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ORIGINAL ARTICLE

A cyber process control system based on pattern recognition and cloud computing

Um sistema de controle de processos cibernéticos com base em reconhecimento de padrões e computação em nuvem

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Abstract: This paper presents a novel simulation model of the Cyber Process Control System (CPCS) by combining pattern recognition and Cloud Computing (CC). This paper's originality arises from its aim to build a cloud computing platform for autonomous machines, and the exploration of manufacturing data to generate interpretable patterns to be used in process control decision making. The combining of Cloud technology and machine learning brings production to Industry 4.0. The proposed system is tested using data Carbon Fiber Reinforced Polymer (CFRP) routing process. The little information available about the manufacturing process of this type of material and the interaction between the production steps makes the manufacturing process quite difficult. This system generates interpretable rules of controllable operating parameters sent to the controller to keep the machining process within the limits of the specifications. The second step is activated during the drifting conditions in the machining step. Also, the simulation of the machining process is illustrated to generate the relations between input and output variables of the machining process. The findings of the corrective actions are illustrated and the interaction between the two industrial steps is simulated. Finally, current and future CPCS and CC applications in Industry 4.0 are discussed.

Keywords: Process control; Pattern recognition; Multi-class logical analysis of data; Cyber-physical system; Industry 4.0; Cloud computing.

Resumo: Este artigo apresenta um novo modelo de simulação do Cyber Process Control System (CPCS) combinando reconhecimento de padrões e Cloud Computing (CC). A originalidade deste artigo decorre de seu objetivo de construir uma plataforma de computação em nuvem para máquinas autônomas e da exploração de dados de fabricação para gerar padrões interpretáveis para serem usados na tomada de decisões de controle de processos. A combinação de tecnologia em nuvem e aprendizado de máquina traz a produção para a Indústria 4.0. O sistema proposto é testado usando o processo de roteamento de polímero reforçado com fibra de carbono (CFRP). A pouca informação disponível sobre o processo de fabricação desse tipo de material e a interação entre as etapas de produção dificulta bastante o processo de fabricação. Este sistema gera regras interpretáveis de parâmetros operacionais controláveis enviados ao controlador para manter o processo de usinagem dentro dos limites das especificações. A

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segunda etapa é ativada durante as condições de deriva na etapa de usinagem. Além disso, a simulação do processo de usinagem é ilustrada para gerar as relações entre as variáveis de entrada e saída do processo de usinagem. Os resultados das ações corretivas são ilustrados e a interação entre as duas etapas industriais é simulada. Finalmente, são discutidas as aplicações atuais e futuras de CPCS e CC na Indústria 4.0.

Palavras-chave: Controle de processos; Reconhecimento de padrões; Análise lógica multiclasse de dados; Sistema ciber-físico; Indústria 4.0; Computação em nuvem.

1 Introduction

In November 2011 the German government implemented the first concept of Industry 4.0, which was a key component of their high-tech strategy for 2020. The term Industry 4.0 previously appeared at the Hannover Industrial Fair in April 2013 as a German national strategy. These appearances support classifying this term as a significant topic among global industries. Industry 4.0 mainly depends on building a Cyber-Physical System (CPS) to build a smart, reconfigurable, highly flexible production process, with real-time interactions between people, production, and devices. Industry 4.0 strategies are aimed at creating smart factories where CPSs and CC are used and able to monitor, control, and make smart decisions for physical processes (Zhong et al., 2017). Making the machine work autonomously with and interact with other production phases become the main research topic in the industrial field. These results in a production that can be standardized solve problems and make adaptive decisions (McFarlane et al., 2003). Some process control systems utilize artificial intelligence (AI), which allows them to learn from historical data to achieve smart control and standardized industrial processes. The autonomous manufacturing model is based on smart sciences that improve the design, management, and enhancement of the interaction between production phases. The smart manufacturing model uses smart sensors, adaptive decision-making models, intelligent devices, and data analytics. Many researchers have proposed studies on classical process control. The classical process control technique is dependent on the expert system that uses experience to find suitable operating conditions to produce conforming surfaces. There has been a recent trend of researchers using intelligent manufacturing techniques to control production processes. For example, Mourtzis et al. (2019) proposed a knowledge-enriched framework with aid of CC and wireless sensor networks to collect the machining parameters from the production process and shared them with a human operator by using mobile devices. Song & Moon (2019) introduced a cyber-manufacturing system architecture that consisted of five component levels and investigate the performance of the proposed system by using simulation techniques. Merdan et al. (2019) proposed a model-driven technique for automatically configuring the control layer of a CPS based on knowledge representation of the environment and component capabilities. The proposed technique includes a control architecture that is examined in two industrial use cases. Huang (2016) developed a decision-making model for surface roughness monitoring for end milling operation. The developed model achieves a higher level of accuracy for surface quality prediction. Furthermore, the decision-making algorithm should be applied to implement a cutting tool monitoring system. This system is; an adaptive control of machining parameters that adjusts the parameters for quality surface roughness for the smart Computer Numerical Control (CNC) machine. De Paula Ferreira et al. (2020) proposed a stat of the art research study on simulation in the field of Industry 4.0 (I4.0). Mourtzis (2020) introduced the significant milestones in the manufacturing system evaluation due to quick response and analysis, low cost, and decreasing the risk of operation. Jiang et al. (2014) proposed an innovative approach to adaptive analyses of machining process stability to improve the quality of the machining process, which is solved with the backpropagation neural network and support vector machine. The equipment model service performance prediction is established to forecast the quality of the machining form features in real-time. Shaban et al. (2017) developed a pattern-based Machine Learning (ML) approach to detect characteristic patterns to control the quality of a machined part at a specific range. The proposed methodology used to find these patterns lead to conforming products. Also, an online machining process control has been implemented by using the experimental results. A process control model shows how two-class Logical Analysis of Data is used to control the routing process by autonomously tuning the routing conditions to always return to the machining zones. The generated model introduces the different patterns of conforming and nonconforming production quality. This use in this paper was a two-class decision-making approach; its use was limited to control of only one conforming quality variable. Additionally, they use a simple multiple linear regression in the simulation of the CFRP machining process.

In this paper, we present a simulation model of a novel CPCS by using ML and online connectivity of the internet. Due to the very rare information available about the machining process of CFRP, and how the interaction between the production stages makes the manufacturing process quite difficult is considered. This paper's originality arises from its aim to build a cloud computing platform for monitoring and control of the Production's performance autonomously, and the exploration of manufacturing data to generate interpretable patterns to be used in process control decision making and simulate the interaction between two production stages. We use Artificial Neural Network (ANN) to simulate machine behavior during the production process. A Graphical User Interface (GUI) was built to simulate the machine-to-machine connection. In section 2, (CPCS) based on internet connectivity is presented. The proposed methodology is introduced in section 3. In section 4, the experimental setup and results are given. In Section 5 the accuracy of the proposed simulation model compared with the most popular machine learning techniques of ANN and Support Vector Machine (SVM) are presented. A simulation online decision-making process is presented in section 6. Finding the autonomous corrective action is the subject of section 7. The sentencing step is illustrated in section 8. Discussion, conclusions, and future work are presented in section 9.

2 The cyber process control system

The process control system has an adaptive control loop with an automatic adjustment of controllable machining variables. The automatic control is used to improve productivity and product quality, which is not commonly available in CNCs (Liang et al., 2004). In this paper, we present the process control in two production steps; the first step is the machining step and the second step is the sentencing step. Figure 1 illustrates the machine-to-machine (M2M) interaction.

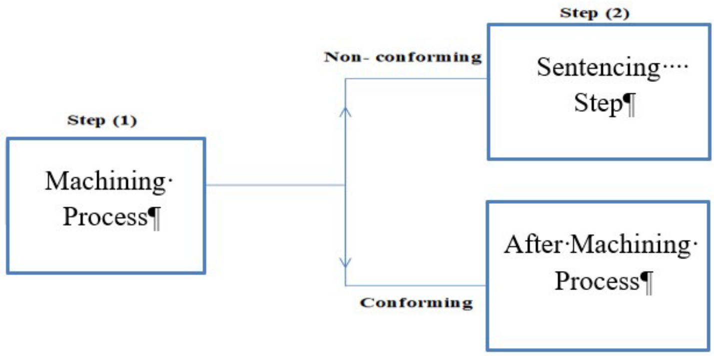


Figure 1. Machine to machine interaction structure.

To produce within the pre-defined specifications, the production process is continuously monitored during its process. Due to continuous monitoring, big data is generated. The big volume of data that is generated during monitoring needs scalable storage space and a parallel processing analyzer. In this paper, we build a production control system based on CC. The main advantages of using CC are accessibility, scalability, security, unlimited storage space, and cost-effectiveness. CC services are provided by Amazon AWS, Dropbox, Google Cloud, IBM, Microsoft Azure, and, 24/7 support is available (Avram, 2014). The benefits of the proposed system include secure access and adjustable storage capacity, ease of use, fast speeds, and efficiently synchronized technology.

The architecture of the CPCS consists of two steps. The first step is divided into four layers which are parameters; sensing, communication, analysis and sentencing, and corrective action.

Parameter sensing (PS): PS consists of sensors connected to the machine to provide parameters' values such as forces, temperature, and pressure. The setup of these sensors has Internet of Things (IoT) capability for wireless communication that enables data transfer via the internet to the higher layer. A combination of a sensor, microprocessor, and communication technology is used to convert environmental inputs into readable data, and to transmit this data onwards to a centralized repository. In contrast, traditional sensors rely on the manufacturer to perform the processing of inputs. Smart sensors allow for data to be transmitted with fewer errors, as the processing happens closer to the source, and can remain within a company's network. A PS comprises an assortment of spatially disseminated and autonomous gadgets that gather data and carefully communicate it over a remote channel. A PS can utilize several sensors, joined by gateways and an organizing gadget, to detect the natural or states of being of a framework, and to screen or control it. Every hub contains at least one sensor that can be detached or dynamic. These sensors speak with one another to send the data to a worker CC that deals with the data of the whole system (Rashvand et al., 2014). Additionally, smart sensors can be more easily customized for specific use cases while traditional sensors are generally mass-produced. In this paper, the monitored cutting forces are measured using a Kister dynamometer 9255B, and temperatures are measured using a FLIR Thermo Vision A20M infra-red camera,

Communication: Communication consists of distributed file storage and parallel processors that connect the virtual and physical sides. CC is the on-request conveyance of IT assets over the Internet with increasing pay requirements only as costs arise. Rather than purchasing, claiming, and keeping up physical server farms and workers, you can get to innovation administrations; for example, registering force, stockpiling, and databases, dependent upon the situation from a cloud supplier. The proposed system doesn't need to over-arrange assets in advance to deal with top degrees of business action later on. Rather, you only arrange the measure of assets that you need. You can scale these assets up or down to immediately develop and shrivel limits as your business needs change. This layer uses the internet to transfer the collected data from smart sensors to the central hub, which is explained below. In this paper, we use Dropbox Cloud storage, with a capacity of 2 Gigabytes.

Sentencing: This layer includes the analyzer software that converts uncontrollable sensing data into useful information. We use historical data in offline learning to build the analyzer. The analyzer compares the offline learning patterns and the new sensing data that comes from the smart sensor. After analyzing the collected data and defining the conforming conditions, the corrective actions are sent back to the following layer.

Implementation of corrective actions: - this layer consists of controllers that receive the corrective actions to adjust the control parameters that produce workpieces within conforming conditions.

This paper presents a simulation model of the CPCS. Figure 2 illustrates the architecture of the proposed model. The proposed architecture is matched with the CPS to achieve Industry 4.0 requirements (Rashvand et al., 2014). We use the ML to convert the historically uncontrollable measuring data of the machining process to generate governor patterns in the offline analysis. Also, we use the controllable variable in the offline analysis to extract the control pattern to start building the online model of the proposed CPCS.

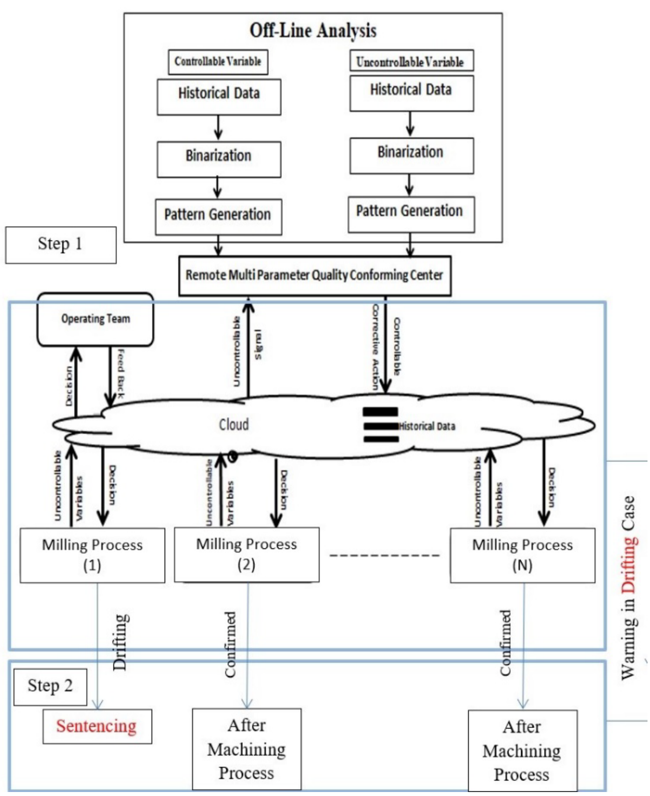


Figure 2. Architecture of the CPCS.

To simulate the proposed process control system, a simulated example for multi-parameter process control is developed using MATLAB 2015/b.

3 Multi-Class Logical Analysis of Data (MC-LAD)

In the following section, the proposed methodology is presented. Logical Analysis of Data (LAD) is a machine learning and knowledge discovery technique that generates patterns that are extracted from the given training data. These patterns represent rules that describe the states of the process during machining. They are interpretable as zones of conditions that lead to conforming or nonconforming products with different anomalies.

The identification of these patterns in any new dataset is an indication of the production output's condition. The cbmLAD (Alexe et al., 2004) software is used. The multi-class LAD methodology is composed of 3-steps; Data Binarization, Pattern Generation, and Theory Formation (Yacout et al., 2012; Moreira, 2000).

4 Case study

We consider the machining of Carbon Fiber Reinforcements Polymer (CFRP) as a case study. The CFRP properties include high specific strength and stiffness, performance to weight ratio, high chemical and thermal stability, and high connectivity and corrosion resistance. These properties make them the backbone of many applications, especially in mechanical engineering, aerospace, aviation, automotive industries, and sports (Mortada et al., 2014; Sharma et al., 2014; Soutis, 2005; Paiva et al., 2009). CFRP is designed to gradually substitute conventional metallic materials (Mallick, 2007). Most CFRP studies are concentrated on its material properties. CFRP machining is more difficult than conventional metal machining due to the different material structures (Tyczyński et al., 2014). This challenge increases the importance of studying machining to reduce the production cost (Che et al., 2014). Milling composite materials is a complex task. Challenges include material heterogeneity, distance error and parallelism during the machining process, and material characteristics and cutting parameters; namely, spindle speed (v), feed (f), length of cut (LOC), and tool overhang length (LOT). The manufacturers of CFRP use milling as a corrective operation to produce a well-defined and high-quality surface that requires the removal of excess material to control tolerance (Ferreira et al., 1999; Sorrentino et al., 2016).

Routing processes were tested on a Quasi-isotropic laminate comprising 35 piles of 8-harness satin woven graphite-epoxy prepared with the final cured thickness of 6.35±0.02mm. The specification of the cutting tool is 6.3mm, 4 flutes, and solid carbide end mill (Davim & Reis, 2005). The experiments were performed on a Makino A88ε machining center. A spindle speed attachment was used to achieve spindle speed up to 40,000 rpm, which has 1 kw of power. The slotting was tested along with the full thickness of the composite material. After each 32mm of cutting distance, tool wear was investigated at the flank and the rake faces. The total cutting distance was 96mm. The experimental test matrix was used with spindle speeds (v-rpm) 10,000, 20,000, 30,000, 40,000, 3 feeds (f-mm/min): 250, 500, 1000, 3 values of cutting distance (C-mm) 24, 31, 38 and 3 overhang lengths (TL-mm) 30, 60, 90. Therefore, the total number of full factorial designs of experiments is 108 observations. The monitored variables are feed force (F_x), transverse force (Fy), axial force (Fz)for different speeds, feeds and tool overhang length of TL1=38mm and TL3=24. The machined slots were characterized in terms of parallelism and a distance error. The specifications of these qualities and characteristics were the following: Parallelism ≤ 1% and a distance error ≤ 0.5%. To consider both quality characteristics, a multi-class pattern generation problem is based on the experimental data. Is solved. Table 1 illustrates a sample of three classes of observations that satisfy quality specifications (class 0), the observations with unsatisfied parallelism (class1), as well as the observations with both unsatisfied parallelism and distance error (class 2). The experimental data illustrate the controllable and uncontrollable parameters which affect machine production.

Table 1. A sample of the experimental results.

v (rpm)	F (mm/min)	TL (mm)	C (mm)	Fx (N)	Fy (N)	Fz (N)	Tmean (C)	Parallelism	Distance error	Parallelism	Distance error	class
Controllable Variable				Uncontrollable Variable								
40000	250	38	30	-9.2	-5.8	-6.5	305	0.0392	0.010622047	1	1	2
40000	500	38	30	-15.4	-11.2	-6.6	385	0.0205	0.04915748	1	1	2
20000	250	31	30	-14.4	-10.8	-5.0	187	0.0082	0.017070866	0	1	1
20000	500	31	30	-22.7	-20.5	-9.7	383	0.00875	0.018031496	0	1	1
40000	500	24	30	-22.1	-10.0	-9.0	267	0.0023	0.003425197	0	0	0
40000	1000	24	30	-29.5	-17.6	-11.1	421	0.00865	0.001283465	0	0	0
30000	250	24	30	-15.4	-8.4	-3.4	204	0.00445	0.000401575	0	0	0
30000	500	24	30	-20.4	-13.6	-6.8	264	0.00325	0.001590551	0	0	0
20000	1000	31	90	-52.1	-44.7	-23.2	502	0.00545	0.019425197	0	1	1
10000	1000	31	90	-100.3	-90.1	-44.8	420	0.01385	0.007795276	1	1	2
40000	250	24	90	-30.0	-7.4	-3.8	372	0.00515	0.004346457	0	0	0
40000	500	24	90	-39.6	-12.3	-9.5	387	0.00445	0.005330709	0	1	1
40000	1000	24	90	-44.1	-19.2	-12.5	463	0.004	0.000850394	0	0	0
30000	250	24	90	-23.2	-8.0	-4.9	281	0.00175	0.002685039	0	0	0
30000	500	24	90	-28.8	-14.2	-7.7	332	0.00245	0.000874016	0	0	0

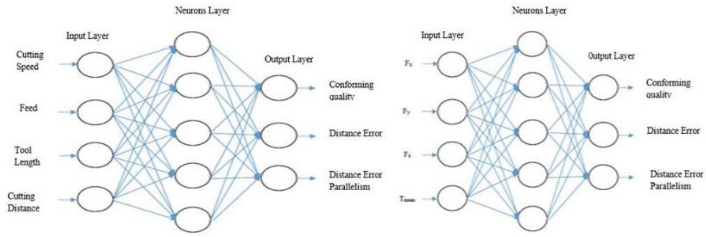
5 Methodology test

In this section, the comparison between the classification accuracy of the proposed machine learning technique (MC-LAD) with the most popular machine learning techniques such as the Artificial Neural Network (ANN) and Support Vector Machine (SVM) was illustrated in the following section.

6 Artificial Neural Network (ANN)

The Artificial Neural Network is the most popular supervised ML approach. In 1943 a computational model for neural networks based on mathematics and threshold logic algorithms was developed (Meshreki et al., 2012). ANN is composed of three layers, the input layer, neuron layer, and output layer. The input layers accept the input attributes. The neuron layer and number of neurons depend on the nonlinearity of the model, which interconnects between the input and output layers (McCulloch & Pitts, 1990).

In this work, there are two models, the monitor, and control model. The input variables in the monitoring model are the feed force, transverse force, axial force, and the average temperature of the machining process. The control model input variables are cutting speed, feed, overhang tool length, and cutting distance. The multivariable output layers in our work are the quality outcomes which are "conforming", “nonconforming with distance error” and “nonconforming with distance error and parallelism error”. In Figures 3a and 3b the controllable and uncontrollable variables are illustrated. The following ANN models were developed to compare the classification accuracy and the proposed ML technique accuracy. The developed ANN models have one hidden layer with five neurons. The training and testing procedure is known as the K-fold cross-validation procedure. In our work, (K=5).



(a) ANN Model With Controllable Variable (b) ANN Model With Uncontrollable Variable

Figure 3. ANN controllable and uncontrollable variables models.

The second ML illustrated is the Support Vector Machine (SVM). SVM is a supervised non-parametric statistical learning technique, therefore there is no assumption. The SVM training algorithm aims to find a hyperplane that separates the dataset into a discrete predefined number of classes in a fashion consistent with the training examples. SVM gives the ability to generalize from a limited amount of training data with variable quality. Compared to alternative methods such as backpropagation neural networks, SVMs can yield comparable accuracy using a much smaller training sample size. This is in line with the “support vector” concept that relies on only a few data points to define the classifier’s hyperplane (Sharma et al.., 2008). The support-vector network implements the following idea: it maps the input vectors into a high dimensional feature space Z through some non-linear mapping chosen a priori. In this space, a linear decision surface is constructed with special properties that ensure a high generalization ability of the network (Cortes & Vapnik, 1995). The advantage of using an SVM includes flexibility in the choice of the threshold separating the solvent from insolvent companies, the use of nonlinear transformations no assumptions about the functional form of the transformation, good out-of-sample generalization, and the ability to deliver a unique solution. The disadvantage includes the inability to represent the score of all companies as a simple parametric function of the financial ratios, since its dimension may be very high, or as a linear combination of single financial ratios, or other simple functional forms.

In this paper, we use the Weka data mining software (Mountrakis et al., 2011) to build multi-class monitored and a multi-class control model. The number of observations of each class is 27, 25, 56 for conforming, distance error, and both distance and parallelism respectively.

The validation and comparison between different ML techniques is a real challenge for researchers (Hall et al., 2009). Usually, to compare techniques for the same problem, the accuracy of each technique is compared. This accuracy metric is obtained from cross-validation with several repetitions. The technique with the highest accuracy is preferable. This comparison method is sufficient in most practical research (Wolpert, 1996). The accuracy testing process is performed by dividing the experimental data into two sets. The first set is the training set which covers the different classes with a constant percentage of each class observation number. The second set is the tests data that test the generated model to find the accuracy of classifying the tested observation with its class. The training and testing procedure is known as the K-fold cross-validation procedure. In our work, (K=5). To calculate the accuracy of the proposed methodology for the same problem we use the software cbmMC-LAD (Alexe et al., 2004). In the Table 2, the accuracy of each ML technique is illustrated.

Table 2. Comparison of the accuracy of MC-LAD, ANN, and SVM.

Model	MC-LAD	ANN	SVM
Control model	93.2819%	88.05% (1 hidden Layer, 5 neurons)	83.643%
Monitored model	94.7604%	70.4% (1 hidden Layer, 5 neurons)	58.8%

Table 2 illustrates how using MC-LAD improves the accuracy of detecting unsatisfied specifications. In Tables 3 and 4, the generated patterns for the controllable variables and the uncontrollable variables are illustrated. We use these patterns in the CPCS to keep the machining process in the zone of patterns in class 0, which is the zone where both quality specifications are satisfied. In the following section, the adaptive process control system is illustrated.

Table 3. Generated pattern for Controllable variables using MC-LAD.

P.#	V rpm*10^4	F mm/min	TL (mm)	C (mm)	Weight
1-Conforming Class (Class 0)					
1	<3.1	<695.18	<24		0.33
2	1.5< v<2.5		<24	<38.77	0.06
3	>3.86	>251.672	<24		0.10
4		<695.518	<24	>30.218	0.33
5	<3.1		<24	>64.114	0.15
2-Distance Error Class (Class 1)					
1		250<f<475	24<Tl<37	>38.77	0.17
2	<3.86	>296 >536	24<Tl<37	30<C<89	0.17
3	1.5<v<2.5		24<Tl<37	38<C<66	0.09
4			24<Tl<30		0.14
5		519<f<991	<37	30<C<42	0.06
6	<2.5	<475.7	24<Tl<37	<89.44	0.17
7	<2.5	<991.9	24<Tl<37	59<C<88	0.22
8	<1.5	>519.921	<37.87	<31.6081	0.02
9	>3.1	<455.148	<30.897	<88.60	0.02
3-Distance and Parallelism Error Class (class 2)					
1			>37.87		0.24
2		>496.485	>30.8972	>89.44	0.08
3	>1.5 >2.5		>30.8972	<60.01	0.20
4	>1.5		>30.8972	<30.07	0.12
5	2.<v<3.1	>991.973			0.06
6	<2.5		>30.8972	>89.44	0.08
7	>3.86		>30.8972		0.13
8		>496.485	<24.0286	59<C<60	0.01
9	<1.5	496<f<503	>30.8972	>59.68	0.04

Table 4. Pattern generated for uncontrollable variables using MC-LAD.

P.#	Fx (N)	Fy (N)	Fz (N)	Tm (C)	Weight
1-Conforming Class (Class 0)					
1	<-14.9	-23< <-7.2		<318.5	0.295
2	<-26.6	>-20.45			0.181
3	<-14.9	>-12.55		<249.5	0.091
4	<-14.9	>-23	<-8.9	<371.5	0.159
5	<-26.6	-20< <-12.5			0.159
6	<-14.9	>-42.2	<-18.0	<497	0.114
2-Distance Error Class (Class 1)					
1	<-12.9	<-10.75		<188	0.046
2	<-12.9	<-12.1	<-9.3	374<<409	0.18
3	<-12.9	<-12.1	<-18.8	374<<409	0.069
4	<-12.95		-5<<-3		0.046
5	>-99.8	<-20.45	<-37.5		0.162
6	<-30.1	-30< <-23	<-10.6	<409	0.162
7	>-19.7		>-5.25	23< < 308	0.046
8	>-22.95	<-12.1	<-7.25	<409	0.046
9	>-55	<-12.1	<-22.2	>325.5	0.046
10	<-27.4	<-12.1		374<<409	0.186
3-Distance and Parallelism Error Class (Class 2)					
1		-93< <-19.6	>-21.4	409<<558	0.158
2	>-26.6	<-5.75	<-3.05	>339.5	0.075
3		-93< <-46	>-37.5	>210.5	0.083
4		-29< <-20	>-14.7	352<<558	0.083
5	>-20.25	-93< <-5.75	<-4.7	>210.5	0.108
6	>-26.6			384<<558	0.066
7	>-26.6	<-5.75	<-3.05	>285	0.116
8	>-18.1	>-7.9		>210.5	0.058
9	>-19.5	<-5.75	<-3.85	>194.5	0.1
10	>-49	>-93.85	<-12.1	20< <558	0.066
11			<-11.4	409<<441	0.083

7 Simulation of the CPCS machining process (Step 1)

In the previous studies, the researchers use linear regression to simulate the machining process and the relation between the input and output of the machining process (Shaban et al., 2017). Due to the non-linearity between the input and output of the machining process of CFRP, the ANN is selected to simulate the machining process. The simulator CPCS for the machining of CFRP was developed by using ANN. We monitored four uncontrollable variables, feed force (F_x), transverse force (F_y), axial force (F_z), and mean temperature (T_{mean}) to detect the state of the machining process. We built the control process by using the controllable variables, spindle speed (v) and feed (f), overhang tool length (TL), and cutting distance (C). In the remote quality conforming center the sensors' data that comes from the machining process (layer1) is checked with the patterns generated from historical data and classified into one of the three specified classes. The sensors' data comes from sensors with wireless connections which send the reading of the uncontrollable variables to the cloud. The second step in the process control is to find the corrective action when the quality is not conforming. The developed ANN models have one hidden layer with two neurons. In the simulation ANN model, the K-fold validation (K) was five. Matlab software was used to simulate this process by using an ANN (McCulloch & Pitts, 1990). Figure 4 illustrates the network of controlled input parameters and the output values of the uncontrollable variables.

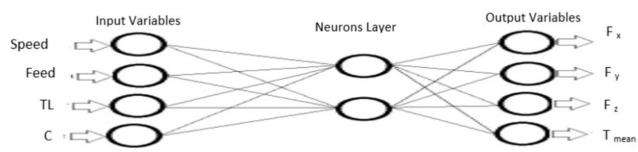


Figure 4. The ANN that simulates the inputs and output of the machining process.

According to the conforming pattern shown in Table 3, the generated patterns illustrate that overhang tool lengths (TL) less than 24 mm produce a conforming production. Also, the cutting distance (C) value is 24 to 96. In Figure 5, the decision-making procedure schematic is presented. This decision-making schematic presents the control loop of the process control. It starts from the inserting of the controllable variables and ends with finding the corrective action of controllable variables if the uncontrollable variable analysis is the nonconforming pattern.

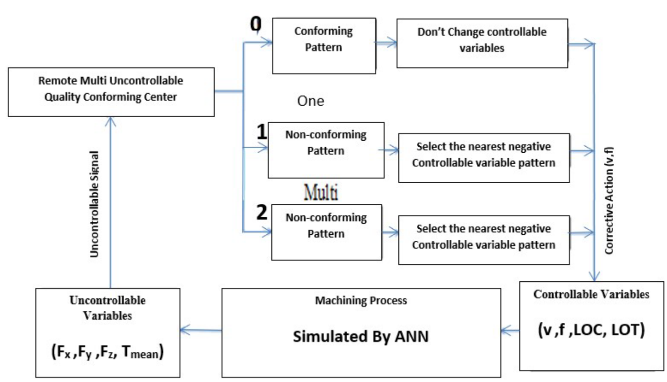


Figure 5. Decision-making procedure schematic.

In the online process, the overhang length and cutting distance cannot be modified, so in our simulation, we predefine and fixed the value of the two variables. For the overhang tool length, we selected a value less than 24mm. For the cutting distance, we used an interval from 24 to 96. In the following table, the new negative pattern of the controllable model is presented. In the online process, the overhang length and cutting distance cannot be modified so for our simulation, we predefined and fixed the value of the two variables. For the overhang tool length, we selected a value that is less than 24mm. For the cutting distance; we used an interval from 24 to 96. In the Table 5, the new negative pattern of the controllable model is presented.

Table 5. Generated Conforming Controllable parameters patterns (feed and speed).

No.	Speed	Feed	Weight
1	v>15000	303.232<f<361.335	0.142857
2	v<25000	409.907<f<471.146	0.142857
3	v<25000	475.746<f<695.518	0.0952381
4	v>25000	398.798<f<414.291	0.047619
5		291.927<f<296.346	0.047619
6	v>25000	455.148<f<519.921	0.238095
7		260<f<261.553	0.047619
8	v>38631.6		0.238095

8 Finding the corrective action

The following graph illustrates the conforming pattern's zoning. The corrective action to return the machining process from the non-controllable condition to the correct condition is illustrated in Table 6.

Table 6. Corrective actions for the controllable variable (feed and speed).

Zone	Speed	Feed	Corrective action V	Corrective action f
A	v<15000	f<300	15000	300
B	v<15000	300<f<700	15000	f
C	v<15000	f>700	15000	700
D	15000<v<38000	F<300	Nearest v	300
E	15000<v<25000	F>700	Nearest v	700
F	25000<v<38000	F>500	Nearest v	Nearest f

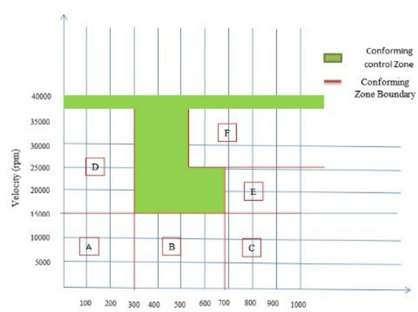


Figure 6. conforming control parameter pattern.

In zone (D, E, F) the controller measures the distance between the controllable parameter (v, f) and the nearest corrective pattern (v_c, fc) according to the following Equation 1.

$$d = \sqrt{(vc - v)^2 + (fc - f)^2} \quad (1)$$

For example in zone (D), if the operation parameter (v, f) is equal to (20000, 200) the corrective action would be (v, 300) or (38000, f) (Equations 2 to 5):

$$d1 = \sqrt{(20000 - 20000)^2 + (300 - 200)^2} \quad (2)$$

$$d1 = 100 \quad (3)$$

$$d2 = \sqrt{(38000 - 20000)^2 + (300 - 300)^2} \quad (4)$$

$$d2 = \frac{18000}{100} = 180 \quad (5)$$

In this case d1<d2 so the corrective action is (v, 300).

In addition, for example if the operation parameter (v, f) in zone (F) is equal to (27000, 600) the corrective action would be (v, 500) or (38000, f) or (25000, f) (Equations 6 to 11):

$$d1 = \sqrt{(27000 - 27000)^2 + (500 - 600)^2} \quad (6)$$

$$d1 = 100 \quad (7)$$

$$d2 = \sqrt{(38000 - 27000)^2 + (600 - 600)^2} \quad (8)$$

$$d2 = \frac{11000}{100} = 110 \quad (9)$$

$$d3 = \sqrt{(25000 - 27000)^2 + (600 - 600)^2} \quad (10)$$

$$d3 = \frac{2000}{100} = 20 \quad (11)$$

In this case d3<d2 and d3<d1 so the corrective action is (25000, 600).

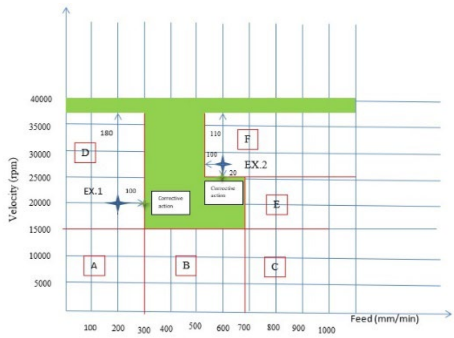
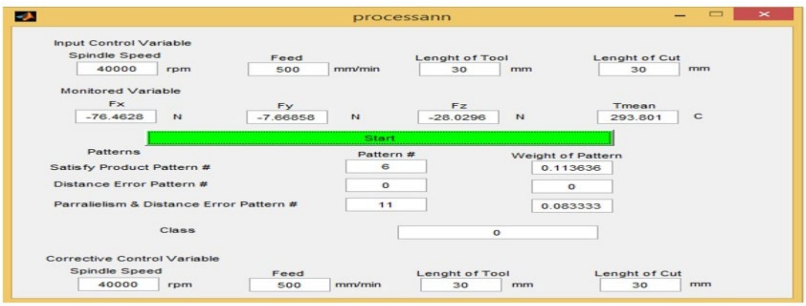
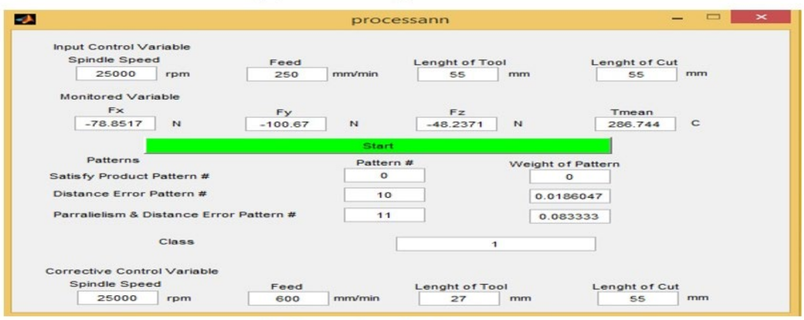


Figure 7. Corrective Action Examples.

Figure 7 illustrates some corrective action examples by computing the minimum distance between the operation condition and the nearest corrective action. In Figure 8 the GUI of CPCS is shown. It simulates the machine's behavior by generating a network between the input controllable variable and the output monitoring variable. Then, the simulator characterizes the quality specifications and indexes them according to the illustrated method in the previous section. After that, the nearest corrective action is computed. If a pattern is non-conforming, the simulator sends the workpieces that have faults to a sentencing station.



(a) Conforming Case



(b) Nonconforming Case

Figure 8. Simulation GUI of CPCS.

9 Sentencing process (step 2)

In this section, the product generated from step (1) is divided into two scenarios as shown in Figure 9. The first scenario is that the workpieces have a geometrical conforming condition. In this case, the workpieces proceed to the second step (sentencing process). The second scenario is that the product has a non-conforming condition. In this scenario, the work piece goes to the manual inspection station. This control system decreases the after machining cost and makes sure that any workpieces in the second step are accepted according to the geometrical requirement. This increases the efficiency of the production process. Figures 1 and 6 illustrate the two scenarios. In our study, the proposed system sends a warning signal with the status of the produced workpieces from the machining step. According to this signal, the production pieces transfer to the after machining process if it is a conforming condition. In the non-conforming case, the product goes to the inspection station to make sure that only the products that conform will transfer to the subsequent production step.

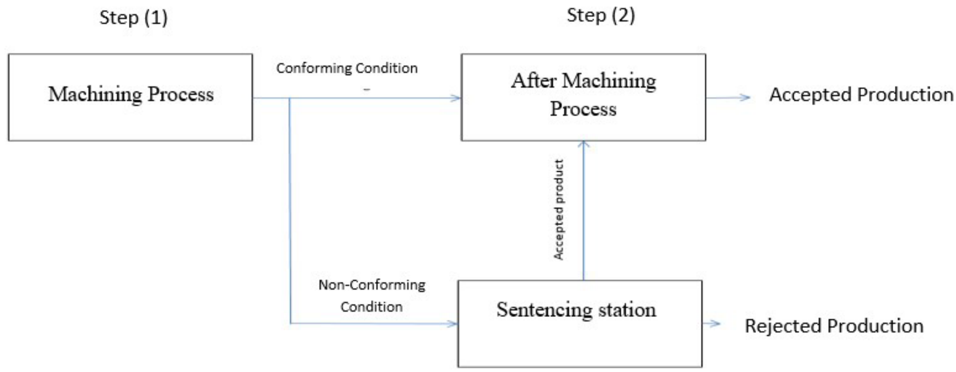


Figure 9. CPCS schematic.

10 Conclusions

In this paper, a novel system for monitoring and controlling a manufacturing process is developed. The proposed CPCS connects autonomously between multi manufacturing processes. The system is based on CC to connect the proposed system layers. The CC gives the ability to monitor, control, and analysis the behavior of the machining process continuously and via distance. The first step of this system consists of four layers, which include the uncontrolled parameter sensing layer, communication layer, analysis and decision making layer, and corrective action layer. The second step of the proposed system is divided into two scenarios conforming and non-conforming. In the case of conforming case, the system completes the manufacturing process and in the non-conforming case, the system feed the corrective action back to save the manufacturing process in the conforming zone. The proposed system is tested by using an experimental result of high-speed routing of CFRP as a study. The new system is developed as a step to convert a traditional factory into a smart factory. The new system is constructed based on a methodology to find interpretable rules that are governed by the generated patterns; these patterns describe the machining process of conforming products. We compare the proposed methodology and the most popular ML techniques ANN and SVM. The results are illustrated in Table 2. This comparison illustrates that the new approach improves the accuracy of the monitor and control models. By using the generated offline pattern from the new technique, shown in Table 3 we build CPCS. In step (1) the simulated machining process control system monitors the uncontrollable variable measured during the machining process and compares them with the offline pattern to classify the quality condition. The second step begins if the quality status is nonconforming by generating corrective control variables to control the machining process. The second step is illustrated in Figure 6. In summary, the implemented system helps to achieve the “Smart Factory” status and enhance the production process.

For future research, we are working on applying the proposed CPCS in a real factory conversation from the traditional production methods to the new smart factories. Also, we are working on improving the communication architecture to achieve minimum time delay between the sensing actions to the corrective actions. We are working on implementing a real-time quality monitoring alarm based on the cyber-physical system.

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