A Hybrid Probabilistic Physics of Failure Pattern Recognition based Approach for Assessment of Multi-unit Causal Dependencies

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ABSTRACT

Isolation, redundancy and diversity are the most widely used strategies to address the complexity of system to enhance reliability and safety of critical systems. That is established with the two unstated assumptions that: (1) redundant and diverse units are able to reduce the probability of systems failure, and (2) the isolated units are completely independent. However, it is not the real case for the complex engineering systems. For instance oil & gas, nuclear and aviation, the multi-unit dependencies are able to affect multiple critical units/systems leading to detrimental impact. The accidents at the Fukushima nuclear power plant highlight the need for consideration of risks from multiple nuclear reactor units co-located at a site. The licensee event report analysis of Schroer [5] also indicated the significance of multi-unit dependencies by reporting that 9% of failure events involve two or more units. Therefore, the possible unit-to-unit interactions and dependencies should be clearly identified, modeled and accounted for in the safety studies. This paper seeks to develop a hybrid approach by combining physics-based models and supervised learning techniques to quantify the likelihood of failures due to both intrinsic and extrinsic causal dependencies. The physics-of-failure approach used in this method allows the underlying physical failure mechanisms (e.g., corrosion, fatigue, etc.) that are induced by common root causes and conditions to be incorporated into the entire modeling. Thus the related interactions of these failure mechanisms can be explicitly modeled to account for the dependencies between units. With the operational data and information of complex systems, a Dynamic Bayesian Belief Network is developed to provide predictions about the probability of occurrence of causal dependencies in multi-unit systems. The pattern recognition techniques can be applied to identify coupling mechanisms among units. The proposed approach will be validated by the multi-sensor data collected from an under-development experiment involving redundant pumping system. Collected sensor data should be of good quality to allow revealing the underlying failure behavior and dependent failures. This provides an understanding of the inherent risk significance of dependencies among multiple units over a wide range of conditions. The proposed approach can also work as the basis for the reliability of multi-unit systems where causal dependencies play a relevant role.

1. INTRODUCTION

Isolation, redundancy and diversity are the most widely used strategies to address the complexity of system to enhance reliability and safety of critical systems. That is established with the two unstated assumptions that: (1) redundant and diverse units are able to reduce the probability of systems failure, and (2) the isolated units are completely independent. However, it is not the real case for the complex engineering systems, where dependencies between the components/units (albeit small) do exist because of specific design features, operating practices, safety culture, economic considerations, and construction layout [1].

The term “dependencies” encompass all non-independent events, which are within the same unit (intra-unit dependencies) as well as between units (inter-unit dependencies). Dependent failures have been one of the most popular topics and most recent studies have only been done in context of single unit. In other words, the failures involving components in different units are not explicitly treated. Furthermore, the scopes are limited to address the simultaneous failures as the direct results of shared causes, which are the so called Common Cause Failures (CCFs). The causal relations among components or units are rarely addressed. It is even worse that some failures are just treated as CCFs once the root causes are unknown and/or are hard to be explicitly modeled [2]. Therefore, it is necessary to address the following issues referred as Multi-Unit Dependencies in this paper: (1) the causal events among components and/or units have to be modeled; and (2) the common-cause events involving multiple units need to be addressed. The multi-unit causal dependencies appear as the most important and difficult coupling mechanism and constitute a prime topic of investigation in this paper.

In several safety-critical industries, such as oil & gas, nuclear, and aviation, the multi-unit dependencies can affect multiple critical units/systems, making the expected isolation, redundancy and/or diversity among units useless to cause detrimental impact. Examples of these dependencies include, certain initiating events simultaneously occurring in multiple units, a transient in one unit affecting some or all of the other units, proximity of the units to each other, shared structures, components (e.g., shared batteries and diesel generators), common operation practices, and substantial procedural and other organizational similarities [1].

According to the International Atomic Energy Agency (IAEA) Power Reactor Information System (PRIS) as of August 2015 [3], thirty countries worldwide are operating 438 nuclear reactors for electricity generation and 67 new nuclear reactors are under construction in 15 countries. All of the operating reactors are located at 189 nuclear power sites respectively. As shown in Figure 1, 69.8% of the whole nuclear power sites are with 2 or more nuclear reactors and equivalently 86.99% of the operating reactors are located in the multi-unit sites. The two-unit-site accounts for 41.27% as the most popularly implemented model worldwide, and only few sites are constructed with 3 or 4 units, or even more than 4 units.

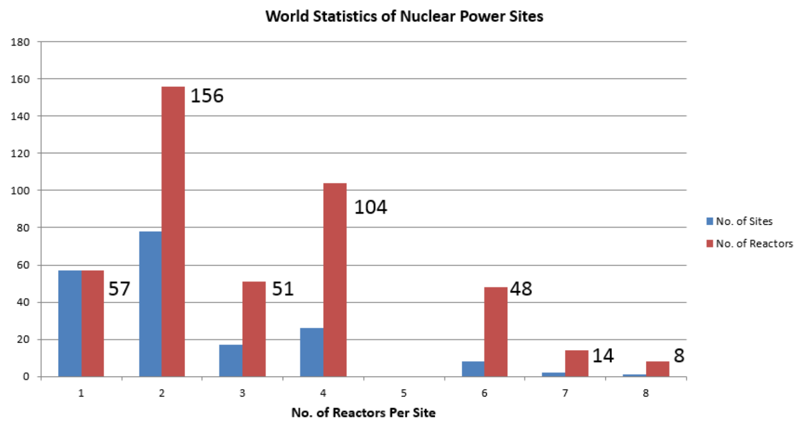

Figure 1 – World statistics of nuclear power sites as of August 2015 [3]

Recent studies of the Fukushima Daiichi accident have also underlined the urgency to consider multi-unit dependencies through the nuclear safety regulations, which would have identified, reduced or even eliminated the vulnerability in terms of multi-unit dependencies. As seen in Figure 2 [4], there are 6 boiling water reactors units that were extensively damage by the Japanese earthquake and tsunami. At that time, Units 1, 2, and 3 were generating electricity, and Units 4, 5 and 6 were shut down. The earthquake attack caused the Units 1, 2, and 3 automatically shut down, and the offsite power source to be lost. Fortunately the backup diesel generators started up as designed to supply power. However, the subsequent tsunami flooded the electrical switchgear for the diesel generators. Most AC power sources in Units 1 to 6 died except only one air-cooled diesel generator that kept operating to support Unit 5 and Unit 6. Note that Unit 4 was out of service for maintenance and all its nuclear fuel had been moved to the spent fuel pool. Fire/explosion did still happen to Unit 4 because of the simultaneous damages that hydrogen escaped from Unit 3 through the shared ductwork with Unit 4. It is also noted that, all the units were exposed to damages by earthquake and tsunami although Units 5 and 6 are located separately from Units 1 to 4.

Figure 2 – Fukushima Daiichi building diagrams [4]

As a result, the Probability Risk Assessment (PRA) community has been motivated to re-examine the PRA studies on nuclear power site safety regulations all over the world. Instead of the current safety regulations in context of single reactor unit, the multiple radioactive sources (i.e. reactor unit, spent fuel pool) should be integrated to the site safety regulation [1]. The United States is operating the largest number of nuclear reactors. According to the U.S. NRC statistics as of August 2015 [5], there are currently 99 licensed commercial nuclear power reactors to operate in the United States. All these reactor units are located in 61 nuclear power sites respectively, 57.38% of which are with 2 or 3 reactor units as shown in Figure 3. In other words, 73.74% of the operating reactors are located in the multi-unit sites.

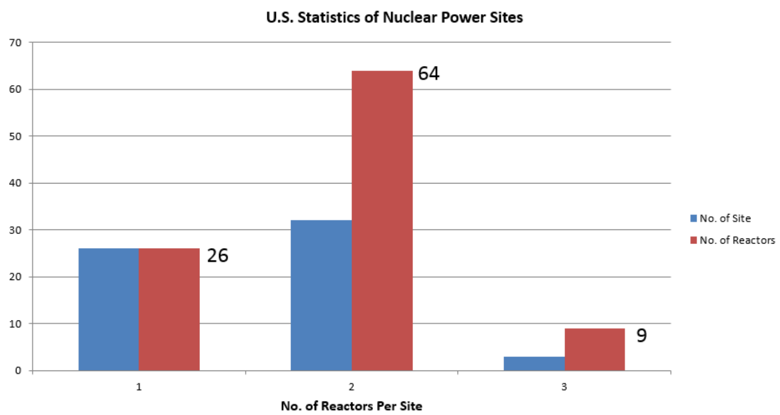

Figure 3 – U.S. statistics of nuclear power sites as of August 2015 [5]

Once there is plant abnormalities, NRC requires the Licensee Event Reports (LERs) to be submitted in accordance with guidelines prescribed in 10 CFR 50.73. Schroer and Modarres [6] have analyzed the LERs submitted between 2000 and 2011, and concluded that 391 of 4207 total LERs affected multiple units on a site which amounts to 9% of the total LERs. Most of these identified multi-unit LERs involving organizational and shared connection types of dependencies. This represents a significant number of multi-unit events involving two or more units.

2. OBJECTIVES

This paper seeks to develop a hybrid approach to integrate the underlying physics of failure and their interactions, ultimately, the causal dependencies between the multiple units. The scope of this paper is mainly limited to the hardware dependencies while the approach is still applicable to address the soft dependencies in terms of human, organization. In particular, it is proposed to incorporate the underlying physical failure mechanisms (e.g. corrosion, fatigue, etc.) that are induced by common root causes and conditions, so that the related interactions of these failure mechanisms can be explicitly modeled to account for the dependencies between units. For instance, the causal chains tied to multiple units can be modeled by addressing the loads imposed by the internal and/or external events, such as the mechanical loads, thermal loads, etc.

All the causal-relationships are modeled using an established and promising causal-based technique: Bayesian Belief Network (BBN) [7]. The BBNs also allow different information to be integrated, such as field data, testing data, expert input, etc. As illustrated in Figure 4, events A and B are demonstrated as the unit-to-unit casual and common-cause relations respectively. The details of BBNs modeling approach will be discussed in the following sections. Once the sources of dependencies among multiple units are explicitly modeled, supervised learning techniques are adopted to quantify the likelihood of failures due to dependency effects. The ultimate goal of this research is to establish an efficient technique to estimate the conditional and marginal probability of the failure of multi-unit system. This provides an understanding of the inherent risk significance of dependencies among multiple units over a wide range of conditions.

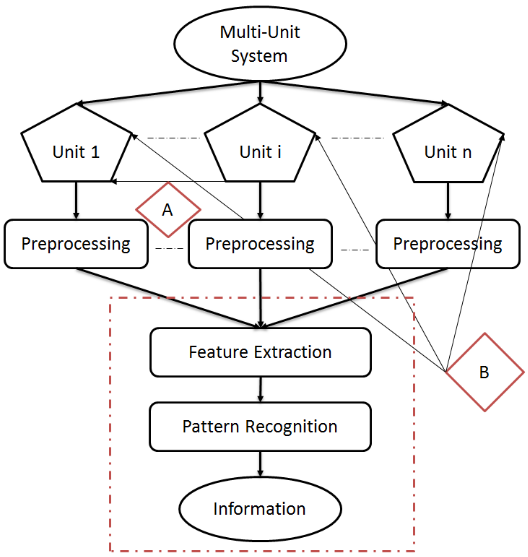

Figure 4 – Multi-unit dependency strategy

An experiment involving redundant pumping system is under developed to illustrate the proposed approach. The degradation and failure of the pumps are accelerated along with monitoring of a diverse set of parameters such as temperature, vibration, corrosion, and acoustic emission whose patterns will be used to reveal the underlying failure behavior and dependent failures in the system. This information is also used to inform probabilistic physics of failure model characterizing the damage of multi-unit systems. The proposed approach can work as the basis for the reliability of multi-unit systems where causal dependencies play a relevant role.

3. METHODOLOGY

The main task is to explicitly model the multi-unit system incorporated with the unit-to-unit dependencies, which requires the hybrid BBNs model formed with discrete and continuous variables. In Section 3.1, a brief discussion of unit-to-unit dependency classification is presented. In Section 3.2, a conceptual hybrid BBN model is proposed with three modules, and each module is further characterized with several levels of indenture to represent unit configuration, failure information, and dependencies relations. An experiment under development is also described in Section 3.3 as a future case study to validate the proposed approach.

3.1 Dependencies Modeling

A few dependencies studies have been conducted in different industries. For example, common cause failure within nuclear reactor unit [8]; dependent-failures in spacecraft [9]; common cause failures of safety instrumented systems in oil and gas industry [10]; and dependent failures in communication networks [11]. However, these studies mainly focus on the dependencies in the context of single unit, and the failures involving components in different units are rarely treated. Some studies have been proposed to deal with interdependencies among hierarchy of systems or complex networks. For instance, interdependencies studies on critical infrastructures [12, 13] and failure of interdependent networks [14]. The typical way to classify the dependent events is based on whether the event is causes-oriented or modes-oriented. Although several ways have been proposed to categorize dependencies in the studies above, it is necessary to develop a consistent and efficient classification to deal with dependencies of multi-unit complex system.

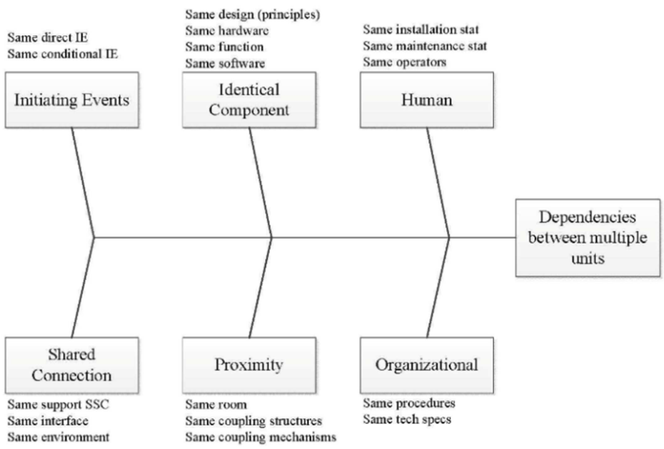

Figure 5 – Classification of dependencies [5]

This study adopts a dependency taxonomy developed by Schroer and Modarres [6]. As shown in Figure 5, the dependent events are categorized into six categories: initiating events, shared connections, identical components, proximity dependencies, human dependencies, and organizational dependencies. In this paper we divide the dependencies in two dimensions: Physical Dimension (Intra-Unit or Inter-Unit) and Logical Dimension (Parametric or Causal), both of which are explained as below.

- Intra-Unit: dependent components are located in only one unit, which is as the same as the scope of the traditional dependencies studies in the context of single unit.
- Inter-Unit: dependent components are located in multiple units, which represents the interactions or dependencies among different units.

* Parametric: dependent components are identical (same components such as an MOV), which is similar to the traditional CCFs while the scope is extended to account for the components located in different units.
* Causal: one event causing another event that can be either identical or dissimilar within one unit and between units. This is the primary interest of this paper.

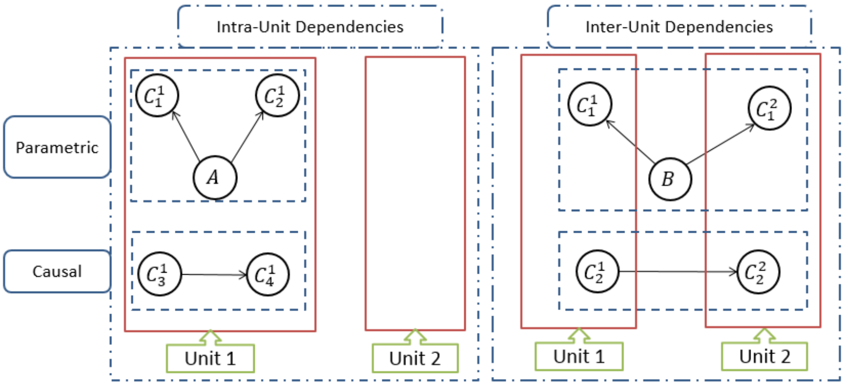

Figure 6 – Approach to integrate dependencies into the hybrid BBNs model

As shown in Figure 6, consider a two-unit system as an example to conceptually illustrate the dependencies modeling, where $\boldsymbol{C_i^n}$ represent the $\boldsymbol{i^{th}}$ Component of Unit n. Each possible dependency is explained as following:

* Parametric and Intra-Unit: the event “A” is the shared root cause leading to the failure of both Component 1 and Component 2 within Unit 1. This is the representative of traditional CCFs.
* Parametric and Inter-Unit: the event “B” causes the failures of both Component 1 in Unit 1 and Component 1 in Unit 2. This is one of the major concerns of multi-unit dependencies.
* Causal and Intra-Unit: the failure of Component 3 in Unit 1 leads to the failure of component 4 of the same Unit 1;
* Causal and Inter-Unit: the failure of Component 2 in Unit 1 leads to the failure of component 2 in Unit 2. This is another important concern of multi-unit dependencies.

3.2 Hybrid Bayesian Belief Networks (BBNs) Modeling

The Bayesian Belief Network model for multi-unit dependencies analysis should reflect the causal chains of dependency relations between each unit as shown in Figure 7. Each node represents a random variable. The directed edge between nodes indicates the probabilistic influence. In particular, the multi-unit system is hierarchically modeled in the first module named “Multi-unit System Specifics Module”. In the second module “Failure Specifics Module”, the failure information is introduced with the underlying physical failure modes and failure mechanisms. Then the root causes and surrounding environment conditions act as the conditions that couple the units together, so that all the possible dependencies are able to be established in the third module “Dependencies Specifics Module”, which produces chains of events and transitions. For each module, there are several levels respectively, each of which could also be represented as a complex BBN model. Note that there could be differences in the choices of levels depending on the modeling purpose. A formal model of the hybrid BBN is explained more details in the following.

The Multi-Unit System Specifics Module is decomposed to four levels to represent the state of multi-unit system S with n units. The state of each unit is then characterized by the required operating functions and the involved components.

- System Level: these discrete nodes represent the state of multi-unit system S, such as the number of failed units, the number of units that not work as expected.
- Unit Level: the nodes are usually featured as discrete variables to indicate whether the unit is working as expected or not. $\boldsymbol{U^i}$ means the $\boldsymbol{i^{th}}$unit of system S, where $\boldsymbol{i = 1, 2 \ldots, n}$;
- Function Level: the nodes represent the functions required for the unit to operate. The nodes can be either discrete or continuous depending on the objectives of model. $\boldsymbol{P_j^i}$ means that the $\boldsymbol{j^{th}}$ function is required by the $\boldsymbol{i^{th}}$ unit where $\boldsymbol{j}$ is any positive integer specified for the corresponding unit.
- Component Level: these continuous nodes are utilized to indicate the states of components exposed to typical failures. All these components usually degrade along the lifetime. Each node in this level can be input of one function, or multiple functions. $\boldsymbol{C_{j,k}^i}$ represents the $\boldsymbol{k^{th}}$ component for the $\boldsymbol{j^{th}}$ function of unit i.

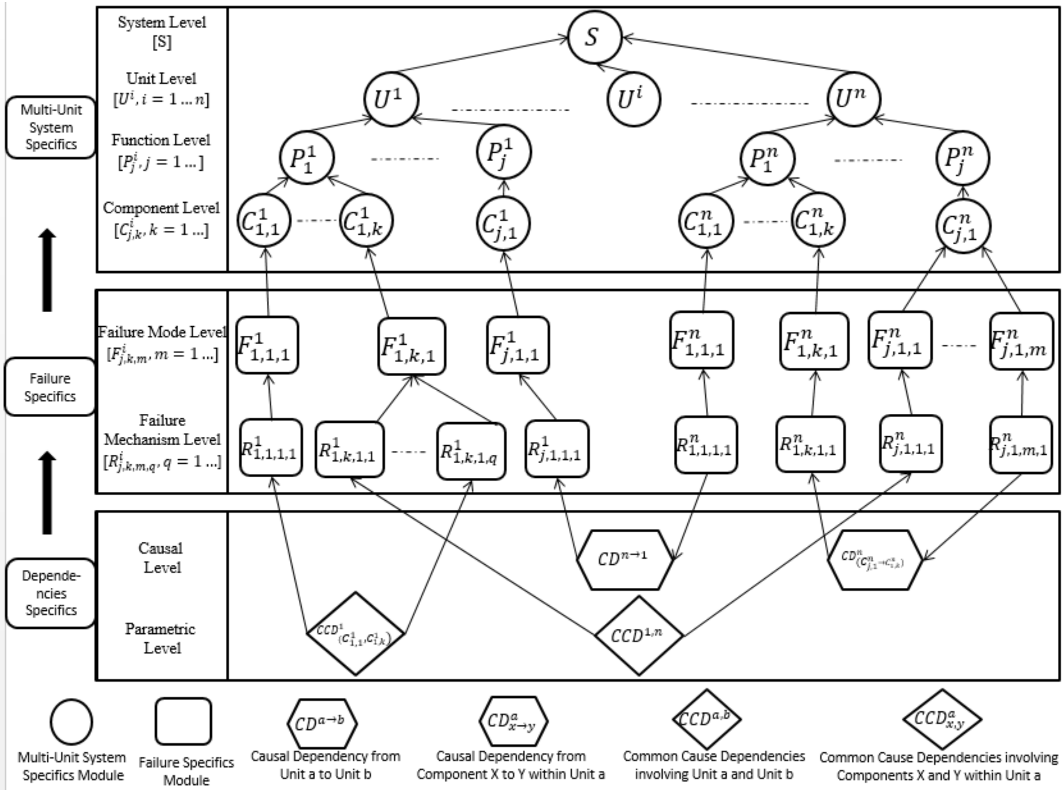

Figure 7 – Conceptual hybrid BBN model for multi-unit dependencies

The Failure Specifics Module is supposed to contain all the typical failure modes and related failure mechanisms, which are the input of the two levels as below. This could be completed according to the expertise, engineering experience, etc.

- Failure Mode Level: these nodes represent the typical failures of interest. $\boldsymbol{F_{j,k,m}^i}$ indicates the $\boldsymbol{m^{th}}$ failure mode of the $\boldsymbol{k^{th}}$ component required to enable the $\boldsymbol{j^{th}}$ function of unit i.
- Failure Mechanism Level: these nodes corresponds the failure mode leading to the components degradation. $\boldsymbol{R_{j,k,m,q}^i}$ means the $\boldsymbol{q^{th}}$failure mechanism contribute to the $\boldsymbol{m^{th}}$ failure mode of the $\boldsymbol{k^{th}}$ component required to act the $\boldsymbol{j^{th}}$ function of unit i.

The failure information above acts as the coupling events to tie to different units or components in the Dependencies Specific Module. These dependencies relations are expressed by causal chains between levels or within the same level. This could be achieved according to the expertise, engineering experience, etc. Otherwise pattern recognition techniques can be applied to identify coupling behaviors among units with the operational data of some complex systems.

- Causal Level: the causal dependencies are expressed by a directed acyclic between different nodes in the level of failure mechanism. $\boldsymbol{CD^{a}_{x\rightarrow y}}$ represents Causal Dependency from Component X to Y within Unit a; $\boldsymbol{CD^{a\rightarrow b}}$ means the Causal Dependency from Unit a to Unit b.
- Parametric Level: the common cause dependencies are denoted as a combination of different nodes in the level of failure mechanism with the same shared event in Parametric Level. It can be which can be external factors such as environmental stresses or temperature, or component internal factors related to material properties or physical characters. $\boldsymbol{CCD^{a}_{x,y}}$ is the Common Cause Dependencies involving Components X and Y within Unit a; $\boldsymbol{CCD^{a,b}}$ is the Common Cause Dependencies involving Unit a and Unit b

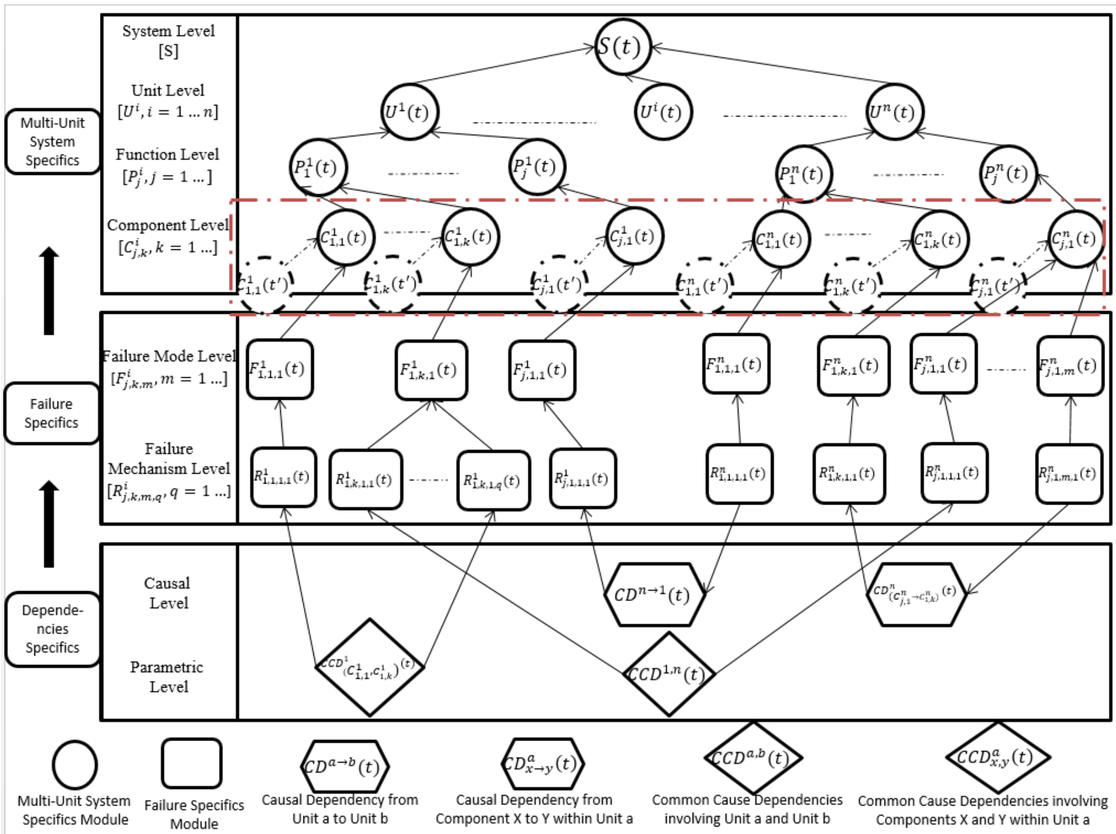

Figure 8 – Two-time-slice representation of a hybrid Dynamic BBN model (from t' to t)

It is indeed that the dependencies are likely to change along lifetime depending on the working status of all the units themselves, and the surrounding environmental stresses. In particular, some units may work at full capacity and some others work at partial capacity or even shut down. Even for the same unit, the operating status is also likely to vary sequentially, such as electrical power output changes due to the seasonal demanding. The degradation or failure of the physical components is also able to affect the possible dependencies. Therefore, it is intuitive to account for the temporal effects on the dependencies, which can be achieved by Dynamic Bayesian Belief Networks (BBNs).

The component variables are the main changes as some important components are susceptible to the surrounding stressing variables (e.g. temperature, loading imposed by other components) and degrade over time [15]. Thus the status of components at a certain time slice depends on their status at the previous time slice and the factors affecting the degradation processes during that transition. As shown in Figure 8, it is a two-time-slice representation of a hybrid Dynamic BBNs, which is essentially a replication of the static BBN with the addition of a set of temporal arcs representing the transition model over time slices $\boldsymbol{t'}$ to $\boldsymbol{t}$ ($\boldsymbol{t'} < \mathbf{t}$). The role of temporal arcs, which is shown as dashed arrows, is to connect the nodes representing the copies of the same variable at different time slices.

3.3 Case Study

The methodology is being validated by a multiple-pump experiment located in a testing chamber designed to accelerate the multi-unit failure due to common stress conditions. In particular, there are three identical small scale centrifugal pumps driven by electric motors. All the pumps are kept independently re-circulating fluid and subject to the same working conditions. The degradation and failure of pumps are accelerated by pumping seawater at elevated temperature (60°C), and being inside the testing chamber as shown in Figure **9** with elevated temperature (60°C) and corrosive conditions (salt spray).

Figure 9 – Environmental testing chamber

With the aging of the pump, adverse events arise as consequences of the interaction between the environment and components of each pump, which include mechanical (hydraulic), chemical (sea water), and thermal (heating, thermal shock). These adverse events can be in any form of damages or degradation in terms of the performance and functionality of pumps, such as decreasing flow, decreasing pressure, abnormal vibration, etc. An advanced sensing system is designed and underway to monitor the overall health and condition of the pump. Whenever there is an incipient failure of components initiates and propagates, the physical properties and dynamic behavior of this component are changed to affect the overall system performance. In this experiment, both vibration and acoustic emission monitoring are employed to monitor the dynamic changes. By continuous monitoring the dynamic behavior of the pump, any anomalies of the pump can be detected and even enable to identify the particular causes. Furthermore, the key performance indicators are carefully selected to ascertain pump operational health [16]. The measurement of quantities include: temperature, pressure, flow rate, and power consumption. A toroidal conductivity sensor is also used to monitor the changes of the conductivity of process fluid to address the corrosion of pumps.

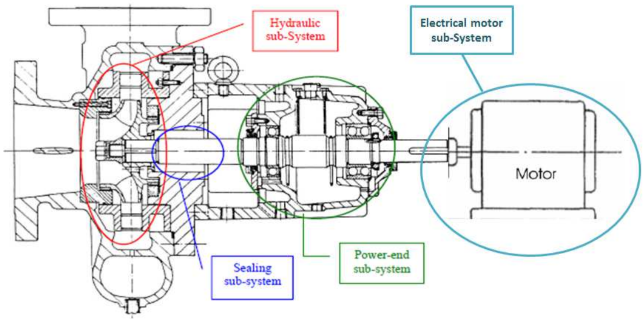

Figure 10 – Main sub-Systems within a centrifugal pump [18]

These three pumps have common-cause dependencies since they share common inter-environmental factors (i.e. salt spray, heating at 60°C, relative humidity) and intra-environmental factors (i.e. heating at 60°C, seawater). The causal relations among units are unknown yet and will be identified by extracting the features of the data collected from the advanced sensing system. As discussed in the previous section, it is required to develop models for the failure mechanisms and interactions to evaluate the pump-to-pump dependencies. Thus it is necessary to understand the centrifugal pump's primary components, failure modes, and failure mechanisms [17, 18]. The first step is to define the failure of each pump and the system boundary, which haven't been decided yet since the behavior of pump is not clear in the actual tests. The general definition of failure could be that the capacity of pump output falls below a specified threshold. As shown in Figure 10, the centrifugal pump can be divided to four sub-systems: hydraulic system, sealing system, power end system, and electrical motor system [18]. The main components and failure modes for each sub-system can be summarized in the Table 1.

Table 1 – Main components and failure modes for the sub-Systems of a centrifugal pump [18]

Sub-Systems	**Components**	**Failure Modes**
Hydraulic system	Impeller	Worn impeller
	Casing	Ruptured casing
Sealing system	Mechanical seal	Seal leakage
Power end system	Pump shaft	Broken shaft
	Pump bearings	Worn/broken bearing
Electrical motor system	Motor shaft	Broken shaft
	Motor bearings	Worn/broken bearing
	Cooling fan	Cooling fan failure
	Circuit breaker	Circuit breaker failure
	Stator	Winding insulation failure
	Rotor	Broken bar

The most critical failure modes will be modeled and have to be selected based on the actual test results. Although it is possible to get information on pump failures from the obtained sensor data, the analysis is still difficult due to the limited boundary of the failure investigation. Therefore, other sources are necessary to complement the analysis, such as expert elicitation, visual inspection, etc. For illustration purpose as seen in Figure 11, the failure of each pump is defined as the capacity fall below the intended threshold, and the critical failure modes are assumed as following:

- Ruptured casing;
- Damaged impeller;

- Seal leakage;
- Broken pump bearings;
- Fracture of motor shaft.

With carefully running the tests, collected sensor data should be of good quality to diagnose the failure mechanisms, which allows us to implement pattern recognition to reveal the underlying failure behavior and dependent failures in the system. Then extract features and establish the relations between these features and possible damages.

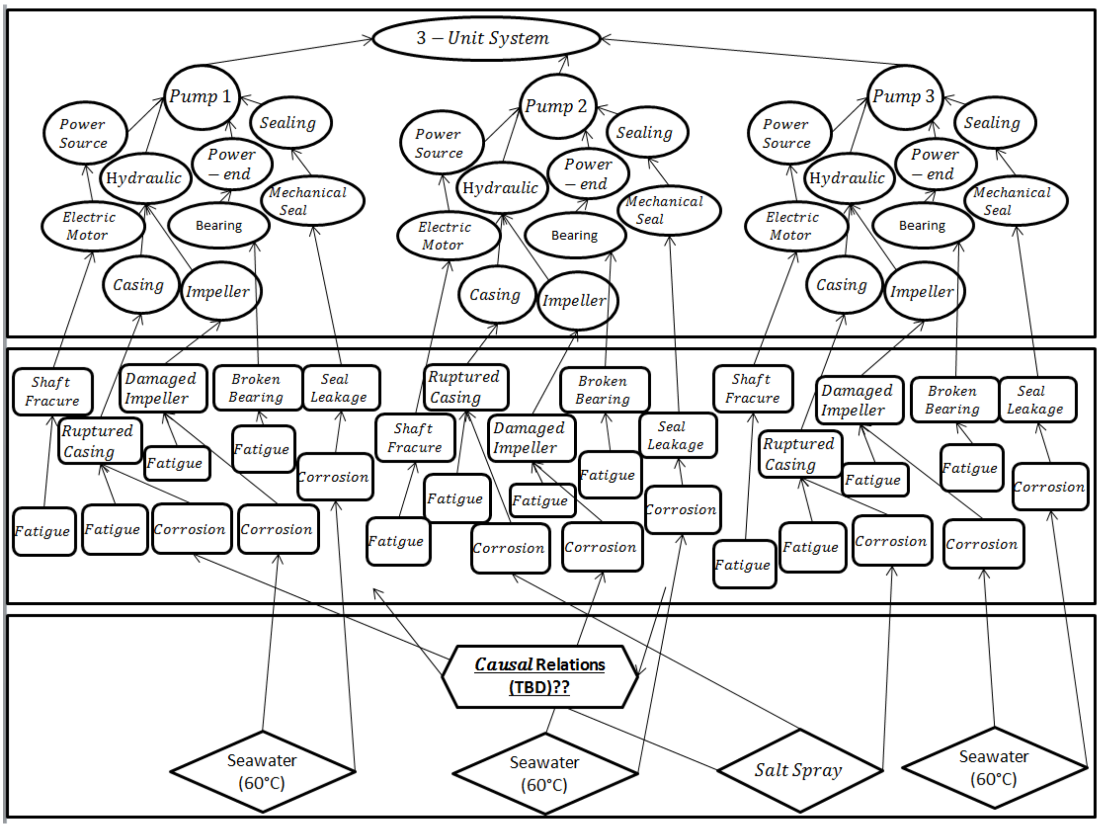

Figure 11 – Illustration of the hybrid BBN model of the redundant pumping System

4. CONCLUSIONS

In this paper, a hybrid approach was proposed to combine physics-based models and supervised learning techniques to quantify the likelihood of failures due to unit-to-unit causal dependencies. This causal-based approach allows the underlying physical failure mechanisms (e.g. corrosion, fatigue, etc.) induced by common root causes and conditions to be incorporated into the entire modeling. With the operational data and information of complex systems, a Dynamic BBN is developed to provide estimation of the probability of occurrence of causal dependencies in multi-unit systems. The proposed approach will be validated by the multi-sensor data collected from an experiment underway involving redundant pumping system, degradation and failure of which are accelerated along with monitoring of a diverse set of parameters such as temperature, vibration, corrosion, and acoustic emission whose patterns will be used to reveal the underlying failure behavior and dependent failures in the system. Collected sensor data should be of good quality so that the pattern recognition techniques can be applied to identify coupling mechanisms among units. This information is also used to inform probabilistic physics of failure model characterizing the damage of multi-unit systems. The proposed approach can also work as the basis for the reliability of multi-unit systems where causal dependencies play a relevant role.

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