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SUPPLY CHAIN MANAGEMENT OF MANUFACTURING PROCESSES USING MACHINE LEARNING TECHNIQUE

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Rezumat. *Extinderea rețelei de procese de producție necesită algoritmi care să permită o mai bună planificare și optimizare a proceselor de producție. Prin urmare, în ultimii ani, evoluțiile din cadrul învățării automate (ML) și ale inteligenței artificiale (AI) au condus la o nouă terminologie, așa-numita Industrie 4.0. Cea mai rapidă creștere a Industriei 4.0 a fost întâlnită în producție, lanț de aprovizionare, servicii și produse. Învățarea automată este predispusă să permită dezvoltarea lanțurilor de aprovizionare și a proceselor de producție inteligente. Prezenta cercetare se referă la adecvarea și eficiența algoritmului de învățare automată pentru lanțul de aprovizionare îmbunătățit în procesele de producție. Rezultatele arată că algoritmul de învățare automată permite și îmbunătățește eficiența proceselor de fabricație prin gruparea mașinilor-unelte și creșterea numărului de componente fabricate în aceeași locație a sculei.*

Abstract. *The expansion of the manufacturing processes network requires algorithms that can enable better planning and optimization of the manufacturing processes. Therefore, in the recent years the developments within the machine-learning (ML) and artificial intelligence (AI) have led to a new terminology, the so-called Industry 4.0. The fastest growth of Industry 4.0 has been encountered in the manufacturing, supply chain, services and products. The machine learning is prone to enable the development of smart supply-chains and manufacturing processes. The present research concerns the suitability and efficiency of the machine learning algorithm for the enhanced supply chain in manufacturing processes. The results show that the machine learning algorithm enables and enhances the efficiency of the manufacturing processes by clustering the machine-tools and increasing the number of manufactured components at the same tool location.*

Keywords: supply chain management, manufacturing process, machine learning, probability, neural networks, Bayesian statistics

1. Introduction

Over the past decades the optimization of the manufacturing systems have focused on the small-scale systems which consisted of simple structures such as serial manufacturing line, single machine, or parallel machine performing the same manufacturing operations. The expansion of the manufacturing processes

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network requires algorithms that can enable better planning and optimization of the manufacturing processes. The large networks of manufacturing processes are usually prone to extensive and expensive preventive maintenance and quality control inspection times. These necessary activities may cause disruptions of the supply chain and thus, they can affect the overall manufacturing process.

Generally, the specialized mass production can increase the efficiency of the manufacturing processes but unfortunately it increases the complexity of manufacturing network. Therefore, dynamic reliability and quality models are needed to mitigate the complex interaction within the network of the manufacturing processes. A flexible manufacturing process allows diverse flow routes of the manufacturing process which can result in a highly complex and challenging to manage manufacturing network. Therefore, one of the main challenges is to determine the optimum flow path that would minimize the route from the raw material to the final product. Since, the flexible manufacturing process allows for various flow routes at different instants in time based on the machines availability within the network, the whole process may be regarded as a non-linear dynamical system.

The network of manufacturing processes exhibits behaviour similar to those similar to the dynamical systems. The intelligence manufacturing systems have undergone a rapidly development and evolution and therefore, their management and coordination require advanced control approaches. Due to their linear/non-linear behaviour, the methods and techniques encountered in the study of dynamical systems can significantly enable the optimum organization and function of various networks of manufacturing processes

A challenging and highly probable scenario of the interactions between the feedstock and machines available within the network is that of the product quality and machine reliability. Therefore, if a machine if supplied with low quality feedstock that machine highly prone to failure. Farther, the deteriorating machine will provide a low quality feedstock to the downstream machines within/outside the network of manufacturing process. If there are no protocols in place that would mitigate the deterioration of the machines and feedstock quality, these would result into a chain reaction affecting the downstream manufacturing processes and thus, compromising the quality of the final product.

There two main failure modes of machines within a manufacturing processes namely called the hard and soft failing modes. Therefore, the hard machine failing mode may occur at a certain instant during the manufacturing process without any priori warnings. This is the most undesirable machine failure mode since its failure causes large disruptions of the manufacturing processes and the feedstock to the downstream machines/processes. The soft failure mode is usually detected during the periodic checks of the machines and in general, it can be mitigate easier and faster and therefore, it has a lower impact on the network of the manufacturing processes.

2. Background

Modern manufacturing plans employ high performance data acquisition systems which allows to collect and transfer data from any manufacturing process within the plan and even remotely outside the plant/country. Usually, various manufacturing process variables are measured and data is stored. This process helps in identifying various machine/process failures and root-cause analysis (RCA). Usually, the collected data may concern the characteristics of the products, machines, production line, human resources that operate the production line, raw materials that are used for the manufacturing process, environmental conditions inside the plant, sensors attached to the machines, machine failure/maintenance, product quality, etc. with the development of these technologies the amount of collected data has grown continuously and handling these large amounts of data became a great challenge. Therefore, in the past two decades the notions of machine learning and data mining become popular.

Therefore, in the recent years the developments within the machine-learning (ML) and artificial intelligence (AI) have led to a new terminology, the so-called Industry 4.0. The fastest growth of Industry 4.0 has been encountered in the manufacturing, supply chain, services and products. The machine learning is prone to enable the development of smart supply-chains and manufacturing processes. Therefore, the AI and ML has seen an exponential growth since 2016. According to recent reports, it is expected that 70% of the businesses globally would employ the machine-learning by 2025, for the management of the supply chain and manufacturing processes. Studies showed that the machine-learning can enable the business in cost estimation, demand forecasting [], zero downtime, failure prediction risk management, sustainable supply chain, and supplier selection. However, the machine-learning techniques prove to have the most impact on the efficiency of supply chains and manufacturing processes.

The field of machine learning branches off in three main components namely, deep learning, ensemble learning and linkage learning. An important research component of machine learning concerns the classification which is the process by which an object is assigned to one of the predefined categories. Another branch of machine learning which concerns the manufacturing process is the clustering which main goal is to partition objects into groups, usually called clusters, based on their similarities.

3. Modeling

In this study the machine learning based on the Bayesian computations will be employed. First, a brief introduction to the Monte Carlo sampling is presented. Monte Carlo is a suitable approach for large number data. Statistical sampling is a convenient alternative to the numerical integration or analytical approximation to compute the outcome expectations that are not in a closed form. The law of large numbers ensures that the estimates are favorably good if the sample is large enough. Let's assume that f is a probability density function and suppose the quantity of interest is a finite expectation of the from

$$E_f h(X) = \int_x h(x) f(x) dx \tag{1}$$

If the independent and identically distributed observations $X_1, X_2, X_3, \ldots$ ....can be generated from the density f, then

$$\overline{h_m} = \frac{1}{m} \sum_{i=1}^{m} h(X_i) \tag{2}$$

converges in probability to $E_f h(X)$. This justifies the use of $\overline{h_m}$ as an approximation for $E_f h(X)$ for large m.

A drawback of the standard Monte Carlo sampling is that complete determination of the functional form of the posterior density is required for their implementation and thefore, the Markov Chain Monte Carlo (MCMC) are usually prefered to mitigate this issue.

A sequeence of random variavbles $\{X_n\}_{n\geq 0}$ is a markov chain if for any n, given the value, $\{X_n\}$, the past $\{X_j : j \leq n-1\}$ and the future $\{X_j : j \geq n+1\}$ are independent. in other words this can be written as

$$P(\{A \cap B | X_n\}) = P(A|X_n) P(B|X_n) \tag{3}$$

where A and B are defined in terms of the apst and the future, respcetively.

One of the most commons Markov Chain Monte Carlo algortithms is is the Metropolis-Hastings algorithm. It is worth mentioning here that the Metropolis-Hastings algorithm has a wide range of applications. Moreover, the Metropolis-Hastings algorithm plays a key role in the Bayesian analysis.

Let's assume S being a finite of countable set and let π be a probability distribution on S. We assume that π is the target distribution.

Let

$$Q \equiv \left((q_{ij}) \right) \tag{4}$$

Be a transition probabiltiy matrix such that for each i , it is computationally easy to generate a sample from the distribution

$$\left\{ q_{ij} : j \in S \right\} \tag{5}$$

Now, let's generate a Markov chain $\{X_n\}$ as follows.
If $X_n = i$, first sample from the distribution presented in equation 5, and denote that observation Y_n. Then, we chose Y_{n+1} from two values X_n and Y_n according to

$$P\left(X_{n+1} = Y_n \middle| Y_{n,} Y_n\right) = \rho\left(X_{n,} Y_n\right) \tag{6}$$

$$P\left(X_{n+1} = X_n \middle| X_{n,} Y_n\right) = 1 - \rho\left(X_{n,} Y_n\right) \tag{7}$$

where

$$\rho(i,j) = min\left\{ \frac{\pi_j\, q_{ji}}{\pi_i\, q_{ij}}, 1 \right\} \tag{8}$$

For all (i,j) such that $\pi_i q_{ij} > 0$.

Itis worth to mention here that $\{X_n\}$ is a Markov chain with transition probability matrix $P = \left((p_{ij}) \right)$ which is given by the equation (9)

$$p_{ij} = \begin{cases} q_{ij}\rho_{ij} \\ 1 - \sum_{k \neq i} p_{ik} \end{cases} \tag{9}$$

$$\pi_i p_{ij} = \pi_j p_{ji} \text{ for all i,j} \tag{10}$$

This implies that for any i

$$\sum_i \pi_i p_{ij} = \pi_j \sum_i p_{ji} = \pi_j \tag{11}$$

The acceptance probabilty is given by equation (12)

$$\rho(x,y) = min\left\{\frac{p(y)q(y,x)}{p(x)q(x,y)}, 1\right\} \tag{12}$$

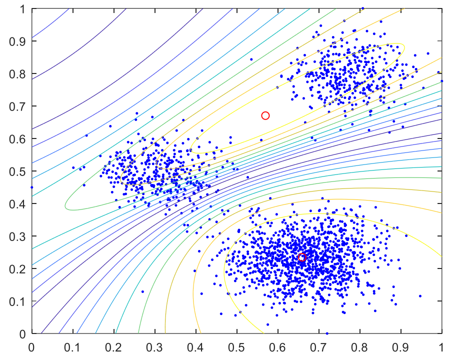
for all (x,y) such that p(x)q(x,y)>0.

4. Results and discussion

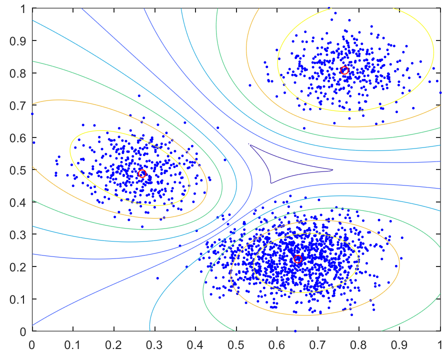
The current research concerns the feasibility of using machine learning in the manufacturing processes to classify and cluster various manufacturing tasks. It is worth to mention here that the clustering machine learning algorithms are a component of the unsupervised learning algorithms. The clustering machine learning algorithm can cluster various manufacturing processes based on the similarity of the manufacturing process and it is able to identify outliers. Generally, the clustering algorithms divides instances to different groups with respect to their similarities. Usually, clustering is performed based on the similarities or distance measures which determine the degree of how similar or how different the data are from each other. The clustering algorithm can be classified as: (i) portioning clustering, (ii) hierarchical clustering and (iii) density-based clustering. Partitioning clustering decomposes the data into k-clusters such that each cluster are closely related to each other. Hieratical clustering builds a tree of clusters by either repeatedly merging smaller clusters into larger ones, or by splitting larger cluster into smaller one.

Density based clustering targets at finding high-density cluster separated by sparse areas that clusters differ in terms of their size and shape. In the current research the density based clustering is employed to detect the clustering of the machine-tools for a better planning and layout of the manufacturing process based on the availability of the machine-tools. The machine learning clustering algorithm would enable an effective and efficient supply chain management.

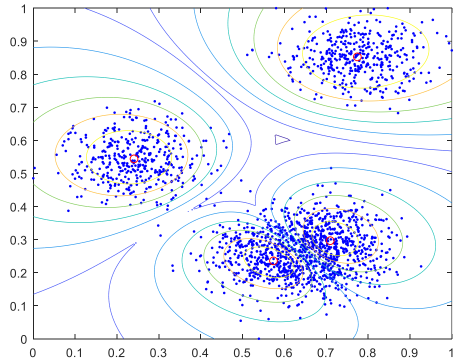
Figure 1 presents the results obtained from the machine learning clustering algorithm. The results shows that the machine learning algorithm can cluster the machine-tools based on their availability. Moreover, the machine learning algorithm clusters the manufacturing processes based on their similarity and logical flux of production with the goal of minimizing the dead times. The machine learning algorithm also clusters the manufacturing processes based on the path distance among the manufacturing processes such that the time from the raw material to the final product is minimized. The machine learning clustering algorithm enables and ensures the optimum number of the manufactured components processed at the same tool position. Therefore, by employing the machine learning algorithm the overall manufacturing process is highly optimized. The clustering of manufacturing processes, using the machine learning algorithm, would enable the project managers, and any personal responsible with the manufacturing process, to better plan the manufacturing flow process.



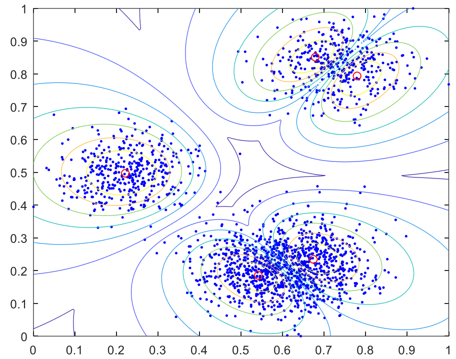
a. Number of clusters = 2



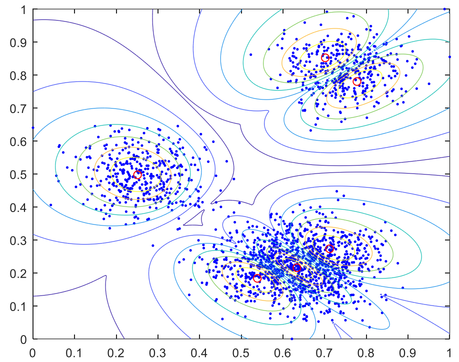
b. Number of clusters = 3



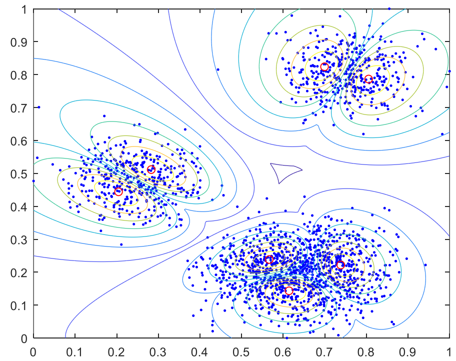
c. Number of clusters = 4



d. Number of clusters = 5

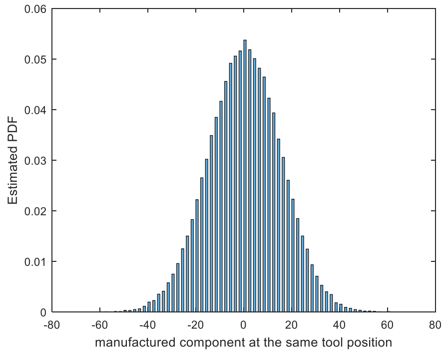


e. Number of clusters = 6

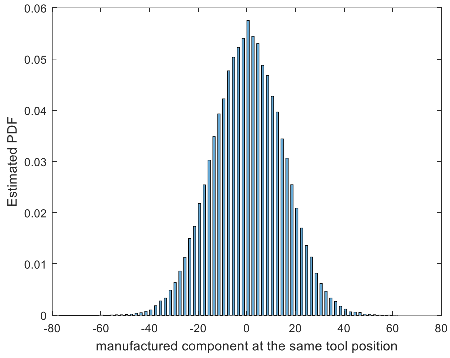


f. Number of clusters = 7

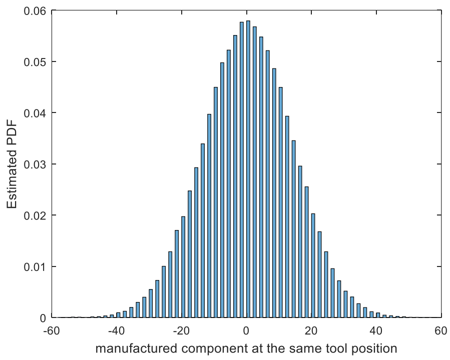
Fig. 1. Clustering of manufactured component at the same tool position



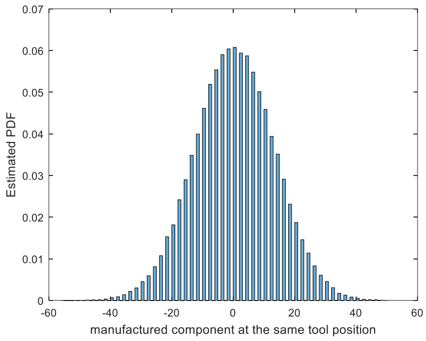
a. Number of clusters = 2



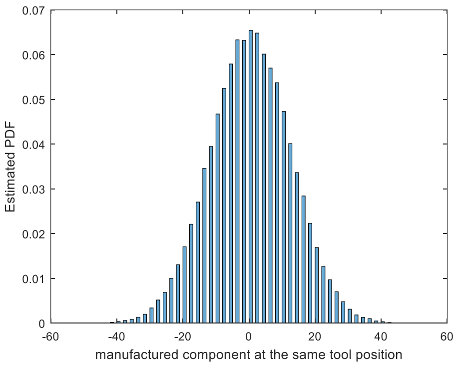
b. Number of clusters = 3



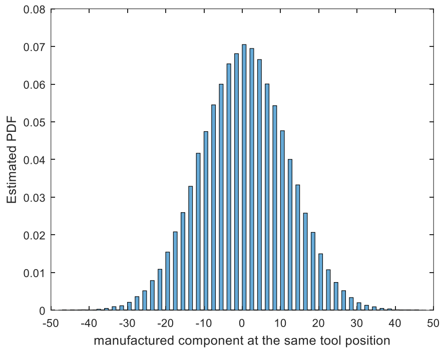
c. Number of clusters = 4



d. Number of clusters = 5



e. Number of clusters = 6



f. Number of clusters = 7

Fig. 2. Probability of manufactured component at the same tool position

Moreover, optimizing the number of the manufactured components at the same tool position enables the release of some machines tools to undergo a dynamic revision maintenance. A better insight into the impact of clustering of manufacturing processes on the planning of the manufacturing flux and use of the machine tools can be obtained by the statistical analysis shown in Figure 2.

Therefore, Figure 2 present the probability density function for the manufacturing process optimized using the clustering machine learning algorithm. The analysis of the data presented in Figure 2 shows that the clustering of the manufacturing processes increases the probability of the number of the manufactured components at the same tool position. The results suggest that an optimum and effective clustering of the machine-tools can enhance the productivity by manufacturing more components using the same machine tool and thus, it eliminates the dead times associated with the transition of the components from one machine-tool to another. The results in Figure 2 shows that the clustering of the manufacturing process increases the probability of the number of manufactured components at the same tool location.

Conclusions

A machine learning clustering algorithm is developed and proposed for the optimization of complex manufacturing processes with the final goal of enabling an efficient supply chain risk management and an efficient and optimum manufacturing process. The present study shows that the clustering of the manufacturing process eliminates the dead time and thus, it enables an efficient supply chain with minimum disruption while the process productivity is maximized. The results of the current research shows that the clustering of the manufacturing process increases the probability of the number of manufactured components at the same tool location.

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