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MECHANISM FOR TESTING AND IMPROVING THE ROBUSTNESS OF SMART MANUFACTURING SYSTEMS

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The purpose of this paper is to highlight how the concept of antifragility can be introduced in the design stage of evolved manufacturing systems, considered as complex adaptive systems capable of maintaining the functionality at optimal parameters under adverse conditions caused by unforeseen changes in context. The paper presents in detail how this approach was applied on a manufacturing line through the development of a digital twin model where uncertainty is handled through decision-making based on failure modes and effects analysis.

Keywords: antifragile, resilience, robustness, smart manufacturing, self-adaptive, uncertainties, decision-making

1. Introduction

Considered to be the "fourth industrial revolution", Industry 4.0 brought as the main novelty the concept of industrial digitization, supported by three other conceptual pillars: Smart Manufacturing (SM), Smart Factory (SF) and Industrial Internet of Things (IIoT). Industrial areas are overwhelmed with the need to go digital. Digitalization in supply chain management (SCM) in recent years has opened up a broad area for academic research, especially oriented to boost supply chain (SC) efficiency internally and externally. The most substantial increase in performance is expected to be in fields of competitiveness, flexibility, and working environment.

As the complexity of the processes driven by SM increases, the methods of monitoring the functioning state and maintaining the performance at optimal parameters became more sophisticated. Preventive maintenance consisting of periodic interventions to verify and correct deviations from normal status based on scenarios built on historical data records is gradually replaced by predictive maintenance solutions that use continuous real-time measurements to detect behavioral anomalies that can lead to failures, but which did not have an obvious

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causality. Limitations of probabilistic approaches based on predefined scenarios can no longer cope with the uncertainty caused by this increasing complexity.

A novel, but somewhat risky solution is to combat uncertainty on the basis of the antifragility paradigm. Antifragility is a concept introduced and developed by Nassim Nicholas Taleb in his book "Antifragile: Things That Gain from Disorder" [1]. According to Taleb, antifragility is more than robustness (the ability to withstand or overcome adverse conditions and therefore to recover from failure) and more than resilience (the ability to resist failure). By definition, antifragility is a property of systems that increase in capability, resilience, or robustness as a result of harmful actions of stressors, shocks, noise, mistakes, faults, attacks, or failures. In other words, the concept of antifragility is that certain things can improve and even grow stronger when subjected to stress.

This paper states that ensuring antifragility property is the safest way to exploit smart manufacturing systems under uncertain conditions, using an association of emerging technologies, such as Artificial Intelligence, Cloud Computing, Big Data Analytics and Digital Twin. The main driving problem for such a system is that the fulfilling of the particular objectives is often conflicting and therefore requires compromise solutions. In our opinion, an utility that ensures the fulfilment of antifragile engineering goals is the Automatization of Predictive Maintenance (APM).

2. Related works

A large group of works is that related to the development of SM applications (derived from the Industry 4.0 paradigm) based on IIoT. Paper [2] is one of the first dedicated to smart manufacturing, describing several scenarios having a logistic-based life-cycle model compatible with Industry 4.0 requirements on efficiency improvement and decentralization assurance. In [3] the authors propose an automatic data acquisition mechanism using IoT technology to ensure predictive maintenance in order to optimize assets management. Paper [4] develops an analysis framework for IIoT that can be used to enumerate and characterize IIoT and Edge devices when studying system architectures and analyzing security threats and vulnerabilities.

Another sector rich in references is the one dedicated to including SCM in the wider SM framework, through digital transformation and digital connection in collaborative networks. In paper [5] a supply chain model which allows to assess its performance in a compactly interconnected with IIoT and Edge devices environment is proposed. The purpose of [6] is to highlight how digitalization ensures the transfer of current knowledge about the supply chain risk into practical solutions to prevent it. Paper [7] describes the expected changes in the control and planning processes determined by the use of Digitalization Elements and proposes an original method of designing them according to the requirements of Industry 4.0 regarding SCM.

The literature on the use of DT in the industrial environment is rich and rapidly expanding. However, we looked only for recent works that associate DT with artificial intelligence, cyber-physical systems or hierarchical computer networks, with the main objective of real-time simulation. Among these, [8] justifies the need to use DT in combination with other technologies and in different fields, including the relation to asset management, and predictive maintenance. In [9], through the association of DT and Big Data, there is presented a method for designing products on manufacturing lines using DT, mentioning the maintenance operation, which includes three stages: performance prediction (without reference to equipment status), manufacturing process verification and function verification. In [10] the author points out that using the information provided by the DT we can predict how the manufactured product will be and then compare the result with the specification in the design phase, an observation that actually underlies the predictive maintenance. Paper [11] points out the importance of including in simulation hazards and uncertainties, which is also a concern of the testing within the simulation framework offered by DT. In [12] the authors point out the use of DT in cooperation with cyber-physical models in predictive maintenance.

3. Automatization of predictive maintenance in smart manufacturing systems

APM facilities are important attributes of the general control system of a manufacturing process, because they allow the migration of control procedures to mixed control, security and maintenance solutions. A first solution is the elaboration of the so-called system models, which are capable of automatically and permanently producing quality forecasts, to indicate the problems and failures at an early stage or to diagnose the future abnormal behaviors of the process. Such models can detect trends in process evolution, and thus can anticipate to what extent the model's outputs correspond to consistent results. On the other hand, the consistency of the models may be affected by the lack of expertise on new processes, still unverified, or evaluated on an insufficient historical database.

An important breakthrough in this direction is the integration of APM technology with a new simulation technology, called Digital Twin (DT) [13] A DT is a virtual representation of a real asset. More than a model, DT can receive continuous real-time data from the process and so can virtually monitor it. A simulation platform based on DT offers a framework for replacing a real device with its virtual counterpart, so as to allow efficient life cycle management, design and reconfiguration of the industrial equipment by performing virtual mapping of the available assets (such as components, software, documents, services, robots, logistics facilities, sensors, units and control components) from the real world in the digital information world. The main strategy in providing APM based on DT technology is to take action when the components or parts exhibit certain behaviors that usually result in a malfunction of the machine, a poor performance or a decrease in product quality.

Predictive maintenance (PdM) is one of the main tools proposed by Industry 4.0 paradigm for improving productivity and optimizing Assets Management. The fulfillment of these objectives is based on three pillars: 1) the collection and primary real-time processing of the data regarding the status of the production process and the resources involved in the work; 2) early detection of anomalies in the evolution of the process or of failures of machines and equipment; 3) accurate prediction of the time interval until the final fall and support for the decision to solve the critical situation in this interval. Therefore, for an antifragile system the optimization algorithms are multi-objective, aiming at the same time to ensure the robustness and resilience of the production process, the optimization of asset management and the optimization of the PdM intervention.

To minimize the differences between real challenges (process control, context awareness, antifragile operation) and control software, focused more on improving production, maintenance and logistic support we developed a method to be applied in a virtual environment.

Failure Mode and Effects Analysis (FMEA) is a structured technique defined in IEC 60812 [14]. Using FMEA allows identification of several performance indicators:

- Failure cause: why the process element failed
- Failure mode: how the process element failed
- Failure effect: the consequence of a defect mode regarding element operation, function or state
- Failure severity: grading the severity associated with the failure of the specific analyzed element or over interconnected elements
- Failure identification: Approach which considers correlated failure severity and frequency of occurrence

To apply this test method on a manufacturing line, we consider splitting it into operational units, and for each component of each unit failure modes must be defined. The effects produced by each failure mode, the severity of the impact on the current unit and potential causes are examined. The initial frequency of occurrence of each failure mode is estimated by experienced engineers.

The cause-effect chain analyzed in a FMEA stage is illustrated in Fig. 1. Each failure mode has a cause, and each consequence is associated with a failure mode. A consequence can lead to unexpected behavior. The severity describes the importance and priority required by a scenario. The occurrence indicator is given by the statistical probability of failure for the specific element.

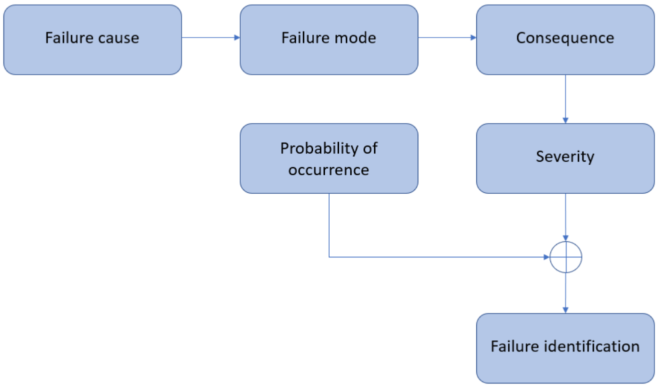

Fig.1. Cause-effect elements in FMEA

4. Dealing with uncertainties in antifragile manufacturing system

The struggle with the uncertainties is given by specific methods following three main principles. The basic principle to be applied is that a decision is good in the same extent that the information on which it is based is good. A second principle is that uncertainty must be overcome at every stage of the life cycle of a project, because it can surprise us with its ambiguity and unpredictability both in the planning stage, in the production launch phase, in the execution phase, even in the completion phase. Finally, the third principle is that uncertainty management is more comprehensive and much more different than just applying risk management techniques, and as such requires more cutting-edge solutions and perhaps surprising ones.

The antifragile approach of the decision process regarding the establishment and reconfiguration of the working parameters opens the way to solve a multi-objective optimization problem (MOP) in conditions of uncertainty. The main MOP challenge is the need to simultaneously optimize several contradictory objectives in the context of uncertain input data. In this respect, the biggest problem is that disturbances can occur in the input data and will propagate through the model affecting the values of the quality parameters. Thus, the propagation of uncertainties affects both the optimization process and the decision-making process. An antifragile MOP can be solved considering that for a system that has been designed to be robust and resilient, i.e. to keep its outputs relatively insensitive in the presence of uncertain inputs. Specifically, objective functions are calculated based on the expected uncertainty estimation using the same method which takes robustness into account.

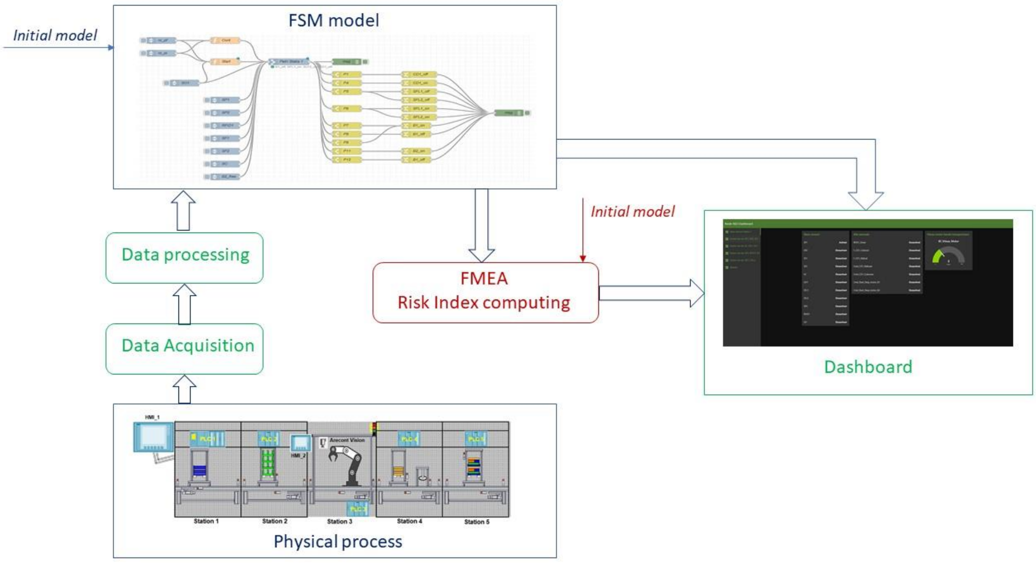

Fig. 2. DT for risk assessment methodology

To support the development of such an approach we propose the use of a digital twin (DT) as a reference for normal process operation, so that deviations can be rapidly identified. We consider a systems approach, where we use data available in the physical process to capture not only individual equipment behavior, but also device-to-device interactions, allowing identification of possible correlations between such deviations. A decisive role is to perform process modelling as a DT representation of the system, with all phases, nodes and dependencies. As illustrated in Fig. 2 this can be done through an FSM (Finite State Machine) representation of the process where different diagrams capture different detail levels of the plant, as well as dependencies between different nodes, allowing a nested top-bottom approach.

Fig. 3 illustrates the steps required to build a behavioural model in such an approach. The system is split in several independent phases, each defined by inputs, events and outputs. Each phase is represented by branch and nodes or final elements. A phase may include several branches, representing different operation flows. A risk factor is assigned to each element, taking into consideration the severity of possible failures, the occurrence and detectability probability. The risk factor of a phase or branch consists in the sum of all included elements. According to this data, a criticality matrix is built to represent elements failure along with their occurrence and severity. The model is updated with real process data, enabling both the verification of the virtual model in an initial testing and validation phase, and also the anomalies identification and classification during process operation.

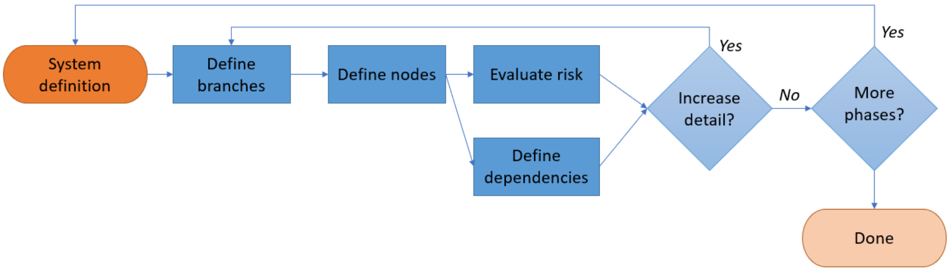

Fig.2. Building the behavior model

5. Experimental results

Testing and validation of the method was carried out on the testbed called SMART Flexible Assembly System offered by the Laboratory L9: Innovative Products and Processes to Increase Life Quality from the Research Center for Smart Products, Processes and Innovative Services (PRECIS) of the Faculty of Automatic Control and Computers, Politehnica University Bucharest, having as main objective the use of advanced modeling and simulation technologies for performance assessment of manufacturing mechatronic lines. The logistic support for performing the tests is a laboratory model for a flexible assembly line of industrial products with 5 workstations (WS 1…WS 5), presented in Fig.3.

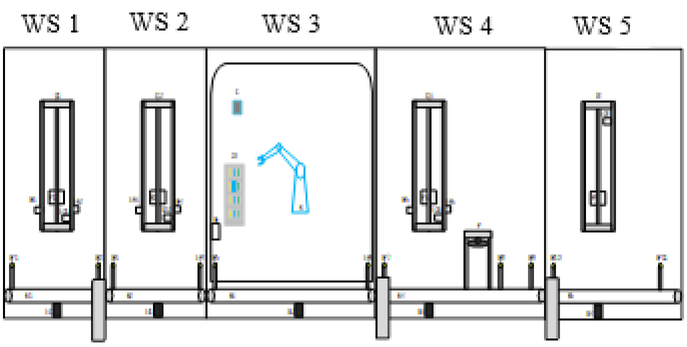

Fig. 3. Block diagram of the mechatronic assembly line

The technological flow consists in the succession of several processing phases, one at each workstation. At the first workstation a pallet base used to store the parts of the finished product is placed on the conveyor belt. At the second workstation on the pallet is placed the first piece (the basis) of the product. At the third workstation, the robotic arm executes assembly with several small parts. The fourth workstation ensures the mounting of the last piece and so a compact product is completed. The fifth workstation is responsible for stacking the product. The local operation of the physical process is implemented using Siemens PLCs, while the DT model was implemented in Node-Red. Standard Modbus communication protocol is used for data acquisition.

For each station of the manufacturing line a FSM (Finite State Machine) representation was built, as a virtual DT representation of the physical process. For example, Station 1 (Fig. 4) was modelled using 10 states and 12 transitions. The states are represented by *nr_pf*, the number of products, and *nr_pi*, the number of components for each product, given by the PLC, two inductive sensors, SP1 and SP2, showing the product entered or exited the conveyor belt, 1 RFID sensor, RFID1, to identify the stop position, one optical sensor SO1, to check pallets availability in the rack, two feedback sensors SF1 and SF2, which confirm the element is in the correct position and can be released from the stack, a capacitive sensor SC for confirming the element reached the belt and B2_free, a parameter confirming the next station accepts new elements. The transitions represented through elements P1 to P12 check the cumulative conditions required for each step for the element to be correctly processed until it leaves the station.

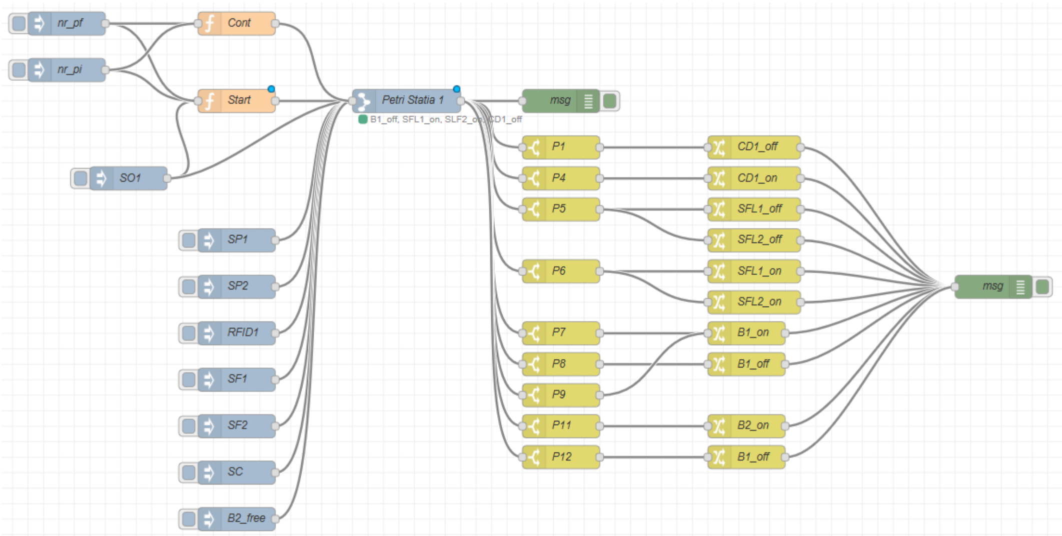

Fig.4. Behavior model example for station 1

We considered for each transition in the FSM model a time parameter, representing the time required to pass from one operational stage to another. This parameter was determined during the initial testing and validation phase by extracting the time between successive events, using the timestamp value of each detected event. Statistical processing functions like mean and standard deviation are used to identify faults from real-time data. This way we can determine, for example, the expected time between the moment a piece handled by the manufacturing line entered a processing phase, and when it should exit towards the next stage. Abrupt changes in the estimated processing time or the measured tendency to go beyond the normal operation range will be signalled either as warnings or as faults, depending on the event severity.

The FMEA analysis was applied on this station taking into consideration for each element possible failure modes, causes and effects and assigning a risk considering a factor between 1 and 10 for the severity of the event, the probability of occurrence and the ease of detecting it. By multiplying these indices, we obtained a risk factor which varies from 1 to 1000. The risk value is denoted RPN (Risk Priority Number).

Starting from the FMEA analysis in our method we consider, at the beginning, the same occurrence index for all elements, with the value 1, thus making the initial risk of operation lower, corresponding to a proper operation. The risk index for an individual element is computed as the maximum value between all RPNs associated with that element. By overlapping the risk indices over the elements represented in the FSM diagram we can compute in real time the overall risk factor as the sum of all possible risks of all linked elements, according to the state of each element. In a manufacturing line where reconfiguration is possible, these values should be computed for all possible links, and are set for each element thought the normal behaviour of the manufacturing line.

We assign these values on each node of the behaviour model illustrated in Fig. 4. During process operation, these values are adjusted to reflect the current risk according to received process data. Fig. 5 illustrates the data acquisition and processing modules, in this case applied for reading signal SP1. Data is collected from the physical process using a Modbus TCP connection and stored in a local database. The real-time value is displayed in the dashboard. Changes in the sensor state trigger the acquisition of a new value. The time between successive data acquisitions is be used to estimate the duration of a phase.

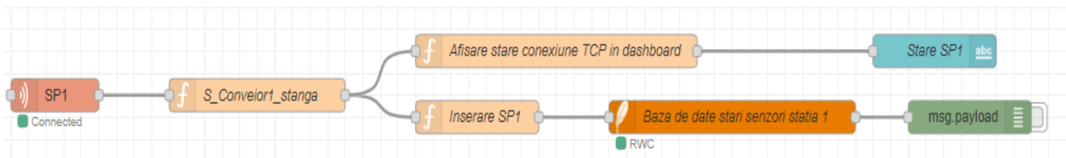

Fig. 5. Signal acquisition, processing and storage example for SP1

We defined blocks to compute the mean and standard deviation for the phase duration (Fig. 6). For this, we created a table for active signals which will store each activation of the inductive sensors, as well as the timestamp of this event. We chose not to store the values for these statistical parameters, but rather to compute them online using database interrogation functions. The standard deviation was computed as: **SELECT AVG ((SP1.time - sub.a) * (SP1.time - sub.a)) as var from SP1, SELECT AVG(time) AS a FROM SP1) AS sub.** The mean was computed as **SELECT value, time, time - LAG (time, 1, 0) OVER (ORDER BY value) diferenta FROM SP1.**

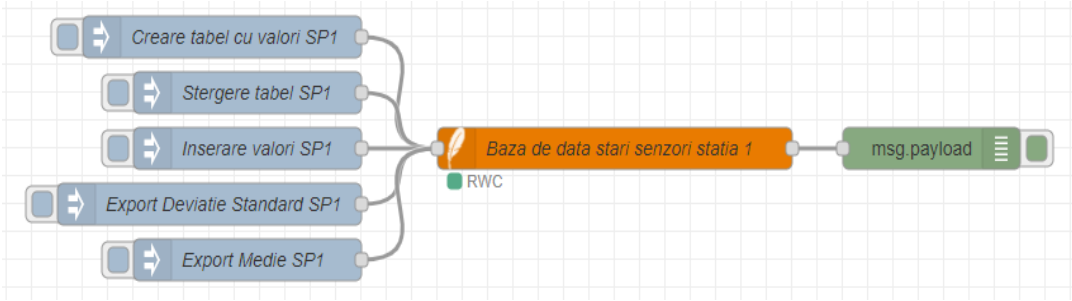

Fig. 6. Detail on computing signal attributes

The following cases are considered for fault identification:

- Communication link state: in case the Modbus client does not receive a response from the server device it automatically triggers an alarm, visible in the dashboard. The link will be marked as ACTIVE if the communication works properly, otherwise INACTIVE.
- Bad value received from the sensor: this is signalled by the communication protocol in case the corresponding register is unavailable. In this case the signal is marked as INACTIVE.
- Untrusted value: each value is analysed according to the mean and standard deviation of its previous values (to determine outlier behaviour), relative to the values of its correlated parameters (to determine either a root or independent failure) or and or/relative to its variation slope (to measure the tendency of exceeding operational limits or under optimal operation). If any of these cases are identified the received signal will be marked as untrusted.

Fig. 7 shows how this information is used to update the parameters of the RPN and adjust its value in real-time, during process operation. For this we compute a new occurrence value according to detected faults, the severity according to the cross-correlation with other parameters and the detection probability according to the percentage of false failure detection in case of signals marked as untrusted values. We used a join node to build a vector from these three values and obtained the RPN values by multiplying these three parameters.

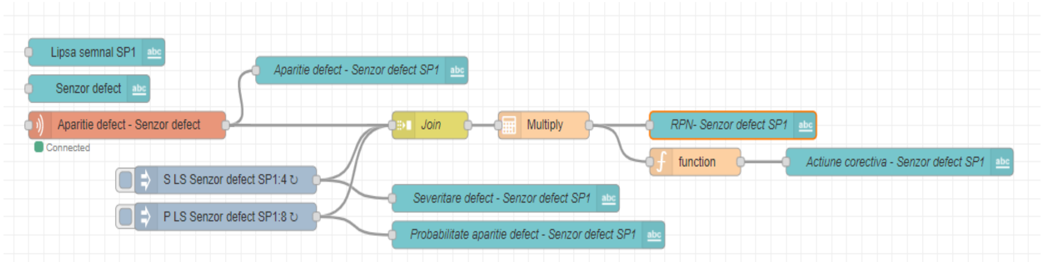

Fig. 7. Example on computing RPN value associated with SP1

The presented results showed how a DT approach can be used to extend traditional monitoring and control applications to support operational activities and provide insight on the process state through a systematic view. The use of Node-Red for the implementation provided flexibility in the integration interfaces with both process and operational levels and in implementing the processing functions. The results of this analysis can be forwarded to predictive maintenance modules or updated to allow process reconfiguration based on alternative routes defined in the FSM model.

4. Conclusions

In this paper we tried to discuss the possibility of designing a special category of complex adaptive systems that permanently maintain performance at optimum parameters, extending the operating time as much as possible, by assuming calculated risk forms. In this aim we proposed an antifragile mechanism that combine a predictive maintenance procedure with a procedure that combats the negative effects of the uncertainties. This implies a fundamental change in process planning policy. For example, if we consider as optimum policy a non-delay schedule, which avoids idle time in the execution phase, the unexpected changes in the environment may cause partially or totally revision of the initial planning, depending on the robustness requirements proposed by the production control antifragile solution. Therefore, the goal is to design a joint model that integrates proactively the production scheduling and the preventive maintenance procedure that will allow the optimization with the double objective of improvement for both quality robustness and functional robustness.

Adding to this bold proposal for dynamic optimization procedure with discrete and continuous variables the real-time simulation facilities in the Digital Twin framework, we consider that the proposed mechanism offers the chance to detect and eliminate hidden vulnerabilities and to facilitate learning and isolation of wrong behavior processes.

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R E F E R E N C E S

[1] *N. N. Taleb*, Antifragile: Things That Gain from Disorder. Random House, 2012.
[2] *E. Hofmann, M. Rüsch*, "Industry 4.0 and the current status as well as future prospects on logistics", in Computers in Industry, Vol. 89, 2017, pp. 23-34.
[3] *A. Cachada, J. Barbosa, P. Leitao, A. Alves, L. Alves, J. Teixeira, C. Teixeira*, "Using Internet of Things Technologies for an Efficient Data Collection in Maintenance 4.0", in IEEE International Conference on Industrial Cyber Physical Systems, 2019, pp. 113-118.
[4] *H. Boyes, B. Hallaq, J. Cunningham, T. Watson*, "The industrial internet of things (IIoT): An analysis framework", in Computers in Industry, Vol. 101, 2018, pp. 1-12.
[5] *M. Bhagawati, E. Manavalan, K. Jayakrishna, P. Venkumar*, "Identifying Key Success Factors of Sustainability in Supply Chain Management for Industry 4.0 using DEMATEL Method", in Proceedings of International Conference on Intelligent Manufacturing and Automation, 2018, pp. 583-591.
[6] *F. Schlutter*, " Procedure Model for Supply Chain Digitalization Scenarios for a Data-Driven Supply Chain Risk Management", Book chapter, in G. A. Zsidisin and M. Henke (eds.), Revisiting Supply Chain Risk, Springer Series in Supply Chain Management, vol. 7, 2019, pp.137-154.
[7] *E. Hetterscheid, U. Beißert*, "Digitalization Elements for Collaborative Planning and Control in Supply Chains", in: Freitag M., Kotzab H., Pannek J. (eds) Dynamics in Logistics, Lecture Notes in Logistics, Springer, 2018.
[8] *M. Grieves*, "Digital Twin: Manufacturing Excellence through Virtual Factory Replication", White Paper 1411.0, Florida Institute of Technology, 2017, pp. 1-7.
[9] *A. El. Saddik*, "Digital Twins: The Convergence of Multimedia Technologies", in IEEE MultiMedia, 25 (2), 2018, pp. 87–92.
[10] *M.Grieves, J. Vickers*, "Digital Twin: Mitigating Unpredictable, Undesirable Emergent Behavior in Complex Systems", in F.-J. Kahlen, S. Flumerfelt, and A. Alves (Eds.), Trans-Disciplinary Perspectives on System Complexity, 2016, pp. 85-114.
[11] *F. Tao, et al*. "Digital twin-driven product design framework." International Journal of Production Research, 2018, pp. 1-19
[12] *Y. Cai, et al.* "Sensor Data and Information Fusion to Construct Digital-twins Virtual Machine Tools for Cyber-physical Manufacturing", Procedia Manufacturing, vol.10, 2017, pp. 1031–1042
[13] *Grieves, M., "Digital Twin*: Manufacturing Excellence through Virtual Factory Replication", White Paper 1411.0, Florida Institute of Technology, 2017, pp. 1-7
[14] *C. Schmittner, T. Gruber, P. Puschner, E. Schoitsch*, Security Application of Failure Mode and Effect Analysis (FMEA), 2017