An Approach to Model-based Fault Diagnosis of Manufacturing Processes and Machines using Probabilistic Boolean Networks

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Abstract: Developing systems and methodologies capable of monitoring the condition and diagnosing multiple faults in industrial/manufacturing systems are topics of active and continuous research. In this paper, a fault diagnosis system inspired on the Probabilistic Boolean Networks (PBN) with Intervention model is suggested as a tool for diagnosing faults of a group of machines in a manufacturing process. The proposed approach considers the failure modes of the machines involved that are affecting the function and performance of the system. Firstly, the modes are identified and divided into two groups: faults and failures. The former implies detectable degradation of system function until the threshold for fault, which is eventual catastrophic loss of system, is surpassed. The latter leads to catastrophic fault. Then, using PBN, both classifications can be diagnosed and actions to mitigate them can be taken. The proposal also allows to forecast a time in hours by which the fault or failure will be imminent. The method herein discussed was applied to an ultrasound welding cycle, and a PBN with interventions model was created, simulated and verified through by means of model checking in PRISM. Results obtained show the validity of this methodology.

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

1. Introduction

For current industry to produce goods of the highest quality, while complying with environmental, safety and other regulations, the efficiency of its processes requires constant improvements. 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 involves 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 [39,41].

Model-based methods make use of either an analytical or computational model of the systems. A varied spectrum of the proposed model-based methods are supported by some basic concepts such as: the parity space, observer approach and the parameters identification or estimation approach [17,14,18]. The authors in [44] show that the observers and parity space methods do not always permit the isolation of actuator faults. For models that are non-linear in nature, the complexity on the observer design method increases, whereas an precise system model is needed for the parity space approach [44]. To overcome these problems a more recent approach based in the solution of an inverse problem using computational intelligence tools has been presented [1,6,7]. In general, the developed researches have been limited to the diagnosis of independently occurring faults.

Diagnosing simultaneous faults is an area not sufficiently addressed in scientific literature. Multiple fault detection in dynamic systems can be challenging, because the effects of a fault may hide or be compensated with the effects of different type of fault, and because equal types of multiple faults can manifest themselves in different forms, considering their order of occurrence. The computational intelligence tools have been the most used to address this area [41,36,27]. In this sense, research has focused on static systems [36], 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 [43] 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, multiple fault diagnosis is a current research area which demands the development of novel strategies for improving the performances of the fault diagnosis systems. The principal 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 loss of 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 inside a cell that interact indirectly with other segments and substances in it to regulate/govern the expression level 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] by extending

Kauffman's Boolean Network (BN) concept [20,21], they combine the rule-based modelling of Boolean Networks with uncertainty principles. These Probabilistic Boolean Network consist of a series of constituent BNs that have assigned selection probabilities, where each BN may be considered a "context". Data for each of the cells comes from dissimilar sources; where each represents a cell context. In each given point in time *t,* a system can be governed by one of these constituent BNs, and the system switches to another constituent BN at another time, with a given switching probability. Figure 1 presents one of the constituent BNs of the Pick and Place PBN, keeping in mind that a PBN is a collection of BNs.

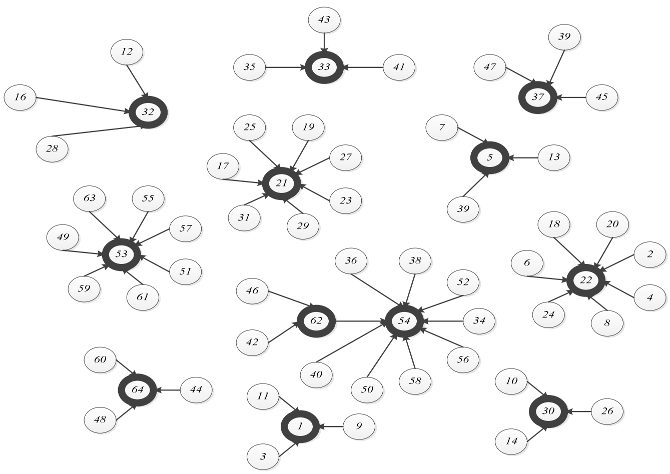

Figure 1: Transition Diagram of one of the Constituent BNs of the Pick and Place PBN

PBNs for manufacturing systems were introduced in Rivera Torres et al. [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 a first contribution of this research. The proposed model allows detection and classification of single and multiple faults which constitute another contribution of the proposal. It allows identification of fault states in which it is possible to continue operation, and those where it is not possible to continue (failure). It also allows to forecast a time in hours by which the fault or failure will be imminent. As a final contribution, the system provides information about the maximum probability of fault and failure occurrence, which allows better maintenance planning. 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. Finally, the conclusions of this research and future works are presented.

2. PROBABILISTIC BOOLEAN NETWORKS IN MANUFACTURING SYSTEMS

Boolean Networks (BN) [20,21] and Probabilistic Boolean Networks [32,33] 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]. This use has been very well documented in literature, for modeling biological systems [2,4,8,13,16,38], and for modeling GRNs [9-11,15,22,38]. The mechanism of intervention [34] is used to steer the evolution of the network and guide it away from undesired states, such as those associated 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 BN. 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 are based on one of the rules of the constituent BNs. These context-sensitive, dynamical and probabilistic BNs 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 it, 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], the authors used the same methodology applied to a manufacturing process to obtain quantitative occurrence data for DFMEA. In [30] the authors expand the application of PBNs in industrial 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. PBNS FOR FDI IN MANUFACTURING SYSTEMS

To present the proposed method, the system introduced in [29-31] is utilized, consisting of three elements, an off-the-shelf ultrasonic welding station, and two off-the-shelf robotic hands, or "pick and place" machines will be modeled. This process has been taken from [29], and is reproduced here for reference. The welding station system is composed of a 2.5 KW power supply unit, an actuator housing a 3-inch air cylinder, a 20-micron converter, a 1:2.0 gain booster and a 20kHz, 1:1 gain horn. This station will join two rigid parts. The "pick and place" has movement in both the x and y axes, and using grip holds, places and removes parts to and from the welder into an assembly line. The pick and place loads the parts into the welding station. Once these parts are welded, a second pick and place will remove the welded parts. Figure 2 presents a finite-state machine of the above described welding system.

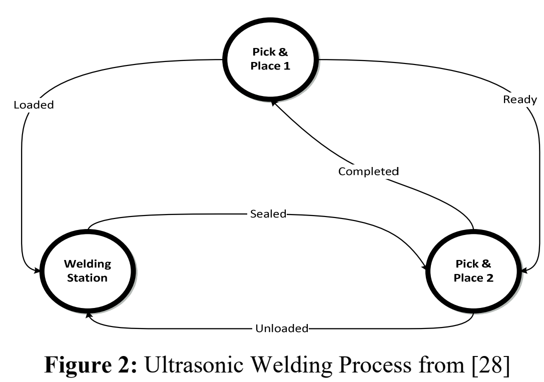

Figure 2: Ultrasonic Welding Process from [28]

The method proposed herein adapts the FDI scheme described in [25], where a model is used for normal operation of the process and another model is used for each one of the different faults. 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 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. The method is very flexible, and the design of the PBN and its state transitions depends on the amount of resolution that the experts need, based on design specifications. The system can grow in complexity and expression depending on the needs of the experts. 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 Mean Time Between Failures (MTBF) data. Each of the system's faults are modeled based of the Design Failure Mode and Effects Analysis (DFMEA) 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 individual components, along with their predictor function, and their probability of selection. 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 Prob. $C_j^{(I)}$
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
	$x_3(t+1) = x_4(t) \mid x_3(t) \mid x_2(t) \mid x_1(t)$	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

As an example, in the case of the second predictor of the Actuator's Converter, the next state of the actuator's converter, with an 88% probability will depend on the current state of the actuatpr/converter, the current state of the power supply, and the current state of the actuator cylinder.

With this structure, it is possible 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 authors propose the establishment of the model using the PRISM model checker [24], in order to validate its use and check its formal correctness 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 produces the failure modes corresponding to 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.

4. Experimental Results

This section details the experimental results of the tests performed to validate the adequacy of the proposed model. PRISM was employed to validate the model quantitatively and to produce data required for statistical tests, 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 its operation, but cannot perform the required task to specifications. These constitute unhealthy system states, where a fault condition can be treated 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 variable is changed, giving us the current state of the machine. In these experiments, time is expressed in hours (h). Control groups were created through modeling and simulation of the systems' relevant components, with the components' corresponding MTBF obtained from real 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 created: PBN model of the system (all involved machines), PBN model of the Pick and Place robots, and PBN model of the Welding Station. Property verification in PRISM was employed for determining the maximum probability of occurrence of any of the failure modes that could lead to fault, for each of the presented 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 both the control and experimental groups (PBN models) were checked. 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 fault occurrence 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 genes, 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, allowing detection and isolation of individual 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 a Probabilistic real time Computational Tree Logic (PCTL) property. 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 look for statistically significant differences among the group means. The null hypothesis states that there is no difference between the Control and PBN groups, or Ho: μ Control = μ PBN. The alternative hypothesis would be finding differences between the Control and PBN Model groups, or Ho: μ control $\neq$ μ PBN. For an α-level of 0.05 for the test, the conclusion is 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 3 and 4. Figures 5 and 6 show the results for the Welding Station, and Figures 7 and 8 show results for the System. In these graphs, time is represented in hours (<u>*h*</u>).

Table 2: Welding Station Constituent BN Vector Functions

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

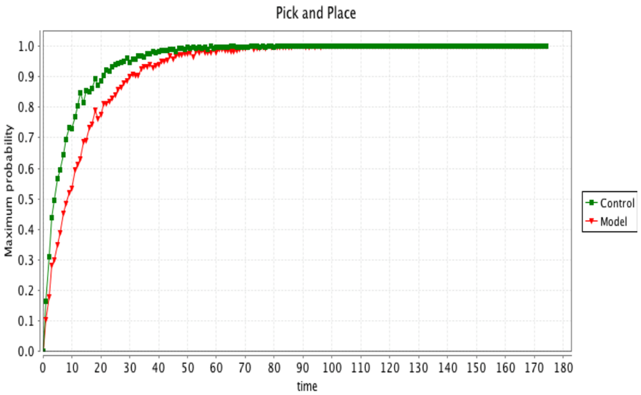

Figure 3: Maximum Probability Pick and Place PBN vs Control

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 ≠): T-Value = 1.71 P-Value = 0.088 DF = 328

Figure 4. Two-sample T Test: Pick and Place PBN vs Control Group

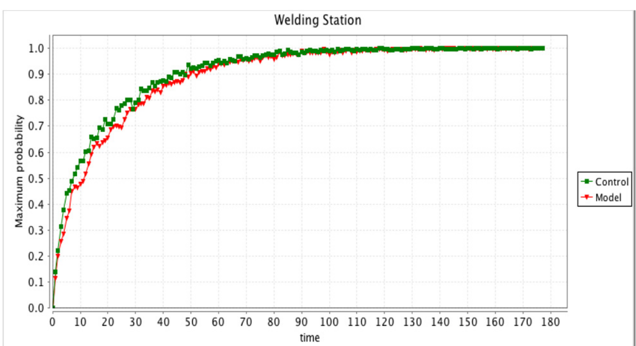

Figure 5: Maximum Fault Occurrence Probability for the Welding Station PBN vs Control

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 ≠): T-Value = 0.85 P-Value = 0.397 DF = 351

Figure 6: Two-sample T Test: Welding Station PBN vs Control Group

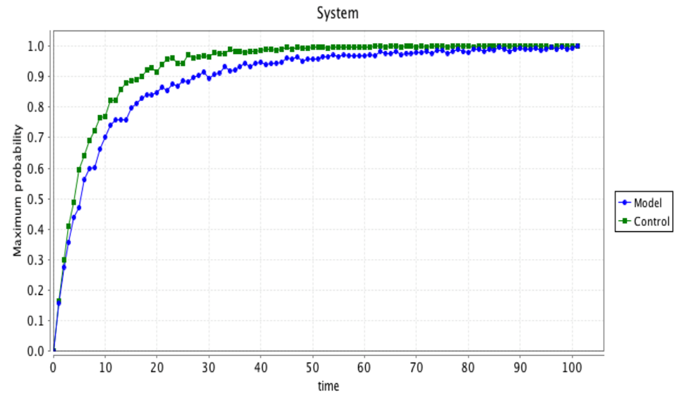

Figure 7: Maximum Probability of Fault Occurrence for the System PBN vs Control

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 ≠): T-Value = -1.63 P-Value = 0.106 DF = 201

Figure 8: 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. Knowing the probability of fault and failure occurrence allows the system designers to make decisions about the interventions needed for the system or machine and minimize the downtime needed for maintenance. For example, *Pmax=? [F<=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 9 shows a plot of this probability, and at 2579 hours a single fault of the grip can be expected.

Single faults may be modeled through verification of other properties, such as, in the welding station's PBN: *Pmax=? [F <= time (powerSupply=true & actuatorCylinder=true & actuatorBooster=true & actuatorConverter=true & actuatorHorn=true & transducer=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 10 illustrates this property verification graphically.

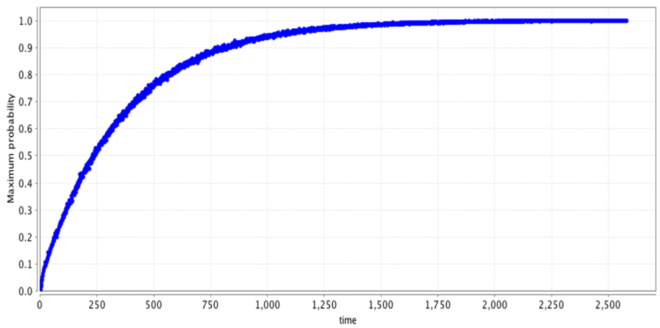

Figure 9: Maximum Probability of Occurrence of Gripper Faults

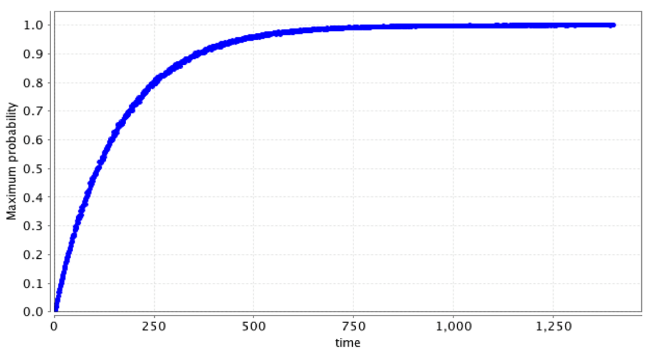

Figure 10: Welding Station Fault Condition: Transducer

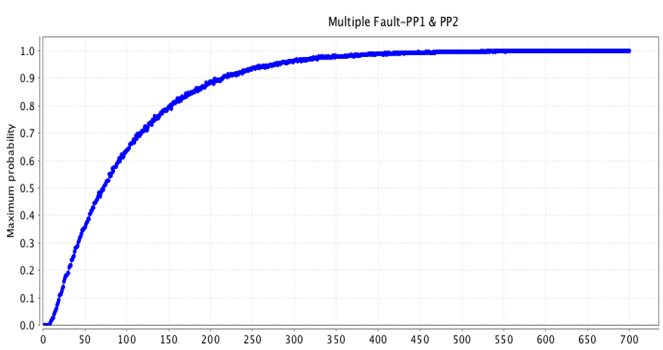

Figure 11: Simultaneous Faults of Pick and Place 1 and Pick and Place 2

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 11 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 11 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.

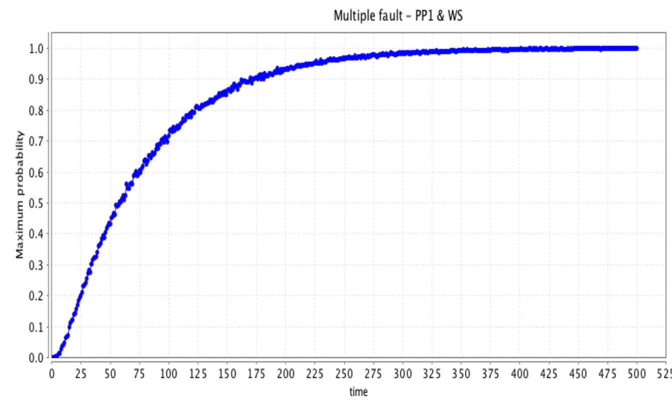

Figure 12: Simultaneous Fault on Pick and Place 1 and the Welding Station

Figure 13 shows a fault on Pick and Place 1 and a failure on Pick and Place 2. This condition can be expected after 1544 hours of operation.

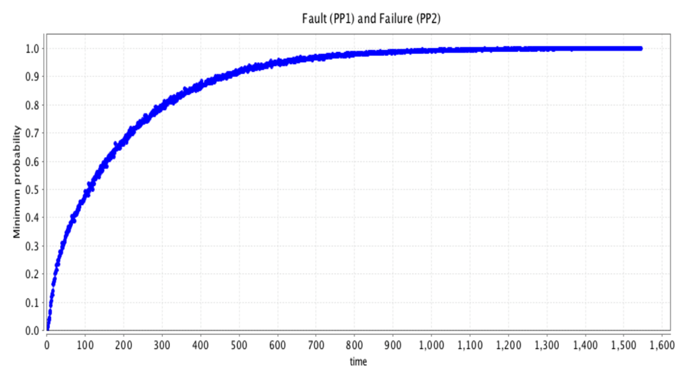

Figure 13: Simultaneous Fault on Pick and Place 1 and Failure on Pick and Place 2

Figure 14 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.With PRISM, it is possible to plot the states of variables in a simulation to track their state changes. Table 3 is an abbreviated table that presents some of the different states of fault, failure and operation in which the Pick and Place model can be. The full table of states has been omitted due to its length, but it consists of the different states that can lead to failure, faults (single and multiple) and the normal operation of the system. In Figure 15, diagnosis of faults and failures is illustrated. States of the Pick and Place 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 (detected and isolated) specifically. Detectability and isolability in this model implies that the system is able to assess the condition of all nodes and relate this condition to a fault or failure as described in Table 3. By singleing out a particular combination of node states, the overall system state can be detected from Table 3. State 64 is the normal operating state of the machine. After 29 hours of normal operation, the 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.

Table 3: States of the Pick and Place PBN

Machine state	Description	Machine state	Description
1	failure due to gripper, motor1a, motor1b, fixed axis, rotary axis, and power	33	failure due to motor1a, motor1b, fixed axis, rotary axis, and power
8	failure due to gripper, motor1a, and motor1b	40	failure due to motor1a, and motor1b
9	failure due to gripper, motor1a, fixed axis, rotary axis, and power	41	failure due to motor1a, fixed axis, rotary axis, and power
15	failure due to gripper, motor1a, and power	47	failure due to motor1a, and power
16	failure due to gripper, motor1a, and motor1b	48	failure due to motor1a, and motor1b
24	failure due to gripper and motor1b	56	failure due to motor1b
25	failure due to gripper, fixed axis, rotary axis, and power	57	multiple fault due to fixed axis, rotary axis, and power
28	failure due to gripper, and fixed axis	60	single fault due to fixed axis
29	failure due to gripper, rotary axis, and power	61	failure due to rotary axis, and power
30	failure due to gripper, and rotary axis	62	single due to rotary axis
31	failure due to gripper, and power	63	failure due to power
32	single fault due to gripper	64	normal operation

Figure 16 shows 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.

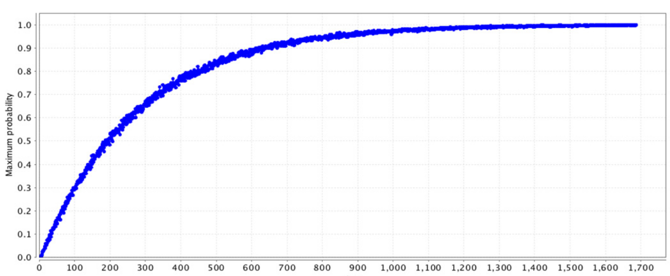

Figure 14: Maximum Probability of Occurrence of Multiple Faults

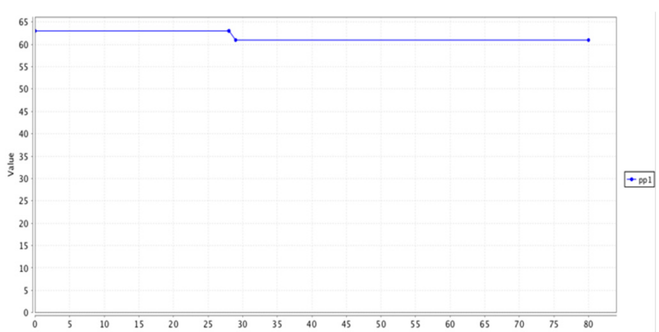

Figure 15: Fault Detection and Diagnosis using the Pick and Place's PBN Model

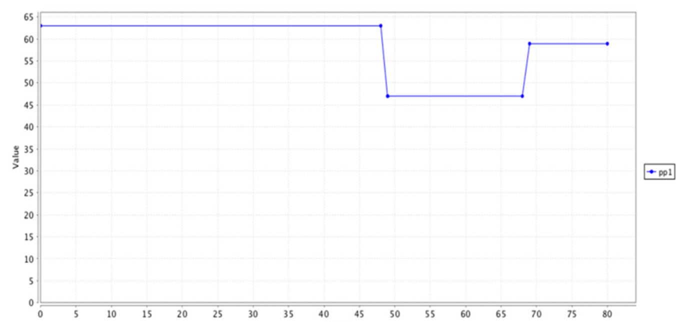

Figure 16: Detection and Diagnosis of Two Faults

5. 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 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. Since these models are based on the definition of the PBNs derived from regulating genes/nodes, this discretization creates a limitation in terms of the possible states that it can represent, but greatly simplifies the analysis. The authors are currently working on new models that may allow new faults to be detected, for further analysis. 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 richer mechanism of expressing fault conditions and failure modes. Another possible avenue of development is the use of the intervention mechanism in FDI-enabled PBN models.

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