



Model-based Fault Detection of Manufacturing Processes and Machines using Model Checking and Probabilistic Boolean Networks

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Abstract—Developing systems and methodologies capable of monitoring the condition and diagnosis of multiple faults in industrial systems is a topic of active and continuous research. This paper presents a fault diagnosis system based on Probabilistic Boolean Networks as a fundamental tool is proposed for diagnosing faults of a group of machines in a manufacturing process, using Model Checking. The proposed approach considers the failure modes of the machines involved that are catastrophic to the function and performance of the system. Firstly, these failure modes are identified and divided into two groups: faults and failures. The former implies detectable degradation of system function until the threshold for fault is eventual catastrophic loss of system is surpassed. The latter leads to catastrophic fault. Then, using Probabilistic Boolean Networks, faults can be diagnosed and actions to mitigate them can be taken. The proposed method is applied to a standard ultrasound welding process. A PBN has been simulated and verified using model checking in the PRISM Model Checking system. The obtained results demonstrate the validity of the proposed methodology.

Keywords — Fault Detection and Isolation, Multiple Faults, Probabilistic Boolean Networks, Reliability.

1.0 INTRODUCTION

For current industry to produce goods of the highest quality, while complying with environmental, safety and other regulations, the efficiency of the processes has to be improved. Any unscheduled stops in production and equipment faults impact negatively system availability, operational and environmental safety, and the productivity and profitability of the business. Proper operation of these systems involve compensating the effects disturbances and changes can have, and in order to assure continuous operation within performance specifications, faults have to be detected, isolated and eliminated, all of which are tasks related to Fault Detection and Isolation (FDI) [19]. FDI methods are mainly divided in two categories, which are model-based and process-history-based [40, 42].

The model based methods make use of an analytical or computational model of the systems. A great variety of the proposed model based methods are supported by a few basic concepts such as: the parity space; observer approach and the parameters identification or estimation approach [17, 14, 18]. In [45] it is recognized that observers and parity space approaches do not always allow the isolation of the actuators faults. For nonlinear models, the complexity on the observer design increases, while an exact model of the system is necessary for the parity space approach [45]. To overcome these problems a more recent approach based in the solution of an inverse problem using computational intelligence tools has been presented [6-7, 1]. In general, the developed researches have been limited to the diagnosis of independently occurring faults.

The diagnosis of simultaneous faults is an area not very addressed in scientific literature. Multiple faults in dynamic systems can be difficult to detect, because the effects of a fault can be hidden or compensated with the effects of another type of fault, and because the same type of multiple fault can manifest itself in different forms, considering their order of occurrence. The computational intelligence tools have been the most used to address this area [43, 36, 27]. In this sense, research has focused on static systems [37], solutions to the multiple faults problem through observations on imperfect tests as in [32], to determine the closest evolution relative to the state of the fault. The authors of [44] postulate an algorithm-based pattern recognition method for diagnostics, which resulted in high efficiency and precision, but with cases in experimental data where particular fault tests didn't have a solution. Other developments include SLAT patterns for multiple fault diagnosis [5], and model-based methods for describing multiple faults in rotor systems [3]. However, the multiple fault diagnosis is a current research area which demand the development of novel strategies for



improving the performances of the fault diagnosis systems. The main objective of this paper is to present a new approach of multiple faults diagnosis in industrial systems by using Probabilistic Boolean Networks (PBN).

Biomimetic methodologies are widely used in manufacturing for the solution of many complex problems. Qualitative frameworks, such as PBNs allow describing large biological networks without losing important system properties, and allowing the representation of complex behavior, such as self-organization. PBNs are used to model Gene Regulatory Networks (GRN); collections of DNA segments within a cell that interact indirectly with other segments and substances in it to govern the expression levels of genes. They are used to understand the general rules that govern gene regulation in genomic DNA. PBNs are transition systems that satisfy the Markov Property, (memoryless, not dependent on the history of the system). Proposed by I. Shmulevich [33] as an extension of Kauffman's Boolean Network (BN) concept, they combine the rule-based modelling of Kauffman's BNs with uncertainty principles. PBNs consist of a group of constituent BNs that have assigned selection probabilities, where each BN can be considered a "context". Data for the cells comes from different sources; each one representing a context of the cell. In each time t , a system can be governed by one of the constituent BNs, and at any other time the system may switch to another constituent BN with a given switching probability. PBNs for manufacturing systems were introduced in [28] and further developed in [29-31].

In this article, the use of PBNs in manufacturing systems will be expanded to allow the consideration of faults that may lead to catastrophic failure, being this the main contribution of this paper. The proposed model allows single and multiple fault detection and classification which constitute another contribution of the proposal. It also allows to forecast a time in hours by which the fault will be imminent.

This paper is organized in the following manner: Section 2 discusses Probabilistic Boolean Networks and their use in manufacturing systems modeling, Section 3 presents how these PBNs can be used for FDI in these systems. Section 4 discusses the experimental results. Section 5 presents the conclusions of this research and future work. Finally, Section 6 has the references.

2.0 PROBABILISTIC BOOLEAN NETWORKS AND THEIR USE IN MANUFACTURING SYSTEMS.

Boolean Networks (BN) [20-21] and Probabilistic Boolean Networks [33-34]. have been proposed as a way of modeling manufacturing systems and process' dynamics (validated through model checking), and predict their future behaviors with statistical analysis and discrete event simulation [28-31]. PBNs are generally used to model Gene Regulatory Networks (GRN); collections of data segments within a cell that can interact in an indirect manner with other substances and cell units to govern gene expression. This use has been very well documented in literature, for modeling biological systems [2, 4, 8, 13, 16, 39], and for modeling GRNs [9, 10, 11, 12, 15, 22, 38]. The mechanism of intervention [34] is used to control the evolution of the network and guide it away from undesired states, such as those associate with disease. BNs are a (finite) set of Boolean variables (nodes), with states approximated to 0 or 1, for which their state is determined by the current state of other nodes in the Boolean Network. It has a set of input nodes called regulatory nodes and a set of Boolean functions (predictors) that regulate the value of a target node. If the set of nodes and their corresponding functions is defined, the BN is defined. PBNs are basically a collection of BNs for which at any discrete time interval, the node state vector transitions based on one of the rules of the constituent BNs. These context-sensitive, dynamical and probabilistic BN satisfy the Markov property. In [28], the authors demonstrated that PBNs are valid for modeling manufacturing systems, by establishing the method, validating it through model checking, and comparing the results obtained through simulation with actual machine data. In [29, 31], the same methodology was applied to a manufacturing process to obtain quantitative occurrence data for DFMEA. Research in [30] expands the application of PBNs in manufacturing systems by incorporating the intervention mechanism to guide a modeled manufacturing system away from possible failure modes, thus delaying eventual failure of the system. For a detailed description of PBNs, see [34].

3.0 PBNs FOR FDI IN MANUFACTURING SYSTEMS

To present the proposed method, the system introduced in [28-30] is utilized, consisting of three machines, an off-the-shelf ultrasonic welding station and two off-the-shelf "pick and place" machines will be modeled. This process is taken from [29], and is reproduced here for reference. The welding station is composed of a 2500 W power supply, and an actuator that houses a 3-inch air cylinder, a 20-micron converter, a 1:2.0 gain booster and a 20 kHz 1:1 gain horn. The welding station joins together two rigid parts. The "pick and place" is a



mechanism that has movement in the x and y axes, and through a grip holds, places and removes the parts to and from the welding station into the assembly line. The pick and place loads the parts into the welding station. Once welded, a second pick and place removes the welded parts. Figure 1 presents a finite state machine of this welding process.

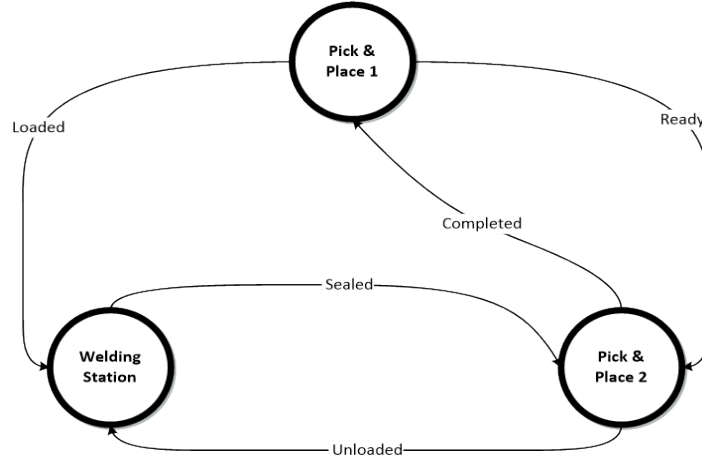


Figure 1: Ultrasonic welding process from [29].

The method proposed in this paper adapts the FDI scheme described in [25], and shown in Figure 2, where a model is used for normal operation of the process and another model is used for each one of the different faults.

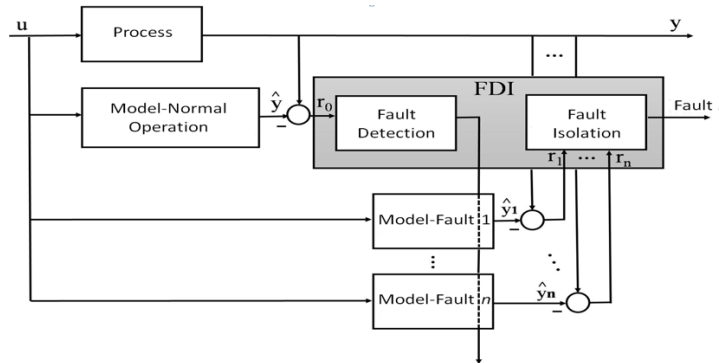


Figure 2: Fault Detection and Isolation Method [25]

PBNs self-organize into attractor states, and these states are related to the different failure modes that the system experiences. Model construction, and semantics are identical to [29]. Through characterization of the failure modes, the models can, with the property verification characterize the state of their relevant components to determine which component failures correlate to machine and/or system fault conditions. A notable difference from past efforts is that this system is modeled as a PBN of PBNs. Each of the node of the systems' PBN is in itself a PBN. The PBN for the Pick and Place machines is detailed in [28] with its components, predictors and selection probabilities for each of the functions, in addition to its BN realizations, vector functions, attractors and the selection probabilities for each realization.

Normal operation is modeled through simulation of the system's machines, based on the reliability analysis performed in [28-29]. This can be modeled for the system as a whole, or for each of the machines that compose it, through simulation of their relevant components, based on each of the component's MTBF data. Each of the system's faults is modeled based of the DFMEAs conducted in [29], and similarly for each of the possible faults for each machine. Therefore, the model is able to detect and isolate single machine and multiple machine faults for the system, and also single and multiple component faults on the individual machines. The Welding Station is also a 6 node PBN. This PBN has 14 constituent BNs. Table 1 describes the Reliability and MTBF of each of the machine components. Table 2 shows each realization, along with its vector function and probability of selection.



Table 1: Predictors and Selection Probability, Welding Station PBN

Component	Predictor	Selection Probability $C_i^{(t)}$
x_1 , Actuator Cylinder	$x_1(t+1) = x_1(t)$	1
x_2 , Power Supply	$x_2(t+1) = x_2(t)$	1
x_3 , Actuator Converter	$x_3(t+1) = x_3(t) \& x_2(t)$	0.12
	$x_3(t+1) = x_3(t) \& x_2(t) \& x_1(t)$	0.88
x_4 , Actuator Booster	$x_4(t+1) = x_4(t) \& x_2(t)$	0.12
	$x_4(t+1) = x_4(t) \mid x_3(t) \mid x_2(t) \mid x_1(t)$	0.88
x_5 , Actuator Horn	$x_5(t+1) = x_5(t) \& x_2(t)$	0.12
	$x_5(t+1) = x_5(t) \mid x_4(t) \mid x_2(t)$	0.88
x_6 , Transducer	$x_6(t+1) = x_6(t) \& x_2(t)$	0.12
	$x_6(t+1) = x_6(t) \mid x_1(t) \mid x_2(t)$	0.88

Table 2: Welding Station constituent BN Vector Functions

BN Realization	Vector Function	Probability
1	$f_1 = (f_1^{(1)}, f_1^{(2)}, f_1^{(3)}, f_1^{(4)}, f_1^{(5)}, f_1^{(6)})$	$u_1 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_1^{(3)} \cdot c_1^{(4)} \cdot c_1^{(5)} \cdot c_1^{(6)} = 0.00020736$
2	$f_2 = (f_1^{(1)}, f_1^{(2)}, f_1^{(3)}, f_1^{(4)}, f_2^{(5)}, f_1^{(6)})$	$u_2 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_1^{(3)} \cdot c_1^{(4)} \cdot c_2^{(5)} \cdot c_1^{(6)} = 0.00152064$
3	$f_3 = (f_1^{(1)}, f_1^{(2)}, f_1^{(3)}, f_1^{(4)}, f_2^{(5)}, f_2^{(6)})$	$u_3 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_1^{(3)} \cdot c_1^{(4)} \cdot c_2^{(5)} \cdot c_2^{(6)} = 0.01115136$
4	$f_4 = (f_1^{(1)}, f_1^{(2)}, f_1^{(3)}, f_2^{(4)}, f_1^{(5)}, f_1^{(6)})$	$u_4 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_1^{(3)} \cdot c_2^{(4)} \cdot c_1^{(5)} \cdot c_1^{(6)} = 0.00152064$
5	$f_5 = (f_1^{(1)}, f_1^{(2)}, f_1^{(3)}, f_2^{(4)}, f_2^{(5)}, f_2^{(6)})$	$u_5 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_1^{(3)} \cdot c_2^{(4)} \cdot c_2^{(5)} \cdot c_2^{(6)} = 0.01115136$
6	$f_6 = (f_1^{(1)}, f_1^{(2)}, f_1^{(3)}, f_2^{(4)}, f_2^{(5)}, f_1^{(6)})$	$u_6 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_1^{(3)} \cdot c_2^{(4)} \cdot c_2^{(5)} \cdot c_1^{(6)} = 0.01115136$
7	$f_7 = (f_1^{(1)}, f_1^{(2)}, f_1^{(3)}, f_2^{(4)}, f_2^{(5)}, f_2^{(6)})$	$u_7 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_1^{(3)} \cdot c_2^{(4)} \cdot c_2^{(5)} \cdot c_2^{(6)} = 0.08177664$
8	$f_8 = (f_1^{(1)}, f_1^{(2)}, f_2^{(3)}, f_1^{(4)}, f_1^{(5)}, f_1^{(6)})$	$u_8 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_2^{(3)} \cdot c_1^{(4)} \cdot c_1^{(5)} \cdot c_1^{(6)} = 0.00152064$
9	$f_9 = (f_1^{(1)}, f_1^{(2)}, f_2^{(3)}, f_1^{(4)}, f_2^{(5)}, f_1^{(6)})$	$u_9 = c_1^{(1)} \cdot c_1^{(2)} \cdot c_2^{(3)} \cdot c_1^{(4)} \cdot c_2^{(5)} \cdot c_1^{(6)} = 0.01115136$
10	$f_{10} = (f_1^{(1)}, f_1^{(2)}, f_2^{(3)}, f_1^{(4)}, f_2^{(5)}, f_2^{(6)})$	$u_{10} = c_1^{(1)} \cdot c_1^{(2)} \cdot c_2^{(3)} \cdot c_1^{(4)} \cdot c_2^{(5)} \cdot c_2^{(6)} = 0.08177664$
11	$f_{11} = (f_1^{(1)}, f_1^{(2)}, f_2^{(3)}, f_2^{(4)}, f_1^{(5)}, f_1^{(6)})$	$u_{11} = c_1^{(1)} \cdot c_1^{(2)} \cdot c_2^{(3)} \cdot c_2^{(4)} \cdot c_1^{(5)} \cdot c_1^{(6)} = 0.01115136$
12	$f_{12} = (f_1^{(1)}, f_1^{(2)}, f_2^{(3)}, f_2^{(4)}, f_2^{(5)}, f_2^{(6)})$	$u_{12} = c_1^{(1)} \cdot c_1^{(2)} \cdot c_2^{(3)} \cdot c_2^{(4)} \cdot c_2^{(5)} \cdot c_2^{(6)} = 0.08177664$
13	$f_{13} = (f_1^{(1)}, f_1^{(2)}, f_2^{(3)}, f_2^{(4)}, f_2^{(5)}, f_1^{(6)})$	$u_{13} = c_1^{(1)} \cdot c_1^{(2)} \cdot c_2^{(3)} \cdot c_2^{(4)} \cdot c_2^{(5)} \cdot c_1^{(6)} = 0.08177664$
14	$f_{14} = (f_1^{(1)}, f_1^{(2)}, f_2^{(3)}, f_2^{(4)}, f_2^{(5)}, f_2^{(6)})$	$u_{14} = c_1^{(1)} \cdot c_1^{(2)} \cdot c_2^{(3)} \cdot c_2^{(4)} \cdot c_2^{(5)} \cdot c_2^{(6)} = 0.59969536$

With this structure, we are able to classify faults and failure modes per machine (through the individual machine's PBN) and system faults and failure modes (through the system's PBN). The author proposes the establishment of the model using the PRISM model checker [24], to validate its use and verify formal correctness through model checking, using Probabilistic Computational Tree Logic (PCTL). The model is composed of an input module, which uses PRISM's local non-determinism to provide the input to the PBNs. Three modules for each PBN model the machines involved in the process, and a fourth system PBN module modules the behavior of the whole process. An output module produces the system state based on the state of the individual modules. This way, given the different faults and failure modes of the individual machines (which are based on the possible fault conditions of their components) the model is able to produce the failure modes of the system. The failure modes for each machine were discussed in [29], and are based of FMEAs conducted on each of the machines involved in the process. The process of producing the PBN for the system is presented graphically in Figure 3.

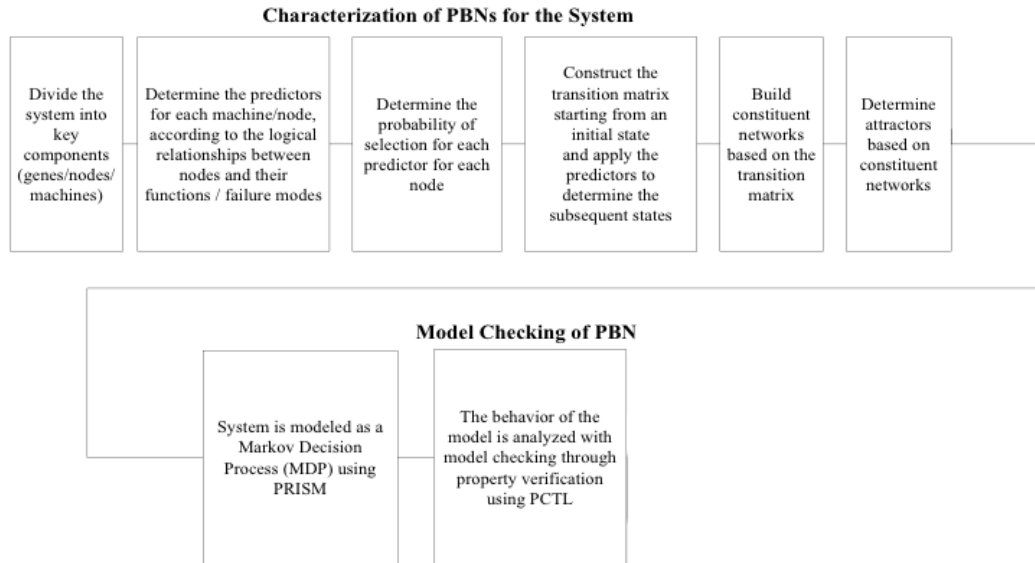


Figure 3: PBN for FDI. Manufacturing System Modeling Process [28]

4.0 EXPERIMENTAL RESULTS

This section details the experimental results of the tests performed to validate the adequacy of the proposed model. PRISM was used to validate the model quantitatively and to produce data required for statistical tests that were used to determine the level of correspondence. Experiments were conducted using three PBN models: a model for the Pick and Place robots, a model for the welding station, and a model representing the process. The models presented in [28-31] were expanded to include fault conditions that may lead to failure on the individual machines and system. This allows the prediction of conditions that may not cause complete failure, but rather failure modes that may lead to situations where the system continues to operate, but does not perform the required task to specifications. These constitute unhealthy system states, where a fault condition can be "treatable" or lead to failure. For each machine, and for the complete process, FMEAs were performed as per [29], and a determination was made of which system components and failure modes can produce a failure or a fault. As an example, the relevant nodes of the Pick and Place PBN are the gripper, a rotary axis, a fixed axis, a motor for the rotary axis, a motor for the fixed axis, and a power supply for the machine. On the Pick and place machines, failure of the gripper, fixed axis or rotary axis will cause a fault on the Pick and place as a whole. Failure of the motors or the power supply will cause a fault on the Pick and place. Three modules constitute the complete models in PRISM, an Input module, a module for the PBN, and an Output module. The current state of the PBN's components is in module Input. The PBN module uses the state of the input variables and applies the corresponding Predictors, as per Section 3, to transition to the next state. Based on the values of these variables, and the fault conditions, the state a global Pick and Place variable is changed, giving us the current state of the machine.

Control groups were established through simulation of the systems' relevant components, with the components' corresponding MTBF obtained from actual technical data sheets. These control groups were established for the Pick and Place, the Welding Station, and the complete system, that involves all three machines. Control data was used to compare against the PBN models, representing expected values. Three experimental groups were established: (1) the PBN model of the system (all three machines); (2) the PBN model of the Pick and Place machines; and (3) the PBN model of the Welding Station. Property verification was used in PRISM to determine the maximum probability of occurrence of any of the failure modes that lead to a fault, for each of the models. From an initial state for each of the machines, such as all the possible failure modes that may lead to fault on the machine, a determination is made about the maximum probability of reaching one of the different identified fault conditions. Statistically significant differences between the control and experimental groups (PBN models) were tested. Property verification in PRISM not only allows us to verify the models, they also allow, through experiments, to reach an estimate in time about when the occurrence of a fault is certain.

Detection:



The models are able to detect faults and failures, based on the application of the PBN. Given the current state of the network nodes, the PBN will select an appropriate context and self-organize into one of the attractor states of their constituent Boolean Networks. As an example, in Table 1 the predictors and selection probability of each predictor is given for the Welding Station. Table 2 illustrates the BN context, and the probability of each of those contexts being selected. Work in [29] equated the context to the different failure modes that can occur. The input module of the model randomizes the current state of the machine, and based on the current state, the PBN module will apply the predictors and select a BN. The output model contains all of the identified fault conditions/failure modes of a machine, and after the application of the predictors evaluates the state of the machine's components, and makes a determination of the state of the machine as a whole. The machine can be in a complete failure condition, or in a fault condition, that can be specifically described based on the condition of the components, thus allowing detection and isolation of each individual fault, or combined faults.

The first test conducted was to determine the maximum probability of reaching any of the failure modes leading to fault of the Pick and Place through verification of the PCTL property:

"Pmax=?[F <= time ((grip1 = false & motor1a = true & motor1b = true & fixed_axis1 = false & rotary_axis1 = false & power1 = true) | (grip1 = false & motor1a = true & motor1b = true & fixed_axis1 = false & rotary_axis1 = true & power1 = true) | (grip1 = false & motor1a = true & motor1b = false & fixed_axis1 = true & rotary_axis1 = false & power1 = true) | (grip1 = false & motor1a = true & motor1b = true & fixed_axis1 = true & rotary_axis1 = true & power1 = true) | (grip1 = true & motor1a = true & motor1b = true & fixed_axis1 = false & rotary_axis1 = false & power1 = true) | (grip1 = true & motor1a = true & motor1b = true & fixed_axis1 = false & rotary_axis1 = true & power1 = true) | (grip1 = true & motor1a = true & motor1b = true & fixed_axis1 = true & rotary_axis1 = false & power1 = true) | (grip1 = true & motor1a = true & motor1b = true & fixed_axis1 = true & rotary_axis1 = true & power1 = true)].

This property was tested for the Pick and place's PBN model, and the control group.

Two sample T-tests were performed using Minitab 16 to verify if there were statistically significant differences among the group means. The null hypothesis is that there is no difference between the data from the Control Group and PBN Model, or $H_0: \mu \text{ Control} = \mu \text{ PBN}$. The alternative hypothesis would be finding differences between the Control and PBN Model groups, or $H_0: \mu \text{ control} \neq \mu \text{ PBN}$. For an α -level of 0.05 for the test, it is concluded that for the Pick and Place, there are no statistically significant differences between the groups (p -value > 0.05). This means that there is no difference between both groups. Results of the two-sample T test are presented in Figures 4 and 5. Figures 6 and 7 show the results for the Welding Station, and Figures 8 and 9 show results for the System. In these graphs, time is represented in hours.

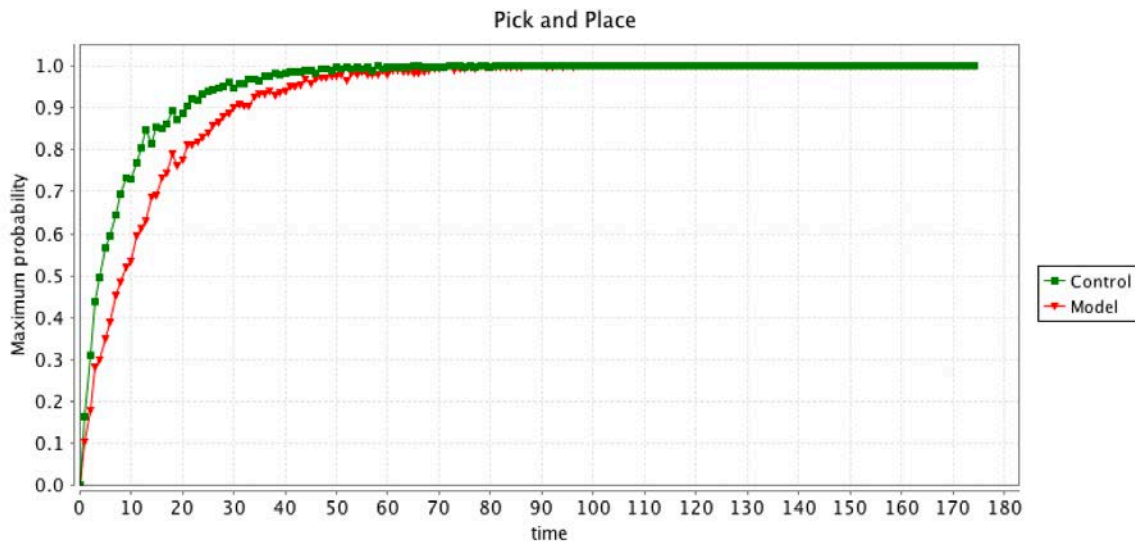


Figure 4: Maximum probability Pick and Place PBN vs control



Two-Sample T-Test and CI: Control-PP, Model-PP

Two-sample T for Control-PP vs Model-PP

	N	Mean	StDev	SE Mean
Control-PP	175	0.953	0.139	0.011
Model-PP	175	0.923	0.178	0.013

Difference = μ (Control-PP) - μ (Model-PP)

Estimate for difference: 0.0292

95% CI for difference: (-0.0043, 0.0628)

T-Test of difference = 0 (vs \neq): T-Value = 1.71 P-Value = 0.088 DF = 328

Figure 5. Two-sample T test: Pick and place PBN vs Control group

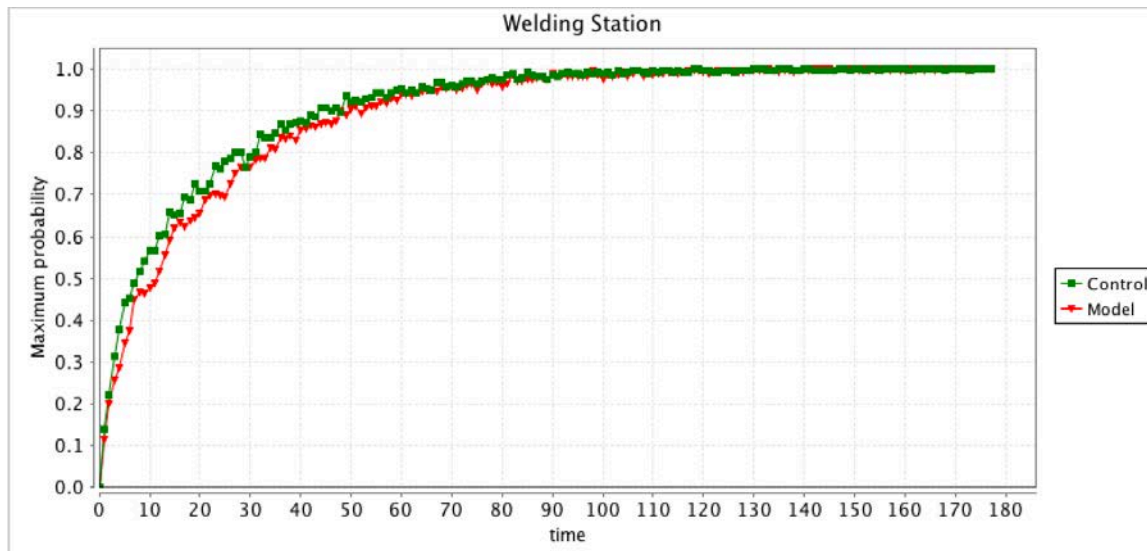


Figure 6: Maximum fault occurrence probability for the Welding Station PBN vs control

Two-Sample T-Test and CI: Control-WS, Model-WS

Two-sample T for Control-WS vs Model-WS

	N	Mean	StDev	SE Mean
Control-WS	178	0.905	0.172	0.013
Model-WS	178	0.888	0.188	0.014

Difference = μ (Control-WS) - μ (Model-WS)

Estimate for difference: 0.0162

95% CI for difference: (-0.0214, 0.0538)

T-Test of difference = 0 (vs \neq): T-Value = 0.85 P-Value = 0.397 DF = 351

Figure 7: Two-sample T test: Welding Station PBN vs Control group

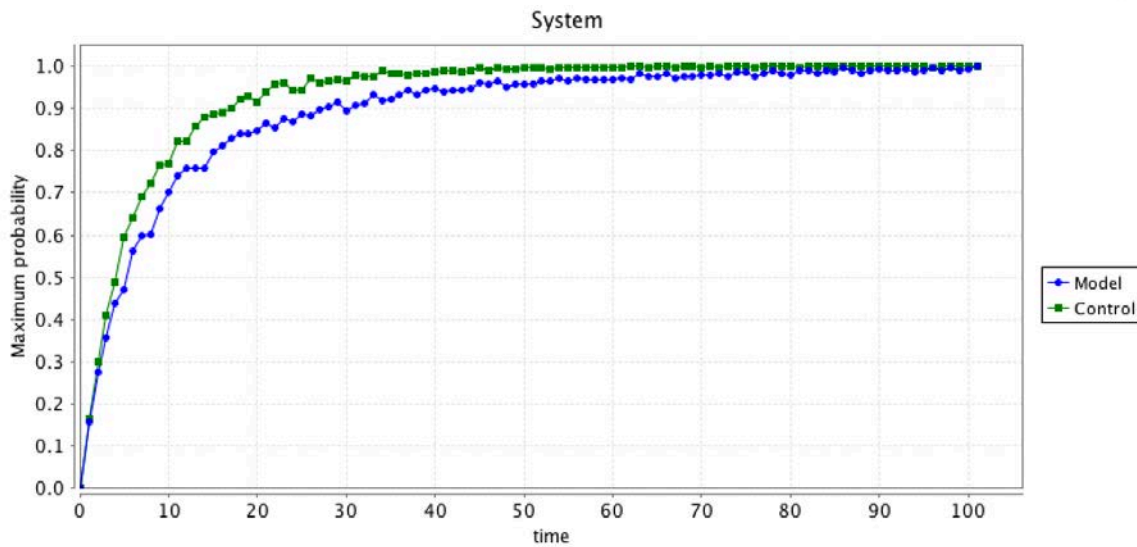


Figure 8: Maximum probability of fault occurrence for the System PBN vs control

Two-Sample T-Test and CI: Control-Sys, Model-Sys

Two-sample T for Control-Sys vs Model-Sys

	N	Mean	StDev	SE Mean
Control-Sys	102	0.887	0.181	0.018
Model-Sys	102	0.927	0.173	0.017

Difference = μ (Control-Sys) - μ (Model-Sys)

Estimate for difference: -0.0403

95% CI for difference: (-0.0891, 0.0086)

T-Test of difference = 0 (vs \neq): T-Value = -1.63 P-Value = 0.106 DF = 201

Figure 9: Two-sample T test: System PBN vs Control group

Diagnosis

Labels in PRISM can be used to single-out specific states, or sets of states. They can be used to single out single faults, or combinations of faults. When the PBN is applied and a constituent BN is selected, these labels provide a way of filtering which fault is occurring, or if the machine is operating correctly. Within the output module, all of the possible failure and fault conditions on the machine caused by the components that have been identified are expressed, and this allows to determine its future state. This allows not only to discern which specific fault or combination of faults is occurring, but through property verification we can make use of these labels to produce a prognosis, an estimate in time of when the fault is expected to occur. For example, $P_{max}=? [F \leq \text{time "singleGripFault"}]$ verifies the maximum probability of occurrence of single grip faults on the Pick and Place model. There are 63 different fault/failure conditions, and a normal operating state. Figure 10 shows a plot of this probability, and at 2579 hours a single fault of the grip can be expected.

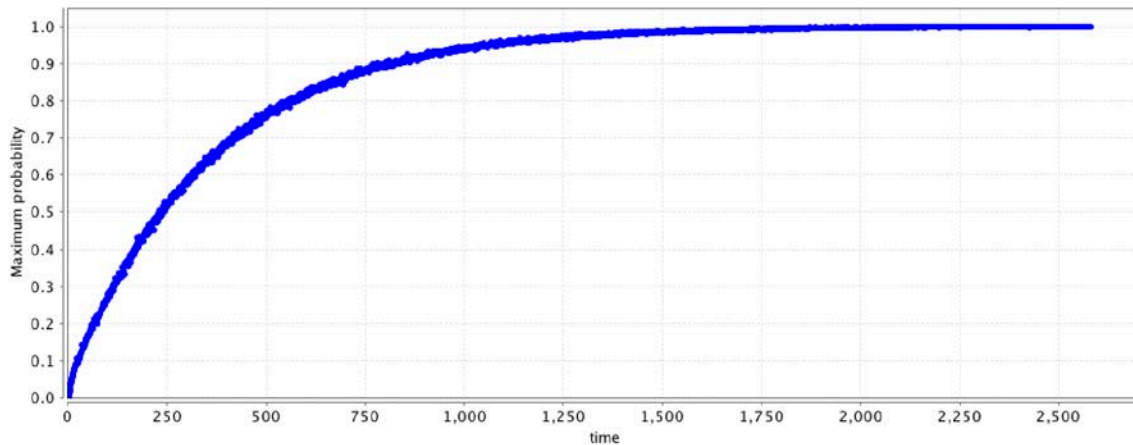


Figure 10: Maximum Probability of occurrence of gripper faults

Single faults may be modeled through verification of other properties, such as, in the welding station's PBN: $P_{max}=? [F \leq \text{time} (\text{powerSupply}=\text{true} \ \& \ \text{actuatorCylinder}=\text{true} \ \& \ \text{actuatorBooster}=\text{true} \ \& \ \text{actuatorConverter}=\text{true} \ \& \ \text{actuatorHorn}=\text{true} \ \& \ \text{transducer}=\text{false})]$. This property yields the maximum probability of occurrence of one of the welding station's failure modes that can lead to a fault on the machine, caused by the transducer. In this way, individual faults are detected and isolated. Figure 11 illustrates this property verification graphically.

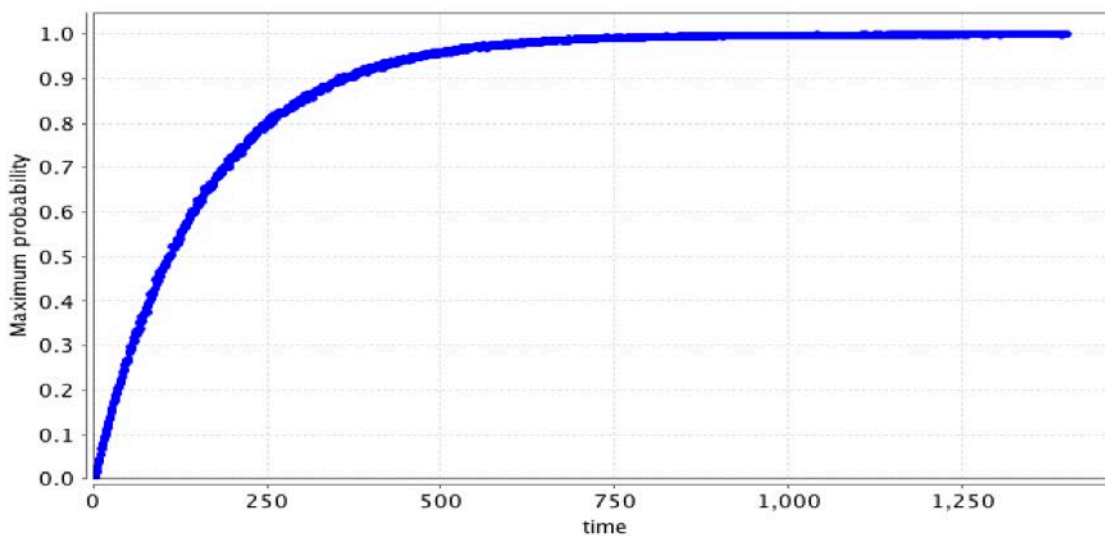


Figure 11: Welding Station Fault condition: Transducer

The system is also capable of detecting multiple simultaneous faults. Experiments were performed to verify the capability of detecting multiple faults of the system, using the System's PBN model, specifically simultaneous faults detected on both Pick and Place machines, simultaneous faults detected on Pick and Place 1 and the Welding Station, and a simultaneous fault on Pick and place 1 and failure on Pick and Place 2. Through property verification, the system is able not only to detect these simultaneous faults, but is also able to tell when the fault is imminent. Figure 12 shows a simultaneous fault on Pick and Place 1 and Pick and Place 2, and shows that the faults will manifest at around 700 hours of continuous operation.

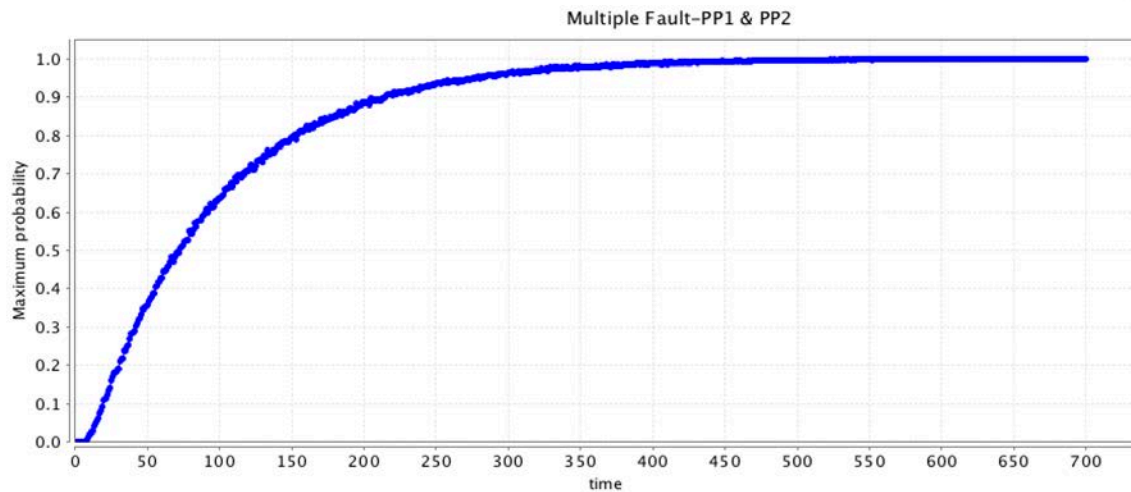


Figure 12: Simultaneous faults of Pick and Place 1 and Pick and Place 2

Figure 13 shows the occurrence of simultaneous faults on Pick and place 1 and the Welding Station, where a combination of failure on those machines will be certain at about 500 hours of operation.

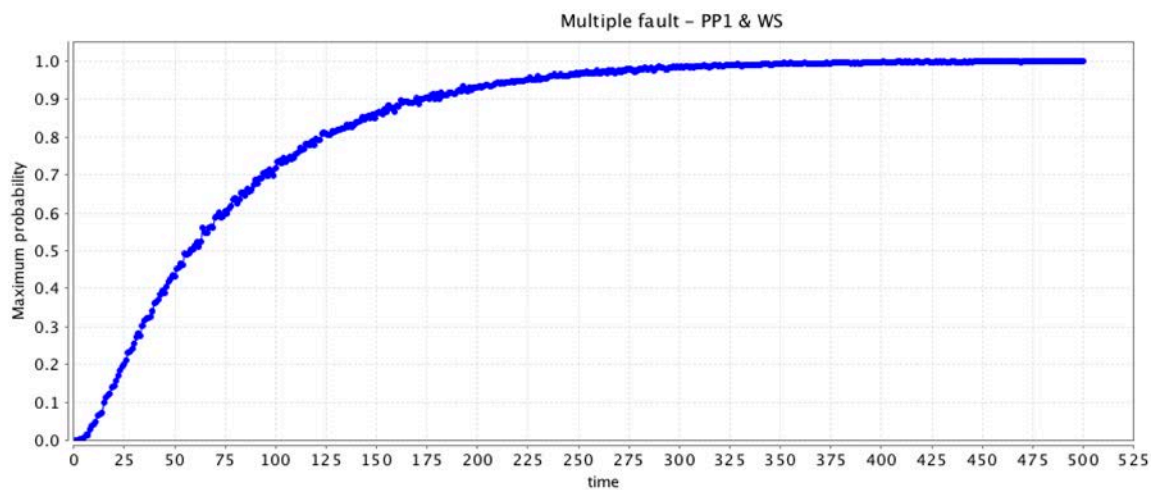


Figure 13: Simultaneous fault on Pick and Place 1 and the Welding Station.

Figure 14 shows a fault on Pick and Place 1 and a failure on Pick and Place 2. This condition can be expected after 1544 of operation.

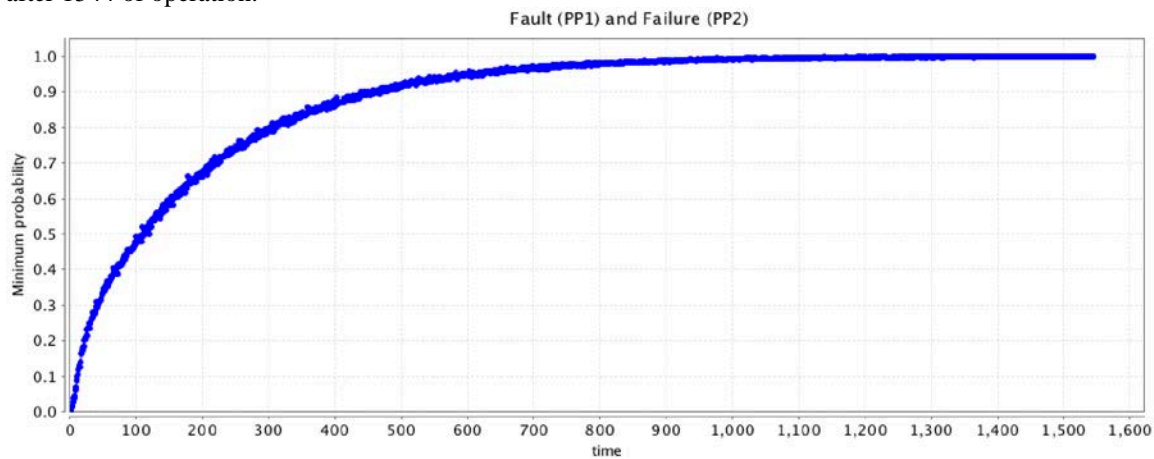


Figure 14: Simultaneous fault on Pick and place 1 and failure on Pick and Place 2



Figure 15 shows the maximum probability of occurrence of a multiple fault, where a condition that can generate a multiple fault will manifest at 1679 hours of operation.

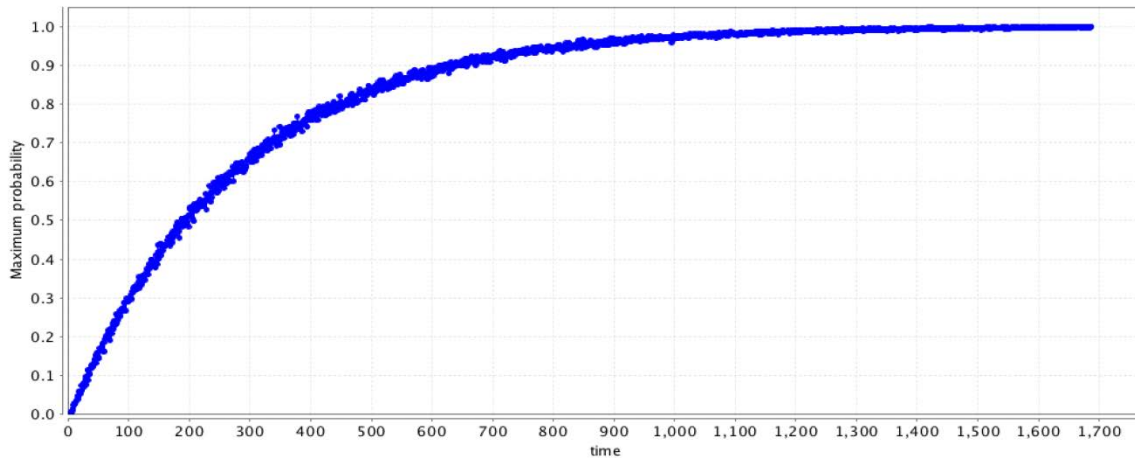


Figure 15: Maximum probability of occurrence of multiple faults.

With PRISM, it is possible to plot the states of variables in a simulation to track their state changes. In Figure 16, diagnosis of faults and failures is illustrated. States of the pick and place machine have been labeled, and each state of the machine can be individually identified. This means that all faults, single or multiple, can be singled out specifically. State 63 is the normal operating state of the machine. After 29 hours of normal operation, the model and simulation identifies a single fault of the rotary axis. If the machine continues to operate without intervention, this fault may develop into a failure. The initial state of the system is presumed to be the normal operating state.

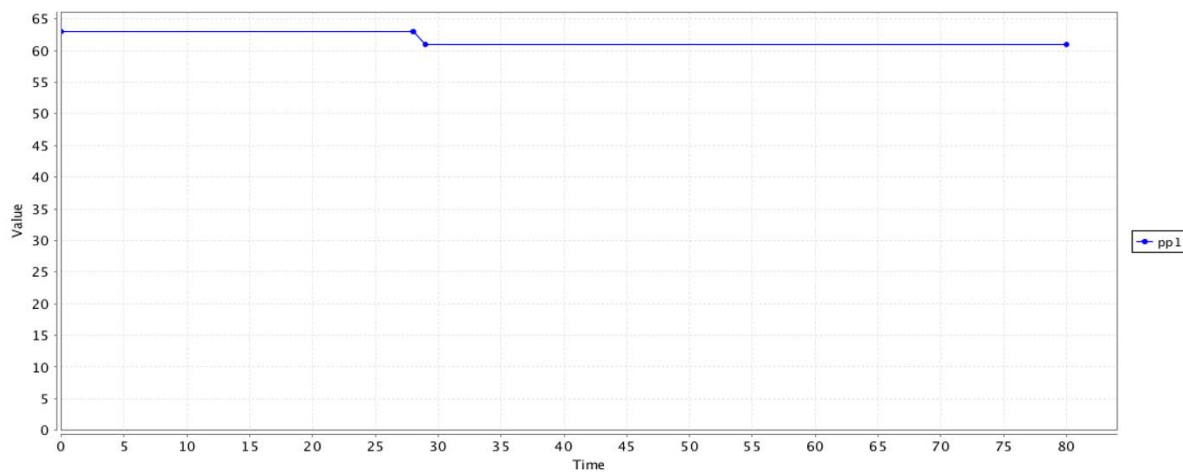


Figure 16: Fault diagnosis using the Pick and Place's PBN model

Figure 17 show another simulation of 80 hours of continuous operation, where after 48 hours of normal operation, the system detects and diagnoses a failure of motor1a at 49 hours, and a fault of the fixed axis at 69 hours.

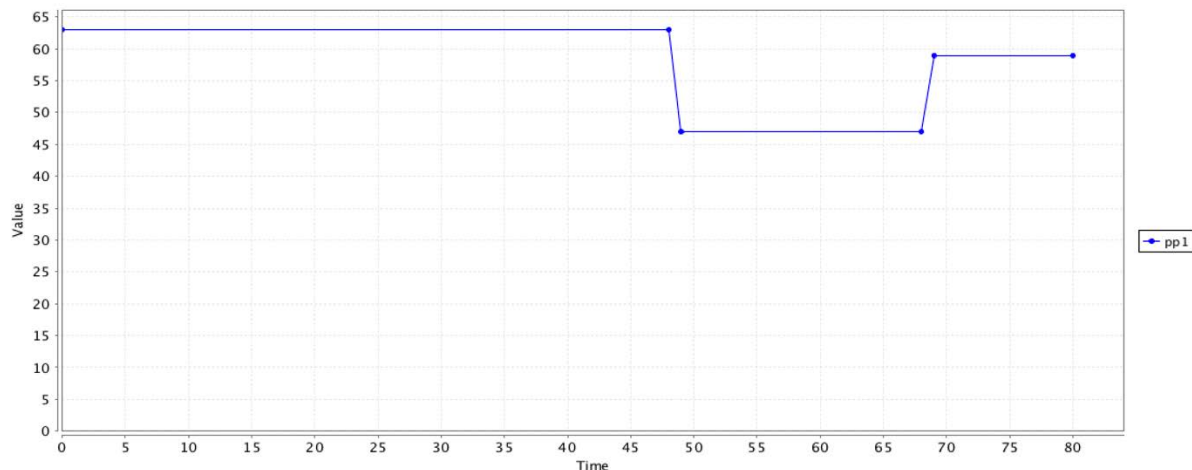


Figure 17: Detection and diagnosis of two faults

This novel method of modeling in manufacturing systems provides a simple, straightforward mechanism of detecting, isolating and classifying single and multiple faults. Through the obtained experimental results, it is statistically demonstrated that model-based PBN FDI performs satisfactorily when examining a machine's possible behavior, for detection, classification and isolation of single and multiple faults. The system will experience a fault condition on any of its components at about 60 hours of operation.

5.0 CONCLUSIONS

This paper presents a bioinspired, complex-adaptive modeling methodology that allows modeling single and multiple faults on manufacturing systems using Probabilistic Boolean Networks. The modifications proposed in this paper to the aforementioned architecture and to this new method allowed the classification of single and multiple failures. These permit the FDI scheme proposed in [25], and shown in Figure 1, the detection and isolation of single and multiple faults, along with an estimate of when these faults will present themselves. Statistical tests performed of this data validate the proposed approach for future use and further development. For future research, an interesting idea is to design a fault diagnosis system based in historical data of the process with the ability to detect and classify multiple and novel faults. Expanding the use of non-binary quantized PBNs will also allow in the future a more rich mechanism of expressing fault conditions and failure modes.

6.0 REFERENCES

1. Acosta Díaz, C., Camps-Echevarría, L., Prieto Moreno A., Silva Neto, A.J. & Llanes-Santiago, O. (2016) A model-based fault diagnosis in a nonlinear bioreactor using an inverse problema approach and evolutionary algorithms. *Chemical Engineering Research and Design* , 114 18-29.
2. Arnosti, D. N., & Ay, A. (2012). Boolean modeling of gene regulatory networks: Driesch redux. *Proceedings of the National Academy of Sciences*, 109(45), 18239–18240.
3. Bachschmid, N., Pennacchi, P., Vania, A. (2002). Identification of multiple faults in rotor systems. *Journal of Sound and Vibration* (254), 327 – 366.
4. Bane, V., Ravanmehr, V., & Krishnan, A. R. (2012). An information theoretic approach to constructing robust Boolean gene regulatory networks. *IEEE/ACM Transactions on Computational Biology and Bioinformatics*, 9(1), 52–65.
5. Bartenstein, T., Sliwinski, D., Huisman, D.H., (2001). Diagnosing combinational logic designs using the single location at-a-time (slat) paradigm. *Proc. IEEE International Test Conference (ITC)*, Baltimore, USA, 287 – 287.
6. Camps Echevarría L., Llanes-Santiago, O., Hernández Fajardo, J.A., Silva Neto, A.J. & Jiménez Sánchez, D. (2014). A variant of the particle swarm optimization for the improvement of fault diagnosis in industrial systems via faults estimation. *Engineering Applications of Artificial Intelligence*. 28, 35-61.
7. Camps Echevarría, Llanes-Santiago, O., Campos Velho, H.F., Silva Neto, A.J. (2019). Fault Diagnosis inverse problems: Solution with Metaheuristics. Springer, Studies in Computational Intelligence Series 763. doi: 10.1007/978-3-319-89978-7.



8. Chaouiya, C., Ourrad, O., & Lima, R. (2013). Majority rules with random tie-breaking in Boolean gene regulatory networks. *PLoS ONE*, 8(7), e69626.
9. Chen, H., & Sun, J. (2014). Stability and stabilisation of context-sensitive probabilistic Boolean networks. *IET Control Theory & Applications*, 8(17), 2115–2121.
10. Chen, X., Jiang, H., & Ching, W.-K. (2012). On construction of sparse probabilistic Boolean Networks. *East Asian Journal on Applied Mathematics*. doi:10.4208/eajam.030511.060911a.
11. Ching, W.-K., Chen, X., & Tsing, N.-K. (2009a). Generating probabilistic Boolean networks from a prescribed transition probability matrix. *IET Systems Biology*, 3, 453–464.
12. Ching, W.-K., Zhang, S.-Q., Jiao, Y., Akutsu, T., Tsing, N.-K., & Wong, A.-S. (2009b). Optimal control policy for probabilistic Boolean networks with hard constraints. *IET Systems Biology*, 3(2), 90–99.
13. Didier, G., & Remy, E. (2012). Relations between gene regulatory networks and cell dynamics in Boolean models. *Discrete Applied Mathematics*, 160(15), 2147–2157.
14. Frank, P.M. Analytical and qualitative model-based fault diagnosis- a survey and some new results. *European Journal of Control*. 2, 6-28.
15. Gao, Y., Xu, P., Wang, X., & Liu, W. (2013). The complex fluctuations of probabilistic Boolean networks. *BioSystems*, 114(1), 78–84.
16. Ghanbarnejad, F. (2012). Perturbations in Boolean networks as model of gene regulatory dynamics (doctoral dissertation). Leipzig: University of Leipzig.
17. Isermann, R (1984). Process fault detection based on modeling and estimation methods – a survey. *Automatica* 20, 387-404.
18. Iserman, R. (2005) Model based fault detection and diagnosis. Status and applications. *Annual Review of Control*. 29, 71-85.
19. Isermann, R.(2011). Fault-diagnosis applications: model-based condition monitoring: actuators, drives, machinery, plants, sensors, and fault-tolerant systems. Springer-Verlag. London, UK.
20. Kauffman, S. A. (1969a). Homeostasis and differentiation in random genetic control networks. *Nature*, 224, 177–178.
21. Kauffman, S. A. (1969b). Metabolic stability and epigenesis in randomly constructed genetic nets. *Journal of Theoretical Biology*, 22, 437–467.
22. Kobayashi, K., & Hiraishi, K. (2010). Reachability analysis of probabilistic Boolean networks using model checking. Presented at the SICE annual conference 2010, proceedings of (pp. 829–832).
23. Kunpeng, Z., San, W., Soon, H., (2009). Wavelet analysis of sensor signals for tool condition monitoring: A review and some new results. *International Journal of Machine Tools & Manufacture* (49), 537 – 553.
24. Kwiatkowska, M. Z., Norman, G., & Parker, D. (2011). PRISM 4.0: Verification of probabilistic real-time systems. In G. Gopalakrishnan & S. Qadeer (Eds.), *Computer Aided Verification. Lecture Notes in Computer Science* (Vol. 6806, pp. 585–591). Berlin, Heidelberg:Springer.
25. Mendonça, L.F., Sousa, J.M., Sá da Costa, J.M.(2009). An architecture for fault detection and isolation based on fuzzy methods. *Expert Systems with Applications*. (36), 1092–1104.
26. Miguel, L.J.D., Blázquez, L.F. (2005). Fuzzy logic-based decision-making for fault diagnosis in a DC motor. *Engineering Applications of Artificial Intelligence* (18), 423 – 450.
27. Rodríguez Ramos, A., Domínguez Acosta, C., Rivera Torres, P. J., Serrano Mercado, E. I., Beauchamp Báez, G., Anido Rifón, L. & Llanes Santiago, O. (2016). An approach to multiple fault diagnosis using fuzzy logic. *Journal of Intelligent Manufacturing*.
28. Rivera Torres, P. J., Serrano Mercado, E.I., & Anido Rifón, L. (2015a). Probabilistic Boolean network modeling of an industrial machine. *Journal of Intelligent Manufacturing*. doi:10.1007/ s10845- 015- 1143-4.
29. Rivera Torres, P. J., Serrano Mercado, E.I., & Anido Rifón, L.(2015b). Probabilistic Boolean network modeling and model checking as an approach for DFMEA for manufacturing systems. *Journal of Intelligent Manufacturing*. doi:10.1007/s10845-015-1183-9.
30. Rivera Torres, P.J., Serrano Mercado, E.I., Llanes Santiago, O., & Anido Rifón, L. (2016a). Modeling preventive maintenance of manufacturing processes with probabilistic Boolean networks with interventions. *Journal of Intelligent Manufacturing*. <https://doi.org/10.1007/s10845-016-1226-x>
31. Rivera Torres, P.J. & Serrano Mercado, E.I. (2016b). Probabilistic Boolean Network Modeling as an aid for DFMEA in Manufacturing Systems. Presented at the 18th Scientific Convention of Engineering and Architecture, Havana, Cuba.
32. Ruan, S., Zhou, Y., Feili, Y., Pattipati, K.R., Willett, P., Patterson-Hine, A. (2009). Dynamic multiple-fault diagnosis with imperfect tests. *IEEE Transactions on Systems, Man and Cybernetics, Part A: Systems and Humans* (39), 1224 – 1236.



33. Shmulevich, I., Dougherty, E., & Kim, S. (2002). Probabilistic Boolean networks: A rule-based uncertainty model for gene regulatory networks. *Bioinformatics*. <http://bioinformatics.oxfordjournals.org.ezproxy.library.wisc.edu/content/18/2/261.short>
34. Shmulevich, I., & Dougherty, E. R. (2010). Probabilistic Boolean networks: Modeling and control of gene regulatory networks. Philadelphia, PA: SIAM.
35. Simani, S., Patton, R.J. (2008). Fault diagnosis of an industrial gas turbine prototype using a system identification approach. *Control Engineering Practice* (16), 769 – 786.
36. Simani, S., Farsoni, S., Castaldi, P. (2015), Wind turbine simulator fault diagnosis via fuzzy modelling and identification techniques, *Sustainable Energy, Grids and Networks*(1), 45–52.
37. Sobhani-Tehrani, E., Talebi, H.A., Khorasani, K. (2014), Hybrid fault diagnosis of nonlinear systems using neural parameter estimators. *Neural*(50),12–32.
38. Trairatphisan, P., Mizera, A., Pang, J., Tantar, A. A., Schneider, J., & Sauter, T. (2013). Recent development and biomedical applications of probabilistic Boolean networks. *Cell Communication and Signaling*, 11, 46.
39. Vahedi, G. (2009). An engineering approach towards personalized cancer therapy. Retrieved from <http://gradworks.umi.com.ezproxy.library.wisc.edu/33/84/3384337.html>
40. Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., (2003a). A review of process fault detection and diagnosis, part 1: Quantitative model-based methods. *Computers and Chemical Engineering* (27), 293 – 311.
41. Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., (2003b). A review of process fault detection and diagnosis, part 2: Qualitative models and search strategies. *Computers and Chemical Engineering* (27), 313 – 326.
42. Venkatasubramanian, V., Rengaswamy, R., Kavuri, S.N., (2003c). A review of process fault detection and diagnosis, part 3: Process history based methods. *Computers and Chemical Engineering* (27), 327 – 346.
43. Vong, C.H., Wong, P.K., Wong, K.I. (2014). Simultaneous-fault detection based on qualitative symptom descriptions for automotive engine diagnosis. *Applied Soft Computing* (22), 238 – 248.
44. Wang, Z., Marek-Sadowska, M., Tsai, K.H., Rajske, J. (2006). Analysis and methodology for multiple-fault diagnosis. *IEEE Transactions on Computer-Aided Design of Integrated Circuits and Systems* (25), 558 – 575.
45. Witczak, M. (2007). Modelling and Estimation Strategies for fault diagnosis of Nonlinear systems. Springer, Lecture Notes in Control and Information Sciences Serie, 354. doi: 10.1007/978-3-540-71116-2
46. Zhang, J., Ma, W., Lin, J., Ma, L., Jia, X. (2015), Fault diagnosis approach for rotating machinery based on dynamic model and computational intelligence. *Measurement*(59), 73–87.

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