OCCUPATIONAL SAFETY DYNAMICS IN ONSHORE LNG RECEIVING TERMINALS: A SYSTEMS MODELING APPROACH

by

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to my family

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This research is intended to be a contribution towards prevention of occupational accidents. I commemorate of those who have been injured and who lost their lives in occupational accidents.

ABSTRACT

OCCUPATIONAL SAFETY DYNAMICS IN ONSHORE LNG RECEIVING TERMINALS: A SYSTEMS MODELING APPROACH

In onshore LNG receiving terminals (LNGRTs), any unsafe condition and/or act that may cause fire and explosion during LNG processes may lead to major occupational accidents that may endanger people, equipment and the environment. Hence, to prevent accidents, determining factors that result in unsafe condition and/or act is crucial. LNGRTs are complex systems of interacting elements of managerial and employee decisions pertaining to occupational safety. Accordingly, in this study, based on system dynamics approach, a dynamic simulation model is developed to unravel the dynamic feedback structures that operate over time and can reveal unsafe conditions and/or acts, which signal probabilities of major occupational accidents. To gain insight into the system, besides literature review, fieldwork is done in a major onshore LNGRT. The model structure comprises the activities of LNG processing, equipment maintenance and repairing, employee training, where the management's time allocation decision under specific resource constraints is the fundamental driver. The model simulates for 5 years and is validated first structurally then behaviorally. Subsequently, system behaviors are analyzed by applying several scenarios and policies on the model. Though these analyses, the model behaviors reveal that possibility of major occupational accidents increases by decrease in allocated labor time for maintenance that increases unsafe conditions and by decrease in allocated labor time for training that increases unsafe acts. The model can also be used as an experimental platform to test the influence of several factors on safety, such as; schedule pressure, incident learning, equipment reliability, turnover rate, overwork, and occupational experience of employee.

ÖZET

KIYI LNG DEPOLAMA VE GAZLAŞTIRMA TERMİNALLERİNDE İŞ GÜVENLİĞİ DİNAMİĞİ: SİSTEM MODELLEME YAKLAŞIMI

Kıyı LNG depolama ve gazlaştırma terminallerinde, LNG işleme faaliyetleri sırasındaki herhangi bir güvensiz durum ve/veya güvensiz davranış, yangın ve patlamaya neden olarak insan sağlığını tehlikeye atabilecek, çevresel hasar ve maddi kayba sebebiyet verebilecek büyük endüstriyel kazalara yol açabilmektedir. Dolayısıyla, kazaların önlenmesi için güvensiz durum ve/veya davranışlara neden olan unsurların belirlenmesi elzemdir. Kıyı LNG depolama ve gazlaştırma terminalleri, iş güvenliği ile ilgili yönetim ve çalışan kararlarının birbirleriyle etkileşimde bulunan unsurlarının oluşturduğu karmaşık bir sistemdir. Bu nedenle, bu çalışmada, sistem dinamiği yaklaşımına dayalı olarak, büyük endüstriyel kaza olasılıklarını işaret eden güvensiz durum ve/veya davranışları belirleyebilen ve zamana bağlı çalışan geribildirim yapılarını ortaya çıkarmak için bir dinamik simülasyon modeli geliştirilmiştir. Sistemin iyi bir şekilde analiz edilebilmesi için literatür çalışmasının yanında kıyı LNG depolama ve gazlaştırma terminallerinin başlıcalarından birinde alan çalışması yapılmıştır. Model yapısı; yönetimin belirli kaynak kısıtları altında, zaman paylaşım kararının temel faktör olduğu bir sistemde LNG işleme, ekipman bakım ve onarım, çalışanların eğitimi aktivitelerini içermektedir. Modelin zaman aralığı beş yıl olup, modelin geçerliliği, öncelikle yapısal, daha sonra davranışsal ölçümleme testleri yapılarak sağlanmıştır. Akabinde, model üzerinde çeşitli senaryo ve politikalar uygulanarak sistem davranışları analiz edilmiştir. Yapılan analizlerden bakım çalışmalarına ayrılan zamanın azalmasının güvensiz durumları; çalışanların eğitimine ayrılan zamanın azalmasının güvensiz davranışları arttırdığı, bu durumun da büyük endüstriyel kazaların yaşanma olasılığını arttırdığı anlaşılmaktadır. Model, aynı zamanda; zaman baskısı, ramak kalalardan ders çıkarma, ekipman güvenirliği, işçi sirkülasyonu, fazla çalışma, çalışanların iş tecrübesi gibi çeşitli faktörlerin iş güvenliğine etkisinin test edilebilmesi için deneysel bir platform da sağlamaktadır.

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LIST OF SYMBOLS/ABBREVIATIONS

Symbol	Explanation	Unit
°C	Celsius	-
m^3	Cubic Meter	-

Abbreviation	Explanation
BOG	Boil of Gas
HP	High Pressure
HSE	Health and Safety Executive
ILO	International Labor Organization
LNG	Liquefied Natural Gas
LNGRT	Liquefied Natural Gas Receiving Terminal
LP	Low Pressure
OSHA	Occupational Safety and Health Administration

1. INTRODUCTION

Natural gas has been widely used as an energy source for years. Depending on global energy demand, the natural gas requirement has increased, therefore; new gas reserves that were thought to be too remote, technologically and economically not feasible for pipeline transportation have drawn attention. Then, natural gas transportation techniques, like liquefaction, have been developed in recent years (Mokhatab et al., 2014).

Liquefaction of natural gas provides significant volume reduction. When natural gas is cooled to approximately -162°C at atmospheric pressure, the phase changes to a liquid and 1/600th volume reduction is provided which eases transportation and storage (Speight, 2018). After the liquefaction process, liquefied natural gas (LNG) is loaded on LNG trucks or LNG ships to be transported to remote areas. Then, arrived LNG to the LNG receiving terminals (LNGRTs) (on-shore or offshore) is unloaded, stored, and gasified. Regained natural gas is sent to the pipeline system to reach end-users (Mokhatab et al., 2014). Figure 1.1 illustrates the basic components of the LNG supply chain.

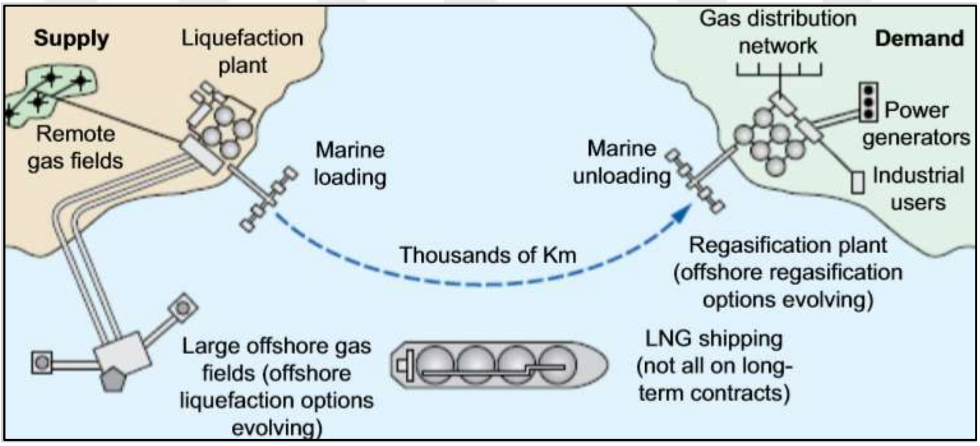

Figure 1.1. Basic components of LNG supply chain (Mokhatab et al., 2014).

However, in the LNG supply chain, during LNG processes, any unsafe condition or unsafe act in terms of occupational safety may cause fire, explosion, and toxic exposure that depend on physical and chemical features of LNG and result in major occupational accidents that may endanger people, equipment and the environment (Mokhatab et al., 2014; Woodward and Pitblado, 2010).

To enlighten LNG processes hazards and its consequences, it is helpful to look at the results of some of the occupational major accidents occurred in LNG plants in history. In 1944, in the LNG plant located in Cleveland USA, the LNG storage tanks were ruptured since the construction material of tanks was improper. After that, LNG spilled into the city sewer system since there was no dike, and due to vaporization and ignition, an explosion occurred and 128 people were killed, 300 people were injured, 80 houses and 10 industrial plants were damaged. In 1973, during repairing processes in the LNG plant in New York, workers used non-explosion-proof equipment, therefore; gas ignited and due to fire and its effects, 37 people were killed. In 2004, refrigerant line leaked in Algeria and the boiler firebox exploded. It caused huge damage to the facility, and 27 employees were killed, 80 employees were injured (Horn and Wilson, 1977; Mokhatab et al., 2014).

To eliminate the possibility of such major occupational accidents in the future, any factor that leads to unsafe condition and unsafe act must be identified and required measures must be taken. Furthermore, it is stated by Bouloiz et al, 2013 and Leveson, 2004 that, since the industrial systems and so occupational safety systems are complex, the causes of major occupational accidents are generated from the interactions of the system components, which consists of dynamic and feedback structure. Therefore, understanding the dynamic interactions of causal mechanisms of unsafe conditions and unsafe acts requires a systemic and holistic conceptualization of the occupational safety system. That is, the system components like LNG processes, maintenance and repairing works, employee training activities, incident learning systems, turnover rate, overwork, equipment reliability, working conditions and the others, and the interactions between these components with each other in terms of causal mechanisms and feedback structures must be considered and analyzed.

Accordingly, in this study, to gain insight into the onshore LNGRTs occupational safety dynamics, a dynamic simulation model based on system modeling approach is developed. The model aims to determine factors that lead to any unsafe condition and/or unsafe act and to analyze the effects of different scenarios and policies on safety system. The ultimate purpose is to demonstrate better policies to prevent future accidents.

2. PROBLEM DESCRIPTION AND RESEARCH OBJECTIVES

In the onshore LNGRTs, arrived LNG is gasified and transmitted to the end-users via pipelines. Terminals mainly include LNG unloading, LNG storage, gasification, and gas send-out processes. At first, LNG is unloaded from the arrived ships to the unloading arms, then to the storage tank through the unloading lines. After that, LNG is warmed under specific conditions, and its phase is changed from liquid to gas by gasification processes. In the end, regained natural gas is delivered into the distribution pipelines to be transmitted to end users. In Figure 2.1, one of the onshore LNGRT top view is presented.

Figure 2.1. An example of the onshore LNGRT top view (BOTAŞ, 2019).

The basic units in the process are LNG unloading system, LNG storage tanks, Low-Pressure (LP) pumps, High-Pressure (HP) pumps, Boil-off-gas (BOG) compressors and recondenser, flare, vaporizers, and gas piping system (Deli, 2013). In Figure 2.2, the process flow diagram for a typical onshore LNGRT is presented.

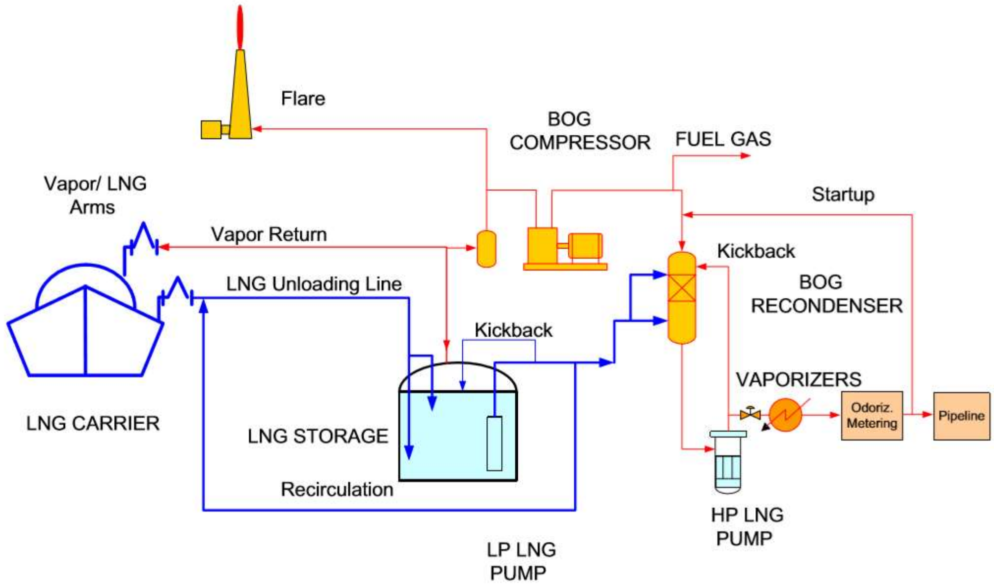

Figure 2.2. LNGRT basic process flow diagram (Mokhatab et al., 2014).

To make process flow clear and give some detail; firstly, arrived LNG carries are connected to unloading arms. Before unloading, unloading units and LNG storage tanks are cooled. After cooling processes and process controls, unloading is started from carriers to storage tanks. LP pumps located in the storage tanks send the stored LNG to recondenser at low pressure. In addition, BOG, which emerges from liquid evaporation caused by heat conduction in storage tanks is also sent to recondenser at low pressure. Both mix at recondenser in LNG form and LNG is sent to HP pumps. In HP pumps, low-pressure LNG is gradually pressurized and sent to the vaporization units in high pressure. Then regenerated natural gas is sent to the end-users via pipeline systems (Deli, 2013).

Furthermore, before unloading, the density differences among arrived and stored LNG must be checked in order not to cause any damage resulting from density differences in the tank. When lighter LNG is unloaded, bottom pipes are used and when heavier LNG is unloaded, top pipes are used. Moreover, generated BOG during processes in LNG storage tanks must be managed to prevent overpressure (Deli, 2013; Mokhatab et al., 2014).

Since LNG is a dangerous chemical in terms of fire and explosion, any unsafe condition or unsafe act during LNG processes like unloading, filling, storage, regasification, and gas send out may cause major occupational accidents that may endanger people, environment and equipment. The fire and explosion hazards are mostly emerged from the physical and chemical characteristics of LNG and have the highest risks for the terminal. Although LNG containments vary depending on the resource properties of natural gas, it contains mainly methane and includes smaller amounts of other hydrocarbons like ethane, propane, butane, pentane, and nonhydrocarbons like carbon dioxide, hydrogen sulfide, nitrogen, and helium (Speight, 2018). It is not flammable in the liquid phase, however; LNG leaks and spills generate BOG and it is vaporized when it meets with surfaces. Then, it may form flammable vapor cloud (typically between 4% and 15% concentration of gas in the air) that may cause fire (vapor cloud flash fire, jet fire, pool fire) and vapor cloud explosion if it meets with an ignition source (Mokhatab et al., 2014).

To eliminate or alleviate the major occupational accident risks, LNGRTs must be constructed and operated depending on safety rules in terms of site selection, design principles, procedures, equipment quality, maintenance, auditing, monitoring, employee qualification, prevention systems, and emergency response systems. To expand, reliable construction design; overpressure management; ventilation systems; temperature sensors; leak detectors; high/low level alarms; spill control systems; ignition source controls; emergency shutdown systems, active and passive fire protection systems; periodic maintenance programs, regular site monitoring; work permit system; trained employees must be provided (Mokhatab et al., 2014; Woodward and Pitblado, 2010).

It is obvious that there are many components related with the occupational safety system in the onshore LNGRTs and to provide safety, these components must be proper and be functional continuingly. Therefore, any unsafe condition or unsafe acts that may ruin the convenience of these components must be identified and required measures must be taken. Depending on this, understanding of the components causing unsafe conditions or unsafe acts is vital.

Furthermore, these components interact with each other through feedback causalities. As it is seen, the onshore LNGRTs and so occupational safety are complex systems. Hence, understanding of the dynamic interactions of the components that leads to unsafe conditions and unsafe acts requires systemic conceptualization of the occupational safety system. That is, the system components and the interactions of these components with each other can be identified and analyzed by the system dynamics method based on dynamic and feedback structure analysis (Bouloiz et al, 2013; Garbolino et al, 2016; Leveson, 2004).

Accordingly, in this study, since it is aimed to determine causes of any unsafe condition and unsafe act that may lead to major occupational accident in the onshore LNGRTs, a dynamic simulation model based on system modeling approach is developed for occupational safety system. To gain insight into the system, besides literature review, fieldwork was done in one of the onshore LNGRTs. Depending on these, the model structure comprises of occupational safety related activities;

LNG processing, equipment maintenance and repairing, employee training, and incident learning where the management's time allocation decision under specific resource constraints is the fundamental driver. Hence, the purpose of the study is to analyze labor time allocation among these activities as a policy for occupational safety. Since the dynamic simulation model also provides us with a tool to analyze how different scenarios and polices affect unsafe condition and unsafe act, and through these analyses it is also aimed to provide a method for implementing better policies without facing major occupational accidents.

3. LITERATURE REVIEW

Determining hazards that may cause occupational accidents is vital to manage risks in industrial systems (Dulac, 2007); therefore, there have been various hazard identification methodologies. Failure Mode and Effect Analysis (FMEA), Fault Tree Analyses (FTA), Hazard and Operability study (HAZOP), Failure Mode Effect Criticality Analysis (FMECA), Preliminary Risk Analysis (PRA) are the examples of traditional methods. These are grounded in the chain-of-event paradigm and describe accidents using sequential models that explain cause and effect linearity of a set of events. They deal primarily with technical dimensions and they do not consider interaction of safety system components such as; organizational issues, human aspect, technical structures, social and political conditions (Bouloiz et al., 2013; Dulac et al., 2005; Leveson, 2004).

Besides the traditional ones, there are methodologies including human and organizational dimensions, such as; TRIPOD, System Action Management (SAM), Technical Analysis, Human and Organizational Security (ATHOS), Cognitive Reliability and Error Analysis Method (CREAM). They ease to analyze the effects of the organizational environment on technical and human factors in the system by using a static model. However, they do not analyze dynamic interactions among system variables (Bouloiz et al, 2013).

On the other hand, industrial systems, accordingly occupational safety systems are dynamically complex. Therefore, occupational accidents arising from the interactions of safety system variables are caused by dynamic complexity. Depending on this, the mentioned methodologies ignoring system dynamics, feedback structures have been criticized for being insufficient to provide an adequate understanding of causal mechanisms of accidents. Consequently, it is claimed that causal mechanisms of occupational accidents must be analyzed by the methods based on dynamic and feedback structure analyzing approach (Bouloiz et al, 2013; Leveson, 2004).

To understand the structure and dynamic behavior of complex systems, the system dynamics approach has emerged in the late 1950s. A group of researchers at the Massachusetts Institute of Technology gave a start with studies about industrial dynamics and strategic management of industrial problems (Barlas, 2002). Accordingly, Forrester (1961) as cited in Sterman (2000) claims that system dynamics is an approach for analyzing important top management problems and states that it focuses on multi-loop, multistate, nonlinear character of feedback system by emphasizing that all decisions occur within the context of feedback loops. Accordingly, since occupational safety problems are systemic problems and have dynamic complexity, to gain insights to such complex systems, studies based on the system dynamics approach have been carried on in the field of occupational safety in the literature.

Cooke (2003) carries on one of the important ones, which analyzes the causes of Westray mine accident. It determines causative mechanisms of the accident with its variables and examines their interactions, feedback loops, time delays, and non-linear relationships to improve understanding of safety system complexity for the mine production industry. In the model, incident is defined as ‘an unplanned event that may or may not result in undesirable consequences’ and accident is defined as ‘an incident with actual negative consequences’. It is stated that incidents are caused by unsafe conditions, unsafe acts, and management tolerance to both of them. It is also observed in the study that when management commitment to production increases due to the growing backlog, management commitment to safety decreases, then employee commitment to safety decreases. This leads to an increase in incident rate. When incident rate reaches to ‘critical mass', accident becomes inevitable. Cooke concludes that the Westray mine accident occurred due to giving priority on production over safety. Moreover, it is stated that elimination or alleviation of accidents is possible if and only if the accidents are accepted as a result of the behavior of the whole system, not due to the individual components such as people, procedures or equipment.

Cooke (2003) also states that more production by skipping safety rules leads to incidents, and incidents cause disasters like a fatal explosion in the mine and eventually creates a ‘vicious cycle’ by resulting in production losses. Vicious cycle behavior is defined in ‘capability trap’ phenomenon by Repenning and Sterman (2001, 2002) in the system dynamic analysis of resource allocation problem in industries. When organizations have a performance gap, they often choose to work harder, which provides an immediate solution. And since the time is a scarce resource for organizations, it leads to a decline in time allocation for improvement issues, which also increases the capability of organizations and close the performance gap. Although working harder decreases the performance gap in a short period, spending time on improvement, which is working smarter, takes a longer time to close the gap. However, it is stated that the working harder provides better-before-worse situations while working smarter has worse-before-better dynamic since the allocation of less time for improvement leads to a gradual decrease in capability (Repenning and Sterman 2001, 2002). By working harder and harder, without fixing the actual problem and relying on shortcuts loop cause a vicious cycle in the reinvestment loop and generates capability trap (Repenning and Sterman 2001, 2002).

To enlighten the work harder and work smarter concept, it is stated by Lyneis and Sterman, (2016) and Repenning and Sterman (2001) that work harder means; speeding up, overtime, shorter breaks, skipping steps, cutting testing, deferring maintenance, failing to follow safety procedures, setting aggressive targets for throughput, imposing penalties for missing those targets. Work smarter means; setting up improvement programs, encouraging people to experiment with new ideas, investing in training programs. Figure 3.1 shows the work harder, work smarter, reinvestment reinforcing and shortcuts loops of performance gap problem dynamics.

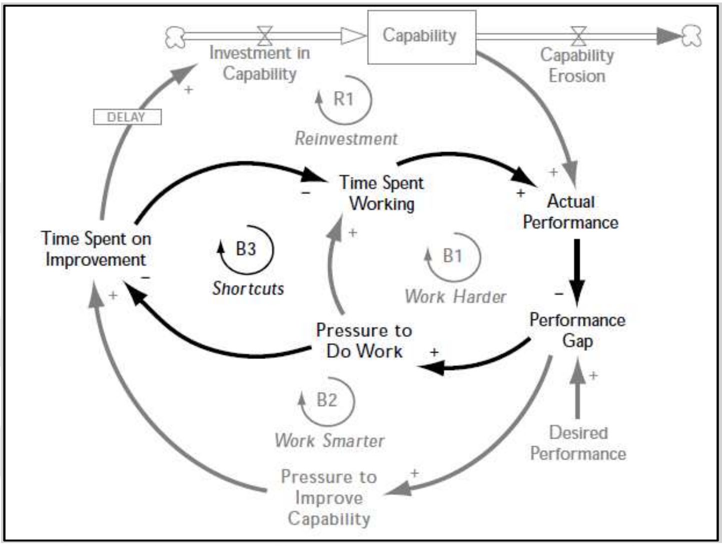

Figure 3.1. Illustration of work harder, work smarter, reinforcing and shortcuts balancing loops (Repenning and Sterman, 2001, 2002).

Another study is carried on by Salge and Milling (2006) who analyze Chernobyl accident causes in the system dynamic approach. They claim that the accident is caused due to the combination of human failures in the design of reactor and on-line operations. It emphasizes that perceived pressure on employees has important role in the accident.

Bouloiz et al (2013) built a system dynamic model for behavioral analysis of safety conditions in a chemical storage unit. The study focuses on the dynamics of technical, organizational and human factors in the system. It is analyzed that, increase in untrained employee leads to a significant decrease in safe behavior. Furthermore, the proper work environment has a positive effect on the safe behavior of employees. Repenning and Sterman (2001) contribute that putting overtime due to work harder is frequently extent overnights and weekends, and steal employee’s time from their family and community activities and that has long-run side effects like decrease in employee performance.

Another study is about the incident learning system. Cooke and Rohleder (2006) analyze the effect of incident learning system on accidents by using a system dynamics approach. In the study, it is stated that accidents are caused by passing over the warning signs of pioneer incidents or being unsuccessful to take lessons from the past. Therefore, the incident learning system is important to determine and examine incidents to correct deficiencies in the system. In the model, the incident learning system includes; identification, reporting, and investigation of incidents and then determining the causal structure of incidents, making recommendations and implementing corrective actions. Incident investigation is determined as an examination of the site, interviewing witnesses, gathering and evaluating all available data to establish the sequence of events and determine exactly what happened.

Lyneis and Stuart (2008) carry on a study about safety climate and organizational learning. Safety and social psychology, safety and organizational theory, organizational learning issues, and basic causal structures for Incident Rate are set in the study. In this structure, the effectiveness of safe behavior is positively related to adherence to rules and procedures and this being negatively related to incident rate. It is concluded that when industries give high priority to safety and learning, the incident rate becomes lower.

Also, System Theoretic Accident Model and Processes (STAMP) is built to analyze constraints in the safety management system (Leveson, 2004). It is based on the hypothesis that safety culture can be modeled, examined and engineered. The model uses a static control structure and system dynamics model together. It is stated that STAMP provides to ease the building of a system dynamics model (Dulac et al, 2005).

Hoffman and Wilkinson (2011) apply system dynamics methodology for barrier-based system management, which is the Swiss Cheese model determined by Reason (1997). They conclude that the quantity of barriers alone does not represent the effectiveness of the safety management system. They claim that monitoring and understanding of the system have significant importance.

Furthermore, La Porte and Consolini (1991), Roberts and Bea (2001), and Weick and Sutcliffe (2001) as cited in Cooke (2006) argue that accidents can be prevented by organizational practices. Rudolph and Repenning (2002) state in their study providing to understand how disasters can be the results of novel events that for an understanding of disasters, novelties and the number of interruptions must be considered.

4. METHODOLOGY

The methodology used in this study is system dynamics modeling and simulation. It is stated as a powerful approach to understand the dynamics of complex systems and causes of dynamic problems to examine policies for eliminating them (Sterman, 2000).

System dynamics is based on the modern theory of nonlinear dynamics and feedback control, which are improved in mathematics, physics, and engineering (Sterman, 2000). It analyses the dynamic (changing over time) problems of systemic, feedback nature (Barlas, 2002). In modeling, causal loop diagrams are useful tools for underlying and schematization of the system feedback structure and illustrate the causal links among variables by using arrows from cause to its effect (Sterman, 2000). Figure 4.1 represents the causality example.

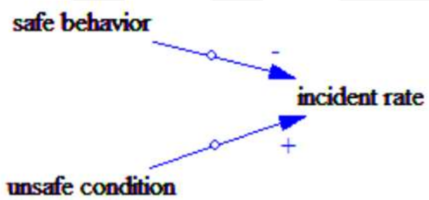

Figure 4.1. Illustration of direct causality (open loop).

Although direct causality gives the idea about causal relationships of variables, it is not sufficient for conceptualization and giving insight about the dynamic behavior of real system variables. It is crucial to identify feedback causalities that operate over time. It is stated (Sterman, 2000) that all dynamics are generated by two types of feedback loops, positive (reinforcing, representing with R) and negative (balancing, representing with B). Figure 4.2 represents an example of negative feedback causality.

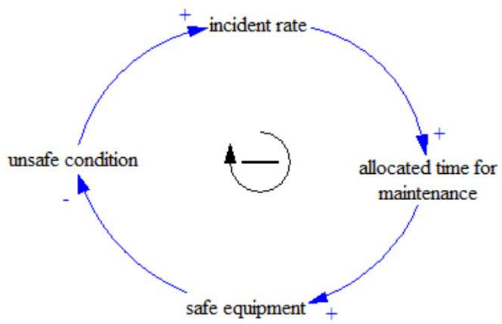

Figure 4.2. Illustration of negative feedback causality.

Stocks and flows are the fundamental building blocks of feedback loops. Stocks are accumulations and describe the state of the system, provide system inertia and memory. It is the source of disequilibrium dynamics and creates delays. It is only altered with its flows. They are representing with rectangles. Flows are rate and make changes in stocks. In system dynamics modeling, after causal loop diagrams and stock-flow structures determined, then they are combined. The stock-flow structure is illustrated by the bathtub metaphor and an example of stock-flow structure embedded in feedback loop are represented in Figure 4.3 and Figure 4.4 (Sterman, 2000).

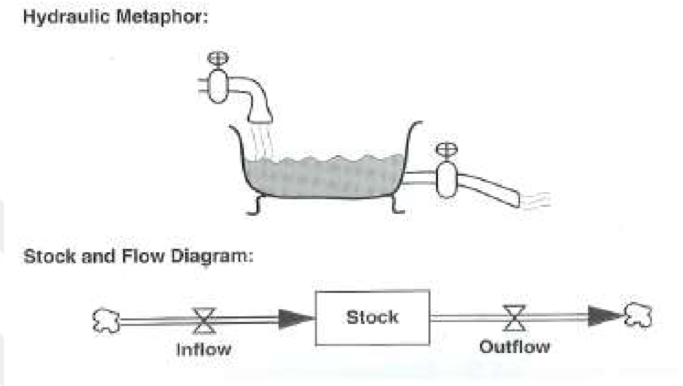

Figure 4.3. Illustration of stock-flow structure.

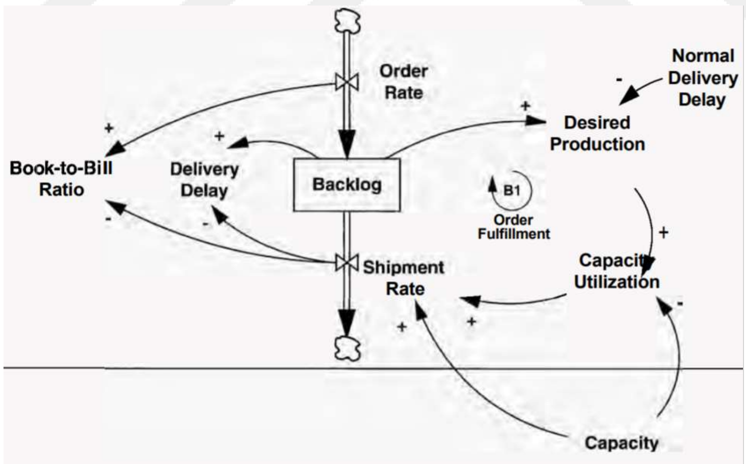

Figure 4.4. An example of stock-flow structure embedded in feedback loop (Sterman, 2000).

In system dynamics methodology, the model structure is built up by determining relevant variables, causalities, feedback loops and stock-flow structures as above. Finally, the model represents the dynamic complexity of the system by consisting of multiple, non-linear feedback loops with time lags. In addition, since the model is a high-order, non-linear system of differential (or difference) equations, for numeric simulation and behavior analysis, there are several software programs, such as; Vensim (Ventana,1996), Powersim (Powersim, 1996), Ithink, STELLA (ISEE,1988).

According to Barlas (2002); system dynamics methodology has the following steps. These are stated as; problem identification and definition, dynamic hypothesis and model conceptualization, formal model construction, model validity testing, analysis of the model, design improvement, and implementation. The details of these steps are given below.

1. ***Problem Identification and Definition (Purpose):***

In system dynamics methodology, the problem being studied must be dynamic and feedback nature. To ease problem identification, some questions can be asked, such as; “Why is it a problem? What are the key variables and concepts that we must consider? How far in the future should we consider? What might their behavior be in the future?” (Barlas, 2002).

2. ***Dynamic Hypothesis (Model Conceptualization):***

This step aims to develop a dynamic hypothesis explaining the causes behind the problem. The problem and relevant issues in literature are examined, variables related to the problem are identified, causal effects and feedback loops between the variables are analyzed, main stocks and flows are determined (Barlas, 2002).

3. ***Formal Model Construction:***

In this step, a formal simulation model is built by making stock and flow diagrams, setting mathematical formulations considering causal relations of each variable, estimating numerical values of variables, and testing model for consistency with purpose and boundary (Barlas, 2002).

4. ***Model Validity Testing***

It is stated that if the structure and behavior of the model give a meaningful description of reality, then the model will be considered as valid. In this step, the structural and behavioral validity is tested. Dimensional consistency, realistic parameter definitions, extreme condition testes are examples of structural validity tests. The behavioral validity test is grounded on comparing pattern components of the model with real behavior (Barlas, 2002).

5. Analysis of the Model

This step aims to understand the main dynamic properties of the model. Generally, analysis is done by simulation experiments that are considered as sensitivity tests. It provides an assessment of how output behavior changes as a result of changes in parameters in the model (Barlas, 2002).

6. Design Improvement

Different policies are designed and then tested by simulation runs to understand what extent they can improve the model (Barlas, 2002).

7. Implementation

It is applicable if the system dynamics study is applied.

5. MODEL DESCRIPTION

In this study, a dynamic simulation model is developed to understand occupational safety system structure and to determine causal mechanisms of major accidents in the onshore LNGRTs. The dynamic model also provides a platform to analyze the effects of different scenarios and management policies on the occupational safety system. It is based on system dynamics method and built on Stella software. The model boundary is an onshore LNGRT, model time unit is set as week and time horizon is selected as 5 years (250 weeks). The model is solved numerically by Euler's method and the computational step is selected as dt=0.125.

In this chapter, firstly, the model is overviewed, and the sector diagram is described. Then, each sector is analyzed in detail; causal loop diagrams, stock-flow structures, assumptions, and important formulations are stated. Furthermore, to gain insight understanding, all equations of the model are presented in Appendix A.

5.1. Overview of the Model

In industrial systems, labor time is a common scarce resource for all subsystems. In the onshore LNGRTs, in a general manner, it is allocated for production, maintenance, repairing, and employee training activities. Depending on this, labor time allocation is at the core of this model. For modeling purposes, the onshore LNGRT safety system is divided into five sectors; labor time allocation, production, maintenance and repairing, training, and incident learning.

As seen from the overview of the onshore LNGRT safety system model represented in Figure 5.1, each sector is in interaction with each other directly or indirectly. All sectors give information about their labor time requirement to labor time allocation sector. Then, total labor time is allocated among these sectors depending on their relative demands. In addition, when there is a labor time gap due to employee shortfall, the labor time allocation sector gives information to the training sector for hiring. The production sector gives information to the maintenance and repairing sector about LNG dispatch, since required labor time for maintenance depends on it. Also, the maintenance and repairing sector gives information about critical equipment in use to the production sector, since production depends on it. Furthermore, information about the schedule pressure generated by production activities are sent from production sector to labor time allocation sector. Unsafe condition and safe behavior affect the incident rate, therefore, maintenance and repairing sector and training sector are related to incident learning sector. Moreover, incident learning sector gives information about learning from incidents to labor time allocation sector.

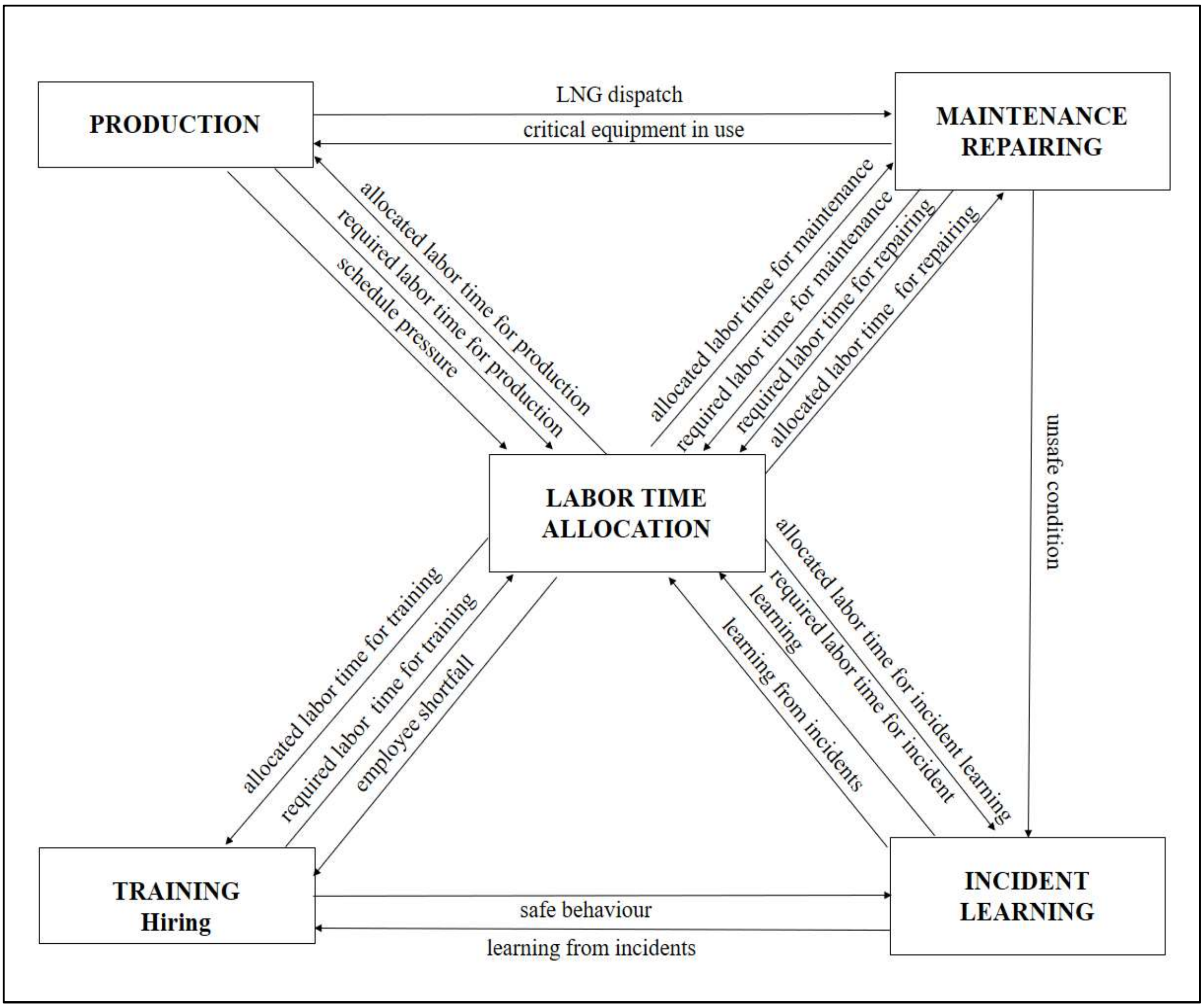

Figure 5.1. The overview of the model.

5.2. Main Assumptions of the Model

Main assumptions of the model is presented below.

- One year is taken as 50 weeks
- Terminal is operated 7 days 24 hours in a week
- Terminal capacity is constant
- Incidents do not cause critical equipment loss or labor time loss
- Both Untrained Employee and Trained Employee work at the site
- All employees are doing all works (production, maintenance, repairing)

- Each critical equipment has the same reference failure time
- Critical equipment in maintenance is not used in the system

5.3. Description of the Sectors

Model sectors are described in detail in this section.

5.3.1. Production Sector

This sector describes production processes in the onshore LNGRTs. The main causal loop diagram of the production sector and simplified stock-flow structure are presented in Figure 5.2 and Figure 5.3.

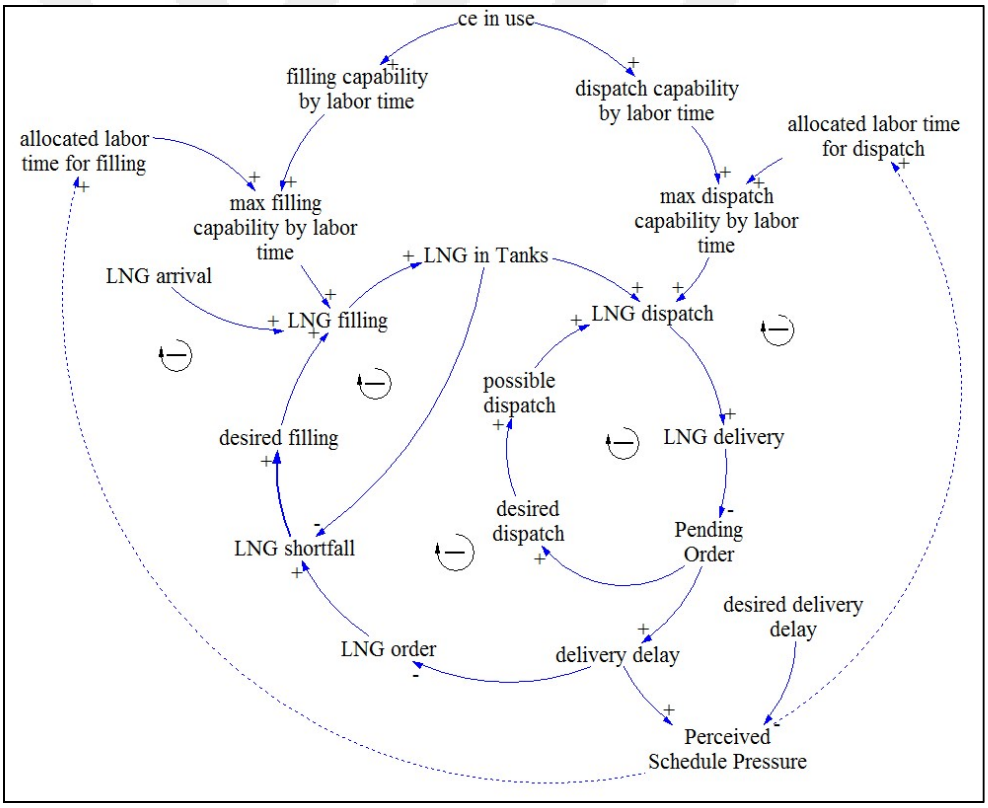

Figure 5.2. Causal loop diagram of production sector.

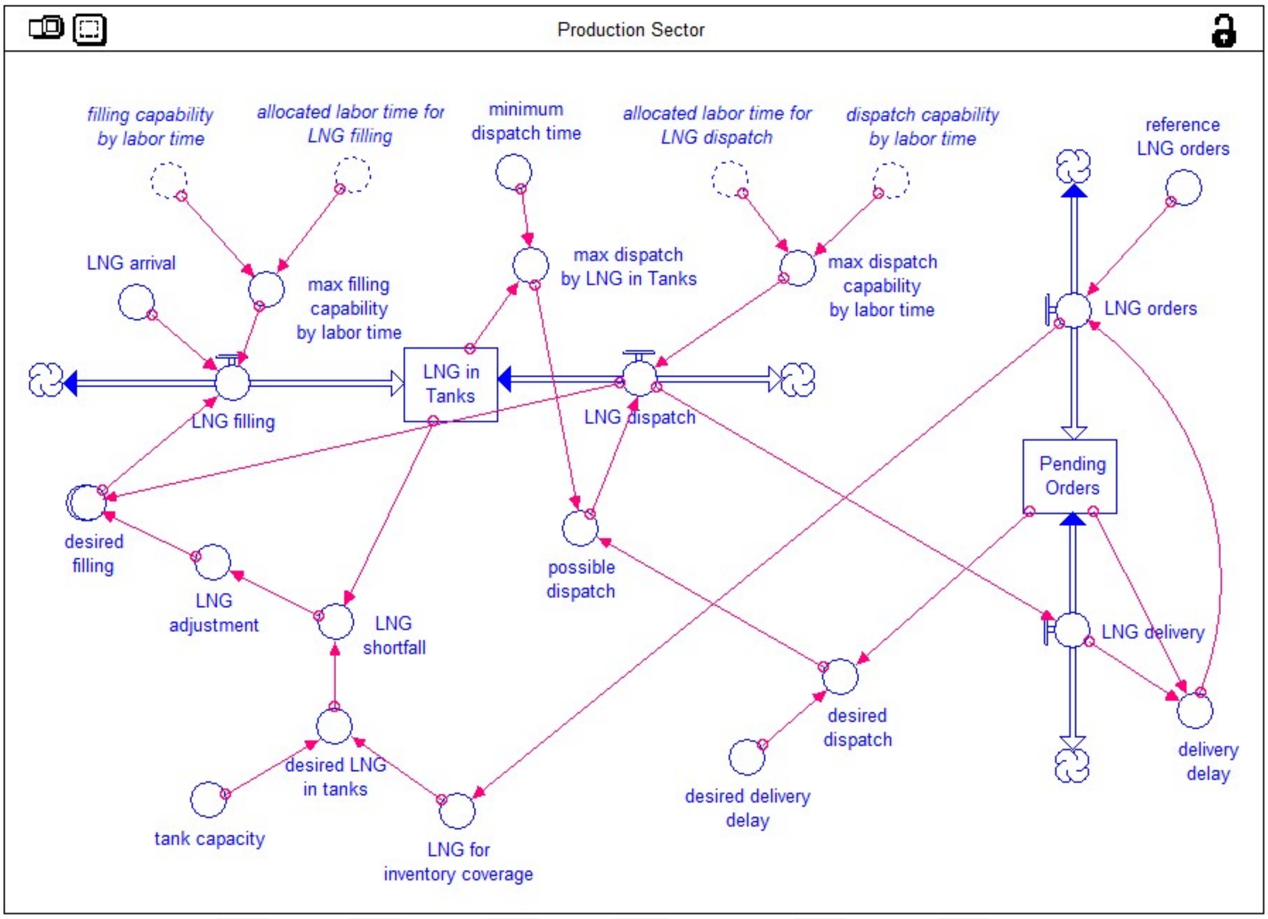

Figure 5.3. Simplified stock flow diagram of production sector.

As it is seen, there are two stocks in this sector; named as LNG in Tanks and Pending Orders. And as shown in causal mechanisms structure, it can be briefly said that when allocated labor time for production (filling and dispatch) increases, LNG filling, LNG in Tanks, and LNG dispatch increases. Then, LNG delivery increases, and so, Pending Orders and delivery delay decreases. Besides, when delivery delay increases, LNG order decreases and so LNG filling decreases. Increase in delivery delay also cause schedule pressure. To understand the causal mechanisms and stock-flow structures, the production sector details are given in the following.

In the onshore LNGRT, as detailed in Chapter 2, arrived LNG is unloaded from LNG ships to LNG storage tanks. Then, LNG is sent to regasification units and finally, obtained natural gas is transmitted to the pipeline system. In the model, LNG unloading processes from LNG carriers to storage tanks are described as LNG filling. Storage of LNG in tanks is represented as LNG in Tanks. LNG sending from storage tanks to regasification units, regasification processes and finally gas send-out processes are described in LNG dispatch. Therefore, LNG in Tanks is increased by LNG filling and decreased by LNG dispatch processes.

Furthermore, LNG filling depends on LNG arrival, filling capability by labor time and allocated labor time for filling (maximum filling capability by labor time), and desired filling. In the model, it is assumed that LNG arrival is exogenous and depending on the fieldwork, it is taken as constant and rounded up 250.000 m^3/week as a reference value. On the other hand, filling capability by labor time is defined in terms of m^3/employee*hours and is affected by critical equipment in use. Furthermore, desired filling depends on LNG shortfall emerging from LNG orders and LNG in Tanks. LNG filling is calculated by taking a minimum of these three converters as shown in Equation 5.1.

LNG filling = MIN (LNG_arrival, desired_filling, max_filling_capability by labor time) $\{m^3/week\}$ (5.1)

Besides, LNG dispatch is determined by dispatch capability by labor time and allocated labor time for dispatch (maximum dispatch capability by labor time), and by possible dispatch. Dispatch capability by labor time depends on critical equipment in use. Possible dispatch depends on maximum dispatch by LNG in Tanks and desired dispatch. LNG dispatch is calculated by taking a minimum of maximum dispatch capability by labor time and possible dispatch as represented in Equation 5.2.

LNG dispatch = MIN (max_dispatch_capability by labor time, possible_dispatch) $\{m^3/week\}$ (5.2)

On the other side, LNG orders is set as 250.000 m^3/week and changes with delivery delay being caused by Pending Orders and LNG delivery as represented in Equation 5.3.

delivery delay = Pending_Orders/LNG_delivery $\{week\}$ (5.3)

When LNG dispatch decreases, LNG delivery decreases and so, Pending Orders increases. Then, delivery delay increases. An increase in delivery delay makes a decrease in LNG orders. The effect of delivery delay on LNG orders is determined depending on interviews at fieldwork. When Perceived Delivery Delay passes to 7 weeks, LNG orders are gradually cancelled. Figure 5.4 represents the relationships.

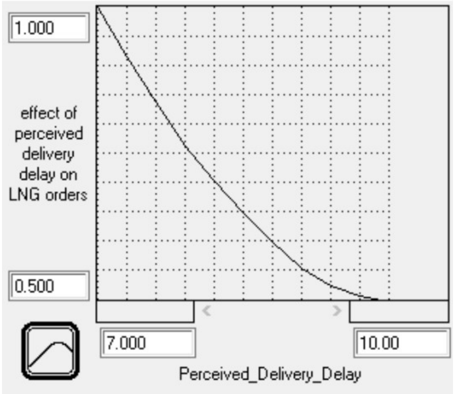

Figure 5.4. Effect of delivery delay on LNG orders.

The desired delivery delay that is one of the policy parameters in the terminal is taken as 1-week. Pending Orders and desired delivery delay affect LNG dispatch via the desired dispatch. When Pending Orders increases and desired delivery delay decreases, the desired dispatch rises. It also makes an increase in possible dispatch and LNG dispatch. The relations are given in Equation 5.4 and 5.5.

$$\textit{desired dispatch} = \textit{Pending\_Orders/desired\_delivery\_delay} \tag{5.4}$$

$$\textit{possible dispatch} = \textit{MIN (desired\_dispatch,max\_dispatch\_by\_LNG\_in\_Tanks)} \tag{5.5}$$

In addition, the ratio between desired delivery delay and delivery delay creates schedule pressure. The increase in schedule pressure equation is given in the Equation 5.6.

$$\textit{increase in schedule pressure} = \textit{((delivery\_delay/desired\_delivery\_delay)-}$$
$$\textit{Perceived\_Schedule\_Pressure)/correction\_time\_for\_schedule\_pressure} \quad \{1/week\} \tag{5.6}$$

When Perceived Schedule Pressure increases, it decreases the labor time allocation for maintenance, training and incident learning. This dynamic is detailed in the labor time allocation sector.

In the model, the terminal capacity is set as the onshore LNGRT that the fieldwork is done. There are three storage tanks, each has 85.000 m^3 capacity. Therefore, tank capacity, which means the total volume of three tanks, is taken 250.000 m^3 by rounding. Furthermore, LNG for inventory coverage is taken as 4 weeks that means the terminal has the policy to make LNG storage to fulfill 4 weeks order. Besides, Perceived Schedule Pressure is dimensionless and it is scaled between 0 to 10.

5.3.2. Training Sector

Training sector describes how safe behavior of employee changes in the terminal. For this purpose, the mechanisms affecting safe behavior are examined. The main causal loop diagram of the training sector and simplified stock-flow structure are presented in Figure 5.5 and Figure 5.6, respectively.

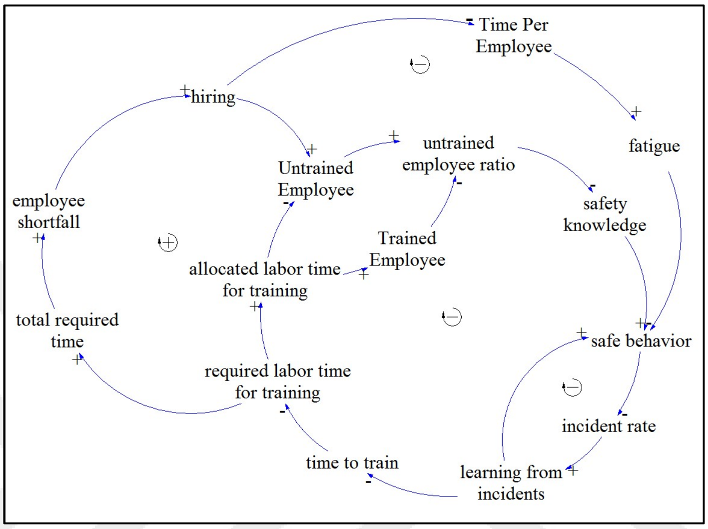

Figure 5.5. Causal loop diagram of training sector.

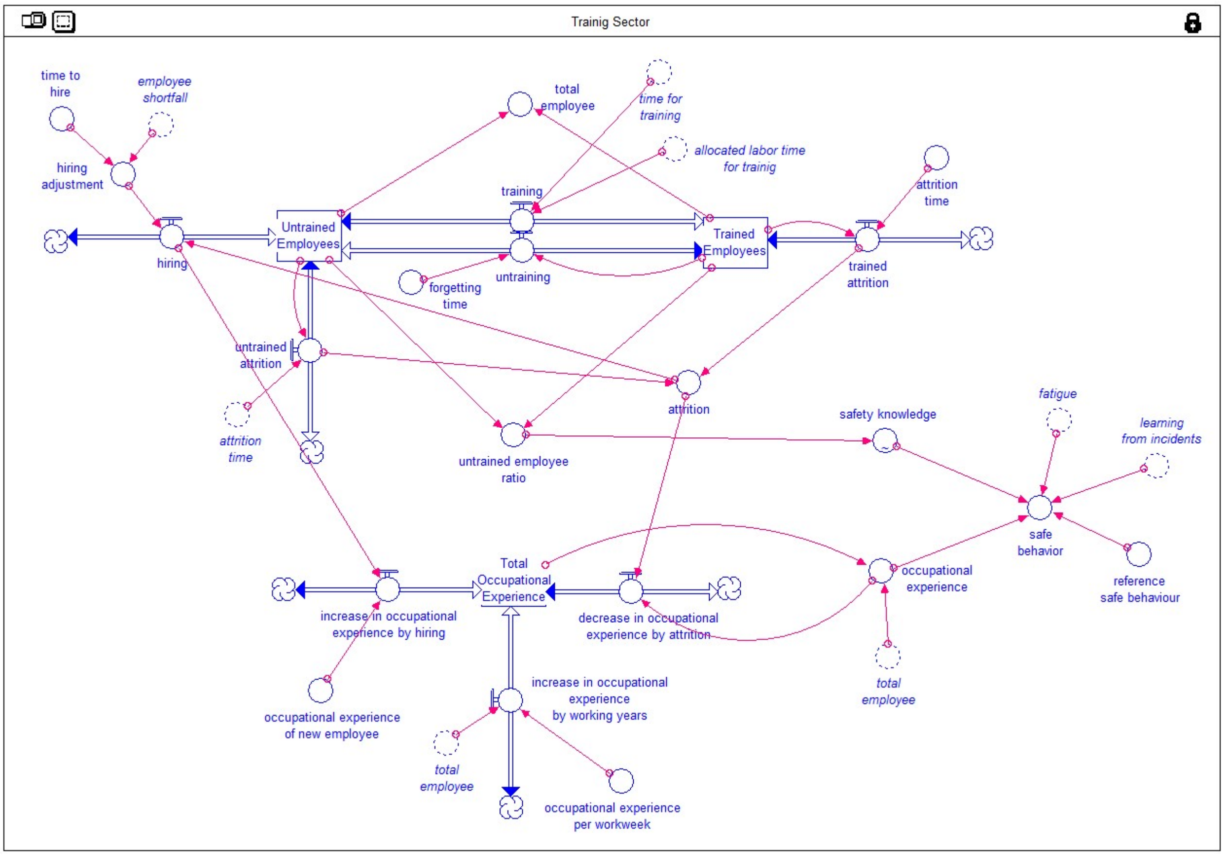

Figure 5.6. Simplified stock-flow structure of training sector.

As it is seen, there are two main stock-flow structures in this sector; training and occupational experience. In addition, as shown in causal mechanisms structure, it can be briefly said that when hiring increases Untrained Employees increases. Moreover, if allocated labor time for training increases, Trained Employees increases and Untrained Employees decreases. Hence, untrained employee ratio decreases and safety knowledge increases that makes increase in safe behavior. Furthermore, when hiring increases, Time per Employee decreases. Then, fatigue decreases which makes increase in safe behavior. Also, it is observed that, decrease in safe behavior leads to increase in incident rate. When incident rate increases, learning from incidents increases. Then, allocated labor time for training and safe behavior increase. To understand the causal mechanisms affecting safe behavior and stock-flow structures, the details given in the following.

Bird and Germain (1992) as cited in McKinnon (2000) state that unsafe acts are the ‘behavior or activity of a person that deviates from normal accepted safe procedure' and may cause an incident. Also, unsafe acts are exemplified as operating equipment without permission, misusage of equipment, making safety devices inactive, using improper equipment, unsuitable loading and placement, ignoring safety rules and cutting corners. Accordingly, in the model, unsafe acts are considered as one of the main elements to cause an incident and placed in the model as in its opposite definition: safe behavior. Depending on the literature (McKinnon, 2000) and fieldwork, it is determined in the model that safe behavior is affected by safety knowledge, occupational experience, fatigue, and incident learning.

Since safety knowledge is gained from training, the structure of the training system is built. That is, when hiring increases, Untrained Employees increases. Untrained Employees makes increase in labor time requirement for training and by allocation of labor time to training; Untrained Employees decreases, then Trained Employees increases. In this mechanism, the ratio between Untrained Employees and Trained Employees gives information about safety knowledge that affects safe behavior of employee.

Accordingly, Bouloiz et al (2013) analyzed that increase in Untrained Employees leads to a significant decrease in safe behavior. Furthermore, it is argued that the proper work environment has a positive effect on the safe behavior of employees. Cooke (2006) also states that an increase in management commitment to safety-that is an increase in allocation time for training in this model-provides an increase in employee commitment to safety-that is an increase safe behavior for this model. It is also claimed that employee commitment to safety makes a decrease in incident rates. Depending on the literature and the fieldwork, it is seen that the ratio of Untrained Employees to

Trained Employees affects safety knowledge negatively. The effect is set as in Figure 5.7. Besides, it is assumed that any employee has at least 10% safety knowledge without training.

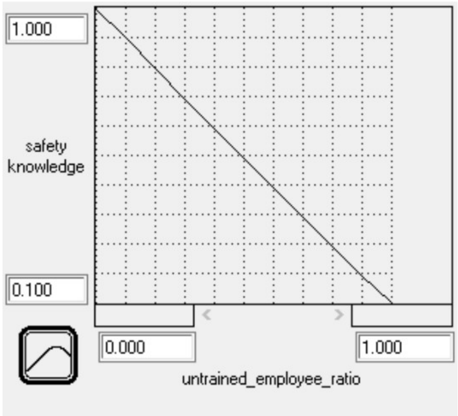

Figure 5.7. Effect of untrained employee to trained employee ratio on safety knowledge.

On the other hand, since occupational experience is determined as one of the effects on safe behavior, hiring and gaining experience relation is analyzed in the model. It is stated that, when the occupational experience of a new employee is higher than the employed ones, hiring increases the occupational experience. When occupational experience increases, safe behavior is affected positively. In the fieldwork, it is stated by the managers that occupational experience increases safe behavior until approximately 16-17 years. Then, self-confidence, nonconformity to technology or new rules cause a decline in safe behavior. Also, it is assumed that any new employee with no experience has 50% safe behavior without any experience. Accordingly, the effect of occupational experience on safe behavior is plotted as in Figure 5.8.

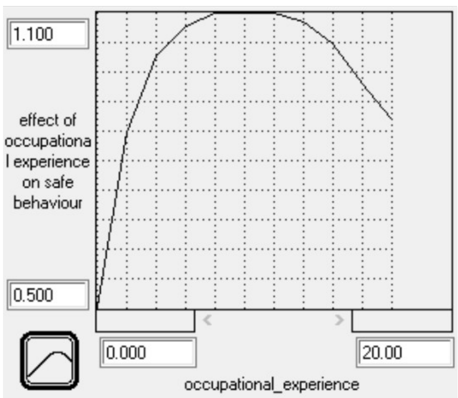

Figure 5.8. Effect of occupational experience on safe behavior.

Another converter affecting safe behavior is fatigue. International Petroleum Industry Environmental Conservation Association and International Association of Oil and Gas Producers report (IPIECA, 2007) states that shift-works, long working hour causes fatigue and it may lead to have poor memory, decrease ability to maintain attention and assessment of risks, reduce communication, increase risk-taking by being more likely to cut corners and may negatively affect safe behavior. It is also claimed (Dembe et al., 2005) that overtime work or extended hours, which means more than 12 hours/day and 60 hours/week, cause fatigue and may increase the incident rate with 37% and 23%, respectively. Repenning and Sterman (2001) contribute that putting overtime due to work harder is frequently extent overnights and weekends and has long-run side effects like a decrease in employee performance. Depending on literature and interviews during the fieldwork, it is determined that when working hours increases-that is defined as Time per Employee in the model-fatigue increases and this causes a decrease in the safe behavior. Accordingly, the severity of fatigue is scaled between 1.0 to 5.0 which correspond to 0 to 60 hour/week. And it is assumed that until the severity of 3.4, which means approximately 41 hour/week, fatigue does not have any effect on safe behavior. After an extension of 41 hour/week, it starts to cause a gradual decrease. This relation is stated as in Figure 5.9.

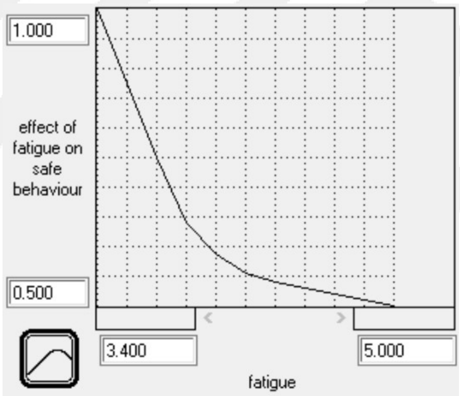

Figure 5.9. Effect of fatigue on safe behavior.

Incident learning is determined as another variable affecting safe behavior in the model. Cooke and Rohleder (2006) analyze the effect of incident learning system on accidents and conclude that the learning system is important to determine and examine incidents to correct deficiencies in the system. Accordingly, it is stated in the model that, safe behavior provides an increase in reporting incidents. By an increase in incident reporting and allocating time for training, learning from incidents increases. When it increases, the allocation of labor time for training and incident learning rises. It is assumed that safe behavior is not affected if there is no incident. However, by an increase in both safe behavior and incident rate, safe behavior increases as represented in Figure 5.10.

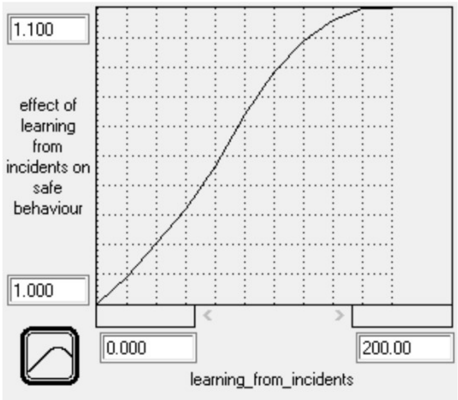

Figure 5.10. Effect of learning from incidents on safe behavior.

In training stock-flow structure, flows are in employee/week, stocks are in employee dimension. To gain an understanding of the difference between Untrained Employee and Trained Employee in terms of safe behavior, it is assumed that both Untrained Employee and Trained Employee work at the site. In addition, all employees do all kinds of works. For the model it means, all employees work for production (filling, storage, and dispatch), maintenance, and repairing. Furthermore, time for training is taken as 30 employee-hour for each employee. It means that an employee is accepted as trained after 30 employee-hour training.

In the training sector, time to hire, which is one of the policy parameters for increase in labor time, effects the hiring rate. By considering the complexity of hiring procedures at the onshore LNGRT, it is taken as 26 weeks. Also, other policy parameters for safe behavior, the occupational experience of a new employee is taken as 2 years, according to fieldwork.

Safe behavior which is the main point of the whole sector is calculated as below.

safe behavior=reference_safe_behaviour x safety_knowledge x effect_of_occupational_experience_on_safe_behaviour x effect_of_learning__from_incidents_on_safe_behaviour x effect_of_fatigue_on_safe_behaviour {dimensionless} (5.7)

where reference safe behavior is taken as 80. It means if safe behavior is calculated as 80 and above (until to 100), it is acceptable. When it is lower than 80, safe behavior affects incident rate negatively.

5.3.3. Maintenance and Repairing Sector

Maintenance and repairing sector gives information about causal mechanisms of unsafe conditions that may lead to an incident in the onshore LNGRTs. The main causal loop diagram of the sector and simplified stock-flow structure are presented in Figure 5.11 and Figure 5.12.

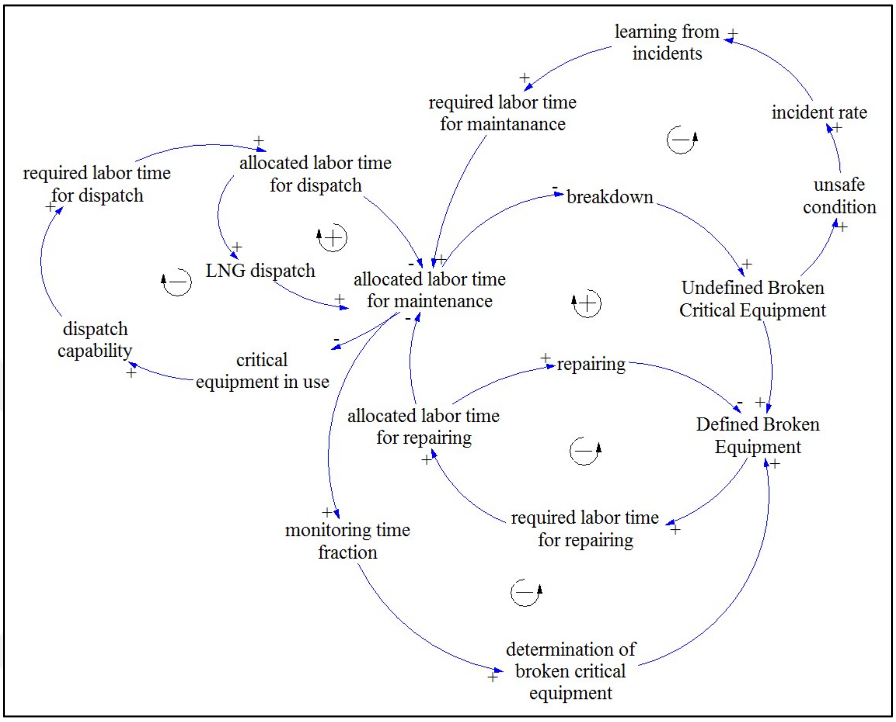

Figure 5.11. Causal loop diagram for maintenance and repairing sector.

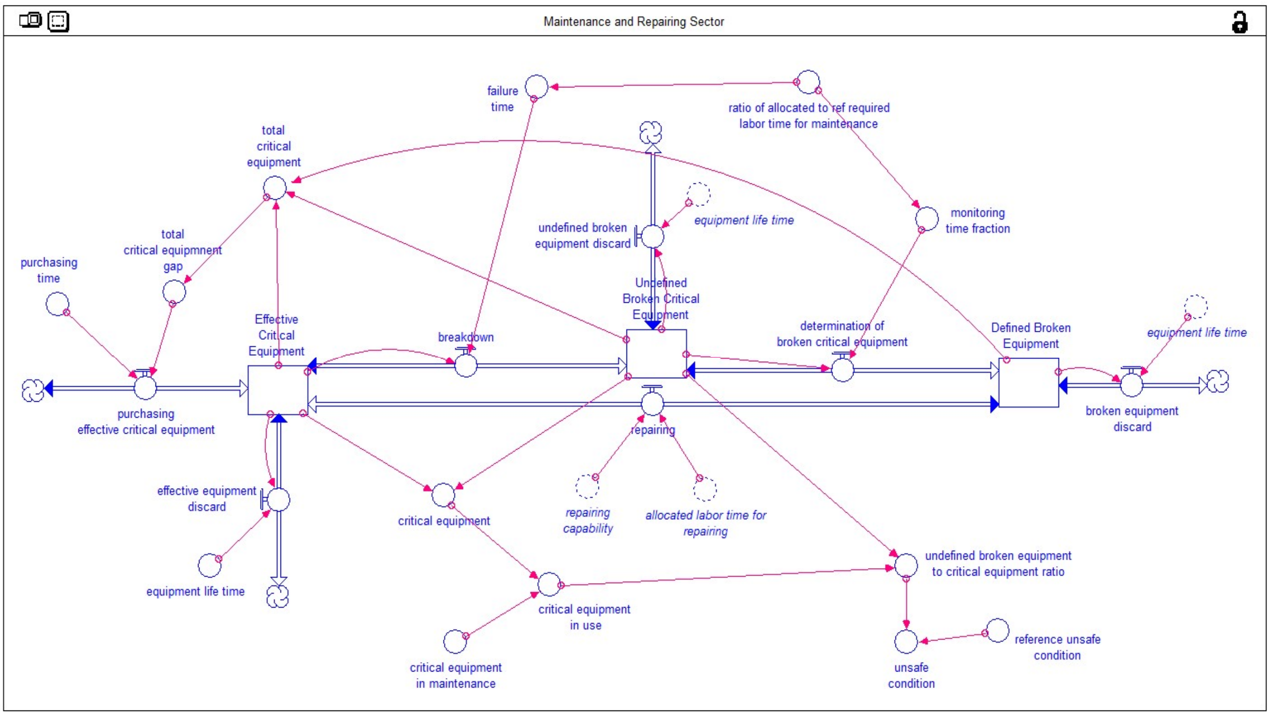

Figure 5.12. Simplified stock-flow structure for maintenance and repairing sector.

As it is seen, in the stock-flow structures, critical equipment is determined as Effective, Undefined Broken and Defined Broken. In addition, as shown in causal mechanisms structure, it can be briefly said that when allocated labor time for maintenance increases, breakdown decreases and monitoring increases. Then, Undefined Broken Critical Equipment decreases. Hence, unsafe condition decreases. On the other hand, by allocated labor time for repairing, repairing increases and Defined Broken Equipment decreases. Besides, increase in unsafe condition leads to increase in incident rate and learning from incidents that makes increase in allocated labor time for maintenance. Furthermore, allocated labor time for maintenance decreases critical equipment in use, and then LNG dispatch. To ease understanding of the causal mechanisms affecting unsafe conditions and stock-flow structures, the sector details given in the following.

As cited in McKinnon (2000), Bird and Germain (1992) define the unsafe condition as ‘a hazard or the unsafe mechanical or physical environment’. Moreover, improper equipment, insufficient equipment, broken equipment, inadequate safety barriers, and protective equipment are stated as unsafe conditions. Accordingly, in the model, equipment suitability, quality, and well-functioning properties are related to unsafe conditions. For modeling purposes, only the critical equipment is considered. The critical equipment consists of safety equipment like temperature sensors, leakage/spill detectors, high/low-level alarms, emergency shutdown systems, relief valves, pumps, metering, vaporizers, compressors, etc. In addition, it is assumed that the total critical equipment in the terminal is 1000.

Furthermore, maintenance is defined in the model as Occupational Safety and Health Administration (OSHA, 1999) states: ‘keeping equipment or a structure in the proper condition through routine, scheduled or anticipated measures without having to significantly alter the structure or equipment in the process. For equipment, this generally means keeping the equipment working properly by taking steps to prevent its failure or degradation'. In this model, these activities are exemplified as periodical critical equipment controls, daily equipment checking and monitoring, calibrations, and visual inspections. On the other hand, repairing is defined as the other activities beyond maintenance and being considered under construction works by OSHA (1999). It is defined as ‘repairing of existing things, replacement of structures or their components'. In this model, repairing refers to the functioning of broken equipment and it takes more effort and more time rather than maintenance activities.

As mentioned, in the model, equipment is separated as Effective Critical Equipment, Undefined Broken Critical Equipment and Defined Broken Equipment by being inspired from the safety barrier division of Hoffman and Wilkinson (2011). Effective Critical Equipment corresponds to proper and functional equipment. Defined Broken Equipment equals to broken and improper equipment being determined and must be repaired to be used. Undefined Broken Critical Equipment corresponds to equipment that is improper or broken, however, not determined yet as Defined Broken Equipment, and be in use.

Accordingly, it is clear that unsafe condition arises from Undefined Broken Critical Equipment. When Undefined Broken Critical Equipment to critical equipment in use increases, unsafe condition increases. The reference Undefined Broken Critical Equipment to critical equipment in use ratio is taken as zero and the relation is represented in the following Equation.

unsafe condition= reference_unsafe_condition +
undefined_broken_equipment_to_critical_equipment_in_use_ratio {dimensionless} (5.8)

Undefined Broken Critical Equipment increases depending on the breakdown of Effective Critical Equipment. Furthermore, breakdown depends on the failure time. It is assumed that each critical equipment has the same reference failure time and according to fieldwork, it is taken as 60 weeks in the model. It is assumed that if a critical equipment has 60 weeks or above failure time, such equipment is reliable. However, failure time changes depending on maintenance activities. When adequate maintenance, which means allocated labor time for maintenance corresponds to reference required labor time for maintenance, is provided failure time of equipment corresponds to reference failure time. Reference required labor time for maintenance is determined by reference maintenance frequency and it means for each 1.000.000 m^3 LNG dispatch, critical equipment must be maintained. However, when ratio of allocated to reference required labor time for maintenance decreases, failure time decreases, and breakdown increases. The effects of maintenance time on failure time is assumed as in Figure 5.13.

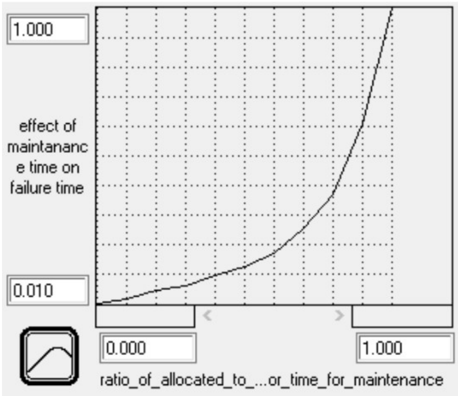

Figure 5.13. Effect of maintenance time on failure time.

On the other hand, Defined Broken Equipment depends on monitoring ability of the system. Allocated maintenance time increases the monitoring time fraction, and it increases the determination of broken critical equipment. The effects of maintenance time ratio on monitoring time is built depending on assumptions considering literature (Hoffman and Wilkinson, 2011) and fieldwork. It is represented in Figure 5.14.

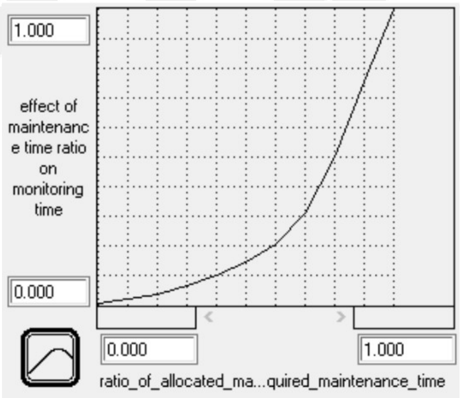

Figure 5.14. Effect of maintenance time ratio on monitoring time.

Besides, Defined Broken Equipment must be repaired for reuse or it can be discarded. Therefore, critical equipment is defined as the sum of Effective Critical Equipment and Undefined Broken Critical Equipment. Depending on allocated labor time for maintenance, some of the critical equipment is in maintenance and this equipment cannot be used in production processes. This means, increase in allocated labor time for maintenance, increases the critical equipment in maintenance and decreases the critical equipment in use. Then, dispatch capability decreases, and allocated labor time for dispatch decreases and so it makes decrease in LNG dispatch. In addition, since maintenance period depends on LNG dispatch, allocated labor time for maintenance also decreases. (see Figure 5.11). To clarify, equations of critical equipment maintenance and critical equipment in use are given below.

critical equipment in maintenance=

*(allocated_time_for_maintenance*maintenance__capability)/week {critical equipment}* (5.9)

critical equipment in use=MAX (critical_equipment-critical_equipment_in_maintenance,0) (5.10)

On the other hand, it is seen from the causal mechanisms that, there is one more negative feedback structure in this sector. That is, increase in unsafe condition leads to increase in incident rate. Hence, learning from incidents increases and so, required labor time for maintenance and allocated labor time for maintenance increase. This makes decrease in breakdown, and Undefined Broken Critical Equipment, and so unsafe condition. The details of learning from incidents effect on maintenance are detailed in incident learning sector.

In this sector, flows are in critical equipment/week, stocks are in critical equipment dimension. In addition, purchasing time, equipment life time, maintenance capability, reference monitoring fraction are determined by assumptions based on field work.

5.3.4. Incident Learning Sector

Incident learning sector aims to understand the structure of learning from incidents effect on occupational safety system in the onshore LNGRTs. The main causal loop diagram of the sector and simplified stock-flow structure are presented in Figure 5.15 and Figure 5.16.

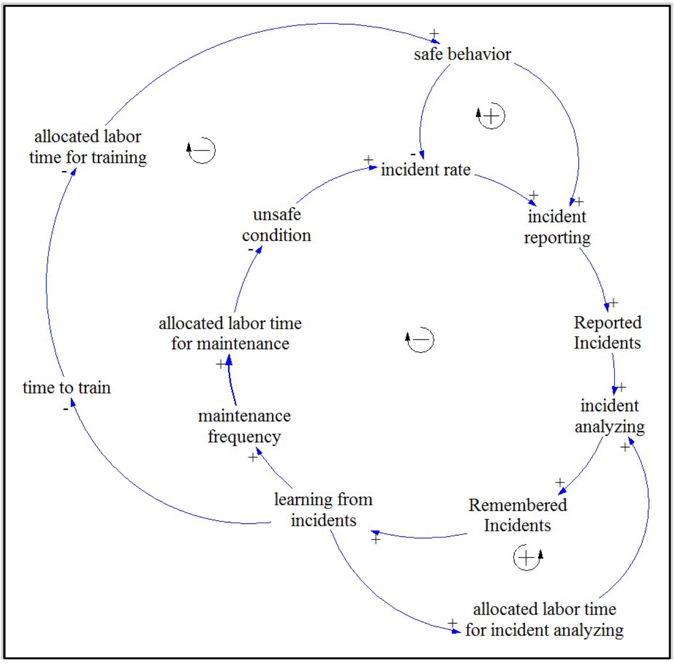

Figure 5.15. Causal loop diagram for incident learning sector.

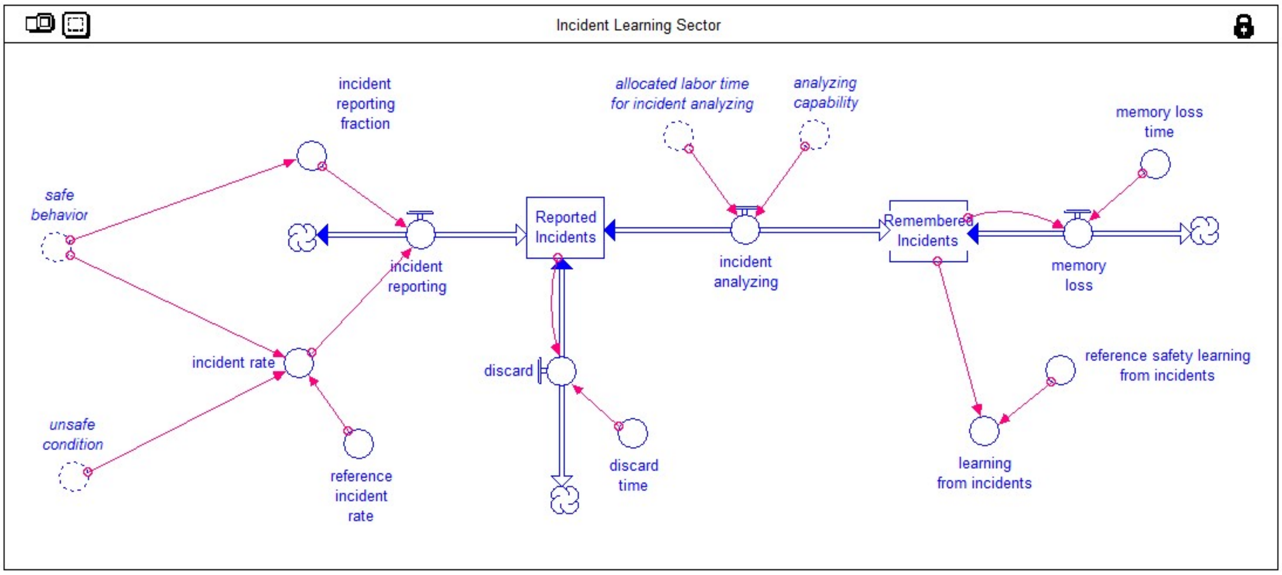

Figure 5.16. Simplified stock-flow structure of incident learning sector.

As it is seen from the stock-flow structure, there are two stocks named as Reported Incidents and Remembered Incidents in this sector. And as shown in causal mechanisms structure, it can be briefly said that when unsafe condition increases and/or safe behavior decreases, incident rate increases. Furthermore, when safe behavior increases, incident reporting increasing, then Reported Incidents increases. Besides, if labor time allocated for incident analyzing, then incident analyzing and Remembered Incidents increase. This makes increase in learning from incidents. On the other hand, learning from incidents makes decrease in time to train and so increase in safe behavior. Also, it makes increase in maintenance frequency and finally decrease in unsafe condition. To ease understanding of the causal mechanisms and stock-flow structures, the sector details given in the following.

Cooke and Rohleder (2006) states that many major accidents have occurred since industries have disregarded warning signals of occurred incidents or have been unsuccessful to take lessons from these incidents. It is added that when incident rate increases to critical mass, accident becomes inevitable. Rudolph and Repenning (2002) also state that disasters can be the results of novel events and for an understanding of disasters, novelties and the number of interruptions must be considered. In addition, as cited in Cooke (2006) that Bird and Germain (1986) states that incidents are hidden below the 'tip of the iceberg' which is considered as major accidents. That is, incidents represent the possibility of major accidents. Thus, learning from incidents and then taking corrective actions can eliminate future accidents (Cooke and Rohleder, 2006).

To begin with, it is helpful to state safety terminology that is used in the model. The incident is defined (HSE, 2004) as 'an event that, while not causing harm, has the potential to cause injury or ill-health'. The accident is defined (HSE, 2004) as 'an event that results in injury or ill-health'. Besides, major occupational accident is defined (Yıldırım, Ö., Gürpınar, Ö., Ercan, Ö., Öcal, A., Tiftik, A.P., Kumru, C., Baş, D, 2012-2014 Project Report) as 'the accidents namely fire, explosion and dispersion including dangerous substances which lead a serious danger to health of large populations, result in high economic costs and causes contamination of natural environment for long term or permanently and requiring large scale emergency intervention'. It is added that major occupational accident risks may be 'the fire emerged due to ignition of flammable substances by means of a flame or heat; the explosion arisen from flammable substance (air) mixture occurred with immediate gas release; release of toxic substances in the air, water or soil'.

Accordingly, since the onshore LNGRTs include major accident risks due to LNG processes, to analyze major accident risks, the incident rate is modeled. The main causes of incidents are stated as unsafe conditions and unsafe acts (Bird and Germain, 1992 cited in McKinnon, 2000). As explained in the training sector, when safe behavior increases, unsafe acts decreases and incident rate decreases. The relation between safe behavior and incident rate is assumed as presented in Figure 5.17.

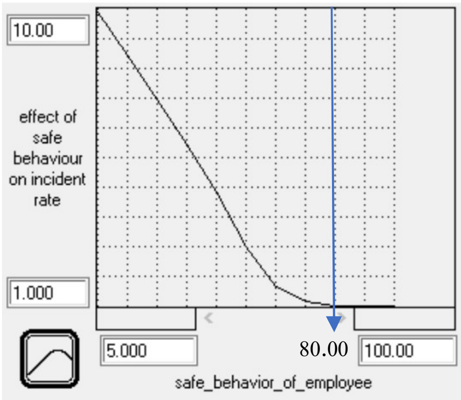

Figure 5.17. Effect of safe behavior on incident rate.

In the model, safe behavior is scaled between 5 to 100, and it is dimensionless. If an employee has 5 or below safe behavior, it results in 10 times increase in incident rate even if the unsafe condition is zero. Moreover, since 80 safe behavior is assumed sufficient for safety, 80 or above safe behavior does not contribute to the incident rate.

On the other hand, an increase in unsafe conditions makes an increase in incident rate and it is assumed that unsafe conditions have a linear effect on incident rate as represented in Figure 5.18.

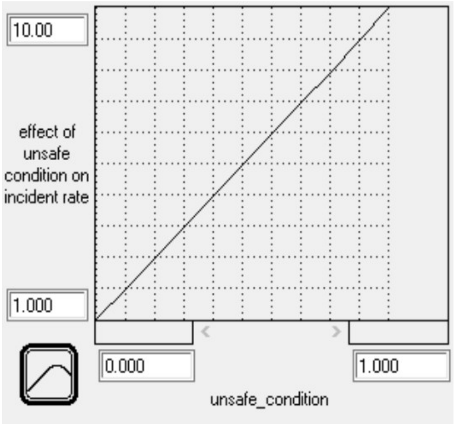

Figure 5.18. Effect of unsafe condition on incident rate.

If there is no Undefined Broken Critical Equipment, the unsafe condition is zero, and it does not affect the incident rate. If all critical equipment is Undefined Broken Critical Equipment, the incident rate becomes 10 times higher even if safe behavior is zero. Incident rate equation is set as in the Equation 5.11.

*incident rate = reference_incident_rate **
(effect_of_safe_behaviour_on_incident_rate+effect_of_unsafe_condition_on_incident_rate)
{incident/week} (5.11)

Reference incident rate is considered as maximum tolerable incident rate, which can be get under control without causing any accident, is taken as 0.25 incident/week depending on the interviews during fieldwork. As it is understood from the equation, unsafe condition and safe behavior effects on incident rate do not dominate each other.

After an incident occurs due to weak safe behavior and/or unsafe conditions, to take lessons from it, there must be an incident learning system. Cooke (2003), Cooke and Rohleder (2006) state that learning, safety climate and management commitment to safety increase employee commitment to safety. Accordingly, the effect of safe behavior on incident reporting ability is built in the model. That is, when safe behavior increases, incident reporting increases. Then, Reported Incidents increase. By allocation labor time for incident analyzing-that is management commitment to safety-learning from incidents increases. Also, learning from incidents makes an increase in allocated labor time for training, maintenance and learning from incidents. As it is understood, there are feedback loops between theses variables (see Figure 5.15). Also, incident analyzing and learning from incidents equations are presented below.

*incident analyzing=allocated_time_for_incident_analyzing*analyzing_capability {incident/week}* (5.12)

*learning from incidents=Remembered_Incidents*reference_learning_from_incidents {learning}* (5.13)

The effects of learning from incident on allocation labor time for training, for maintenance and incident analyzing is explained in the labor time allocation sector.

5.3.5. Labor Time Allocation Sector

This sector is the core of the model. Since labor time is a common source for the onshore LNGRTs, it is allocated among subsystems that are stated as production, maintenance, repairing, training, and incident analyzing. Accordingly, labor time allocation sector aims to describe time allocation dynamics. The main causal loop diagram of the sector and simplified stock-flow structure are presented in Figure 5.19 and Figure 5.20, respectively.

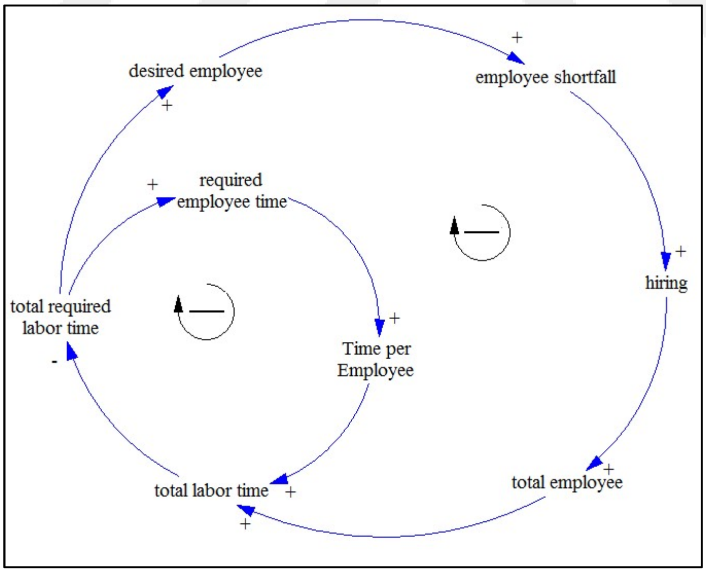

Figure 5.19. Causal loop diagram for labor time dynamics (hiring and overwork).

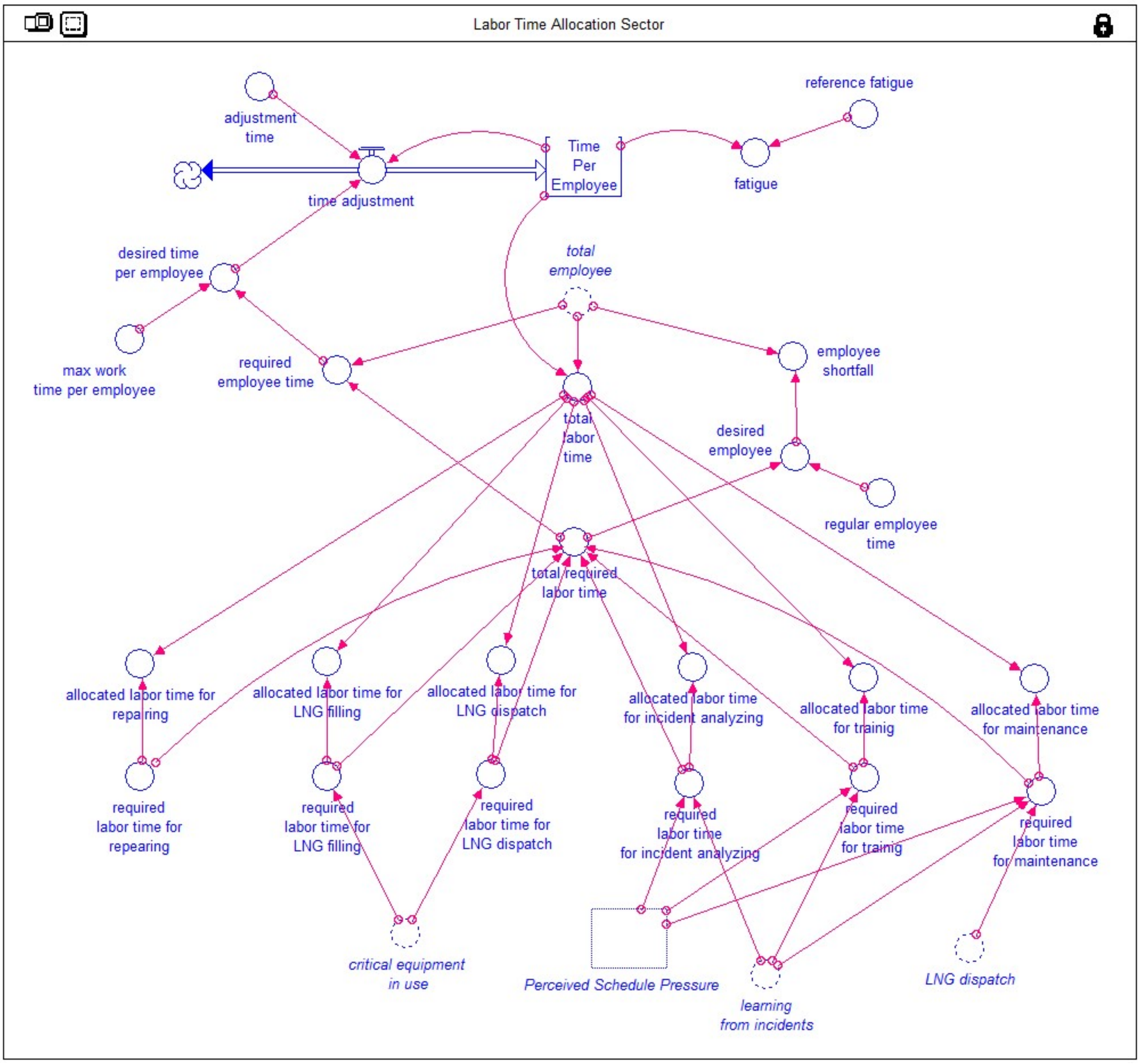

Figure 5.20. Simplified stock-flow structure of labor time allocation sector.

As seen from the causal loop diagram, it can be briefly said that each sector gives its required labor time information to the labor time allocation sector. The sum of them is regarded as the total required labor time. Besides, the system has also total labor time depending on employee quantity and regular employee time. When total required labor time is equal to or lower than total labor time, it is allocated to each subsystem depending on the required labor time fraction. However, if the total required labor time is higher than total labor time, there occurs time shortfall. At that time, for providing labor time to the system, time shortfall can be closed either by hiring or by increasing Time per Employee. As it is stated, the total required labor time is the sum of the required labor time of production, repairing, maintenance, training, and incident analyzing activities. To understand the mechanisms, each of them is explained in the following.

Firstly, for production, filling and dispatch processes are considered in terms of time requirements. Required time for filling is affected by desired filling and filling capability by labor time. The desired filling is increased by LNG shortfall and the mechanisms are explained in the production sector in detail. Required labor time for dispatch is affected by possible dispatch and dispatch capability by labor time. Possible dispatch is positively related with Pending Orders and details are explained in the production sector. Both filling capability by labor time and dispatch capability by labor time are positively affected by critical equipment in use. That means, LNG filling and LNG dispatch also depend on maintenance activities. The relation between critical equipment in use and filling capability by labor time, and dispatch capability by labor time are represented in Figure 5.21.

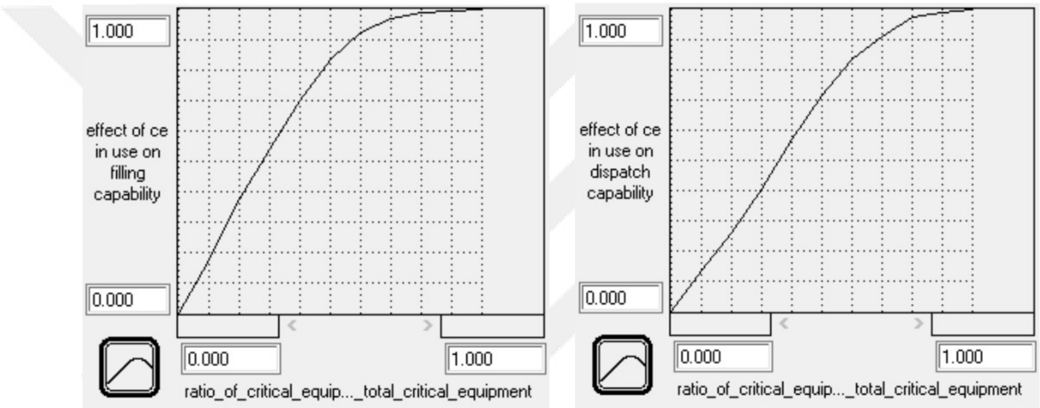

Figure 5.21. Effect of critical equipment in use on filling and dispatch capability by labor time.

The equations for filling and dispatch capability by labor time, required labor time for filling and dispatch are given below.

filling capability by labor time =
*reference_filling_capability*effect_of_ce_in_use_on_filling_capability* $\{m^3/employee*hour\}$ (5.14)

*dispatch capability by labor time= reference_dispatch_capability **
effect_of_ce_in_use_on_dispatch_capability $\{m^3/employee*hour\}$ (5.15)

Depending on fieldwork, reference filling capability by labor time is taken as 10.500 $\{m^3/employee*hour\}$, and reference dispatch capability by labor time is taken as 2.400 $\{m^3/employee*hour\}$. However, because of the critical equipment in use to total critical equipment ratio, it is assumed that, if the filling capability by labor time is below 20% of reference filling capability by labor time, then the required labor time for filling is taken as zero. Also, if dispatch capability by labor time is below 20% of reference dispatch capability by labor time, then the required labor time for dispatch is taken as 10 employee*hour/week to provide heel LNG to the system.

Secondly, the required labor time for repairing is determined by Defined Broken Equipment, repairing capability and time to repair. Lower allocated labor time for maintenance means higher Defined Broken Equipment, and then it means an increase in required labor time for repairing. Time to repair is taken as low as possible since the Defined Broken Equipment can not be used unless it is repaired. Required labor time for repairing is calculated as below.

required labor time for repairing= (Defined_Broken_Equipment) /
*(repairing_capability*time_to_repair)   {employee*hour/week}* (5.16)

Thirdly, required labor time for maintenance is affected by critical equipment, maintenance capability, and maintenance period that depends on maintenance frequency and LNG dispatch. It means maintenance depends on the production. If you dispatch more LNG, equipment hour increases, therefore, the maintenance period increases and then required labor time for maintenance increases. Furthermore, reference maintenance frequency is affected by schedule pressure and learning from incidents. An increase in schedule pressure makes a decrease in maintenance frequency since it desires more time for production and tries to eliminate any time loss because of the other activities. The effects of Perceived Schedule Pressure on maintenance frequency is assumed as in Figure 5.22.

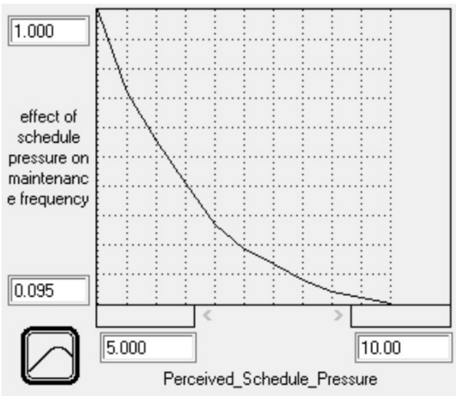

Figure 5.22. Effect of perceived schedule pressure on maintenance frequency.

Perceived Schedule Pressure is scaled between 0-10 and dimensionless. If Perceived Schedule Pressure is 5 or above, the maintenance frequency gradually decreases. Perceived Schedule Pressure, maintenance frequency are calculated as below.

*Perceived Schedule Pressure (t) = Perceived_Schedule_Pressure (t-dt) + (increase_in_schedule_pressure)*dt {dimensionless}* (5.17)

increase in schedule pressure= ((delivery_delay/desired_delivery_delay)-Perceived_Schedule_Pressure)/correction_time_for_schedule_pressure {1/week} (5.18)

*maintenance frequency = reference_maintanance_frequency_depending_on_production*effect_of_learning_from_incidents_on_maintanance_frequency*effect_of_schedule_pressure_on_maintanance_frequency {1/m^3}* (5.19)

Accordingly, it is seen that, Perceived Schedule Pressure depends on delivery delay/desired delivery delay. Since the desired delivery delay is taken as 1-week, it means 5 weeks delivery delay is the starting point for schedule pressure effect on maintenance. The assumptions are made depending on the fieldwork.

Besides, learning from incidents affects maintenance frequency positively. It means, if the system has ability to take lessons from incidents, they tend to give importance to safety, that is, they desire to allocate more time for maintenance. The effect of learning from incidents on maintenance frequency is given in Figure 5.23.

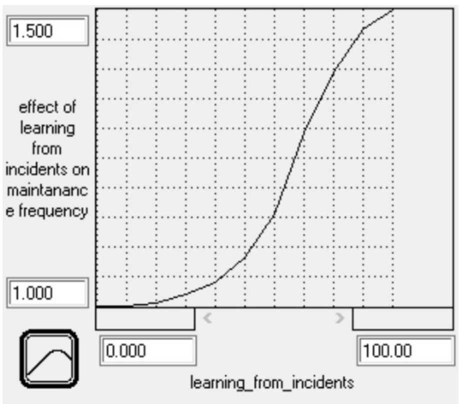

Figure 5.23. Effect of learning from incidents on maintenance frequency.

Required labor time for maintenance is calculated as in Equation 5.20.

*required labor time for maintenance= (critical_equipment/maintenance__capability) * maintanance_period {employee*hour/week}* (5.20)

Fourthly, required labor time for training depends on Untrained Employees, time to train and time for training. As it is explained in the training sector in detail when the time for training increases or when Untrained Employees increases, the required time for training increases. However, time to train affects the required labor time negatively. Reference time to train is taken as 2 weeks that means, the system must train an Untrained Employee in 2 weeks. Required labor time for the training equation is given below.

*required labor time for training= time_for_training*Untrained_Employees/time_to_train {employee*hour/week}* (5.21)

As in the maintenance, schedule pressure makes decrease and learning from incidents makes increase in the required time for training by affecting time to train. The effects are presented in Figure 5.24 and the equation of time to train is given below.

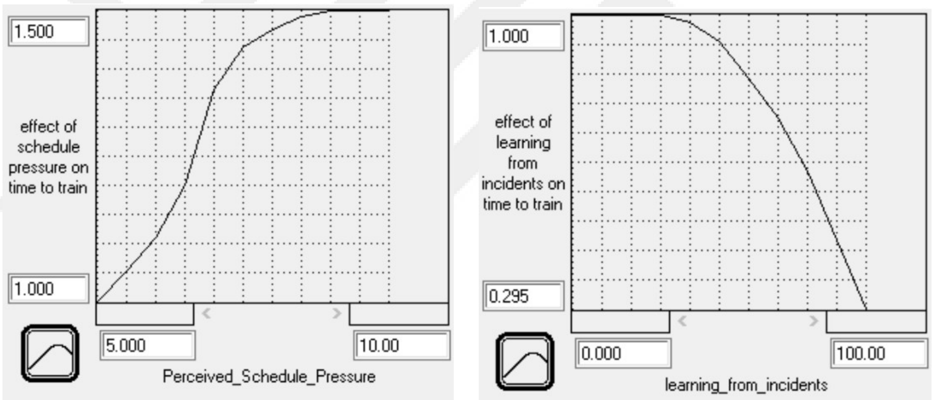

Figure 5.24. Effect of schedule pressure and learning from incidents on time to train.

time to train =
*reference__time_to_train*effect_of_schedule_pressure_on_time_to_train*effect_of_incident_learning_on_time_to_train {week}* (5.22)

Fifthly, required labor time for incident analyzing is affected by Reported Incidents, analyzing capability, and time to analyze. When Reported incidents increases, the required time increases. As in the maintenance and training systems, Perceived Schedule Pressure and learning from incidents affect time requirement. When Perceived Schedule Pressure increases, time to analyze increases, and required labor time decreases. On the other hand, when learning from incidents increases, time to analyze decreases, and then the required time increases. The equations and effects of Perceived Schedule Pressure and learning from incidents on time to analyze are given below.

required labor time for incident analyzing=

*(Reported_Incidents/analyzing_capability)/time_to_analyze {employee*hour/week}* (5.23)

time to analyze =

*reference_time_to_analyze*effect_of_schedule_pressure_on_time_to_analyze*effect_of_incident_learning_on_time_to_analyze {week}* (5.24)

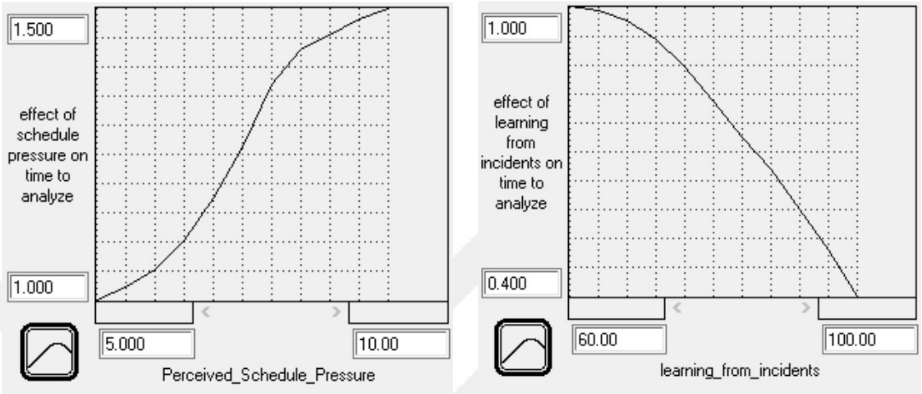

Figure 5.25. Effects of perceived schedule pressure and learning from incidents on time to train.

Another point worth mentioning is that repairing capability, maintenance capability, analyzing capability values are taken depending on general assumptions gained during fieldwork. While making assumptions, care is taken not to make any logical failure. For example, maintenance capability and repairing capability are determined by considering that maintenance takes less time than repairing.

6. MODEL VALIDATION

Model validation is an important step in system dynamics modeling. The aim is to demonstrate that the model sufficiently represents the real life problem under study. It has two aspects; structural and behavioral validation. While structural validation tries to understand whether the model structure has a meaningful description of real life problem or not; behavioral validation tries to understand whether dynamic patterns of the model are close to real life dynamics or not. In addition, it is stated that since the behavior of a system emerges from system structure, firstly, structural validation must be done.

6.1. Structural Validation with Indirect Structure Tests

The indirect structural validation tests (structure-oriented behavior) are extreme condition tests, parameter sensitivity tests, boundary adequacy tests and the others (Barlas, 1996). Accordingly, in this study, extreme condition tests and parameter sensitivity tests are applied for structural validation with indirect structural tests and the details are given in the following sections.

6.1.1. Extreme Condition Tests

In extreme condition tests, models should behave as factual under extreme conditions (Sterman, 2000).

During the modeling process, extreme condition tests are applied for each sector with different extreme parameters to demonstrate their validity. In this section, some of the extreme condition tests and their results are given.

6.1.1.1. No LNG arrival. In this test, LNG arrival is taken as zero, and all sectors are run. To be able to analyze weekly changes in detail, this test results are shown for the first 25 weeks. It is expected that, since there is no LNG arrival, LNG filling is zero, and after an instant increase, LNG dispatch becomes zero. Also, after an instant decrease, LNG orders gets its minimum value and becomes constant. Since there is no LNG production, Pending Orders and Perceived Schedule Pressure increase. As understood in Figure 6.1, the results correspond to the model theory.

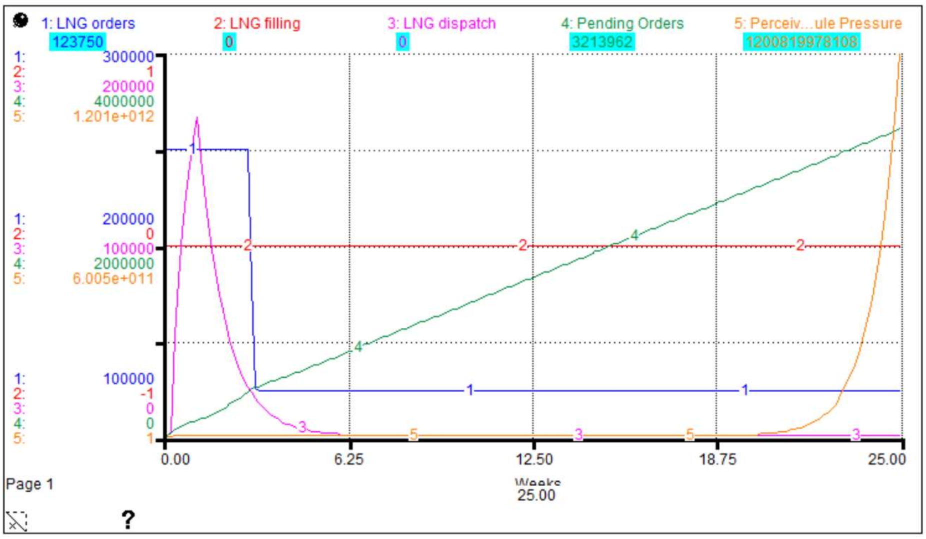

Figure 6.1. Extreme condition (no LNG arrival) test results (being run by all sectors).

6.1.1.2. No LNG orders. In this test, LNG orders is taken as zero, and only the production sector is run. To be able to analyze weekly changes in detail, the test results are shown for the first 10 weeks. Since there is no order, it is anticipated that there is no production and since Pending Orders decreases, there must be no Perceived Schedule Pressure. The test results, which comply with expected behavior and are represented in Figure 6.2.

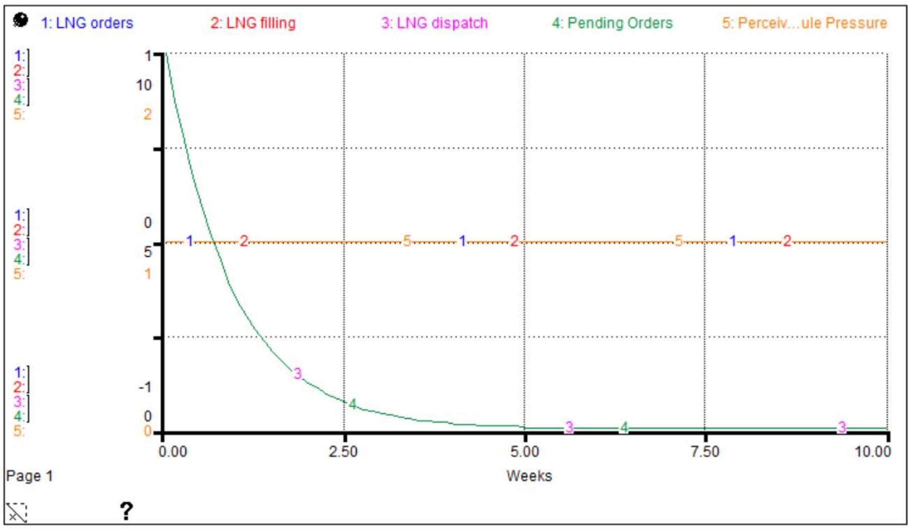

Figure 6.2. Extreme condition (no LNG order) test results (isolated run).

6.1.1.3. Minimizing allocated labor time for training. In this test, time to train set to an extremely high value. It is multiplied by 1000. It is expected that since required labor time for training minimized, then allocated labor time for training is minimized. Hence, while Trained Employees decrease, Untrained Employees increases. In addition, safety knowledge and then safe behavior must decrease, incident rate must increase as in the model theory. As seen in Figure 6.3, the results obtained by running all sectors match up with expected model behavior in such extreme conditions.

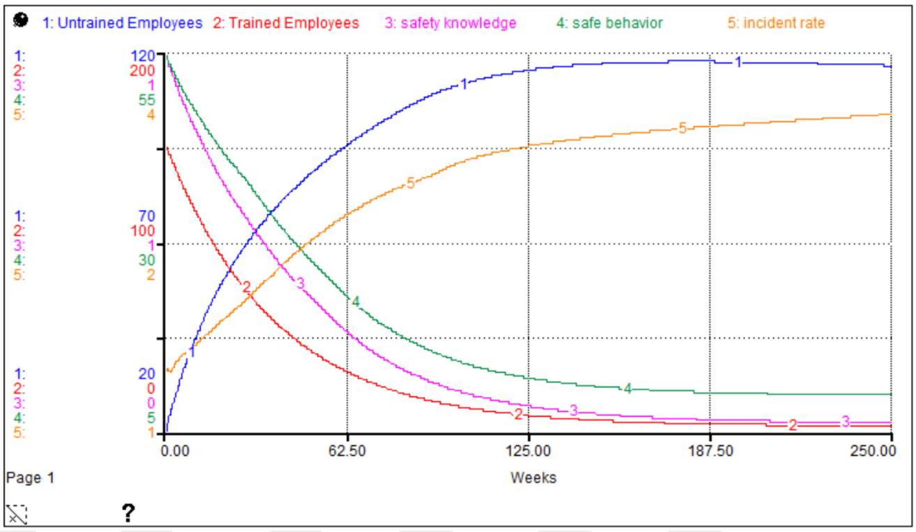

Figure 6.3. Extreme condition (minimizing allocated labor time for training) test results (being run by all sectors).

<u>*6.1.1.4. No labor time for maintenance.*</u> In this test, allocated labor time for maintenance is set as zero, and only maintenance and repairing sector and learning from incidents sector are run. To be able to analyze weekly changes in detail, the test results are shown for the first 10 weeks. Since there is no maintenance activity, Effective Critical Equipment decreases. In addition, since monitoring decreases, determination of undefined critical equipment decreases, That is, all critical equipment is accumulated in Undefined Broken Critical Equipment, therefore; unsafe condition and incident rate sharply increases. The results correspond to model theory and shown in Figure 6.4.

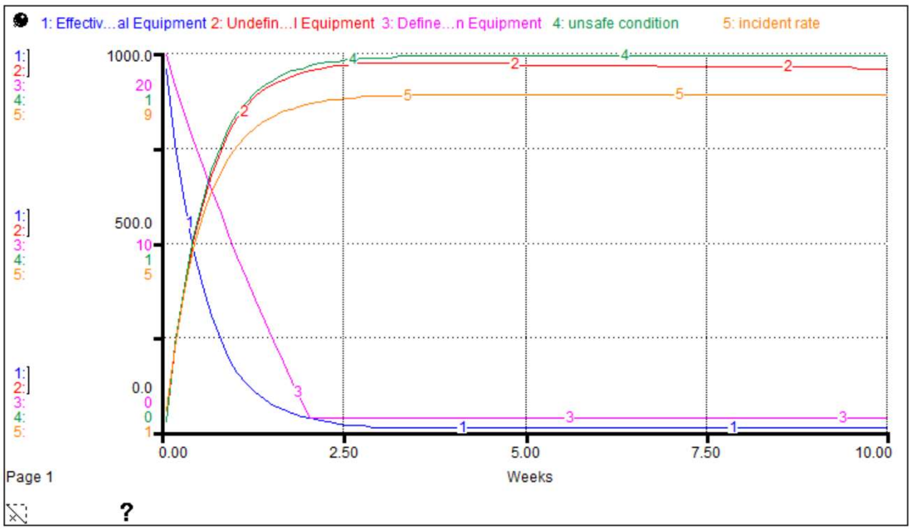

Figure 6.4. Extreme condition (no labor time allocation for maintenance) test results (isolated run).

6.1.1.5. Maximum unsafe condition and minimum safe behavior. In this test, unsafe condition is multiplied by 100 and safe behavior is multiplied by 0.01 and all sectors are run. Then, as it is anticipated, incident rate increases and reaches to 24.77 incident/week. Furthermore, as expected, since there is no safe behavior, although incident rate increases, incident reporting gets close to zero. Therefore, Reported Incidents and learning from incidents get their minimum values. The test results are presented in Figure 6.5.

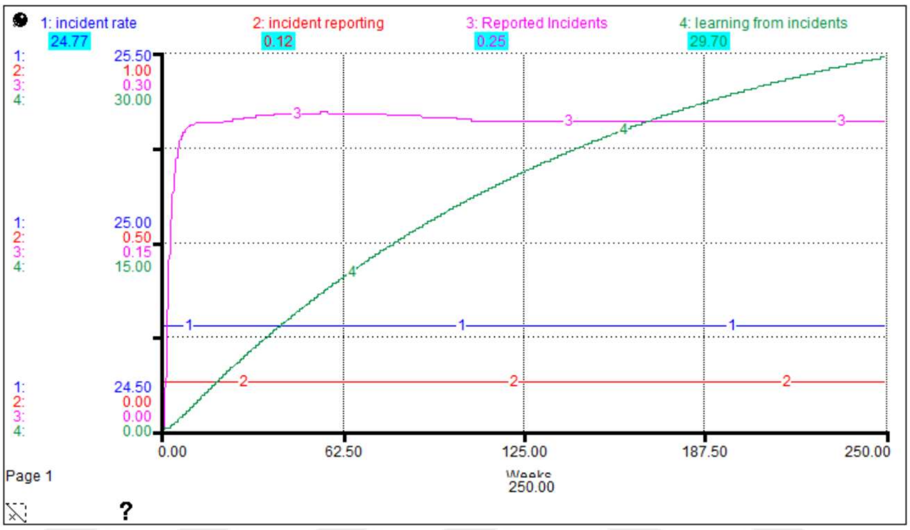

Figure 6.5. Extreme condition (maximum unsafe condition, minimum safe behavior) test result (being run by all sectors).

6.1.1.6. Maximizing regular employee time. In this test, regular employee time is taken as 60 hours/week that corresponds to maximum work time and causes maximum fatigue. Moreover, the run is done by all sectors. Since regular employee time is taken as 60 hours/week, Time per Employee starts from 60 hours/week. Also, the initial total employee is same as the reference model, 170 employees. Since in the reference model, total employee and regular employee time are initially set as 170 employees and 40 hours/week, and in the extreme conditions, the values are 170 employees and 60 hours/week, at first, total employee and Time per Employee decrease. Also, fatigue decreases, safe behavior increases, and then incident rate decreases. After 41.88 weeks, Time per Employee starts to increase while total employee continually decreases. Then, since Time per Employee increase to 60 hours/week, fatigue starts to increase, and then safe behavior decreases, incident rate increases. In the end, fatigue gets its maximum value, and incident rate increases. The results fit the model theory and are represented in Figure 6.6.

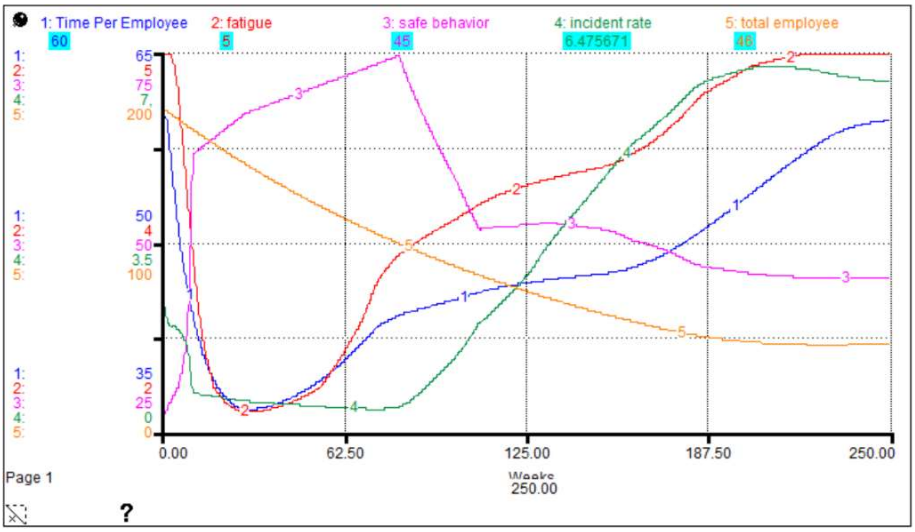

Figure 6.6. Extreme condition (maximizing regular employee time) test results (being run by all sectors).

6.1.1.7. Minimizing critical equipment. In this test, critical equipment is multiplied by 0.001 and run is done by all sectors. Since critical equipment affects dispatch and filling capability by labor time negatively, when it is minimized, it is expected that LNG dispatch and LNG filling reach their minimum values. Besides, Perceived Schedule Pressure must increase. As it is seen in Figure 6.7, the model also verifies the expected behavior in the extreme condition test. The run is done by all sectors.

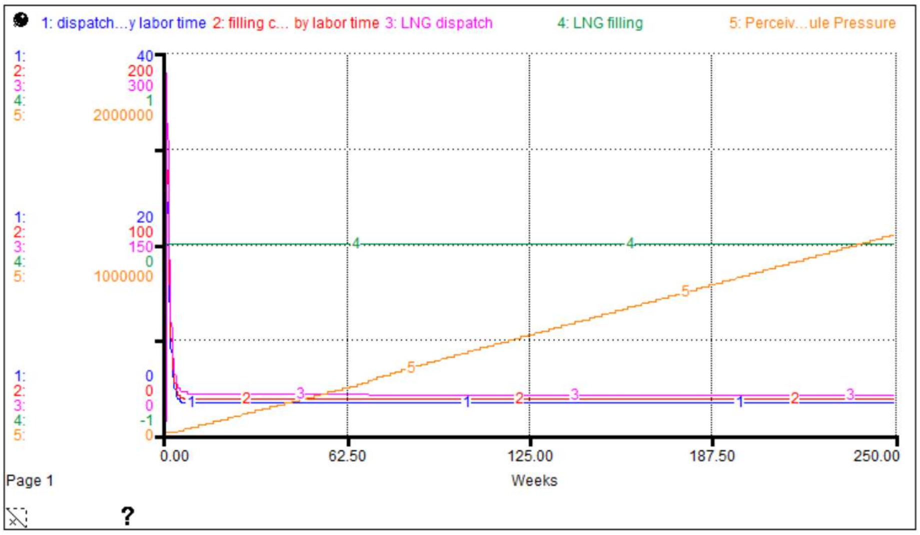

Figure 6.7. Extreme condition (minimizing critical equipment) test results (being run by all sectors).

6.1.2. Parameter Sensitivity Test

6.1.2.1. Sensitivity analysis of learning from incidents to incident rate. A sensitivity analysis is made to understand the sensitivity of incident rate to change in learning from incidents. Accordingly, learning from incidents is taken as 0, 100, and 200 learning, respectively. These values are minimum, average and maximum values of learning from incidents in the model. The model theory states that when learning from incident increases, safe behavior increases and unsafe condition depending on maintenance activities decreases. Therefore, the incident rate decreases. As represented in Figure 6.8, the results comply with expectation. Run is made for all sectors, and run 1, run 2 and run 3 represent the behavior when learning from incidents are equal to 0, 100 and 200 learning, respectively.

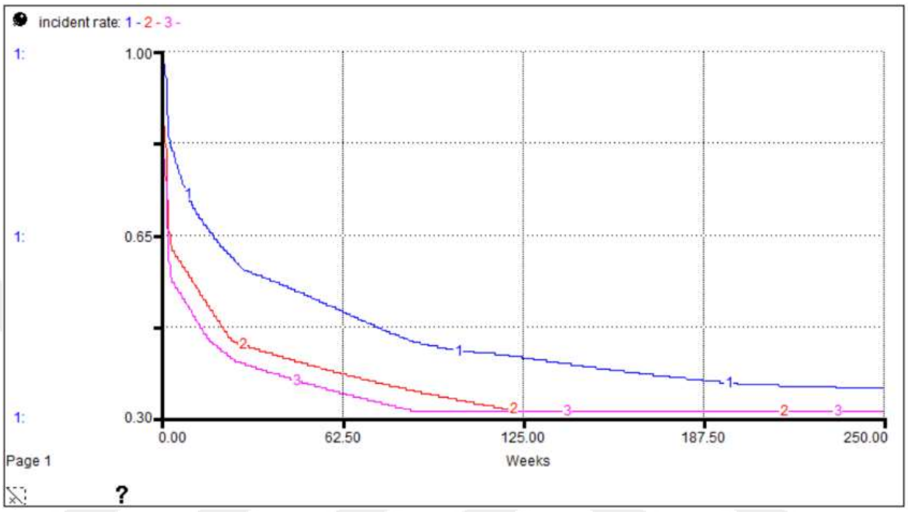

Figure 6.8. Sensitivity analysis of learning from incidents to incident rate.

6.1.2.2. Sensitivity analysis of occupational experience to incident rate. In this sensitivity analysis, the purpose is to assess the sensitivity of incident rate to change in occupational experience. In the model, it is stated that when occupational experience increases up to 8 years, safe behavior increases. Between 8 and 10 years, safe behavior is in its maximum value. And after 10 years, safe behavior starts to decrease until 20 years. Therefore, sensitivity analysis is performed by 0, 10 and 20 years of occupational experience. As it is anticipated, when the occupational experience is taken as 0, the result of incident rate (run 1) is higher than the other runs. When it is taken as 10, the result (run 2) is lower than other runs. In the test, all sectors are run and the result is represented in Figure 6.9.

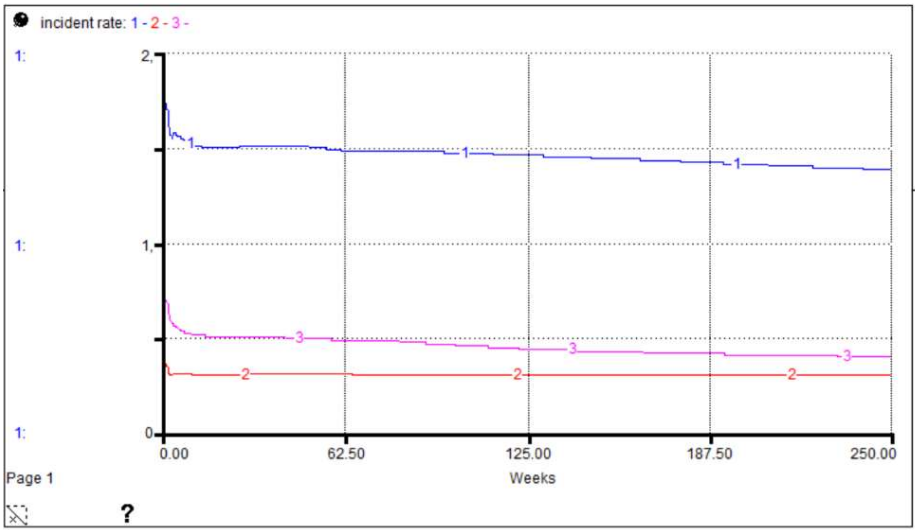

Figure 6.9. Sensitivity analysis of occupational experience to incident rate.

6.1.2.3. Sensitivity analysis of Perceived Schedule Pressure to safe behavior. In this test, it is aimed to analyze the sensitivity of Perceived Schedule Pressure to safe behavior. For this purpose, the effect of Perceived Schedule Pressure on time to train is taken as in Figure 6.10.

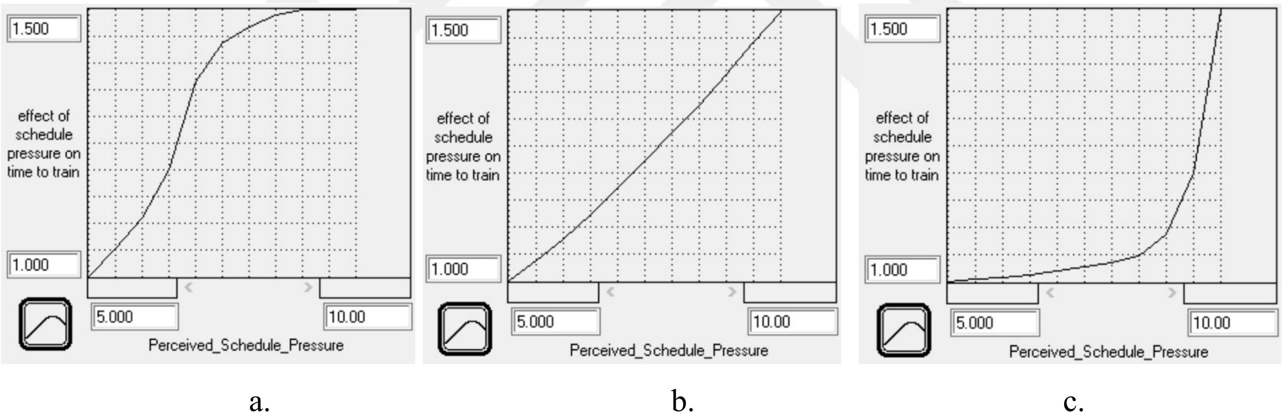

Figure 6.10. Different effects of perceived schedule pressure on time to train (a,b,c, respectively).

Also, when Perceived Schedule Pressure increases, time to train increases. That means, a decrease in allocated labor time for training, and so safe behavior decreases. As seen in Figure 6.11, the test results correspond to model theory. All sectors are run and run 1, run 2 and run 3 display the results of a, b, c given above, respectively.

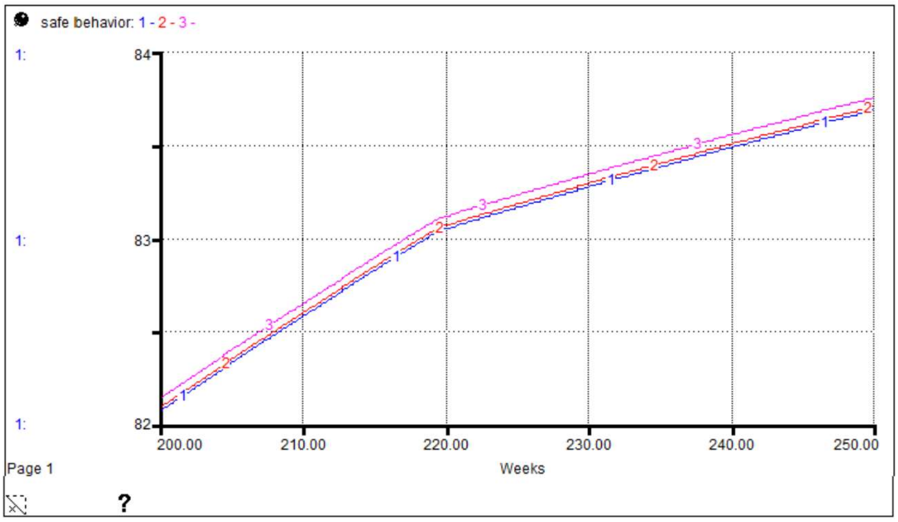

Figure 6.11. Sensitivity test of Perceived Schedule Pressure to safe behavior.

As understood from the results of the structural validation tests, it can be stated that the structural validity of the model is sufficiently provided.

6.2. Behavioral Validation Test

It is worth mentioning is that, since system dynamics models are used to understand behavior patterns, the validity of the model behavior is tested after the structural validity is sufficiently provided (Barlas, 1996, 2002; Saysel, 1999). The model structure is a description of occupational safety dynamics, essentially based on the observations at a specific onshore LNGRT. The observed variables of LNG filling and LNG dispatch; Effective and Undefined Broken Critical Equipment, Defined Broken Equipment, Untrained Employees and Trained Employees are in steady state during normal operational condition. To expand; in the fieldwork, it is stated that LNG filling and LNG dispatch are 250.000 m^3/week. In addition, it is stated that when allocated labor time for maintenance and repairing correspond to reference required labor time, Unbroken Critical Equipment and Defined Broken Critical Equipment are far fewer than Effective Critical Equipment and unsafe condition get close to zero. Furthermore, it is stated that when allocated labor time for training corresponds to required labor time, Untrained Employees are far fewer than the Trained Employees. Therefore, model behavioral validity analyzing choses an arbitrary initial simulation time and when the model is run, it is observed that the model behavior matches with these steady state observations. The examples of behavioral validation test results are given in Figure 6.12, Figure 6.13 and Figure 6.14.

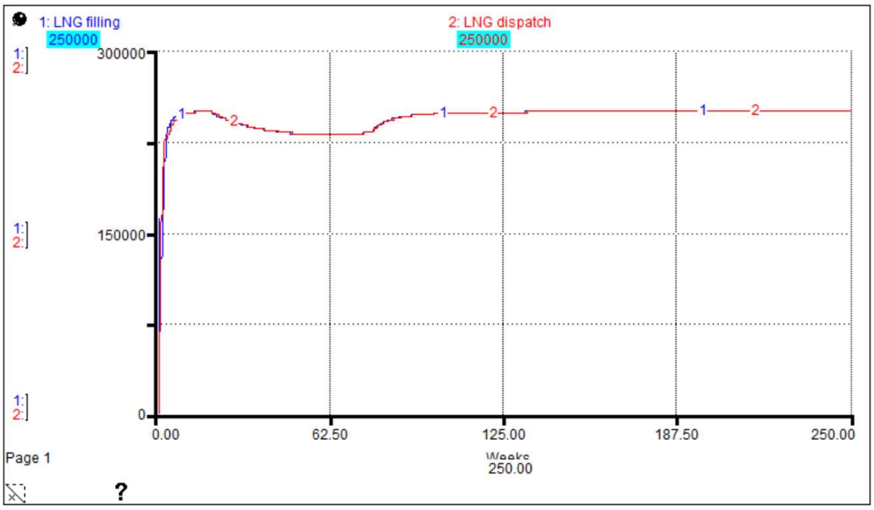

Figure 6.12. Behavioral validation test of LNG filling and LNG dispatch.

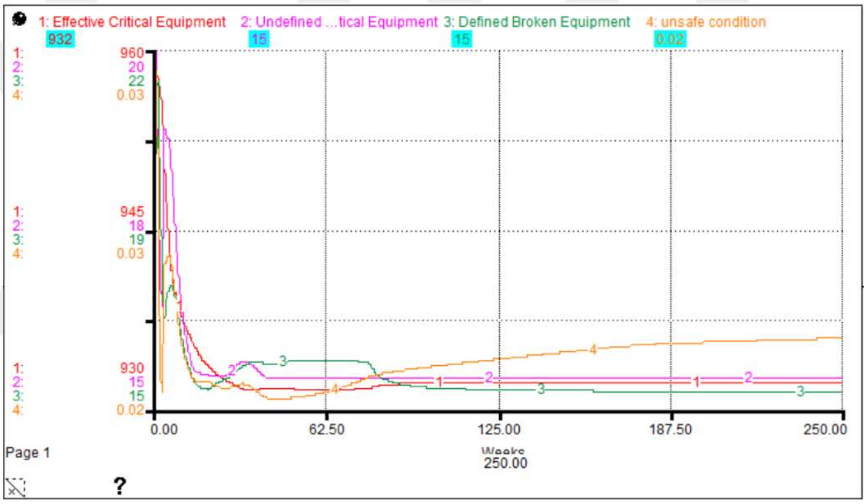

Figure 6.13. Behavioral validation test of Effective, Undefined Broken and Defined Broken Critical Equipment.

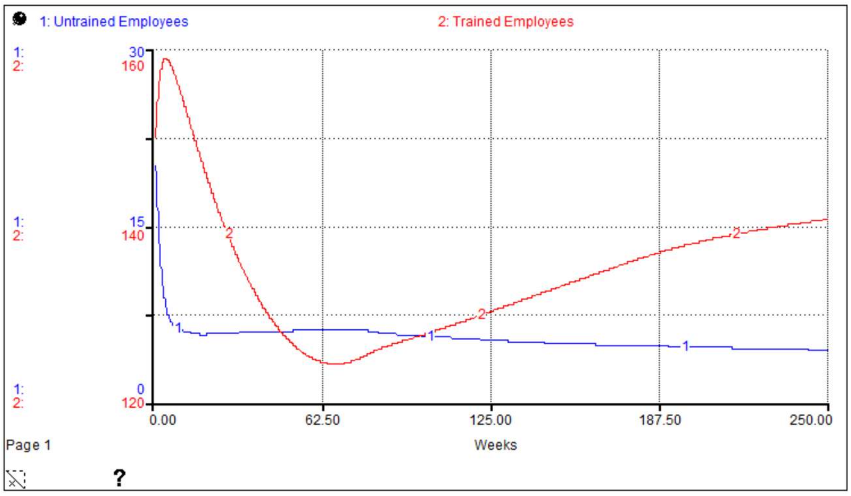

Figure 6.14. Behavioral validation test of Untrained and Trained Employees.

7. REFERENCE MODEL BEHAVIOR

According to the initial parameters and assumptions described in Chapter 5, the reference behavior of the model is analyzed in detail in this chapter.

In the onshore LNGRT, depending on LNG orders, arrived LNG is unloaded to the storage tanks. Then, gasified LNG is dispatched to the pipeline system in order to transmit natural gas to the end-users. For normal conditions, reference LNG orders and LNG arrival are taken as 250.000 m^3/week that is average of the year. Depending on this, it is desired to 250.000 m^3 LNG dispatch in a week. After all sectors are run, it is observed that allocated labor time for filling and dispatch correspond to required labor time and the system approaches to the production purpose immediately after a transient behavior. After a while, LNG filling, LNG in Tanks, LNG dispatch and LNG orders becomes constant at 250.000 m^3/week. The results are given in Figure 7.1.

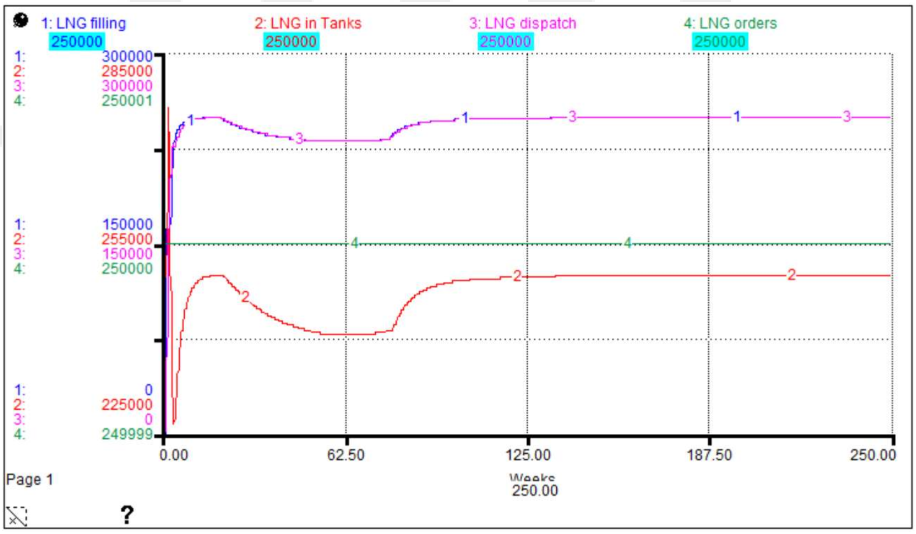

Figure 7.1. Reference behavior of LNG filling, LNG in Tanks, LNG dispatch, LNG orders.

Besides production processes, critical equipment must be maintained in order not to cause any production (filling and dispatch) capability loss and any unsafe condition that may lead to an incident. In addition, Defined Broken Equipment must be repaired to regain critical equipment to the system. When the model is run, it is observed that, maintenance period gets the same or higher value than reference maintenance period. Then, allocated labor time for maintenance corresponds to the reference required labor time. Depending on, the ratio of allocated to reference required labor time for maintenance gets 1.00 or higher values for 250 weeks. After an instant transient behavior, Effective Critical Equipment, breakdown, Undefined Broken Critical Equipment, determination of broken critical equipment and Defined Broken Critical Equipment are balanced. The results are given in Figure 7.2 and Figure 7.3.

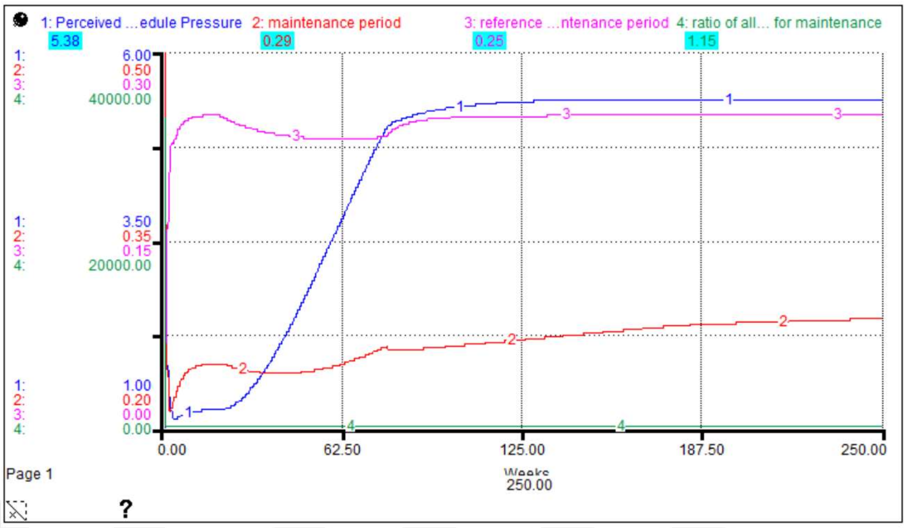

Figure 7.2. Reference behavior of Perceived Schedule Pressure, maintenance period, reference maintenance period and ratio of allocated to reference required labor time for maintenance.

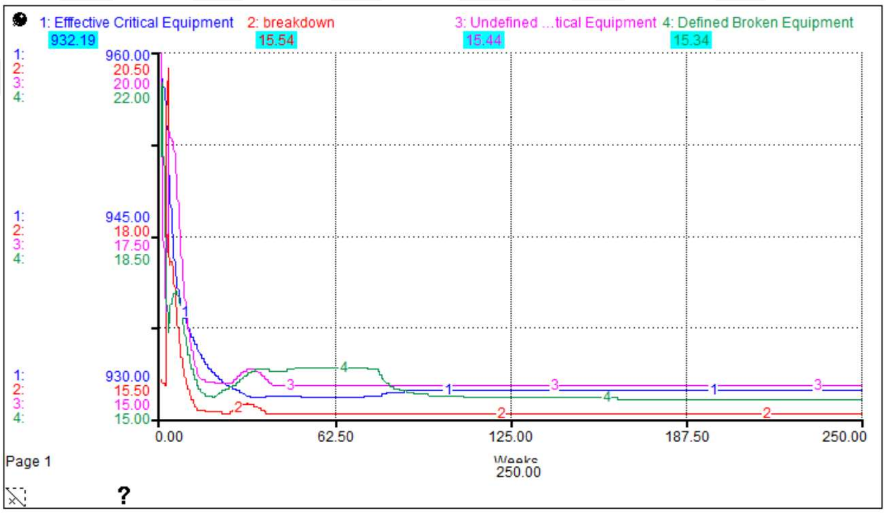

Figure 7.3. Reference behavior of Effective, Undefined Broken Critical Equipment, Defined Broken Equipment, and breakdown.

On the other hand, training of employees is another issue being directly related to safety knowledge and safe behavior that affects incident rate. When the model is run, it is observed that time to train equals or takes lower values than the reference time to train and finally decreases to 1.18 weeks. Depending on change in total employee (see Figure 7.5), Trained Employee also decreases until 62.50 weeks and increases after this time. Since Untrained Employee does not change as Trained Employee, untrained employee ratio increases until 62.50 weeks, and then decreases to 0.03.

Accordingly, safety knowledge firstly decreases, then it increases to 0.97. The results are represented in Figure 7.4.

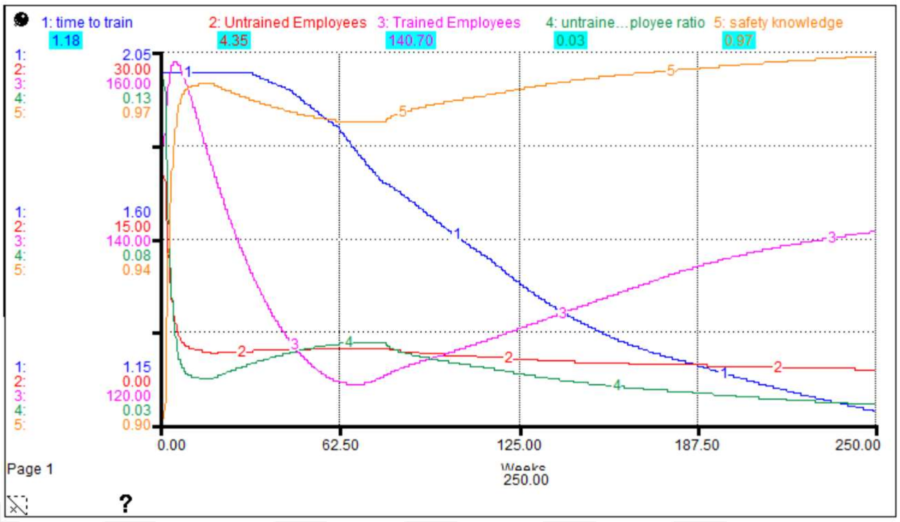

Figure 7.4. Reference behavior of time to train, Untrained Employees, Trained Employees, untrained employee ratio and safety knowledge.

Moreover, Time per Employee and fatigue are the parameters depending on total employee. When the model is run, it is observed that fatigue increases depending on total employee decrease. However, it stays at tolerable levels during model time horizon. Time Per Employee ranges between 34 hours/week and 41 hours/week. Since fatigue is in tolerable levels, it has no effect on safe behavior. The results are given in Figure 7.5.

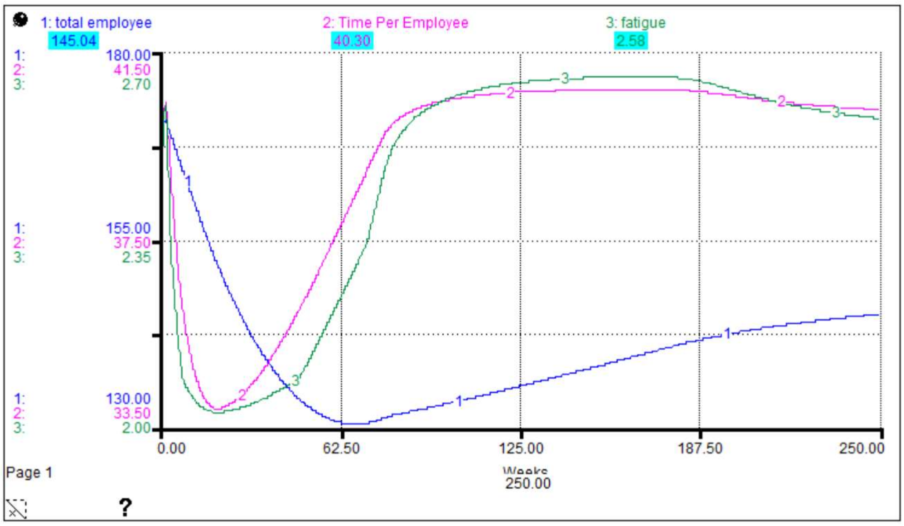

Figure 7.5. Reference behavior of total employee, employee shortfall, time per employee, fatigue.

Furthermore, safe behavior is also affected by occupational experience. When the model is run it is observed that safe behavior increases with occupational experience. The model behavior is represented in Figure 7.6.

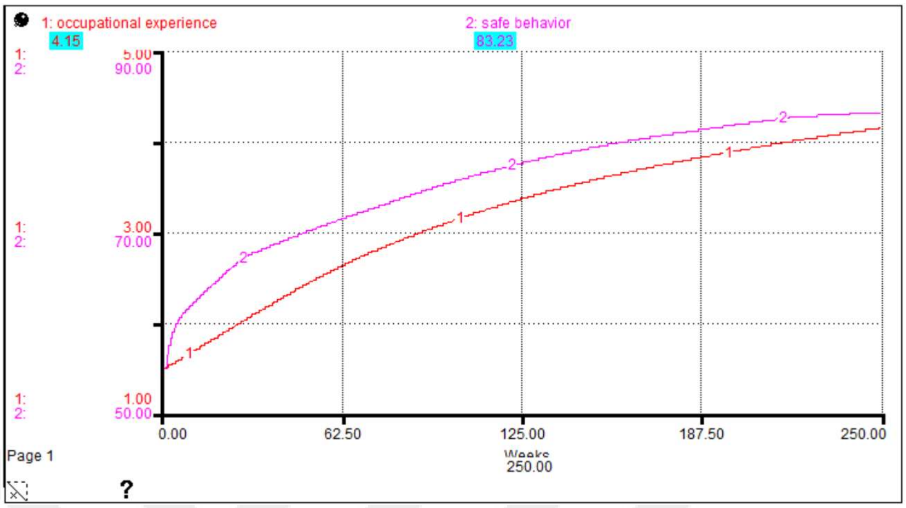

Figure 7.6. Reference model behavior of occupational experience and safe behavior.

Hence, when the model is run, it is observed that safe behavior increases from 54.67 to 83.21; unsafe condition decreases from 0.03 to 0.02 and incident rate decreases from 0.98 to 0.30. The results are given in Figure 7.7.

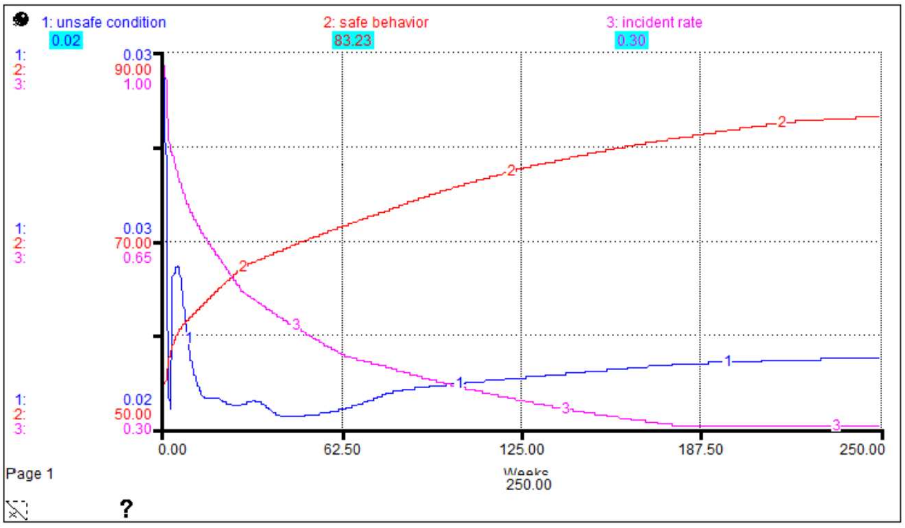

Figure 7.7. Reference behavior of safe behavior, unsafe condition and incident rate.

On the other hand, it is also observed that since safe behavior increases as mentioned, effect of safe behavior on incident reporting fraction increases to 1.00. That means, incident reporting corresponds to incident rate since each incident is reported. Furthermore, since time to analyze equals or lower than the reference time to analyze, all Reported Incidents are analyzed. Hence, incident analyzing also corresponds to incident rate and learning from incident increases Accordingly, learning from incidents makes increase in safe behavior and maintenance frequency, it makes decrease in time to train and time to analyze. The results are represented in Figure 7.8.

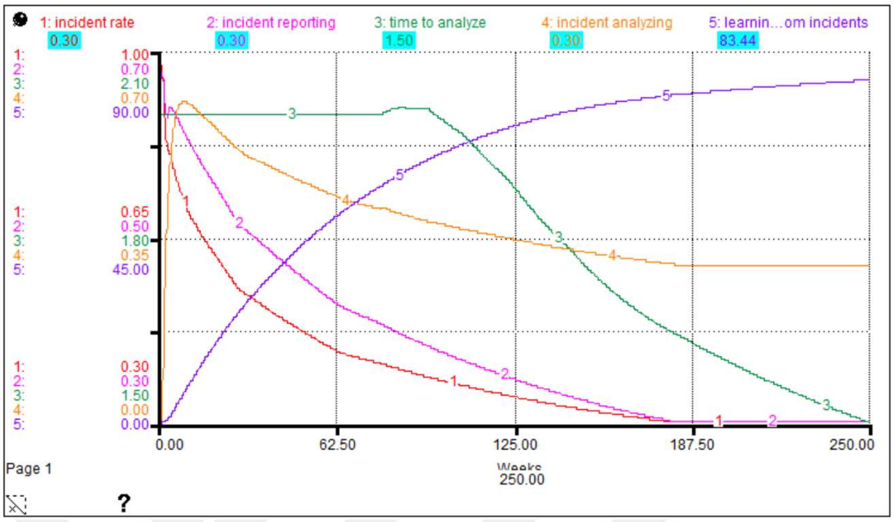

Figure 7.8. Reference behavior of incident rate, incident reporting, time to analyze, and incident analyzing and learning from incidents.

8. SCENARIO and POLICY ANALYSIS

In this Chapter, different scenarios and management policies are analyzed to understand the onshore LNGRT safety system dynamics.

8.1. Scenario Analysis

In this section, scenario analysis related to delivery delay tolerance, turnover rate and reliable critical equipment usage are discussed.

8.1.1. Scenario Analysis Related to Seasonal Delivery Delay Tolerance

In the onshore LNGRT, it is understood in the fieldwork that market delivery delay and so desired delivery delay decreases in the winter term. While 1-week delivery delay is tolerable under normal conditions, there is no toleration for more than 1/2 weeks delivery delay in the winter. According to this scenario, market delivery delay and desired delivery delay are taken as 1/2 weeks to see the delivery delay effect on the safety system.

When the model is run and the model behavior given in Figure 8.1 is compared to Figure 7.2 that represent the reference model behaviors, it is seen that Perceived Schedule Pressure increases to 6.80. Since after 55 weeks it passes to 5.00 that is tolerable limit, it makes decrease in maintenance period. Then, required labor time for maintenance and allocated labor time for maintenance decrease. Therefore, the ratio of allocated to reference required labor time for maintenance decreases to 0.58 while it gets near and up to 1.00 in the reference run. That is, allocated labor time for maintenance does not correspond to the reference required time. Figure 8.1 is given below.

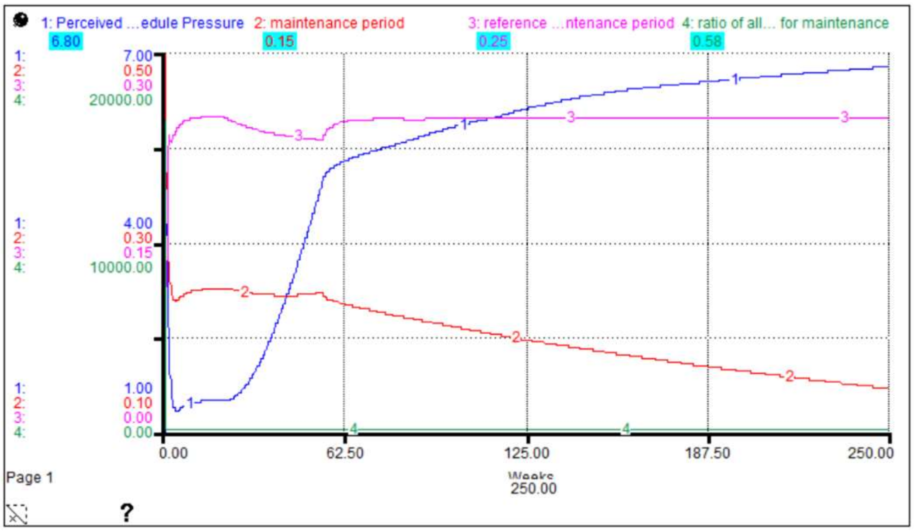

Figure 8.1. Change in Perceived Schedule Pressure, maintenance period, reference maintenance period, and ratio of allocated to reference required labor time for maintenance (desired and market delivery delay is halved).

Accordingly, since allocated labor time for maintenance is lower than the reference required labor time, it is also observed (see Figure 8.2) that breakdown increases after schedule pressure effect. Hence, Effective Critical Equipment decreases and Undefined Broken Critical Equipment increases. Besides, although decrease in ratio of allocated to reference required labor time for maintenance causes a decrease in monitoring time fraction and so determination of broken critical equipment does not increase as much as breakdown, Defined Broken Equipment also increases (compared with Figure 7.3). Then, when unbroken critical equipment increases, unsafe condition and incident rate increases as seen from Figure 8.3 (compared with Figure 7.7).

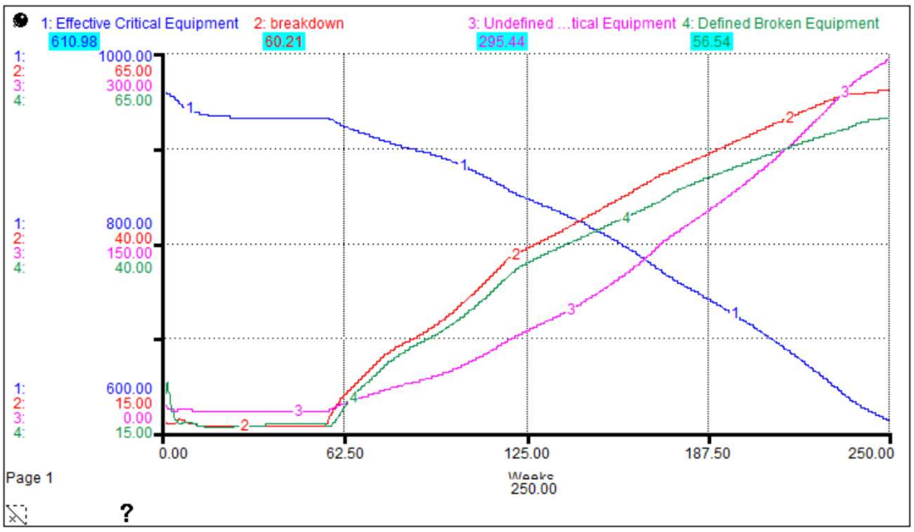

Figure 8.2. Change in Effective Critical Equipment, breakdown, Undefined Broken Critical Equipment, and Defined Broken Equipment (desired and market delivery delay is halved).

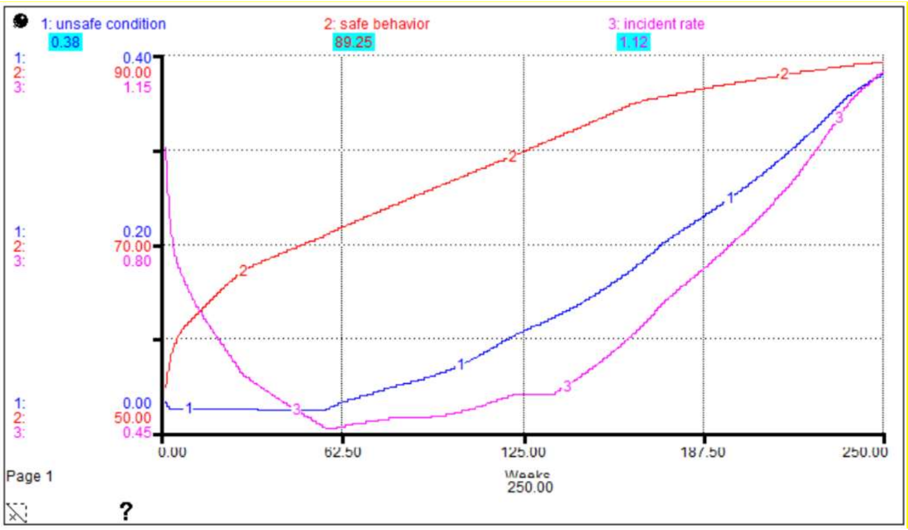

Figure 8.3. Change in unsafe condition, safe behavior and incident rate (desired and market delivery delay is halved).

On the other hand, since Perceived Schedule Pressure increases, it makes increase in time to train and time to analyze. That means, required and allocated labor time for training and incident analyzing decrease. However, since incident rate increases due to increase in unsafe conditions as mentioned, learning from incidents also increases as seen Figure 8.4, which makes decrease in time to train and time to analyze at the same time. When the model behavior represented in Figure 8.4 is compared to the reference model behaviors represented in Figure 7.4, Figure 7.8, and it is observed that increase in Perceived Schedule Pressure and learning from incidents finally cause decrease in time to train until 0.77 weeks and decrease in time to analyze until 0.92 weeks while they are balanced at 1.18 weeks and 1.5 weeks, respectively in the reference run. That is, required and allocated labor time for training and incident analyzing are higher than the reference model and so that situation affects safe behavior positively. In addition, since learning from incidents is higher than the reference model behavior, effect of learning from incidents on safe behavior is also higher. Hence, as seen from Figure 8.3, safe behavior is a bit higher than the reference model behavior represented in Figure 7.7. However, although safe behavior is higher than the reference model behavior depending on learning from incidents effect, this scenario implies that, when schedule pressure increases, unsafe condition increases, and this leads to increase in incident rate. Figure 8.4 is given below.

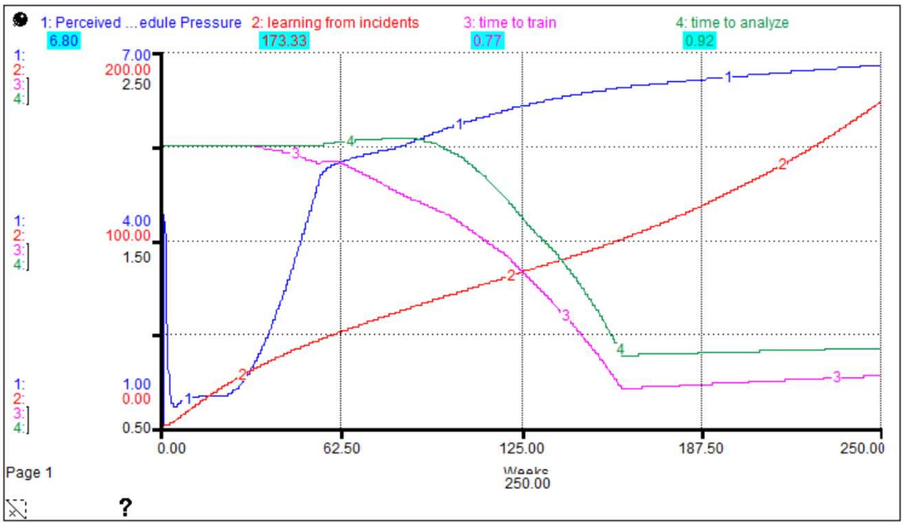

Figure 8.4. Change in Perceived Schedule Pressure, learning from incidents, time to train, time to analyze (desired and market delivery delay is halved).

8.1.2. Scenario Analysis Related to Increase in Turnover Rate Depending on Working Conditions

In industries, turnover rate may increase when there are heavy working conditions, low wage policies, stressful environment, negative relationships, lack of trust and others. In addition, preferring subcontracting rather than employing full-time employee means having high turnover rate. Accordingly, in this scenario analyzes, it is aimed to understand how turnover rate affects the occupational safety system in the onshore LNGRTs. For this purpose, attrition time is decreased by 10 times. That is, it is taken as 150 weeks in the reference model, now it is taken as 15 weeks.

When the model is run and the model behaviors represented in

Figure 8.5, Figure 8.6, and Figure 8.7 are compared to Figure 7.4, Figure 7.6 and Figure 7.7, it is observed that in the beginning, since Trained Employees decreases more, untrained employee ratio increases, then safety knowledge decreases. Besides, since attrition time is lower, it is also seen that occupational experience, which also affect safe behavior positively until 16-17 years, is lower than the reference model behavior. Hence, it is seen that although unsafe condition is similar to the reference model behavior, since safety knowledge and occupational experience decrease, safe behavior decreases and incident rate increases. However, it is observed that after a while, since time to train starts to decrease depending on increase in learning from incidents as seen from Figure 8.8 (compared with Figure 7.4 and Figure 7.8) Trained Employees increases, Untrained Employees and untrained employee ratio decreases. Therefore, safety knowledge increases to 0.96. Moreover, increase in learning from incidents also makes increase in effect of learning from incidents on safe behavior, then safe behavior increases. The model behaviors are given below.

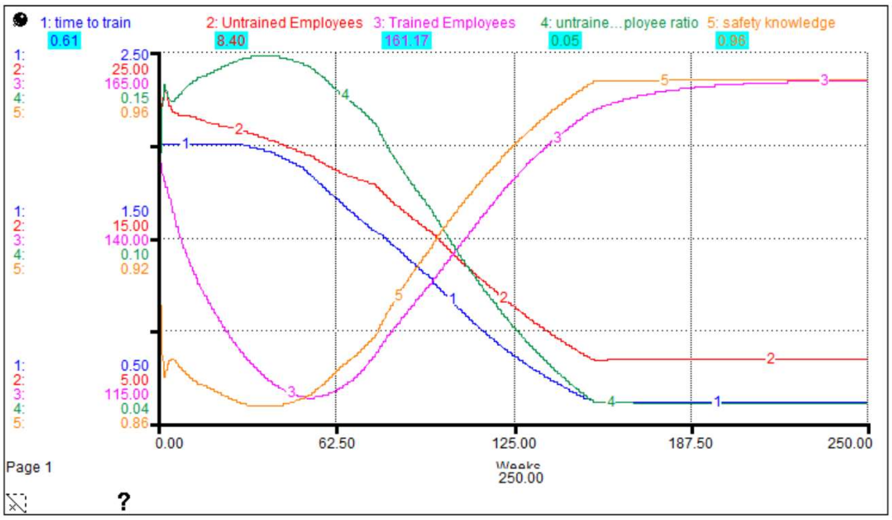

Figure 8.5. Change in time to train, Untrained and Trained Employees, untrained employee ratio, and safety knowledge (attrition time is decreased by 10 times).

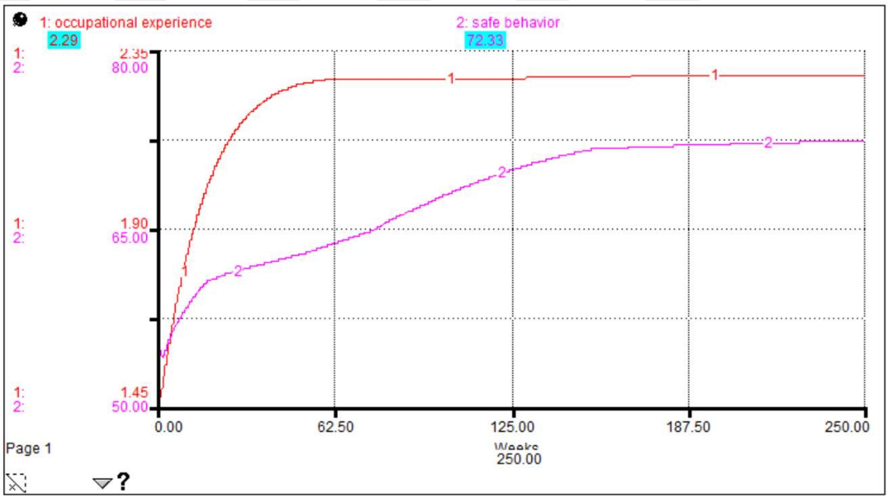

Figure 8.6. Change in occupational experience and safe behavior (attrition time is decreased by 10 times).

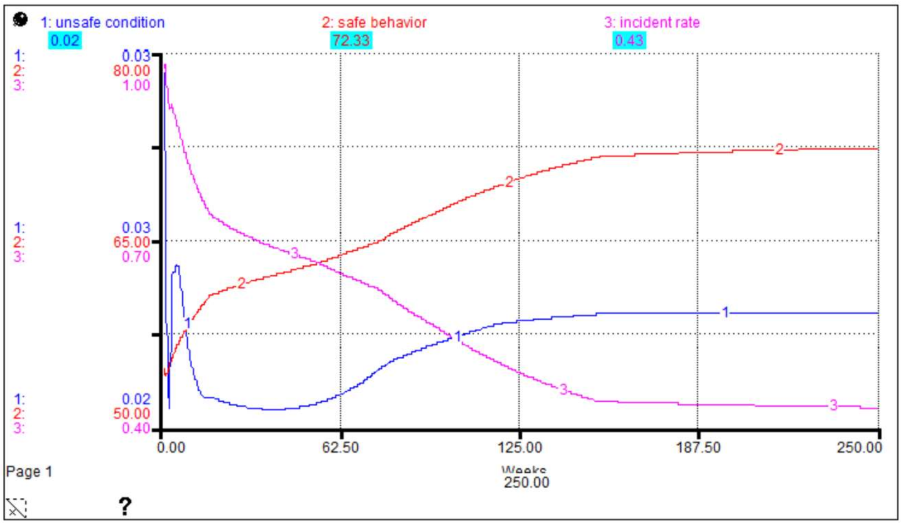

Figure 8.7. Change in unsafe condition, safe behavior and incident rate (attrition time is decreased by 10 times).

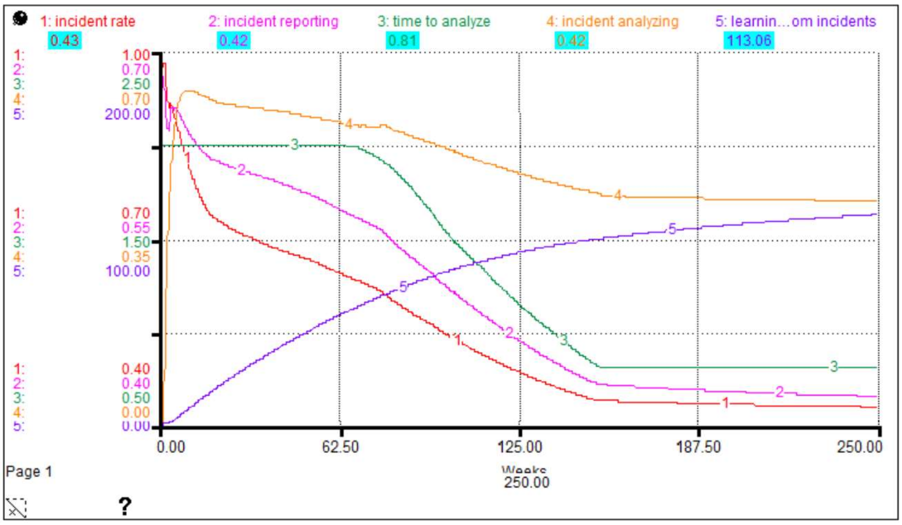

Figure 8.8. Change in incident rate, incident reporting, time to analyze, incident analyzing, and learning from incidents (attrition time is decreased by 10 times).

However, since safety knowledge and occupational experience effects on safe behavior is higher than the effect of learning from incidents, safe behavior decreases. Accordingly, this scenario implies that when turnover rate increases, incident rate increases.

8.1.3. Scenario Analysis Related to Reliable Critical Equipment

In this scenario, it is aimed to analyze how usage of reliable critical equipment affects the safety system in the onshore LNGRTs. For this purpose, the reference failure time is halved. That means, critical equipment is less reliable and breaks down more frequently than the reference model.

When the model is run and the model behavior (see Figure 8.9) is compared to the reference model behavior represented in Figure 7.3, it is observed that since breakdown increases due to decrease in failure time, Effective Critical Equipment decreases while Undefined Broken Critical Equipment and Defined Broken Equipment increase.

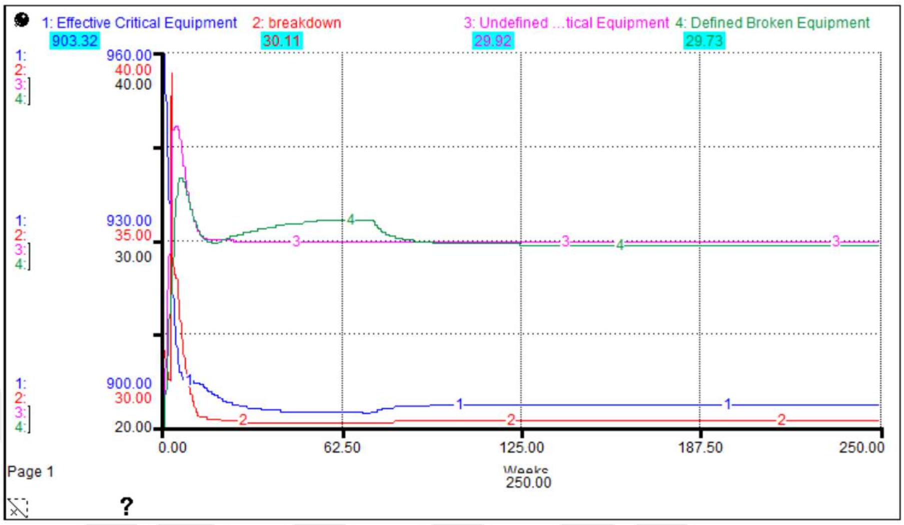

Figure 8.9. Change in Effective, Undefined Broken Critical Equipment, Defined Broken Equipment, breakdown (reference failure time is halved).

Accordingly, since unsafe condition increases, incident rate increases although safe behavior is a bit higher due to increase in learning from incidents and effect of learning from incidents on time to train, time to analyze and safe behavior. The results are given in Figure 8.10.

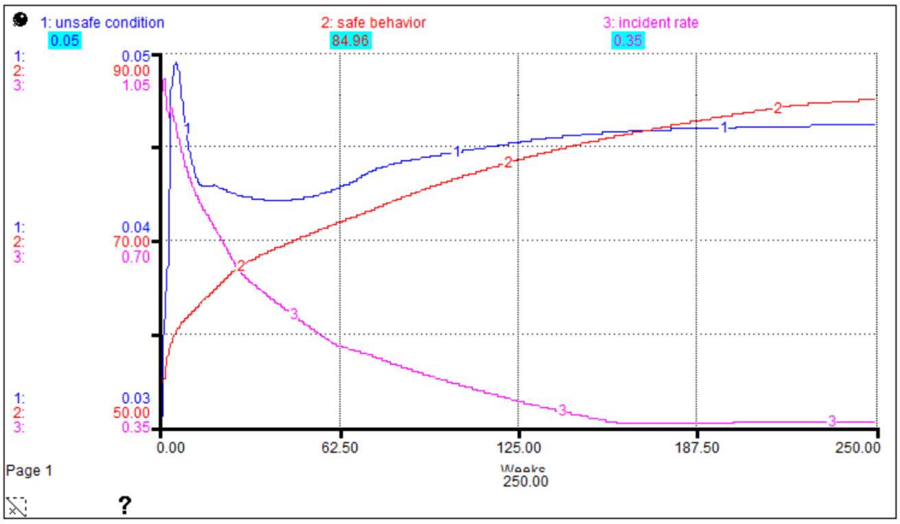

Figure 8.10. Change in unsafe condition, safe behavior and incident rate (reference failure time is halved).

Moreover, to understand the effect of using more reliable critical equipment on safety system, now reference failure time is doubled. Then, it is observed (Figure 8.11 and Figure 8.12) that, since breakdown decreases, Undefined Broken Critical Equipment decreases. Hence, unsafe condition and incident rate are lower than the reference model behavior (compare with Figure 7.3 and Figure 7.7). Consequently, it is seen that using more reliable critical equipment makes decrease in unsafe condition and so incident rate.

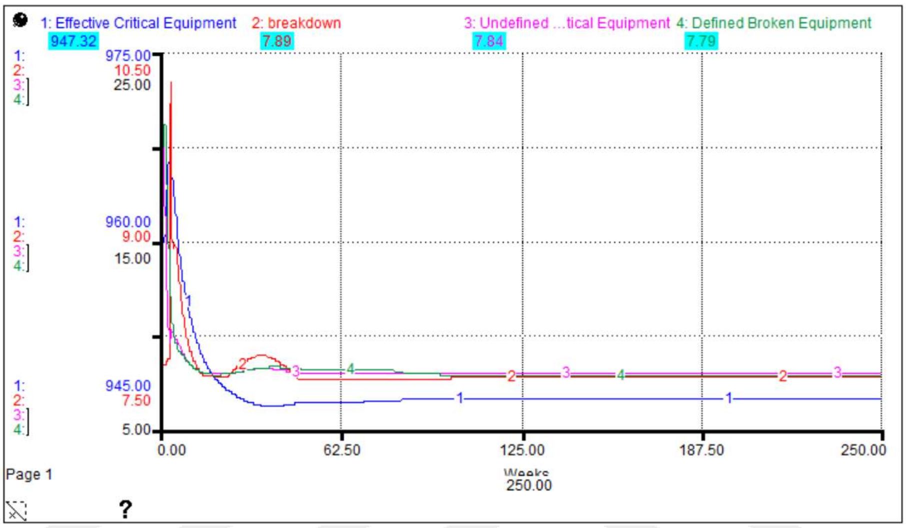

Figure 8.11. Change in Effective, Undefined Broken Critical Equipment, Defined Broken Equipment, breakdown (failure time is doubled).

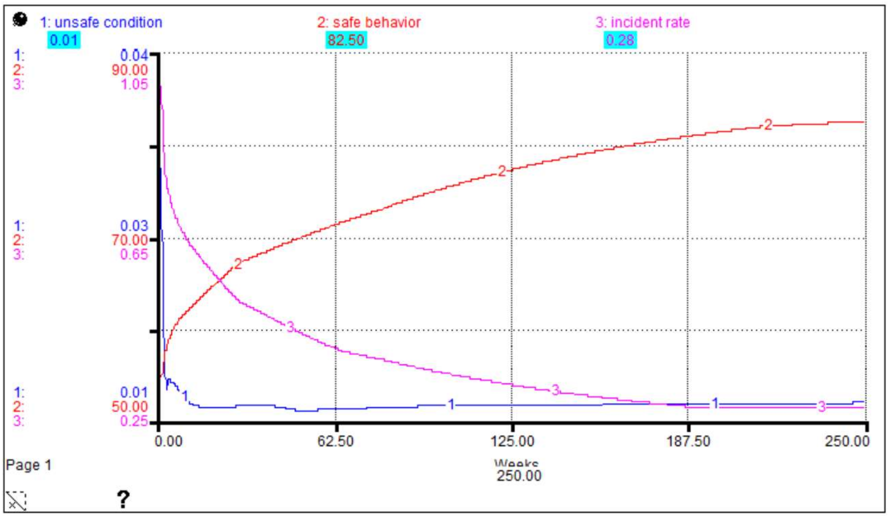

Figure 8.12. Change in unsafe condition, safe behavior and incident rate (reference failure time is doubled).

8.2. Policy Analysis

In this section, it is aimed to understand how different management policies affect the occupational safety system in the onshore LNGRTs. For this purpose, policy analysis related to time to train, time to incident analyzing, maintenance period and hiring are discussed in the following.

8.2.1. Policy Analysis Related to Time to Train

In this policy analyzing, it is aimed to demonstrate how training affects occupational safety system in the onshore LNGRTs. For this purpose firstly, time to train which affects allocated labor time for training is doubled. When the model is run and the model behavior represented in Figure 8.13 is compared to the reference model behavior represented in Figure 7.4, it is observed that since time to train is higher than the reference model behavior, untrained employee ratio is higher. Hence, safety knowledge is lower. The results are given in the Figure 8.13.

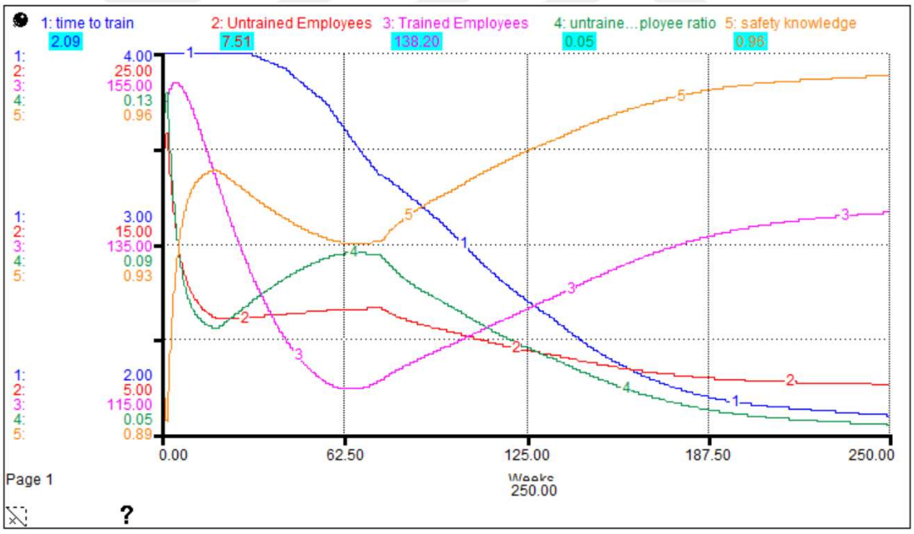

Figure 8.13. Change in time to train, Untrained and Trained Employees, untrained employee ratio, and safety knowledge (time to train is doubled).

Accordingly, it is observed (see Figure 8.14) that safe behavior is lower than the reference model behavior represented in Figure 7.7. Therefore, although unsafe condition is approximately same, incident rate is higher than the reference behavior and it can catch the 0.30 incident/week value at 201.13 weeks in this policy, while it can take this value at 176.38 weeks in the reference model behavior. Figure 8.14 is given below.

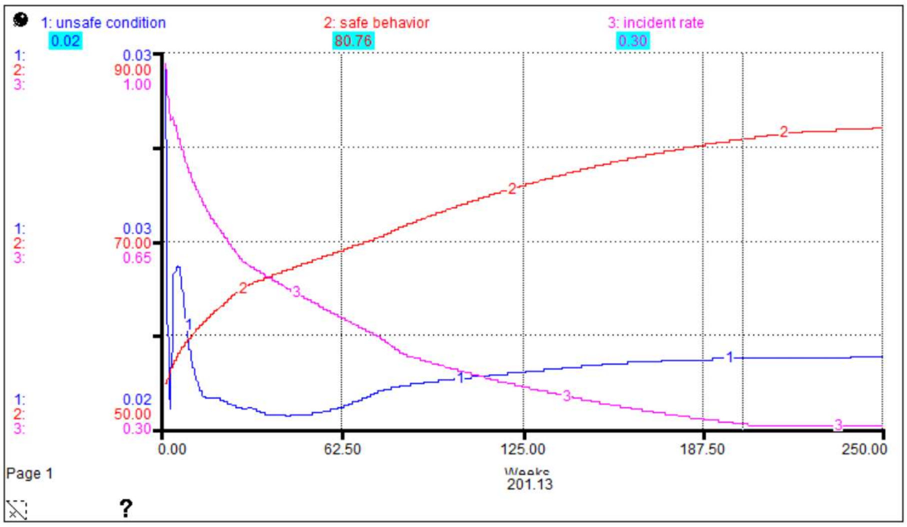

Figure 8.14. Change in unsafe condition, safe behavior and incident rate (time to train is doubled).

It is also worth to mention that, when the model behavior represented in Figure 8.15 is compared to the reference model behavior given in Figure 7.4, Figure 7.7 and Figure 7.8, it is also seen that since incident rate is higher, learning from incident is higher than the reference model. Hence, it makes decrease in time to train. In addition, safe behavior is increased by learning from incidents directly on the one hand. That is, learning from incidents prevents more increase in time to train, more decrease in safe behavior, and accordingly, more increase in incident rate. Figure 8.15 is given below.

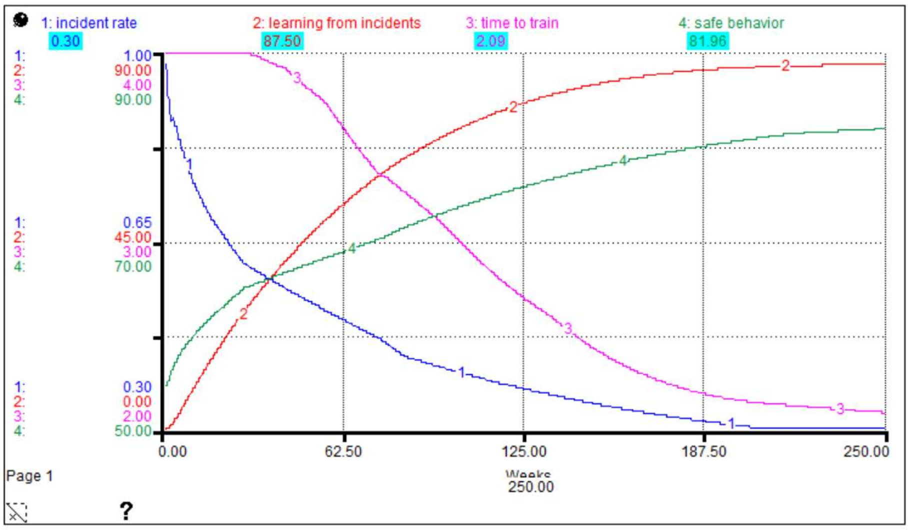

Figure 8.15. Change in learning from incidents, effect of learning from incidents on safe behavior, and time to train (time to train is doubled).

To understand about how time to train policy affects the occupational safety system, now, it is taken as 25 times higher. It means, it is assumed that managers give decision to train Untrained Employee in 50 weeks. When the model is run and the model behavior given in Figure 8.16 is compared to the reference model behavior and to the first policy behavior of which time to train is doubled represented in Figure 7.4 and Figure 8.13, respectively, it is observed that since time to train gets higher values than the other model behaviors, untrained employee ratio increases to 0.53 and safety knowledge decreases to 0.51 at 76 weeks. Accordingly, when the model behavior given in Figure 8.17 is compared to the reference and first policy model behaviors represented in Figure 7.7 and Figure 8.14, respectively, it is seen that although unsafe condition is approximately same as the other model behaviors, since safe behavior decreases to 38.88, incident rate increases to 1.5 incident/week at 78 weeks. However, after then, it is observed that (see Figure 7.8, Figure 8.15 and Figure 8.18) since learning from incidents also increases more in this policy, and depending on, its effect makes higher decrease in time to train, and higher increase in safe behavior on the one hand. Then untrained employee ratio decreases from 0.53 to 0.29 in 250 weeks. Hence, safety knowledge increases from 0.51 to 0.73. Moreover, safe behavior increases from 38.88 to 64.18. Hence, incident rate decreases to 0.63 incident/week. However, although increase in learning from incidents prevent more increase in time to train, it is seen that in this policy of which time to train increased to 50 weeks, incident rate increases more. Figure 8.16, Figure 8.17 and Figure 8.18 are given in the following.

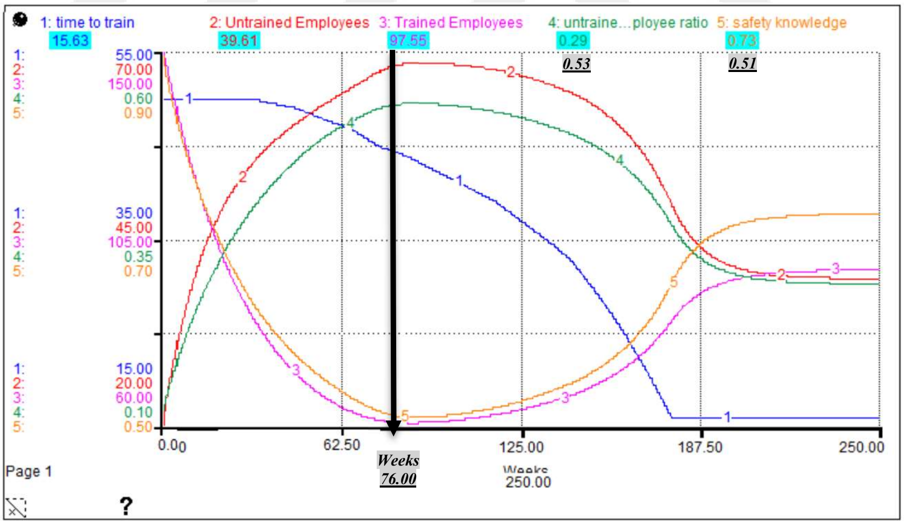

Figure 8.16. Change in training sector variables (time to train is multiplied by 25).

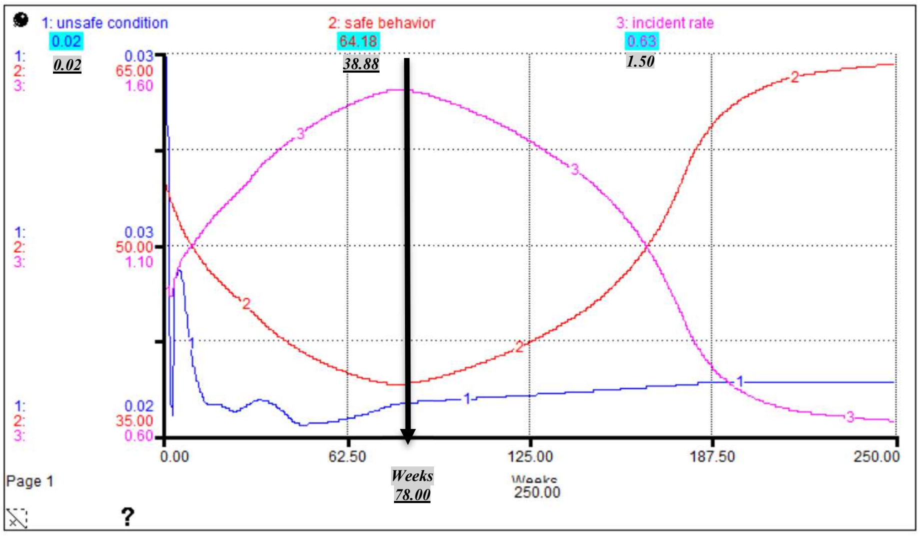

Figure 8.17. Change in unsafe condition, safe behavior and incident rate (time to train is multiplied by 25).

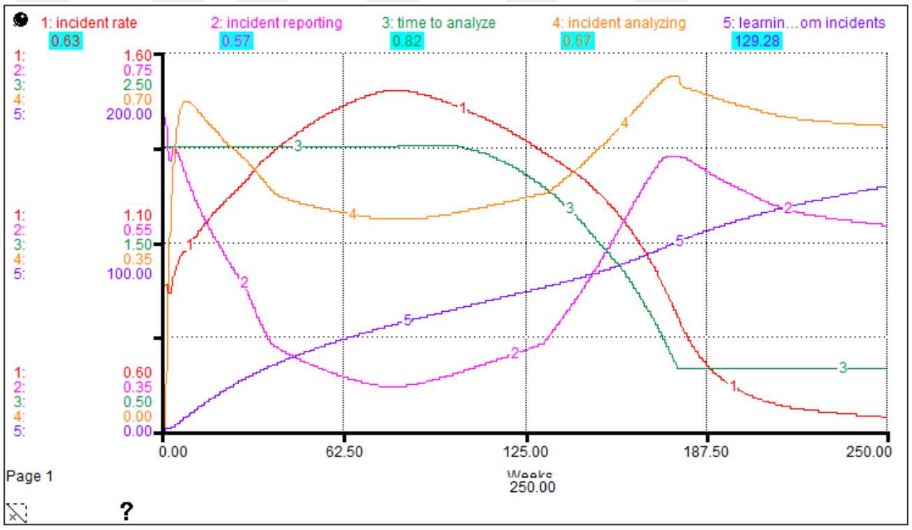

Figure 8.18. Change in learning from incidents, effects of learning from incident on safe behavior, and time to train (time to train is multiplied by 25).

Time to train policies also show that learning from incidents has important effects on the occupational safety system in the onshore LNGRTs. Hence, to see how incident learning sector affects the system, time to analyze policies are examined in the following section.

8.2.2. Policy Analysis Related to Time to Analyze

As mentioned in Chapter 5, when learning from incidents increases, time to train decreases. That means, training increases, untrained employee ratio decreases and safety knowledge increases. Hence, safe behavior increases. Besides, an increase in learning from incidents also makes increase in safe behavior. Here, to analyze how learning from incidents affects the occupational safety system, time to analyze is taken as constant and 250 weeks that means there is no labor time allocation for incident analyzing along the model time horizon. In addition, for ease understanding, the policy analysis in the 8.2.1. section for time to train multiplied by 25 is continued.

When the model is run and the model behavior represented in Figure 8.19 is compared to the reference model behavior given in Figure 7.7 and the model behavior of which time to train is multiplied by 25 given in Figure 8.17, it is seen that since safe behavior decreases, and unsafe condition increases, incident rate increases more.

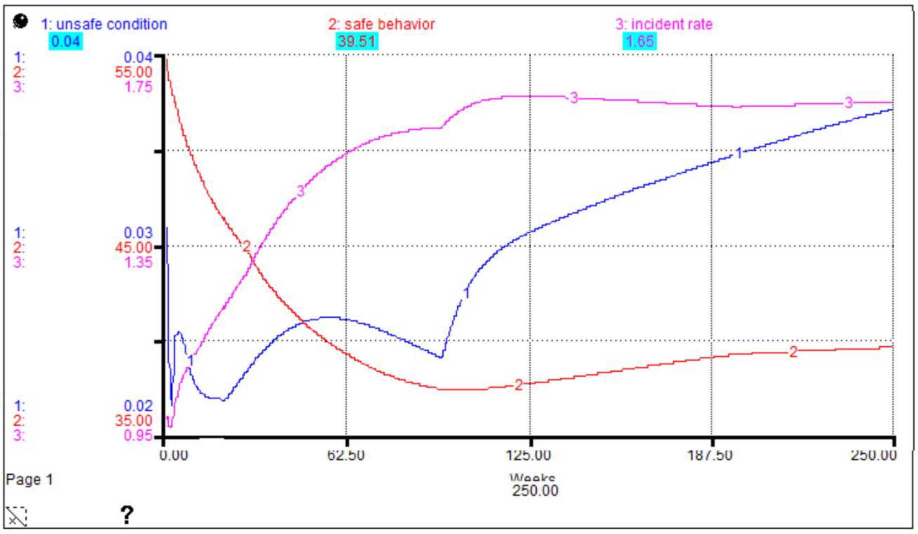

Figure 8.19. Change in unsafe condition, safe behavior and incident rate (time to train is multiplied by 25 and time to analyze is taken as 250 weeks).

Accordingly, it is seen (see Figure 8.20) that although incident rate increases, since safe behavior is lower, effect of safe behavior on incident reporting fraction decreases and so incident reporting decreases. In addition, since time to analyze is taken as 250 weeks, incident analyzing also decreases (compare with Figure 7.8). That means, incidents are neither reported nor analyzed efficiently in this policy. Figure 8.20 is given below.

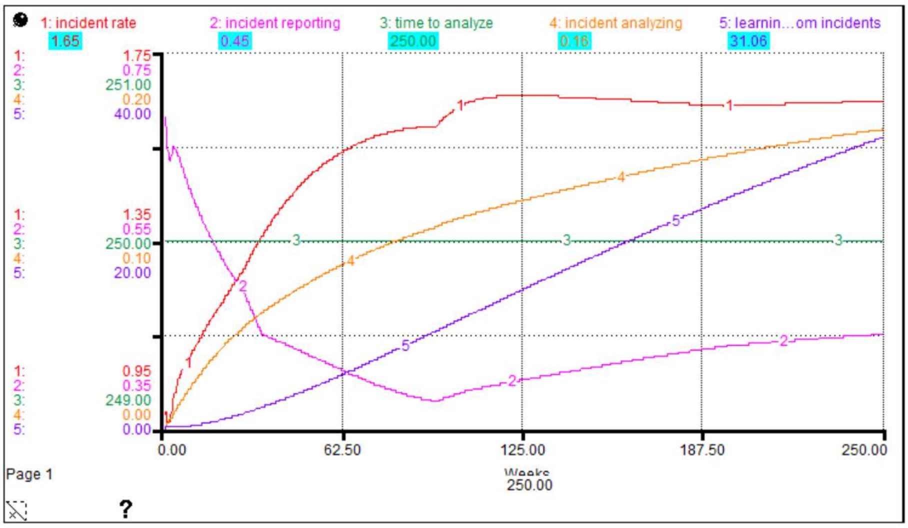

Figure 8.20. Change in effect of safe behavior on incident reporting fraction, incident rate, incident reporting, time to analyze, and incident analyzing (time to train is multiplied by 25 and time to analyze is taken as 250 weeks).

Depending on these, although incident rate in the model behavior is higher than the reference model behavior and the model behavior of which time to train is multiplied by 25, it is observed (see Figure 8.20) that learning from incidents is lower. Moreover, it does not have any effect on time to train its effect on safe behavior and maintenance frequency decrease Hence, as seen from Figure 8.21, time to train increases, untrained employee ratio increases and safety knowledge decreases to 0.48 (compare with Figure 7.4 and Figure 8.16).

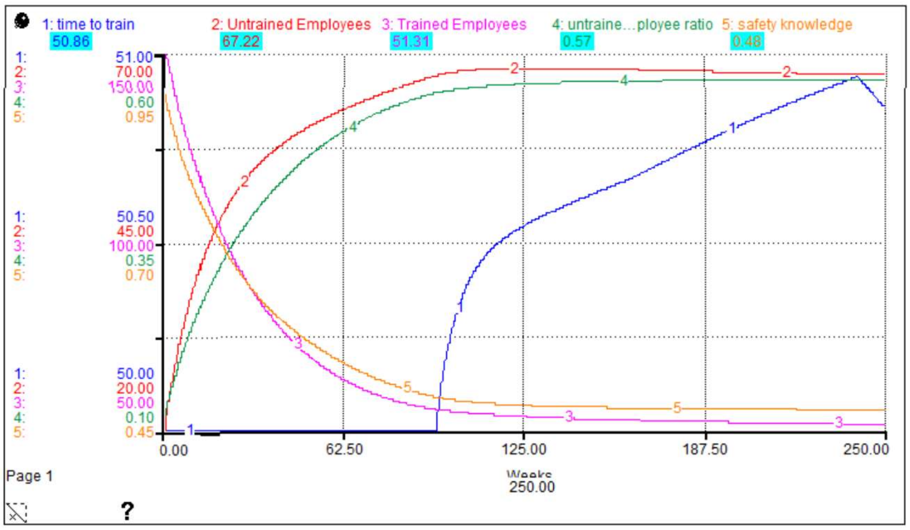

Figure 8.21. Change in time to train, Untrained and Trained Employee, untrained employee ratio, and safety knowledge (time to train is multiplied by 25 and time to analyze is taken as 250 weeks).

Moreover, since effect of learning from incidents on maintenance frequency decreases, maintenance period also decreases below the reference maintenance period and ratio of allocated to reference required labor time for maintenance decreases as seen in Figure 8.22. Hence, Undefined Broken Critical Equipment increases and unsafe condition increases as seen in Figure 8.19 (compare with Figure 7.2 and Figure 7.3).

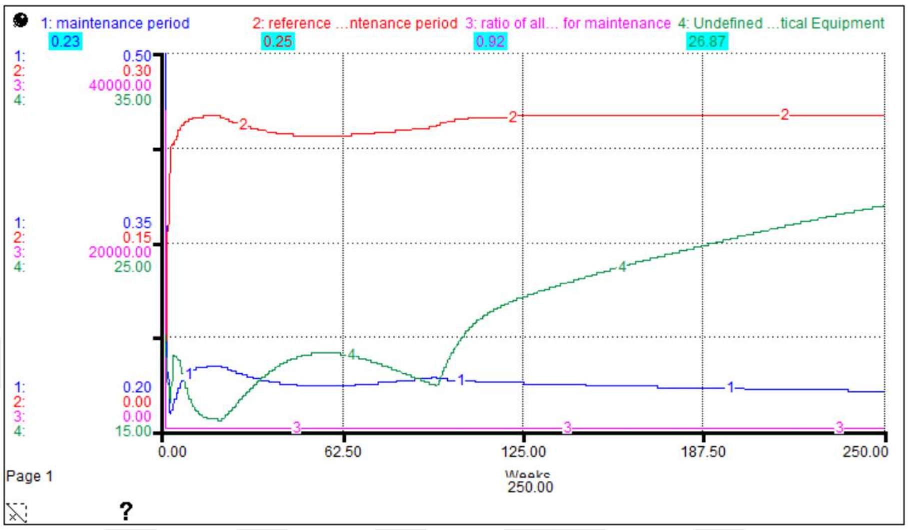

Figure 8.22. Change in maintenance period, reference maintenance period, ratio of allocated to reference required labor time allocation, and undefined broken critical equipment (time to train is multiplied by 25 and time to analyze is taken as 250 weeks).

This policy implies that when there is not incident learning and then taking corrective action system in the onshore LNGRTs, incident rate increases more since safe behavior decreases and unsafe condition increases more.

8.2.3. Policy Analysis Related to Maintenance Period

Maintenance period is one of the policy parameters for the occupational safety system in the onshore LNGRTs. It is determined by maintenance frequency and LNG dispatch. That is, under the normal operational conditions as in the reference model, each critical equipment must be maintained for each 1,000,000 m^3 LNG dispatch to prevent any unsafe condition. In this section, since it is aimed to analyze how maintenance period affects the safety system, maintenance frequency is taken as constant and halved. Now, it is 1/2,000,000 $1/m^3$.

When the model is run, it is observed (see Figure 8.23) that since maintenance frequency is halved, maintenance period decreases approximately to half of the reference maintenance period and breakdown increases. Then, Effective Critical Equipment decreases, and so Undefined Broken Critical Equipment increases. Since decrease in ratio of allocated to reference required labor time for maintenance causes a decrease in monitoring time fraction and so decrease in determination of broken critical equipment, Undefined Broken Critical Equipment accumulates more. Therefore, undefined broken critical equipment ratio increases. Accordingly, it is seen (see Figure 8.24) that unsafe condition and so incident rate increases (compare with Figure 7.3 and Figure 7.7).

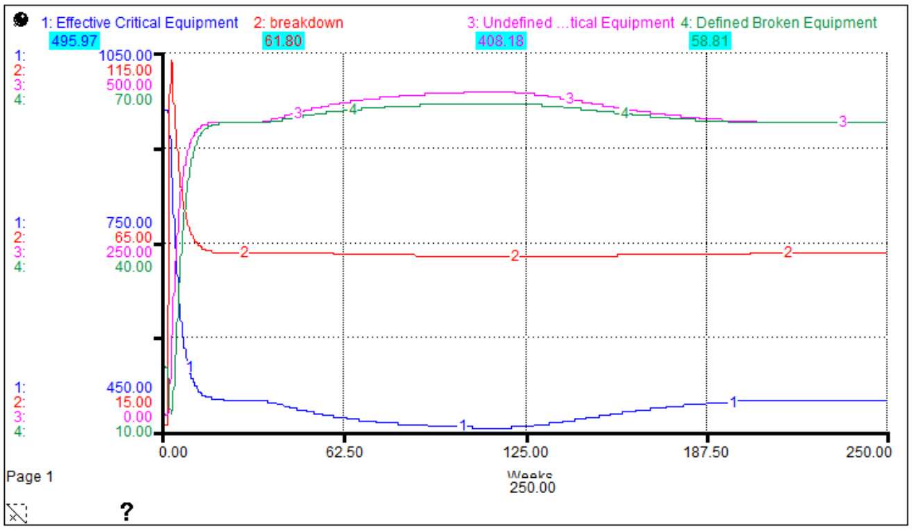

Figure 8.23. Change in Effective, Undefined Broken Critical Equipment, Defined Broken Equipment, unsafe condition (maintenance frequency is halved).

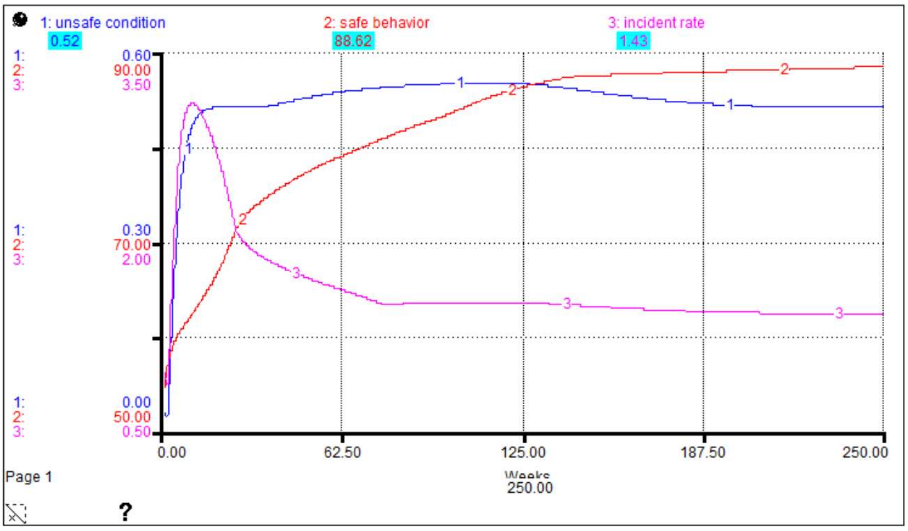

Figure 8.24. Change in unsafe condition, safe behavior, and incident rate (maintenance frequency is halved).

Furthermore, since incident rate increases and safe behavior is high enough to report incidents, and the Reported Incidents are analyzed, learning from incidents also increases as observed in the other policy analysis. Then, safe behavior increases more compared to the reference model behavior. Therefore, as seen from the Figure 8.24, safe behavior is higher. However, since unsafe condition is higher, decreasing maintenance period policy implies that when maintenance frequency is decreased, incident rate increases in the onshore LNGRTs.

8.2.4. Policy Analyzes Related to Hiring

In this section, it is aimed to analyze hiring policy effect on the onshore LNGRTs. For this purpose, hiring is quartered. That is, while hiring is approximately corresponds to attrition in the reference model, now it is lower than the attrition.

When the model is run and the model behavior (see Figure 8.25) is compared to the reference model behavior given in Figure 7.5, it is observed that as in the reference model behavior, total employee decreases. However, since employee shortfall starts after 54 weeks but hiring does not corresponds to the employee gap, total employee can not increase as in the reference behavior. Then, the system tries to close the required labor time gap by increasing Time per Employee. As seen, it increases to 48.09 hours/week at the end of 250 weeks. Accordingly, fatigue increases to 4.22 and when it passes to tolerable levels after 200 weeks, it makes decrease in safe behavior. Figure 8.25 is given in below.

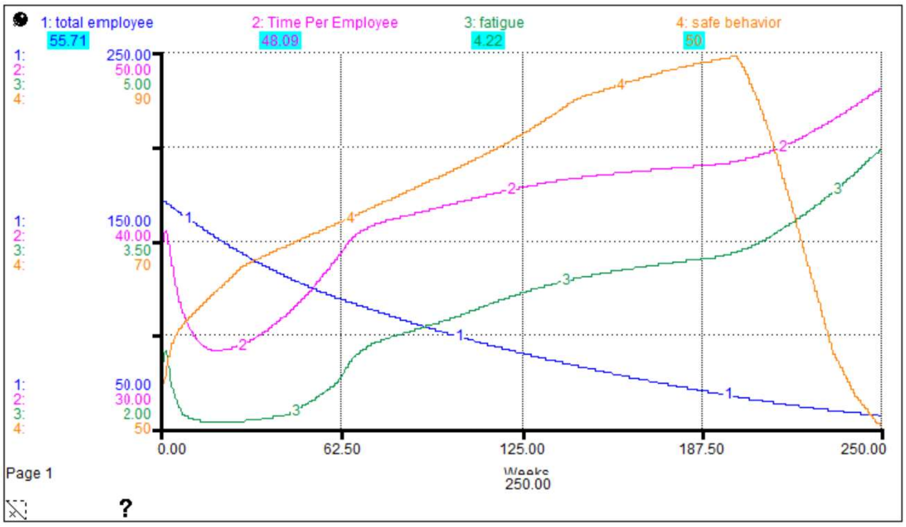

Figure 8.25. Change in total employee, Time per Employee, fatigue and safe behavior (hiring is quartered).

Besides, it is observed that since the labor time gap can not be closed immediately after an increase in labor time requirement as in the reference model behavior because of the delay depending on time adjustment of Time per Employee, allocated labor time may not correspond to required labor time instantly. Accordingly, as seen from Figure 8.26, when Perceived Delivery Delay passes 7 weeks, then LNG orders and so LNG dispatch decreases (compare with Figure 7.1).

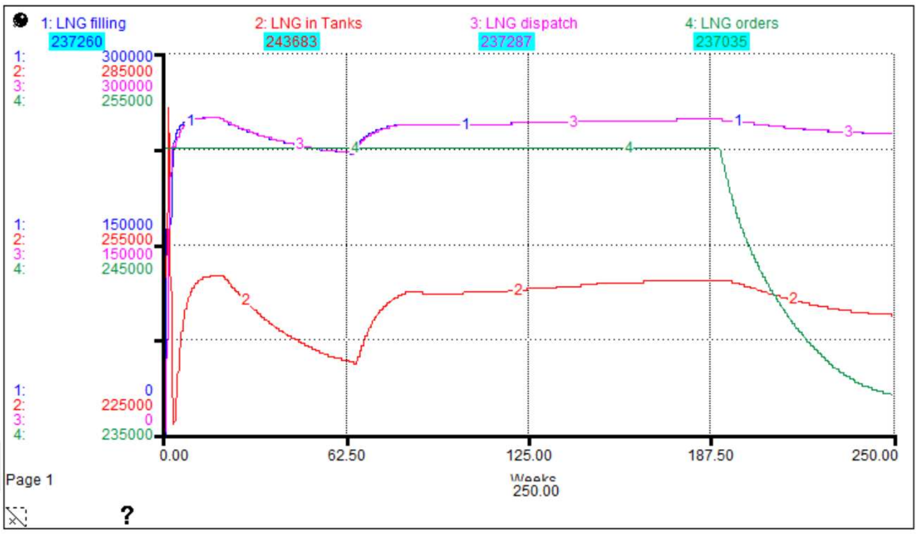

Figure 8.26. Change in LNG filling, LNG in Tanks, LNG dispatch, and LNG orders (hiring is quartered).

Furthermore, since Perceived Schedule Pressure increases, it is observed (see Figure 8.27 and Figure 8.28) it makes decrease in maintenance period, and then ratio of allocated to reference required labor time for maintenance decreases, breakdown increases. Hence, Undefined Broken Critical Equipment increases which leads increase in unsafe condition and so incident rate as illustrated in Figure 8.29 (compare with Figure 7.2, Figure 7.3 and Figure 7.7). Moreover, learning from incidents increases depending on incident rate increase, then safe behavior increases more as mentioned in the other policy results. However, after passing the fatigue tolerance, it decreases sharply, then incident rate increases rapidly. The model behaviors are represented below.

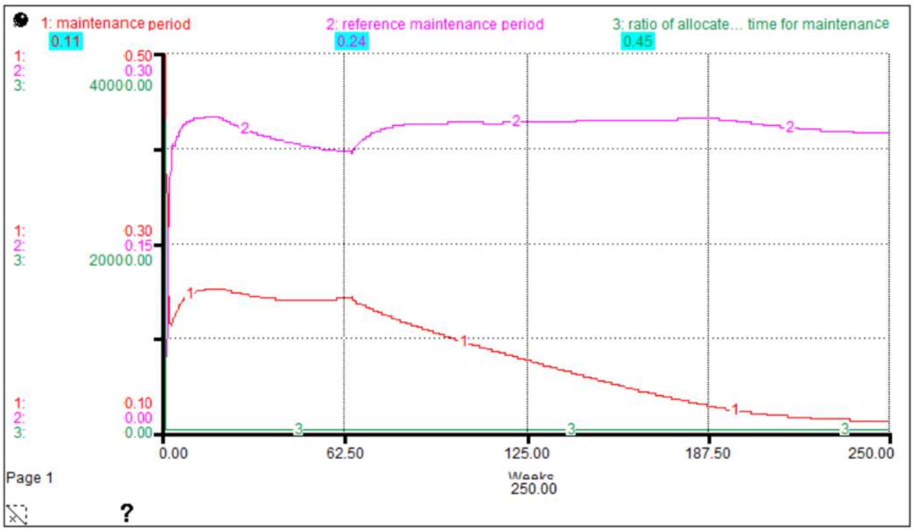

Figure 8.27. Change in maintenance period, reference maintenance period, and ratio of allocated to reference required labor time for maintenance (hiring is quartered).

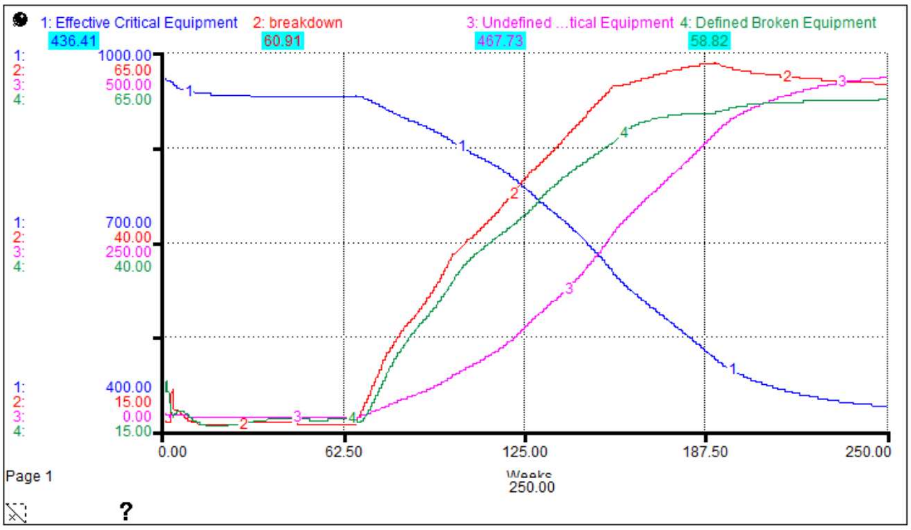

Figure 8.28. Change in Effective, Undefined Broken Critical Equipment, and breakdown (hiring is quartered).

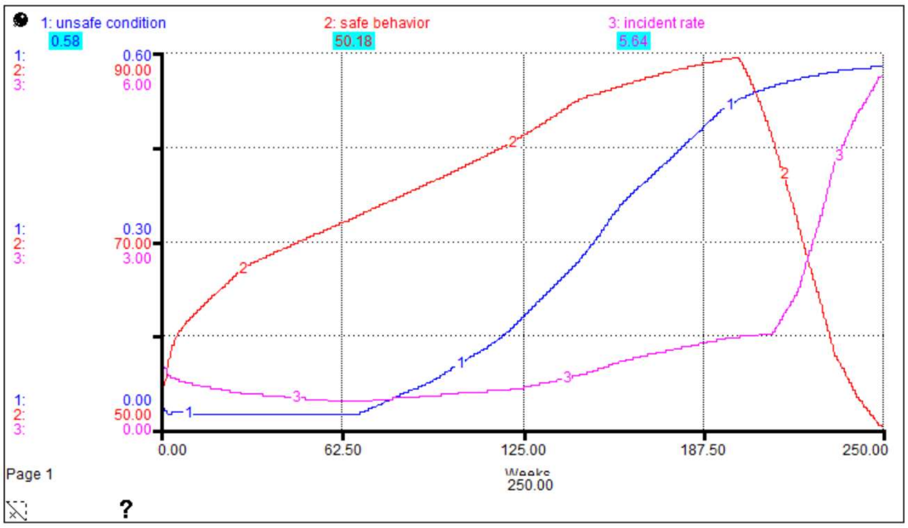

Figure 8.29. Change in unsafe condition, safe behavior and incident rate (hiring is quartered).

Hence, policy related to hiring implies that when hiring decreases, labor time requirement is provided by increase in Time per Employee and this leads to fatigue. In addition, allocated labor time may not correspond to required labor time instantly as in the reference model behavior, then production decreases, schedule pressure increases, maintenance decreases, then unsafe condition increases. Since fatigue passes to tolerance levels, safe behavior decreases. Hence, incident rate increases.

9. DISCUSSION

In this chapter, how occupational safety system in the onshore LNGRTs is affected depending on different scenarios and management policies performed in Chapter 8 are discussed in detail.

In the base model, initial parameters are defined and taken by considering normal operational conditions. Then, when the model is run for an arbitrary initial simulation time, it is observed that model behaviors correspond to the expected outcomes. For instance, as demonstrated in Chapter 7, LNG filling and dispatch get their maximums; maintenance, repairing, training and incident analyzing activities are well done. Hence, unsafe condition, safe behavior and so incident rate are close to their reference values. This means, the system minimized the possibility of facing the risk of major accidents. Besides, to gain insight to occupational safety system, several scenario and policy analyses are performed on the base model.

The first scenario is about the market and so, desired delivery delay tolerance depending on the season. In the fieldwork, it is stated that market and desired delivery delay tolerance is lower than the normal conditions in the winter. Depending on this, they are halved. When the model is run, it is observed that Perceived Schedule Pressure increases and passes tolerable limits for managers. Then, it makes decrease in maintenance frequency and increase in time to train and time to analyze in order to prevent any time loss because of the other activities. Since maintenance period decreases, allocated labor time for maintenance decreases. This means, allocated labor time for maintenance does not correspond to the reference required labor time. Accordingly, breakdown increases and Effective Critical Equipment decreases. This leads to increase in Undefined Broken Critical Equipment. Then, unsafe condition and incident rate increases. It is worth to mention that, time to train and time to analyze are also affected by Perceived Schedule Pressure and learning from incidents. While they are increased by Perceived Schedule Pressure, at the same time, they are decreased by increase in learning from incidents. When the model is run, it is observed that increase in Perceived Schedule Pressure and learning from incidents finally cause decrease in time to train and time to analyze. Furthermore, since learning from incidents is higher than the reference model behavior, effect of learning from incidents on safe behavior is also higher. Hence, safe behavior is higher than the reference model behavior. However, although safe behavior is higher than the reference model behavior depending on learning from incidents effect, this scenario implies that, when schedule pressure increases, unsafe condition increases, and this leads to increase in incident rate.

In the second scenario, turnover rate is assumed higher than the reference model due to heavy working conditions, low wage policies, stressful environment, negative relationships, lack of trust and others. In addition, preferring subcontracting rather than employing full-time employee also means having high turnover rate. Accordingly, when the model is run, it is observed that since attrition time decreases, initially Trained Employees decreases, and Untrained Employees increases. Then, since untrained employee ratio increases, safety knowledge decreases. Furthermore, since occupational experience is lower than the reference model behavior, its effect on safe behavior decreases. Hence, though unsafe condition does not change significantly, incident rate increases. After a while, since time to train starts to decrease depending on effect of learning from incidents, which increases because of the incident rate, Trained Employees increases and Untrained Employees decreases. Then, safety knowledge increases. However, consequently, since safe behavior is lower than the reference run, it can be concluded that high turnover rate leads to increase in incident rate. In other words, having good working conditions or abandoning the subcontracting provides decrease in incident rate.

In industries, less reliable critical equipment may be used since it is economic or its supply is easier although they have less failure time and break downs more. Therefore, in the third scenario, it is aimed to analyze how using less reliable critical equipment affects the safety system. For this purpose, reference failure time is halved. When the model is run, it is seen that since breakdown increases, Undefined Broken Critical Equipment increases. Therefore, unsafe condition and incident rate increase and are higher than the reference model behavior. On the other hand, how using more reliable critical equipment affects to safety system is also analyzed by doubling reference failure time. Then, it is seen that breakdown is lower, Undefined Broken Critical Equipment decreases. Hence, unsafe condition and incident rate decreases below the reference model behavior. The results imply that using less reliable critical equipment makes increase in incident rate, and possibility of major accidents.

Besides these scenarios, to demonstrate effect of different management policies on safety system, several policy analyzes are performed.

Firstly, it is aimed to understand how training policies affect the safety system. Therefore, time to train is doubled, and then multiplied by 25. When the models are run, it is observed that increase in time to train makes decrease in required and so allocated labor time for training. Hence, untrained employee ratio increases and safety knowledge decreases. Decrease in safety knowledge causes decrease in safe behavior and increase in incident rate. In addition it is also seen that, incident learning system prevents more decrease in safe behavior, and do more increase in incident rate. To gain insight into the incident learning system effect on safety system, in the second policy, time to analyze policy is analyzed. For this purpose, in addition to time to train policy, time to analyze is taken as 250 weeks that means the system does not allocate any time for incident learning. When the model is run and model behavior is compared to the reference and time to train policy, it is observed that safe behavior decreases much more and unsafe condition increases. Hence, incident rate increases more. Consequently, these policies imply that training and incident learning system affect incident rate significantly. To minimize possibility of facing major accidents, training and incident analyzing must be provided.

Thirdly, to understand how maintenance activities affect safety system, maintenance period policies are analyzed. Hence, maintenance frequency is halved. When the model is run and the model behavior is compared to the reference model behavior it is observed that, decrease in maintenance frequency leads to breakdowns and decrease in determination of broken equipment. Then, Undefined Broken Critical Equipment increases which causes increase in unsafe conditions. Then, incident rate increases.

Fourthly, to analyze hiring policy, hiring is quartered. Then, it is observed that employee shortfall increases, and the labor time gap is tried to be closed by increase in Time per Employee. Hence, fatigue increases and so safe behavior decreases. On the other hand, since hiring is decreased and there is much more delay to adjust labor time than the reference model, Perceived Schedule Pressure increases, maintenance period decreases. Then unsafe condition also decreases. Consequently, incident rate increases.

It is also worth to mention that, when the model is run, there occurs transient behaviors in the beginning since the initial values can not be assigned to variables proper. Therefore, while analyzing the model behaviors, such transient behaviors are ignored.

10. CONCLUSION

In this research, the causal mechanisms of major occupational accidents in the onshore LNGRTs that may endanger people, equipment and the environment are analyzed. Since the onshore LNGRTs and their occupational safety systems are complex and the causal mechanisms of the accidents arising from the interactions of the system variables have feedback structure, the dynamic simulation model based on system dynamic methodology is developed to explore and understand the whole system. The model structure comprises of occupational safety related activities; LNG processing, equipment maintenance and repairing, employee training, and incident learning where the management's time allocation decision under specific resource constraints is the fundamental driver. Hence, the purpose of the study is to analyze labor time allocation among these activities as a policy for occupational safety. Since the dynamic simulation model also provides us with a tool to analyze how different scenarios and polices affect unsafe condition and unsafe act, and through these analyses it is also aimed to provide a method for implementing better policies without facing major occupational accidents.

The model is built depending on literature reviews, fieldworks and interviews done in one of the major onshore LNGRT. Then, the confidence of the model is provided through the validation procedures taking place in the scope of the system dynamic methodology. First, the model sectors and then the whole model are validated by structurally. Then, the model is behaviorally validated.

The dynamic model is simulated by choosing an arbitrary initial time. Since the parameters are taken considering normal operational conditions, the reference model behavior implies that production, maintenance, repairing, training and incident learning activities are well operated, therefore; unsafe condition and safe behavior, which cause increase in incident rate, are close to the tolerable and reference levels.

To gain insight to the safety system dynamics, different scenario and policies are analyzed. Though these analyzes, it is seen that decrease in allocated labor time for maintenance leads to increase in unsafe condition. Furthermore, decrease in allocated labor time for training makes decrease in safe behavior. And when unsafe condition increases and/or safe behavior decreases, incident rate increases that mean possibility of facing major occupational accidents increases. Besides, analyses demonstrate that increase in schedule pressure makes decrease in allocated labor time for maintenance and training. However, incident learning system and according to taking corrective actions prevent more increase in unsafe condition and more decrease in safe behavior. That is, learning from incidents to take corrective actions has important effect on safety system to prevent increase in possibility of future incidents. On the other hand, it is also understood that, using less reliable critical equipment increases unsafe condition while using more reliable ones decreases unsafe conditions and incident rate. In addition, the model implies that high turnover rate because of the heavy working conditions, low wage policies, stressful environment, negative relationships, lack of trust and/or preferring subcontracting policy lead to high turnover rate that makes decrease in safe behavior, therefore; increase in incident rate. Besides, it is observed that preferring overwork rather than hiring policy makes increase in fatigue that leads to decrease safe behavior and increase incident rate.

Consequently, though this research, many causal mechanisms and feedback structures of the components that lead to unsafe condition and unsafe act are identified under favor of system dynamics methodology. This enables a better understanding of the occupational safety dynamics in the onshore LNGRTs. Moreover, a dynamic simulation model also provides a platform to analyze effects of different scenarios and policies on safety system. Hence, it is a useful tool for the managers to prevent incidents. Thus, it can contribute to eliminate future major occupational accidents. For this purpose, the results of the model will be shared with the onshore LNGRTs and other interested organizations. On the other hand, the model built in this study aims to make contribution to occupational safety system dynamics literature.

In the model, total labor time is allocated among the activities in the onshore LNGRTs depending on their relative demands. As future work this labor time allocation structure could be made more realistic. Besides, collecting field data regarding time for training, reference maintenance frequency, reference incident rate, and the effects of components on each other etc. from different onshore LNGRTs, and analyzing them would make the model more sound.

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APPENDIX A: LIST OF EQUATIONS FOR THE WHOLE MODEL

Production Sector

Expected_Dispatch(t) = Expected_Dispatch(t - dt) + (expectation_correction) * dtINIT

Expected_Dispatch = 250000 {m^3/week}

INFLOWS:

expectation_correction = (LNG_dispatch-Expected_Dispatch)/correction_time {m^3/week*week}

LNG_in_Tanks(t) = LNG_in_Tanks(t - dt) + (LNG_filling - LNG_dispatch) * dtINIT

LNG_in_Tanks = 250000 {m^3}

INFLOWS:

LNG_filling = MIN(LNG_arrival,desired_filling,max_filling_capability_by_labor_time) {m^3/week}

OUTFLOWS:

LNG_dispatch = MIN(max_dispatch_capability_by_labor_time,possible_dispatch){m^3/week}

Pending_Orders(t) = Pending_Orders(t - dt) + (LNG_orders - LNG_delivery) * dtINIT

Pending_Orders = 10 {m^3}

INFLOWS:

LNG_orders = reference_LNG_orders*effect_of_perceived_delivery_delay_on_LNG_orders {m^3/week}

OUTFLOWS:

LNG_delivery = LNG_dispatch {m^3/week}

Perceived_Delivery_Delay(t) = Perceived_Delivery_Delay(t - dt) + (increase_in_perceived_delay) * dtINIT Perceived_Delivery_Delay = 1

INFLOWS:

increase_in_perceived_delay = ((delivery_delay/market_reference_delivery_delay)-Perceived_Delivery_Delay)/correction_time_for_delivery_delay {1/week}

Perceived_Schedule_Pressure(t) = Perceived_Schedule_Pressure(t - dt) + (increase_in_schedule_pressure) * dtINIT Perceived_Schedule_Pressure = 1

INFLOWS:

increase_in_schedule_pressure = ((delivery_delay/desired_delivery_delay)-Perceived_Schedule_Pressure)/correction_time_for_schedule_pressure {1/week}

correction_time = 1 {week}

correction_time_for_delivery_delay = 1 {week} correction_time_for_schedule_pressure = 1 {week}

delivery_delay = Pending_Orders/LNG_delivery {week}

desired_delivery_delay = 1{week}

desired_dispatch = Pending_Orders/desired_delivery_delay {m^3/week}

desired_filling = MAX (LNG_adjustment+Expected_Dispatch,0) {m^3/week}

desired_LNG_in_tanks = MIN (LNG_for_inventory_coverage,tank_capacity) {m^3}

inventory_coverage_time = 4 {week}

LNG_adjustment = LNG_shortfall/LNG_adjustment_time {m^3/week}

LNG_adjustment_time = 1 {week}

LNG_arrival = 250000 {m^3/week}

LNG_for_inventory_coverage = LNG_orders*inventory_coverage_time {m^3}

LNG_shortfall = desired_LNG_in_tanks-LNG_in_Tanks {m^3}

market_reference_delivery_delay = 1 {week}

max_dispatch_by_LNG_in_Tanks = LNG_in_Tanks/minimum_dispatch_time {m^3/week}

max_dispatch_capability_by_labor_time =
dispatch_capability_by_labor_time*allocated_labor_time_for__LNG_dispatch {m^3/week}

max_filling_capability_by_labor_time =
filling_capability_by_labor_time*allocated_labor_time_for_LNG_filling {m^3/week}

minimum_dispatch_time = 1 {week}

possible_dispatch = MIN (desired_dispatch,max_dispatch_by_LNG_in_Tanks) {m^3/week}

reference_LNG_orders = 250000 {m^3/week}

tank_capacity = 250000 {m^3}

effect_of_perceived_delivery_delay_on_LNG_orders = GRAPH(Perceived_Delivery_Delay)
(7.00, 1.00), (7.30, 0.913), (7.60, 0.838), (7.90, 0.762), (8.20, 0.703), (8.50, 0.647), (8.80, 0.598), (9.10, 0.55), (9.40, 0.522), (9.70, 0.505), (10.0, 0.495)

Training Sector

Total__Occupational_Experience(t) = Total__Occupational_Experience(t - dt) + (increase_in_occupational_experience_by_hiring + increase_in_occupational_experience_by_working_years - decrease_in_occupational_experience_by_attrition) * dtINIT Total__Occupational_Experience = 250 {employee*year}

INFLOWS:

increase_in_occupational_experience_by_hiring =

hiring*occupational_experience_of_new_employee {employee*year /week}

increase_in_occupational_experience_by_working_years =

occupational_experience_per_workweek*total_employee{employee*year/week}

OUTFLOWS:

decrease_in_occupational_experience_by_attrition = occupational_experience*attrition {employee*year/week}

Trained_Employees(t) = Trained_Employees(t - dt) + (training - untraining - trained_attrition) * dtINIT Trained_Employees = 150 {employee}

INFLOWS:

training = allocated_labor_time_for_trainig/time_for_training {employee/week}

OUTFLOWS:

untraining = Trained_Employees/forgetting_time {employee/week}

trained_attrition = Trained_Employees/attrition_time {employee/week}

Untrained_Employees(t) = Untrained_Employees(t - dt) + (untraining + hiring - training - untrained_attrition) * dtINIT Untrained_Employees = 20 {employee}

INFLOWS:

untraining = Trained_Employees/forgetting_time {employee/week}

hiring = MAX (0,hiring_adjustment+attrition){employee/week}

OUTFLOWS:

training = allocated_labor_time_for_trainig/time_for_training {employee/week}

untrained_attrition = Untrained_Employees/attrition_time {employee/week}

attrition = trained_attrition+untrained_attrition {employee/week}

attrition_time = 150 {week}

forgetting_time = 52 {week}

hiring_adjustment = employee_shortfall/time_to_hire {employee/week}

occupational_experience = Total__Occupational_Experience/total_employee {year}

occupational_experience_of_new_employee = 2 {year}

occupational_experience_per_workweek = 1/52 {year/week}

reference_safe_behaviour = 80 {dimensionless}

safe_behavior =

reference_safe_behaviour*effect_of_occupational_experience_on_safe_behaviour*safety_knowledge*effect_of_learning__from_incidents_on_safe_behaviour*effect_of_fatigue_on_safe_behaviour {dimensionless} time_to_hire = 25 {week}

total_employee = (Trained_Employees+Untrained_Employees) {employee}

untrained_employee_ratio = Untrained_Employees/(Trained_Employees+Untrained_Employees) {dimensionless}

effect_of_fatigue_on_safe_behaviour = GRAPH(fatigue)

(3.40, 1.00), (3.56, 0.875), (3.72, 0.748), (3.88, 0.64), (4.04, 0.588), (4.20, 0.555), (4.36, 0.54), (4.52, 0.53), (4.68, 0.52), (4.84, 0.51), (5.00, 0.5)

effect_of_learning__from_incidents_on_safe_behaviour = GRAPH(learning_from_incidents)

(0.00, 1.00), (20.0, 1.01), (40.0, 1.02), (60.0, 1.03), (80.0, 1.05), (100, 1.06), (120, 1.08), (140, 1.09), (160, 1.10), (180, 1.10), (200, 1.10)

effect_of_occupational_experience_on_safe_behaviour = GRAPH(occupational_experience)

(0.00, 0.5), (2.00, 0.857), (4.00, 1.01), (6.00, 1.07), (8.00, 1.10), (10.0, 1.10), (12.0, 1.10), (14.0, 1.08), (16.0, 1.04), (18.0, 0.956), (20.0, 0.884)

safety_knowledge = GRAPH(untrained_employee_ratio)

(0.00, 1.00), (0.1, 0.915), (0.2, 0.811), (0.3, 0.717), (0.4, 0.622), (0.5, 0.537), (0.6, 0.447), (0.7, 0.361), (0.8, 0.267), (0.9, 0.181), (1, 0.1)

Maintenance and Repairing Sector

Defined_Broken_Equipment(t) = Defined_Broken_Equipment(t - dt) + (determination_of_broken_critical_equipment - broken_equipment_discard - repairing) * dtINIT Defined_Broken_Equipment = 20 {critical equipment}

INFLOWS:

determination_of_broken_critical_equipment = Undefined_Broken_Critical_Equipment*monitoring_time_fraction {critical equipment/week}

OUTFLOWS:

broken_equipment_discard = Defined_Broken_Equipment/equipment_life_time {critical equipment/week}

repairing = allocated_labor_time_for_repairing*repairing_capability {critical equipment/week}

Effective_Critical_Equipment(t) = Effective_Critical_Equipment(t - dt) + (purchasing_effective_critical_equipment + repairing - breakdown - effective_equipment_discard) * dtINIT Effective_Critical_Equipment = 960 {critical equipment}

INFLOWS:

purchasing_effective_critical_equipment = total_critical_equipmnent__gap/purchasing_time {critical equipment/week}

repairing = allocated_labor_time_for_repairing*repairing_capability {critical equipment/week}
OUTFLOWS:
breakdown = (Effective_Critical_Equipment / failure_time){critical equipment/week}
effective_equipment_discard = Effective_Critical_Equipment/equipment_life_time {critical equipment/week}
Undefined_Broken_Critical_Equipment(t) = Undefined_Broken_Critical_Equipment(t - dt) + (breakdown - determination_of_broken_critical_equipment - undefined_broken_equipment_discard) * dtINIT Undefined_Broken_Critical_Equipment = 20 {critical equipment}

INFLOWS:
breakdown = (Effective_Critical_Equipment / failure_time){critical equipment/week}
OUTFLOWS:
determination_of_broken_critical_equipment = Undefined_Broken_Critical_Equipment*monitoring_time_fraction {critical equipment/week}
undefined_broken_equipment_discard = Undefined_Broken_Critical_Equipment/equipment_life_time {equipment/week}
critical_equipment = (Effective_Critical_Equipment+Undefined_Broken_Critical_Equipment) {critical equipment}
critical_equipment_in_maintenance = (allocated_labor_time_for_maintenance*maintenance__capability)/week {critical equipment}
critical_equipment__in_use = MAX (critical_equipment-critical_equipment_in_maintenance,0) {critical equipment}
equipment_life_time = 156 {week}
failure_time = effect_of_maintenance_time_on_failure_time*refence__failure_time {week}
monitoring_time_fraction = reference_monitoring_fraction*effect_of_maintenance_time_ratio_on_monitoring_time {1/week}
purchasing_time = 6 {week}
ratio_of_allocated_to_ref_required_labor_time_for_maintenance = allocated_labor_time_for_maintenance/reference_required_labor_time_for_maintenance {dimensionless}
refence__failure_time = 60 {week}
reference_critical_equipment_number__in_terminal = 1000 {critical equipment}
reference_maintenance_period = LNG_dispatch*reference_maintenance_frequency_depending_on_production {1/week}

reference_monitoring_fraction = 1 {1/week}

reference_required_labor_time_for_maintenance = (critical_equipment/maintenance__capability)*(reference_maintenance_period) {employee*hour/week}

reference_unsafe_condition = 0 {unsafe condition/week}

total_critical_equipmnent__gap = IF total__critical_equipment<reference_critical_equipment_number__in_terminal THEN (reference_critical_equipment_number__in_terminal-total__critical_equipment) ELSE 0 {critical equipment}

total__critical_equipment = Defined_Broken_Equipment+Effective_Critical_Equipment+Undefined_Broken_Critical_Equipment {critical equipment}

undefined_broken_equipment_to_critical_equipment_ratio = Undefined_Broken_Critical_Equipment/critical_equipment__in_use

unsafe_condition = (reference_unsafe_condition+undefined_broken_equipment_to_critical_equipment_ratio)

week = 1 {week}

effect_of_maintenance_time_on_failure_time = GRAPH(ratio_of_allocated_to_ref_required_labor_time_for_maintenance)

(0.00, 0.01), (0.1, 0.0248), (0.2, 0.0545), (0.3, 0.0694), (0.4, 0.104), (0.5, 0.134), (0.6, 0.178), (0.7, 0.262), (0.8, 0.376), (0.9, 0.614), (1, 1.00)

effect_of_maintenance_time_ratio_on_monitoring_time = GRAPH(ratio_of_allocated_to_ref_required_labor_time_for_maintenance)

(0.00, 0.005), (0.1, 0.02), (0.2, 0.035), (0.3, 0.065), (0.4, 0.1), (0.5, 0.145), (0.6, 0.205), (0.7, 0.31), (0.8, 0.5), (0.9, 0.755), (1, 1.00)

Incident Learning Sector

Remembered_Incidents(t) = Remembered_Incidents(t - dt) + (incident_analyzing - memory_loss) * dtINIT Remembered_Incidents = 0 {incident}

INFLOWS:

incident_analyzing = allocated_labor_time_for_incident_analyzing*analyzing_capability {incident/week}

OUTFLOWS:

memory_loss = Remembered_Incidents/memory_loss_time {incident/week}

Reported_Incidents(t) = Reported_Incidents(t - dt) + (incident_reporting - incident_analyzing - discard) * dtINIT Reported_Incidents = 0 {incident}

INFLOWS:

incident_reporting = incident_rate*incident_reporting_fraction {incident/week}

OUTFLOWS:

incident_analyzing = allocated_labor_time_for_incident_analyzing*analyzing_capability {incident/week}

discard = Reported_Incidents/discard_time {incident/week}

discard_time = 168 {week}

incident_rate = reference_incident_rate*(effect_of_safe_behaviour_on_incident_rate*effect_of_unsafe_condition_on_incident_rate){incident/week}

incident_reporting_fraction = reference_incident_reporting_fraction*effect_of_safe_behaviour_on_incident_reporting_fraction {incident/incident}

learning_from_incidents = Remembered_Incidents*reference_safety_learning_from_incidents {learning}

memory_loss_time = 150 {week}

reference_incident_rate = 0.25 {incident/week}

reference_incident_reporting_fraction = 1 {incident/inident}

reference_safety_learning_from_incidents = 2 {learning/incident}

effect_of_safe_behaviour_on_incident_rate = GRAPH(safe_behavior)

(5.00, 9.91), (14.5, 8.61), (24.0, 7.25), (33.5, 5.77), (43.0, 4.46), (52.5, 3.29), (62.0, 2.30), (71.5, 1.45), (81.0, 1.00), (90.5, 1.00), (100, 1.00)

effect_of_safe_behaviour_on_incident_reporting_fraction = GRAPH(safe_behavior)

(5.00, 0.005), (14.5, 0.045), (24.0, 0.105), (33.5, 0.175), (43.0, 0.33), (52.5, 0.645), (62.0, 0.87), (71.5, 0.985), (81.0, 1.00), (90.5, 1.00), (100, 1.00)

effect_of_unsafe_condition_on_incident_rate = GRAPH(unsafe_condition)

(0.00, 1.00), (0.1, 1.90), (0.2, 2.75), (0.3, 3.65), (0.4, 4.69), (0.5, 5.59), (0.6, 6.49), (0.7, 7.34), (0.8, 8.15), (0.9, 9.05), (1, 10.0)

Labor Time Allocation Sector

avarage_ce_in_use(t) = avarage_ce_in_use(t - dt) + (correction_for_ce_in_use) * dtINIT avarage_ce_in_use = 10 {critical equipment}

INFLOWS:

correction_for_ce_in_use = (critical_equipment__in_use-avarage_ce_in_use)/correction_time_for_ce_in_use {critical equipment/week}

avarage_production(t) = avarage_production(t - dt) + (correction_for_production) * dtINIT

avarage_production = 500000 {m^3/week}

INFLOWS:

correction_for_production = (LNG_dispatch-avarage_production)/correction_time_for_maintenance {m^3/week*week}

Time_Per_Employee(t) = Time_Per_Employee(t - dt) + (time_adjustment) * dtINIT

Time_Per_Employee = regular_employee_time{hour/week}

INFLOWS:

time_adjustment = (desired_time_per_employee-Time_Per_Employee)/adjustment_time {hour/week*week}

adjustment_time = 12 {week}

allocated_labor_time_for_incident_analyzing = MIN (required_labor_time_for_incident_analyzing,total_labor_time*requied_labor_time_fraction_for_incident_analyzing) {employee*hour/week}

allocated_labor_time_for_LNG_filling = MIN (required_labor_time_for_LNG_filling,total_labor_time*required_labor_time_fraction_for_LNG_filling) {employee*hour/week}

allocated_labor_time_for_maintenance = MIN (required_labor_time_for_maintenance,total_labor_time*required_labor_time_fraction__for_maintenance) {employee*hour/week}

allocated_labor_time_for_repairing = MIN (required__labor_time_for_repearing,total_labor_time*required_labor_time_fraction__for_repairing) {employee*hour/week}

allocated_labor_time_for_trainig = MIN(required_labor_time_for_trainig,total_labor_time*required_labor_time_fraction_for_trainig) {employee*hour/week}

allocated_labor_time_for__LNG_dispatch = MIN (required_labor_time_for__LNG_dispatch,total_labor_time*required_labor_time_fraction_for_LNG_dispatch){employee*hour/week}

analyzing_capability = 0.5 {incident/employee*hour}

correction_time_for_ce_in_use = 1 {week}

correction_time_for_maintenance = 1 {week} desired_employee = total_required_labor_time/regular_employee_time {employee}

desired_time_per_employee = MIN (max_work_time_per_employee,required_employee_time) {hour/week}

dispatch_capability_by_labor_time = reference_dispatch_capability_by_labor_time*effect_of_ce_in_use_on_dispatch_capability {m^3/employee*hour}

employee_shortfall = desired_employee-total_employee {employee}

fatigue = reference_fatigue*effect_of_time_on_fatigue {dimensionless}

filling_capability_by_labor_time = reference_filling_capability_by_labor_time*effect_of_ce_in_use_on_filling_capability {m^3/employee*hour}

maintenance_period = avarage_production*maintenance__frequency {1/week}

maintenance__capability = 0.05 {critical equipment/employee*hour}

maintenance__frequency = reference_maintenance_frequency_depending_on_production*effect_of_learning_from_incidents_on_maintenance_frequency*effect_of_schedule_pressure_on_maintenance_frequency{1/m^3}

max_work_time_per_employee = 60 {hour/week}

ratio_of_critical_equipment_in_use_to_total_critical_equipment = avarage_ce_in_use/total__critical_equipment

reference_dispatch_capability_by_labor_time = 2400 {m^3/employee*hour}

reference_fatigue = 2 {dimensionless}

reference_filling_capability_by_labor_time = 10500 {m^3/employee*hour}

reference_maintenance_frequency_depending_on_production = 1/1000000{1/m^3}

reference_time_to_analyze = 2 {week}

reference__time_to_train = 2 {week}

regular_employee_time = 40 {hour/week}

repairing_capability = 0.1 {critical equipment/employee*hour}

requied_labor_time_fraction_for_incident_analyzing = required_labor_time_for_incident_analyzing/total_required_labor_time {dimensionless}

required_employee_time = total_required_labor_time/total_employee {hour/week}

required_labor_time_for_incident_analyzing = (Reported_Incidents/analyzing_capability)/time_to_analyze {employee*hour/week}

required_labor_time_for_LNG_filling = IF filling_capability_by_labor_time>(reference_filling_capability_by_labor_time*0.2) THEN desired_filling/filling_capability_by_labor_time ELSE 0 {employee*hour/week}

required_labor_time_for_maintenance =
(critical_equipment/maintenance__capability)*maintenance_period {employee*hour/week}
required_labor_time_for_trainig = time_for_training*Untrained_Employees/time_to_train
{employee*hour/week}
required_labor_time_for__LNG_dispatch = IF
dispatch_capability_by_labor_time>(reference_dispatch_capability_by_labor_time*0.2) THEN
possible_dispatch/dispatch_capability_by_labor_time ELSE 10{employee*hour/week}
required_labor_time_fraction_for_LNG_dispatch =
required_labor_time_for__LNG_dispatch/total_required_labor_time {dimensionless}
required_labor_time_fraction_for_LNG_filling =
required_labor_time_for_LNG_filling/total_required_labor_time {dimensionless}
required_labor_time_fraction_for_trainig =
required_labor_time_for_trainig/total_required_labor_time {dimensionless}
required_labor_time_fraction__for_maintenance =
required_labor_time_for_maintenance/total_required_labor_time {dimensionless}
required_labor_time_fraction__for_repairing =
required__labor_time_for_repearing/total_required_labor_time {dimensionless}
required__labor_time_for_repearing =
(Defined_Broken_Equipment)/(repairing_capability*time_to_repair) {employee*hour/week}
time_for_training = 30 {employee*hour/employee}
time_to_analyze =
reference_time_to_analyze*effect_of_schedule_pressure_on_time_to_analyze*effect_of_learning_from_incidents_on_time_to_analyze {week}
time_to_repair = 1 {week}
time_to_train =
reference__time_to_train*effect_of_schedule_pressure_on_time_to_train*effect_of_learning_from_incidents_on_time_to_train {week}
total_labor_time = Time_Per_Employee*total_employee {employee*hour/week*week}
total_required_labor_time =
required_labor_time_for_incident_analyzing+required_labor_time_for__LNG_dispatch+required_labor_time_for_maintenance+required__labor_time_for_repearing+required_labor_time_for_trainig+required_labor_time_for_LNG_filling {employee*hour/week}
effect_of_ce_in_use_on_dispatch_capability =
GRAPH(ratio_of_critical_equipment_in_use_to_total_critical_equipment)

(0.00, 0.00), (0.1, 0.135), (0.2, 0.26), (0.3, 0.405), (0.4, 0.565), (0.5, 0.715), (0.6, 0.835), (0.7, 0.91), (0.8, 0.975), (0.9, 0.99), (1, 1.00)

effect_of_ce_in_use_on_filling_capability =
GRAPH(ratio_of_critical_equipment_in_use_to_total_critical_equipment)
(0.00, 0.00), (0.1, 0.175), (0.2, 0.375), (0.3, 0.54), (0.4, 0.7), (0.5, 0.835), (0.6, 0.925), (0.7, 0.97), (0.8, 0.99), (0.9, 0.995), (1, 1.00)

effect_of_learning_from_incidents_on_maintenance_frequency =
GRAPH(learning_from_incidents)
(0.00, 1.00), (10.0, 1.00), (20.0, 1.00), (30.0, 1.02), (40.0, 1.04), (50.0, 1.08), (60.0, 1.16), (70.0, 1.29), (80.0, 1.40), (90.0, 1.47), (100, 1.50)

effect_of_learning_from_incidents_on_time_to_analyze = GRAPH(learning_from_incidents)
(60.0, 1.00), (64.0, 0.994), (68.0, 0.97), (72.0, 0.931), (76.0, 0.874), (80.0, 0.805), (84.0, 0.727), (88.0, 0.661), (92.0, 0.58), (96.0, 0.496), (100, 0.4)

effect_of_learning_from_incidents_on_time_to_train = GRAPH(learning_from_incidents)
(0.00, 1.00), (10.0, 1.00), (20.0, 1.00), (30.0, 1.00), (40.0, 0.98), (50.0, 0.935), (60.0, 0.845), (70.0, 0.75), (80.0, 0.625), (90.0, 0.46), (100, 0.295)

effect_of_schedule_pressure_on_maintenance_frequency = GRAPH(Perceived_Schedule_Pressure)
(5.00, 1.00), (5.50, 0.747), (6.00, 0.595), (6.50, 0.466), (7.00, 0.335), (7.50, 0.262), (8.00, 0.215), (8.50, 0.167), (9.00, 0.13), (9.50, 0.109), (10.0, 0.095)

effect_of_schedule_pressure_on_time_to_analyze = GRAPH(Perceived_Schedule_Pressure)
(5.00, 1.00), (5.50, 1.02), (6.00, 1.05), (6.50, 1.10), (7.00, 1.17), (7.50, 1.26), (8.00, 1.37), (8.50, 1.43), (9.00, 1.45), (9.50, 1.48), (10.0, 1.50)

effect_of_schedule_pressure_on_time_to_train = GRAPH(Perceived_Schedule_Pressure)
(5.00, 1.00), (5.50, 1.05), (6.00, 1.11), (6.50, 1.20), (7.00, 1.37), (7.50, 1.44), (8.00, 1.47), (8.50, 1.49), (9.00, 1.50), (9.50, 1.50), (10.0, 1.50)

effect_of_time_on_fatigue = GRAPH(Time_Per_Employee)
(30.0, 1.00), (33.0, 1.00), (36.0, 1.04), (39.0, 1.17), (42.0, 1.44), (45.0, 1.79), (48.0, 2.10), (51.0, 2.34), (54.0, 2.46), (57.0, 2.50), (60.0, 2.50)