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Title: Developing a systematic methodology to build a systems dynamics model for assessment of non-technical risks in power plants.

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Abstract:

In a dynamic business environment like the energy sector, power plants face several complex risks, including both technical and non-technical risks. These risks are not isolated, as their impact may affect a series of interrelated risks. Those risks may change with time, which in turn, makes the strategic decision-making process less effective. Understanding the dynamic behaviour of a complex system is very important to achieve a more sustainable overall performance of the power plants. Thus, it is important to further develop a systematic risk assessment methodology that could help to identify and analyse the interdependencies among risks and to understand the dynamics of these risks in complex systems. This paper develops a system dynamics (SD) methodology to support the development of risk assessment models. This paper highlights the environmental perspective. The first step to develop a SD model will be applied, while the final SD model will be discussed in another paper.

Keywords: system dynamic; risk assessment; failure mode and effect analysis; non-technical risks.

1. Introduction

In a modern society, where the complexity and competition are increased, the importance of assessing risks; particularly the difficult predictable one that has significant impacts on the economy are also increased (Radivojević and Gajović, 2014). Along with that, increasing complexity and dynamics of organisations in modern society leads to an increase in the level of risks. Accordingly, the risk management process has increased in various sectors (Verbano and Venturini, 2011). Risk management is an increasingly important driver of an organisations success. Thus, organisations have become more worried about risk. Organisations consider risks as a driver of strategic decisions which may affect the organisation's performance. Therefore, implementing a comprehensive risk approach that covers all risk types will increase organisation benefits. To achieve the organisation's objectives, there is a need to understand these risks. Hence, organisations need to understand and determine the overall level of risks within their process activities. Accordingly, risk management is a crucial part of the strategic management of an organisation (AIRMIC, ALARM and IRM, 2010) so, It's essential to understand and manage risks that affect the performance of an organisation (Garbuzova-schlifter and Madlener, 2016). The key part of risk management is the assessment step of significant risks. This step helps in achieving maximum sustainability value of the organisation, furthermore, helps in improving the understanding of the potential risks that may affect the performance of an organisation. Therefore, this step increases the organisation's success and reduces the failure, disruption or uncertainty of the organisation. Risk assessment is a key part of the decision-making process (AIRMIC, ALARM and IRM, 2010). Risks and uncertainties (ex. uncertainties in demand, fuel prices,…etc.) affect the long term planning (Alishahi, Moghaddam and Sheikh-El-Eslami, 2012). ISO 31000 Risk Management guidelines define risk as to the effect of uncertainty on objectives. (Moura Carneiro, Barbosa Rocha and Costa Rocha, 2013) describe the risks like the possibility of occurring undesired events and how while the risk management has been defined as the tool that has been utilised to various risks in machines or process. Risk assessment is a key activity (or sub-process) of the larger risk management process.

Risk assessment is a process to evaluate the occurrence and the severity of uncertain events. Current risk assessment approaches may not consider the dynamics of risks, as these may change with time. In addition, these current approaches may not consider the interdependencies of different risks. The evidence in the literature demonstrates that research opportunities exist to address the dynamic nature of interdependencies of risks along different stages of the life cycle of power plants the occurrence of potential risks can disrupt operations in a critical way, and cause significant losses (Li, Ren and Wang, 2016). (Pan, Korre and

Durucan, 2016). These risks could be catastrophic events like fire, floods or smaller events like failures and breakdowns. All these risks will cause revenue losses, reduction of production rates, affecting planned production goals, and these may lead to reduced reliability. These could also damage the reputation of the company.

Industries have various technical and non-technical risks. Non-technical risks are the risks that arise from the internal interactions of a business with a wide range of external stakeholders. These interactions include interactions with the regulatory, economic, public, social, and environmental and governmental organisation (Adekoya and Ekpenyong, 2016). Non-technical risks are risks rise from external stakeholders/environment(non-contractor) and cause undesirable deviation from the aim. Non-technical risks can be categorised into socio-economic risks, environmental, security risks (ex. human right abuses by project security), regulatory risks, political risks, commercial risks , organisational risks, human risks, and health risks (Ite, 2016). Industries have not to match between technical and no-technical risks. However, non-technical risks in the oil and gas industries are more complex. Thus, industries need more attention to risk assessment and management of the non-technical risks. Sources of non-technical risk can be categorized to legal security, stakeholders risks, local contracting, environmental, partners, contractor and communities (Adekoya and Ekpenyong, 2016). In addition, technical and non-technical factors is a crucial element in the successful implementation of a risk management process includes seven areas. Non-technical risks influence the decision-making process. non-technical factors include economic factors, environmental, employment, infrastructure, availability of resources, and regulatory (International Atomic Energy Agency, 2002).

Industries and organisations have focused more on the technical part over the years. However, the non-technical risks are the main cause losses in organisation performance, for example, the non-technical risks cause 75% of cost losses in projects (Ite, 2016). Furthermore, 65% of project failures raise from people, organisations and governance, 21% results from management process and procurement strategies, and 14% due to external factors (government intervention, environmental failures) (Adekoya and Ekpenyong, 2016). On the other hand, these types of risks can't quantify easily (Ite, 2016). Generally, if non-technical risks are managed effectively, the overall risks can be reduced. effective management of non-technical risks contribute to better returns on investment and achieve sustainability for organisations (Ite, 2016). Effective asset management decision-making is an essential part to increase the organisation value (IAM, 2015).

Understanding the nature of system interdependencies plays a crucial role in minimising the probabilities and consequences of cascading risks in interdependent systems (Katina *et al.*, 2014). To be sustainable, a balance between the economic, environmental and social perspectives in the decision-making process are required (Ite, 2016). To analyse long term effects, a dynamic model to assess risks in the long term is essential. Due to the complexity and the dynamic nature over time of systems, the risk assessment and analysis in a complex system is challenging furthermore, the available risk assessment tools can't consider the interdependency through risks which mean that the behavior of the system can't predict (Jamshidi et al., 2018). Thus, Industries need more risk assessment for effective identification and management of non-technical risks where technical and non-technical risks will continue to increase significantly in industries (Ite, 2016). Similarly, for moving to a sustainable energy system, a method that recognises the complexity of energy systems in relation to technological, social, environmental, and economic perspectives are required (Bale, Varga and Foxon, 2015).

Various risk analysis approached are available to assess risks. However, these risks don't talk into account the dynamic nature of risks or feedback loops, furthermore, can't quantify the full impact of various risks. thus, these tools are inefficient to assess the actual influences of risks. Where most of these tools assess the risks from a qualitative perspective. While SD approach has the capability of risk quantification of the full impact of various risks and consider the direct and indirect effects of each risk through the feedback loop analysis thus each impact of risk can be quantified (Nasirzadeh, Afshar and Khanzadi, 2008). Lack of knowledge regarding cause-effect makes the risk assessment process as a difficult process using traditional methods (Jensen and Aven, 2018).

The available risk assessment models focus only on the technical part (operational level). Industries have various technical and non-technical risks. Non-technical risks are the risks that arise from the internal interactions of a business with a wide range of external stakeholders. These interactions include interactions with the regulatory, economic, public, social, and environmental and governmental organisation (Adekoya and Ekpenyong, 2016). Non-technical risks are risk rise from external stakeholders/environment (non-contractor) and cause undesirable deviation from the aim. Non-technical risks can be categorized to socio-economic risks, environmental, security risks (ex. human right abuses by project security), regulatory risks, political risks, commercial risks , organisational risks, human risks, and health risks (Ite, 2016). Industries have not to match between technical and no-technical risks. However, non-technical risks in the oil and gas industries are more complex. Thus, industries need more attention on risk assessment and management of the non-technical risks (Adekoya and Ekpenyong, 2016).

On the other hand, the current risk assessment and management research focus on assessing and managing the low probability-high impact systemic risk and ignore the low impact risks (WEF, 2013). The complexity of systems is considered as a source of deviation from normal behaviour and source of unpredictable system behaviour due to the interaction between the entire elements. The traditional sequential models don't consider the entire interactions thus, are not suitable for analysing complex systems (Bouloiz et al., 2013). Accordingly, there is a need to develop a framework for assessing various types of risks specifically, at the strategic level. The most challenging problems in building complex systems today arise in the interfaces between components (Leveson, 2000).

The current risks assessment tools ignoring outcomes of uncertainty and the outcomes of dispersion (Grimsey and Lewis, 2002). Current risk assessments tools typically use various models to deal with risks, but these approaches don't take into account the internal interactions between risks (International Atomic Energy Agency, 2002). Similarly, there are many risk analysis methods such as structural decomposition and expert investigation method. These methods didn't take the linkages (interaction) between risk factors into account (Wan and Liu, 2014). Traditional risk models are ineffective in dealing with human error and decision- making in complex systems and environment (Komljenovic, Loiselle and Kumral, 2017).

On the other hand, a complex system is a network of a number of components that interact with each other. To describe these interdependencies, conceptual, mathematical, and computational tools are developed. Organisational mapping of complex systems includes seven areas the first part is the historical roots for the complex systems (systems theory, nonlinear dynamics, and game theory) and the second part is more studied area (evolution and adaptation, collective behaviour, pattern formation, and networks) (Sayama, 2015). Complexity is the difficulty of predicting system behaviour. The main challenge of complexity in a risk assessment context is that the knowledge of the overall system is limited even the knowledge of sub-activity (sub-system) is strong. Current risk analysis approaches are based on models reflecting the knowledge of the sub-activity and ignoring the overall activity (Jensen and Aven, 2018).

Energy is one of the most significant factors of national socio-economic strength. The effects of environmental, economic, and social perspectives of energy are key to the development of all societies (Azadeh and Vafa Arani, 2016). Thus, given the importance of energy for societies. Power plants failures may cause significant financial impacts. For example, thermal power plants in Malaysia reached losses of $43M USD due to operational availability in a period of 2.5 years (Wai Foon and Terziovski, 2014). In addition, Spada et al. (2018) state that accidents in the energy sector have short-term impacts on energy security, where catastrophic events may lead to energy policy changes with the purpose to increase long-term energy security. Risk management is very important to support the successful and sustainable performance of the energy sector, and more specifically, of power plants. Energy sector requires more significant integrated management for technical and non-technical risks (Ite, 2016).

As stated above, it is clear that the available risk assessment models focus only on the technical part (operational level), not to the strategic level additionally, the current risk assessment research focuses on assessing and managing the low probability-high impact risk and ignore the low impact risks. Furthermore, the current research doesn't consider the interdependencies and the dynamic nature of risks over time which will affect the long term of organisations. Thus, there is a need to develop a framework for assessing various types of risks specifically, the hidden and the non-technical risks at the strategic level. This research will provide and generate a strategic system dynamics risk model to show how the systematic approach help in developing the framework.

This paper presents a systematic methodology to build System Dynamics (SD) models to assess non-technical risks in the energy sector, specifically applied to power plants. A strategic approach (long-term view) will be applied to the identification and assessment of non-technical risks. This will ensure a risk assessment for a more sustainable performance of the organisation. This kind of system dynamics model can help decision makers (e.g. risk managers) to understand the interdependencies of key risks in different stages of the life cycle of an energy plant and the behaviour of those risks over time. In this way, managers will be better informed to design effective risk management plans.

The paper initiates with a literature review on complexities in power plants, system dynamics approach, system dynamics applied to the energy sector, principles of process modelling, the proposed methodology to build a system dynamics model for risk assessment is explained in section 3. Various risks perspectives to assess risks and applying the methodology to environmental perspective are clarified in section 4. A discussion on the benefits of the approach is included in the last section. This research contributes to the development of an SD methodology to support risk assessment as a strategic decision-support tool.

2. Literature Review

2.1 Power Plants as a Complex System:

Power plants are considered as complex systems where catastrophic effects will have resulted from failures and risks (Orme & Venturini , 2011) along with, Sterman,(2000) describes the main characteristics for complex systems as Dynamic and changes over time; tightly coupled, which leads to feedbacks ; Nonlinearity due to interacting various factors in decision making; Time delays in feedback (trade-offs) and Policy resistant. In the same context, (Kang and Golay, 2000) confirm that it cannot be decomposed the system complexities in a systematic way and expound the complex interrelationships between various variables within the system. Decision-making regarding risks is very complex thus, SD approach will be applied in this research to help in understanding the behavior of the system in the long term at the strategic level (Jonkman, Van Gelder and Vrijling, 2003). From engineering and economics disciplines, the energy sector has been dominated by hard modelling approaches (Dyner, 2000). The interactions in complex systems vary at various layers of the hierarchy (Efatmaneshnik, Ryan and Bradley, 2016).

Complex systems are modelled as a hierarchy of organizational levels. For understanding the complex environmental, social, and economic factors contributing to poor decision making and providing a policy to improve the risk decision-making process, SD can be used (Komljenovic, Loiselle and Kumral, 2017). Complexity is the uncertainty of confidence in risk assessment (Johansen and Rausand, 2014).

In the current system dynamic literature, a hierarchy has received little attention. Furthermore, SD has two crucial problems firstly, it is misapplied and secondly, people have misinformed the goals, the limitations and the expected outcomes. On the other hand, SD needs good communication with the public and technical people ((Barlas, 2002); (Featherston and Doolan, 2012)). Hard modelling approach like SD is needed if the level of uncertainty increase (Dyner & Larsen, 2001). In complex systems, policy makers can assess the probabilities but not the certainties of particular outcomes (Dekker, Cilliers and Hofmeyr, 2011). At the strategic level, there is very little application of hard modelling methods where uncertainties are enormous and the risk is high at the strategic level, therefore, it is difficult to depend on mathematical modelling for strategic decisions. Along with that, (Kotir et al., 2016) affirm that offering a learning tool for decision makers for improving their understanding of the long term dynamics behavior is the main aim of the modelling process.

2.2 System Dynamics as a Methodology to Model Complex Systems:

A complex system can be modelled by Discrete Event Simulation (DES), Agent-Based Simulations (ABS) and System Dynamics (SD). These approaches are utilised to improve the decision-making process of complex systems (Konstantinos Mykoniatis, 2015). The main used approaches to deal with complex systems are SD, and Agent-Based Modelling (ABM) (Ding et al., 2018) (Kunc, Morecroft and Brailsford, 2018).

SD is a top-down approach allows for the construction and validation convenient model. SD is an approach to visualise, analyse, and understand complex dynamic feedbacks. The core of this method is the feedback structure with high order, loops and nonlinearity. SD is based on the accumulation of flows in stocks. SD doesn't depict individual differences and can't provide full understandings of how the emergent macro phenomena can be affected by the microscopic stakeholders' behaviour (Ding *et al.*, 2018). SD is applied to analyse problems from a comprehensive thinking and macro perspective. SD can be applied to analyse a dynamic evaluation process under various states. SD can't understand explain the behavior of the micro-behaviour system because SD ignoring the relationships between the macro and micro behaviour. SD focuses on the feedback and relationships (flow) which simulate the behavior of a SD. SD is proper for analysing the interactions between various elements. SD is not considering spatial interactions. SD can over various levels of aggregation. Thus, SD has the highest abstraction level. SD is not proper for a complex system with unknown structures. Because it is based on equations to quantify the relationships between variables.

SD and Agent-Based Simulation (ABS) are the two most commonly used modelling methods in complex systems. SD is a continuous time simulation model and focusing on macro-level problems (Kunc, Morecroft and Brailsford, 2018); (Ding *et al.*, 2018). SD approach mapping a problem onto a generic structure that helps-understanding the causal causes and the system's behaviours' (Greasley, 2009). The Discrete Event Simulation (DES) replicating the structure of the systems and allowing performance to be measured under various scenarios (Greasley, 2009). Simulation is categorised into a continuous and discrete event. Continuous simulation is utilised to model systems that vary continuously with time. SD has applied this approach then it becomes a crucial tool for analysing human-based systems and enabling organisational learning ((Seng, 1994); (Forrester, 1961); and (Greasley, 2009)). The human systems in SD can be described in terms of delays and feedback.

Discrete event simulation is concerning with modelling of systems that can be represented by a series of events. The simulation defines each event and moves from one to the next. SD understanding why things happen by identifying the structure and behaviour. The structure leads to certain types of behavior. SD modelling the transformation of resources as a sequence of linked (levels/stocks). However, the system behavior is difficult to predict, due to the delays and feedback loops. SD approach models at a high organisational level and aggregates the movement of a number of individual items into a flow rate. Furthermore, SD revealing statistics of measures at an aggregate level and plotting to observe and understand the behaviour of the system over the long-term periods due to the long time scales of operating feedback loops in strategic systems (Greasley, 2009). SD providing a methodology to help business and government organisations in strategy development, analysis dynamics process, and in policy options. SD can capture the factors that affect the system behavior in a causal loop diagram. SD shows the links and feedback loops through the elements in the systems. SD software allowing a policymaker to adjust parameters of a system, add new linkages and feedback loops, and rearrange (structure) components of the system. Thus, policymakers can observe system behavior under various scenarios and conditions. SD is proper to model continuous processes, systems where behavior changes in a non-linear way, SD is used in strategic policy analysis. SD models continuous processes and human behavior plays a crucial role in SD models and this is more difficult to quantify (Sweetser, 1999). SD dealing with "deterministic complexity" and the unfolding future is significantly pre-determined by enduring feedback structure (Kunc, Morecroft and Brailsford, 2018). SD is recommended more for understanding complex systems while ABS for learning behavior. SD is applied to explore systems at a high aggregation and abstraction level (Konstantinos Mykoniatis, 2015). SD is applied on meso to macro level for fewer details of abstraction. SD is recommended for strategic complex problems, macroscopic policy, and aggregated perspectives. SD is applied to gain in-depth understanding and learning of complex systems behavior in the long term. SD focuses more on the flow and dynamic feedback behavior of a certain complex scenario and is applied in policy making at the strategic level (Konstantinos Mykoniatis, 2015).

Discrete events simulation (DES) is used to model strategic issues, as well as non-linear relationships, feedback loops, and continuous systems. SD is focused more on the analysis of systems. In SD, the structure is crucial in determining system performance. SD is less proper to provide a detailed representation of a system DES simulation replicating the structure then the behavior is identified. The structure can be replicated by collected data on process flows, demand patterns, and process times. The model provides a useful suitable prediction of real system performance. Discrete-event simulation describing the system behavior by modelling their stochastic nature. However, the overall effect of changes to the system is hard to predict due to the linkages between processes. DES, modelling operational process (ex. manufacturing service facilities). The operational performance measures (ex. production output levels and customers served) are needed. It is not proper to analyse decision making in operations strategy. Discrete-event simulation is moderating tool between functional areas (ex. marketing and operations) and helping change at a strategic level. Building a process map is the first step in discrete event simulation. In this step, the logical relationship between the elements in the process can be defined. Discrete-Event simulations modelling humans a resource rather than reflecting their behavior on performance. Discrete event simulation taking the known structure of a system (ex. the process flow) and trying to discover how it behaves under various conditions using scenario analysis. Discrete-event approach providing performance measures at a discrete level because it is able to carry information about each entity within the model ((Greasley, 2009); (Sweetser, 1999). Discrete-event simulation dealing with “stochastic complexity” and the unfolding future is partly and significantly determined from multiple interacting random processes (Kunc, Morecroft and Brailsford, 2018). DES replicating the performance of a system and providing a policy-maker insight into if the system is modified, how that system can perform. DES model needs accurate data on how the system operated in the past, or accurate estimates on the operating characteristics of a proposed system (Sweetser, 1999). DES is focused more on models’ particular processes, not entire systems. In DES, the structure is important and accurate historical data or estimates of future performance are required to populate the model and produce statistically valid results. DES models discrete and reflecting analysis of historical data (Sweetser, 1999).

Discrete Event Simulation (DES) is applied on meso to micro level for more details of abstraction. ABS approach is recommended for strategic complex problems, interacting entities, spatial distributions, and heterogeneity. DES is applied for stochastic variations and linear relationships occur in complex systems. DES is more suitable for queuing systems or to assess and compare alternative scenarios and is described as a process-centric approach, furthermore, it is applied to help in decision and prediction making in operational and tactical organisational levels. DES is suitable to capture emergent phenomena and identify interactions and operations of agents (Konstantinos Mykoniatis, 2015).

Agent-Based Simulation (ABS) is applied to study the emergent phenomena of diverse structure (Konstantinos Mykoniatis, 2015). ABM combines a time dimension with a space dimension. ABM needs a lot of details to simulate over a long period of time due to the large numbers of parameters and rules. These parameters are difficult in the identification and to determine the prediction robustness, extensive sensitivity analysis is required. However, ABM can process a relatively small number of agents due to ABM sensitivity od the small variations. In addition, ABM ignores the interactions between macro factors and agents. ABM considering the spatial factors and ignoring the feedback relationship of various economic and social factors. ABM capturing the final level of detail. Thus, ABM can be applied at lower abstraction levels. ABM representing the complex systems based on a certain number of simple rules (Ding *et al.*, 2018)

System dynamic is a system modelling and dynamic simulation approach for capturing the dynamic complexity in socio-economic and biophysical systems (Guo and Guo, 2015). The aim of SD is in identifying how the model structure and decision policies help in producing the observable behaviour of a system to implement decision policies (Qudrat-Ullah and Seong, 2010). System dynamic is a computer-aided approach to policy analysis and design which has been applied to dynamic issues in complex systems. To organise available information into computer simulation models; SD utilises concepts from the feedback control field (Forrester, 1991). Furthermore, SD is an effective tool that analyses various systems to a qualitative and quantitative approach (Sisodia, Sahay and Singh, 2016). SD offers a conceptual (qualitative) and quantitative approaches for simulation complex interdependencies; nonlinearity interactions and feedbacks among systems variables

(Elsawah et al., 2017). SD enables modelling interactions among systems and of various sub-systems models. SD enables representing models as a feedback system to mimic the entire interactions through the system. SD can be applied for complex models, contain many feedbacks, and highly dynamic (Thompson and Bank, 2010). SD helps in understanding the complex systems using the feedback loops and stock-flow diagrams (Liu and Zeng, 2017).

Along with that, SD is a powerful tool for understanding the dynamics of decision making in complex systems over time, particularly feedback. SD focuses on modelling the changes in the behavior of a system ((Nabavi, Daniell and Najafi, 2017); (Aslani, Helo and Naaranoja, 2014); (Shafiei et al., 2015); (Park, Kim and Jung, 2014); (Kotir et al., 2016); and (Sterman, 2000)). Similarly, SD is a strategic tool for analysing the effects of various policies and scenarios on the system's behavior (Dastkhan and Owlia, 2014). policy-makers and researchers have extensively used SD in management and social systems (Anand, Vrat and Dahiya, 2006). System dynamics is a suitable tool to enhance and accelerate organisational and managerial learning under the complexity of competitive technological innovation (Lomi and Larsen, 1999). For improving the provision of decision support process; SD can be integrated with MCDM methods (Elsawah et al., 2017).

SD is an analysis method which combines between the qualitative and quantitative analysis and used for nonlinear complex systems to understand the underlying behavior of these systems over time ((Liu and Zeng, 2017); (Forrester, 1961); and (Wei et al., 2012)). SD shows how complex system behavior change over time. SD deals with two aspects: a dynamic study of system behavior and systemic study of the feedback principle (Bouloiz et al., 2013). SD helps in capturing the internal feedbacks and time delay which affect the entire system behavior (Xi and Poh, 2014). SD is applied to analyse various systems economic, social, and environmental systems (Park, Nepal and Dulaimi, 2004).In addition, SD focuses on the policies and dynamic behavior of the system which is the crucial strategic feature of the top management (Coyle, 1996). SD is a modelling approach allows of representing the system in terms of feedback (Bouloiz et al., 2013). SD is applied to support decision-making processes by utilising different tools. These tools are qualitative such as causal loop diagrams and quantitative by using the mathematical language to identifying the relationships between variables (Barnabè, 2011). SD is a tool used to define different strategic issues and different kinds of risks (Lomi and Larsen, 1999).

SD differs from other modelling approaches which deal with steady-state solutions. SD simulates the dynamic response and system behavior with time. To model feedback interactions, the dynamic behavior of the system is created by following the changes in stocks and flows values over time (Elsawah et al., 2017). System dynamics is the theory of system structures (studying the causal interactions between system components) (Bouloiz et al., 2013). Variables of system dynamics have been categorised into auxiliary variables, stock, and rate. The behaviors of systems have been saved in the system memory (the stock variable). While the input and output of the (memory) stock variable and the rate variables are obtained by the auxiliary variable. Stock variables and delays cause dynamics of the system. Delays (delays include information delays and physical delays) happen when a variable does not affect another variable. SD has some characteristics such as: considering both short and long terms effects of variables in the modelling of system dynamics. All dynamics arise from the interaction of positive (reinforcing) loops; and negative (balancing) loops ((Azadeh and Vafa Arani, 2016); (Meyers, 2009); (Meyers, 2009); (Barnabè, 2011); and (DE LA BARRA, 1989)). The positive loop amplifies what is happened in the system and generate exponential growth or decay to reflect the dynamics' behavior. The negative loop tries to respond to the trends within a system and tries to make a balance ((Barnabè, 2011); (DE LA BARRA, 1989)). However, SD depends on quantitative data for generating feedback and building the model (Luna-Reyes and Anderson, 2003).

System dynamics model is a powerful tool for understanding and analysing the system behavior and improving the knowledge about companies, competitors and market. Furthermore, helping in build effective policies of management and develop the most suitable decisions for companies ((-Bach and Čerić, 2007); (Morecroft, 2015); (Yeo, Pak and Yang, 2013); (McLaughlin and Olson, 2017); and (Dastkhan and Owlia, 2014)). The usefulness of simulation models is on the ability of these models to link system behavior patterns with the system structures. SD as a policy model; is built to analyse policy and assigned the possible future scenarios, and management purposes (Qudrat-ullah, 2012). However, SD can be utilised to collect data, stakeholder participation and thinking and learning (Elsawah et al., 2017).

Developing a SD model needs a wide range of sources of knowledge. This knowledge covers qualitative and quantitative data from experts, stakeholder groups, policy makers or practitioners, document analysis; Interviews, workshops and focus group (Elsawah et al., 2017). It cannot be decomposed the system complexities in a systematic way and expound the complex interrelationships between various variables within the system (Kang and Golay, 2000).

Complex behavior of a system emerges from the interaction between the system components (Dekker, Cilliers and Hofmeyr, 2011). Establishment of a causal relationship between the variables is the core of the system dynamics model. CLD is used to analyze the complex interactions between the system's internal variables, the polarity of the causal link can be increased or decreased (Wan and Liu, 2014). The relationship between variable (A) and variable (B) can be represented by an arrow. The direction of the arrow starting from the cause variable (A) and directed to the effect variable (B). If the relationship between variables (A) and (B) is positive (+) this means that an increase/decrease in the variable (A) causes an increase/ decrease in the variable (B). If the relationship between variables (A) and (B) is negative (-) this means that an increase/ decrease in the variable (A) cause a decrease/ increase in the variable (B). Thus, the feedback can be negative or positive. The variables in the (positive) loop (reinforcing loop "R") increase or decrease. Variables in the (negative) loop (balancing loop) stabilising with time. A relationship between variables (A) and (B) is depicted in Figure 1.

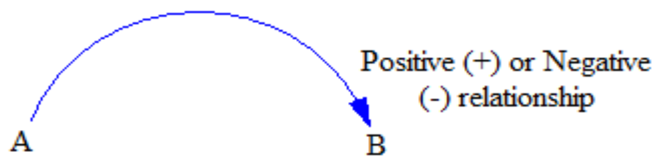

Figure 1 : Cause-Effect Relationship Between Variable (A) and (B)

2.3 System Dynamics Applied to the Energy Sector

System dynamic approach has been widely applied to research on capacity expansion mechanism, performance improvement and policy analysis of energy industry (Pan, Liu and Li, 2017a). SD is applied to study and analyse the impact of the climate changes on cooling systems, efficiency and the power production of German thermal power plants and quantifies possible output reductions of these power plants in mid and long terms (Hoffmann, Häfele and Karl, 2013).

In contrast, SD is used to construct a simulation model of China's PV power development and they consider the economic and technical factors. SD method cannot only model system's real behavior, but also clarify the relationship between main variables within the system (Guo and Guo, 2015). As well as, SD is applied for China's oil industry from a supply chain aspect and they concentrate on the issues related to the over-capacity problem and energy security issues and also, they develop a system dynamic model for oil supply chain analysis (Pan, Liu and Li, 2017b).

Energy is one of the most significant factors of socio-economic strength. Effects of environmental, economic, and social energy are obvious facts in all societies (Azadeh and Vafa Arani, 2016). In the electricity sector, system dynamics models have been using to get the interaction between the variables of the electricity system such as electricity generation cost, investments, demand, production capacity, environmental sensitivity, pricing of electricity, and allow of the inconsistency in the elasticity of substitution through the competing electricity generating technologies nuclear, hydro, and thermal. The national energy policy evaluation, energy investments and uncertainty, conservation policy analysis, inter-fuel substitution, privatisation of electricity industry, energy efficiency and electricity substitution, energy consumption analysis, and electricity-related emission assessments have been studied. The complexity of the system comes from interactions of dynamic and non-linear variables. Dynamic variables have been including. Various stocks of electricity generation capacity, fuel supply and price dynamics, regulatory regimes, and advances and challenges in technologies for electricity generation where this complexity makes the decisions of sustainable policy as a difficult task (Qudrat-Ullah, 2013).

SD is a suitable tool to simulate complex energy systems and analyse their dynamics (Dastkhan and Owlia, 2014). SD is utilised for constructing a simulation model to understand the behavior of the photovoltaic (PV) sector in Spain, which is a very complex system with a response, feedback and long-time frame (Movilla, Miguel and Blázquez, 2013). SD deals with internal feedback loops and time delay which affects the behavior of the system.

A system dynamic model of China's oil supply based on a simplified framework is established. A hybrid system dynamics-mathematical programming approach is developed to design a biodiesel supply chain from biomass areas to consumption markets (Pan, Liu and Li, 2017b).

System dynamics is considered as one of the most powerful tools for strategic planning. SD is a tool for system thinking that helps researchers to build complex integrated problems (Azadeh and Vafa Arani, 2016). To overcome the drawbacks of the current risk analysis methods, SD approach is applied to analyse the investment risks in renewable energy which helps investors in understanding which risks are more probable to occur then a suitable scientific decision can be taken (Liu and Zeng, 2017). In the same energy area, SD model is built to study and analyse the effect of using a circular economy of the coal power and cement in China, where analysing the effects means, how circular economy can reduce the emission and the pollution of the plant and increase the profit. However, parameters of variables in SD have been taken from enterprise and government survey data. The results of the SD model show that solid waste and waste heat recycling can make massive profits for coal power and cement plants (Dong et al., 2017).

SD method is extremely relevant for sustainable development research, as the integration of various sectors and ecosystem-based management in larger models have been allowed (Deenapanray and Bassi, 2015). SD model is a powerful tool for understanding and analysing the system behavior. Furthermore, helps in building effective policies of management and finding the most suitable decision for companies (-Bach and Čerić, 2007).

SD has been applied to analyse various systems economic, social, and environmental systems (Park, Nepal and Dulaimi, 2004). SD is applied in the various area (social science and engineering) (Thompson and Bank, 2010). System dynamics is a tool for energy systems analysis and is suitable to model complex environments where the interactions of the environment and socio-economic variables are clearly demonstrated (Xiao et al., 2017).In addition, SD is a crucial part of modelling the influence of feedbacks inherent in energy systems where this helps in providing appropriate energy policies (Mutingi, Mbohwa and Kommula, 2017).

2.4 Principles of Process Modelling

As mentioned before, the developed model to assess none-technical risk in this research includes nine risk sub-systems as illustrated in Figure 2. Each sub-system includes various risk variables. In this paper, the environmental sub-model will be developed and explained by applying the developed SD stages that are explained in the research methodology section.

3. The Improved Methodology to Develop System Dynamics models

The aim of system dynamics modelling is to improve the understanding process of complex systems regarding companies' performance which is related to the internal and operating structure and policies. This complexity generates through the interactions between system variables (in our research between various risk variables).

The developed methodology in this research is based on literature review and data collected in power plants in the Middle East through a questionnaire survey and focus groups interviews. The details of the collected data method will are clarified in future in another paper due to limitation where this paper focuses only, on describing the improved stages to develop a SD model..

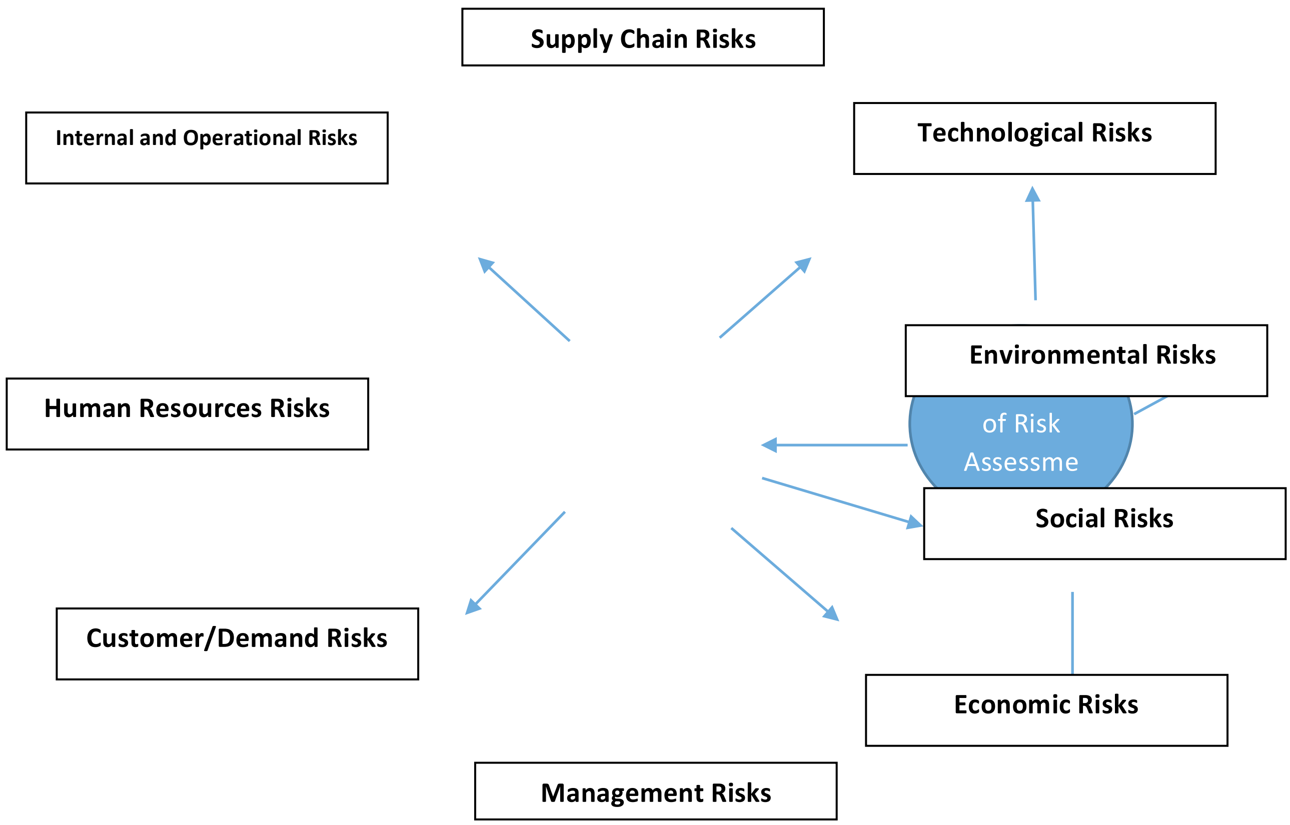

Figure 2 : SD Model Structure for Non-Technical Risks

To construct a SD model, typical stages are followed as described in the literature. The current literature shows that the applied steps to develop SD model are very general, not clear and missing many activities required to develop a robust model with minimum errors and time. Furthermore, SD illustrates the structure of the decision-making process but not the seen structure on a personnel organisation chart (Forrester, 1992). However, in this research, systematic (step-by-step) and enhanced and clear stages for developing a robust SD model are clarified as shown in this section. SD is a complex graphical modelling technique to represent and understand the behavior of complex systems over time. To enhance the understanding process, SD utilises various qualitative tools such as Causal Loop Diagrams (CLD), Stock and Flow Diagrams (SFD) and system archetypes.

In the decision-making process, management is the process to convert information to action. The decision-making is the process of converting the fluctuating flows of information into control signals that determine rates of flow in a system. The policy (or decision rule) is a description of how the information is converted into actions in the decision-making process. However, the policy is a rule showing the day-by-day operating decisions, which are the actions taken. Thus, the policy gives the relationship between information inputs and decision flows. Depending on the definition of the management term, the success of management based on the selected information and on the conversion process. In formulating the policies in modelling (the rate equations), decisions are generated from the available variables at the decision points. In the dynamics of information feedback systems, humans are not powerful problem solvers therefore, using a simulation software will help in understanding the problem (Forrester, 1992).

However, practitioners opinions and judgments on methodologies are vital for improving the quality of the model results (Elsawah et al., 2017). Modelling as a continual process of iteration, can’t build by starting the first step then continuing in the sequence of activities (Sterman, 2000). Most practitioners develop the model in a single stage afterwards, test the model where this will not provide a high quality and robust model that reflects the reality (-Bach and Čerić, 2007). For example, Yeo et al., (2013) formulate SD steps from (Ahmad and Simonovic, 2000) framework, these two frameworks are covered general steps to develop a SD model and missing many stages that are required to build a clear and robust model. Thus, in this research, the mentioned issue will be resolved by building a robust SD in clear and deep analysed stages. This will help in understanding the model behavior and build more reliance model with high accuracy and minimum errors. According to Forrester and Coyle’s, there are no clear steps to show the validation process (test the mode, verification and the final validation). In addition, the conceptualisation, CLD and SFD stages are omitted in Forrester's chart. These stages should be clear enough to trace the error in the developed model and reducing any accumulation of errors. To develop a SD model, four steps should be followed according to (Forrester, 1961) articulating of the problem (define the aim of the model and identify the components), describing the causal relationships between these components through a causal loop diagram or influence diagram, developing the stock and flow diagram, and finally, formulating simulation model.

The current methodologies are not systematic. In addition, the current steps are not clear; and provide a general idea for the final developed model without giving any clarification of how each sub-model is constructed where the SD deals with complex systems and breaking down step is required to build a robust model and increase the accuracy and the confidence in the developed model. However, the improved SD simulation process for this research can be summarised as the following systematic stages which have been described below.

As shown in Figure 3, the required phases to develop a SD model include four main stages which are:

1. Model conceptualization (problem identification; determining the system boundary; creating sub-models from the main causal loop diagram).
2. Model Simulation (deploying equations for the step-by-step model (systematically); model expanding after the first step of verification; Re-conducting the evaluation tests; test sub-model; developing the final stock-flow diagrams; model formulation; model simulation software).
3. Model Validation (model test; model verification; model validation).
4. Model Implementation (recommendation of implementation; implementation plan, model implementation, policy design and evaluation).

However, there is no optimal procedure to build a useful model (Barnabè, 2011). To overcome the limitation in the current structure of developing a SD model, the following clear and systematic stages can be applied to develop any system dynamic model.

To overcome the limitation in the current structure to develop an SD model, the following clear stages can be applied to develop a system dynamic model. However, variations can be found depending on the nature of the problem but generally, the main clear stages of modelling are clarified and explained as follow:

1. **Problem Identification (Define simulation objectives)**

The available information is a crucial step to build a SD model. From the available data, the problem can be identified which reflects the difficulty in the real system. The available data includes the current literature review and any mental data that can be acquired by survey questionnaires or interviews. The success of SD modelling depends on the identification of the importance and purpose of the model (Forrester, 1991). Thus, the first stage to develop a SD model is to define the problem and the aim for developing the model ((Aslani, Helo and Naaranoja, 2014); (Park, Kim and Jung, 2014)). In this step, the dynamic issue of risks impacts of power plants performance will be studied. The effects of various risks on the availability, efficiency and operational and maintenance cost of power plants have been studied. For example, 7% of the revenue cash flow is consumed by operation and maintenance activities of the plant. 8% of these costs result from unplanned (forced outages) maintenance.

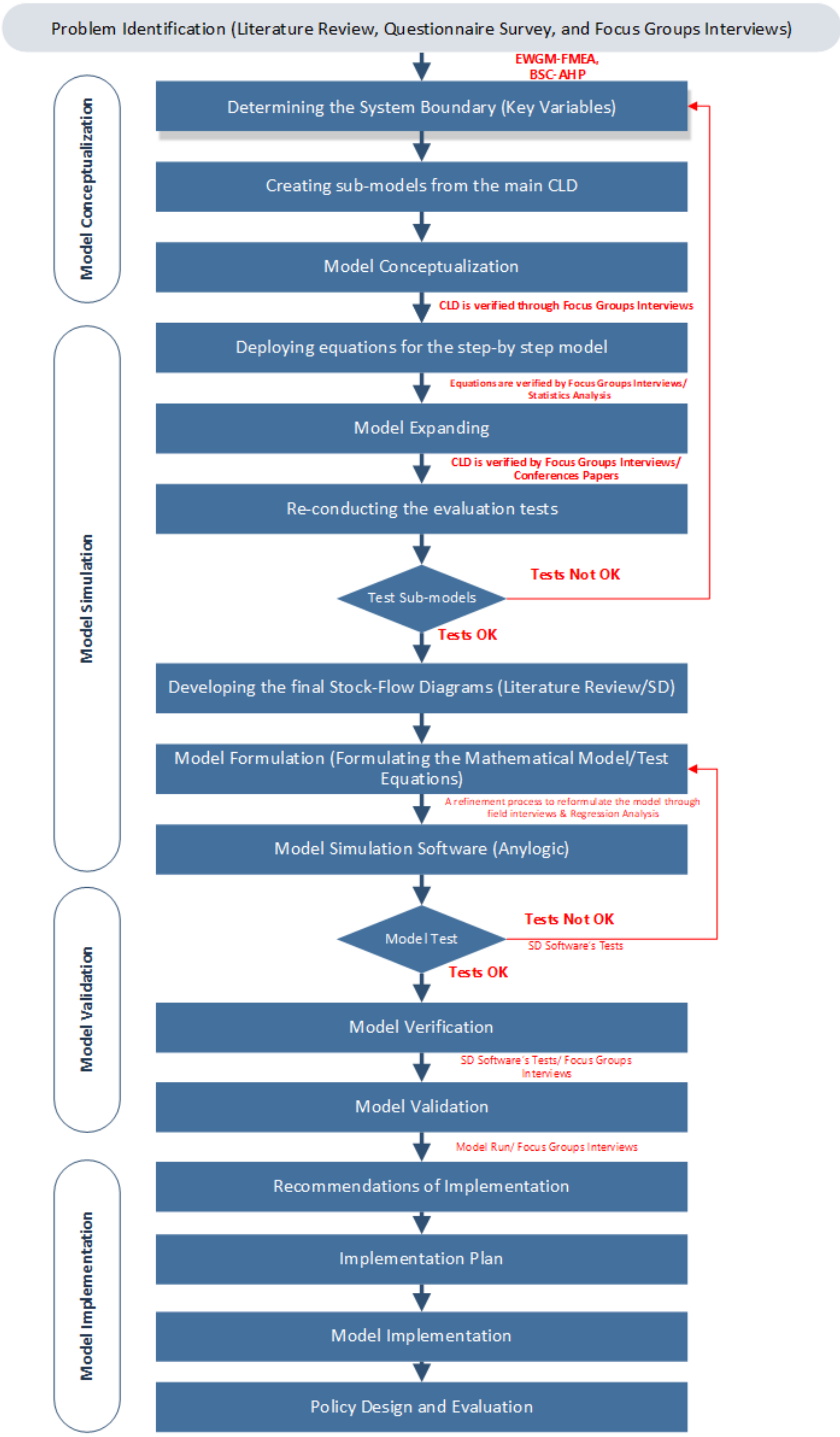

Figure 3: SD Model Developing Stages

The unplanned events will cause a significant impact on plant profitability due to the high repairing cost of these activities. Accordingly, the profitability and insurer's competitiveness of an organisation can be enhanced by improving the risk management process. Therefore, alleviating risks will reduce the insurance cost and help in the continuity of the operating plants (Orme and Venturini, 2011). Unplanned (forced outages) accident will cause of revenue loss and damage the business operation reputation and credibility. In addition, assess the impact of risk on performance, broad risk measures have been used such as availability, probabilistic safety assessment, reliability, component unavailability, total accident frequency, downtime period (Mohammad Hadi Hadavi, 2009). In the same context, factors that have been affected by risks and impacted on the performance of power plants can be efficiency, availability, degradation, and outages (NOH, 2012).

2. Determining the System Boundary (Key Variables)

Formulation of the dynamic hypothesis including a clear determination of exogenous and endogenous variables (determining the system boundary) (Elsawah et al., 2017). After the problem is identified, the second step to build the system dynamic model is to determine the system boundary. A model boundary summarises the scope of the model by determining the endogenous variables, the exogenous parameters and the excluded variables ((Ackermann et al., 2007); (Wei et al., 2012); (Kotir et al., 2016); and (Luna-Reyes and Anderson, 2003)). The SD can be categorised to exogenous parameters; endogenous variables; and the flow of the system behavior with time (DE LA BARRA, 1989).

Exogenous variables are the variables "arising from without" which means from outside the system boundary interaction ((Sterman, 2000); (Ackermann et al., 2007)). Exogenous parameters are parameters outside the system. These parameters are constant and will not change their behavior over time within the model (DE LA BARRA, 1989). Exogenous parameters inputs are needed to show how the variables change from time to time (DE LA BARRA, 1989). The Exogenous parameters are external parameters that affect different subsystems but are not influenced by them (Dastkhan and Owlia, 2014).

On the contrary, endogenous variables are the dynamic factors that arise within the system (DE LA BARRA, 1989) and generating the dynamics of a system through variables interaction ((Sterman, 2000); and (Ackermann et al., 2007)). However, if the endogenous variables are more; that indicates the “model generates interesting dynamic behavior from within the system’’ (Pasaoglu Kilanc and Or, 2008).

In SD, the focusing is on endogenous explanations with a small number of exogenous factors. There are many mapping system structure tools help in constructing the system boundary and represent the causal loop structure such as model boundary diagrams, Causal Loop Diagrams (CLD), and Stock and Flow Diagrams (SFD) (Ackermann et al., 2007). However, the hardest steps in successful modelling are identifying the system boundary and the degree of aggregation (Ackermann et al., 2007).

3. Creating sub-models from the main CLD

Breaking down the CLD structure to create the first simple model by considering one stock and flow while other indicators can be considered as variables or parameters. Risk Indicators can Identify potential sources of complexity, determine the critical sources of complexity, indicate confidence in risk evaluation. Thus, risk indicators help to acknowledge, reduce, and describe complexity in risk assessment (Johansen and Rausand, 2014). CLD can explain how flows influence stocks while SFDs give more detailed and quantified the graphically the relationships between stocks and flows (Lane, 2016).

4. Model Conceptualization

After the problem has been identified, the main variables that have a significant effect on the performance have been determined (Aslani, Helo and Naaranoja, 2014). The conceptual model is the mathematical/verbal representations (mimic) of the problem. Is developed through a modelling and analysis stage (Kleijnen, 1995). Model conceptualisation focuses on the model scope (Elsawah et al., 2017). Thus, The first stage is the conceptualization process stage. This stage includes problem identification; determining the system boundary; and creating sub-models from the main causal loop diagram.

5. Developing the Stock-Flow Diagrams for each sub-system

SFD is a quantitative model introducing the time dimension by considering the rate of change over time (Bouloiz et al., 2013). The Stock-Flow Diagrams are developed, and the equations are quantified after the CLD's have been constructed. Quantitative analysis can be simplified using SFD. Simulation the SFD will help in evaluating the system's behavior under multiple scenarios (Nabavi, Daniell and Najafi, 2017). CLD's show the feedback structure of systems. SFDs show the physical structure where the material, money and information accumulation among the system are tracked ((Ackermann et al., 2007); (Wei et al., 2012); and (Luna-Reyes and Anderson, 2003)). Furthermore, the integration process is the process of flows accumulating and de-cumulating in stocks (Meyers, 2009). Hence, it is recommended to build the SFD after analysing the system (-Bach and Čerić, 2007). However, the importance and the magnitude of causal relationships between different variables can be explained through the SFD but not in the CLD (Dastkhan and Owlia, 2014). The concept of SDF is focused on the understanding of system causality (Nielsen and Nielsen, 2015).

The complex nonlinearity of systems can be very sensitive to the initial conditions (Hämäläinen and Lahtinen, 2016). Changing the state (levels) of the system will change the system behavior (Nielsen and Nielsen, 2015). SFD encourage numerical thinking. These are much more difficult for stakeholders to understand thus, training is needed to allow stakeholders developing SFD's (Elsawah et al., 2017).

Quantifying SD models variables is a challenge (Howick et al., 2008). Similarly, translating the CLD into the numerical model is a challenging iterative process (Elsawah et al., 2017). The SFD starting after the verification step of the CLD. The modeller should identify the stocks and flows in the system, then articulate a model that reflects the reality (Breierova, 2001). In the same context, converting the CLD to SFD provides more quantitative data to show the cause-effect relation through various variables in CLD (Yeo, Pak and Yang, 2013). Furthermore, SFD provides more detailed information comparing with the CLD. A dynamic hypothesis could be a statement, CLD, or SFD that could be proven if it is correct or wrong after a comprehensive investigation. These hypotheses are dynamically depending on the interdependency (cause-effect) of various risks indicators (variables) through the whole risk model. Conceptualising the dynamic hypothesis is describing of how to structure and policies generating the dynamic behavior (Elsawah et al., 2017).

However, there is no model can be ideal. According to that; a refinement process should be done for all hypothesis (Ranganath and Rodrigues, 2008). In this research, the risk variables are obtained depending on various data collection (literature review, focus groups and survey questionnaires); as clarified previously.

6. **Quantifying the relationships of the model by establishing equations for each sub-model (Model Formulation)**

SD enabling of building initial system model with starting approximated values. Providing that the model structure is well defined. The overall model can be determined based on this initial model. SD model is a group of differential algebraic equations developed based on experiential and measured data. SD model consists of three elements stock, flow and auxiliary variables and constants (Thompson and Bank, 2010).

SD is designed for understanding dynamic complexity and cause-effect over time. These cause-effect relationships are translated into mathematical expression in the SFD (Seng, 1994). As a consequence, after the relationships (cause-effect) between variables are determined, it would be quantified by establishing a simple mathematical expression for all variables, stocks, flows and assigned the parameters constants values (Aslani, Helo and Naaranoja, 2014). CLD and SFD are translated into equations in a specialised system dynamics language (Dyner, 2000). Due to implementing differential equations in SD; system dynamic is a quantitative model (Teufel et al., 2013). Understanding systems variables and their interactions are very important to analyse the behavior of complex systems, such as energy systems (Mutingi, Mbohwa and Kommula, 2017). However, SD does not require complex mathematical expression to develop the model (Ahmad and Simonovic, 2000). Afterwards, model performance can be checked. In this step, the errors or analogical relations can be caught thus, it is easier to rebuilt and complete the model systematically. System dynamic can signify these relationships between variables either linear or non-linear. Accordingly, this will help in addressing the dynamic influence of various risks on complex systems such as power plants.

After all above steps, the hypothesis can be tested through experiments in the real system or data collection ((Ackermann et al., 2007); (Wei et al., 2012); (Kotir et al., 2016); and (Luna-Reyes and Anderson, 2003)). However, CLD and SFD describe the interrelations between the model variables. SD depends on quantitative data for generating the feedback and building the model while qualitative data are utilised at all modelling process levels (Luna-Reyes and Anderson, 2003). Similarly, SD is combined with qualitative and quantitative methods where it can deal with non-linear, multiple feedback and complex time-varying system problems (Xiao et al., 2017).

7. **Model Expanding**

After the errors have been checked and corrected, expanding the model with one or more feedbacks should also be verified by field experts.

8. **Re-conducting the evaluation tests (as clarified in stage 10)**

Depending on the test results, the modeller can determine if the new feedback should be inserted, then the tests also repeated until the model is satisfied.

9. **Developing the final Stock-Flow Diagrams**

After the important policies are described, this description will be translated into a computer simulation model. However, the simulation model does not include complex mathematics (Forrester, 1991). The Stock-Flow Diagrams (SFDs) have been developed and the equations are formulated depending on the previous stages. Sub-models behavior will be compared with information for the real system. This information is collected either from expert knowledge (survey questionnaires; focus groups interviews; historical data or literature review). A comparison will yield changes, these changes must be adjusted through returning to the previous stage to reconstruct the model either by testing the values of the parameters or checking the available data. Afterwards, modify the model structure to align between the reality of the system behavior and the model behavior.

10. **Model Test, Verification and Validation**

Model calibration is the process to estimate the model parameters to match between simulated and observed behavior (Xi and Poh, 2014). Model verification is the process of checking that the computerised model and its implantations are accurate and satisfy the identified purpose (Sargent, 2011); (Li and Lu, 2018).

Model testing is a vital step of the modelling process and assists in building confidence in the developed model (Elsawah et al., 2017). Similarly, the model calibration, direct structural tests, and sensitivity analysis are performed to increase the confidence in the model (Xi and Poh, 2014).

Verification and validation focus on model tests (structure and behavior) (Elsawah et al., 2017). Model validation and verification is a critical step of quantifying the confidence, predicting the accuracy of the engineering prediction or model calculations and building credibility in numerical models thus, supporting the policy-makers of the needed information to take high-consequence decisions (Thacker et al., 2002). Verification is the process for assuring that the model is correct and agreed with the specifications and assumptions (Min, Yang and Wang, 2010). Verification is the process for assuring that the model is correct and agreed with the specifications and assumptions ((Min, Yang and Wang, 2010); and (Kleijnen, 1995)). Model verification is checking if the computer program of the computerised model and the related implementation are correct (Sargent, 2013). Verification is the process to determine if the conceptual model is correct with the model implementation. The verification process is concerned with errors removing and identification by comparing the analytical solutions with the numerical solutions (Thacker et al., 2002).

11. Model Simulation

Simulation models are a powerful tool to test possible organisational changes (Howick et al., 2008). A simulation model is a mathematical computer model that can be used for policy analysis and scenario analysis (Barnabè, 2011). Simulation models represent all the links between the model variables by algebraic relationships which determine the behavior of the model (Forrester, 1968). Simulation is the only method to expose hidden behavior in the model structure and determine the behavior in complicated nonlinear systems, where the needed data of the interdependencies and the decision policies converting to a computer simulation model by translating the original descriptive structure to computer instructions (Forrester, 1991). Simulation is the last stage of hypothesis furthermore, they assert that this step is a key role of behavior prediction of the complex systems (Ranganath and Rodrigues, 2008).

Simulation is rapidly increased to simulate the system behavior to solve problems and help policy-makers in their decision-making process instead of physical experiments in many several fields like engineering design, risk analysis, and performance estimation (Sargent, 2011); (Li and Lu, 2018). Simulation modelling of risk management helps in understanding the behavior of systems (Zio, 2018). The decision-making process based on the results of the developed model (Sargent, 2011). However, before the simulation run, initial conditions for each variable must be defined (Bouloiz et al., 2013).

12. Recommendations for Implementation

Analysis of the simulation output is the most important step in the validation process of models (Min, Yang and Wang, 2010). However, after the model has been validated, recommendations would be communicated for the power plants top management team. At the implementation stage, the modelling team needs to translate the study vision to the users. In this stage, a deep discussion is required. However, understanding the simulation output by policy-makers consider as a challenges stage during the modelling process (Luna-Reyes and Anderson, 2003).

13. Implementation Plan

The modeller can meet the management team in the organisation to draw the plans for the recommendations.

14. Model Implementation

Implementation: focuses on the model application (Elsawah et al., 2017). The model can be implemented depending on the implementation plan. After the validation process of the developed model.

15. Policy Design and Evaluation

After the model structure and behavior have been constructed and validated, it will be used to evaluate and design policies for enhancement. Accordingly, management strategies that will meet the long-term operation goals of the system (Park, Kim and Jung, 2014). Policies will change by changing the parameters then, a new simulation can be run. The new policy behavior will be compared with the old policy behavior to evaluate the most suitable policy.

However, SD is a powerful decision support tool for strategic policy testing and selection (Xi and Poh, 2014).

The key aim of SD is policy design. The policy design consists of formulating new strategies, decisions and structure but not only changing the values of the parameters. Policy design includes re-designing the stock and flow structure, reducing time delays, and changing the flow and the quality of information at the decision points and process. Besides, assessment for the robustness of policies and their sensitivity to uncertainties in model parameters and structure should be done to check the performance under a wide range of alternative scenarios (Vogstad et al., 2006). Furthermore, the interactions of different policies should be considered (Sterman, 2000). Along with that, the relative desirability of the policies can be evaluated by comparing the behavior from the new policy with the behavior from the old policy (Forrester, 1992).

4. Partially Application of the Methodology to Develop an Environmental Risks Perspective

4.1 Development of Various risk perspectives to assess risks

Due to the complexity and larger number of risk categories covered (nine risk categories), SD risk model in this research is breaking down to nine sub-system models to better understating of the model these sub-models are related to risk categories as the following but, a case study example for the environmental risk is developed in this research.

1. Supply chain sub-model:

From our previous work, BSC-AHP framework shows that the supply chain perspective includes two risk indicators production risk and disruption risk. These two risks have a significant impact on power plants performance.

2. Customer/Demand Risk Sub-model:

These risks may generate from demand forecasting problem or from the policy and & regulations.

3. **Social Risk Sub-model:**

Regarding the social perspective, the impact of energy sources available in social wellbeing in terms of employment opportunities, poverty, pollution and health; community development and culture; education; and employment opportunities. However, the social perspective is influenced by the economic perspective (Vera et al., 2005). According to (Kytle and Ruggie, 2005) social risk management strategies are extremely complex. Social risk occurs when an empowered stakeholder takes up a social issue area and applies pressure on a corporation thus, companies will change policies in the marketplace. Social risks arise from business decisions. For example, taking a decision to employ workers in a developing country without full acknowledgement to international labour standards could cause a company to overcome labour rights which cause unwanted public criticism of its value chain practices. Social risks may include lack of motivation for staff, lack of innovation, the poor relationship between parties, labour strikes risk and social challenges.

4. **Economic Risk Sub-model:**

Risks which result from inflation and interest rate, supplier price risk (fuel price), the price of electricity risk and asset depreciation risk. On the other hand, Organizations utilising assets to meet their needs. The implementation of identified risks should be integrated with the asset management implementation plan. Organisations should manage their risks at many organisational levels. Operating, technical, and enterprise-wide. However, risk management is a crucial supporting part of an asset management system. Risk management plans can be integrated into the asset management plan or created separately (International Standard Organization, 2012).

5. **Environmental Risk Sub-model:**

Environmental risks are the risks which may result from environmental regulations or human toxicity risk, noise impact caused by energy systems, bad odours risk, solid waste risk and GHG emissions. (Dastkhan and Owlia, 2014) assert that the environment subsystem is dealt with the environmental aspects of the electricity generation system.

Energy production will produce pressures on the environment which means that the environmental dimension is influenced by the economic and social perspectives (Vera *et al.*, 2005). (Cimren, Bassi and Fiksel, 2010) claim that no integrated model can be found in the current literature that links the influence of environment and sustainable energy policies. To compare the effects of the decision-making process in policy design and business development plans in the electricity sector, several scenarios are modelled. These scenarios should consider environmental policies (Foley *et al.*, 2010).

6. Technological Risk Sub-model:

The technological risk is the potential for technology to cause an effect on company performance and cause disruption such as obsolescence risk, improved fuel efficiency/efficiency of the combustion risk and sustainable technology innovation risk. (Dastkhan and Owlia, 2014) clarify that the technology perspective is dealt with the effect of technology development programs on the pollution reduction to be sustainable for the long term. (Aon Risk Solutions, 2017) shows the importance of the technologies/innovation where it is added for the risk categories and ranked it as 20 where it is expected to be number 10 globally and in the second rank for the technology industry.

7. Internal and Operational Risk Sub-model:

Internal and operational risks are the risk that is related to the internal and operational business process such as technical risk, material or equipment quality risk, start-up cost risk, operating cost risk, and scarcity of resources risk (Shortage of materials and equipment). Operational risks cover regulators and industry and are difficult in measuring and managing (Bodnar, Marston and Hayt, 1998).

8. Human Resources Risk Sub-model:

Risks that may occur due to loss of key personnel, poor labour productivity, poor training, sick leave, IT infrastructure (scarcity of skills/technique) and inappropriate employee's safety. (Aon Risk Solutions, 2017) assert that if the companies haven't a motivation procedure to their employees that will lead to falling behind the competition. risk analysis is affected more by the organisational factors than behavioural and physical performances. Furthermore, the dynamic nature as human-machine interaction. The human contribution to risk assessment is a crucial and integral part of risk analysis. In the last 2 decades, a dramatic human contribution to accident development has been increased with 70%–80% (Cacciabue, 2000) . Along with that, the individual human behavior is impacted by the environment (Komljenovic, Loiselle and Kumral, 2017). Complexity and uncertainties create risks.

Complexity is a crucial factor in influencing organisations. To better understanding and managing of complexity, top management must recognise how employees see it at all levels thus the added value is retained while the unadded values are removed. Thus, the complex dynamics of organisations are incorporated into management thinking (Gorzeń-Mitka and Okręglicka, 2015)

9. **Management Risk Sub-model:**

These risks are related to top management decisions thus, various management risks can cause a significant effect on the company performance, some example of these risks are partnership relationship risk, inappropriate organisational response to changing environment risk, inappropriate organisational structure risk, ineffective integrating and managing enterprise resources risk, unclear strategy for achieving organisational objectives, poor coordination, mismatch between organisational strategy and culture, interaction between stakeholders and Information sharing problems. The key source of risk today is the organization itself (Komljenovic, Loiselle and Kumral, 2017) .

Power plants are a complex system which is illustrated by a set of nonlinearity equations and multiple feedback loops which will change system behaviour over time. These nine categories of risks interact with each other and will generate feedbacks loops. To assess these risks and take appropriate decisions, companies need to develop a clear understanding of this complex system. (Ang, Choong and Ng, 2015) describe how some risk affects each other, for example, exchange rates and purchasing power of certain currencies play a key role to determine how much payment should people and country pay for energy import. Prices changes of fuel will cause problems in securing energy which in turn affect the decision maker's ability for planning in the short term.

On the other hand, (NOH, 2012) has been identified the factors that have been affected by risks and impacted on the performance of power plants. These factors are efficiency, availability, degradation and outages. In the same context,((Oyedepo *et al.*, 2014) ; (Raja, 2006); (Wai Foon and Terziovski, 2014)) demonstrate that power plants performance (ex. efficiency, reliability) has socio-economic importance on the company operating the plant and the nation. In addition, they confirm that the top measures for power plants performance are efficiency, reliability, the capacity of the plant, plant factors (utilisation factor, capacity factor, and load factor), availability, generation unit cost, fuel cost per unit generation staff productivity, breakdown maintenance, etc.

However, in this research three factors are utilised to study the power plant performance which affected by various risks. These factors are availability, efficiency and operational and maintenance cost. Thus, the developed SD methodology will help to understand how various risks affect the power plants performance (availability, efficiency and operational and maintenance cost) in the long term.

4.2 Apply the Methodology to the Environmental Perspective:

The following section explains the developed SD methodology which can be applied to assess and model SD risk model.

To build the SD model for assessing the environmental risks, the problem is identified then the system boundaries are addressed as shown in Table 1. Accordingly, the CLD has been created for the environmental sub-model as revealed in Figure 4.

Table 1 : Risk Factors (Endogenous and Exogenous) affecting the strategic Environmental Perspective and define the system boundaries

Code	Endogenous Variable
ER1	Environmental Risks
ER2	Environmental Uncertainties
ER3	Environmental Certainties
ER4	Availability Risk
ER5	Outage Hours
ER6	Power Plants Efficiency risk
ER7	Technical Risks
ER8	Risk of Operational and Maintenance Cost
ER9	Aggravation of Operational and Maintenance Cost
ER10	Waste Handling Risk
ER11	Noise Impact Risk
ER12	GHG Emissions
ER13	Lost Time Injuries Risk
ER14	Bad Odours Risk
ER15	Soil Pollution Risk
ER16	Solid Waste Risk
ER17	Human Toxicity Risk
ER18	Industrial Water Reuse Risk
ER19	Accident Fatalities Risk

ER20	Recycling of Treated Water Risk
Code	**Exogenous Variable**
ER21	Disruption Risks
ER22	Mortality Risk
ER23	Environmental Regulations Risk

Table 1 shows the exogenous and endogenous variables for the environmental sub-model, depending on this table the cause-effect and interrelation between various variables can be utilised to create the CLD.

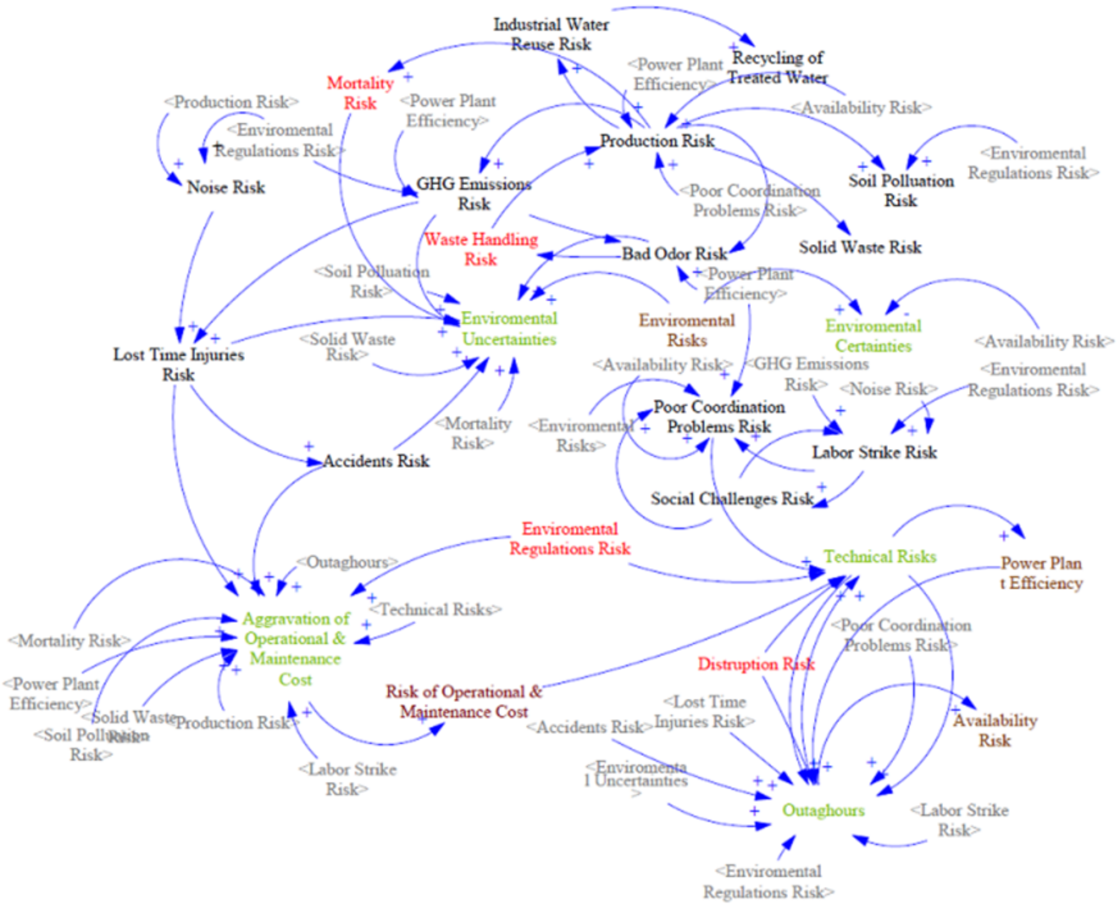

Figure 4 : Causal Loop Diagram of the Environmental Risks

As depicted in Figure 4, the environmental risks in power plants will be generated from various variables, these variables are interconnected through each other. Cause-effect though social challenges, disruption risk, production risk, poor coordination problems, mortality risk, environmental regulations, waste handling, noise impact, GHG emissions, lost time injuries, bad odours risk, soil pollution, solid waste, human toxicity, industrial water reuse risk, accident fatalities, and recycling of treated water risk. These risks affect the power plant performance (availability of power plant, the efficiency of the power plant, and the operational and maintenance cost). However, the results of the developed model will be explained in detail in future paper.

Environmental risks are the risks of the environmental systems and to human health (Chen et al., 2011). The environment subsystem is dealt with the environmental aspects of the electricity generation system (Dastkhan and Owlia, 2014). The complexity of environmental issues and decision making have a group of challenges for utilising SD as a methodology for modelling environmental problems (Elsawah et al., 2017). Energy production will produce pressures on the environment which means that the environmental dimension is influenced by the economic and social perspectives (Vera et al., 2005). However, no integrated model can be found in the current literature that links the influence of environment and sustainable energy policies (Cimren, Bassi and Fiksel, 2010). However, to compare the effects of the decision-making process in policy design and business development plans in the electricity sector, several scenarios are modelled. These scenarios should consider environmental policies (Foley et al., 2010).

5. Discussion and Conclusion

In the created CLD for the environmental sub-model, the interrelations between various environmental risk variable impact the availability, efficiency, and operational and maintenance cost of the power plant are described. From the system boundary in **Error! Reference source not found.**1, the CLD is created and presented in Figure 4. Environmental, social, and internal and business process risks interact together. The influences of lost time injuries, GHG emissions, solid waste risk, noise risk, soil pollution, bad odour risk affect the performance of a power plant. The interaction between solid waste risk, soil pollution risk, bad odour risk, lost time injuries, accident risk and the environmental uncertainties will lead to producing the environmental, health and safety risks. These risks affect the availability, efficiency, and operational and maintenance cost risks. This paper developed clear and systematic stages to develop an SD model for non-technical risks in power plants. Understanding these risks is a vital step to manage the risk.

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