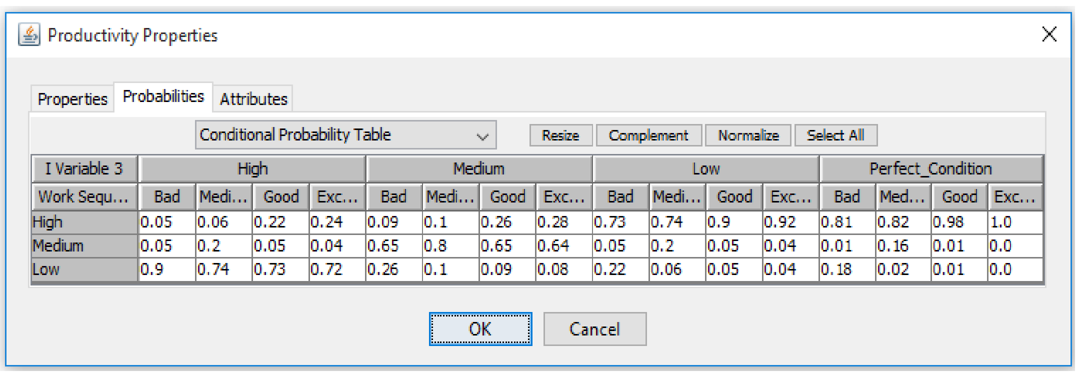
Overtime	High				Medium				Low				No_Overtime			
Changes	High	Medium	Low	No_...	High	Medium	Low	No_...	High	Medium	Low	No_...	High	Medium	Low	No_...
High	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Perfect_Con...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure 5.34: CPT of "Information Availability"



Overtime	High				Medium				Low				No_Overtime			
Changes	High	Med...	Low	No_...	High	Med...	Low	No_...	High	Med...	Low	No_...	High	Med...	Low	No_...
High	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Perfect_Con...	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure 5.35: CPT of "Tools/Material Availability"



I Variable 3	High				Medium				Low				Perfect_Condition			
Work Sequ...	Bad	Medi...	Good	Exc...	Bad	Medi...	Good	Exc...	Bad	Medi...	Good	Exc...	Bad	Med...	Good	Exc...
High	0.05	0.06	0.22	0.24	0.09	0.1	0.26	0.28	0.73	0.74	0.9	0.92	0.81	0.82	0.98	1.0
Medium	0.05	0.2	0.05	0.04	0.65	0.8	0.65	0.64	0.05	0.2	0.05	0.04	0.01	0.16	0.01	0.0
Low	0.9	0.74	0.73	0.72	0.26	0.1	0.09	0.08	0.22	0.06	0.05	0.04	0.18	0.02	0.01	0.0

Figure 5.36: CPT of "Productivity"

Figure 5.37: Combination of the “Changes” and “Overtime” Networks

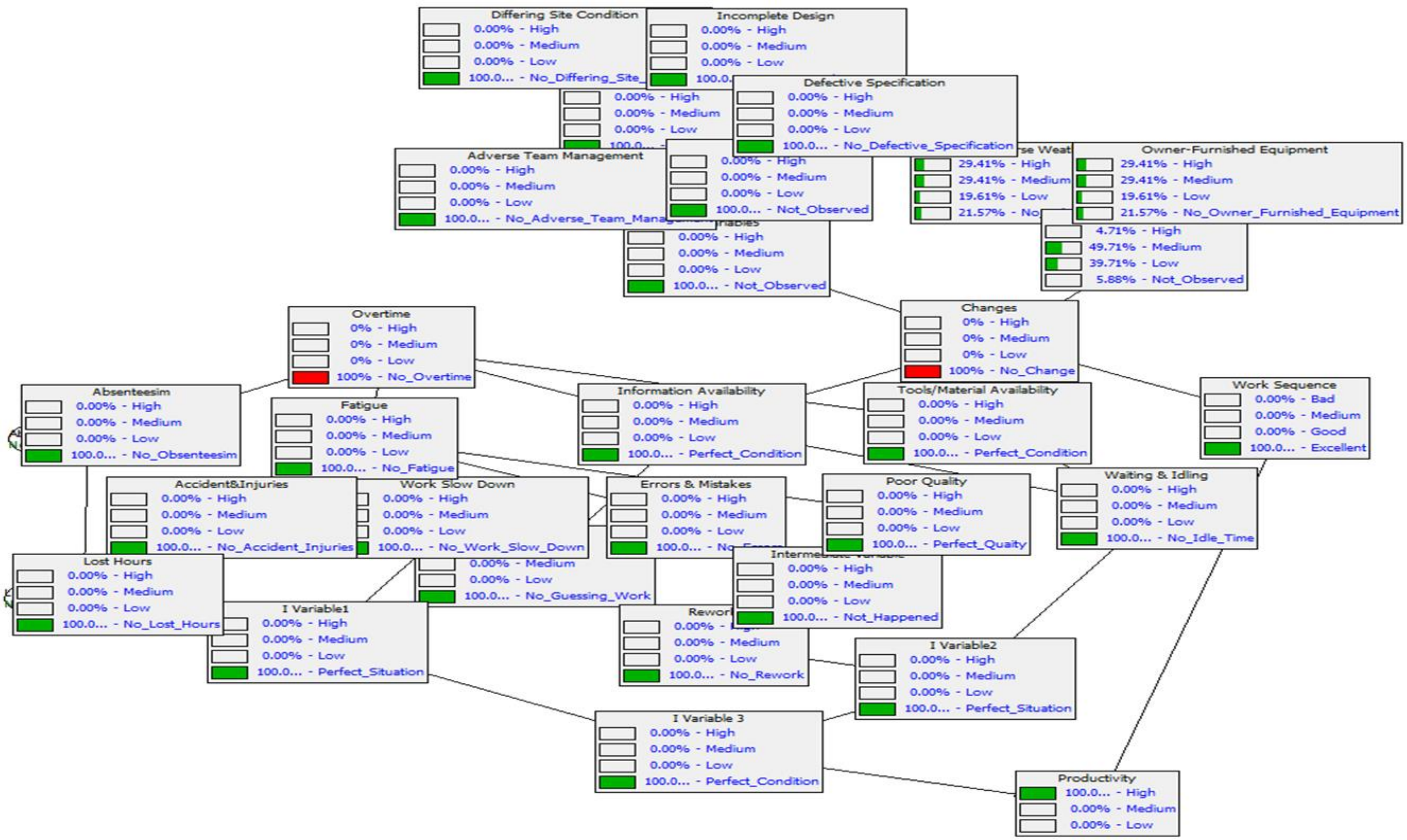


Figure 5.38: Setting "Overtime" and "Changes" into Perfect State and Observing no Productivity Loss as a Model Combination Approach Verification

5.4 The Comprehensive Model

The comprehensive model consists of 99 nodes and 166 edges. It has 16 root variables, 81 internal variables, and two leaf nodes. The network information is represented in the appendix A and B. In the appendix A, each node's parent(s) and child or children are represented. In the appendix B, each node's CPT is represented and in the appendix C a snapshot of the model with its marginal distribution are represented.

Chapter 6

Model Validation and Sensitivity Analysis

According to Lucko and Rojas "validation of the research methodology and its results is a fundamental element of the process of scholarly endeavor" (2010). Several approaches are used to validate the model then by applying sensitivity analysis, the effects of different variables on labor productivity are investigated in depth. The results can be used as a decision support system for project managers to increase their projects' productivity.

6.1 Model Validation

For validating the model, three approaches are used. These are "Root Nodes Boundary Conditions Validation," "Internal Nodes Boundary Condition Validation" and "Face Validation." "Root Nodes Boundary Conditions Validation" and "Internal Nodes Boundary Condition Validation" use the concept of testing the model under extreme conditions. According to this concept, the model should be correct whenever the inputs are in their possible maxima and minima (Lucko and Rojas 2010). The "Face Validation" approach use the idea of validating the model by the experts or industry practitioner. Lucko and Rojas stated that "face validity requires the "approval" of no researchers regarding the validity of a study" (2010).

6.1.1 Root Nodes Boundary Conditions Validation

In this method for validating the model, the root nodes are set into their extreme conditions and the probability of productivity should be within the expected boundary. When all of the 16 root variables are in their perfect conditions, for example adverse weather is in the “Not_Observed” state and workers experience is in the “Excellent” state, it is expected that the probability of high productivity should be 100%. This verification is shown in the figure 6.1. Similarly, when all the root nodes are in their worst conditions, based on what we have defined in chapter 5, it is expected that the probability of low productivity be 90%, medium productivity be 5 %, and high productivity be 5%. By setting these variables in the worst conditions, it can be seen that the probability of high productivity is 89.21%, medium productivity is 5.35% and low productivity is 5.44 %. The comparison of the model’s outcome and what it is expected to be shows that the model’s error is negligible for these extreme conditions. This verification is shown in figure 6.2.

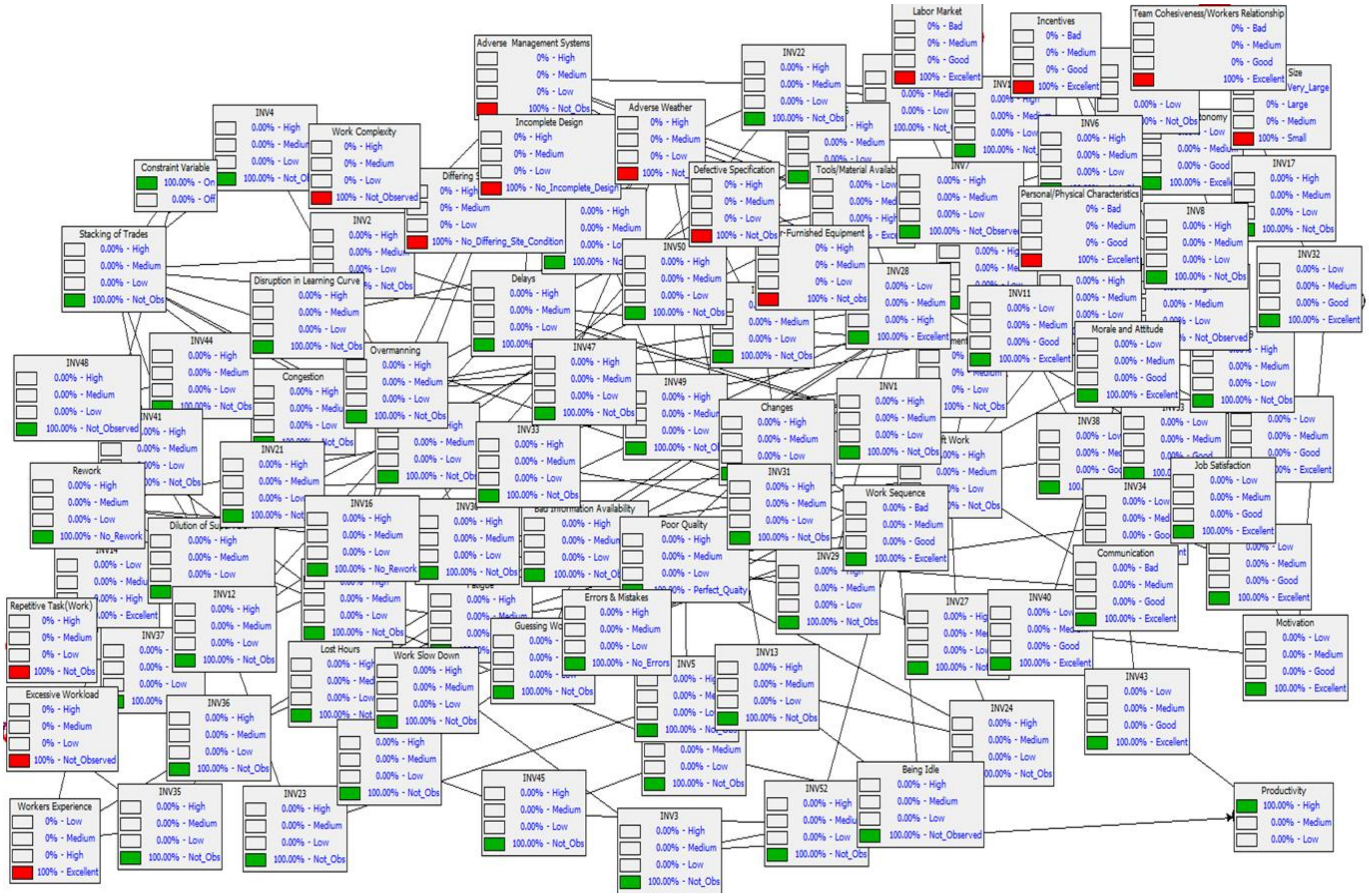


Figure 6.1: Model Verification through Root Nodes' Perfect Conditions

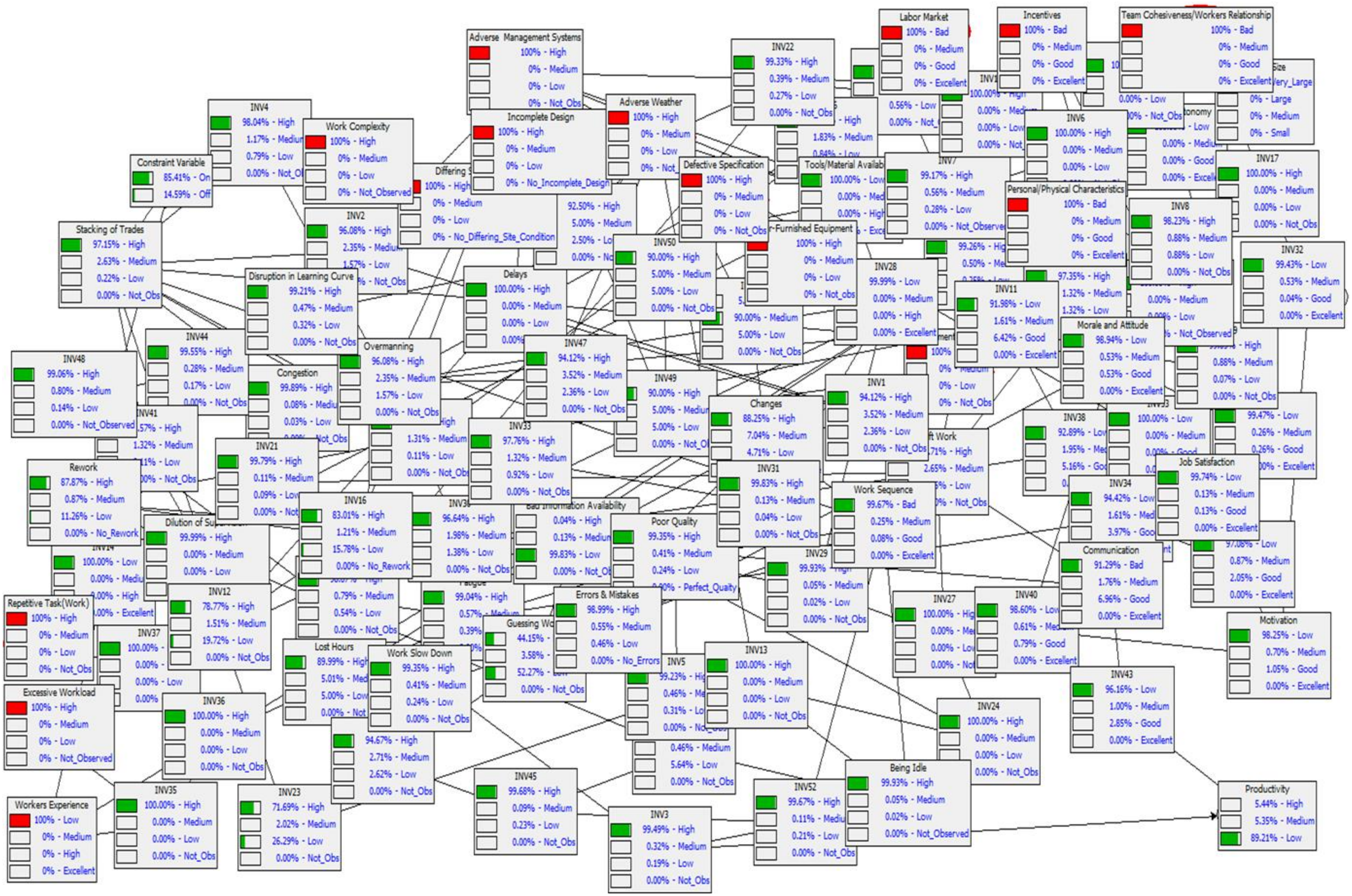


Figure 6.2: Model Verification through Root Nodes' Worst Conditions

6.1.2 Main Nodes Validation

The model is a combination of 12 sub models. It means that when these 12 main variables are set to their perfect or worst conditions, the model should have the same results as an individual sub model. In the first step, by setting these variables in their perfect conditions, it is expected that the probability of “High productivity” will be 100%. This validation is shown in figure 6.3.By applying the same procedure, it is expected that whenever the model’s main variables are in their worst condition, the probability of “Low productivity” will be 90%, medium be 5%, and high be 5%. This verification is shown in figure 6.4. The model’s error for these two boundary conditions are zero percent.

When the model’s main variables are in their “Low” or Good” state, it is expected that the probability of “High productivity” be 90%, medium be 5%, and low be 5%. By setting the model’s main variables into this state, it can be seen from figure 6.5 that the probability of “High productivity” is 88.28%, medium is 5.57%, and low is 6.14%. In the same way, when the main variables are in their “Medium” state it is expected that probability of medium productivity be 90% and high and low productivity be 5% respectively. Setting the model’s main variables into medium state, it can be seen from the figure 6.6 that the probability of high productivity is 5.57%, medium is 88.24%, and low is 6.14%. The error of the model is also negligible in these states.

This validation, along with root nodes validation, guarantee that all the queries that can be done with this model are in the expected range and probability of producing abnormal results is low.

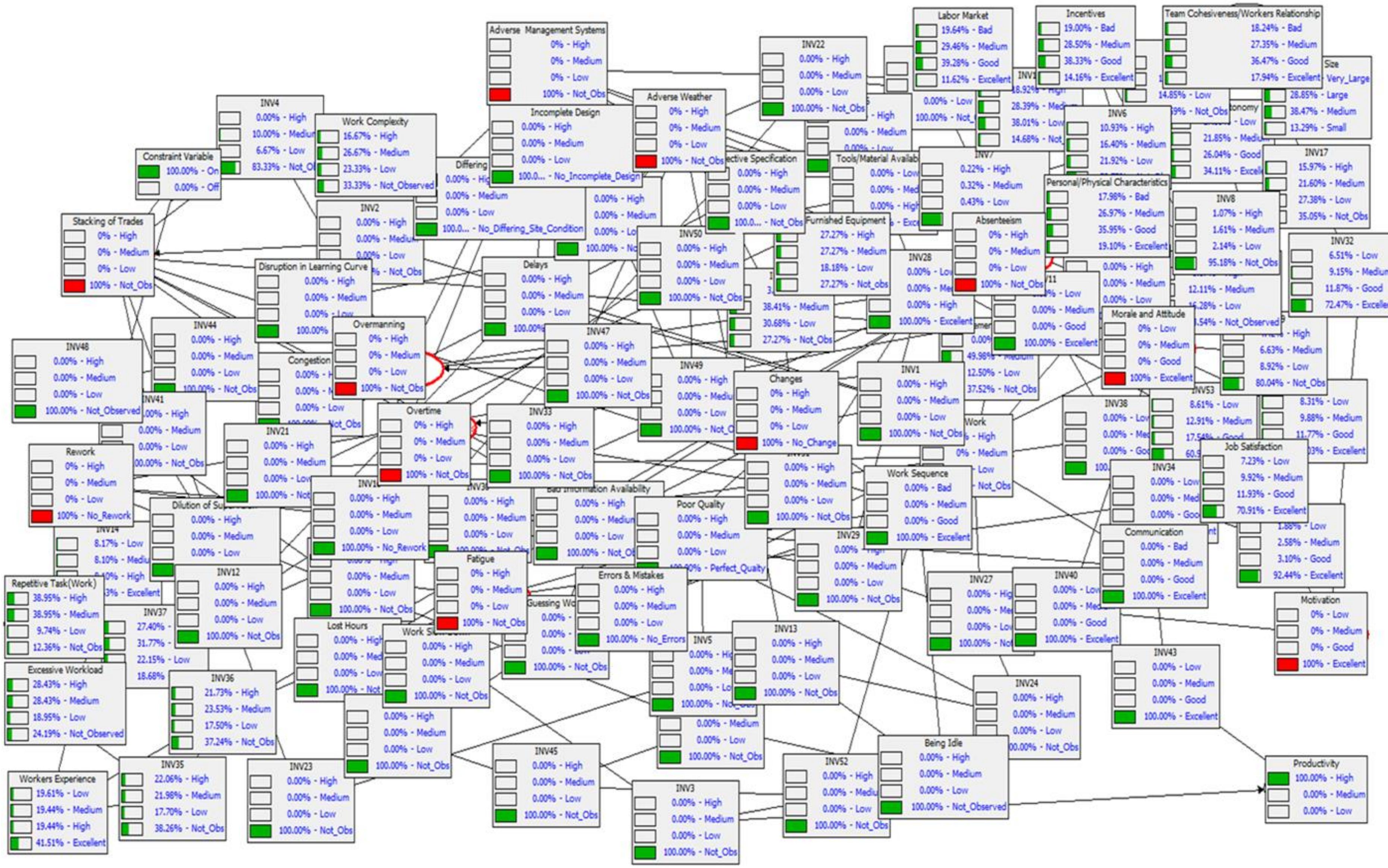


Figure 6.3: Model Verification through Main Nodes' Perfect Conditions

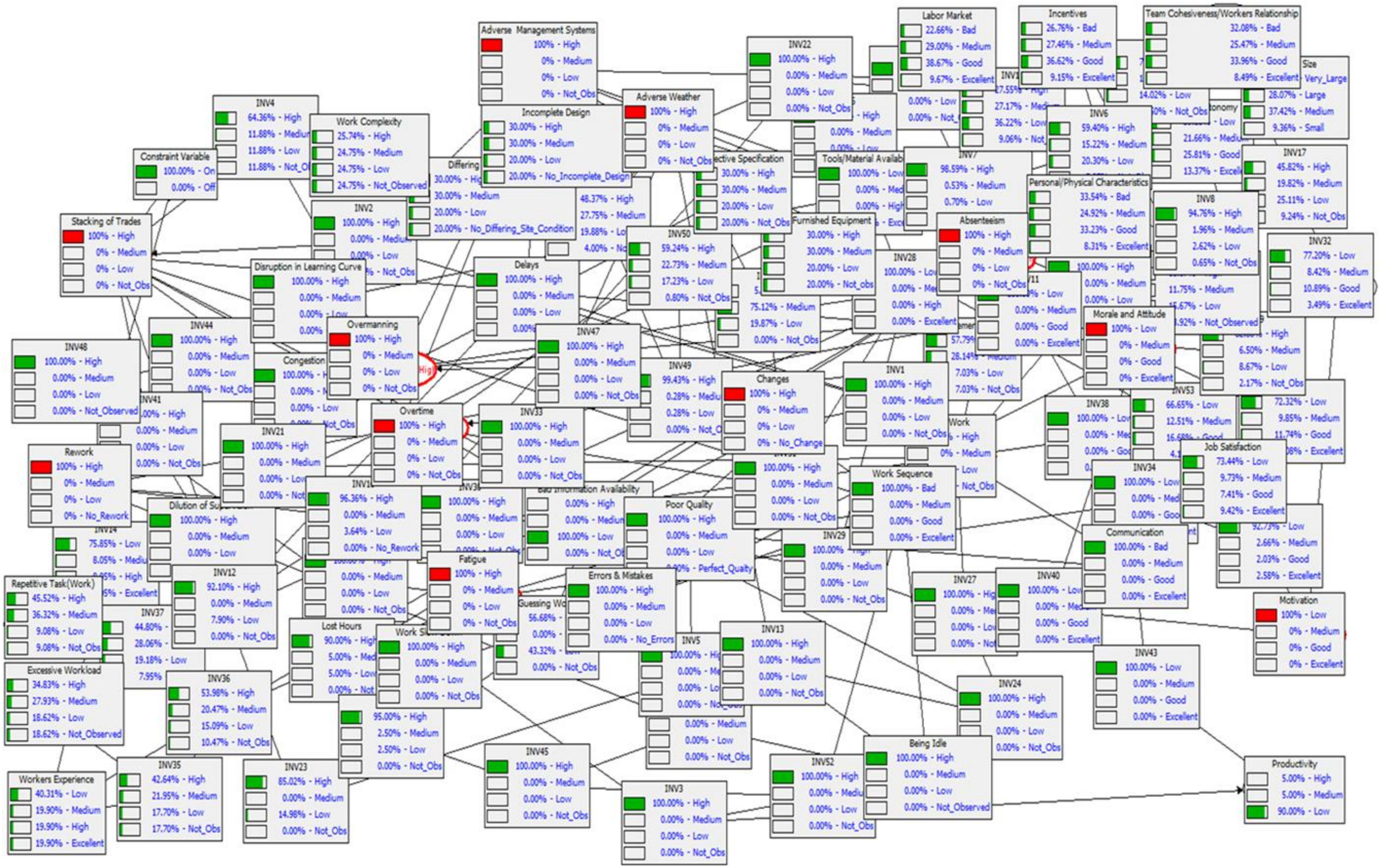


Figure 6.4: Model Validation through Main Nodes' Worst Conditions

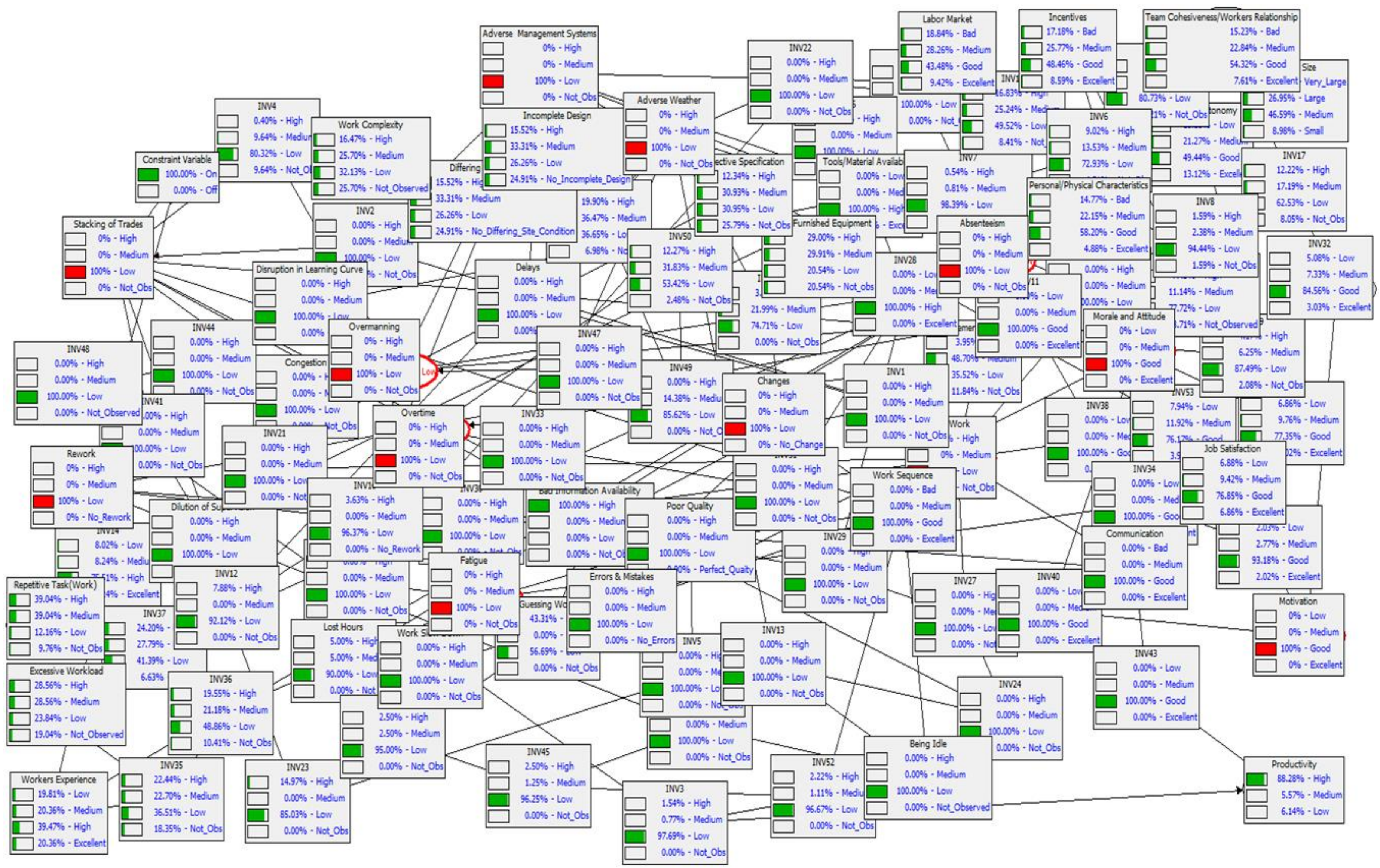


Figure 6.5: Model Validation through Main Nodes' Low Conditions

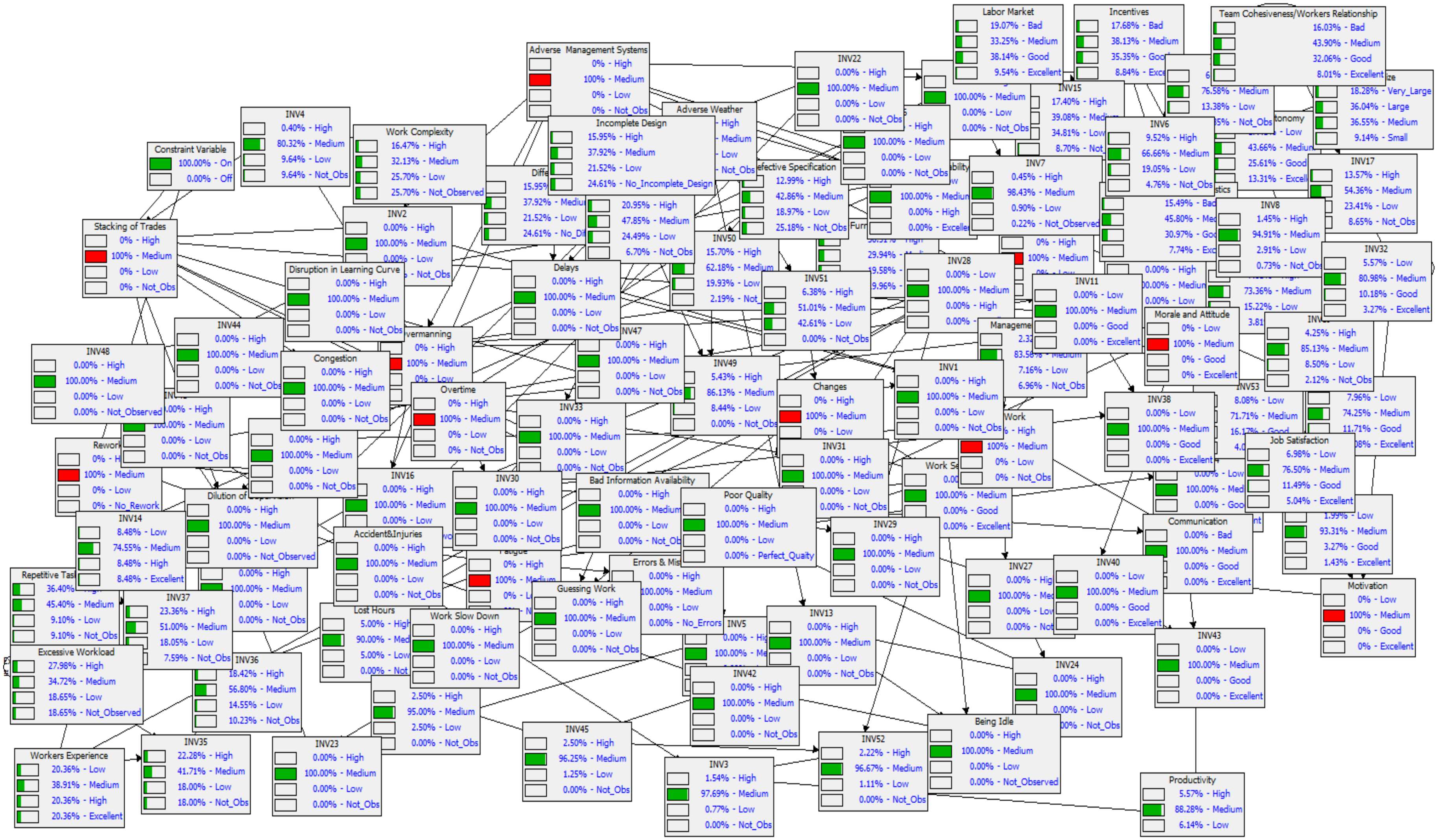


Figure 6.6: Model Validation through Main Nodes' Medium Conditions

6.1.3 Face Validation

Lucko and Rojas stated that "arguably the strongest way to establish face validity is the involvement of domain experts, also known as subject matter experts, before (a priori), during, after (a posteriori), or throughout the research." For the face validation of the model, the "Kiewit Corporation" is selected. The reasons behind this selection is that "Kiewit Corporation" is one the fortune 500 companies and also it is one of the best in the construction industry. "Kiewit Corporation" headquarter is located in the Omaha which allows to access operation manager, project managers, and preconstruction experts of the company. For the purpose of face validation, interviews with operation manager and preconstruction experts were conducted. After explaining the model for experts of the company, questions about the situations of different completed projects were asked and experts also determined level of productivity for those specific projects before entering the data to the model. The opinions of experts for different projects were entered to the model and the result compared with actual level of productivity. The projects in this validation range from residential to industrial projects. For example, one of the interesting validation was with the project manager of "University of Nebraska Omaha Mammel Hall." This project was one the most successful projects of the company with high level of labor productivity which the model confirmed it. Table 6.1 shows the validation through root variables and tables 6.2 shows the validation through main variables. From the tables 6.1 and 6.2, it can be seen that the model can predict level of construction labor productivity in an acceptable range. For the purpose of being confidential, the projects are named A, B, C, D, E, and F.

Table 6.1: Face Validation through Root Variables

	Root Variables (1= Adverse Management Systems, 2= Adverse Weather, 3= Defective Specification, 4= Differing Site Condition, 5= Excessive Workload, 6= Incentives, 7= Incomplete Design, 8= Labor Market,9= Management Request, 10= Owner-Furnished Equipment, 11= Personal/Physical Characteristics, 12= Project Size, 13= Repetitive Task(Work), 14= Team Cohesiveness, 15= Work Complexity, 16= Workers Experience) and (B= Bad, H=High, M=Medium, L=Low, N=Not Observed, E=Excellent, L=Large, VL=Very Large, S=Small, G=Good)																Model Prediction of Productivity	Actual Productivity
Projects	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16		
Project A	M	H	H	H	H	M	M	B	H	N	M	VL	H	M	H	M	P(High)=6.09 P(Medium)=14.88 P(Low)=79.03	Low
Project B	N	N	N	N	L	G	N	E	M	N	G	L	H	G	L	H	P(High)=83.92 P(Medium)=7.96 P(Low)=8.12	High
Project C	H	L	H	M	N	B	H	B	N	N	B	S	H	M	L	M	P(High)=13.12 P(Medium)=9.16 P(Low)=77.71	Low
Project D	N	N	N	N	N	E	N	E	M	N	E	M	H	E	L	H	P(High)=86.24 P(Medium)=6.56 P(Low)=7.20	High
Project E	M	L	M	L	L	M	M	M	M	N	M	L	M	G	L	H	P(High)=32.34 P(Medium)=45.16 P(Low)=22.05	Overall Medium
Project F	M	H	L	H	N	E	L	G	H	N	G	L	H	G	L	H	P(High)=13.55 P(Medium)=13.81 P(Low)=72.65	Low

Table 6.2: Face Validation through Main Variables

	Main Variables (1= Adverse Management Systems, 2= Adverse Weather, 3= Absenteeism,4= Changes, 5= Fatigue, 6= Morale and Attitude,7= Motivation, 8= Overmanning, 9= Overtime, 10= Rework, 11= Shift Work, 12= Stacking of Trades) and (B= Bad, H=High, M=Medium, L=Low, N=Not Observed, E=Excellent, L=Large, VL=Very Large, S=Small, G=Good)												Model Prediction of Productivity	Actual Productivity
Projects	1	2	3	4	5	6	7	8	9	10	11	12		
Project A	M	H	M	H	H	L	M	M	H	M	M	H	P(High)=5.29 P(Medium)=15.54 P(Low)=79.17	Low
Project B	N	N	L	L	L	G	G	L	M	L	M	L	P(High)=84.55 P(Medium)=9.76 P(Low)=5.69	High
Project C	H	L	H	H	H	L	L	L	M	H	M	M	P(High)=11.09 P(Medium)=20.20 P(Low)=68.71	Low
Project D	N	N	L	L	L	G	E	L	M	L	M	L	P(High)=84.96 P(Medium)=9.55 P(Low)=5.49	High
Project E	M	L	L	M	L	M	M	L	M	M	M	M	P(High)=30.92 P(Medium)=62.93 P(Low)=6.14	Overall Medium
Project F	M	H	M	H	M	M	M	M	H	H	H	M	P(High)=5.00 P(Medium)=24.66 P(Low)=70.37	Low

6.2 Model Sensitivity Analysis

The goal of building probabilistic networks is to support and solve problems of belief update and decision making under uncertainty (Kjærulff and Madsen 2013). The problem of belief update is investigated thoroughly in this chapter. The posterior probability of productivity under different belief updates of other variables is of interest in this chapter. The evidence set can be a single or a group of evidence that impact the hypothesis variable (here productivity).

Evidence sensitivity analysis can give answers to the following questions (Kjærulff and Madsen 2013):

- What are the maximum and minimum beliefs produced by observing a variable?
- Which evidence acts in favor or against of a hypothesis?
- Which set of evidence has the highest effects on hypothesis variable?

For the purpose of answering these questions, various sensitivity analyses are used to investigate the model in depth and answer the questions of how different variables alone, and in the group, affect labor productivity. In the section 6.2.1, effects of single variables on labor productivity is investigated and in the section 6.2.2 the behavior of productivity under the effects of different subsets of variables is evaluated.

6.2.1 Effects of Single Variables on Perfect Condition

One of the questions that sensitivity analysis should answer is "What are the maximum and minimum beliefs produced by observing a variable?" (Kjærulff and Madsen 2013). For the purpose of answering this question, two kinds of sensitivity analysis are investigated. The first sensitivity analysis (SA) is "Root Variables Sensitivity Analysis." In this SA, after setting all root variables in their perfect states, by changing a single variable state from its perfect state to the other states, the probability of "High Productivity" is measured. In the figure 6.7, the effects of different root variables on the probability of "High Productivity" is shown. Each variable has four states, for example, the variable "Excessive Workload" has the following four states: "High," "Medium," "Low," and "Not- Observed." But, a variable like "Incentive" has these four states: Bad, Medium, Good, and Excellent. Therefore, for variables like "Incentives," "Excellent" is equivalent to "Not-Observed," "Good" is equivalent to "Low," and "Bad" is equivalent to "High". By looking at figure 6.7, the following facts can be seen:

- There are several root factors that their effects on labor productivity are similar to each other and cause at most 10% decline in the probability of "High Productivity." Also, the effects of variables in this group on labor productivity is a linear function of variables' states. This group consists of "Incentives," "Workers Experience," " Team Cohesiveness," "Repetitive Task (Work)," " Excessive Workload," " Owner Furnished Equipment," " Personal/Physical Characteristics," and " Project Size." For future references, these variables are named "Group A."

- There are two variables, “Work Complexity” and “Management Request for Overtime/Shift Work,” that have minor effects on the probability of “High Productivity” whenever they are in “Not_Observed,” “Low,” and “Medium” states. In the “High” state, these variables have “severe” effects on the probability of “High Productivity” and it decreases to less than 70%. Some explanation for this occurrence is that shift work and overtime up to some extent are tolerable, but when they exceed a threshold, they become detrimental. For future references, these two variables are named “Group B.”
- “Adverse Weather,” “Defective Specification,” “Differing Site Conditions,” and “Incomplete Design” are the variables that have “severe” effects on the probability of “High Productivity.” These variables are not linear functions of their inputs. “Defective Specification,” “Differing Site Conditions,” and “Incomplete Design” have similar behavior in terms of their effects on labor productivity. In the worst case, these variables can decline the probability of “High Productivity” to 45%, individually. For future references, these variables are named “Group C.”
- “Adverse Management Systems” effects on labor productivity is severe. This factor can decline the probability of “High Productivity” to less than 25%, individually. The effects of “Adverse Management Systems” on labor productivity is much more severe than other variables in groups A, B, and C. For future references, “Adverse Management Systems” is named as “Group D.”

In the next step, the effects of different main internal variables on productivity is investigated. In the figure 6.8, the effects of different main internal variables on the probability of “High Productivity” is shown. By looking at figure 6.8, the following facts can be concluded:

- All variable have similar effects whenever their states change from “Not_Observed” to “Low” or “Excellent” to “Good.” In this state change, the probability of “High productivity” only declines less than 5%. Also, The behavior of these variables whenever their states change from “low” to “Medium” and “Medium” to “High” are different from each other.
- “Motivation” and “Morale and Attitude” have the least detrimental effects on the probability of “High Productivity.” In the worst case, these variables cause the probability of “High Productivity” to decrease up to 5%. For future reference, these two variables are named as “Group A1.”
- “Shift Work” up to the “Medium” state has insignificant effects on the probability of “High Productivity.” From the “Not_Observed” state to the “Medium” state, it causes around 5% decline in the probability of “High Productivity” while from the “Medium” state to “High” state it causes a 20% decline in the probability of “High Productivity.” For future references, “Shift Work” is named as “Group B1.”
- “Overtime” effects on labor productivity is similar to “Shift Work” but with a higher severity degree. From the “Not_Observed” state to the “Medium” state, it causes around a 10% decline in the probability of “High Productivity” while from the “Medium” state to “High” state it

causes a 50% decline in the probability of “High Productivity.” For future references, “Overtime” is named as “Group C1.”

- There are a group of factors that their effects on labor productivity are similar to each other. “Absenteeism,” “Rework,” “Fatigue,” “Overstaffing,” and “Changes” have similar effects on labor productivity. From the “low” state to the “High” state, these variable effects on labor productivity is a linear function of their inputs and in the worst case they cause between a 25% to 35% decline in the probability of “High Productivity.” For future references, these variables are named as “Group D1.”
- “Stacking of Trades” has the most severe effects on labor productivity. Even one state change causes a considerable decline in the probability of “High Productivity.” In the worst case, it causes about a 55% decline in the probability of “High Productivity.” The effects of “Stacking of Trades” on the labor productivity is similar to variables in the group C. For future references, “Stacking of Trades” is named as “Group E1.”

The effects of different root and internal variables on the probability of “High Productivity” are shown in the figure 6.9 and figure 6.10. Figure 6.9 shows that the effects of different root factors on productivity are almost the same and they can increase at most 5% the probability of “High Productivity.” This shows that whenever a project’s overall situation is bad, by improving one factor it is not probable to achieve “High productivity.”

Figure 6.10 shows the effects of different internal main variables on the hypothesis variable. It is obvious from the figure that in the best case these variables can increase the probability of “High Productivity” about 5% whenever a project is in its worst conditions. In this figure, for several variables like “Changes,” “Overstaffing,” and “Shift Work” whenever state changes from “Low” to “Not_ Observed” the probability of “High Productivity” declines to zero. It means that for whenever these internal variables is in their worst conditions, it is not possible one variable be in its excellent situation.

The investigation of different variables effects on labor productivity reveals interesting facts about each variable. The next section investigates the effects of a group of variables on labor productivity. This investigation shows how these variables affect labor productivity whenever they affect productivity concurrently.

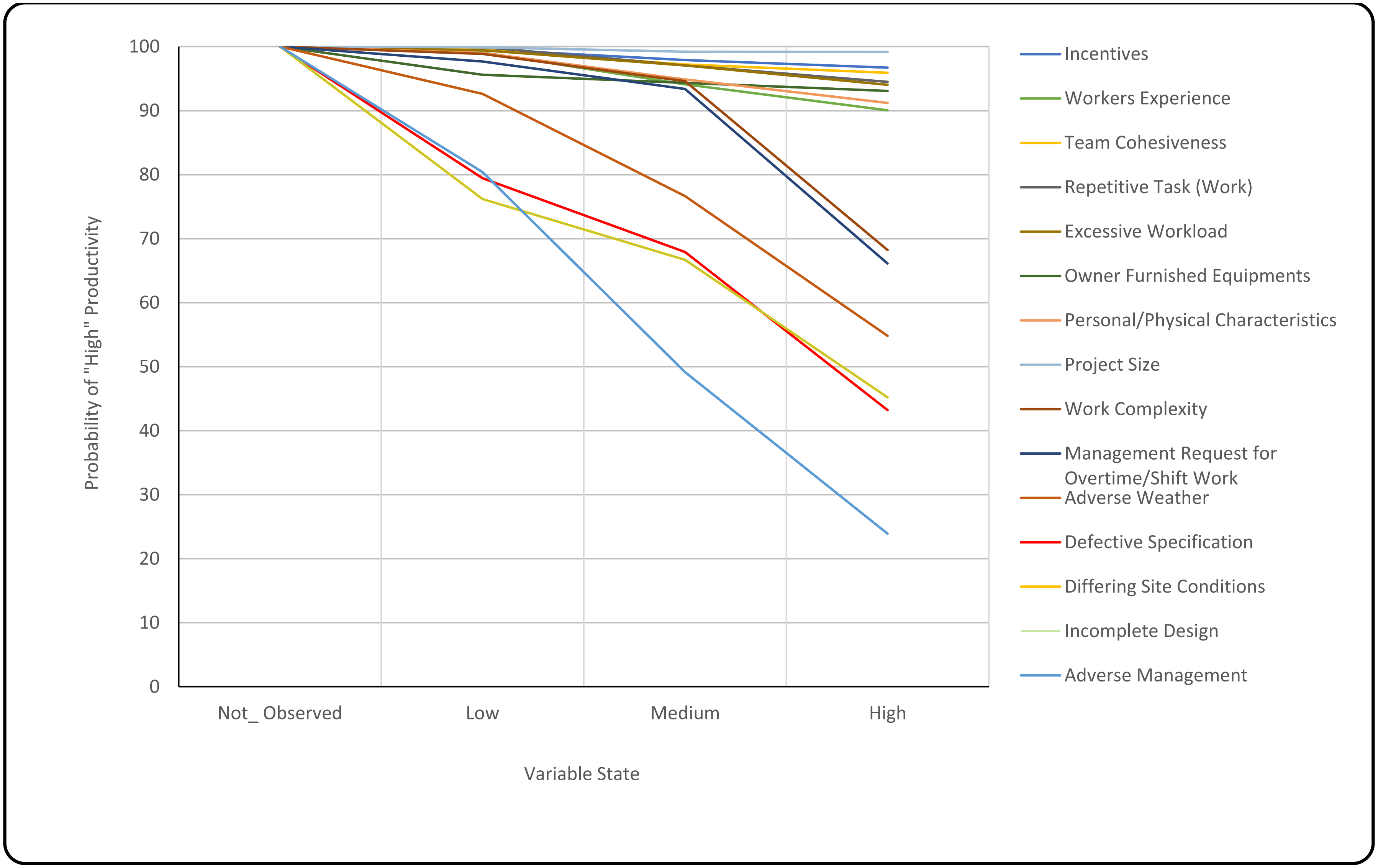


Figure 6.7: Effects of Different Root Variables on the Probability of "High Productivity" Whenever Everything is in its Perfect Condition

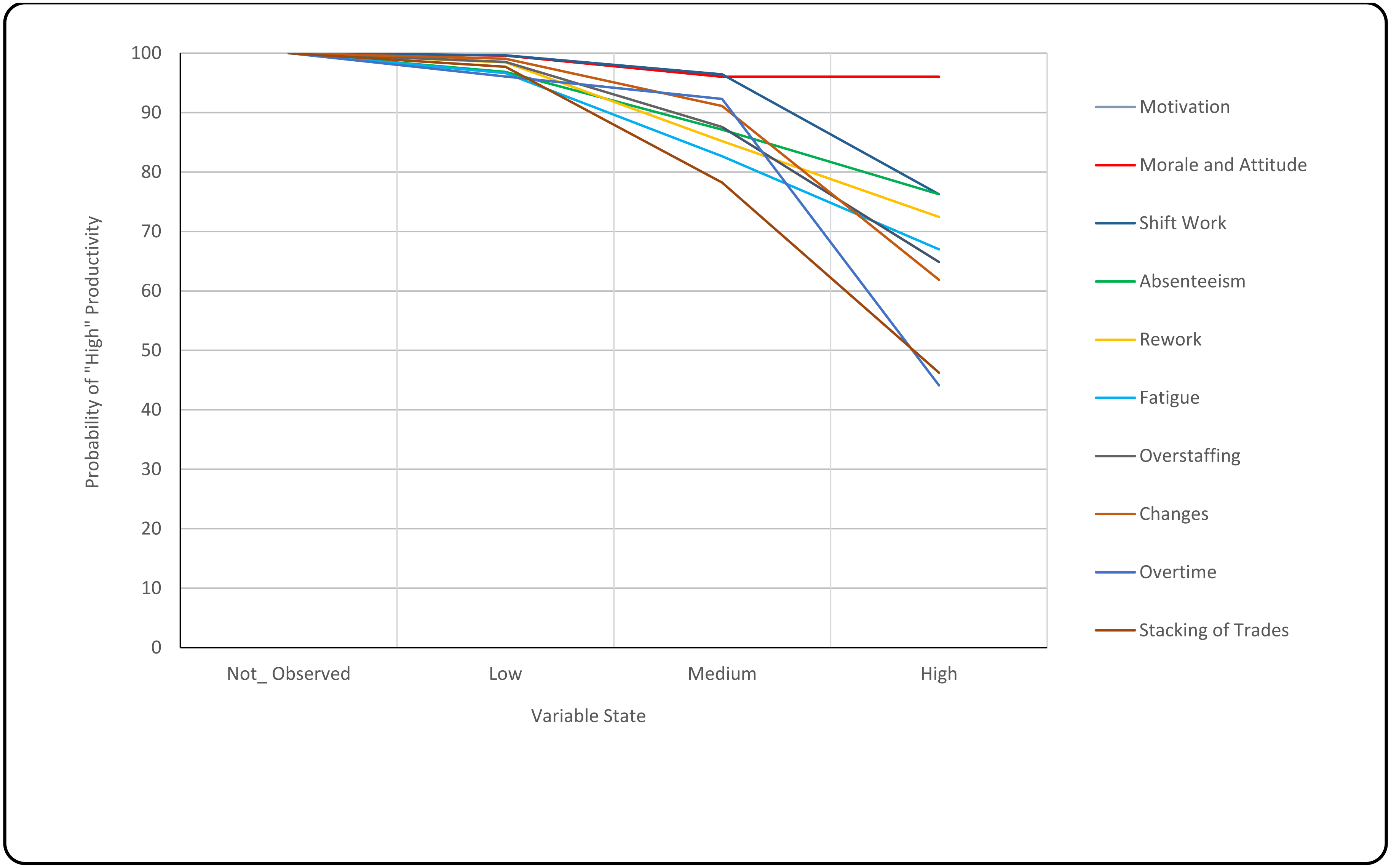


Figure 6.8: Effects of Different Main Internal Variables on the Probability of “High Productivity” Whenever Everything is in its Perfect Condition

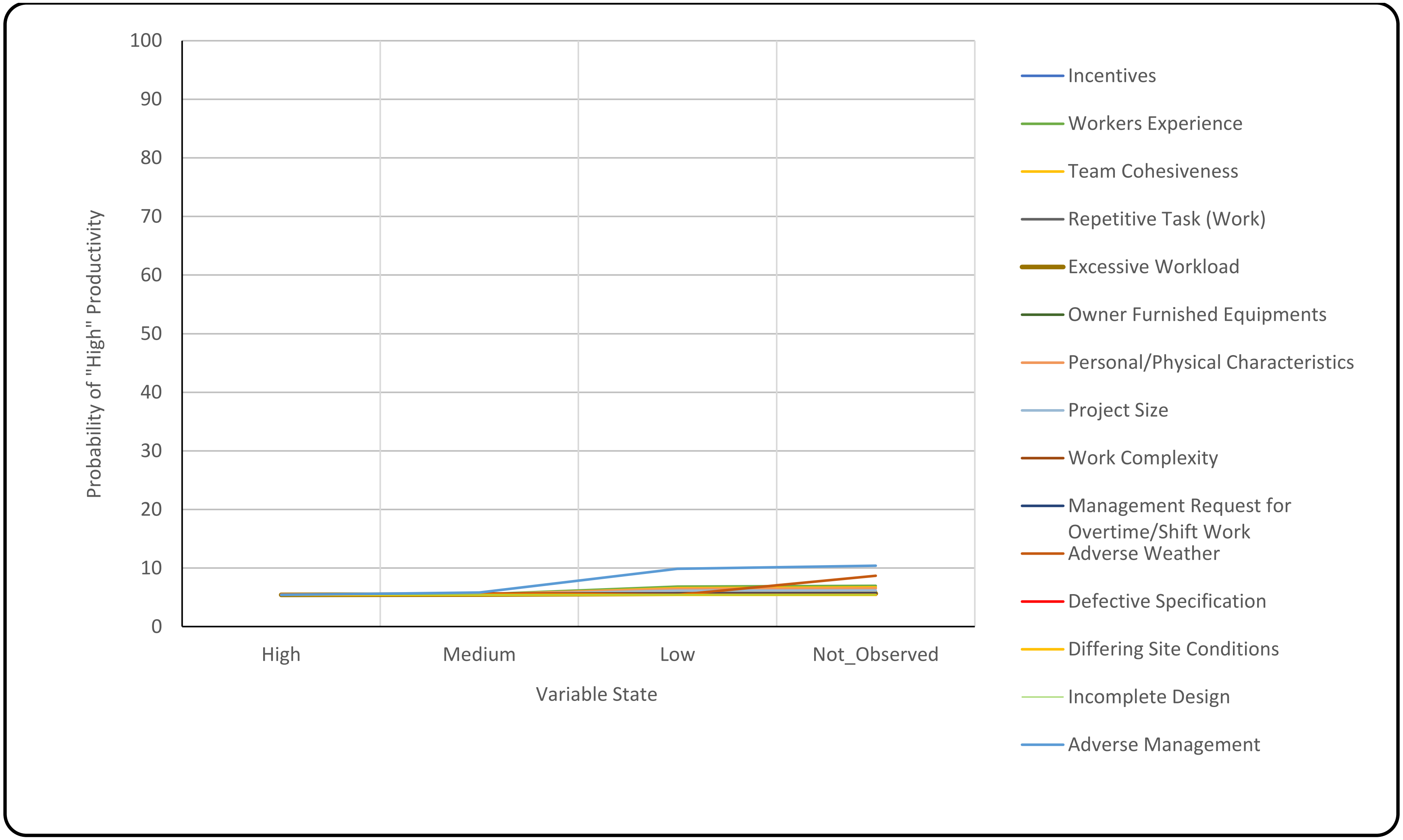


Figure 6.9: Effects of Different Root Variables on the Probability of "High Productivity" Whenever Everything is in its Worst Condition

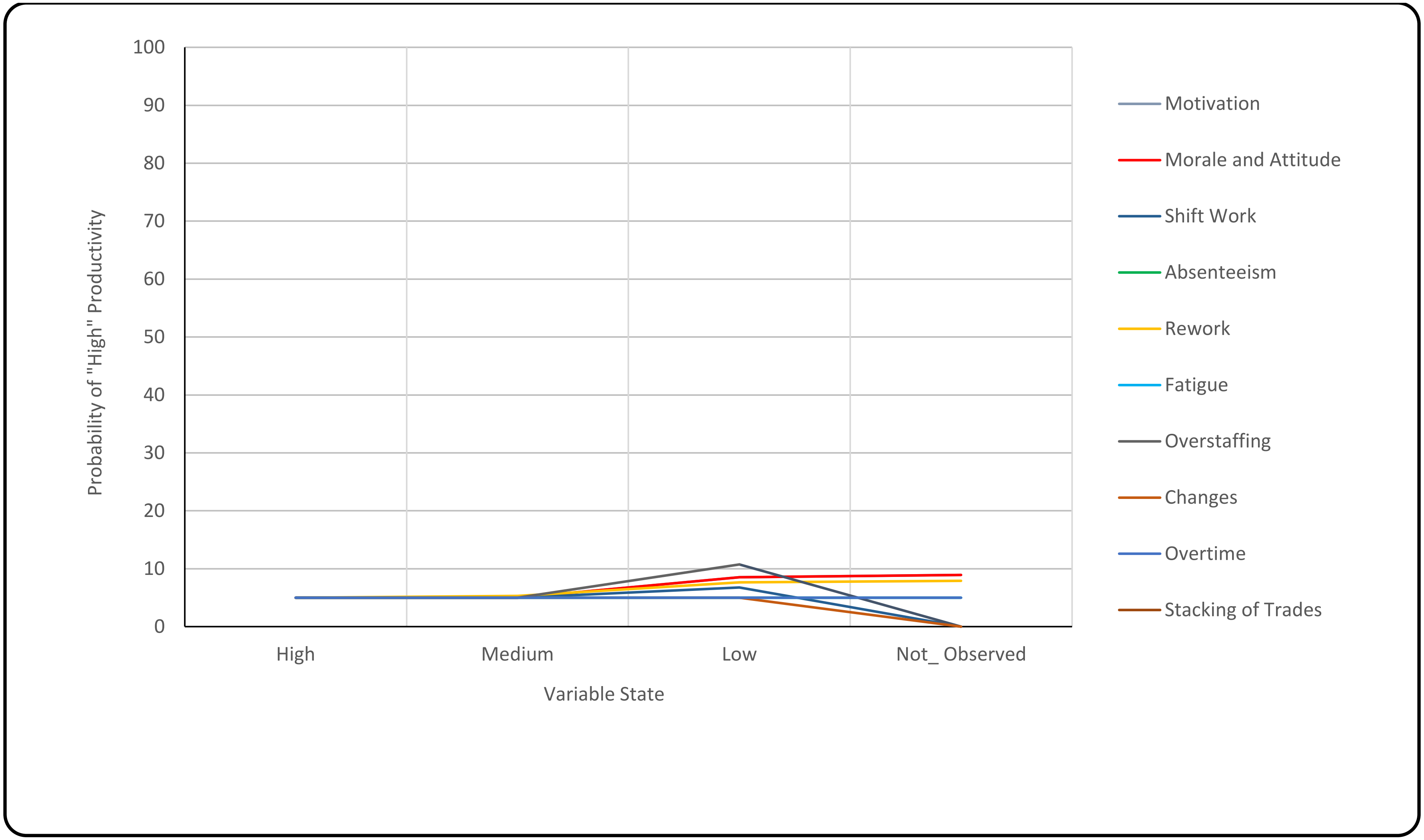


Figure 6.10: Effects of Different Main Internal Variables on the Probability of "High Productivity" Whenever Everything is in its Worst Condition

6.2.2 Impact of Evidence Subsets

According to Kjærulff and Madsen's investigations, the impact of different subsets of the evidence ε on each state of a hypothesis variable is a useful part of SE (2013). This helps to determine which subsets of evidence have the most impact on a hypothesis variable and how their combinations work. For investigating the impact of each subset, a Normalized Likelihood (NL) is obtained. Then, comparing different NL among different subsets allows the behavior of different subsets to be investigated. Kjærulff and Madsen defined NL as:

$$NL = \frac{p(x|\varepsilon')}{p(x)} \tag{6.1}$$

where ε' is a subset of evidence set or $\varepsilon' \subseteq \varepsilon$ and x is any state of hypothesis variable (2013).

In the next section, the effects of different subsets of root variables and main internal variables on the hypothesis variable, the probability of "High Productivity," are investigated. For this purpose, the investigations reveal how different subsets affect the probability of "High productivity." The normalized likelihood helps to do this comparison. The comparisons reveal numerous results. This investigation can be done in two ways. These are how different subsets of evidence can increase the probability of "High Productivity," and vice versa. Also, the effects of these subsets for different network instantiations are also investigated which shows the behavior of a subset is network parameter dependent.

6.2.2.1 Root Variables Subsets Effects on Productivity

This section investigates the effects of subsets of size three on the probability of “High Productivity.” Table 6.3 shows the effects of different subsets of size three of the variables in the group A on the probability of “High Productivity.” From this table the following facts can be concluded:

- Whenever three variables are combined to each other, their cumulative effects on labor productivity is not equivalent to the sum of their individual variable effect. The sum of individual variable effects is slightly higher or lower than the effects of their combination. For example, by setting “Incentives,” “Workers Experience,” and “Team Cohesiveness” individually to their perfect condition, the probability of “High Productivity” changes from 17.14% to 17.60%, 18.72%, and 17.95%, respectively. By adding the amount of each individual increase to 17.14, the sum of individual increases becomes 19.99% which is slightly lower than 20.07%. It is higher for the subset 7 from the table 6.3.
- “Workers Experience,” “Personal/ Physical Characteristics,” and “Owner-Furnished Equipment” have the highest impact on productivity, individually. But, it is not the case for their combination. There exist subsets that the sum of the impact of their individual variables are less than case number 5, but the combination of their effects is higher than case 5.
- If a project manager wants to increase the probability of “High Productivity” with variables in this group, this table gives enough insight

to the project manager to make decision. It can be seen that subsets that have "Incentives" as an element causes more increase in the probability of "High Productivity." Therefore, the best choice for a project manager can be subset number 4, and subset number 7 is the least effective decision that can be made.

The next reasonable question that may arise is "Are these subsets behaves the same for different root variables' CPTs?" To answer this question, by setting all root variable to their worst state, with changing the state of each variable in each subset, the posterior probability of "High Productivity" is obtained. Table 6.4 shows this results. The comparison between NL of the table 6.3 and 6.4 reveals the following facts:

- For different subsets, the NL is not constant for different network instantiations. The average NL of subsets in the table 6.3 is 1.15 while the average NL of subsets in the table 6.4 is 1.47. On average, the effects of each subset on the probability of "High productivity" is higher whenever the network instantiation results in the lower probability of "High Productivity."
- Except for subsets number 4 and 7, which are the most effective and the least effective subsets, the order of importance of other subsets also are not constant. For example, while the subset 1 and 2 has the same effect on the probability of "High Productivity" in the network with instantiation shown in the appendix B, by setting the root variable to the worst case, the effects of these subsets are no longer similar.

- The nonlinearity behavior of different subsets causes the decisions of a project manager about how to increase productivity, depends on the situations of other factors. For each situation, a set of best actions exist, and by focusing on them, it is more probable to increase productivity.
- The above findings show that the problems of selecting the best action is a hard problem. It means that for a specific situation, the exhaustive search among all combinations of variables should be done. From the algorithmic point of view, this exhaustive search is a factorial running time algorithm which needs too much time to be solved.
- The above discussion conclude that it is sometimes necessary to develop a heuristic to solve the decision making problems regarding the selection of the best approach to increase productivity.

Table 6.3: Effects of Subsets of Size Three of Variables in Group A on the Probability of “High Productivity”

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" | E)	P(Productivity="High")	NL
1	Incentives	Workers Experience	Team Cohesiveness	20.07	17.14	1.17
2	Incentives	Workers Experience	Repetitive Task	20.1	17.14	1.17
3	Incentives	Workers Experience	Excessive Workload	19.89	17.14	1.16
4	Incentives	Workers Experience	Personal/ Physical Characteristics	20.45	17.14	1.19
5	Workers Experience	Personal/ Physical Characteristics	Owner-Furnished Equipment	19.91	17.14	1.16
6	Team Cohesiveness	Repetitive Task	Excessive Workload	19.4	17.14	1.13
7	Owner-Furnished Equipment	Repetitive Task	Excessive Workload	18.5	17.14	1.08
8	Owner-Furnished Equipment	Team Cohesiveness	Workers Experience	19.56	17.14	1.14

Table 6.4: Effects of Subsets of Size Three of Variables in Group A on the Probability of “High Productivity” with another Network Instantiation

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" |E)	P(Productivity="High")	NL
1	Incentives	Workers Experience	Team Cohesiveness	8.97	5.44	1.65
2	Incentives	Workers Experience	Repetitive Task	8.08	5.44	1.49
3	Incentives	Workers Experience	Excessive Workload	8.08	5.44	1.49
4	Incentives	Workers Experience	Personal/ Physical Characteristics	9.06	5.44	1.67
5	Workers Experience	Personal/ Physical Characteristics	Owner-Furnished Equipment	8.32	5.44	1.53
6	Team Cohesiveness	Repetitive Task	Excessive Workload	7.19	5.44	1.32
7	Owner-Furnished Equipment	Repetitive Task	Excessive Workload	5.87	5.44	1.08
8	Owner-Furnished Equipment	Team Cohesiveness	Workers Experience	8.28	5.44	1.52

The procedure explained for the “Group A” variables is also repeatable for other groups’ variables and their combinations. The factors in the “Group B” have different behaviors on the probability of “High Productivity” than the factors in “Group A,” whenever they combine with each other. In the table 6.5, the effects of different combinations of factors from “Groups A” and “Group B” with the network instantiation that is documented in appendix B is shown. Table 6.6 shows the effects of the same subsets with another network instantiation. In this instantiation, the prior probability of “High Productivity” is related to the worst case scenario for all root variables and the posterior probability is obtained by setting a subset of variables in their perfect state. The comparison of the numbers in table 6.5 and 6.6 with each other and with the numbers from the tables 6.3 and 6.4, reveals the following facts about the network:

- The average NL of the subsets in the 6.5 is 1.23 while in the table 6.6 it is 1.21. This shows that the effects of different subsets in the table 6.5 is more effective whenever the project’s overall situation is better. This is in contrast with tables 6.3 and 6.4. In the table 6.3 the average NL of the subsets is 1.15 while in the table 6.4, it is 1.47. This shows that the combination of variables in “Group A” is more effective whenever the project status is worse.
- The average increase in the probability of “High productivity” for table 6.6 is calculated from the following formula :

$$\frac{\sum_1^8 P(productivity = "High"|E) - P(Productivity = "High")}{8}$$

This average is 1.12% for table 6.6. The comparison between this number and the effects of variables in “Group B” on the perfect conditions shows that whenever the probability of “High Productivity” is low, improving two or three factors related to groups A and B can increase the probability of “High Productivity” slightly; however, whenever the project situation is perfect, as shown in the figure 6.7, the state change of any of variables in “Group B” can decline the probability of “High Productivity” more than 30% which is at least 25 times higher than the previous increase.

Tables 6.7 and 6.8 show the effects of different subsets of “Group C” variables for two different network instantiations. Although the average NL for table 6.8 is higher than table 6.7 (1.67 vs 1.43), the range of NL for table 6.7 is much lower than table 6.8. It means that the effects of different subsets of variables in group C is more consistent whenever the probability of “High Productivity” is higher.

In the tables 6.9, effects of different subsets of “Adverse Management Systems” and two variables from group A is shown. Similarly, in the table 6.10, effects of different subsets of “Adverse Management Systems” with variables in group B and C is shown. It can be seen that “Adverse Management Systems” individually can increase the probability of “High Productivity” about 10%, while it can decline it more than 75%, and whenever “Adverse Management Systems” combines with two variables from group B and C it can decline more than 80%. This shows that whenever in a project “Management system” is not ideal, it is not probable to achieve “High Productivity.”

In the figure 6.11, the comparison of different combinations is shown graphically. It is clear from the figure, that how the “Adverse Management Systems” in combination with the variables from group B and C is important for achieving or losing productivity.

Table 6.5: Effects of Subsets of Size Three of Variables in Group B and One Variable in Group A on the Probability of "High Productivity"

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" | E)	P(Productivity="High")	NL
1	Management Request	Work Complexity	–	20.34	17.14	1.19
2	Management Request	Work Complexity	Incentives	20.84	17.14	1.22
3	Management Request	Work Complexity	Workers Experience	22.05	17.14	1.29
4	Management Request	Work Complexity	Excessive Workload	20.99	17.14	1.22
5	Management Request	Work Complexity	Personal/ Physical Characteristics	21.55	17.14	1.26
6	Management Request	Work Complexity	Team Cohesiveness	21.19	17.14	1.24
7	Management Request	Work Complexity	Owner-Furnished Equipment	20.32	17.14	1.19
8	Management Request	Work Complexity	Repetitive Task	21.2	17.14	1.24

Table 6.6: Effects of Subsets of Size Three of Variables in Group B and One Variable in Group A on the Probability of "High Productivity" with another Network Instantiation

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" |E)	P(Productivity="High")	NL
1	Management Request	Work Complexity	–	5.91	5.44	1.09
2	Management Request	Work Complexity	Incentives	6.56	5.44	1.21
3	Management Request	Work Complexity	Workers Experience	7.58	5.44	1.39
4	Management Request	Work Complexity	Excessive Workload	6.14	5.44	1.13
5	Management Request	Work Complexity	Personal/ Physical Characteristics	7.05	5.44	1.30
6	Management Request	Work Complexity	Team Cohesiveness	7.18	5.44	1.32
7	Management Request	Work Complexity	Owner-Furnished Equipment	5.92	5.44	1.09
8	Management Request	Work Complexity	Repetitive Task	6.14	5.44	1.13

Table 6.7: Effects of Subsets of Size Three of Variables in Group C on the Probability of “High Productivity”

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" |E)	P(Productivity="High")	NL
1	Adverse Weather	Defective Specification	Differing Site Conditions	24.94	17.14	1.46
2	Adverse Weather	Defective Specification	Incomplete Design	24.94	17.14	1.46
3	Differing Site Conditions	Incomplete Design	Adverse Weather	24.89	17.14	1.45
4	Differing Site Conditions	Incomplete Design	Defective Specification	21.66	17.14	1.26
5	Adverse Weather	Defective Specification	Work Complexity	25.26	17.14	1.47
6	Adverse Weather	Defective Specification	Management Request	26.48	17.14	1.54
7	Differing Site Conditions	Defective Specification	Management Request	21.34	17.14	1.25
8	Work Complexity	Management Request	Adverse Weather	26.96	17.14	1.57

Table 6.8: Effects of Subsets of Size Three of Variables in Group C on the Probability of “High Productivity” with another Network Instantiation

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" |E)	P(Productivity="High")	NL
1	Adverse Weather	Defective Specification	Differing Site Conditions	8.69	5.44	1.60
2	Adverse Weather	Defective Specification	Incomplete Design	8.69	5.44	1.60
3	Differing Site Conditions	Incomplete Design	Adverse Weather	8.69	5.44	1.60
4	Differing Site Conditions	Incomplete Design	Defective Specification	5.44	5.44	1.00
5	Adverse Weather	Defective Specification	Work Complexity	9.73	5.44	1.79
6	Adverse Weather	Defective Specification	Management Request	10.21	5.44	1.88
7	Differing Site Conditions	Defective Specification	Management Request	5.65	5.44	1.04
8	Work Complexity	Management Request	Adverse Weather	15.73	5.44	2.89

Table 6.9: Effects of Subsets of Size Three of “Adverse Management Systems” and Two Variable from Group A on the Probability of “High Productivity”

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" |E)	P(Productivity="High")	NL
1	Adverse Management Systems	_	_	25.98	17.14	1.52
2	Adverse Management Systems	Incentives	Workers Experience	28.38	17.14	1.66
3	Adverse Management Systems	Incentives	Team Cohesiveness	27.37	17.14	1.60
4	Adverse Management Systems	Project Size	Personal/ Physical Characteristics	27.72	17.14	1.62
5	Adverse Management Systems	Personal/ Physical Characteristics	Workers Experience	29.23	17.14	1.71
6	Adverse Management Systems	Repetitive Task	Excessive Workload	27.78	17.14	1.62
7	Adverse Management Systems	Personal/ Physical Characteristics	Incentives	27.85	17.14	1.62
8	Adverse Management Systems	Owner-Furnished Equipment	Excessive Workload	26.73	17.14	1.56

Table 6.10: Effects of Subsets of Size Three of “Adverse Management Systems” and Two Variable from Group B and C on the Probability of “High Productivity”

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High"| E)	P(Productivity="High")	NL
1	Adverse Management Systems	Management Request	Work Complexity	31.9	17.14	1.86
2	Adverse Management Systems	Management Request	Adverse Weather	37.52	17.14	2.19
3	Adverse Management Systems	Work Complexity	Adverse Weather	35.75	17.14	2.09
4	Adverse Management Systems	Defective Specification	Differing Site Conditions	31.85	17.14	1.86
5	Adverse Management Systems	Differing Site Conditions	Incomplete Design	31.74	17.14	1.85
6	Adverse Management Systems	Defective Specification	Adverse Weather	35.54	17.14	2.07
7	Adverse Management Systems	Incomplete Design	Adverse Weather	35.16	17.14	2.05
8	Adverse Management Systems	Differing Site Conditions	Adverse Weather	35.16	17.14	2.05

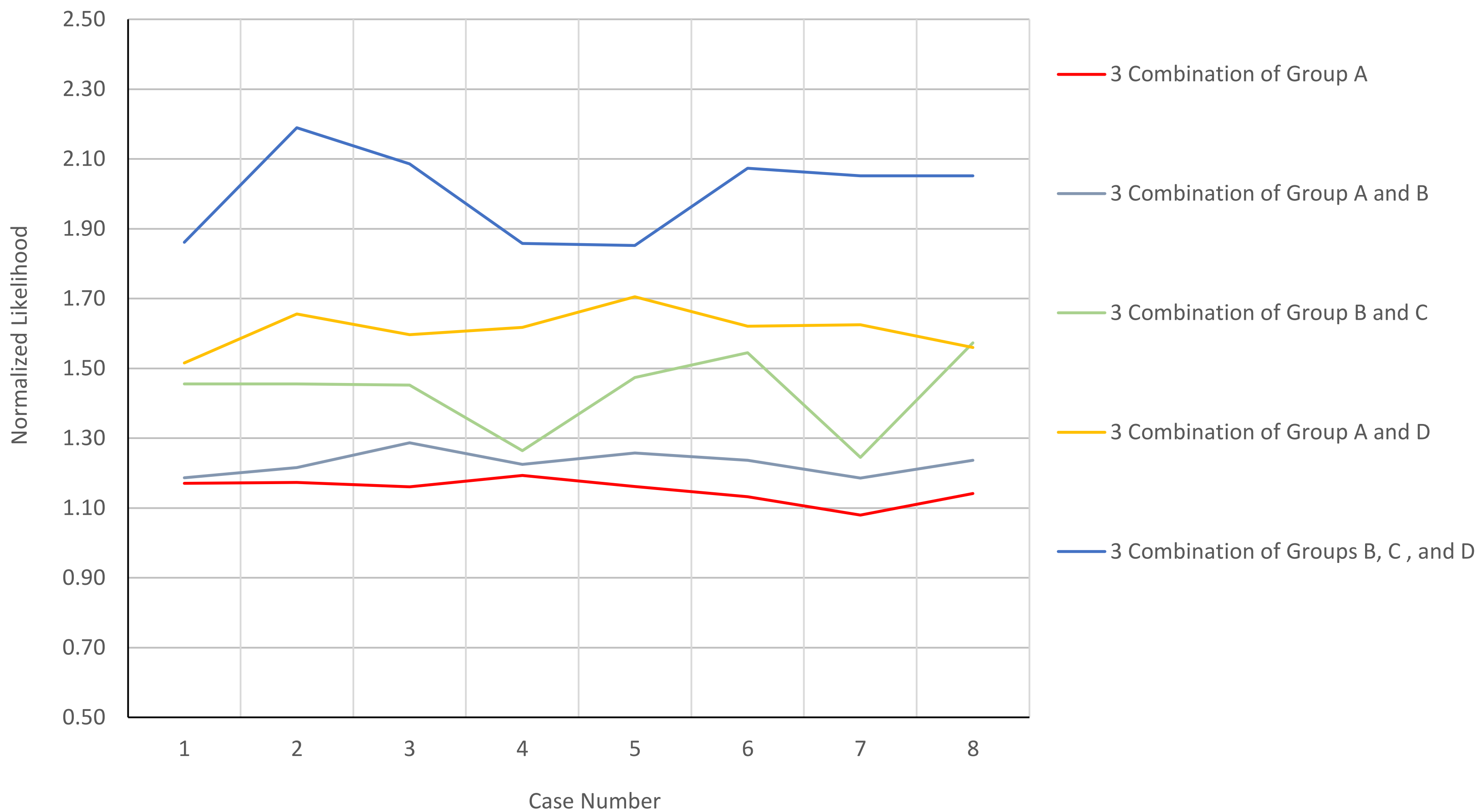


Figure 6.11: Effects of Combination of Different Variables on the Probability of “High Productivity”

6.2.2.2 Main Variables Subsets Effects on Productivity

This section investigates the effects of different subsets of the main internal variables on the hypothesis variable. Table 6.11 shows the effects of size two and three subsets of variables in the groups A1, B1, and C1 with the network instantiations that is documented in the appendix B on the hypothesis variable. The average NL for this table is 2.45 which is higher than all the subsets of size three of root variables. The reasons for this higher NL value is the following:

- Each internal variable is the effect's node or child of several root variables which means each main internal variable represents the effects of one or more root variables on the hypothesis variable. This causes the internal variables to have higher effects on the hypothesis variable.
- Since the internal variables are closer to the hypothesis variable (there exists a shorter path), by setting an internal variables to a specific state, its effects dampens in the network less than the root variables.

Table 6.12 shows the effects of the same subsets with another network instantiations on the hypothesis variables. Note that with this network instantiations it is not possible to set "Shift Work" to its "Not_Observed" state. Therefore, for investigating the effects of each subset, the "Shift Work" is set to "Low." The average NL for this table is 2.20 which is a bit lower than table 6.11. This also shows that whenever the overall situations of a project is better, improving the state of the internal variables is more effective to increase the probability of "High Productivity."

Another finding from these tables is that while “Motivation” and “Morale and Attitude” have the least detrimental effects on the hypothesis variable, whenever a project is in its excellent situation, but combined together their effects on the hypothesis variable, whenever a project is in its worst conditions, has a high positive impacts. Furthermore, the order of NL in the tables 6.11 and 6.12 are not the same and it is also proof that deciding about the best set of actions depends on a project’s situation.

The effects of different subsets of variables in the “Group D1”shows that in the worst case conditions improving the states of three variables is impossible and the network doesn’t provide any solution except for one case. Table 6.13 shows this fact and the only possible combination of variables in this group that can improve worst case condition situations are “Absenteeism,” “Rework,” and “Fatigue.” However, whenever a project’s conditions improves a bit, the effects of the subsets of size 3 of the variables in this group on the hypothesis variable is considerable. Table 6.14 shows the effects of subsets with size three on the hypothesis variable with network instantiations that is documented in appendix B.

Table 6.11: Effects of Subsets of Sizes Two and Three of Variables in Groups A1, B1, and C1 on the Probability of "High Productivity"

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High"| E)	P(Productivity="High")	NL
1	Motivation	Morale and Attitude	_	29.07	17.14	1.70
2	Motivation	Shift Work	_	41.48	17.14	2.42
3	Morale and Attitude	Shift Work	_	38.36	17.14	2.24
4	Motivation	Overtime	_	40.58	17.14	2.37
5	Shift Work	Overtime	_	43.39	17.14	2.53
6	Motivation	Morale and Attitude	Shift Work	43.41	17.14	2.53
7	Motivation	Morale and Attitude	Overtime	44.73	17.14	2.61
8	Morale and Attitude	Shift Work	Overtime	47.11	17.14	2.75
9	Motivation	Shift Work	Overtime	49.4	17.14	2.88

Table 6.12: Effects of Subsets of Sizes Two and Three of Variables in Groups A1, B1, and C1 on the Probability of “High Productivity” with another Network Instantiation

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" | E)	P(Productivity="High")	NL
1	Motivation	Morale and Attitude	_	12.86	5	2.57
2	Motivation	Shift Work	_	10.7	5	2.14
3	Morale and Attitude	Shift Work	_	10.7	5	2.14
	Motivation	Overtime	_	8.93	5	1.79
4	Shift Work	Overtime	_	6.77	5	1.35
5	Motivation	Morale and Attitude	Shift Work	14.63	5	2.93
6	Motivation	Morale and Attitude	Overtime	12.86	5	2.57
7	Morale and Attitude	Shift Work	Overtime	10.7	5	2.14
8	Motivation	Shift Work	Overtime	10.7	5	2.14

Table 6.13: Effects of Subsets of Size Three of Variables in Groups D1 on the Probability of "High Productivity" in Worst Case Network Instantiations

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" | E)	P(Productivity="High")	NL
1	Absenteeism	Rework	Fatigue	25.62	5	5.12
2	Absenteeism	Rework	Overstaffing	?	5	?
3	Absenteeism	Rework	Changes	?	5	?
4	Rework	Fatigue	Overstaffing	?	5	?
5	Rework	Fatigue	Changes	?	5	?
6	Fatigue	Overstaffing	Changes	?	5	?
7	Fatigue	Overstaffing	Absenteeism	?	5	?
8	Overstaffing	Changes	Absenteeism	?	5	?
9	Overstaffing	Changes	Rework	?	5	?

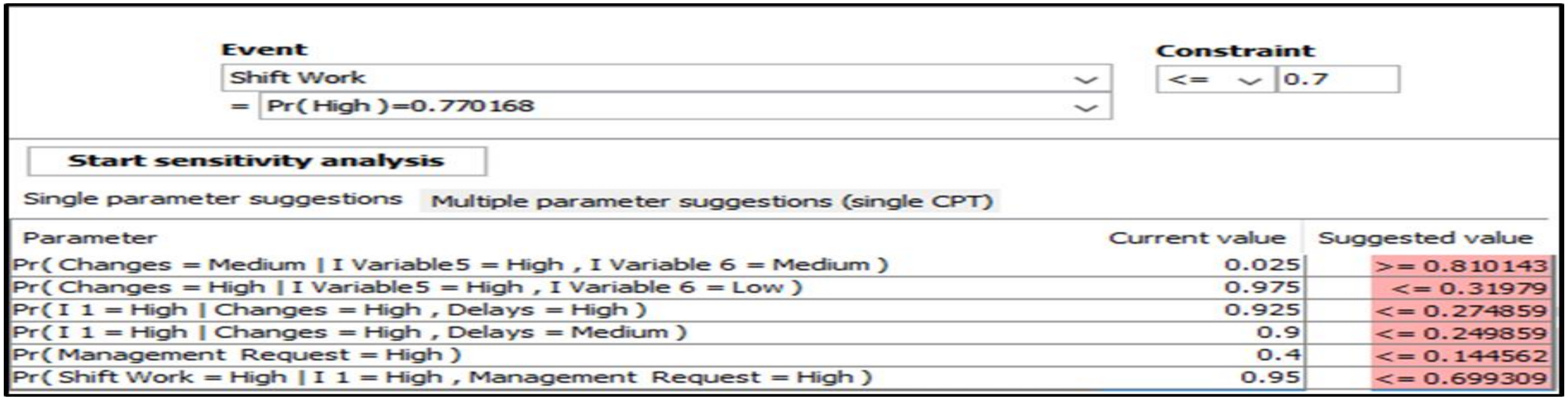
Table 6.14: Effects of Subsets of Size Three of Variables in Groups D1 on the Probability of "High Productivity" with Network Instantiations Documented in Appendix B

Number	Evidence			Prior and Posterior Probability of "High" Productivity		Normalized Likelihood
	E1	E2	E3	P(Productivity="High" | E)	P(Productivity="High")	NL
1	Absenteeism	Rework	Fatigue	48.92	17.14	2.85
2	Absenteeism	Rework	Overstaffing	46.98	17.14	2.74
3	Absenteeism	Rework	Changes	66.39	17.14	3.87
4	Rework	Fatigue	Overstaffing	52.96	17.14	3.09
5	Rework	Fatigue	Changes	74.52	17.14	4.35
6	Fatigue	Overstaffing	Changes	69.94	17.14	4.08
7	Fatigue	Overstaffing	Absenteeism	45.55	17.14	2.66
8	Overstaffing	Changes	Absenteeism	58.38	17.14	3.41
9	Overstaffing	Changes	Rework	61.39	17.14	3.58

6.2.3 Single and Multiple Parameter Suggestions

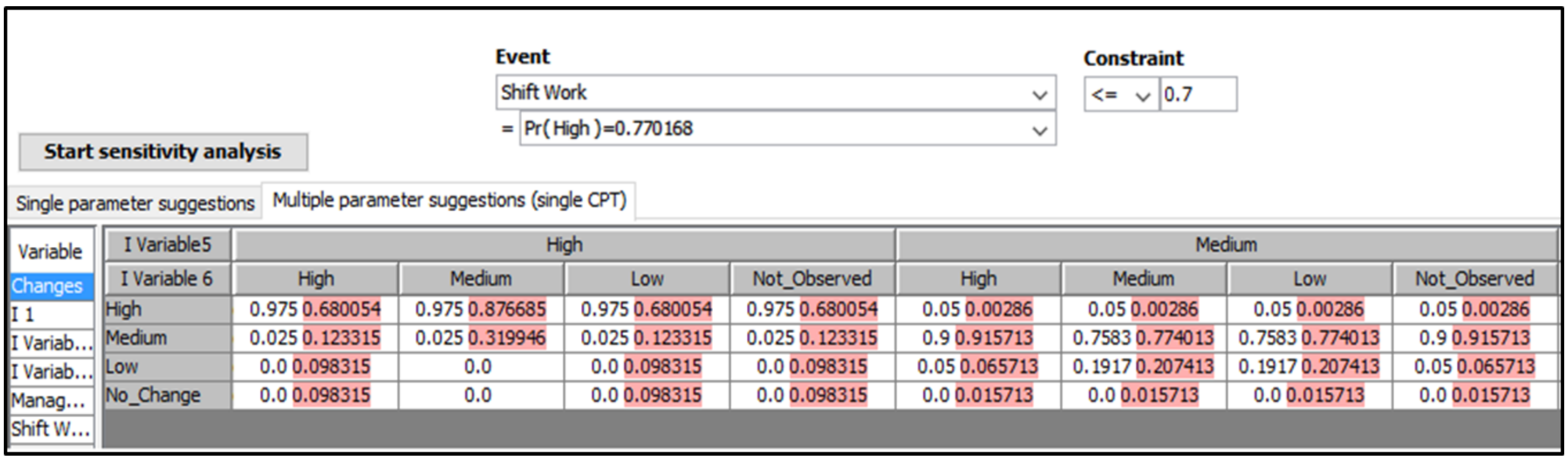
Single and multiple parameter (CPT) changes is another kind of sensitivity analysis that the model can do. This part of sensitivity analysis can be done by the SAMIAM toolbox and there is no need for additional computation. Figure 6.12 shows single parameter suggestions for the current network CPT, whenever a constraint is set for a variable. In this figure, the current probability of "High Shift Work" is 0.7701 and it is desired to decrease it to less than 0.7. The SAMIAM suggests six single parameter changes in several CPTs. Figure 6.13 shows multiple parameters suggestions which shows there exist six multiple parameters suggestions for different CPTs.

This kind of sensitivity analysis is useful whenever the CPTs are chosen randomly or they are not accurate. These suggestions in parameters changes may not make sense in several situations. Therefore, these kind of sensitivity analysis won't be investigated any further.



Parameter	Current value	Suggested value
Pr(Changes = Medium | I Variable5 = High , I Variable 6 = Medium)	0.025	>= 0.810143
Pr(Changes = High | I Variable5 = High , I Variable 6 = Low)	0.975	<= 0.31979
Pr(I 1 = High | Changes = High , Delays = High)	0.925	<= 0.274859
Pr(I 1 = High | Changes = High , Delays = Medium)	0.9	<= 0.249859
Pr(Management Request = High)	0.4	<= 0.144562
Pr(Shift Work = High | I 1 = High , Management Request = High)	0.95	<= 0.699309

Figure 6.12: Single Parameter Suggestions for Changes



I Variable5	High				Medium			
I Variable 6	High	Medium	Low	Not_Observed	High	Medium	Low	Not_Observed
High	0.975 0.680054	0.975 0.876685	0.975 0.680054	0.975 0.680054	0.05 0.00286	0.05 0.00286	0.05 0.00286	0.05 0.00286
Medium	0.025 0.123315	0.025 0.319946	0.025 0.123315	0.025 0.123315	0.9 0.915713	0.7583 0.774013	0.7583 0.774013	0.9 0.915713
Low	0.0 0.098315	0.0	0.0 0.098315	0.0 0.098315	0.05 0.065713	0.1917 0.207413	0.1917 0.207413	0.05 0.065713
No_Change	0.0 0.098315	0.0	0.0 0.098315	0.0 0.098315	0.0 0.015713	0.0 0.015713	0.0 0.015713	0.0 0.015713

Figure 6.13: Multiple Parameter Suggestions for Changes

Chapter 7

Conclusions and Recommendations

This chapter summarizes the results from the previous chapters regarding the comprehensive causal model for predicting construction labor productivity. Uncertainty in the construction industry is a common phenomenon. There are uncertainties in all aspects of the industry such as cost engineering, scheduling, and quality control. Researchers and industrial practitioners have tried to decrease the level of uncertainty and risk by employing various methodologies with their decision making processes. Construction labor productivity is one of the main factors that play an important role in the project's cost and time. Predicting or estimating construction labor productivity is a part of any cost estimation or scheduling program. Predicting construction labor productivity is a vital task in the construction industry. The multitude of factors that affect construction labor productivity, the cause-effect relationships among those factors and labor productivity, and inherent uncertainty make these predictions tough. Despite all the research that has been done, the problems remained unsolved due to of lack of a comprehensive model that can represent causal effects among factors, along with the uncertainty that exists. The primary goal of this dissertation is to investigate the feasibility of developing such a model that can predict construction labor productivity while considering causal relationships among variables and inherent uncertainty in the construction industry. After reviewing different approaches, the probabilistic graphical modeling and one of its categories, known as Bayesian Belief Networks was selected.

7.1 Findings and Contributions

The primary goal of this dissertation was to develop a comprehensive causal network to support project managers in making decisions in labor productivity, with the presence of uncertainty. The major findings can be categorized as follows:

a. Feasibility

After extensive literature review, 12 main variables that affect construction labor productivity were selected. For each of those factors, several cause-effect diagrams were extracted from other researchers' publications. Applying different structure techniques such as "Parent divorcing," "Temporal transformation" and "Bidirectional relations," along with parameters approaches such as "Set value by intervention," "Weighted Average" and "Combined Method," were used to obtain CPTs. The 12 sub models were then combined into a comprehensive causal map that can predict construction labor productivity. At the end of chapter 5, it is shown that it is feasible to develop such a complex model. The final network has around 100 nodes and more than 150 edges. Since the model is so complex, all inference can be done by this model is through approximate algorithms such as "Loopy belief propagation" while an exact algorithm such as "Recursive conditioning" cannot solve the problem of belief update in the network.

b. Applicability

This probabilistic graphical model has several applications in the construction industry. The diversity of factors along with causal relationships allows project managers to understand how a certain action can increase or decrease the probability of different states of productivity. This understanding can help project managers regarding their decisions about time and cost. This model can help project managers and legislators in the claim management and resolution area. It will help contractors to negotiate in a better way regarding loss of labor productivity claims. The model helps mangers to understand their flaws which cause lose labor productivity. This model is a comprehensive causal map with numerous factors, but it is also possible to use it for a specific scenario where a limited number of factors play major roles by using the “Set value by intervention” approach or just use different sub models separately.

c. Contributions

This dissertation contributes to the body of knowledge in the several ways:

- It applies one of the modern techniques in the area of machine learning to solve a complex problem in the construction industry. It opens avenues for other areas of the construction industry such as safety, quality, etc. to use this powerful technique to solve complicated cause-effect problems that are inherently uncertain.
- There is a large body of research in construction labor productivity that investigates the effects of different factors on construction labor productivity. This dissertation investigates various publications from journal papers and technical reports from four decades to extract the

causal relationships for different variables. This comprehensive review of the main factors provides a basis to develop the comprehensive model. At the present time, there is not a model in the area of construction labor productivity that considers the causal relationships among more than 40 factors for predicting construction labor productivity. The model in this dissertation can predict productivity while considering both causal relationships and uncertainty for numerous factors.

- Another contribution of this dissertation is the way that are developed CPTs from literature review. Using the concept of “Base Network” and adding one variable at a time to the model along with an iterative process allows to extract the model’s parameters. Although the concept of “Weighted Average” method is a common sense and numerous researchers used this approach in their research in the area of probabilistic graph modeling, using the concept of “Combined Method” for extracting CPTs is innovative.

- Chapter 6 provides various contributions to the body of knowledge which are significant for the decision making process. Various sensitivity analyses reveal several facts about the behavior of different root and main factors, individually. The similarity among the behavior of some factors gives the opportunity to categorize different factors in different groups and investigate their effects in terms of their groups.

- “Adverse Management System” has the most destructive effects on the probability of “High productivity.” This factor can reduce the probability of “High productivity” more than 70% whenever the project is in its perfect state. Whenever the project is in its worst condition, improving this factor individually can only increase the probability of “High productivity” to 10% or less.

- One of the factors that has strange effects on the probability of “High productivity” is “Stacking of Trades.” This factor can decrease the probability of “high productivity” up to 55%, whenever the project is in its perfect situation.
- There are a group of root factors that have effects on labor productivity and are similar to each other and can cause at most 10% decline in the probability of “High Productivity.”
- “Work Complexity” and “Management Request for Overtime/Shift Work” have similar behavior and they have minor effects on the hypothesis variable whenever they are in the “Not observed,” “Low” and “Medium” states while they have “Severe” effects on the hypothesis variable whenever they are in the “High” state.
- Whenever variables are combined to each other, their cumulative effects on labor productivity is not equivalent to the sum of their individual variable effect. The sum of individual variable effects is slightly higher or lower than the effects of their combination.

- The effects of a specific subset of variables on the hypothesis variable for different network's instantiations is not constant and it depends the project situation and state of other factors.

- Effects of different subsets of variables in different groups reveal the fact that for finding the best action, it is necessary to do exhaustive search. The behavior of different subsets have network instantiation dependency, which makes the problem of decision making a complicated and time consuming process.

- The nonlinearity and chaotic behavior of the model shows that why the construction industry has a complex environment in terms of predicting and decision making. This model provides some guidelines for project managers to decide the best actions whenever they are in different situations.

7.2 Research Limitations

This research has several limitations. Model limitations are mostly related to the model's structure and parameter. Some of the limitations are listed as follows:

- This research only investigates the factors that have the most literature available about them. This limits the research from having various factors that may have severe effects on labor productivity, but because of the lack of scholarly research they have been ignored. For example, "sexual harassment" obviously has some effects on labor productivity, but because of the lack of publications about it in the construction industry it has been ignored. It is possible to add some nodes among different variables in the model through common sense, but those edges also have been ignored for the same reason.

- The second limitation of this research is that it only considers discrete probability distribution for nodes' CPTs. However, almost all variables can have continuous probability distribution as their CPTs.

- The biggest hypothesis of this dissertation is that it assumes that all publications from different areas of the construction industry with different time frames are valid sources and they are applicable for any other kind of projects.

7.3 Research Recommendations

For overcoming the research limitation, a list of ways are recommended here. These are as follows:

- Using continuous CPTs for this research was doable if other commercial software packages like "AgenaRisk" are used. However, acquisition of those commercial packages is costly. Finding the continuous CPT for each node is possible by fitting the best curve for the discrete CPT.

- For modifying and enhancing the structure of the network, it is necessary to do research in the areas that lack scholarly publications. This improvement takes time and it needs its own resources.

Chapter 8

Future Research

This chapter investigates future ways of expanding research. Since probabilistic graphical modeling techniques is new in the construction industry research, the potential of applying it to solve various problems is high. The following areas are potential future research related to this dissertation:

i. It is possible to apply BBN to solve other problems in the construction industry. Whenever cause-effect relationships along with uncertainty exist among some variables, BBN is a powerful approach to address those problems. Predicting site safety, construction equipment productivity, quality of works, claim investigations, and cost estimation are examples that can utilize BBN.

ii. There are various BBN types. The applicability of different types of BBN such as "Dynamic BBN" for the construction industry problems need more investigation.

iii. "Fuzzy Bayesian Network" is one of the BBN types that it valuable to do research about how to apply it in the area of labor productivity. Many factors that affect construction labor productivity are linguistic variables, Fuzzy BBN is an appropriate way to investigate this kind of vagueness.

iv. One of the potential research area is to investigate the effect(s) of a certain action on the project schedule. It is necessary to combine BBN with the project's schedule. Since the activity time is inherently uncertain, it means that in future research, it is possible to combine BBN with "Stochastic Activity Network" and find the effect(s) of a specific action on different project's activities throughout the project's life span. This Combination is useful for predicting "Alternative Future" in the construction projects. This prediction can give managers the ability to see different futures and set up different strategies to overcome different problems throughout the project's life span with lower cost.

v. The network structure has been obtained through extensive review of other scholars, and network parameters through a proposed approach. It is possible to extract the structure and parameters of the network through "Learning BBN." In one potential future study, it is possible that a researcher(s) gather data for a specific project and use a learning method, to extract the structure and parameters of the network. This approach can be used for different sub models with a limited number of factors, individually.

vi. Another potential future research is developing a web-based decision support system for construction project managers for predicting construction labor productivity. In this research, project managers enter the project status regarding different factors and they will see the probability distribution of productivity, instantly. It is also feasible to develop a mobile application to do this.

vii. Other approaches in the area of probabilistic graphical modeling also have the capability to solve some complicated problems in the construction industry. "Markov Chains" is one of the approaches that has an exceptional capability to handle uncertainty. In the future, researchers can utilize this approach to investigate about the "steady state" of some specific actions in the area of construction productivity.

viii. Validating this research results can also be a potential for future research. Since, the model has been validated with a limited number of actual construction projects, it is possible to investigate the usefulness and preciseness of this model in more details in the future.

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Appendix A

Model Structure

In this section, for each node, its parent(s) and child (children) are represented in the tables A.1 to A.3. The root nodes are represented in table A.1, the internal nodes are represented in table A.2, and the leaf nodes are represented in table A.3.

Table A.1: Root Nodes Information

Node Name	Parent(s)	Child(Children)
Adverse Management Systems	–	Overstaffing, Delays, INV2, INV9, INV10, INV16, INV18, INV49, INV53
Adverse Weather	–	Delays, Tools/Material Availability, INV12, INV13, INV22, INV33, INV51
Defective Specification	–	INV50
Differing Site Condition	–	INV46
Excessive Workload	–	INV35
Incentives	–	INV15, INV18, INV53
Incomplete Design	–	INV46
Labor Market	–	INV15
Management Request	–	Shift Work, Overtime
Owner-Furnished Equipment	–	INV51
Personal/Physical Characteristics	–	Absenteeism, INV8, INV37
Project Size	–	Workers Autonomy
Repetitive Task(Work)	–	INV37

Table A.1: Root Nodes Information (Continuation)

Node Name	**Parent(s)**	**Child(Children)**
Team Cohesiveness/Workers Relationship	–	INV9, INV17
Work Complexity	–	INV4
Workers Experience	–	Workers Autonomy, INV14, INV35

Table A.2: Internal Nodes Information

Node Name	**Parent(s)**	**Child(Children)**
Absenteeism	Personal/Physical Characteristics. INV7	Lost Hours
Accident & Injuries	Fatigue, Overstaffing	Lost Hours, INV22
Bad Information Availability	Changes, Overtime	Guessing Work, INV29
Being Idle	Work Sequence ,INV13	INV42
Changes	INV49, INV51	Work Sequence, Bad Information Availability, Guessing Work, INV1, INV31, INV47
Communication	Shift Work, Rework	INV43
Congestion	Overstaffing, Stacking of Trades	INV44
Delays	Adverse Weather, Adverse Management Systems	INV1, INV47
Dilution of Supervision	Stacking of Trades, INV21	INV41
Disruption in Learning Curve	Overstaffing, Tools/Material Availability	INV44
Errors & Mistakes	Fatigue, Morale and Attitude	INV5

Table A.2: Internal Nodes Information (Continuation)

Node Name	**Parent(s)**	**Child(Children)**
Fatigue	INV33, INV36	Accident & Injuries, Errors & Mistakes, Poor Quality, Work Slow Down, INV34
Guessing Work	Changes, Bad Information Availability	INV23
INV1	Changes, Delays	Shift Work, INV2
INV2	Adverse Management Systems, INV1	Stacking of Trades
INV3	INV48, INV22	Productivity
INV4	Overstaffing, Work Complexity	Stacking of Trades
INV5	Errors & Mistakes, Poor Quality	INV23
INV6	INV15, INV9	INV7
INV7	INV25, INV6	Absenteeism
INV8	Personal/Physical Characteristics, INV10	Morale and Attitude
INV9	Team Cohesiveness/Workers Relationship, Adverse Management Systems	INV6
INV10	Shift Work, Adverse Management Systems	INV8
INV11	Overstaffing, Rework	INV38
INV12	Adverse Weather, INV23	INV16
INV13	Adverse Weather, INV24	Being Idle
INV14	Workers Experience, Tools/Material Availability	Rework
INV15	Labor Market, Incentives	INV6
INV16	Adverse Management Systems, INV12	Rework

Table A.2: Internal Nodes Information (Continuation)

Node Name	Parent(s)	Child(Children)
INV17	Workers Autonomy, Team Cohesiveness/Workers Relationship	Morale and Attitude, INV32
INV18	Adverse Management Systems, Incentives	INV19
INV19	Stacking of Trades, INV18	INV32
INV20	Job Satisfaction, INV34	Motivation
INV21	Shift Work, Overstaffing	Dilution of Supervision
INV22	Adverse Weather, Accident & Injuries	INV25
INV23	Guessing Work, INV5	INV12
INV24	Stacking of Trades, INV27	INV13
INV25	INV22, INV26	INV7
INV26	Overtime, Overstaffing	INV25
INV27	Shift Work, INV29	INV24
INV28	Overstaffing, INV31	Tools/Material Availability, INV29
INV29	Bad Information Availability, INV28	INV27
INV30	Shift Work, Overtime	INV33
INV31	Changes, Overtime	INV28
INV32	INV17, INV19	Motivation
INV33	Adverse Weather, INV30	Fatigue
INV34	Fatigue, INV38	INV20
INV35	Excessive Workload, Workers Experience	INV36
INV36	INV35, INV37	Fatigue
INV37	Personal/Physical Characteristics, Repetitive Task(Work)	INV36
INV38	Shift Work, INV11	INV34
INV39	Lost Hours, Work Slow Down	INV45
INV40	Morale and Attitude, Motivation	INV43

Table A.2: Internal Nodes Information (Continuation)

Node Name	**Parent(s)**	**Child(Children)**
INV41	Dilution of Supervision, Stacking of Trades	INV48
INV42	Being Idle, Rework	INV45
INV43	Communication, INV40	Productivity
INV44	Congestion, Disruption in Learning Curve	INV48
INV45	INV39, INV42	INV52
INV46	Differing Site Condition, Incomplete Design	INV50
INV47	Changes, Delays	Overstaffing
INV48	INV41, INV44	INV3
INV49	Adverse Management Systems, INV50	Changes
INV50	Defective Specification, INV46	INV49
INV51	Adverse Weather, Owner-Furnished Equipment	Changes
INV52	Work Sequence, INV45	INV3
INV53	Adverse Management Systems, Incentives	Job Satisfaction
INV54	Morale and Attitude, Workers Autonomy	Job Satisfaction
Job Satisfaction	INV53, INV54	INV20
Lost Hours	Absenteeism, Accident & Injuries	INV39
Motivation	INV20, INV32	INV40
Overstaffing	Adverse Management Systems, INV47	Accident & Injuries, Congestion, Disruption in Learning Curve, INV4, INV11, INV21, INV26, INV28
Poor Quality	Fatigue, Work Sequence	INV5

Table A.2: Internal Nodes Information (Continuation)

Node Name	Parent(s)	Child(Children)
Rework	INV14, INV17	Communication, Constraint Variable, INV11, INV42
Shift Work	Management Request	Communication, INV10, INV21, INV27, INV30, INV38
Stacking of Trades	INV2, INV4	Congestion, Constraint Variable, Overtime, Dilution of Supervision, Work Sequence, INV19, INV24, INV41
Tools/Material Availability	Adverse Weather, INV28	Disruption in Learning Curve, INV14
Workers Autonomy	Project Size, Workers Experience	INV17, INV54
Work Sequence	Changes, Stacking of Trades	Poor Quality, Work Slow Down, Being Idle, INV52
Work Slow Down	Fatigue, Work Sequence	INV39

Table A.3: Leaf Nodes Information

Node Name	Parent(s)	Child(Children)
Constraint Variable	Rework, Stacking of Trades	
Productivity	INV3, INV43	

Appendix B

Model CPTs

The following list of figures relates to the model CPTs. Figure B.1 to B.16 are related to the root variables. Figures B.17 to B.97 are related to the internal variables, and Figures B.98 to B.99 are related to the leaf variables.

B.1 Root Variables

Root Variables CPTs can be anything. They can be observed or have a specific distribution. In this section, root variables' CPTs are shown.

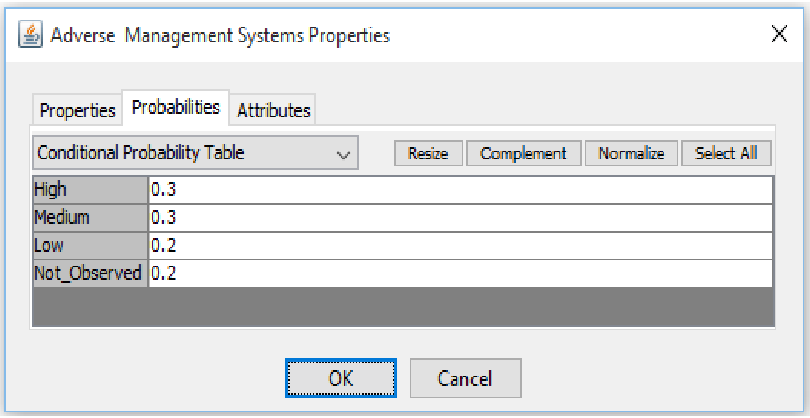


Figure B.1: Adverse Management Systems CPT

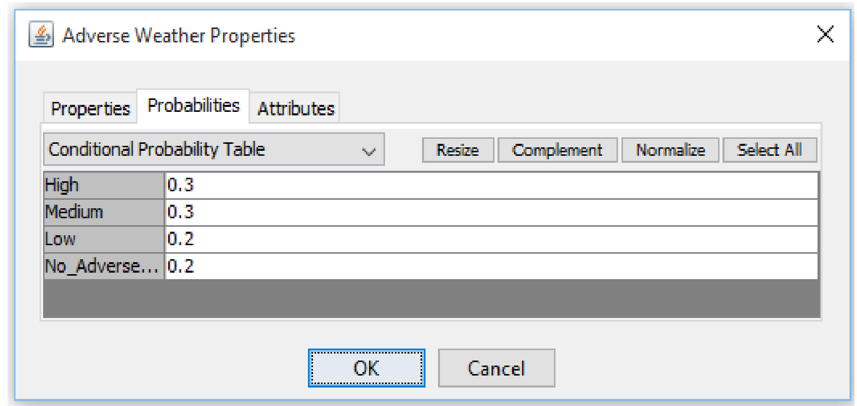


Figure B.2: Adverse Weather CPT

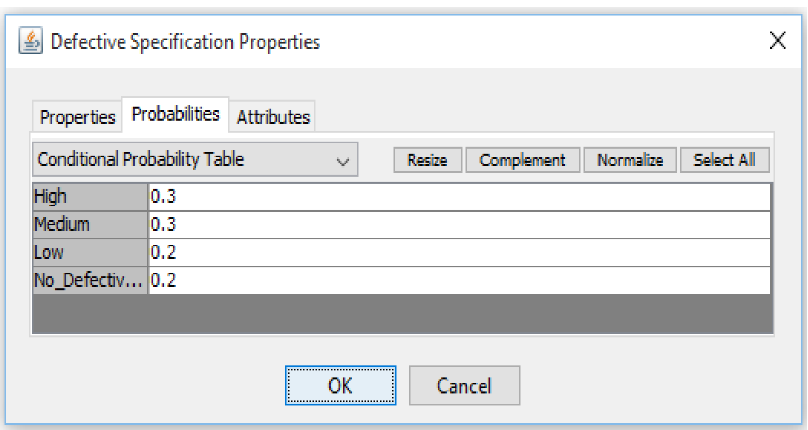


Figure B.3: Defective Specification CPT

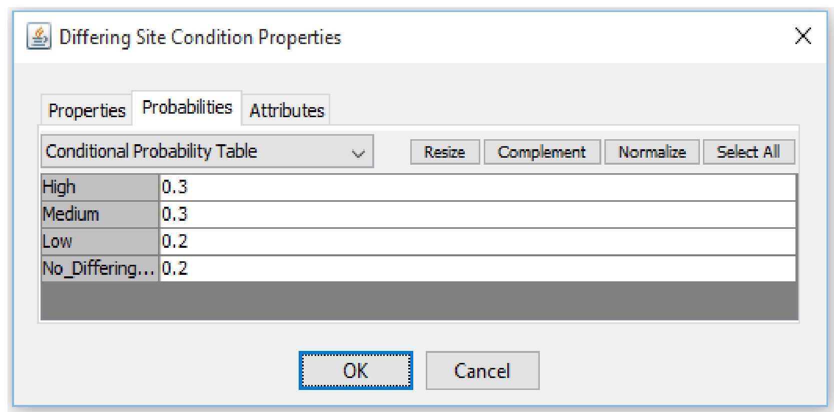


Figure B.4: Differing Site Condition CPT

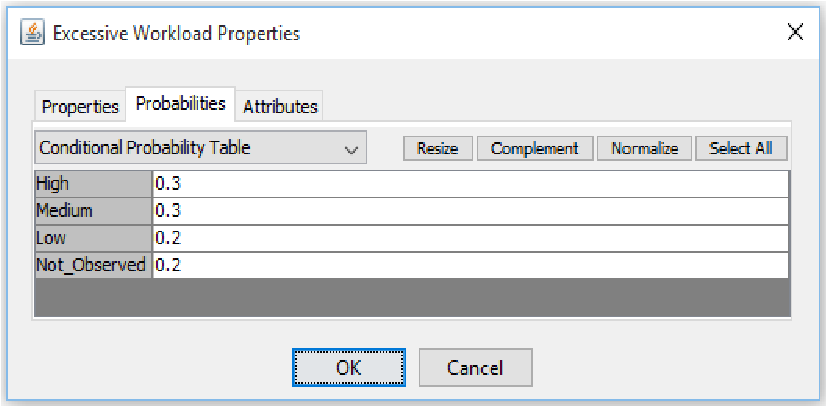


Figure B. 5: Excessive Workload CPT

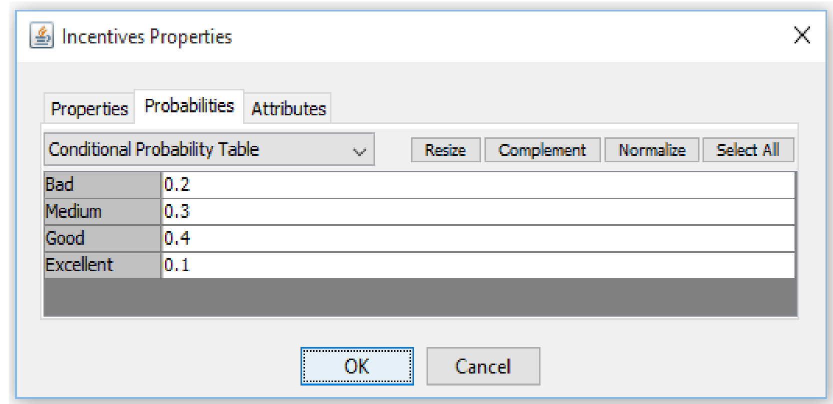


Figure B.6: Incentives CPT

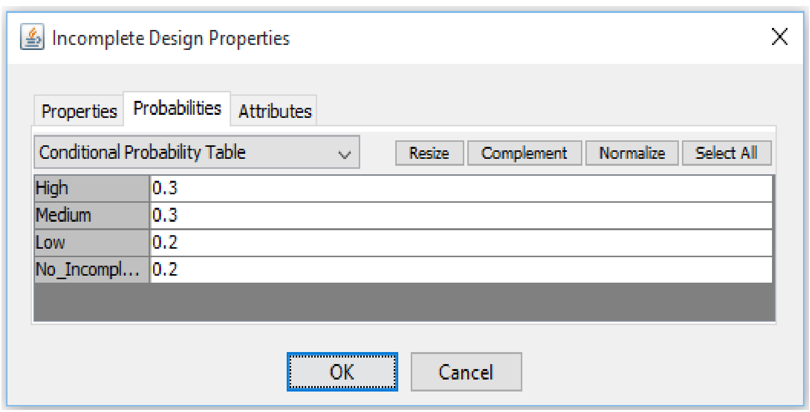


Figure B.7: Incomplete Design CPT

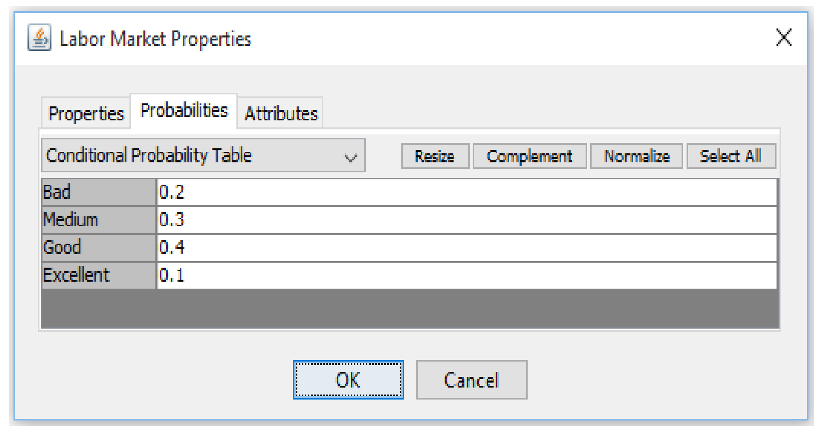


Figure B.8: Labor Market CPT

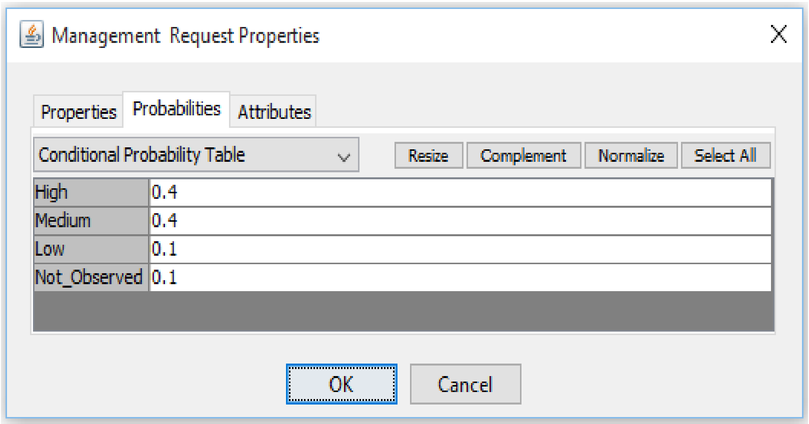


Figure B.9: Management Request CPT

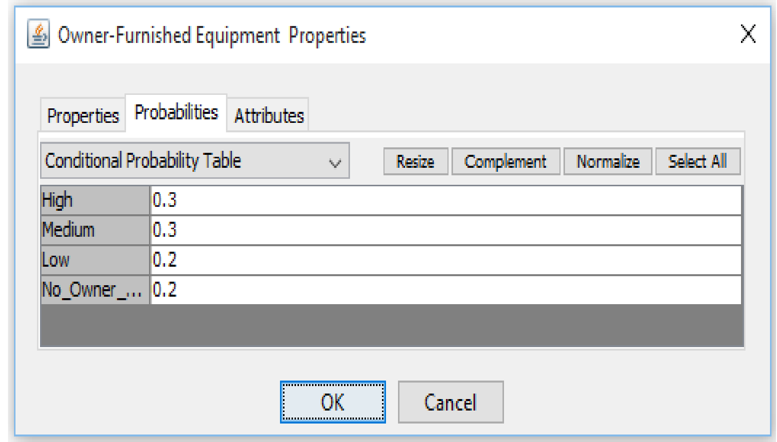


Figure B.10: Owner-Furnished Equipment CPT

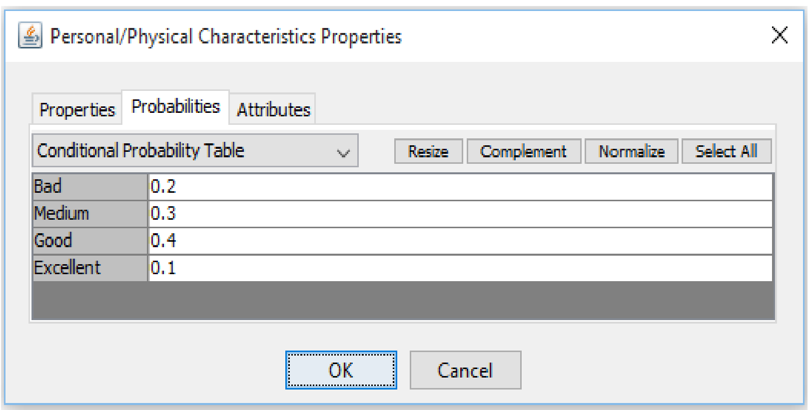


Figure B.11: Personal/Physical Characteristics CPT

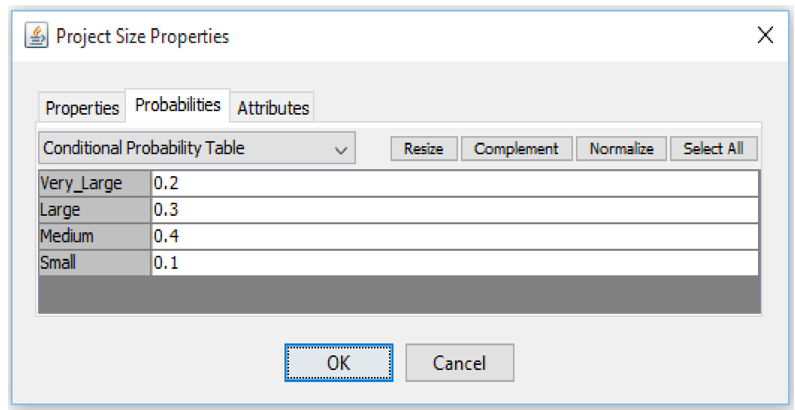


Figure B.12: Project Size CPT

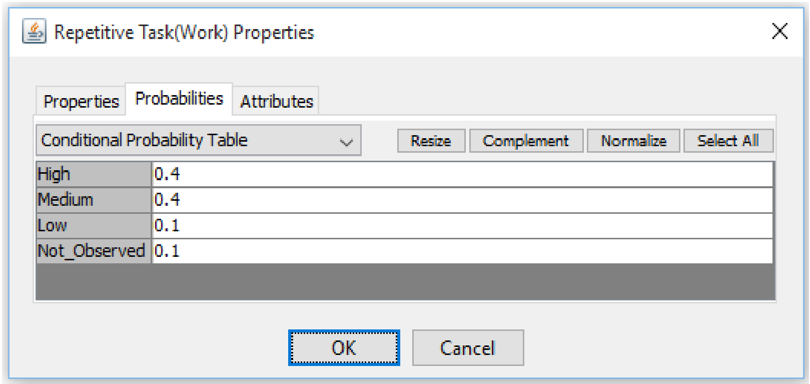


Figure B.13: Repetitive Task (Work) CPT

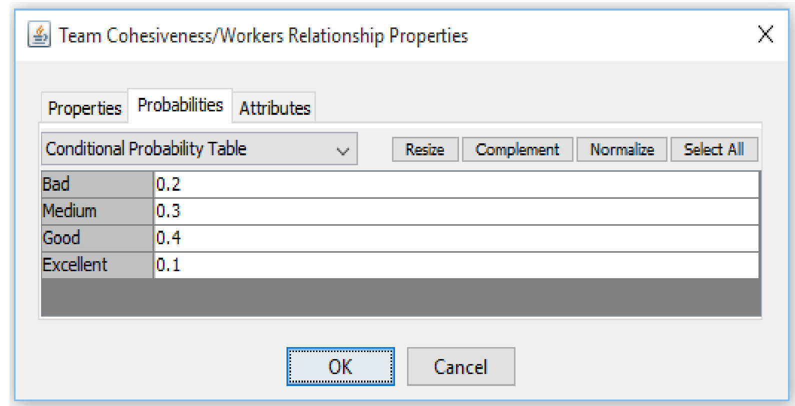


Figure B.14: Team Cohesiveness/Workers Relationship CPT

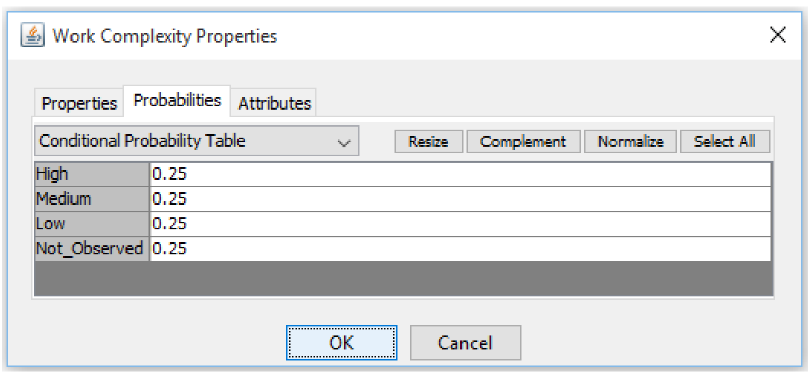


Figure B.15: Work Complexity CPT

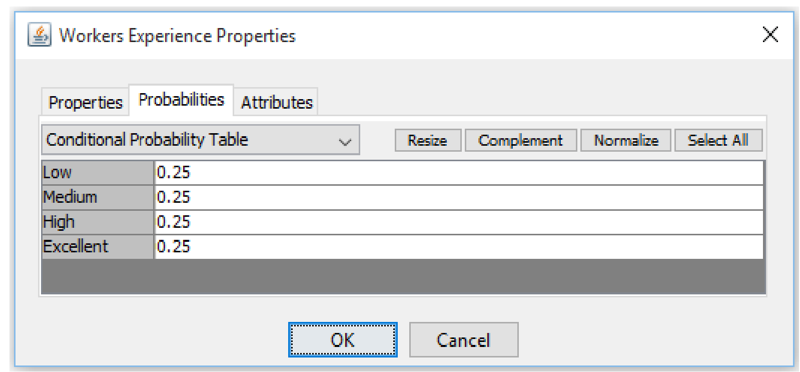


Figure B.16: Workers Experience CPT

B.2 Internal Variables

In this section the internal variables CPTs are represented. In these CPTs “Not_Obs” means “Not_Observed.”

Absenteesim Properties

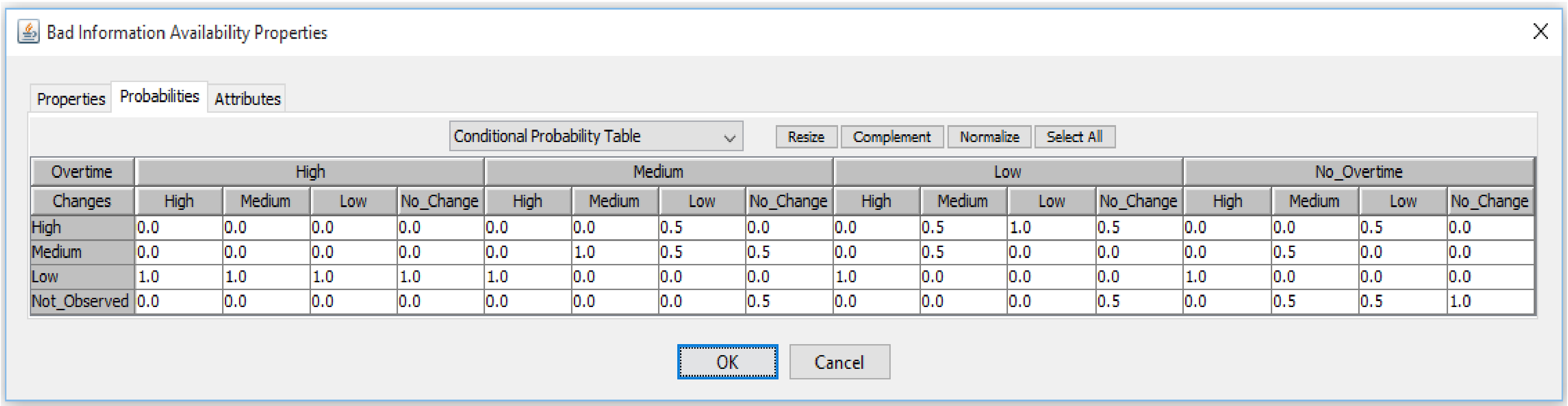
INV7	High				Medium				Low				Not_Observed			
Personal/Ph...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.89	0.89	0.89	0.11	0.0	0.0	0.0	0.11	0.0	0.0	0.0	0.11	0.0	0.0	0.0
Medium	0.0	0.11	0.0	0.0	0.89	1.0	0.89	0.89	0.0	0.11	0.0	0.0	0.0	0.11	0.0	0.0
Low	0.0	0.0	0.11	0.0	0.0	0.0	0.11	0.0	0.89	0.89	1.0	0.89	0.0	0.0	0.11	0.0
No_Obsente...	0.0	0.0	0.0	0.11	0.0	0.0	0.0	0.11	0.0	0.0	0.0	0.11	0.89	0.89	0.89	1.0

Figure B.17: Absenteeism CPT

Accident&Injuries Properties

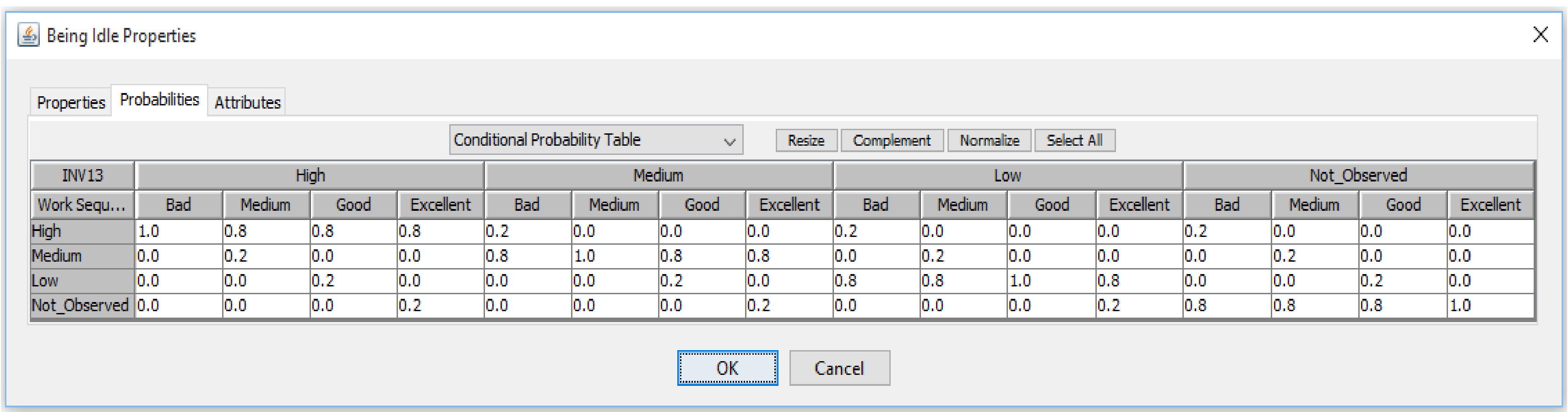
Overmanning	High				Medium				Low				Not_Obs			
Fatigue	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.125	0.125	0.125	0.875	0.0	0.0	0.0	0.875	0.0	0.0	0.0	0.875	0.0	0.0	0.0
Medium	0.0	0.875	0.0	0.0	0.125	1.0	0.125	0.125	0.0	0.875	0.0	0.0	0.0	0.875	0.0	0.0
Low	0.0	0.0	0.875	0.0	0.0	0.0	0.875	0.0	0.125	0.125	1.0	0.125	0.0	0.0	0.875	0.0
No_Accident...	0.0	0.0	0.0	0.875	0.0	0.0	0.0	0.875	0.0	0.0	0.0	0.875	0.125	0.125	0.125	1.0

Figure B.18: Accident & Injuries CPT



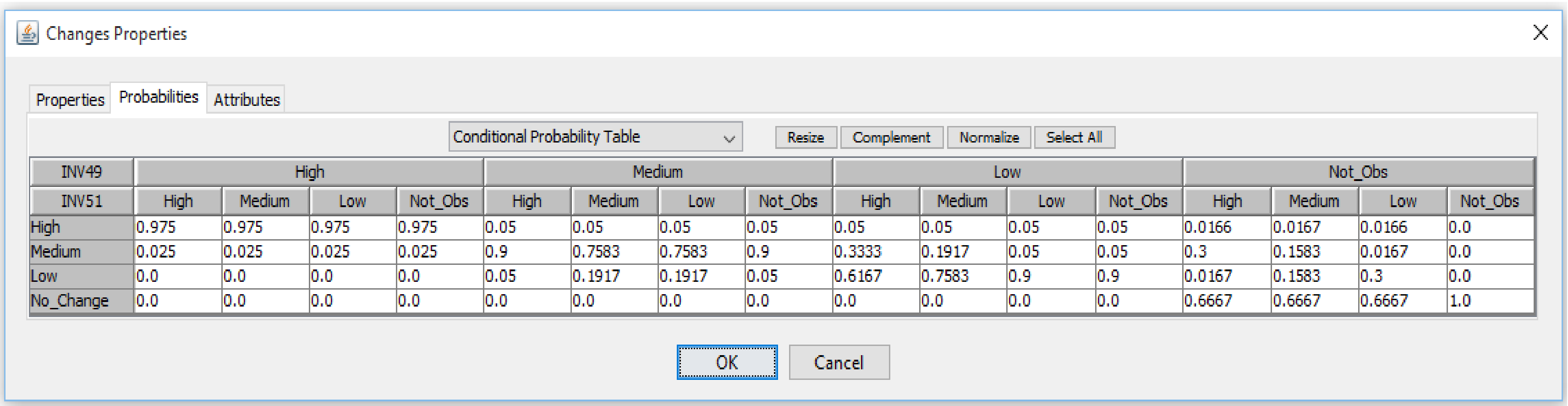
Overtime	High				Medium				Low				No_Overtime			
Changes	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change
High	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Not_Observed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure B.19: Bad Information Availability CPT



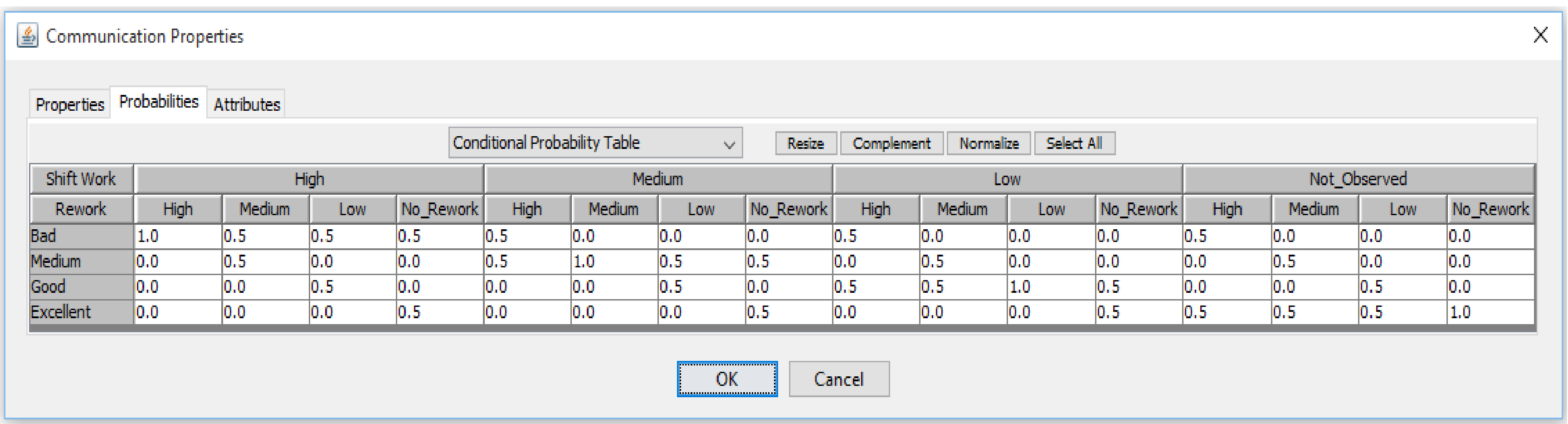
INV13	High				Medium				Low				Not_Observed			
Work Sequ...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.8	0.8	0.8	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0
Medium	0.0	0.2	0.0	0.0	0.8	1.0	0.8	0.8	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0
Low	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.8	0.8	1.0	0.8	0.0	0.0	0.2	0.0
Not_Observed	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.8	0.8	0.8	1.0

Figure B.20: Being Idle CPT



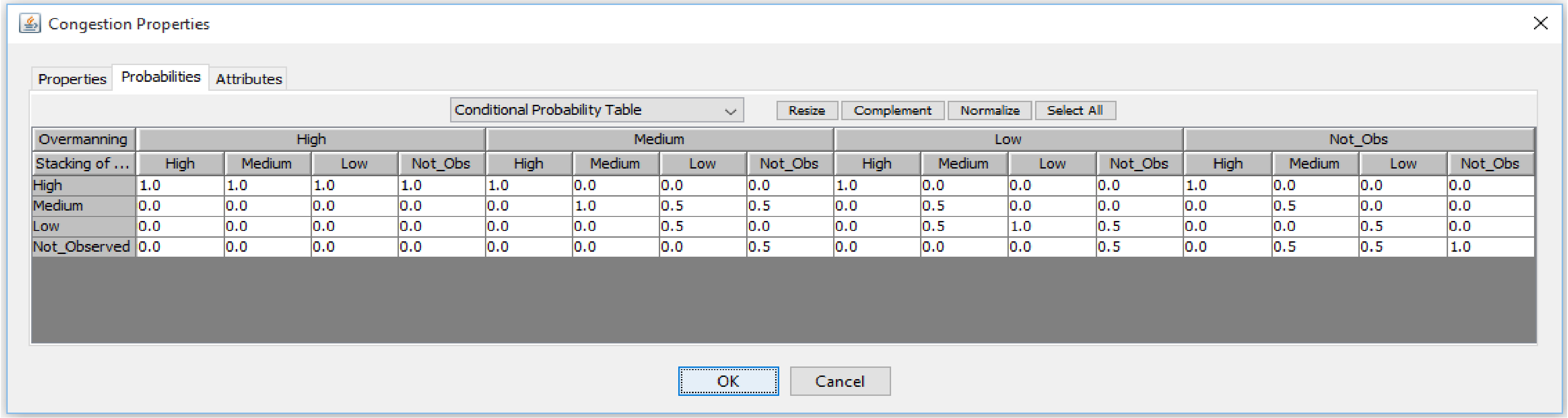
INV49	High				Medium				Low				Not_Obs			
INV51	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	0.975	0.975	0.975	0.975	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.0166	0.0167	0.0166	0.0
Medium	0.025	0.025	0.025	0.025	0.9	0.7583	0.7583	0.9	0.3333	0.1917	0.05	0.05	0.3	0.1583	0.0167	0.0
Low	0.0	0.0	0.0	0.0	0.05	0.1917	0.1917	0.05	0.6167	0.7583	0.9	0.9	0.0167	0.1583	0.3	0.0
No_Change	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6667	0.6667	0.6667	1.0

Figure B.21: Changes CPT



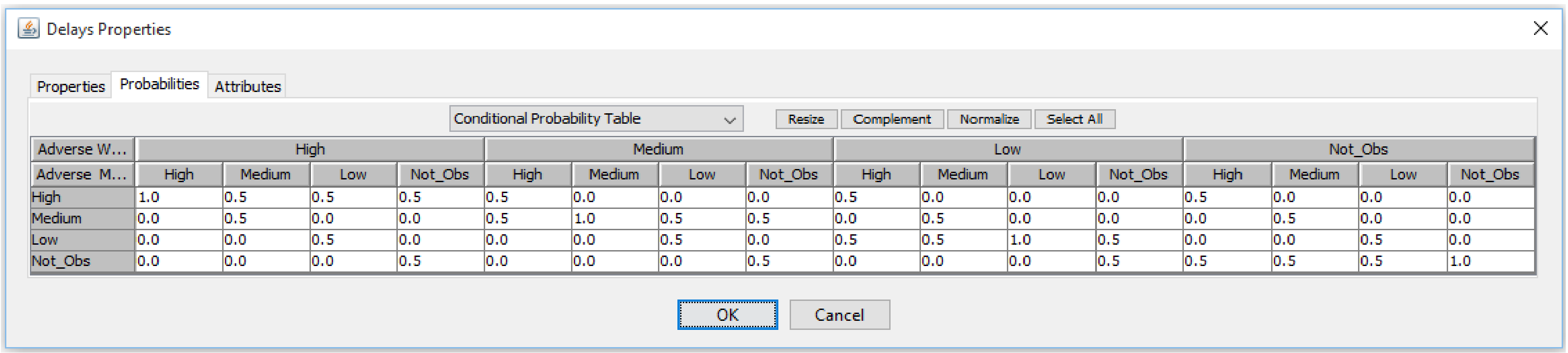
Shift Work	High				Medium				Low				Not_Observed			
Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework
Bad	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.22: Communication CPT



Overmanning	High				Medium				Low				Not_Obs			
Stacking of ...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Observed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure B.23: Congestion CPT



Adverse W...	High				Medium				Low				Not_Obs			
Adverse M...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.24: Delays CPT

Dilution of Supervision Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Stacking of ...	High				Medium				Low				Not_Obs			
INV21	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.667	0.667	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.0
Low	0.0	0.0	0.0	0.0	0.0	0.0	0.333	0.0	0.0	0.667	1.0	0.667	0.0	0.0	0.333	0.0
Not_Observed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.667	0.667	1.0

OK | Cancel

Figure B.25: Dilution of Supervision CPT

Disruption in Learning Curve Properties

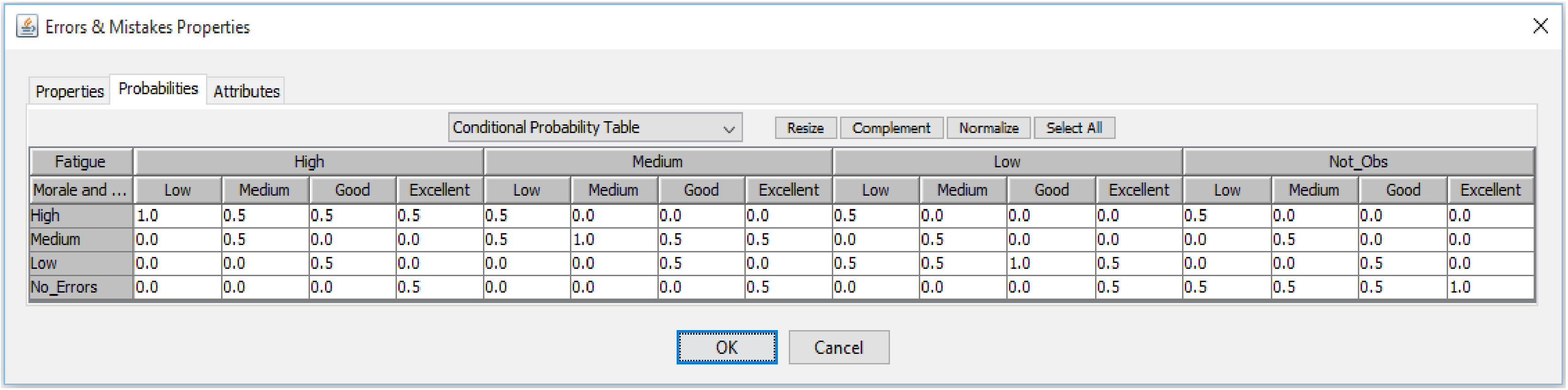
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Overmanning	High				Medium				Low				Not_Obs			
Tools/Mater...	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent
High	1.0	0.2	0.2	0.2	0.8	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.8	0.0	0.0	0.0
Medium	0.0	0.8	0.0	0.0	0.2	1.0	0.2	0.2	0.0	0.8	0.0	0.0	0.0	0.8	0.0	0.0
Low	0.0	0.0	0.8	0.0	0.0	0.0	0.8	0.0	0.2	0.2	1.0	0.2	0.0	0.0	0.8	0.0
Not_Obs	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.8	0.0	0.0	0.0	0.8	0.2	0.2	0.2	1.0

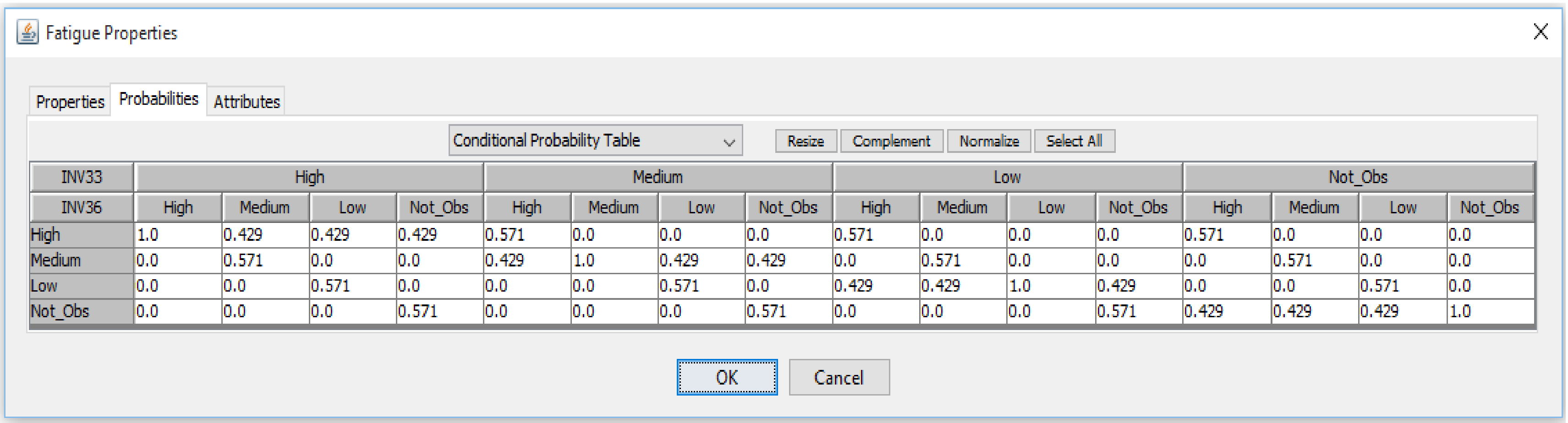
OK | Cancel

Figure B.26: Disruption in Learning Curve CPT



Fatigue	High				Medium				Low				Not_Obs			
Morale and ...	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
No_Errors	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.27: Errors & Mistakes CPT



INV33	High				Medium				Low				Not_Obs			
INV36	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.429	0.429	0.429	0.571	0.0	0.0	0.0	0.571	0.0	0.0	0.0	0.571	0.0	0.0	0.0
Medium	0.0	0.571	0.0	0.0	0.429	1.0	0.429	0.429	0.0	0.571	0.0	0.0	0.0	0.571	0.0	0.0
Low	0.0	0.0	0.571	0.0	0.0	0.0	0.571	0.0	0.429	0.429	1.0	0.429	0.0	0.0	0.571	0.0
Not_Obs	0.0	0.0	0.0	0.571	0.0	0.0	0.0	0.571	0.0	0.0	0.0	0.571	0.429	0.429	0.429	1.0

Figure B.28: Fatigue CPT

Guessing Work Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Bad Inform...	High				Medium				Low				Not_Observed			
Changes	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

OK | Cancel

Figure B.29: Guessing Work CPT

INV1 Properties

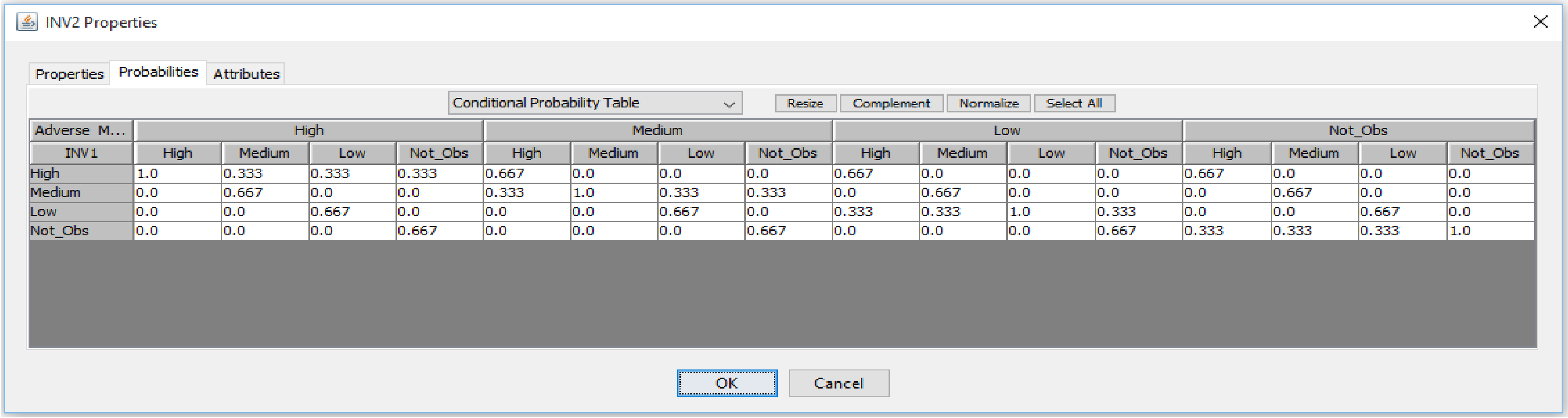
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Changes	High				Medium				Low				No_Change			
Delays	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

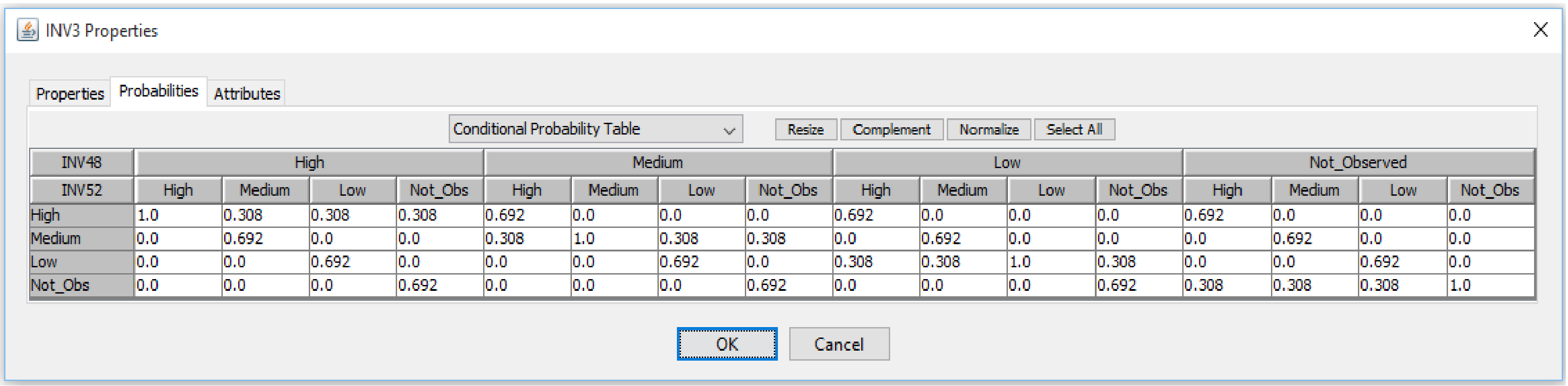
OK | Cancel

Figure B.30: INV1 CPT



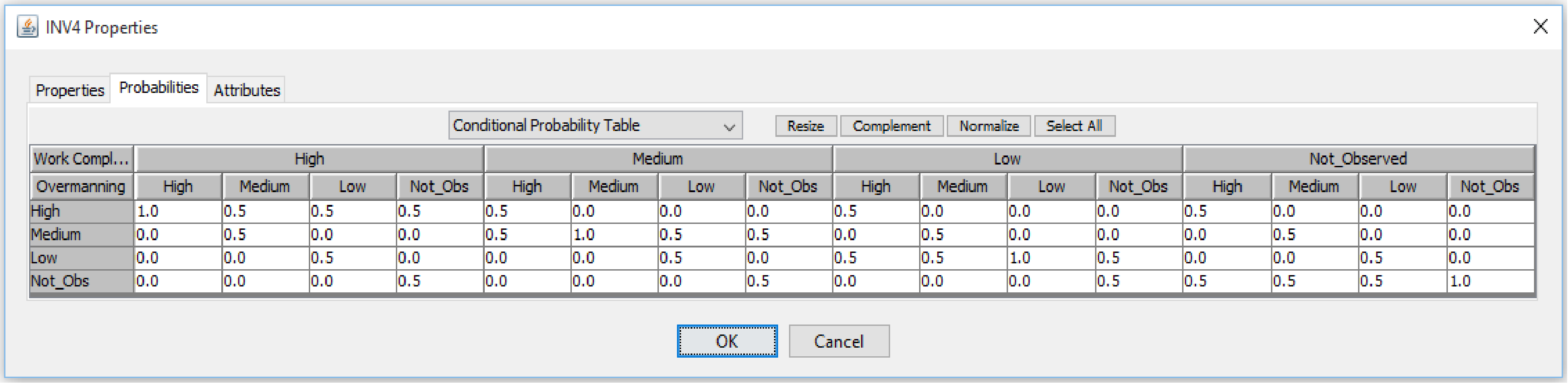
Adverse M...	High				Medium				Low				Not_Obs			
INV1	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.333	0.333	0.333	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0
Medium	0.0	0.667	0.0	0.0	0.333	1.0	0.333	0.333	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0
Low	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.333	0.333	1.0	0.333	0.0	0.0	0.667	0.0
Not_Obs	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.333	0.333	0.333	1.0

Figure B.31: INV2 CPT



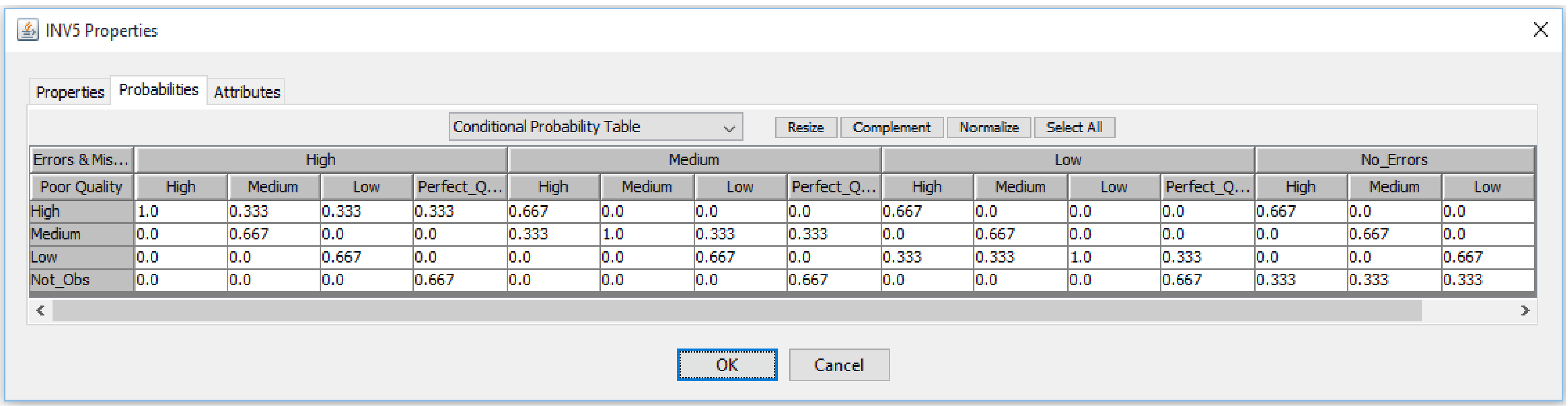
INV48	High				Medium				Low				Not_Observed			
INV52	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.308	0.308	0.308	0.692	0.0	0.0	0.0	0.692	0.0	0.0	0.0	0.692	0.0	0.0	0.0
Medium	0.0	0.692	0.0	0.0	0.308	1.0	0.308	0.308	0.0	0.692	0.0	0.0	0.0	0.692	0.0	0.0
Low	0.0	0.0	0.692	0.0	0.0	0.0	0.692	0.0	0.308	0.308	1.0	0.308	0.0	0.0	0.692	0.0
Not_Obs	0.0	0.0	0.0	0.692	0.0	0.0	0.0	0.692	0.0	0.0	0.0	0.692	0.308	0.308	0.308	1.0

Figure B.32: INV3 CPT



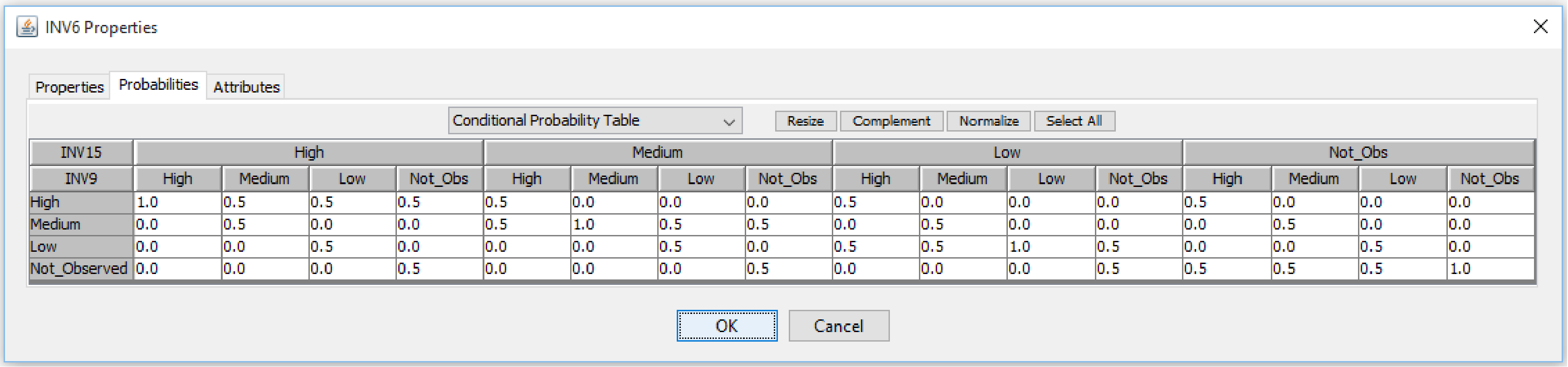
Work Compl…	High				Medium				Low				Not_Observed			
Overmanning	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.33: INV4 CPT



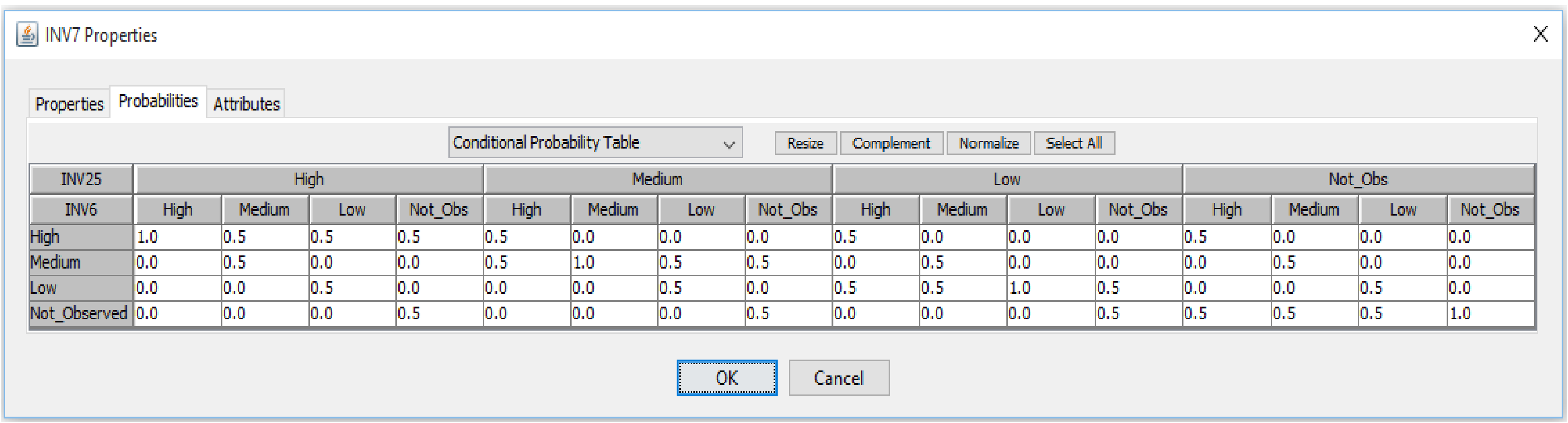
Errors & Mis…	High				Medium				Low				No_Errors		
Poor Quality	High	Medium	Low	Perfect_Q…	High	Medium	Low	Perfect_Q…	High	Medium	Low	Perfect_Q…	High	Medium	Low
High	1.0	0.333	0.333	0.333	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0
Medium	0.0	0.667	0.0	0.0	0.333	1.0	0.333	0.333	0.0	0.667	0.0	0.0	0.0	0.667	0.0
Low	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.333	0.333	1.0	0.333	0.0	0.0	0.667
Not_Obs	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.333	0.333	0.333

Figure B.34: INV5 CPT



INV15	High				Medium				Low				Not_Obs			
INV9	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Observed	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.35: INV6 CPT



INV25	High				Medium				Low				Not_Obs			
INV6	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Observed	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.36: INV7 CPT

INV8 Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

INV10	High				Medium				Low				Not_Observed			
Personal/Ph...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.667	0.667	0.667	0.333	0.0	0.0	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.0	0.0
Medium	0.0	0.333	0.0	0.0	0.667	1.0	0.667	0.667	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.0
Low	0.0	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.667	0.667	1.0	0.333	0.0	0.0	0.333	0.0
Not_Observed	0.0	0.0	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.0	0.0	0.667	0.667	0.667	0.667	1.0

OK | Cancel

Figure B.37: INV8 CPT

INV9 Properties

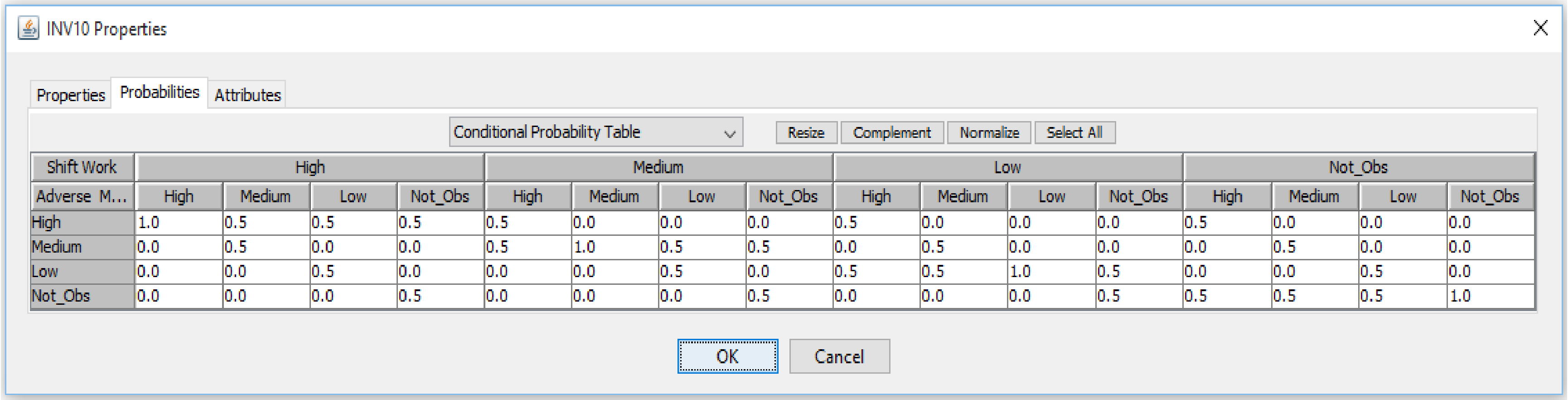
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Team Cohe...	Bad				Medium				Good				Excellent			
Adverse M...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

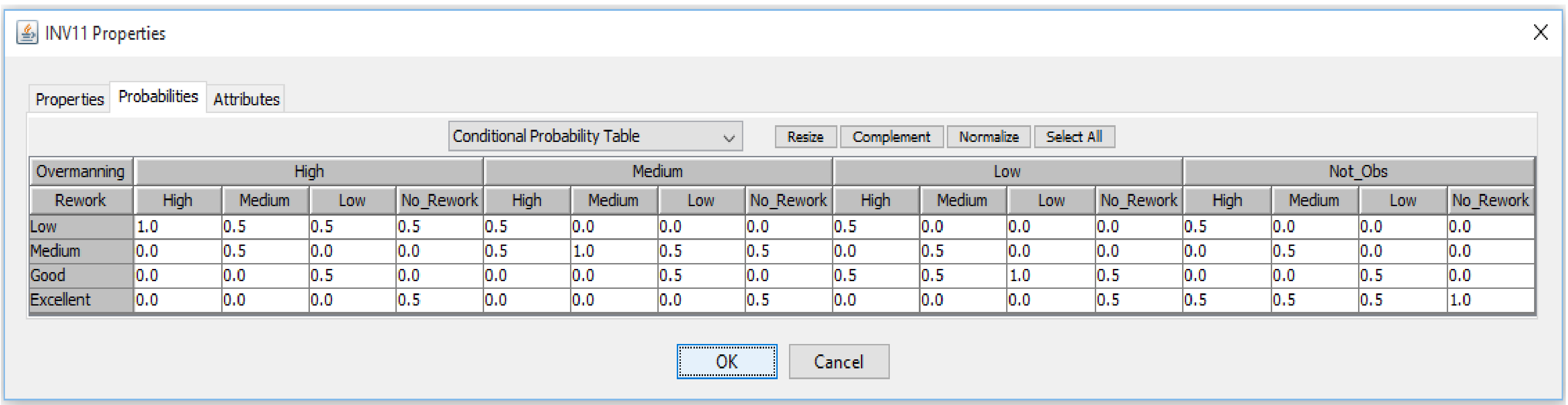
OK | Cancel

Figure B.38: INV9 CPT



Shift Work	High				Medium				Low				Not_Obs			
Adverse M...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.39: INV10 CPT



Overmanning	High				Medium				Low				Not_Obs			
Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.40: INV11 CPT

INV12 Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

INV23	High				Medium				Low				Not_Obs			
Adverse W...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.75	0.75	0.75	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0
Medium	0.0	0.25	0.0	0.0	0.75	1.0	0.75	0.75	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0
Low	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.75	0.75	1.0	0.75	0.0	0.0	0.25	0.0
Not_Obs	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.75	0.75	0.75	1.0

OK | Cancel

Figure B.41: INV12 CPT

INV13 Properties

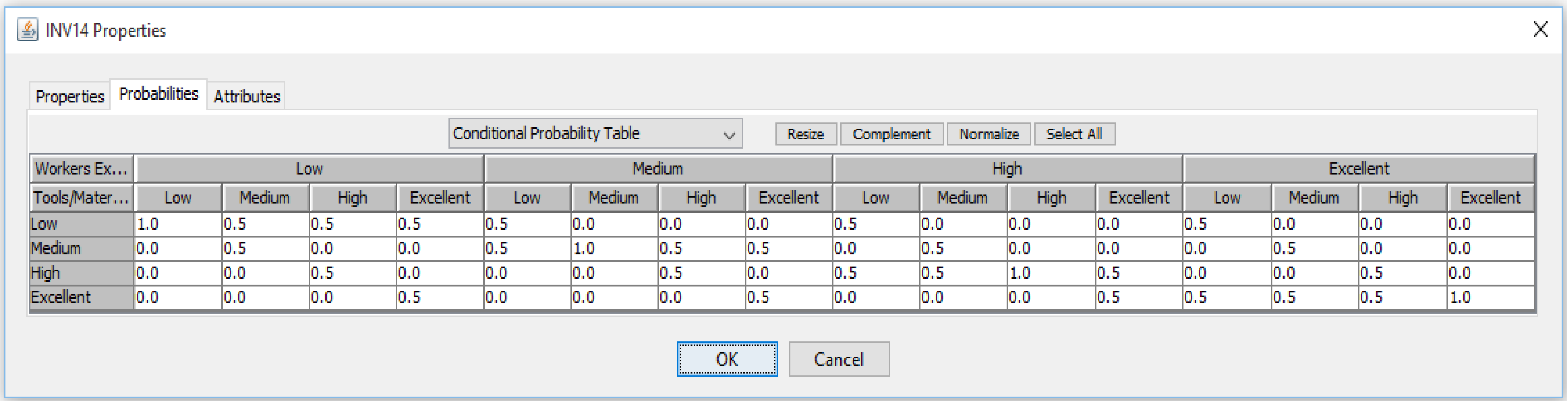
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Adverse W...	High				Medium				Low				Not_Obs			
INV24	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.25	0.25	0.25	0.75	0.0	0.0	0.0	0.75	0.0	0.0	0.0	0.75	0.0	0.0	0.0
Medium	0.0	0.75	0.0	0.0	0.25	1.0	0.25	0.25	0.0	0.75	0.0	0.0	0.0	0.25	0.0	0.0
Low	0.0	0.0	0.75	0.0	0.0	0.0	0.75	0.0	0.25	0.25	1.0	0.25	0.0	0.0	0.25	0.0
Not_Obs	0.0	0.0	0.0	0.75	0.0	0.0	0.0	0.75	0.0	0.0	0.0	0.75	0.25	0.75	0.75	1.0

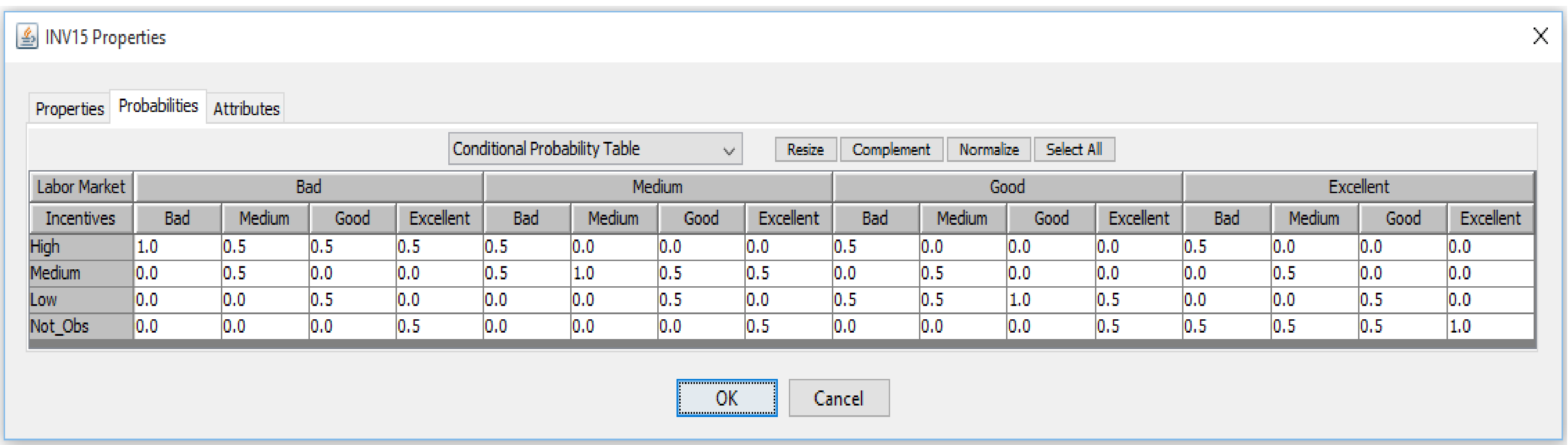
OK | Cancel

Figure B.42: INV13 CPT



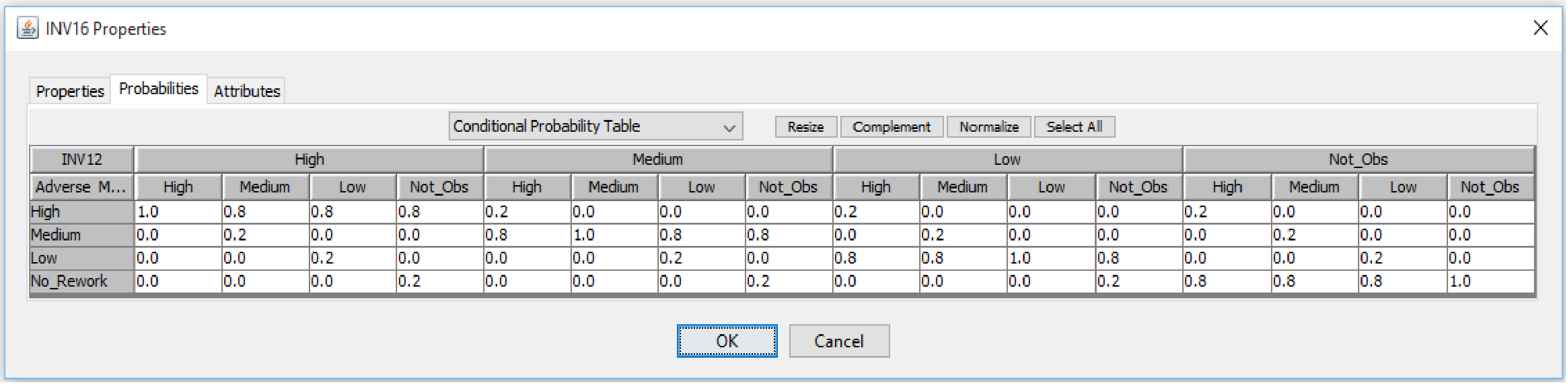
Workers Ex...	Low				Medium				High				Excellent			
Tools/Mater...	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
High	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.43: INV14 CPT



Labor Market	Bad				Medium				Good				Excellent			
Incentives	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.44: INV15 CPT


INV16 Properties

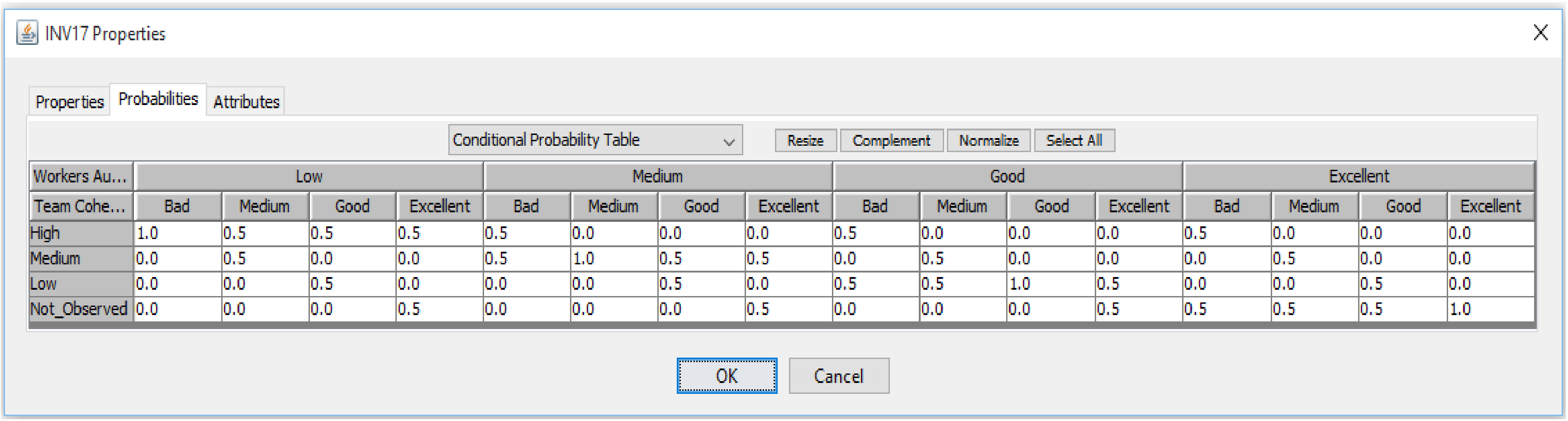
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

INV12	High				Medium				Low				Not_Obs			
Adverse M...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.8	0.8	0.8	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0
Medium	0.0	0.2	0.0	0.0	0.8	1.0	0.8	0.8	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0
Low	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.8	0.8	1.0	0.8	0.0	0.0	0.2	0.0
No_Rework	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.8	0.8	0.8	1.0

OK | Cancel

Figure B.45: INV16 CPT


INV17 Properties

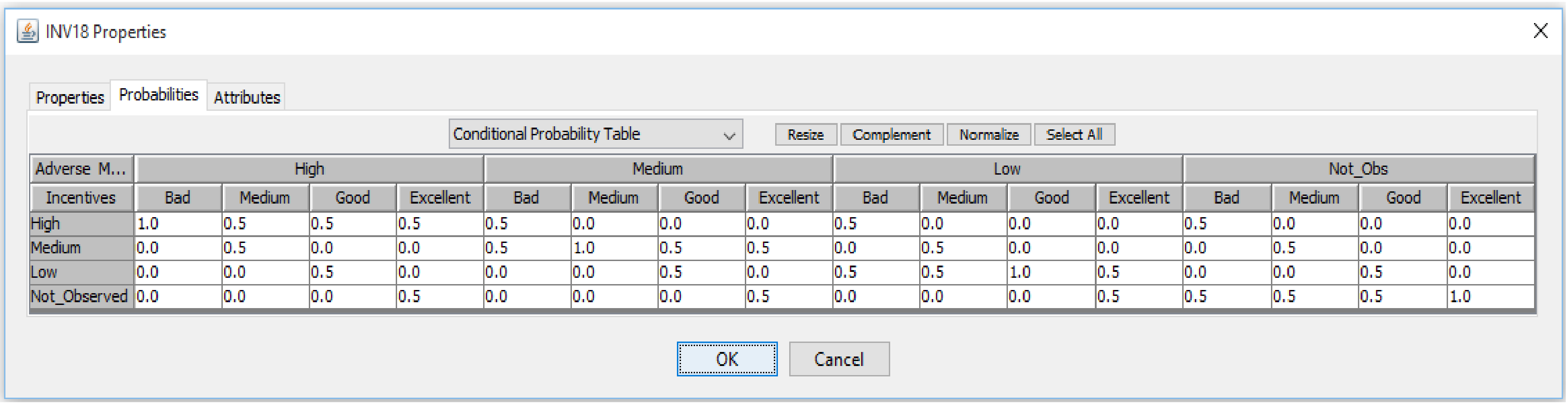
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Workers Au...	Low				Medium				Good				Excellent			
Team Cohe...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Observed	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

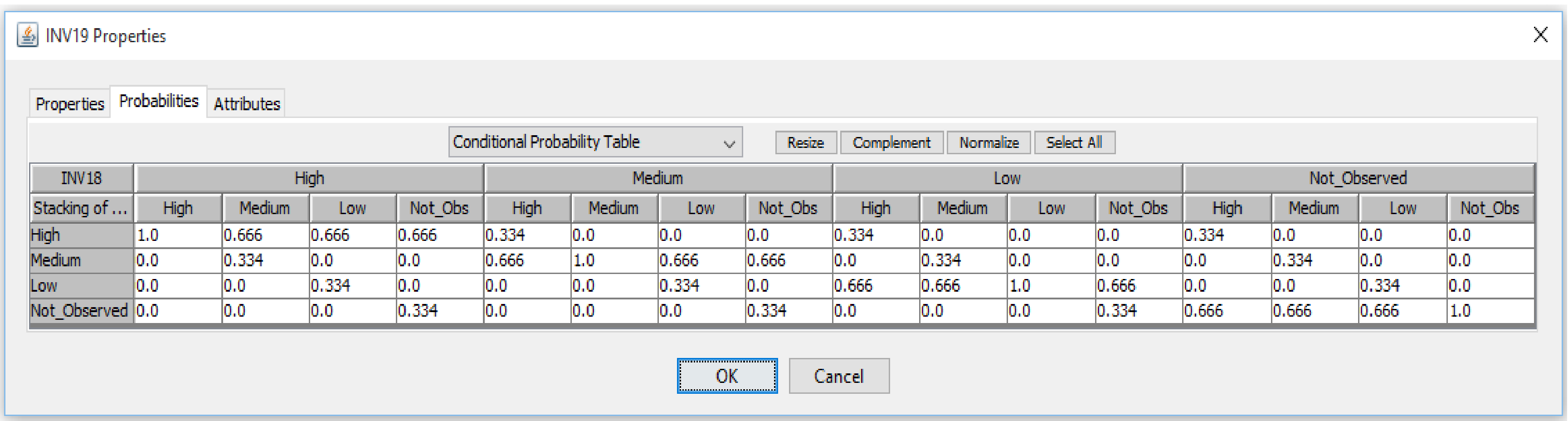
OK | Cancel

Figure B.46: INV17 CPT



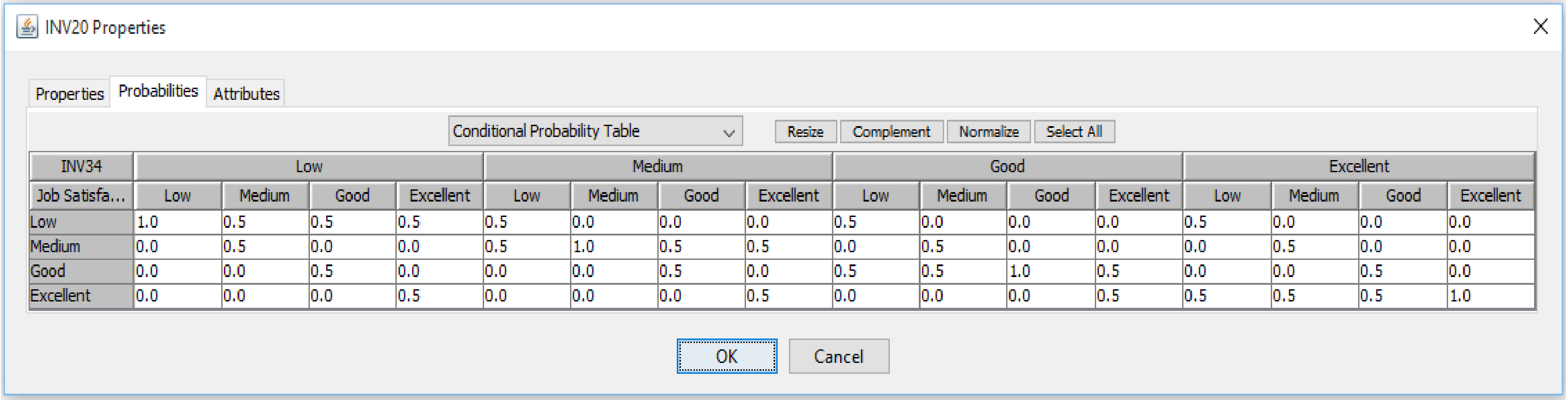
Adverse M...	High				Medium				Low				Not_Obs			
Incentives	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Observed	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.47: INV18 CPT



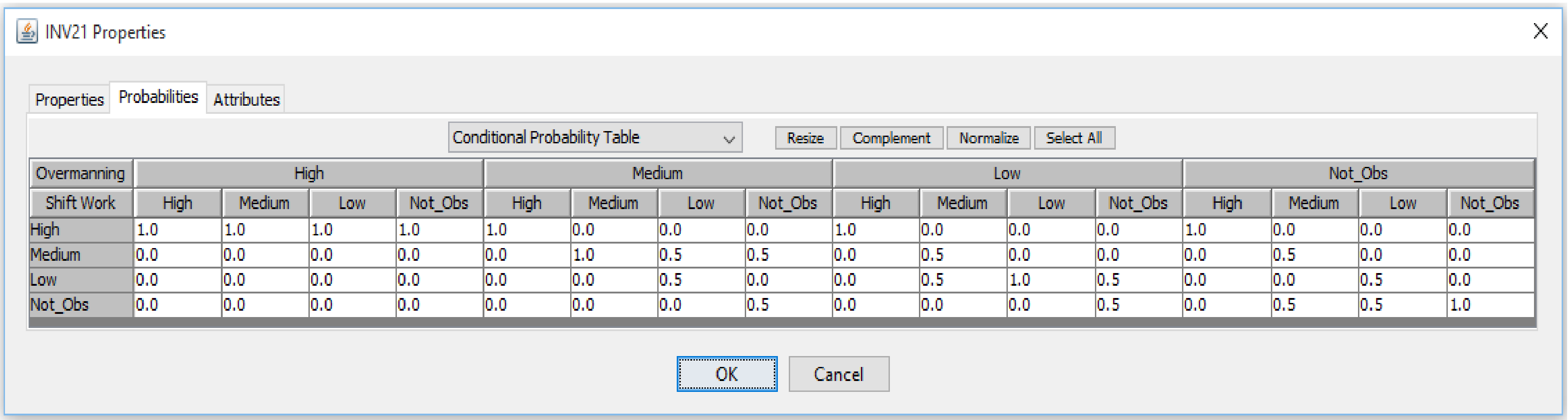
INV18	High				Medium				Low				Not_Observed			
Stacking of ...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.666	0.666	0.666	0.334	0.0	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.0	0.0
Medium	0.0	0.334	0.0	0.0	0.666	1.0	0.666	0.666	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.0
Low	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.666	0.666	1.0	0.666	0.0	0.0	0.334	0.0
Not_Observed	0.0	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.666	0.666	0.666	1.0

Figure B.48: INV19 CPT



INV34	Low				Medium				Good				Excellent			
Job Satisfa...	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.49: INV20 CPT



Overmanning	High				Medium				Low				Not_Obs			
Shift Work	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure B.50: INV21 CPT

INV22 Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Accident&I...	High				Medium				Low				No_Accident_Injuries			
Adverse W...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

OK | Cancel

Figure B.51: INV22 CPT

INV23 Properties

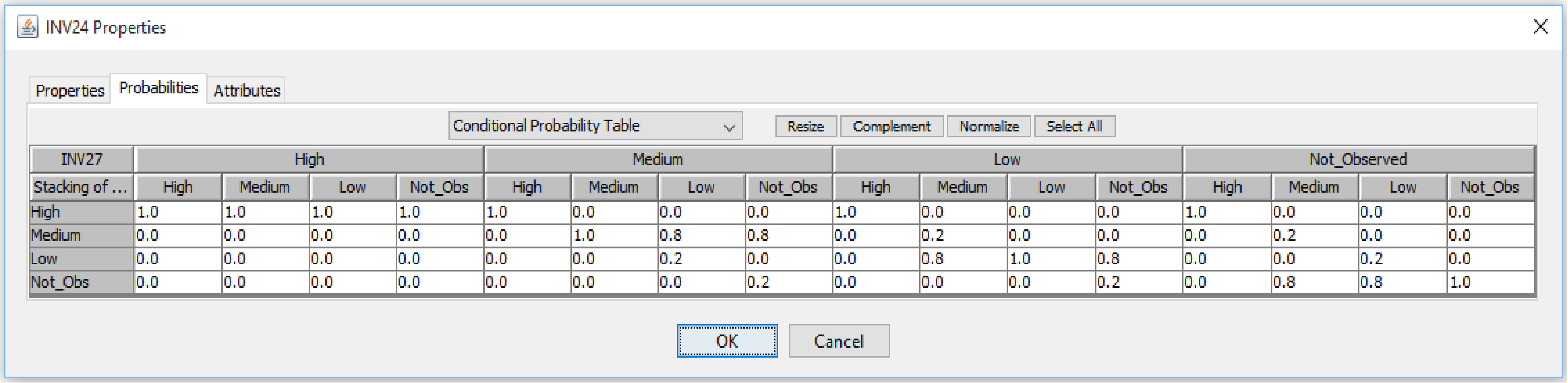
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Guessing W...	High				Medium				Low				Not_Obs			
INV5	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

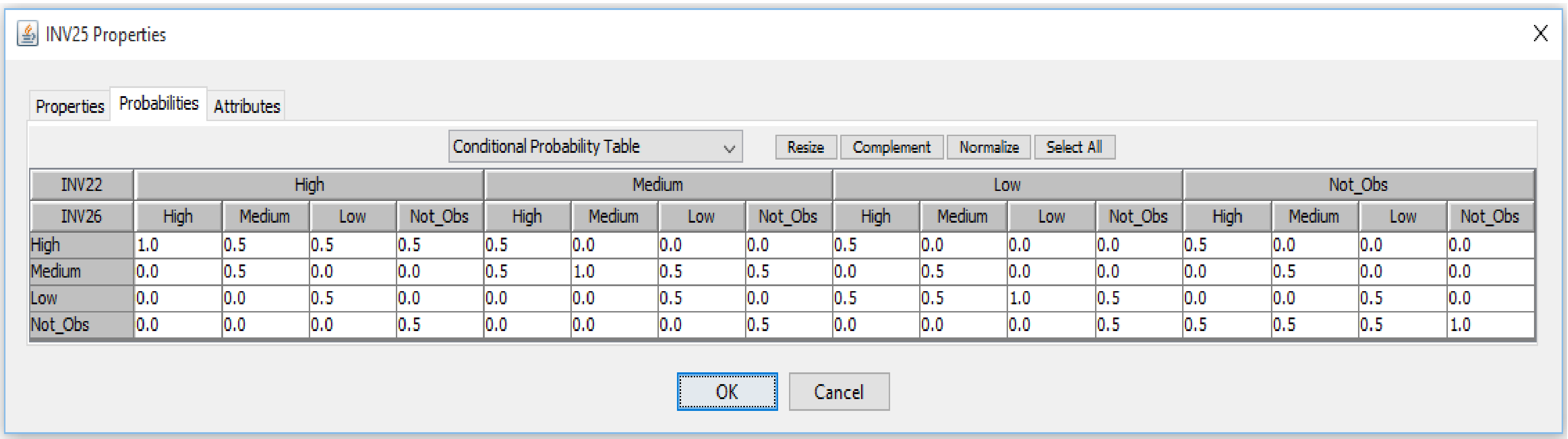
OK | Cancel

Figure B.52: INV23 CPT



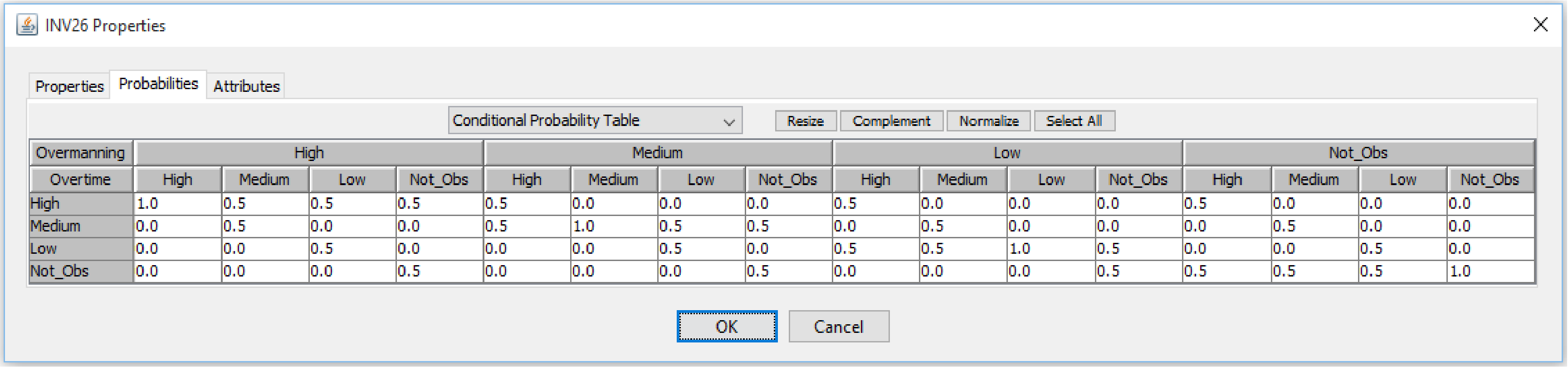
INV27	High				Medium				Low				Not_Observed			
Stacking of ...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.8	0.8	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.0
Low	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.8	1.0	0.8	0.0	0.0	0.2	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.2	0.0	0.0	0.0	0.2	0.0	0.8	0.8	1.0

Figure B.53: INV24 CPT



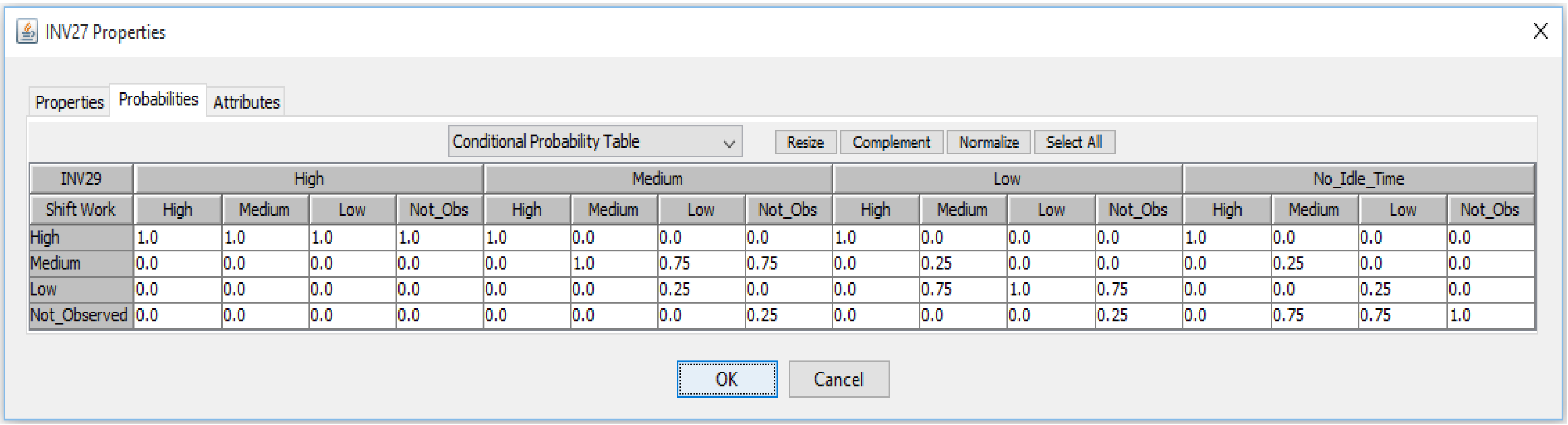
INV22	High				Medium				Low				Not_Obs			
INV26	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.54: INV25 CPT



Overmanning	High				Medium				Low				Not_Obs			
Overtime	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.55: INV26 CPT



INV29	High				Medium				Low				No_Idle_Time			
Shift Work	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.75	0.75	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0
Low	0.0	0.0	0.0	0.0	0.0	0.0	0.25	0.0	0.0	0.75	1.0	0.75	0.0	0.0	0.25	0.0
Not_Observed	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.75	0.75	1.0

Figure B.56: INV27 CPT

INV28 Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Overmanning	High				Medium				Low				Not_Obs			
INV31	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
Low	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.3333	0.3333	0.0	0.6667	0.0	0.0	0.0	0.6667	0.0	0.0
High	0.0	0.0	0.0	0.0	0.0	0.0	0.6667	0.0	0.0	0.3333	1.0	0.3333	0.0	0.0	0.6667	0.0
Excellent	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6667	0.0	0.0	0.0	0.6667	0.0	0.3333	0.3333	1.0

OK | Cancel

Figure B.57: INV28 CPT

INV29 Properties

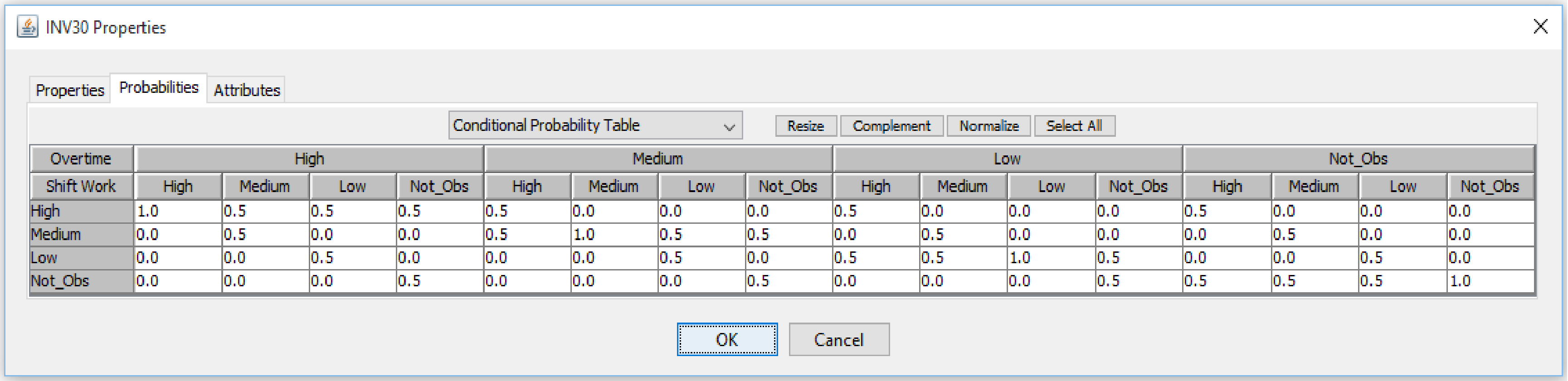
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Bad Inform...	High				Medium				Low				Not_Observed			
INV28	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent
High	0.6	0.0	0.0	0.0	0.6	0.0	0.0	0.0	1.0	0.4	0.4	0.4	0.6	0.0	0.0	0.0
Medium	0.0	0.6	0.0	0.0	0.4	1.0	0.4	0.4	0.0	0.6	0.0	0.0	0.0	0.6	0.0	0.0
Low	0.4	0.4	1.0	0.4	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.0
Not_Obs	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.4	0.4	0.4	1.0

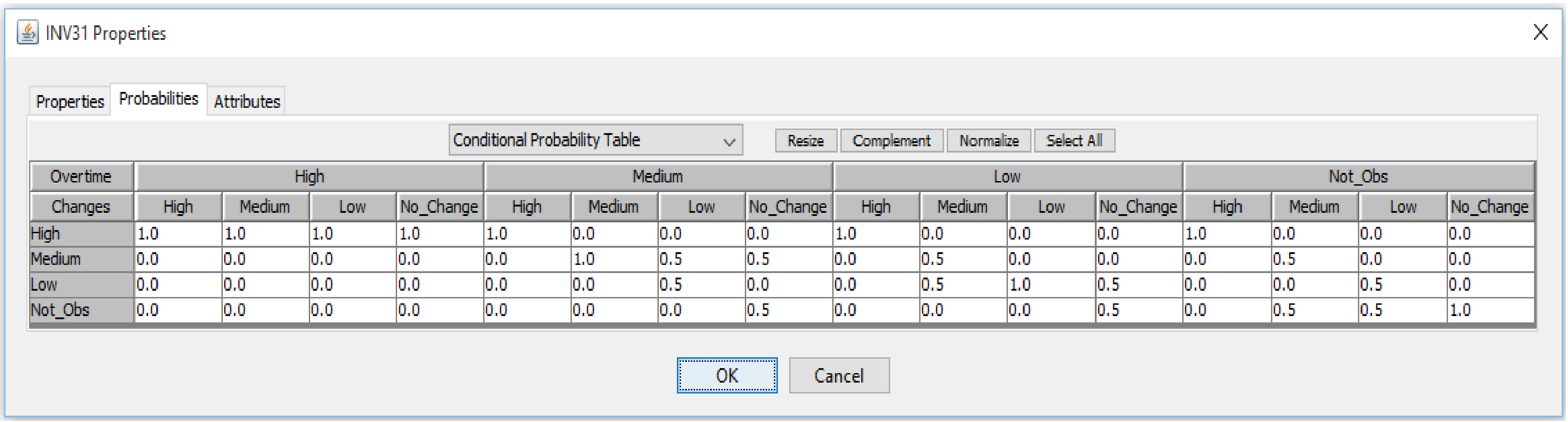
OK | Cancel

Figure B.58: INV29 CPT



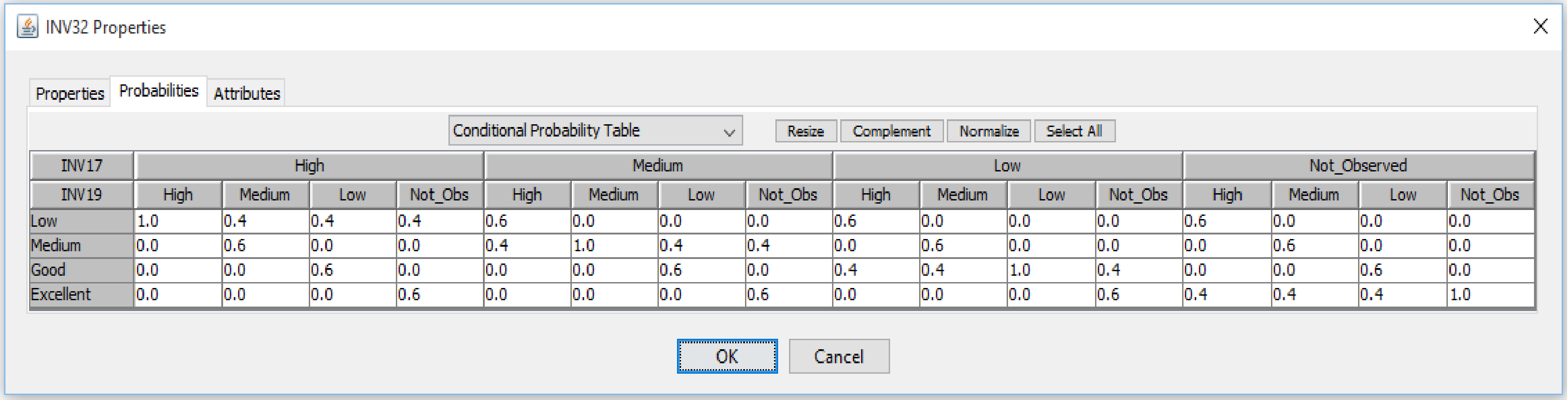
Overtime	High				Medium				Low				Not_Obs			
Shift Work	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.59: INV30 CPT



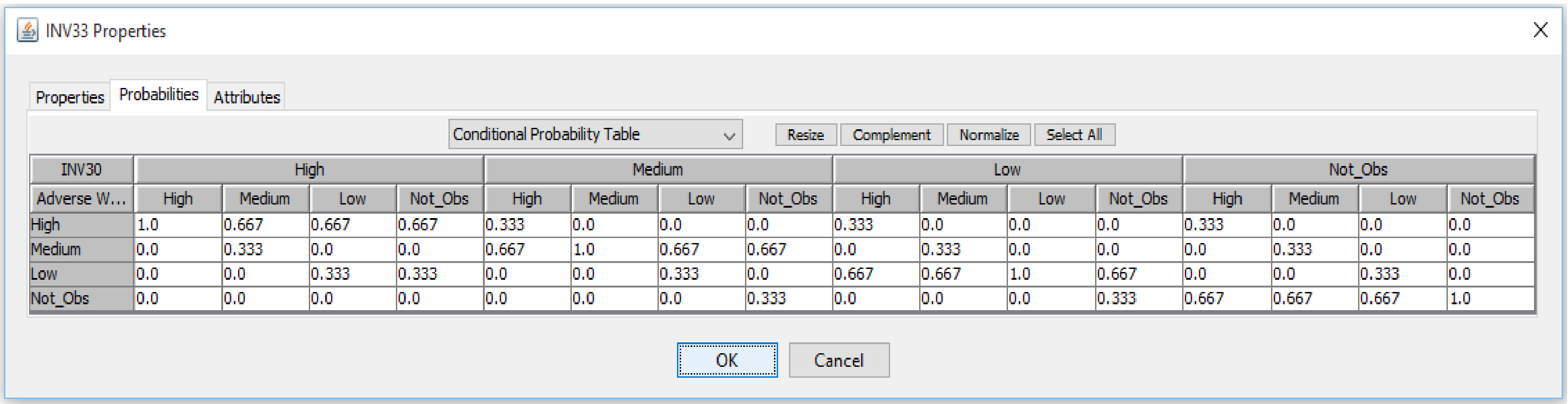
Overtime	High				Medium				Low				Not_Obs			
Changes	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change
High	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure B.60: INV31 CPT



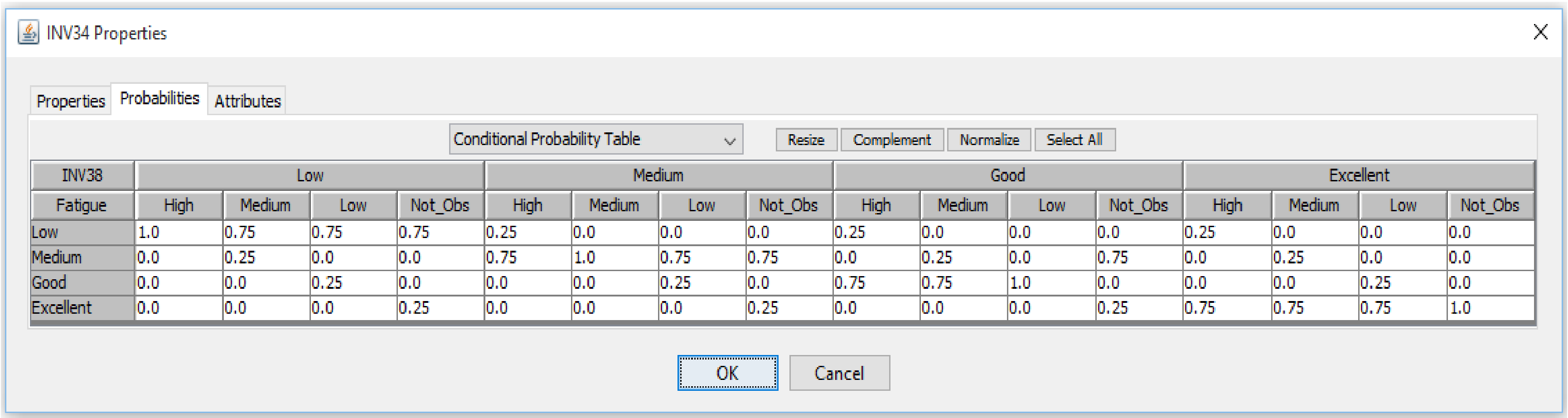
INV17	High				Medium				Low				Not_Observed			
INV19	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
Low	1.0	0.4	0.4	0.4	0.6	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.0	0.0	0.0
Medium	0.0	0.6	0.0	0.0	0.4	1.0	0.4	0.4	0.0	0.6	0.0	0.0	0.0	0.6	0.0	0.0
Good	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.0	0.4	0.4	1.0	0.4	0.0	0.0	0.6	0.0
Excellent	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.6	0.4	0.4	0.4	1.0

Figure B.61: INV32 CPT



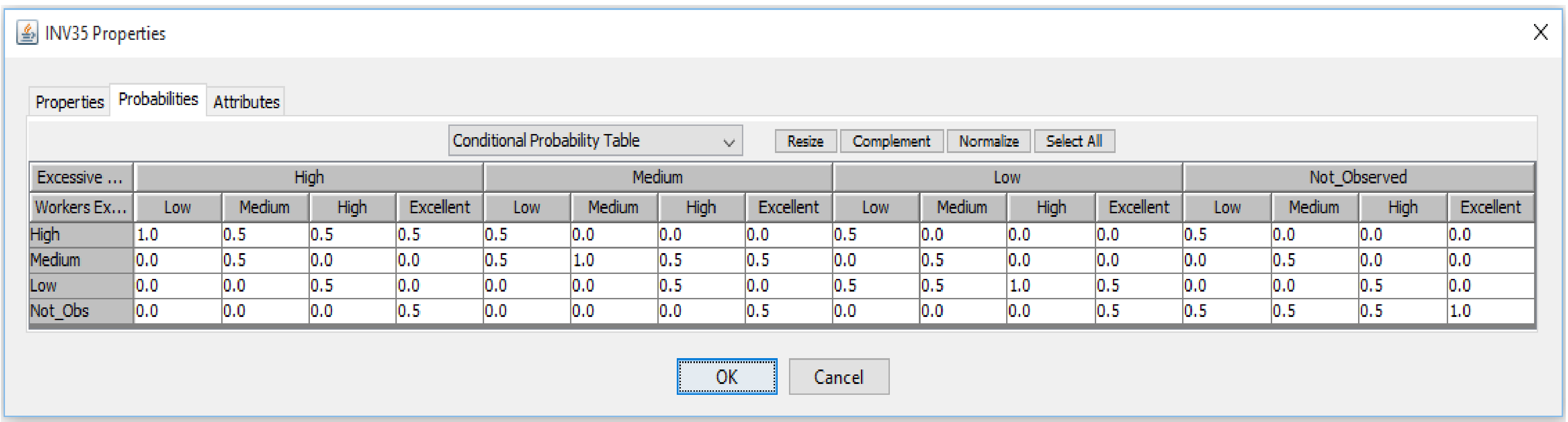
INV30	High				Medium				Low				Not_Obs			
Adverse W...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.667	0.667	0.667	0.333	0.0	0.0	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.0	0.0
Medium	0.0	0.333	0.0	0.0	0.667	1.0	0.667	0.667	0.0	0.333	0.0	0.0	0.0	0.333	0.0	0.0
Low	0.0	0.0	0.333	0.333	0.0	0.0	0.333	0.0	0.667	0.667	1.0	0.667	0.0	0.0	0.333	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.333	0.0	0.0	0.0	0.333	0.667	0.667	0.667	1.0

Figure B.62: INV33 CPT



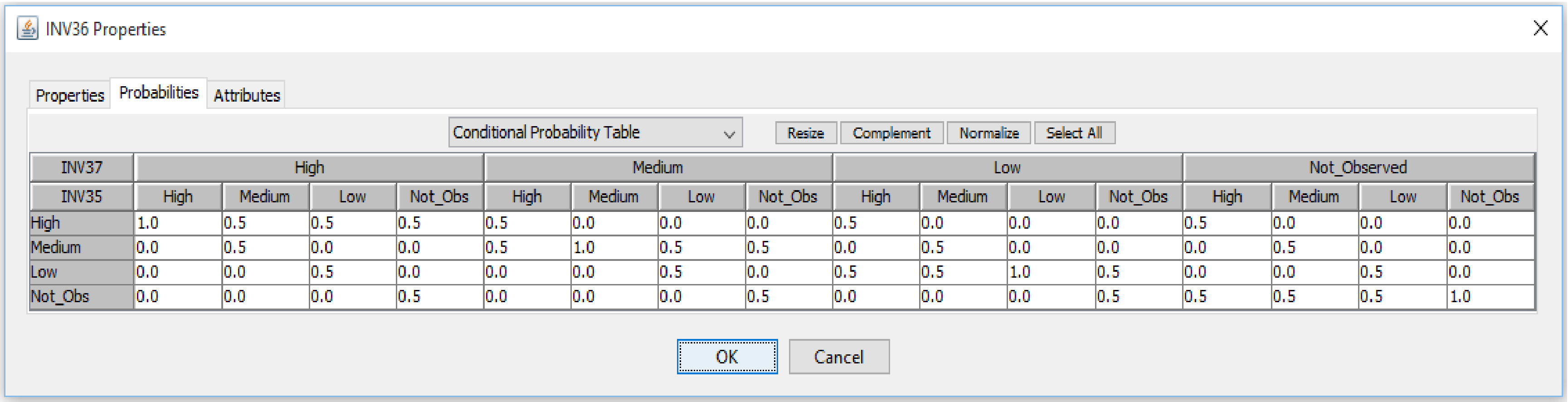
INV38	Low				Medium				Good				Excellent			
Fatigue	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
Low	1.0	0.75	0.75	0.75	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0
Medium	0.0	0.25	0.0	0.0	0.75	1.0	0.75	0.75	0.0	0.25	0.0	0.75	0.0	0.25	0.0	0.0
Good	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.75	0.75	1.0	0.0	0.0	0.0	0.25	0.0
Excellent	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.75	0.75	0.75	1.0

Figure B.63: INV34 CPT



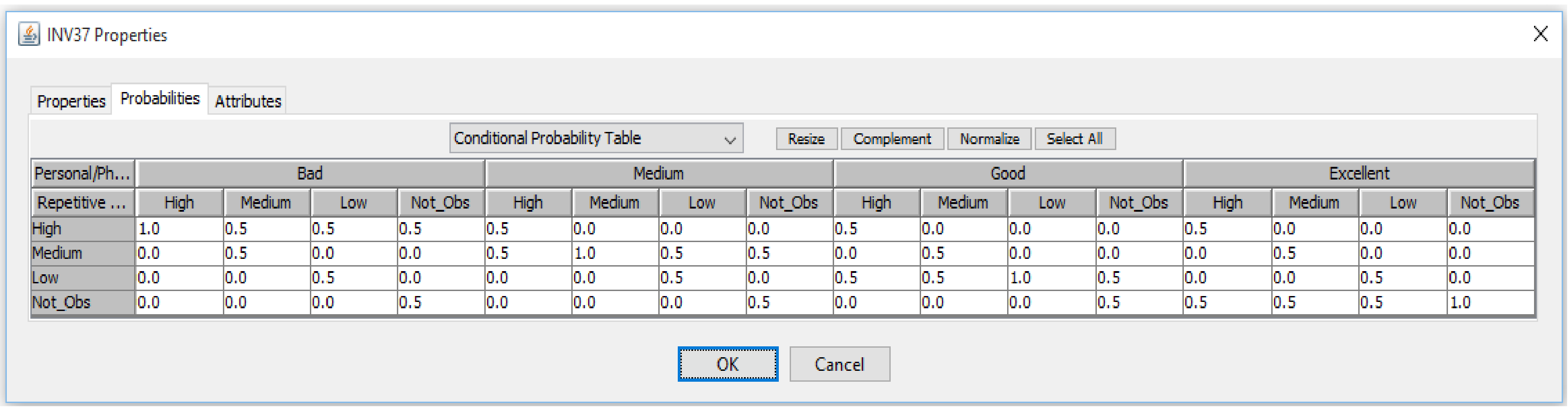
Excessive ...	High				Medium				Low				Not_Observed			
Workers Ex...	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent	Low	Medium	High	Excellent
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.64: INV35 CPT



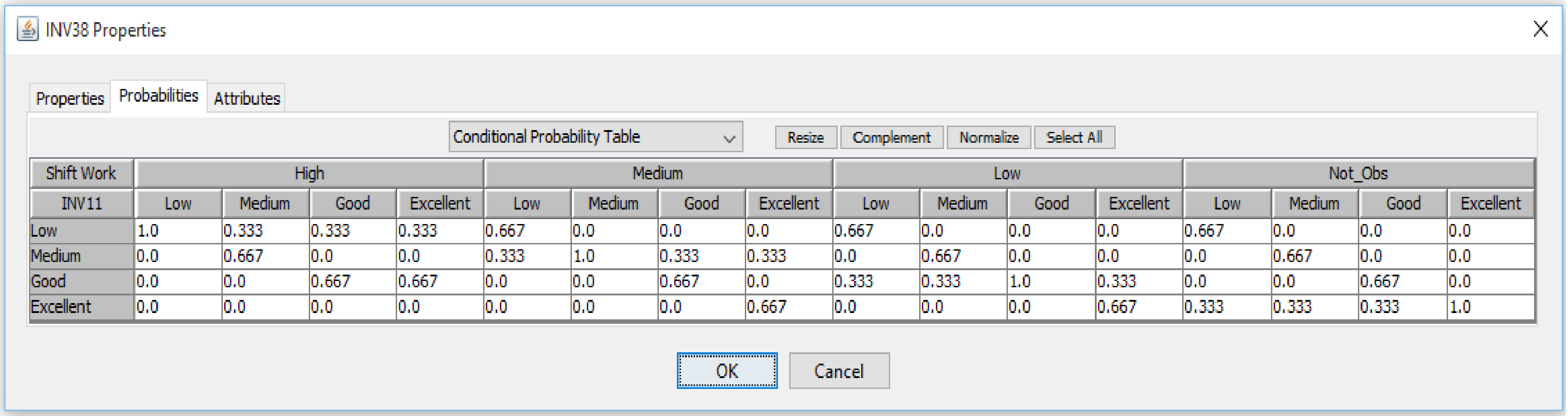
INV37	High				Medium				Low				Not_Observed			
INV35	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.65: INV36 CPT



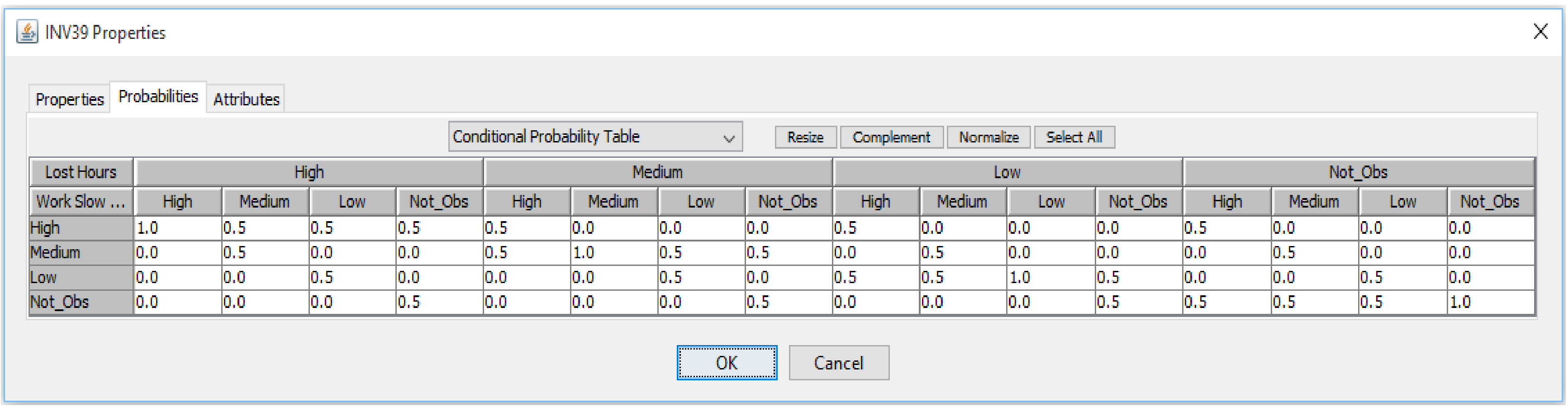
Personal/Ph...	Bad				Medium				Good				Excellent			
Repetitive ...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.66: INV37 CPT



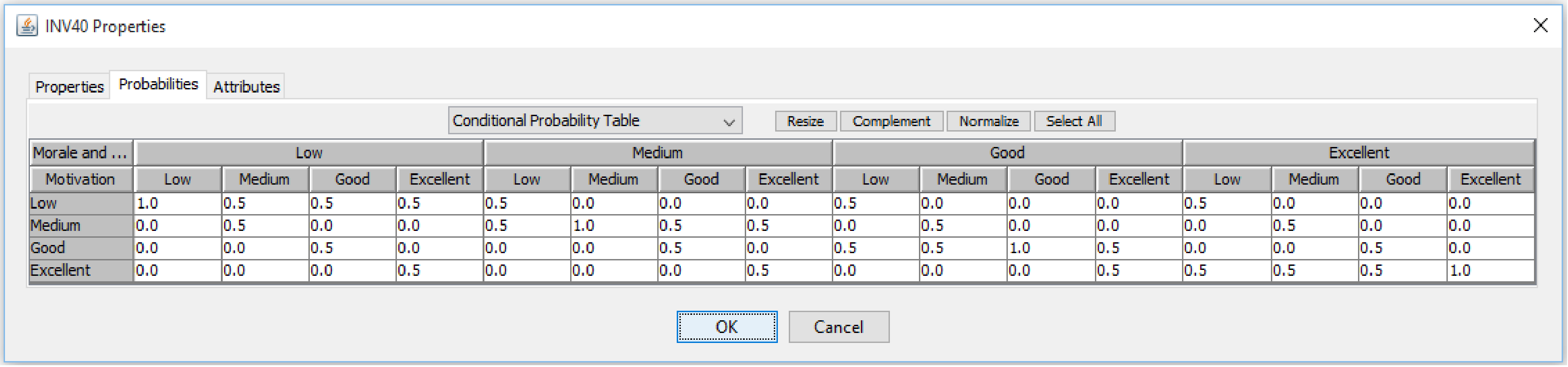
Shift Work	High				Medium				Low				Not_Obs			
INV11	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
Low	1.0	0.333	0.333	0.333	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0
Medium	0.0	0.667	0.0	0.0	0.333	1.0	0.333	0.333	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0
Good	0.0	0.0	0.667	0.667	0.0	0.0	0.667	0.0	0.333	0.333	1.0	0.333	0.0	0.0	0.667	0.0
Excellent	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.333	0.333	0.333	1.0

Figure B.67: INV38 CPT



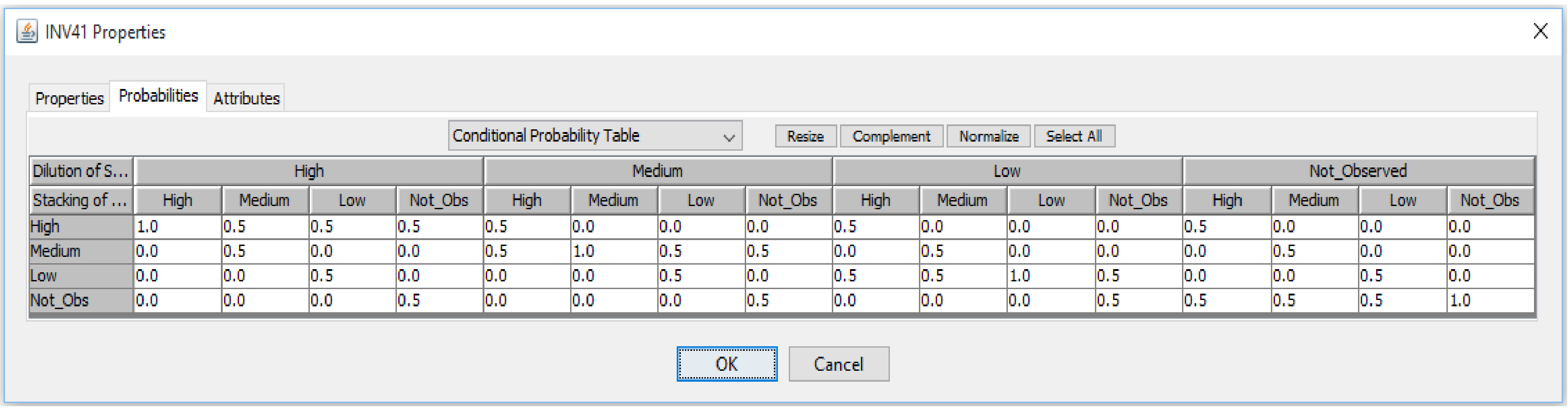
Lost Hours	High				Medium				Low				Not_Obs			
Work Slow ...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.68: INV39 CPT



Morale and ...	Low				Medium				Good				Excellent			
Motivation	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.69: INV40 CPT



Dilution of S...	High				Medium				Low				Not_Observed			
Stacking of ...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.70: INV41 CPT

INV42 Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Being Idle	High				Medium				Low				Not_Observed			
Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

OK | Cancel

Figure B.71: INV42 CPT

INV43 Properties

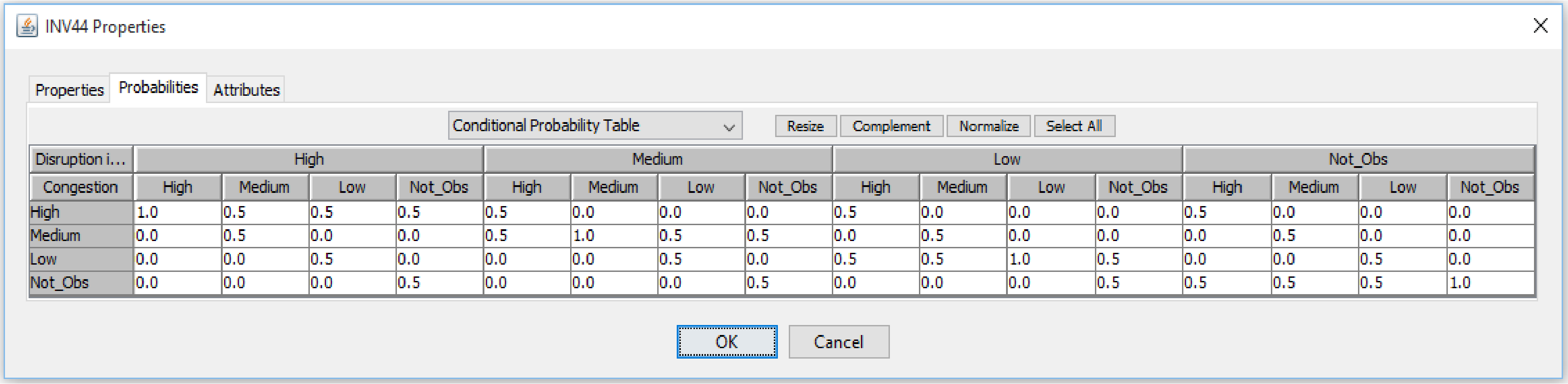
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

INV40	Low				Medium				Good				Excellent			
Communica...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
Low	1.0	0.666	0.666	0.666	0.334	0.0	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.0	0.0
Medium	0.0	0.334	0.0	0.0	0.666	1.0	0.666	0.666	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.0
Good	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.666	0.666	1.0	0.666	0.0	0.0	0.334	0.0
Excellent	0.0	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.666	0.666	0.666	1.0

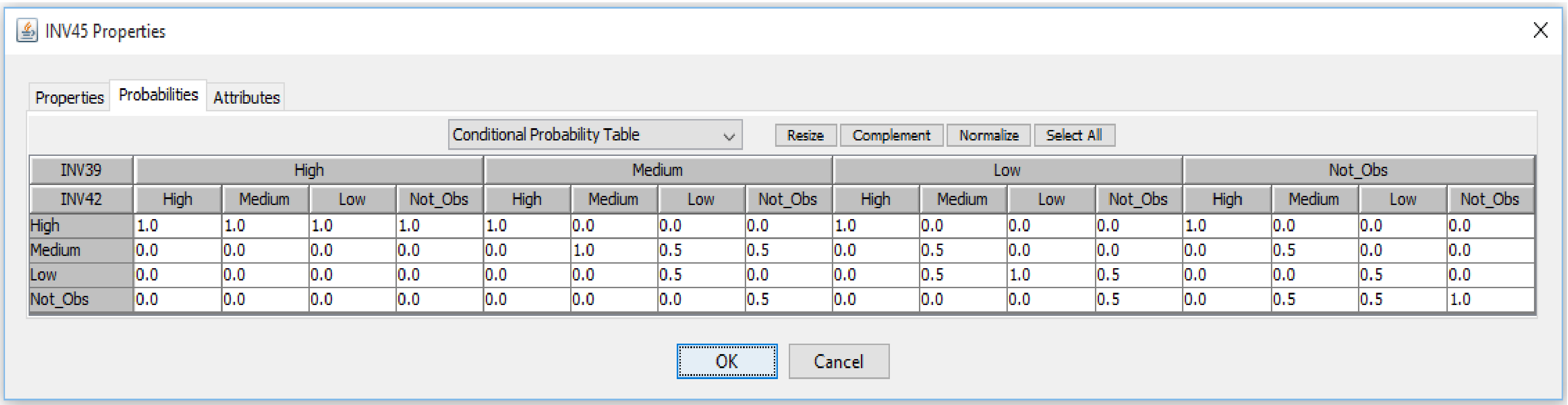
OK | Cancel

Figure B.72: INV43 CPT



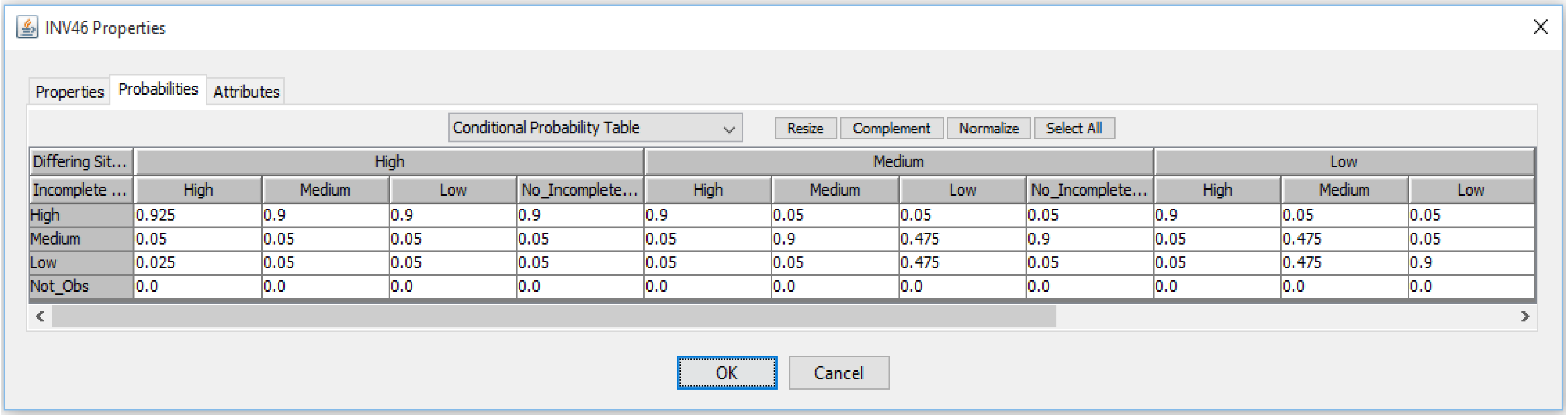
Disruption i...	High				Medium				Low				Not_Obs			
Congestion	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.73: INV44 CPT



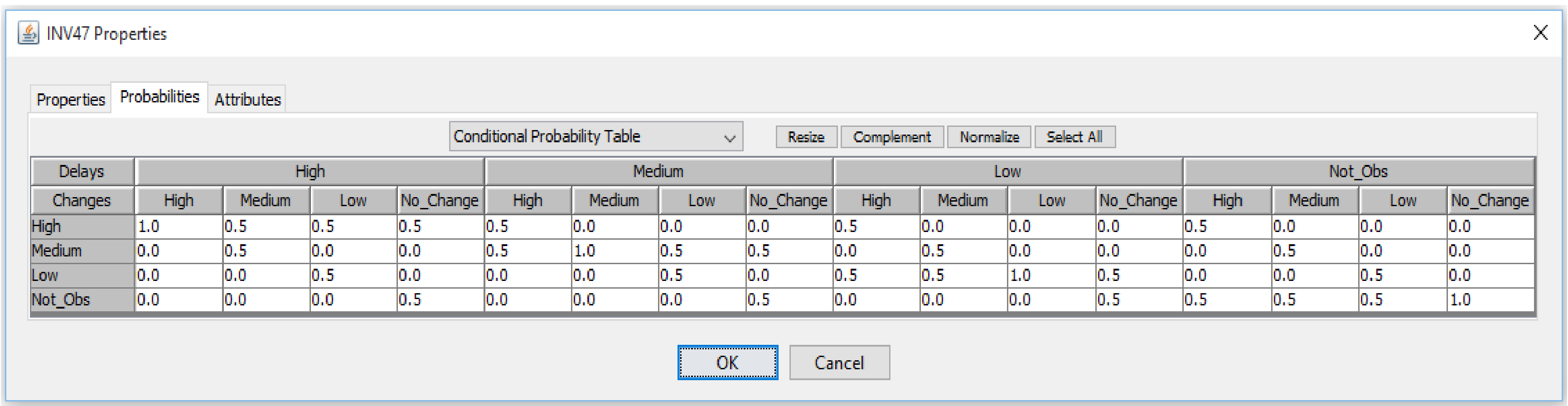
INV39	High				Medium				Low				Not_Obs			
INV42	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure B.74: INV45 CPT



Differing Sit...	High				Medium				Low		
Incomplete ...	High	Medium	Low	No_Incomplete...	High	Medium	Low	No_Incomplete...	High	Medium	Low
High	0.925	0.9	0.9	0.9	0.9	0.05	0.05	0.05	0.9	0.05	0.05
Medium	0.05	0.05	0.05	0.05	0.05	0.9	0.475	0.9	0.05	0.475	0.05
Low	0.025	0.05	0.05	0.05	0.05	0.05	0.475	0.05	0.05	0.475	0.9
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Figure B.75: INV46 CPT



Delays	High				Medium				Low				Not_Obs			
Changes	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change	High	Medium	Low	No_Change
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.76: INV47 CPT

INV48 Properties

Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

INV44	High				Medium				Low				Not_Obs			
INV41	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Observed	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

OK | Cancel

Figure B.77: INV48 CPT

INV49 Properties

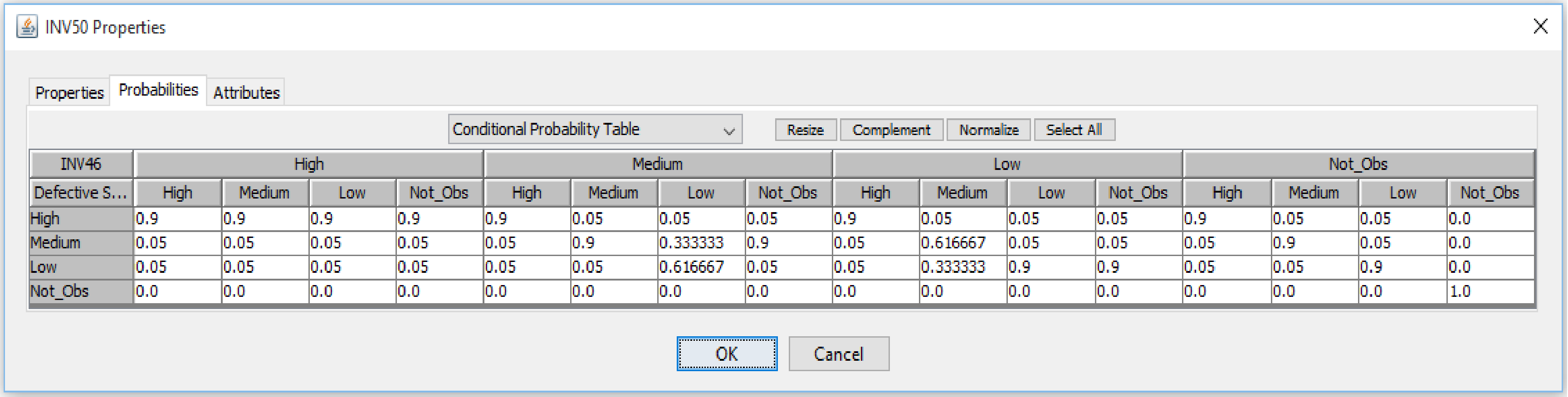
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Adverse M...	High				Medium				Low				Not_Obs			
INV50	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	0.9	0.9	0.9	0.9	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.0
Medium	0.05	0.05	0.05	0.05	0.05	0.9	0.2625	0.9	0.05	0.6875	0.05	0.05	0.05	0.9	0.05	0.0
Low	0.05	0.05	0.05	0.05	0.05	0.05	0.6875	0.05	0.05	0.2625	0.9	0.9	0.05	0.05	0.9	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

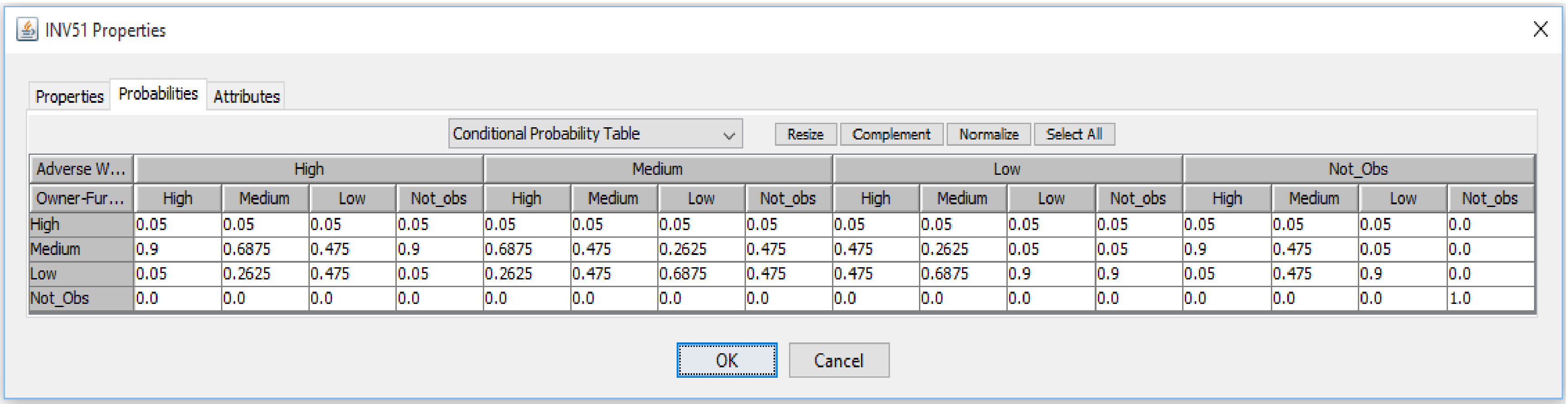
OK | Cancel

Figure B.78: INV49 CPT



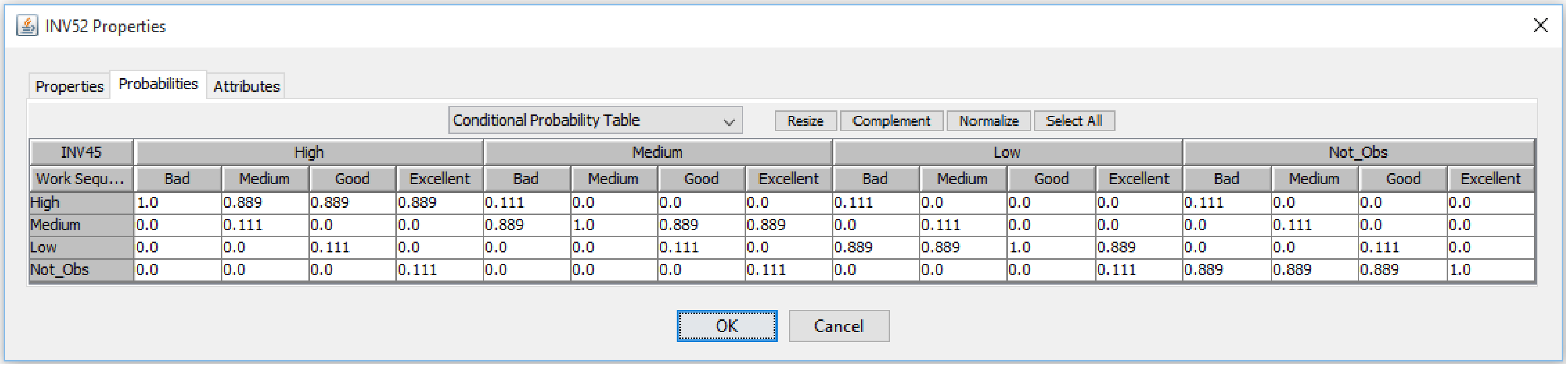
INV46	High				Medium				Low				Not_Obs			
Defective S...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	0.9	0.9	0.9	0.9	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.0
Medium	0.05	0.05	0.05	0.05	0.05	0.9	0.333333	0.9	0.05	0.616667	0.05	0.05	0.05	0.9	0.05	0.0
Low	0.05	0.05	0.05	0.05	0.05	0.05	0.616667	0.05	0.05	0.333333	0.9	0.9	0.05	0.05	0.9	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure B.79: INV50 CPT



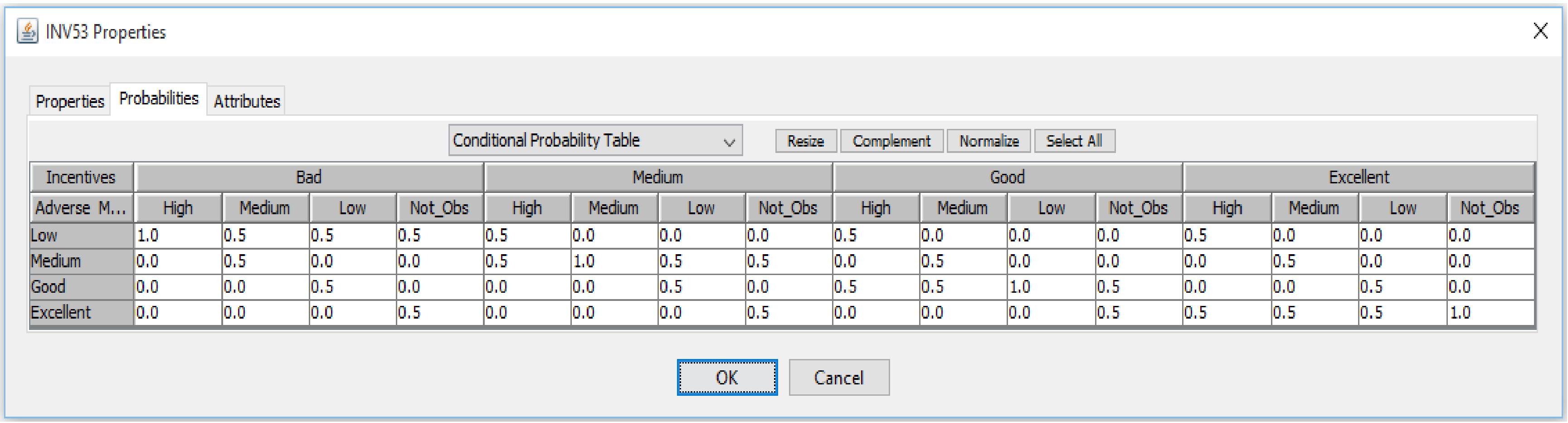
Adverse W...	High				Medium				Low				Not_Obs			
Owner-Fur...	High	Medium	Low	Not_obs	High	Medium	Low	Not_obs	High	Medium	Low	Not_obs	High	Medium	Low	Not_obs
High	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.0
Medium	0.9	0.6875	0.475	0.9	0.6875	0.475	0.2625	0.475	0.475	0.2625	0.05	0.05	0.9	0.475	0.05	0.0
Low	0.05	0.2625	0.475	0.05	0.2625	0.475	0.6875	0.475	0.475	0.6875	0.9	0.9	0.05	0.475	0.9	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure B.80: INV51 CPT



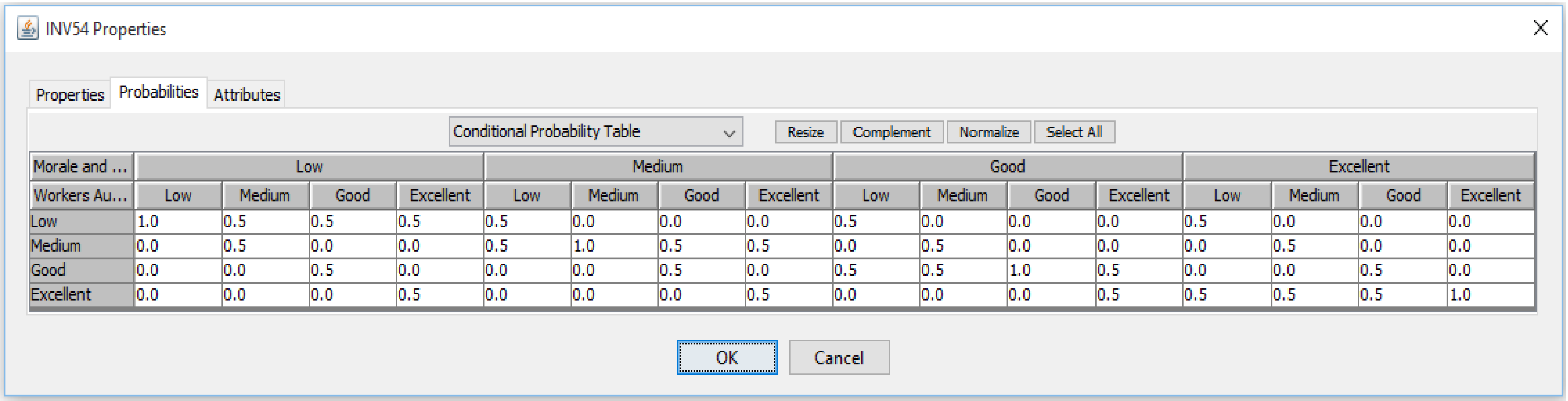
INV45	High				Medium				Low				Not_Obs			
Work Sequ...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.889	0.889	0.889	0.111	0.0	0.0	0.0	0.111	0.0	0.0	0.0	0.111	0.0	0.0	0.0
Medium	0.0	0.111	0.0	0.0	0.889	1.0	0.889	0.889	0.0	0.111	0.0	0.0	0.0	0.111	0.0	0.0
Low	0.0	0.0	0.111	0.0	0.0	0.0	0.111	0.0	0.889	0.889	1.0	0.889	0.0	0.0	0.111	0.0
Not_Obs	0.0	0.0	0.0	0.111	0.0	0.0	0.0	0.111	0.0	0.0	0.0	0.111	0.889	0.889	0.889	1.0

Figure B.81: INV52 CPT



Incentives	Bad				Medium				Good				Excellent			
Adverse M...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.82: INV53 CPT



INV54 Properties

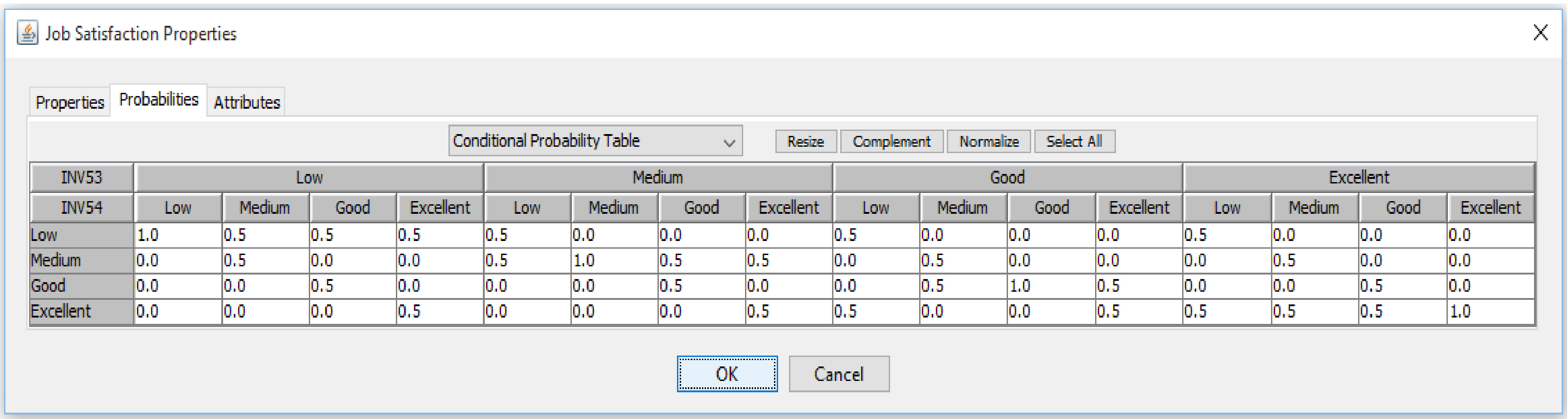
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

Morale and ...	Low				Medium				Good				Excellent			
Workers Au...	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

OK | Cancel

Figure B.83: INV54 CPT



Job Satisfaction Properties

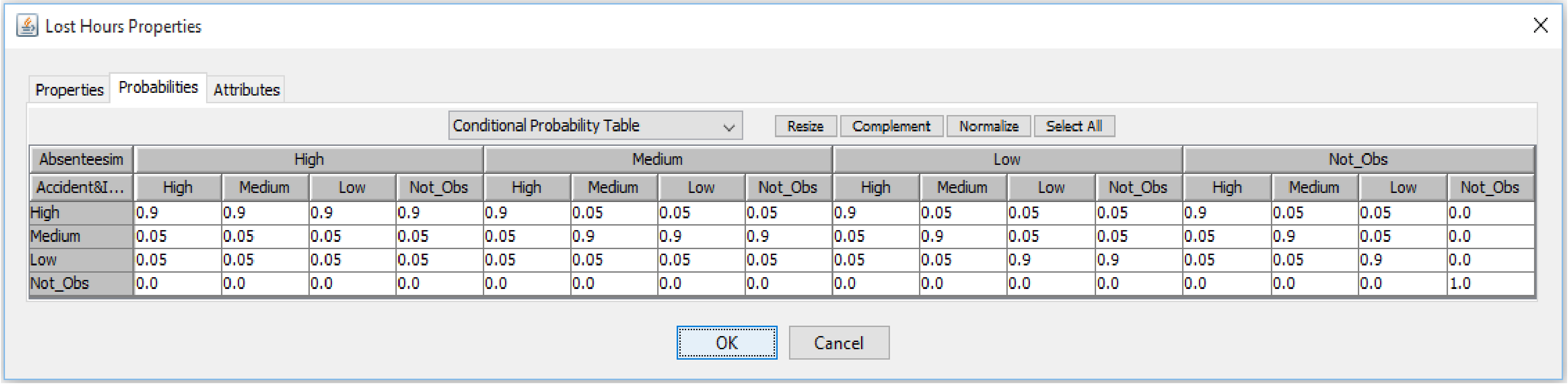
Properties | Probabilities | Attributes

Conditional Probability Table | Resize | Complement | Normalize | Select All

INV53	Low				Medium				Good				Excellent			
INV54	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.0	0.0	0.5	0.5	0.5	0.5	1.0

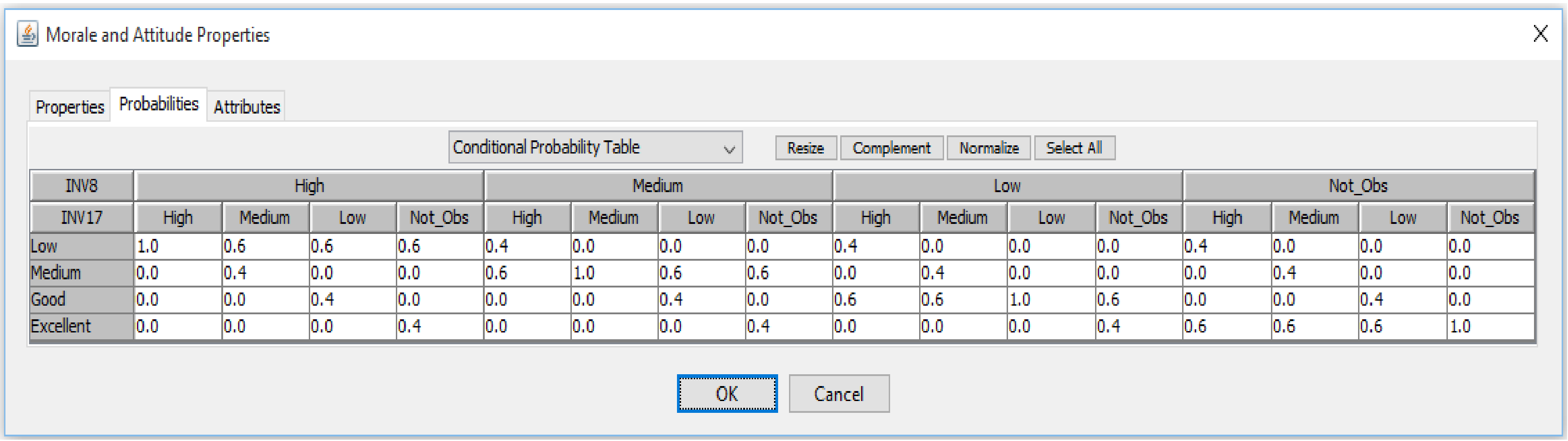
OK | Cancel

Figure B.84: Job Satisfaction CPT



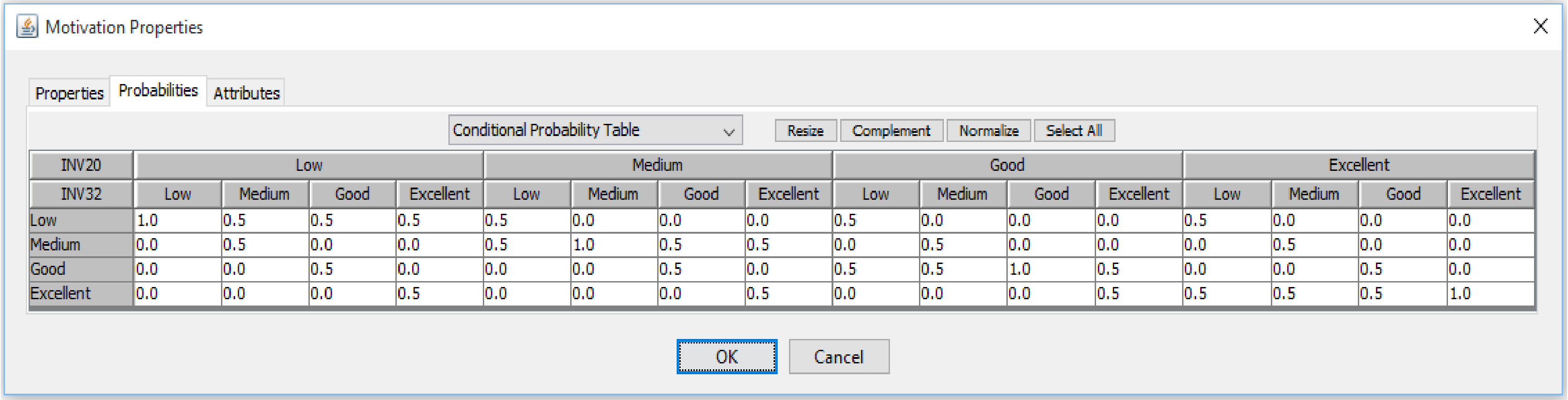
Absenteesim	High				Medium				Low				Not_Obs			
Accident&I...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	0.9	0.9	0.9	0.9	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.05	0.9	0.05	0.05	0.0
Medium	0.05	0.05	0.05	0.05	0.05	0.9	0.9	0.9	0.05	0.9	0.05	0.05	0.05	0.9	0.05	0.0
Low	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.9	0.9	0.05	0.05	0.9	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0

Figure B.85: Lost Hours CPT



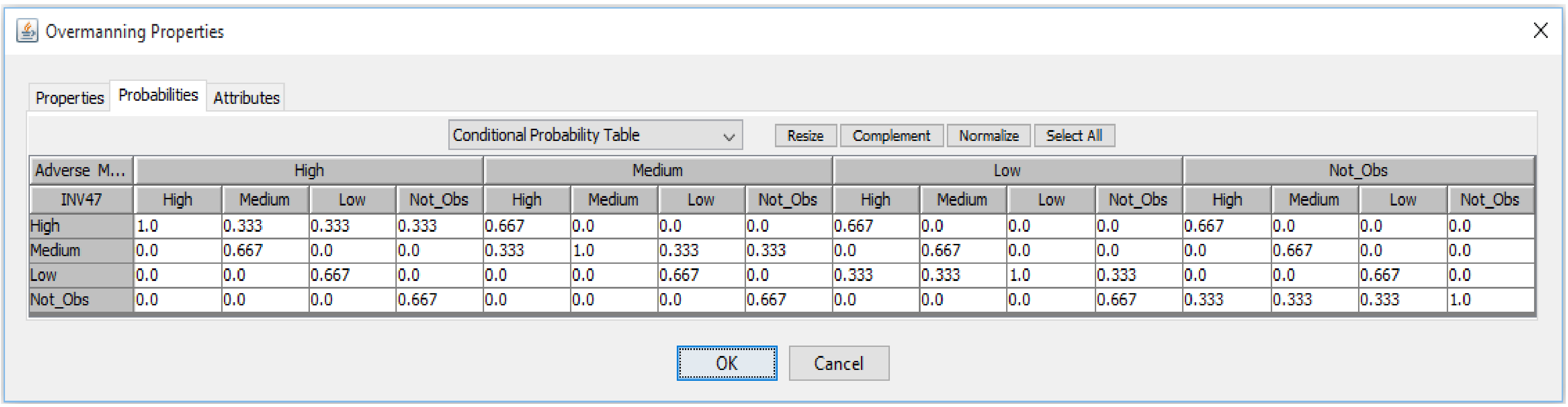
INV8	High				Medium				Low				Not_Obs			
INV17	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
Low	1.0	0.6	0.6	0.6	0.4	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.4	0.0	0.0	0.0
Medium	0.0	0.4	0.0	0.0	0.6	1.0	0.6	0.6	0.0	0.4	0.0	0.0	0.0	0.4	0.0	0.0
Good	0.0	0.0	0.4	0.0	0.0	0.0	0.4	0.0	0.6	0.6	1.0	0.6	0.0	0.0	0.4	0.0
Excellent	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.4	0.0	0.0	0.0	0.4	0.6	0.6	0.6	1.0

Figure B.86: Morale and Attitude CPT



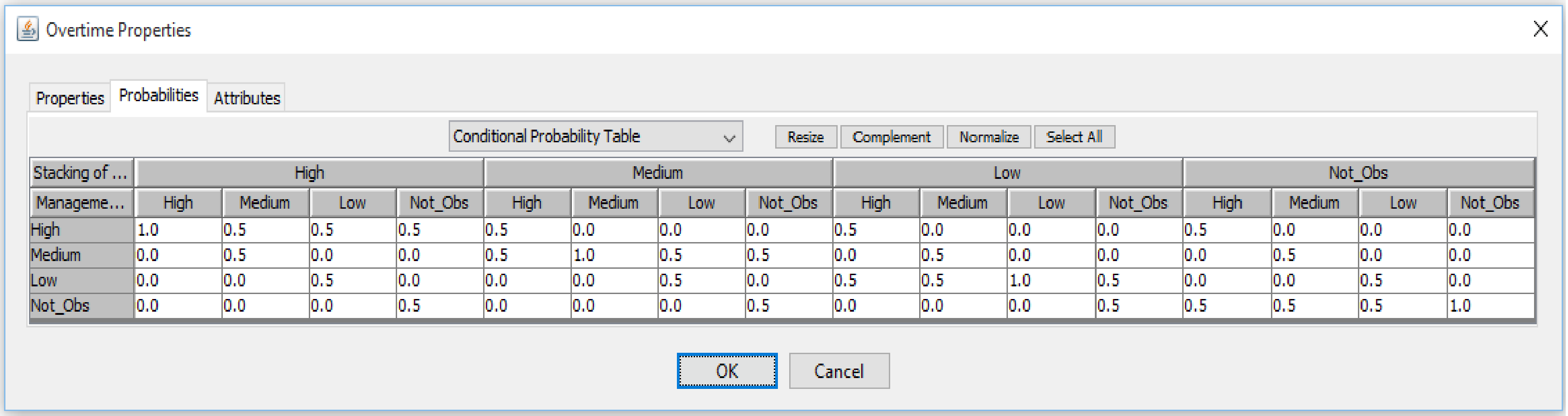
INV20	Low				Medium				Good				Excellent			
INV32	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.87: Motivation CPT



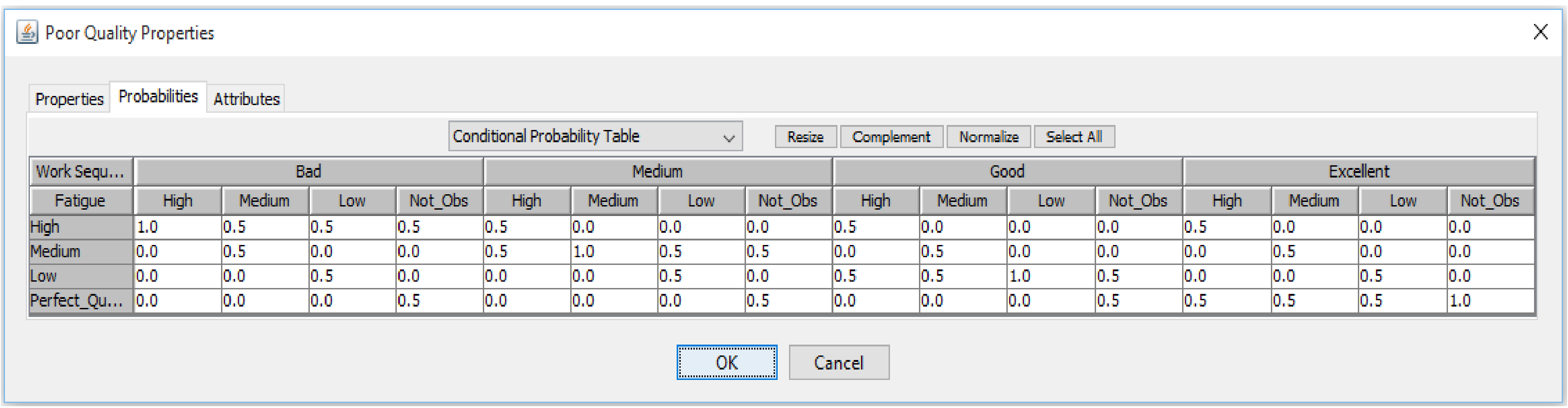
Adverse M...	High				Medium				Low				Not_Obs			
INV47	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.333	0.333	0.333	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0
Medium	0.0	0.667	0.0	0.0	0.333	1.0	0.333	0.333	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0
Low	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.333	0.333	1.0	0.333	0.0	0.0	0.667	0.0
Not_Obs	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.0	0.0	0.0	0.667	0.333	0.333	0.333	1.0

Figure B.88: Overmanning CPT



Stacking of ...	High				Medium				Low				Not_Obs			
Manageme...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.89: Overtime CPT



Work Sequ...	Bad				Medium				Good				Excellent			
Fatigue	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Perfect_Qu...	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

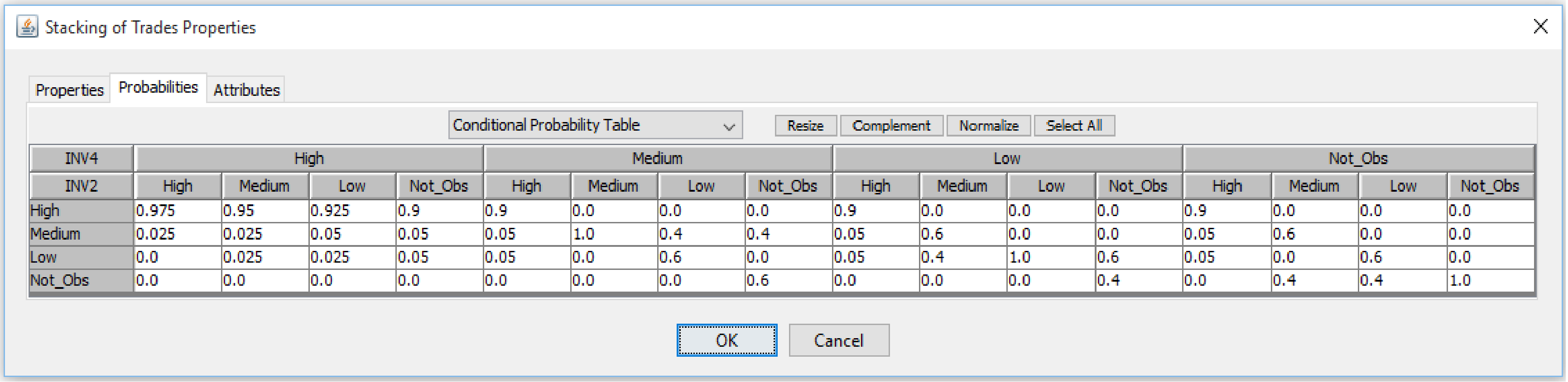
Figure B.90: Poor Quality CPT

INV14	Low				Medium				High				Excellent			
INV16	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework
High	1.0	0.286	0.286	0.286	0.714	0.0	0.0	0.0	0.714	0.0	0.0	0.0	0.714	0.0	0.0	0.0
Medium	0.0	0.714	0.0	0.0	0.286	1.0	0.286	0.286	0.0	0.714	0.0	0.0	0.0	0.714	0.0	0.0
Low	0.0	0.0	0.714	0.0	0.0	0.0	0.714	0.0	0.286	0.286	1.0	0.286	0.0	0.0	0.714	0.0
No_Rework	0.0	0.0	0.0	0.714	0.0	0.0	0.0	0.714	0.0	0.0	0.0	0.714	0.286	0.286	0.286	1.0

Figure B.91: Rework CPT

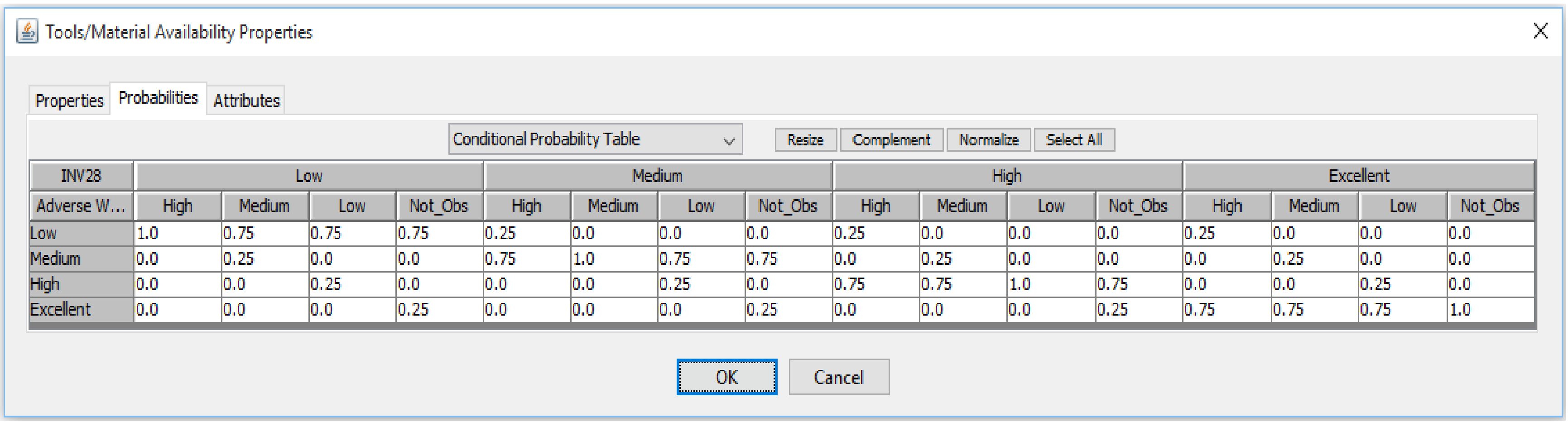
INV1	High				Medium				Low				Not_Obs			
Manageme...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	0.95	0.925	0.925	0.925	0.9	0.05	0.05	0.033	0.9	0.05	0.05	0.033	0.9	0.017	0.017	0.0
Medium	0.025	0.05	0.05	0.05	0.05	0.9	0.617	0.6	0.05	0.333	0.05	0.033	0.05	0.3	0.017	0.0
Low	0.025	0.025	0.025	0.025	0.05	0.05	0.333	0.033	0.05	0.617	0.9	0.6	0.05	0.017	0.3	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.334	0.0	0.0	0.0	0.334	0.0	0.666	0.666	1.0

Figure B.92: Shift Work CPT



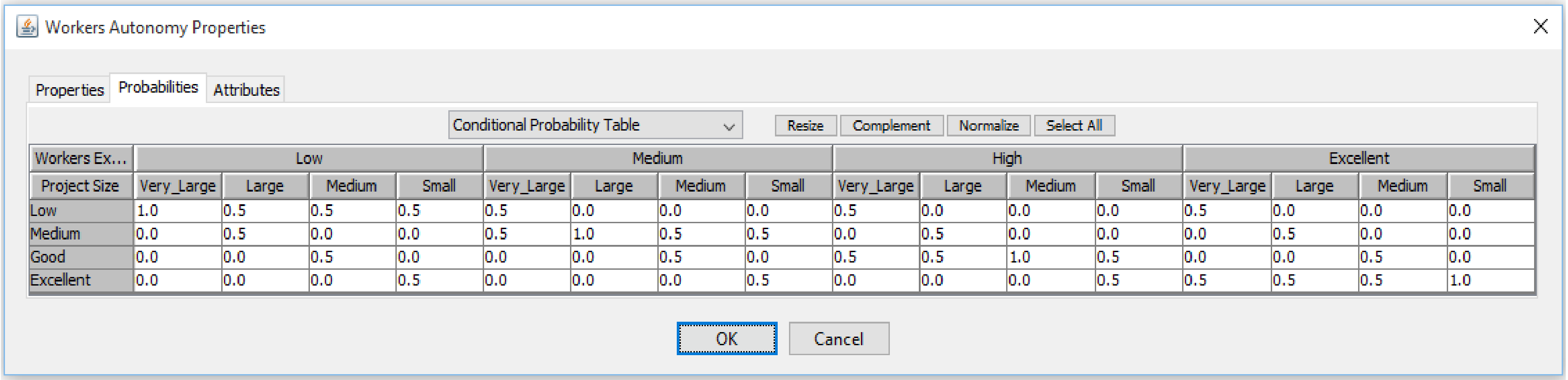
INV4	High				Medium				Low				Not_Obs			
INV2	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
High	0.975	0.95	0.925	0.9	0.9	0.0	0.0	0.0	0.9	0.0	0.0	0.0	0.9	0.0	0.0	0.0
Medium	0.025	0.025	0.05	0.05	0.05	1.0	0.4	0.4	0.05	0.6	0.0	0.0	0.05	0.6	0.0	0.0
Low	0.0	0.025	0.025	0.05	0.05	0.0	0.6	0.0	0.05	0.4	1.0	0.6	0.05	0.0	0.6	0.0
Not_Obs	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.6	0.0	0.0	0.0	0.4	0.0	0.4	0.4	1.0

Figure B.93: Stacking of Trades CPT



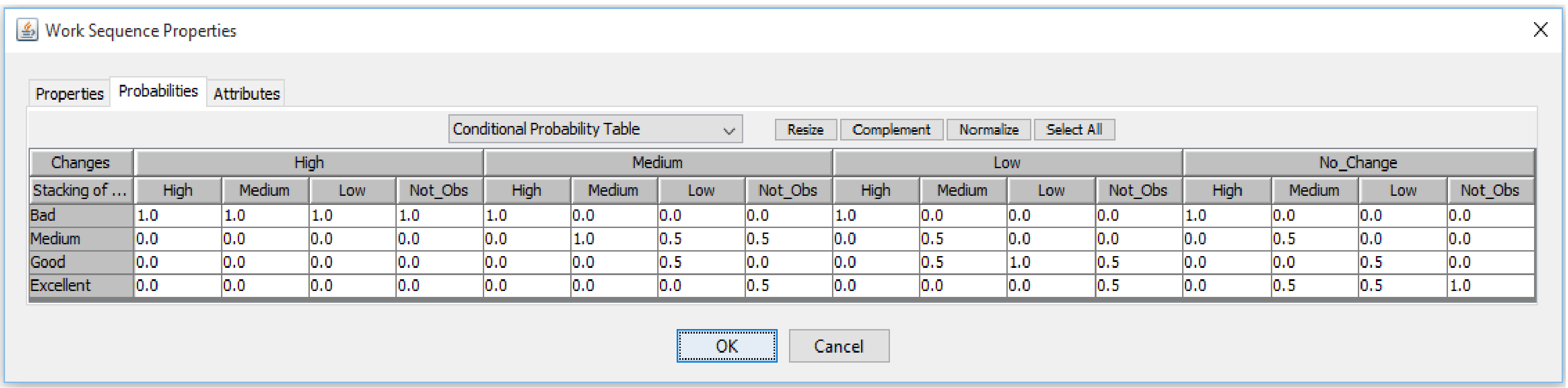
INV28	Low				Medium				High				Excellent			
Adverse W...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
Low	1.0	0.75	0.75	0.75	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0
Medium	0.0	0.25	0.0	0.0	0.75	1.0	0.75	0.75	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0
High	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.75	0.75	1.0	0.75	0.0	0.0	0.25	0.0
Excellent	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.0	0.0	0.0	0.25	0.75	0.75	0.75	1.0

Figure B.94: Tools/Material Availability CPT



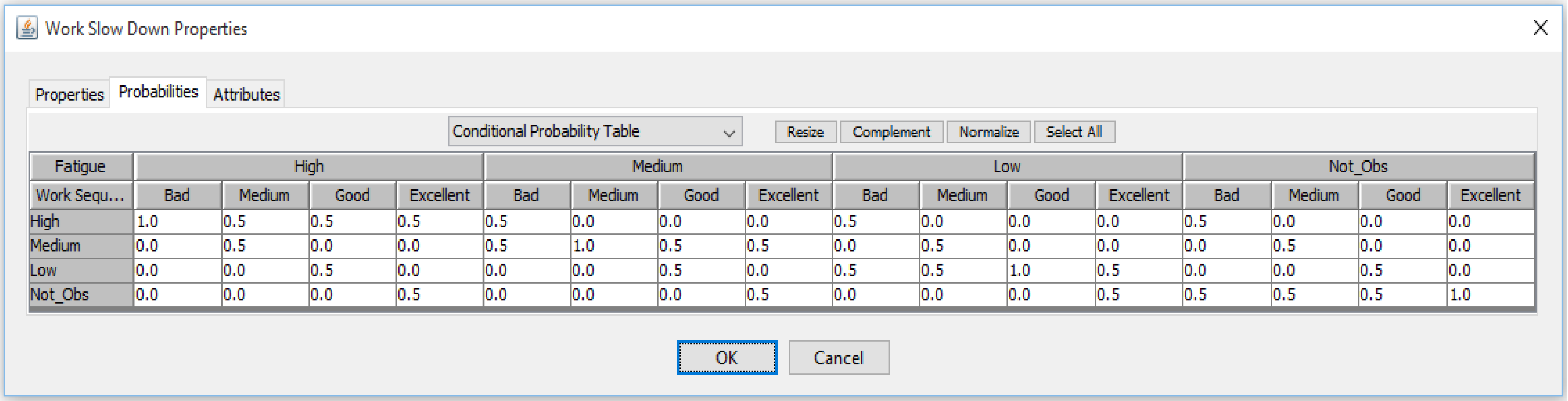
Workers Ex...	Low				Medium				High				Excellent			
Project Size	Very_Large	Large	Medium	Small	Very_Large	Large	Medium	Small	Very_Large	Large	Medium	Small	Very_Large	Large	Medium	Small
Low	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.95: Workers Autonomy CPT



Changes	High				Medium				Low				No_Change			
Stacking of ...	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs	High	Medium	Low	Not_Obs
Bad	1.0	1.0	1.0	1.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0
Medium	0.0	0.0	0.0	0.0	0.0	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Good	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Excellent	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0

Figure B.96: Work Sequence CPT

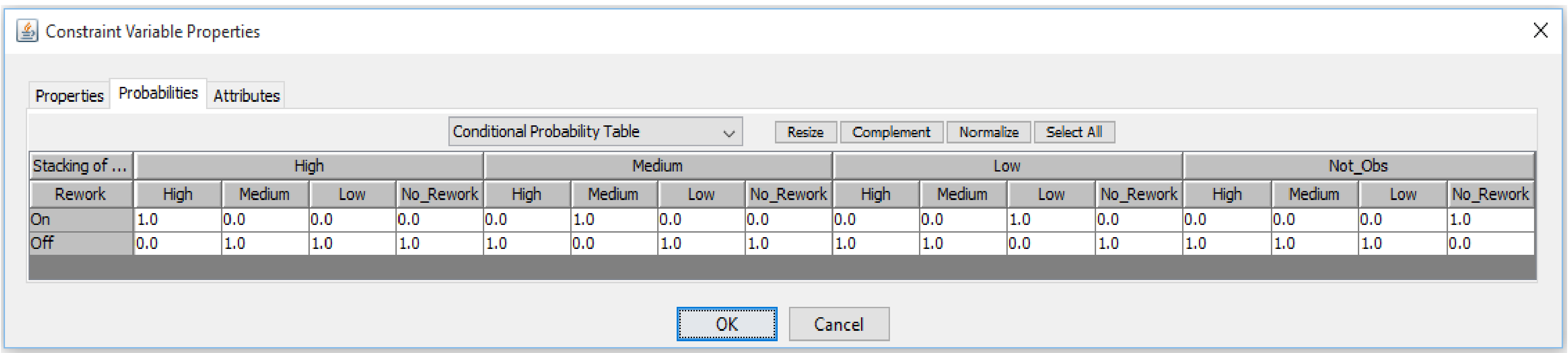


Fatigue	High				Medium				Low				Not_Obs			
Work Sequ...	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent	Bad	Medium	Good	Excellent
High	1.0	0.5	0.5	0.5	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0
Medium	0.0	0.5	0.0	0.0	0.5	1.0	0.5	0.5	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0
Low	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.5	0.5	1.0	0.5	0.0	0.0	0.5	0.0
Not_Obs	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.0	0.0	0.0	0.5	0.5	0.5	0.5	1.0

Figure B.97: Work Slow Down CPT

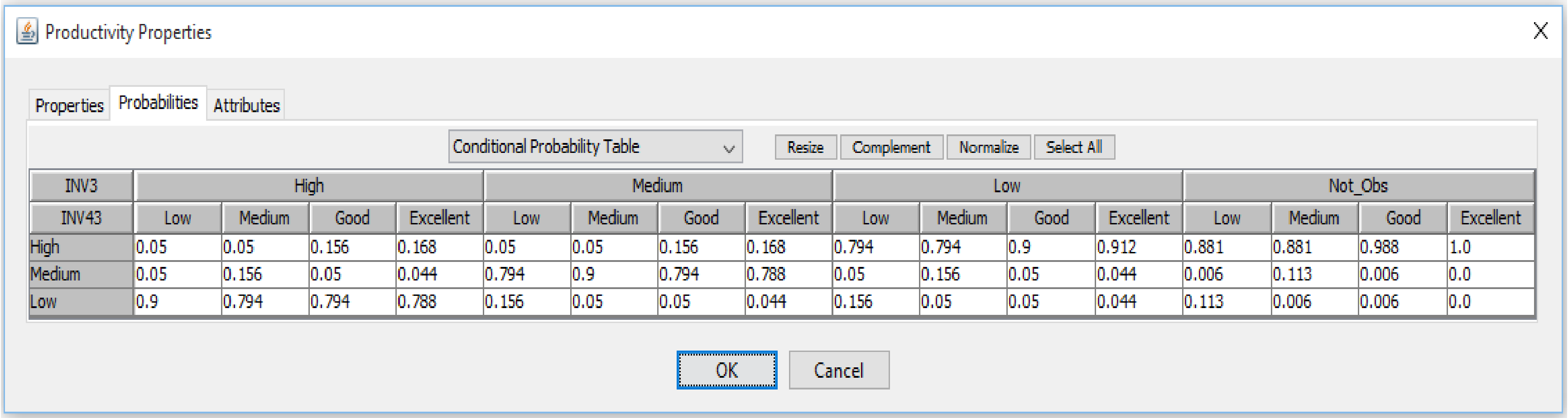
B.3 Leaf Variables

The model has two leaf variables.



Stacking of ...	High				Medium				Low				Not_Obs			
Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework	High	Medium	Low	No_Rework
On	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	0.0	1.0
Off	0.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.0

Figure B.98: Constraint Variable CPT



INV3	High				Medium				Low				Not_Obs			
INV43	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent	Low	Medium	Good	Excellent
High	0.05	0.05	0.156	0.168	0.05	0.05	0.156	0.168	0.794	0.794	0.9	0.912	0.881	0.881	0.988	1.0
Medium	0.05	0.156	0.05	0.044	0.794	0.9	0.794	0.788	0.05	0.156	0.05	0.044	0.006	0.113	0.006	0.0
Low	0.9	0.794	0.794	0.788	0.156	0.05	0.05	0.044	0.156	0.05	0.05	0.044	0.113	0.006	0.006	0.0

Figure B.99: Productivity CPT

Appendix C

Model Snapshots

In this section a snapshot of the model is shown in the figure C.1 and a snapshot of the model marginal distribution is shown in figure C.2.

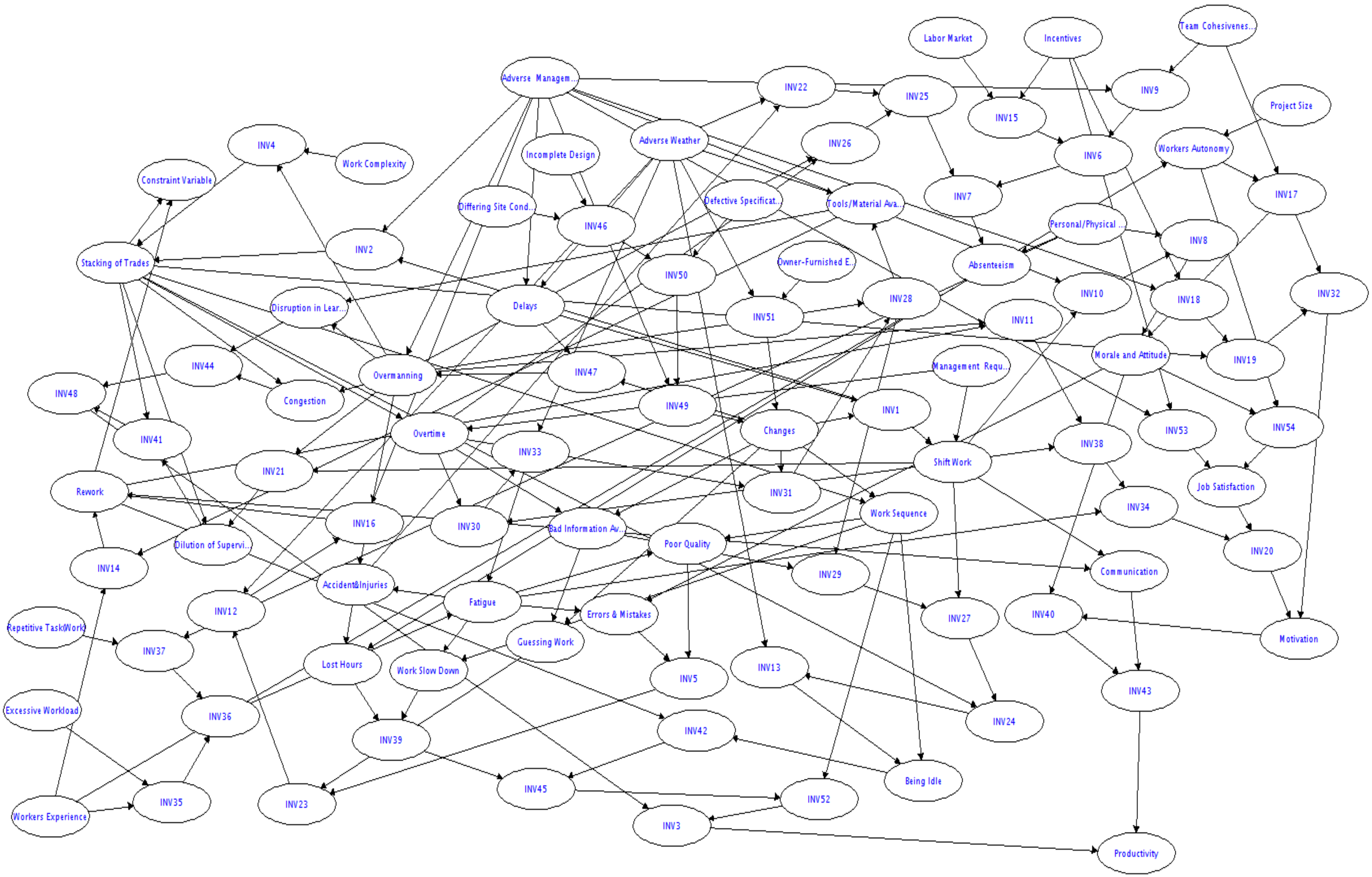


Figure C.1: Model Snapshot

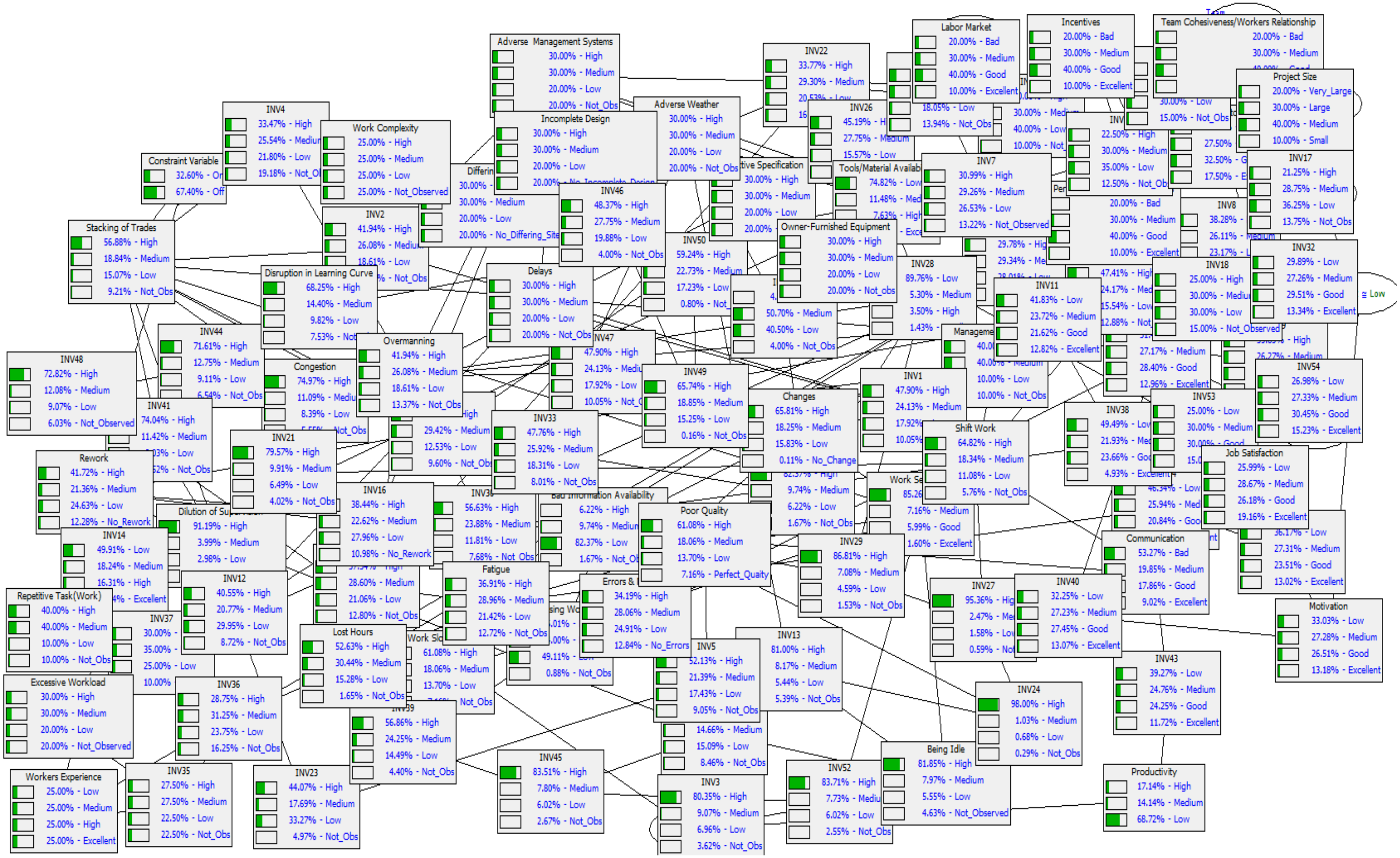


Figure C.2: Model's Marginal Distribution