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A System Dynamics Simulation Model for Environmental Risk Assessment at Strategic level in Power Plants.

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Abstract

In a constantly changing business environment, a systematic approach is needed for risk assessment in order to allow for a more long-term strategic view. The System Dynamics modelling technique can be applied as an effective approach to understand the dynamic behaviour of a system over time. This understanding can be subsequently explicitly reflected on policies, strategic plans and operational procedures. This paper presents a System Dynamics model to assess environmental risk in power pants. The model considers a long-term strategic view. The model helps to understand the long-term behaviour of the system under study. A questionnaire and focus group interviews have been conducted to help understanding the relationship among various key risks. Causal Loop Diagrams (CLDs) are developed to identify key risks and define their interdependencies. Stock and Flow Diagrams (SFD) are built to quantify these interdependencies. Two scenarios were considered for simulation of the impact of waste handling risk and environmental regulation risk. The SD model has been validated with two power plants in the Middle East. The developed SD model highlighted the impact of key environmental risks on the performance of power plants. This performance considers availability factor, efficiency and operational and maintenance cost. Although the SD model focuses on risk assessment in power plants, it can be easily adapted to other industry sectors.

Keywords: System dynamic, non-technical risks, FMEA, EWGM

1. Introduction

An industrial system can be considered a complex multiple loop and interconnected system (Forrester, 1992). Electricity generation is one of the most critical components of infrastructure, which enables countries to achieve sustainable economic growth (Dwivedi and Chakraborty, 2016). Therefore, it is important to assess the risks of such industrial complex systems, as it is the case of power plants. Currently, risk management in the energy sector, particularly in developed countries has faced many challenges due to the complexity rising from various economic, social, environmental and technological risks. In the same context, environmental issues have risen significantly, which in turn increase these challenges (H. Liu et al., 2015). The Middle East encounters substantial obstacles in the economic, environmental and governmental structure particularly in the energy sector (Dastkhan and Owlia, 2014). These obstacles cause a complex situation for energy planners. The key part of risk management is the assessment step. This step helps in achieving the maximum sustainability value of an organisation. On the other hand, increasing environmental problems (water, air and soil pollution, resource depletion and excessive land use) is threatening the earth life support systems. Hence, there is a need for a sustainable system to curb its effect and overcome drawbacks and economic challenges. In the sustainability area, the tradeoff between the long-term and short-term responses to policies is problematic due to the delay in the long-term ecological and economic process (Sterman, 2012). However, one of the key attributes that affect sustainability in most human-environmental systems is the system feedbacks (H. Liu et al., 2015). SD improves the understanding regarding how a system changes with time additionally, how feedbacks can lead to non-linearity behaviour in complex systems (Allington et al., 2017). Furthermore, SD can be applied to evaluate the potential effect of policy changes (Allington et al., 2017).

Non-linear feedbacks, strategic interactions and varying time scales of socio-environmental systems are the main challenges that affect sustainability systems. Understanding these challenges will provide a clear picture of these systems and can implement the most effective design of policies. This complexity prevents socio-environmental management (Levin et al., 2013). However, management decisions can be improved by considering the combined effects of system dynamics and reducing the possibilities of adverse side-effects of policy decisions (Kotir et al., 2016).

For providing a clear structure for cumulative effects assessment, environmental risk assessment is utilised. However, there is no standard approach for risk assessment thus, it plays a crucial role in integrating science, policy and management (Piet et al., 2017). System Dynamics is a suitable tool to model complex environments, where the interactions of the environmental and socio-economic variables are clearly demonstrated (Sterman, 2012; Xiao et al., 2017). SD approach can be applied to clarify and link between the environment and the social aspects furthermore, represent how are the entire interactions affect dynamics (Allington et al., 2017). On the other hand, it is needed to develop a systemic approach illustrates the socio-economic feedbacks. These feedbacks determine the future dynamics of systems to adapt management practices for the long-term. Modelling complexity systems emerges from the needs of supporting policymakers in their decision-making process (Girard et al., 2015). However, the current literature of applying SD in electricity energy planning is focused on a certain part of the energy system and does not consider all the related subsystems and variables (Dastkhan and Owlia, 2014). In the same context, improving management decision and mitigating the effects of policies can be achieved by combining the effects of SD by estimating the economic, social and environmental impacts (Simonovic, 2009). However, involving the stakeholders in the model development process or part of the model theoretically leads to a better understanding of the related system thus, the acceptability and credibility of the developed model will increase (Girard et al., 2015).

This paper provides a novel risk assessment approach by engaging various qualitative and quantitative data to assess the environmental risks at the strategic level. This paper provides a systematic and clear methodology to create the causal interdependency and feedbacks among risks in power plants. The main objectives of this paper are to provide a better understanding of the dynamic behaviour over time of assessing the environmental risks in the energy sector, furthermore, evaluate the influence of various policy scenarios to help the policymakers in their decision-making process at the long-term. Where SD is a powerful tool to support decisions and mange of policy strategies. The CLD is constructed using Vensim©, while the SFD is built using Anylogic. These are specialised software applications for system dynamics. Focus group interviews and questionnaires survey are applied to create various inputs values to predict risk consequence.

2. Modelling Approach:

2.1 System Dynamics Modelling Approach

Systems dynamics is a computer-aided approach for policy analysis and design, which is applied to dynamics issues in complex systems. Furthermore, SD is an effective tool that analyses various systems to a qualitative and quantitative approach (Sisodia et al., 2016). Along with that, SD is a powerful tool for understanding dynamics of decision making in complex systems over time, particularly feedback (Aslani et al., 2014; Nabavi et al., 2017; Shafiei et al., 2015). SD is a suitable tool to enhance and accelerate organisational and managerial learning under the complexity of competitive technological innovation (Lomi and Larsen, 1999). SD is a tool for energy systems analysis additionally, it is a suitable tool to model complex environments, where the interactions of the environment and socio-economic variables are clearly demonstrated (Xiao et al., 2017). SD is utilised to study the effects of different policies on the electric industry (Ford, 1983). Furthermore, it is a natural format to test questions of stability and dynamics (Kadoya et al., 2005).

The SD modelling technique is a powerful approach to understand and analyse system behaviour. The implementation of the SD technique also helps to improve the acquisition of knowledge about the organisation, its competitors and its market. SD helps to define key variables, which affect system behaviour (-Bach and Čerić, 2007). In this way, SD allows understanding how changes in one variable of the system may impact other variables, affecting the overall performance of the system in the long-term (Ahmad and Simonovic, 2000) (Pereira and Saraiva, 2011). SD provides a holistic understanding of long-term strategic problems in complex systems. This understanding of system behavior can consequently support strategic decisions which can be explicitly reflected on policies, operational procedures, strategic plans, and other key documentation (-Bach and Čerić, 2007; Dastkhan and Owlia, 2014; McLaughlin and Olson, 2017; Morecroft, 2015; Yeo et al., 2013).

SD is an analytical method for addressing systems behaviour generated by the information feedback and analysing the dynamics of complex system performance using qualitative and quantitative data (Li et al., 2016; Yeo et al., 2013). However, although the simulation-based models are popularly used in energy planning, they don’t have flexibility in the number of variables and analysing the dynamics of the more complex energy systems (Dastkhan and Owlia, 2014).

On the other hand, policymakers and researchers have extensively used SD in management and social systems (Anand et al., 2006). Models can help to determine what are the decisions should be taken to achieve the aim (Simonovic, 2009). However, the main challenge for the decision-makers is how could an effective and efficient energy policy subject to sociotechnical constraints be designed (Qudrat-Ullah, 2016). Generally, the design of an effective energy policy is a complex process.

A simulation model is based on representing the policies in the decision-making process. The decision-making process includes of formulation of concepts, which show the desired conditions, the observations of appearing of the actual conditions and the generated corrective actions to change the current conditions to desired conditions. A simulation model is based on explicit statements of policies (or rules) that govern decision making in accordance with conditions that may arise within the system being modelled (Forrester, 1992).On the other hand, simulation models will help in minimising the decision-making errors (Lemke and Latuszynska, 2013; R G Sargent, 2013). Simulation and optimisation models are a bottom-up approach. However, optimisation models try to optimise a system with given boundaries, while the simulation models try to simulate the effects of different actions (Teufel et al., 2013). In the same context, modelling and simulation have been applied to help decision-makers in the domain of energy policy (Qudrat-Ullah, 2015). Along with that, simulation-based models as SD are frequently used in energy planning, where in most cases the simulation-based models are mid-term or short-term with a lot of details. Furthermore, simulation-based models are the best models to consider the dynamics of systems and have a level of accuracy and flexibility in system analysis (Dastkhan and Owlia, 2014). In this research, SD is employed to assess the environmental risks in power plants. This refers to the ability of SD to address the dynamics behaviour over time.

2.2 Applying the SD approach For Modelling Environmental Risks

To construct a SD model, typical stages the as described in the literature. The current literature shows that the applied steps to develop a SD model are very general and not clear. In addition, SD illustrates the structure of the decision-making process, but not the seen structure on a personnel organisation chart. Furthermore, SD is applied to understand, and study how does the influence of alternative policies change system behaviour. The dynamic behaviour of information feedback can dynamic by the way of the effect of one variable in another. SD is a complex graphical modelling technique to represent and understand the behaviour of complex systems over time. However, to enhance the understanding process, SD utilises various tools such as causal loop diagrams, stock and flow diagrams and system archetypes.

Overall, a SD model starts by the conceptualization of the model through constructing the causal loop diagrams based on the system boundary table, then quantifying the cause-effect relationships using stock and flow diagrams. Afterwards, the model will be tested and validated. In checking the model performance, the errors or analogical relations can be caught thus, it is easier to rebuild and complete the model step-by-step. SD is designed to understand the dynamics complexity and cause-effects over time. These cause-effect relations are translated into mathematical expressions (Seng, 1994). CLD and SFD are translated into equations in a specialised SD language (Dyner, 2000). Various equations are used in SD to model the interdependencies between various variables of the model. Due to implementing differential equations in SD, SD is a quantitative model (Teufel et al., 2013). However, SD does not require complex mathematical expression to develop the model (Ahmad and Simonovic, 2000).

The first stage to develop a SD model is to define the problem and the aim for developing the model (Aslani et al., 2014; Park et al., 2014). Along with, the system boundaries are determined by defining the endogenous variables and exogenous parameters thus, the interactions between these variables can be addressed. Afterwards, these relations will form the CLD. Subsequently, these CLDs will be interpreted to SFDs by writing the related equations finally, the model will be tested, validated and developed.

In this paper, the system dynamics approach is utilised to assess various types of risks in power plants and select a suitable policy for risk assessment. Thus, a dynamic integrated model is developed and validated with real case studies in power plants in the Middle East. The sensitivity analysis is utilised to analyse various scenarios and policies. To assess the risks, various data are used, these data include the practitioner's knowledge through focus group interviews, questionnaires survey and literature.

The developed model addressing the risks in power plants and analysing the impact of these risks on the power plants performance by applying a novel and integrated SD approach with AHP and Improved Failure Mode and Effect Analysis (IFMEA). The AHP tool is applied into two phases. Firstly, to assess the risks in terms of three risk factors (S, O and D) next, assess the risks according to the three performance measures (availability, efficiency and operational and maintenance cost), where the RPNs help in building the comparison matrices. The IFMEA integrates the exponential and weighted geometric mean (EWGM) in order to improve the conventional FMEA. The EWGM method is applied for ranking RPNs. Combining AHP with EWGM allows avoiding repetition of FMEA results. The results of the developed methodology reveal that the duplication of RPNs has been decreased and facilitate an effective risk ranking by offering a unique value for each risk. Furthermore, the proposed methodology considers other risk factors (O and D) and not only focuses on high severity values for risk ranking thus, but the risk assessment process is also improved (AL Mashaqbeh et al., 2019a). The RPNs-EWGM values are inserted as input to build the AHP risk framework. These values help to construct the comparison matrices in AHP by providing a proper value-form Saaty's scale (11-9), which provides more accurate results. Figure 1 shows the proposed integrated methodology (IFMEA-AHP). However, for data collection, a questionnaire survey and focus group interviews in two power plants are conducted to develop the IFMEA and construct the AHP framework. The priorities outcomes of the AHP risk framework are populated as inputs to build the SD model. The priorities (weights) of risks are inserted as initial values (for stocks and exogenous parameters) in the SD model.

As a whole, a SD model is developed by four main stages that comprise many steps. These improved stages are highlighted below. See (AL Mashaqbeh et al., 2019b) for the deep explanation.

1. Model conceptualization (problem identification; determining the cause and effect relationships based on system boundary; creating causal loop diagram).
2. Model Simulation (creating stock and flow diagram, deploying equations for the step-by-step model; verification; test model; model formulation; model simulation software).
3. Model Validation (model test; model verification; model validation) where various scenarios have been created to understand the system behaviour.
4. Model Implementation (recommendation of implementation; implementation plan, model implementation, policy design and evaluation).

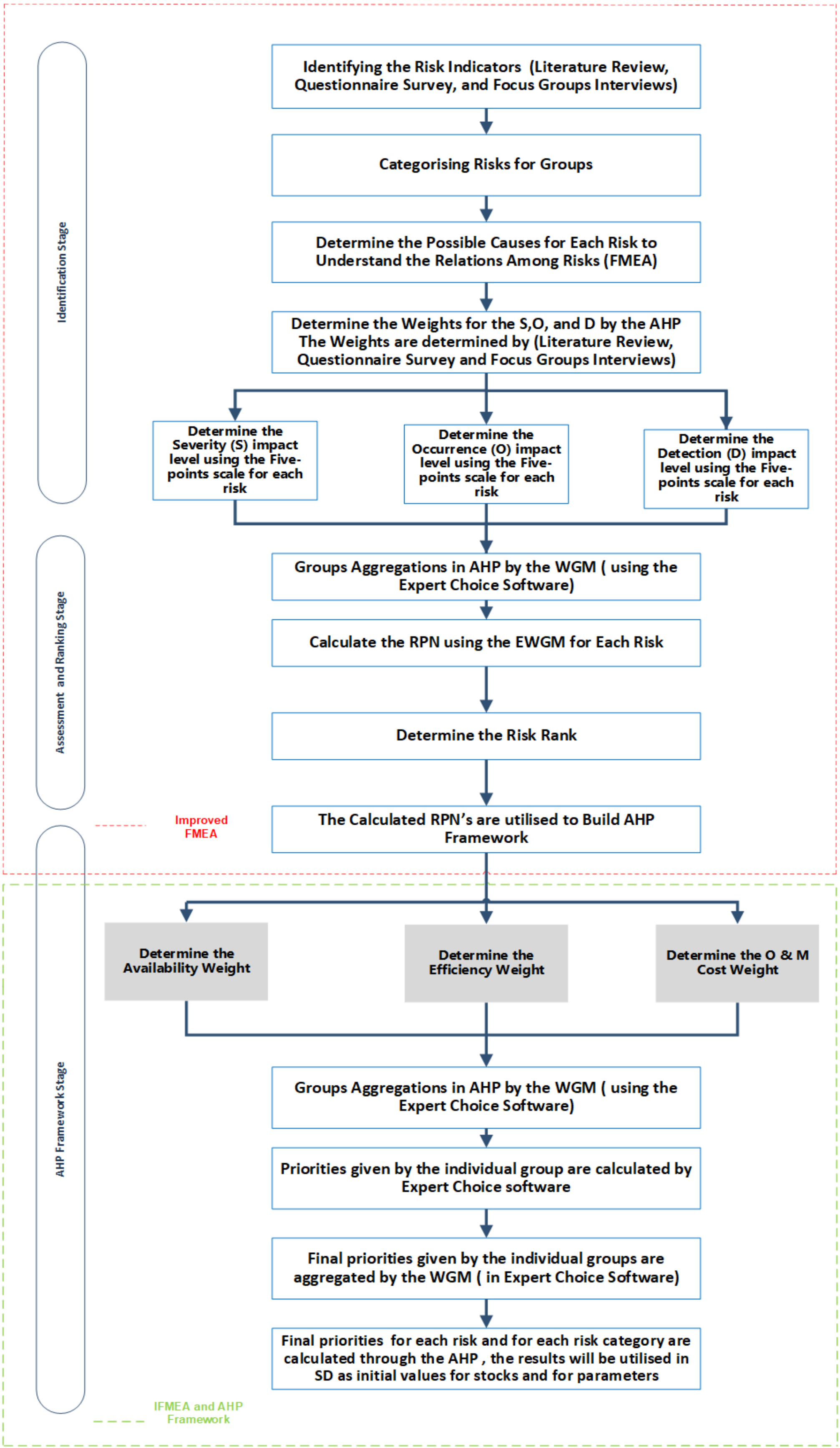

Figure 1: IFMEA and AHP Integration Methodology

In this paper, the effects of various risks on the availability, efficiency and operational and maintenance cost of power plants have been studied. For example, seven per cent of the revenue cash flow is consumed by operation and maintenance activities of the plant. Eight per cent of these costs result from unplanned (forced outages) maintenance. 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 continuity the operating plants (Orme and Venturini, 2011). Unplanned (forced outages) accidents will cause a revenue loss and damage the business operation reputation and credibility. In addition, to assess the impact of risks on performance, broad risk measures are used such as: availability; probabilistic safety assessment; reliability; component unavailability; total accident frequency and downtime period (Mohammad Hadi Hadavi, 2009). In the same context, the key factors that have been affected by risks and impacted on the performance of power plants are efficiency, availability, degradation and outages (NOH, 2012).

Power plants failures may cause significant risks to the plant operators financially, for example, the losses for thermal power plants in Malaysia reach to (AUD$58m) due to availability losses among 2.5 years (Wai Foon and Terziovski, 2014). Power plants performance (ex. efficiency, reliability) has socio-economic importance on the company operating and the nation. On the other hand, the top measures for power plants performance are efficiency, reliability, a 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 (Oyedepo et al., 2014). In the same context, Raja,(2006) asserts that the main factors of power plants performance are load factor, utility factor, plant capacity factor, demand factor, diversity factor, operational costs and cost of fuel. SD can be applied to analyse various systems economic, social and environmental systems (Park et al., 2004). Similarly, SD is applied in various area (social science and engineering) (Thompson and Bank, 2010).

2.3 Model Development Process:

2.3.1 Model conceptualization

This paper provides a decision support tool that facilitates environmental risk assessment in power plants. The causal interdependencies between environmental risks and other risks will be formalised. The available information is a crucial step to build a SD model. The available data includes the current literature review and any mental data that can be acquired by questionnaire survey 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 to develop a model (Aslani et al., 2014; Park et al., 2014). In this step, the dynamics 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. Focus group interviews and questionnaire survey are conducted in order to assess the risks levels at power plants, which in turns, helps in creating an initial causal loop diagram. On the other hand, to evaluate system behaviour, SD can be run with various initial and boundary conditions (Allington et al., 2017).

In this paper, thirteen major environmental non-technical risks at the strategic level are identified from the literature, focus groups interviews and a questionnaire survey in power plants in the Middle East. These risks are waste handling risk; GHG emissions; lost time injuries risk; bad odours risk; noise impact risk; soil pollution; solid waste risk; human toxicity; industrial water reuse risk; mortality risk; accident fatalities risk; recycling of treated water risk and environmental regulations Risk.

As observed in Figure 1, the outputs of the IFMEA (EWGM-RPN) help in building the AHP framework. The EWGM-RPN values support the selecting process of the most proper value form the Saaty's scale (1-9). The outcomes of the AHP framework are populated into the SD model (initial values of stocks and exogenous parameters). See (AL Mashaqbeh et al., 2019a), this reference covers the first step to calculate the RPNs as shown in Figure 1, afterwards, these values help to build the AHP framework by calculating the priority of each risk under three power plants performance measures. The comparison AHP matrix of the environmental risks is illustrated in Table 1. The final results and the priorities for risks are shown in Table 2.

Table 1: Comparison Matrices with respect to Availability, Efficiency and, Operational & Maintenance Cost for Environmental Risks

Criteria	Risk Indicator	Waste Handling Risk	Noise Impact Risk	GHG Emissions	Lost Time Injuries Risk	Bad Odours Risk	Soil Pollution	Solid Waste Risk	Human Toxicity	Industrial Water Reuse Risk	Mortality Risk	Accident Fatalities Risk	Recycling of treated water Risk	Environmental Regulations Risk	Priority	Ideal Priority	Rank
	Waste Handling Risk		1.048	1.076	1.076	1.076	1.086	1.076	1.034	1.117	3.252	1.438	4.924	4.35	0.093	0.920792	8
	Noise Impact Risk			1.027	1.027	1.027	1.036	1.027	1.014	1.17	3.408	1.507	5.16	4.558	0.097	0.960396	6
	GHG Emissions				1	1	1.009	1	1.041	1.202	3.5	1.548	5.298	4.681	0.1	0.990099	2
	Lost Time Injuries Risk					1	1.009	1	1.041	1.202	3.5	1.548	5.298	4.681	0.1	0.990099	2
	Bad Odours Risk						1.009	1	1.041	1.202	3.5	1.548	5.298	4.681	0.1	0.990099	2
	Soil Pollution							1.009	1.05	1.213	3.532	1.562	5.347	4.724	0.101	1	1
Availability	Solid Waste Risk								1.041	1.202	3.5	1.548	5.298	4.681	0.1	0.990099	2
	Human Toxicity									1.154	3.362	1.487	5.09	4.497	0.096	0.950495	7
	Industrial Water Reuse Risk										2.913	1.288	4.41	3.896	0.083	0.821782	9
	Mortality Risk											2.261	1.514	1.337	0.028	0.277228	11
	Accident Fatalities Risk												3.424	3.025	0.064	0.633663	10
	Recyling of treated water Risk													1.132	0.019	0.188119	13
	Environmental Regulations Risk	CI=0.01, λ_{max} = 13.2													0.021	0.207921	12
	Waste Handling Risk		1.191	1.313	1.313	1.313	1.426	1.313	1.161	1.242	2.727	1.346	3.29	3.156	0.054	0.284211	5
	Noise Impact Risk			1.102	1.102	1.102	1.197	1.102	1.026	1.479	3.247	1.603	3.917	3.758	0.046	0.242105	8
	GHG Emissions				1	1	1.086	1	1.307	1.631	3.579	1.767	4.318	4.142	0.045	0.236842	9
	Lost Time Injuries Risk					1	1.086	1	1.307	1.631	3.579	1.767	4.318	4.142	0.045	0.236842	9
	Bad Odours Risk						1.086	1	1.307	1.631	3.579	1.767	4.318	4.142	0.045	0.236842	9
Effeincy	Soil Pollution							1.086	1.228	1.772	3.889	1.92	4.691	4.5	0.038	0.2	13
	Solid Waste Risk								1.307	1.631	3.579	1.767	4.318	4.142	0.045	0.236842	9
	Human Toxicity									1.442	3.166	1.563	3.819	3.663	0.049	0.257895	7
	Industrial Water Reuse Risk										2.195	1.084	2.648	2.54	0.054	0.284211	5
	Mortality Risk											2.026	1.206	1.157	0.148	0.778947	3
	Accident Fatalities Risk												2.444	2.344	0.073	0.384211	4
	Recycling of treated water Risk													2.44	0.169	0.889474	2
	Environmental Regulations Risk	CI=0.03, λ_{max}= 13.56													0.19	1	1
	Waste Handling Risk		1.05	1.017	1.017	1.017	1.133	1.017	1.133	1.3	2.517	3.267	1.6	1.817	0.051	0.46789	12
	Noise Impact Risk			1.033	1.033	1.033	1.079	1.033	1.079	1.238	2.397	3.11	1.524	1.73	0.054	0.495413	10
	GHG Emissions				1	1	1.115	1	1.115	1.279	2.475	3.213	1.573	1.787	0.052	0.477064	11
	Lost Time Injuries Risk					1	1.115	1	1.115	1.279	2.475	3.213	1.573	1.787	0.074	0.678899	6
	Bad Odours Risk						1.115	1	1.115	1.279	2.475	3.213	1.573	1.787	0.074	0.678899	6
O&M Cost	Soil Pollution							1.115	1	1.147	2.221	2.882	1.412	1.603	0.064	0.587156	9
	Solid Waste Risk								1.115	1.279	2.475	3.213	1.573	1.787	0.074	0.678899	6
	Human Toxicity									1.147	2.221	2.882	1.412	1.603	0.076	0.697248	5
	Industrial Water Reuse Risk										1.936	2.513	1.231	1.397	0.097	0.889908	3
	Mortality Risk											1.298	1.573	1.385	0.101	0.926606	2
	Accident Fatalities Risk												2.042	1.798	0.109	1	1
	Recycling of treated water Risk													1.135	0.09	0.825688	3
	Environmental Regulations Risk	CI=0.055, λ_{max}= 14.19													0.082	0.752294	4

Table 2: Results of Final AHP-IFMEA Model Decision Making Priorities for Environmental Perspective Risks

Risk Priority				Final Risk Priority		
Risk Indicator	Availability	Efficiency	O&M Cost	Priority	Ideal Priority	Rank
Waste Handling Risk	0.093	0.054	0.051	0.074	0.913580247	12
Noise Impact Risk	0.097	0.046	0.054	0.075	0.925925926	10
GHG Emissions	0.1	0.045	0.052	0.076	0.938271605	6
Lost Time Injuries Risk	0.1	0.045	0.074	0.079	0.975308642	2
Bad Odours Risk	0.1	0.045	0.074	0.079	0.975308642	2
Soil Pollution	0.101	0.038	0.064	0.076	0.938271605	6
Solid Waste Risk	0.1	0.045	0.074	0.079	0.975308642	2
Human Toxicity	0.096	0.049	0.076	0.079	0.975308642	2
Industrial Water Reuse Risk	0.083	0.054	0.097	0.076	0.938271605	6
Mortality Risk	0.028	0.148	0.101	**0.076**	0.938271605	6
Accident Fatalities Risk	0.064	0.073	0.109	0.074	0.913580247	12
Recycling of treated water Risk	0.019	0.169	0.09	**0.075**	0.925925926	10
Environmental Regulations Risk	0.021	0.19	0.082	0.081	1	1

Formulation of the dynamic hypothesis includes a clear determination of exogenous parameters and endogenous variables (determining the system boundary) (Elsawah et al., 2017). After the problem is identified, the second step to build the system dynamics 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; Kotir et al., 2016; Luna-reyes et al., 2003; Wei et al., 2012). Exogenous parameters inputs are needed to show how are the variables changed 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) and "arising from within "and generating the dynamics of a system through variables interaction (Ackermann et al., 2007; Sterman, 2000). Exogenous parameters are parameters outside the system. These parameters are constant and will not change their behaviour over time within the model (DE LA BARRA, 1989). On the contrary, endogenous variables are the variables "arising from without" which means from outside the system boundary interaction (Ackermann et al., 2007; Sterman, 2000). endogenous variables are the dynamic factors the arise within the system (DE LA BARRA, 1989). However, if the endogenous variables are more; that indicates the model generates interesting dynamic behaviour from within the system' (Pasaoglu Kilanc and Or, 2008). Table 3 includes the endogenous variables and exogenous parameters. As risks are interrelated, various social and operational risk are considered with environmental risks.

Table 3: System Boundary for Environmental Sub-Model

Code	Endogenous Variable
ER1	Waste Handling Risk
ER2	Noise Impact Risk
ER3	GHG Emissions
ER4	Lost Time Injuries Risk
ER5	Bad Odours Risk
ER6	Soil Pollution
ER7	Solid Waste Risk
ER8	Human Toxicity
ER9	Industrial Water Reuse Risk
ER10	Accident Fatalities Risk
ER11	Recycling of treated water Risk
Code	**Exogenous Parameters**
ER12	Disruption risks
ER13	Mortality Risk
ER14	Environmental Regulations Risk

Subsequently, the CLD or "influence diagrams can be created. CLD is a graphical tool represents a better understanding of the internal relationships between variables (Aslani et al., 2014; Nabavi et al., 2017; Park et al., 2014). CLDs are beneficial and flexible tools to emphasise the feedback structure of systems. The cause and effect relationships between the developed system/sub-systems variables should be addressed. CLD is a crucial tool for addressing the variables relationships (Dastkhan and Owlia, 2014; Yeo et al., 2013). CLDs can be valuable for analysts and decision-makers in the field of energy policy formulation (Mutingi et al., 2017). Furthermore, CLD is the initiating step to develop a dynamics hypothesis (Elsawah et al., 2017) additionally, it is a powerful qualitative tool to represent the interdependencies between variables. These interdependencies are quantified to develop the SFD. SFD helps in simulating system behaviour over time (Kotir et al., 2016; H. Liu et al., 2015).

The CLD for environmental risks is represented in Figure 2. The model is developed through focus group interviews and questionnaires survey. The conceptual model (CLD) represents the qualitative feedback phase of the risk assessment model. The developed conceptual model also is validated and refined by the focus group interviews.

Environmental risks are the risks of the environmental systems and risks related to human health (Chen et al., 2011). The environment subsystem is dealt with by the environmental aspects of the electricity generation system (Dastkhan and Owlia, 2014). The complexity of environmental issues and decision making have many 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 economic and social perspectives (Vera et al., 2005). Environmental, social and internal and operational business process risks interact together. The influences of various risks (lost time injuries risk, GHG emissions risk, solid waste risk, noise risk, soil pollution risk and bad odour risk) on the performance of power plants can be observed.

As observed in Figure 2, the production risk leads to an increase in GHG emissions risk consequently, environmental uncertainties increase. As environmental uncertainties increase, the outages hours and the availability risk increase. Further, production risk increases the industrial water reuse risk, which in turns, increases recycling of treated water. In this causal loop diagram, the interactions among variables can be determined. In this paper, the interactions among various risks related to power plant performance factors (power plants efficiency risk; availability risk, operational and maintenance cost risks) are defined.

The interactions among solid waste risk, soil pollution risk, bad odour risk, lost time injuries, accident risk and the environmental uncertainties will produce environmental, health and safety risks. These risks affect the availability, efficiency and operational and maintenance cost risks. The lost time injuries risk has impacts on the accident risk, aggravation of operational and maintenance cost, environmental uncertainties and outages hours. Additionally, the GHG risk will increase the bad odour risk, environmental uncertainties, labour strike risk, and lost time injuries risk. The CLD displays how environmental risks can lead to social risks like labour strike risk

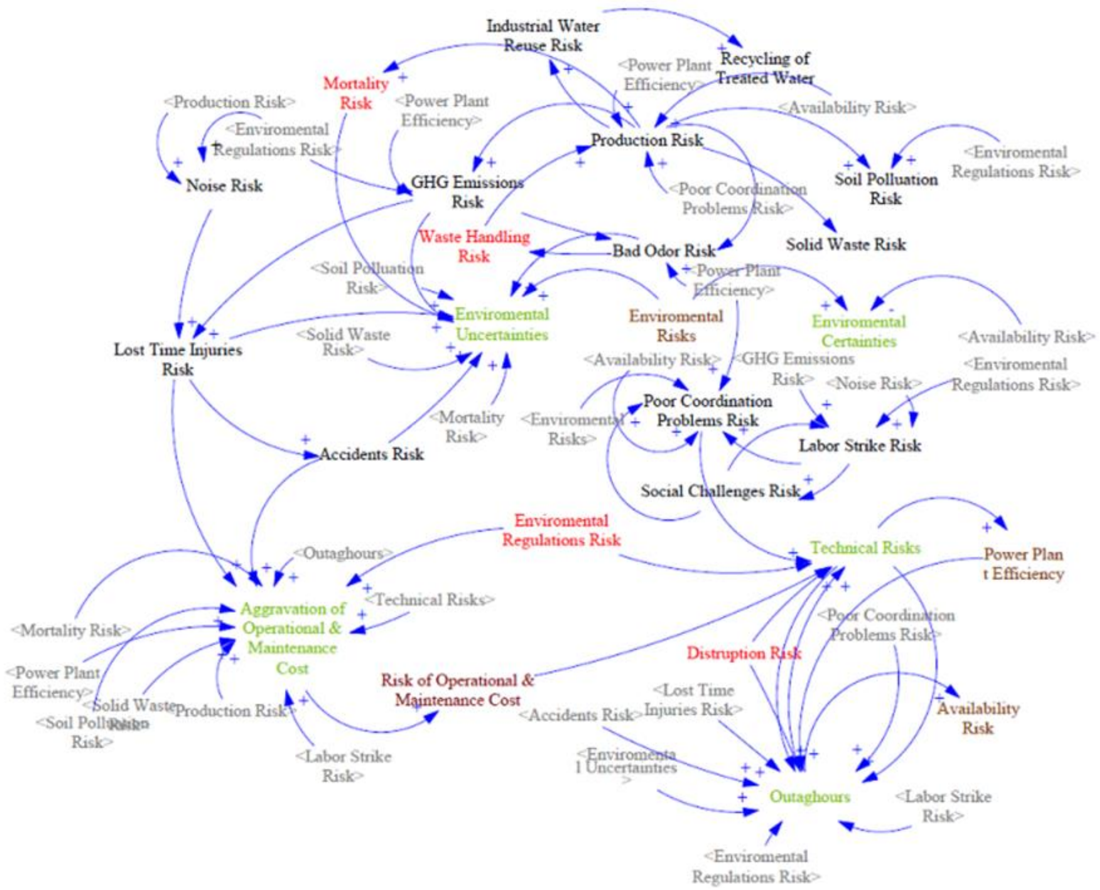

Figure 2: Causal Loop Diagram for Environmental, Health and Safety Risks Sub-Model

2.3.2 Model Simulation:

CLD is a qualitative model and cannot be utilised to simulate the system behaviour over time. Quantitative analysis can be simplified using the SFD. Simulation helps in evaluating the system's behaviour under multiple scenarios (Nabavi et al., 2017). CLDs 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; Luna-reyes et al., 2003; Wei et al., 2012). The importance and the magnitude of the 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 assumption of SFD is that systems are collections of stocks and flows, so energy or materials can be accumulated in stocks and moved though flows (Voinov and Bousquet, 2010).

SD comprises of three various types of variables : stock (levels), which represents the status of systems or the quantities with time; flow rate variables, which represents the speed of in/outflow of the stocks; auxiliaries variables, which elaborates the flow and stock connections (H. C. Liu et al., 2015).

In this paper, the CLDs have been quantified for SFDs, the interaction among various risks in power plants have been addressed and the simulation run over a 20-year period (2018-2038). 2038 is selected to show the long-term dynamics behaviour compared with the baseline.

Based on the created CLD, the SFD is constructed as shown in Figure 3. To simulate the SFD, the state of the system should be specified thus, the initial conditions for each stock (state) must be determined. These values are the outcomes of the AHP risk framework as shown in Figure 1. An assessment scale (1-5) is used to evaluate the risk level and the impacts of the risks on the power plants performance. Depending on the developed SFD, sensitivity analysis for various variables can be carried out.

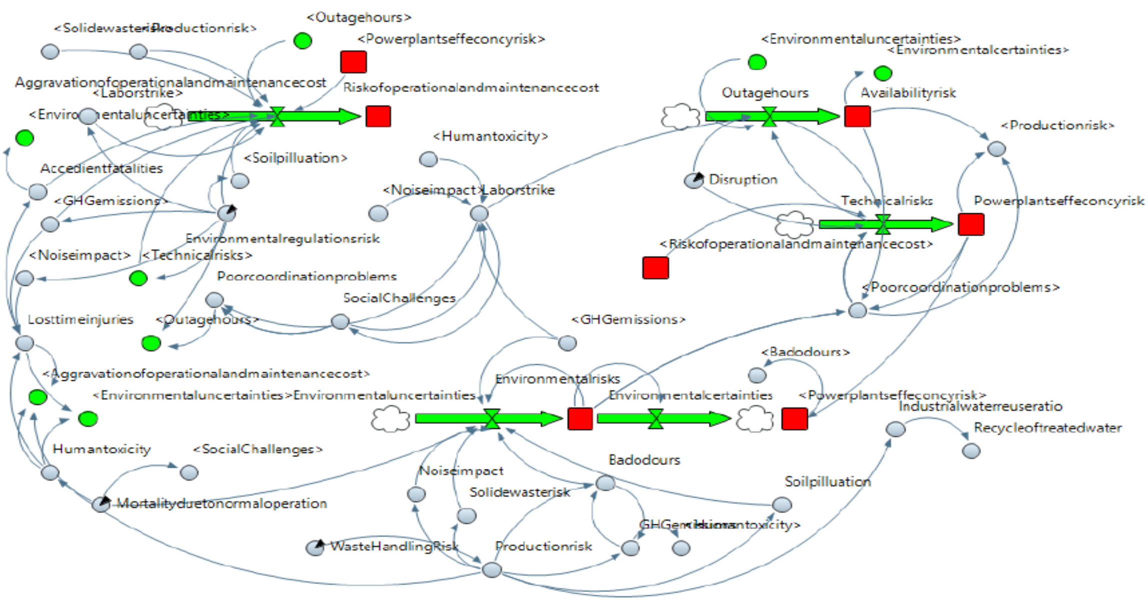

Figure 3: Stock and Flow Diagram of Environmental, Health and Safety Risks

Environmental risks, availability risk, power plant efficiency risk and risk of operational and maintenance cost are stocks. The related flow rates are the rate variables (environmental uncertainties, outages hours, technical risks and aggravation of operational and maintenance cost). Auxiliary variables are other variables such as production risk and solid waste risk. These auxiliaries' variables are utilised to control rate variables. The governing equations for system parameters calculation for the environmental risks model are shown in Appendix 1.

2.3.3 Model Validation:

Verification and validation processes focus on model tests (structure and behaviour) (Elsawah et al., 2017). The test model is a vital step of the modelling process and assists in building confidence in the developed model (Elsawah et al., 2017). The model calibration, direct structural tests and sensitivity analysis are performed to increase the confidence in the model (Xi and Poh, 2014).

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 policymakers with 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 (Kleijnen, 1995; Min et al., 2010). Furthermore, the verification process is checking if the computer program of the computerised model and the related implementation are correct (R. G. 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). The aim of the verification and validation processes is to check if the model reflects the predicted performance of the real world. Validation is the process to establish confidence in the model which can be enhanced gradually (Forrester and Senge, 1978; Groesser and Schwaninger, 2012). Likewise, the model validation is checking if the computerised model within its domain of applicability has an accuracy comparing with the purposed model. Thus, the validation process is always a matter of degree, not an absolute property (R. G. Sargent, 2013). However, validation is noted absolute and there is no 100% validated or verified the model. The model behaviour is an approximation of the system's behaviour (Carson, 2002). To check the developed model, various tests have been categorised in different ways. The validations tests can be categorised into two types, structural validity tests and behaviour validity tests (Barlas, 1989). However, testing starts by checking the dimensional consistency and checking the model structure by running the model (SD software offers options to check the units and the model structure). Models should be tested under extreme conditions that may never have been observed (Ackermann et al., 2007; Coyle, 1996; Li et al., 2016; Luna-reyes et al., 2003). A validation test of models can be categorised as, test for model structure, test for model behaviour and test for policy implications. Test of a model structure includes structure and parameter verification tests, extreme condition test, boundary structure test and dimensional consistency test (Forrester and Senge, 1978; Lemke and Latuszynska, 2013; Sargent, 2007; Senge, 1980). The most difficult test to formalise and perform a model is the structure validation tests (Barlas, 1996). To test the risk assessment model, various tests are conducted as suggested by (Barlas, 1996; Sterman, 2000). However, the assurance of model validity is a big challenge for dynamics modelling and simulation (Groesser and Schwaninger, 2012). Similarly, the validation process of the model is a significant part of simulation validation (Barlas, 1989).

To check the accuracy and applicability in the developed model, the model is validated by applying the dimensional consistency test and the behaviour replication test. The behaviour replication test is applied as a verification test to check the model ability in reproducing the behaviour of parameters.

As a part from the validation process, a sensitivity analysis test is conducted to evaluate the reliability of the simulation results due to the parameter's uncertainties of system dynamics models (Hekimoglu and Barlas, 2010). SD is exploring the system behaviour and making comparisons of system behaviours under various scenarios, but doesn't not providing a prediction of variables (Allington et al., 2017).

A sensitivity analysis can be constructed to evaluate how is the change in certain variable affects the system behaviour thus, the most impacted variables on the dynamic of the system behaviour can be determined, which helps policymakers to pay attention more of policy scenarios. Sensitivity analysis test can be applied to tests the model reliability. The generated results can be utilised to identify the most affected parameters in system behaviour therefore, they will help in analysing and understanding the future scenario (H. Liu et al., 2015). Furthermore, sensitivity analysis test analyses how the model outputs change with inputs variations. In addition, sensitivity analysis test develops intuition about the model structure (Hekimoğlu and Barlas, 2010; Sterman, 2000). Generally, in SD, the behaviour patterns of variables are more important than the numerical values of the model variables (Hekimoglu and Barlas, 2010).

To observe the sensitivity degree of each variable, each parameter is offset (decreased or increased by 5-10%) from their steady-state. The model is run for a (20 years) period of time with 2018 being considered as the initial year to generate potential decisions.

2.4 Simulation Results and Discussion

Through the time span run period of the model (2018-2038), the potential changes policies design and behaviour pattern are analysed. This helps in understanding the system behaviour with time. Among the internal interactions of various risks, the impacts of the environmental, health and safety risks on power plants performance can be explored. The dynamics simulation results of the environmental risks sub-model are shown in Figures 4-7.

As shown in Figure 4, the environmental, health and safety risks decline exponentially from 41.7% to 0% by 2038. The dynamics patterns show that the environmental, health and safety risks, waste handling risk and environmental regulations risk interacting with poor coordination problems risk, technical risks and labour strike risk. These risks affect the efficiency of power plants due to start-stop operation (availability-unavailability of power plants). From Figure 5, the power plant efficiency risk turns to take a third-order shape and the risk increases from 0% to 18.3 % at the end of 2038. Regarding the operational and maintenance cost risk, the dynamics pattern turns to a quadratic second-order polynomial function and increases from 0% to 89.3% as shown in Figure 6. The dynamics patterns show that the availability risk turns to linear function shape due to the impact of waste handling and environmental regulation risks as shown in Figure 7. In this research, the simulation period was set as 20 years. The risk assessment simulation results under initial operating conditions are depicted in Figure 4. The dynamic pattern of the initial base run in Figure 4 turns to decay gradually. The dynamics patterns of the availability risk, power plant efficiency risk and operational and maintenance cost turn to be exponentially. This forms from the interacting among variables as shown.

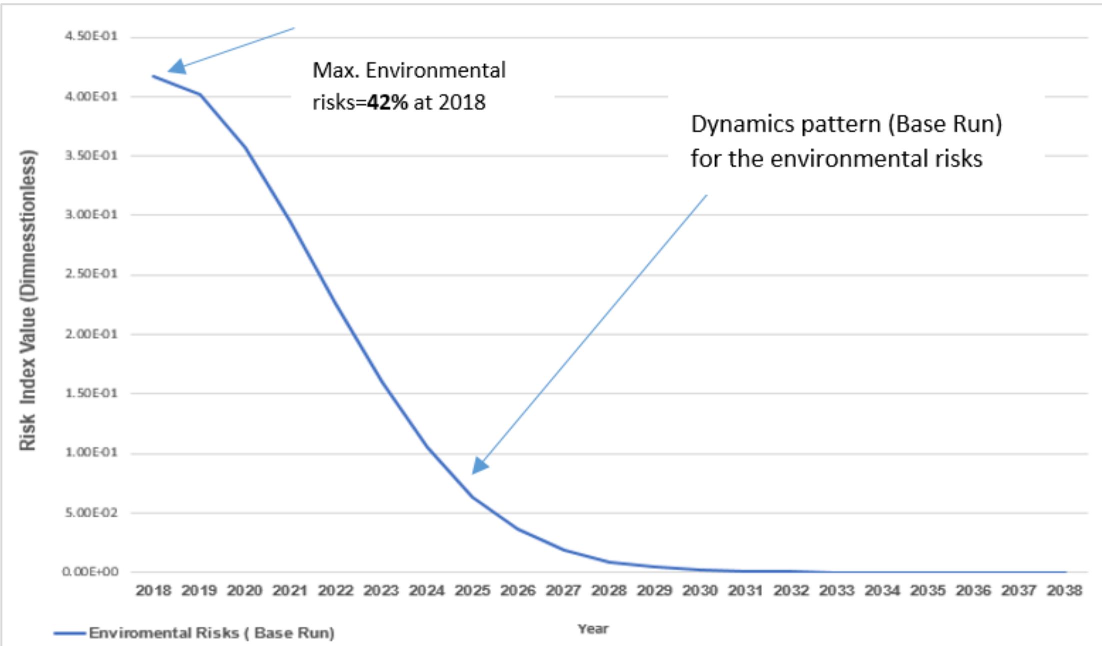

Figure 4: Simulation Patterns Results for Environmental, Health and Safety Risks

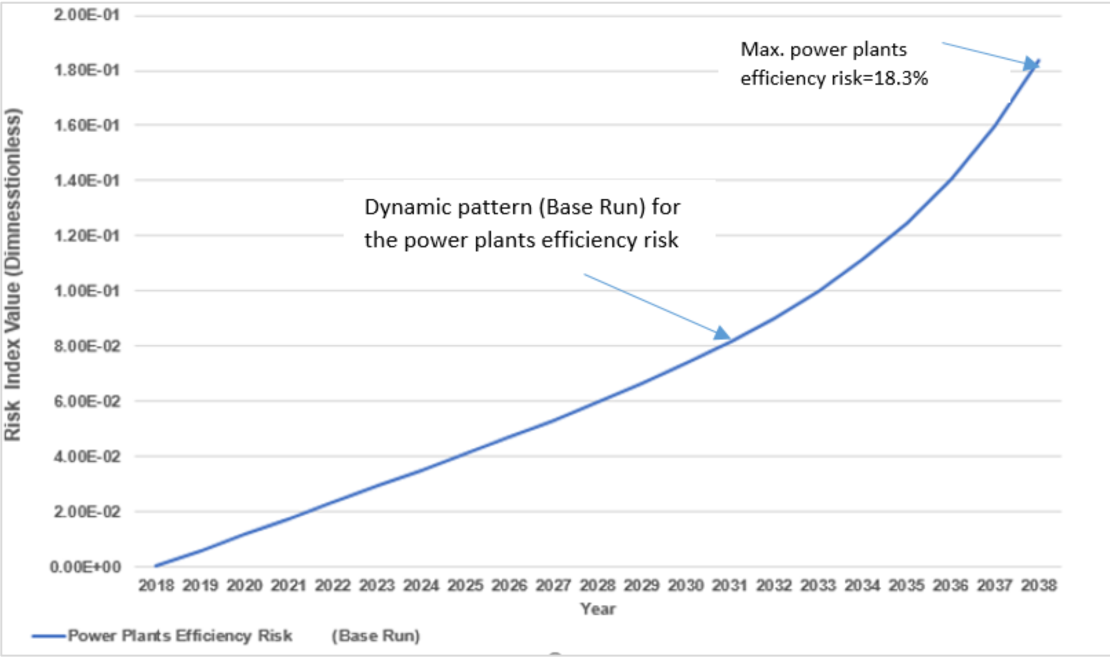

Figure 5: Simulation Patterns Results for Power Plants Efficiency Risk

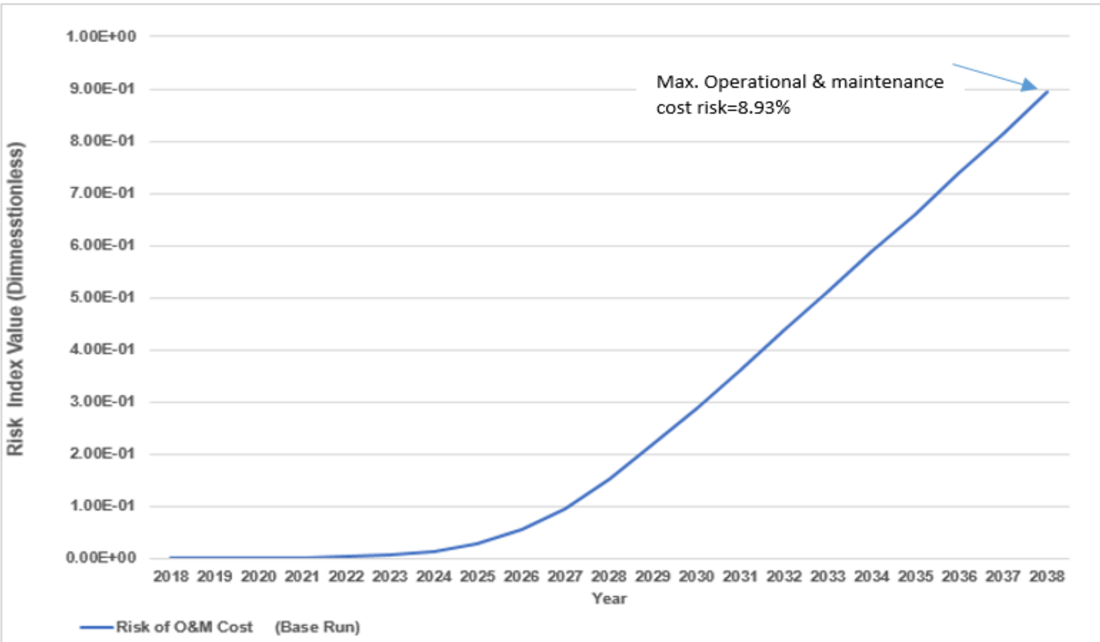

Figure 6: Simulation Patterns Results for Risk of Operational and Maintenance Cost

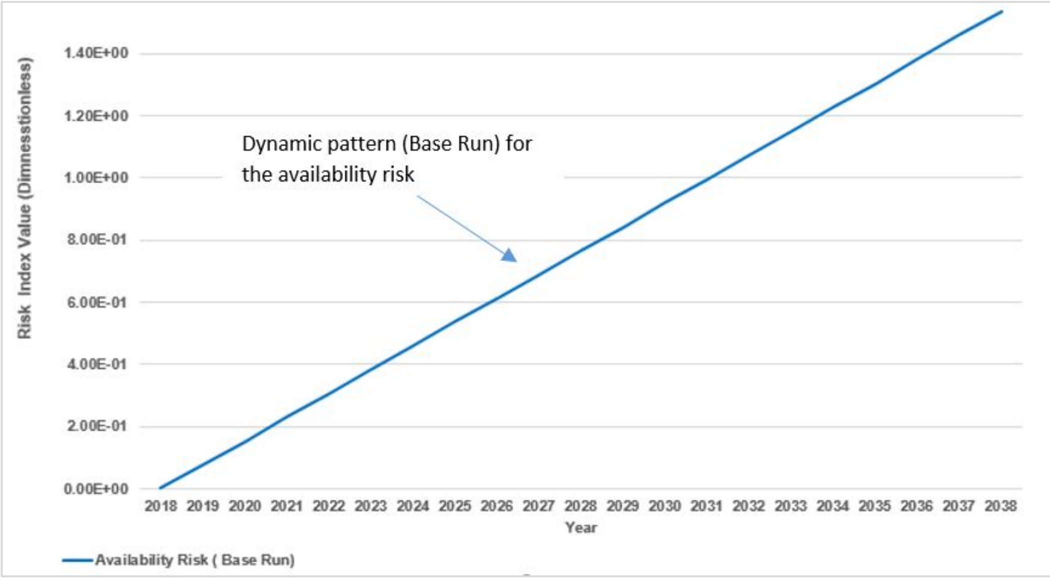

Figure 7: Simulation Patterns Results for Availability Risk

2.4.1 Sensitivity Analysis

To simulate different scenarios in SD, values of key parameters should be changed. These changes reflect the potential changes in policies (Allington et al., 2017). Overall, SD is a scenario-based approach, where the impacts of parameters variations on the behaviour of systems can be constructed. Thus, the impact of variations in the exogenous parameter values is simulated. For example, if the waste handling risk and disruption risk are decreased/increased by 20% from the initial value, these variations affect the environmental, health and safety risks as well as, affect the performance of power plants as shown in Figure (8-11).

In the model simulation, the effects of changing variables can be analysed. In this paper, an increase/decrease of 20% of the two variables is simulated. The simulation period is 20 years, which shows the long-term strategic plan. The effects of (An increasing/decreasing of 20% of waste handling risk and disruption risk) on power plants performance are simulated and the results are selected in order to test the model sensitivity as shown in Figures (8-11). However, to test the sensitivity of the models, a range of (10-20%) is selected in literature.

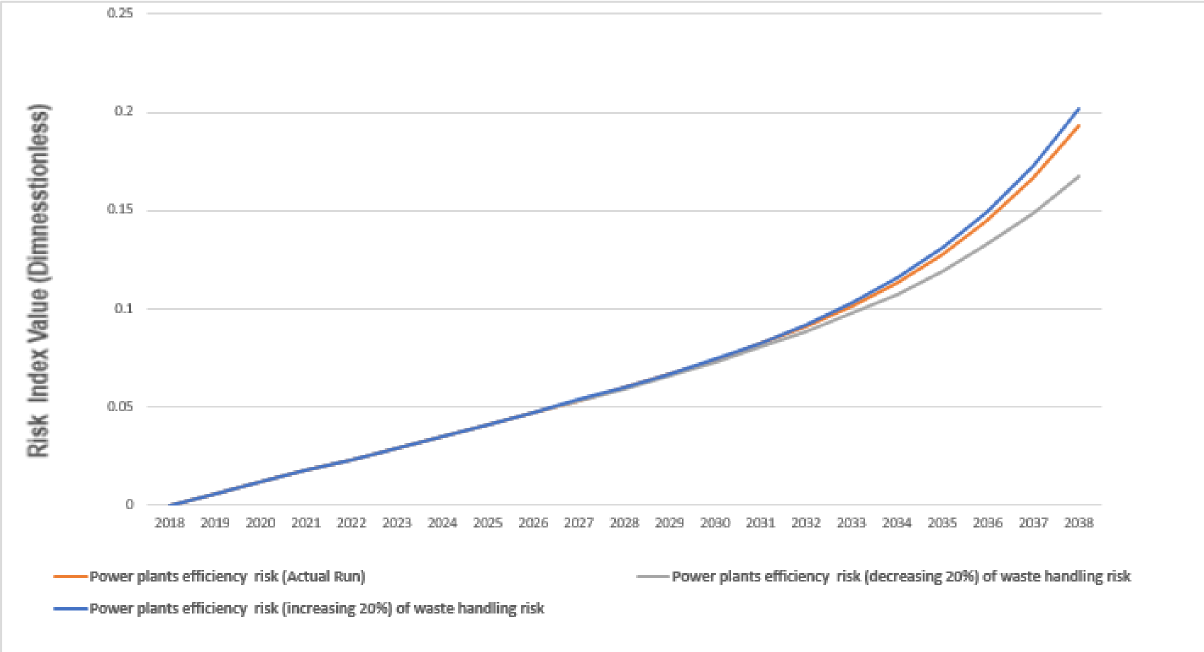

Figure 8: Sensitivity Test Analysis Patterns of Power Plant Efficiency Risk if Waste Handling Risk Change

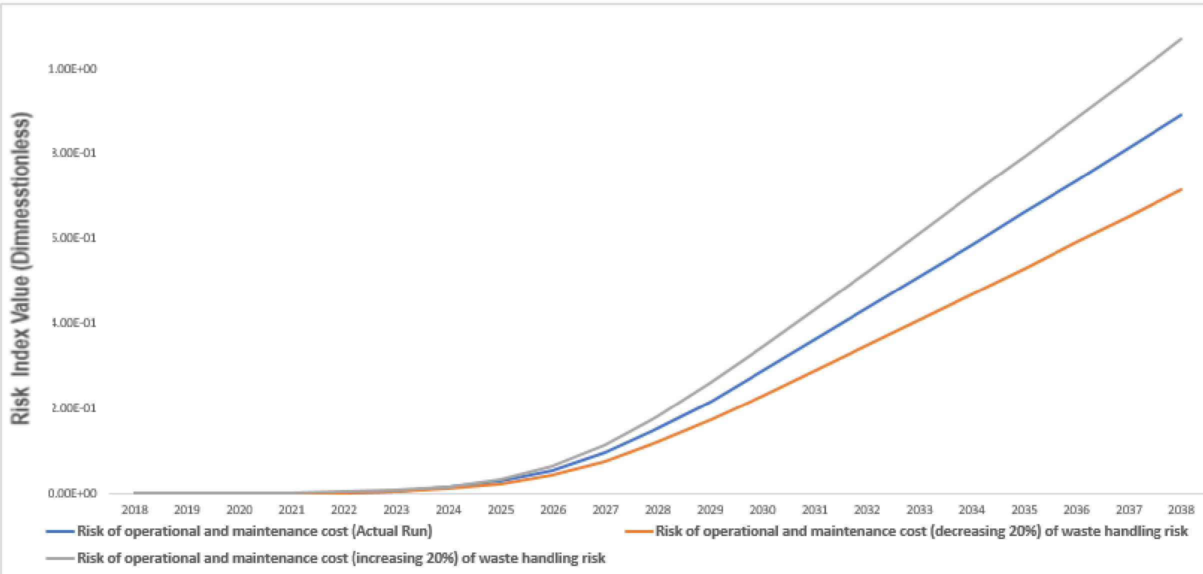

Figure 9: Sensitivity Test Analysis Patterns of Operational and Maintenance Cost Risk if Waste Handling Risk Change

When the waste handling risk decreases/increases, power plant efficiency is affected. A 20% decrease in the waste handling risk decreases the power plant efficiency risk by 6.72% as shown in Figure 9. If the disruption risk is increased, power plant efficiency is also affected. Similarly, a high disruption risk will affect the power plant efficiency and the operational and maintenance cost. A high disruption rate can increase the risk of power plant efficiency by a highly significant amount as shown in Figure 10. This reveals that policymakers should pay attention to the reason that leads to a disruption in power plants and try to decrease the disruption rate.

On the other hand, the power plants efficiency risk is changed with changing the waste handling risk under different scenarios. At the base run, the power plant efficiency risk is 18.4%, while the power plant efficiency risk declines to 11.6% when the waste handling risk is zero as shown in Figure 12. Furthermore, the waste handling risk has a significant impact on the operational and maintenance cost risk; at the base run, the operational and maintenance cost risk is 89.3%, while if the waste handling is 0%, the operational and maintenance cost risk declines dramatically to 0.64% as shown in Figure 13. Hence, policymakers in power plants should pay attention to the waste handling risk due to their significant impacts on the efficiency and operational and maintenance cost of power plants.

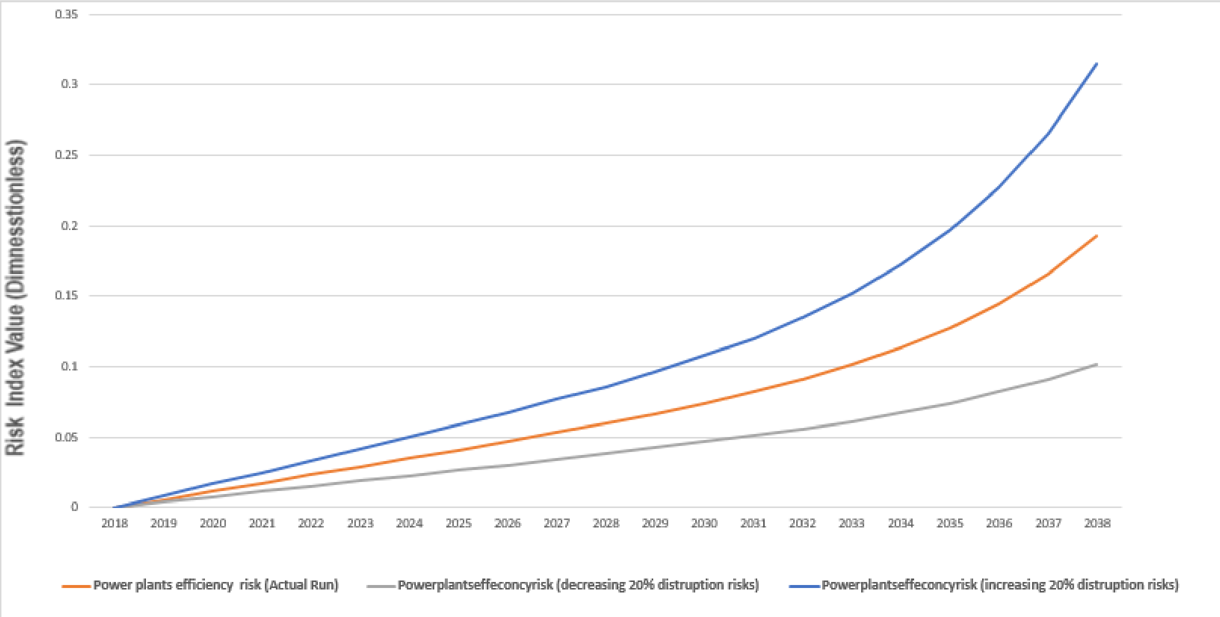

Figure 10: Sensitivity Test Analysis Patterns of Power Plant Efficiency Risk if Disruption Risk Change

Figure 11: Sensitivity Test Analysis Patterns of Operational and Maintenance Cost Risk if Disruption Risk Change

Various scenarios help in analysing the effects of exogenous parameters on the power plants performance as stated above. In this paper, the Analogic software provides a powerful tool of dimension calculation. After the validation of the system has been completed, the system behaviour of various risk assessment scenarios can be addressed. The data from practitioners in power plants are collected through a questionnaire survey and focus group interviews. The provided data involve the inputs values for the developed model, which help to stimulate the SD model through different risk scenario. The practitioners have been asked to assess the risks and assigning values for the effect of risks on the power plants performance. The data are inserted to develop the model then run the simulation. The developed SD risk assessment model package could help the policymakers in their decision-making process and can consider as a continuous improvement the system performance through the better understanding of the system behaviour and taking the suitable decision regarding the inherent risks.

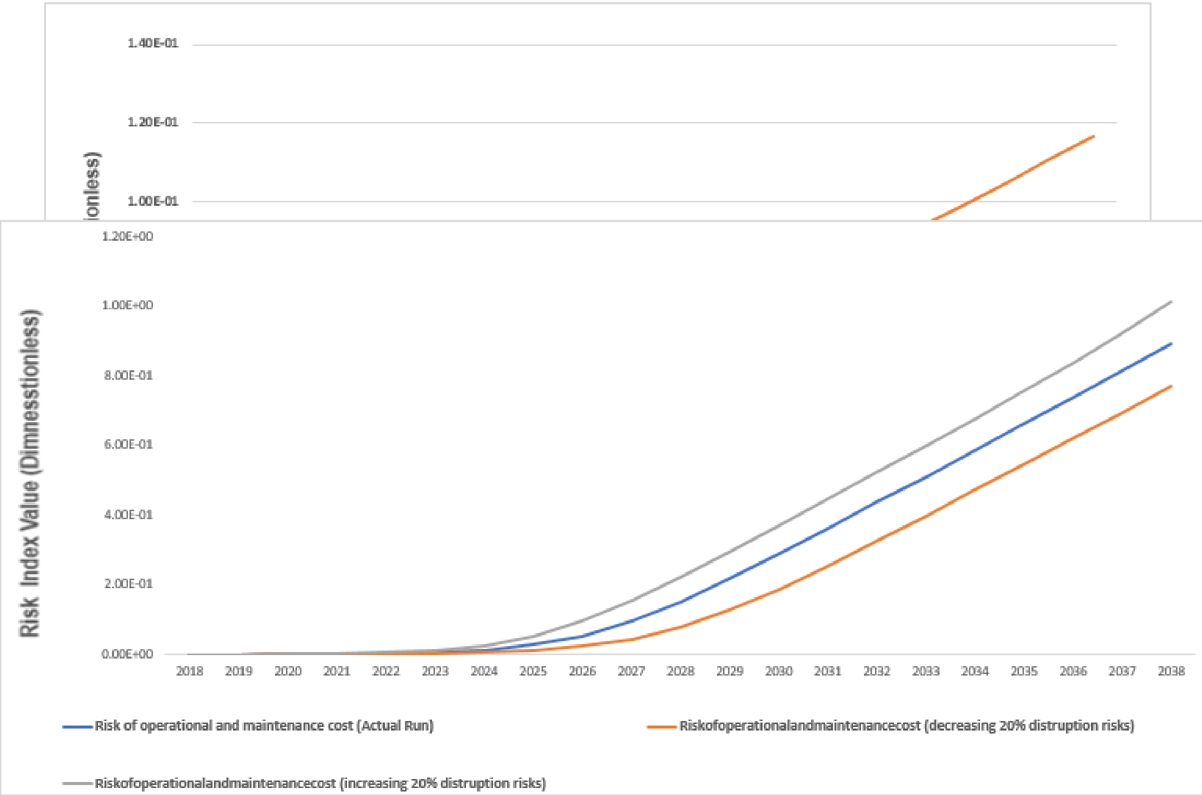

Figure 12: Simulation Patterns Results for Power Plant Efficiency Risk (Waste Handling Risk=0)

Conclusions and Summary:

Risks and uncertainness will cause disruptions in supplying energy. To addressing these issues various risk assessment tools have been adopted. For the non-technical risks particularly, in the energy sector there are limited approaches take the interdependency and the internal interactions between various risks. This paper shows a developed SD for environmental, health and safety risks assessment in power plants, the interactions and feedbacks among various risk are captured

This paper applies the SD to address the dynamics effects of various non-technical risk in power plants. The data are collected from practitioners in power plants through focus group interviews and designed a questionnaire for identifying and assessing the risks. The developed SD model can be used as a powerful decision making and management tool for risk assessment (as a decision-making tool for continuously improving the system performance).

The simulation results help in understanding the impact of various variables on power plants performance. The model is used as a tool to provide a better understanding of the long-term dynamics behaviour over time of the environmental, health and safety risks in power plants and as a policy scenario for risk assessment. Overall, the model results in this paper could play an important role in risk assessment in power plants. The results show that the disruption risk and waste handling risk can affect the power plant efficiency and the operational and maintenance cost risk.

The result of the simulation of the risk assessment model highlighted that the system is influenced influenced significantly by disruption risk and moderately by waste handling risk. Policymakers and managers should pay attention to decrease the waste handling risk even if an increase in this risk has not a high significant effect. Ignoring the waste handling risk has an effect on power plant performance in the long-term. The results also show that the disruption risk has a significant effect on power plant efficiency. The results also reveal that the developed model helps in improving the understanding of risk assessment process in power plants as a complex system. Additionally, SD should be considered a tool for continuous improvement.

One of the limitations of this study is the source of data and time needed to develop the model (define variables, creating and simulating the model).

For future research, the created system dynamics model can be implemented in other countries and for various power plants, types and the results can be compared with current work.

Appendix 1: Model Equations for the Environmental Risks Model

Environmental Sub Model	Type	Environmental risk (0.417)
Environmental Risks	Stock	d(Environmental risks)/dt= ((Environmental Uncertainties-Environmental Certainties),0.417)
Environmental Uncertainties	Flow	((Environmental risks) * (Recycle of treated water * Bad odours * Soil pollution * Solid waste risk * GHG emissions * Human toxicity))/year() + (Mortality due to normal operation* Lost time injuries*Accident fatalities)
Environmental Certainties	Flow	(Environmental risks * Availability risk)/year()
Availability Risk	Stock	d(Availability Risks)/dt=(Outage Hours,0)
Outage Hours	Flow	(Technical risks * Environmental regulations risk+ Environmental uncertainties * Poor coordination problems)+ (Disruption + Labour strike)/year()
Power plant efficiency risk	Stock	d(Power plants efficiency risk)/dt=(Technical risks,0)
Technical Risks	Flow	(Risk of operational and maintenance cost * Poor coordination problems * Environmental regulations risk) /year() + (Outage hours*Disruption)
Risk of operational and maintenance cost	Stock	d(Risk of operational and maintenance cost)/dt=(Aggravation of operational and maintenance cost,0)
Aggravation of operational and maintenance cost	Flow	(((Outage hours * Technical risks * Power plants efficiency risk*year()/Environmental regulations risk +Labour strike cost)/year()) +(Losttimeinjuries*Accedientfatalities*Mortalityduetonormaloperation) + (Solid waste risk * Soil pollution * Human toxicity))+ Production risk
Noise Impact Risk	Variable	Production risk
GHG Emissions	Variable	Production risk /Environmental regulations risk
Lost Time Injuries Risk	Variable	(Human toxicity * GHG emissions * Noise impact)
Bad Odours Risk	Variable	Production risk * GHG emissions
Soil Pollution	Variable	Production risk /Environmental regulations risk
Solid Waste Risk	Variable	Production risk
Human Toxicity	Variable	GHG emissions * Production risk * Bad odours
Industrial Water Reuse Risk	Variable	Production risk
Accident Fatalities Risk	Variable	Lost time injuries + Disruption
Recycling of treated water Risk	Variable	Industrial water reuse ratio
Environmental Regulations Risk	Parameter	Constant (0.081)
Disruption risks	Parameter	Constant (0.094)
Mortality Risk	Parameter	Constant (0.074)
Waste Handling Risk	Parameter	Constant (0.074)

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