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Research Article

Behaviour-based Manufacturing Control with Soft Computing Techniques

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Abstract

Soft Computing methods have been widely used in recent years to address the challenges posed by disturbances handling and uncertainty management in Manufacturing Execution Systems (MES). The focus of this research paper is on the application of Soft Computing methods for classification problems in Behaviour Based Control.

The paper proposes the use of classification techniques to determine the behavior of a production system. This is an important task as it enables the detection of anomalous behavior and allows for the implementation of appropriate corrective measures. The proposed classification method is based on the use of Neural Networks and Fuzzy logic. Neural Networks are a powerful tool for classification tasks due to their ability to learn from data and make predictions based on patterns. The proposed method uses a feedforward neural network with a single hidden layer to classify the behavior of the production system. The inputs to the network are features extracted from the production system, while the output is the classification result. Fuzzy logic is also used in the proposed classification method to handle uncertainty in the input data. In conclusion, this research paper presents a novel approach to classification problems in Behaviour Based Control using Soft Computing methods. The proposed method shows promising results in handling disturbances and uncertainty in manufacturing systems. Further research in this area could lead to the development of more advanced Soft Computing methods for manufacturing systems, enabling more efficient and effective control and management of production processes

Keywords: Soft Computing, Manufacturing Execution Systems, Behaviour Based Control.

Yumuşak Hesaplama Teknikleri ile Davranış Tabanlı Üretim Kontrolü

Öz

Esnek Hesaplama yöntemleri, Üretim Yürütme Sistemlerinde (MES) bozulmaların ele alınması ve belirsizlik yönetiminin ortaya koyduğu zorlukları ele almak için son yıllarda yaygın olarak kullanılmaktadır. Bu araştırma makalesinin odak noktası, Davranış Tabanlı Kontroldeki sınıflandırma problemlerine yönelik Esnek Hesaplama yöntemlerinin uygulanmasıdır.

Makale, bir üretim sisteminin davranışını belirlemek için sınıflandırma tekniklerinin kullanılmasını önermektedir. Bu, anormal davranışın tespit edilmesini sağladığı ve uygun düzeltici önlemlerin uygulanmasına izin verdiği için önemli bir görevdir. Önerilen sınıflandırma yöntemi, Yapay Sinir Ağları ve Bulanık mantık kullanımına dayanmaktadır. Sinir Ağları, verilerden öğrenme ve kalıplara dayalı tahminler yapma yetenekleri nedeniyle sınıflandırma görevleri için güçlü bir araçtır.

Anahtar Kelimeler: Soft Computing, Manufacturing Execution Systems, Behaviour Based Control.

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1. Introduction

This paper explores potential strategies for managing uncertainty in production processes. The practical model for addressing multi-task, multi-resource problems is nonlinear, as processes are defined by both internal relationships and external constraints. Due to the limited technological intensity of tasks, production bottlenecks, unstable states, and unwanted delays can occur, which may adversely affect production processes.

Process indicators (also known as key performance indicators [1]) are used to evaluate production processes, with the primary objective of fulfilling production orders while adhering to specified constraints [9]. However, this objective can be met at different costs and within varying timeframes. The performance indicators are dependent on predictive planning, scheduling, and allocations. When operating at the margin of overload, systems are prone to bottlenecks and critical processes, which may cause chaotic behavior. Small changes in scheduling can lead to dramatic changes in performance indicators, as stochastic events increase the likelihood of deviations from planned states. Unfortunately, disturbances are often unavoidable in these situations. The most common sources of disturbances of a production system are as follows:

- Tool breakage, interruption of operations.
- Machine breakdown, outage of resources.
- High rejects rate.
- Unexpectedly low production intensity.
- Human errors.
- Material outage, supply chain delays.
- Long set-up times.
- Outage of labour resources.
- High rate of demands.
- Change in the priority of the jobs.
- Appearance of urgent jobs.

1.1. Handling Uncertaınıty in MES

The methods of uncertainty handling at the MES level includes:

1. Develop performance indicators from the local data which allows the global state of whole system to be determined.
2. Identify the most important situations based on the global indicators.
3. Classify the situations into appropriate number of classes to allow interactions to be done in real time.
4. Assess the state of the production and make decision on the behaviour of production control. This defines a Behaviour-Based Control whose interactions are assigned to behaviour classes.
5. Select the appropriate actions based on the selected behaviour. The possible actions and their parameters should be modelled beforehand. The inter-actions should direct the production processes towards a stable, planned state.
6. The interactions affect the whole schedule.
7. Following the interactions new situations arise.

Behaviour-Based Control relies heavily on the possible and permitted interactions between various components. These interactions occur at different hierarchical levels, with corrections initiated in an upward or downward direction. Higher-level corrections may supersede decisions made by lower hierarchical levels, and decisions made at lower levels may even be prohibited. In hierarchical Behaviour-Based Control, new constraints are disseminated from the upper level to the lower level, while the identification of anomalies spreads in a bottom-up direction.

2. Behaviour-Based Control

Behaviour-Based Control (BBC) is an approach to control systems that emphasizes the importance of behavior as the fundamental unit of control. Rather than focusing on specific actions, BBC focuses on defining and regulating the behaviors of individual system components to achieve desired outcomes. This is accomplished by designing the system to exhibit a set of desired behaviors in response to various stimuli or inputs. The interactions between these behaviors, and between the system and its environment, then determine the overall behavior of the system. BBC is often used in complex systems with multiple interacting components, such as robotics or manufacturing, where it can be difficult to explicitly program all possible scenarios. By emphasizing behavior over specific actions, BBC provides a more flexible and adaptable approach to control, enabling systems to respond more effectively to changing conditions and unforeseen events.

2.1. A possible classification of behaviours

Experiments show that a few numbers of classes are favoured in practical applications. For production processes the following general global states are suggested:

- Normal,
- Deviated,
- Critical,
- Dangerous.

Normal state requires no interaction. In deviated situation the process does not go as planned: readiness for delivery is decreasing, jobs late, waste rate increasing, etc. The situation is critical if the original schedule becomes unmaintainable. Usually rescheduling is required. The situation is dangerous if the master production plan becomes unfeasible.

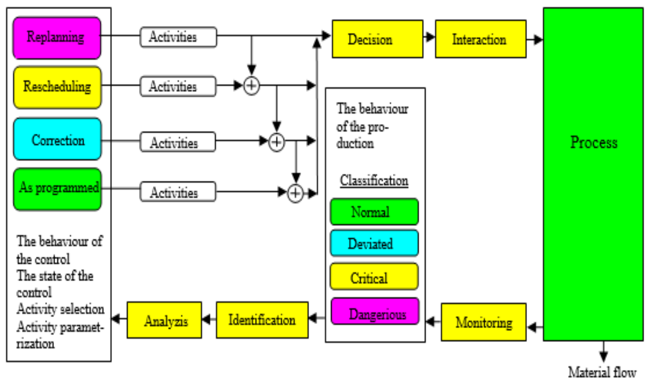

Figure 1. Behaviour based approach in manufacturing control

3. Softcomputing Methods for Classification

3.1. Methods Used

There are several ways to classify the system state into the aforementioned categories. Soft computing methods are widely accepted and used by researchers. In the scope of this research work the following methods were investigated:

- Backpropagation Neural Network,
- Radial Basis Neural Network,
- Probabilistic Neural Network,
- Fuzzy Logic.

A pilot application has been created for each of the methods to evaluate them. The classification problem was inspired by a case study explained in [8].

The Backpropagation Neural Network (BPNN) employs a hard-limit transfer function that is well-suited for classification problems. The decision boundary line at W.p + b = 0 divides the input space into two classification regions, where W represents the weight vector, p represents the input value, and b represents the bias. This study utilized a network with one hidden layer. Since there were four distinct statuses, a binary code was assigned to each status, necessitating two bits at the output. To facilitate learning, the perceptron learning rule algorithm was employed

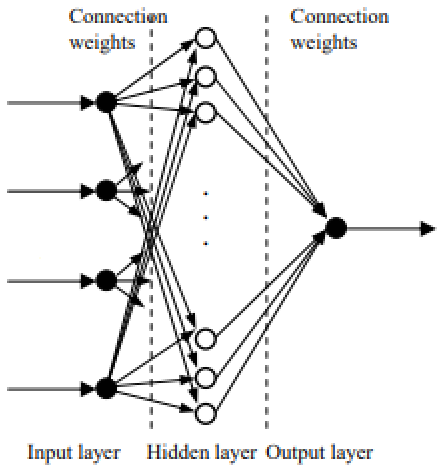

Figure 2. Neural network with single hidden layer

Radial Basis Function Neural Network (RBF) consist of two layers: a hidden radial basis layer and an output linear layer. The first layer determines the distance of an input vector v. If the vector is close to the weight vector of the neuron then the output is close to 1. If the distance between the vectors is greater then the output is close to 0. The higher the output of the neurons of the first layer are the more importance they have in the second layer.

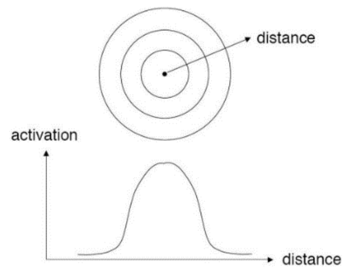

Figure 3. RBN activation **Hata! Başvuru kaynağı bulunamadı.**

Probabilistic networks perform classification where the target variable is categorical value

PNN networks have advantages and disadvantages compared to Multilayer Perceptron networks [3]:

Properties of Probabilistic Neural Networks (PNN):

- PNN is a type of feedforward neural network that performs classification tasks for categorical target variables.
- PNN can be much faster to train than other neural network models like multilayer perceptron (MLP).
- PNN often generates more accurate predictions than MLP networks.
- PNN is relatively insensitive to outliers.
- PNN networks can generate accurate predicted target probability scores.
- PNN networks approach Bayes optimal classification.
- PNN networks require more memory space to store the model.
- PNN networks can be slower than MLP networks when classifying new cases.

The Fuzzy Logic model was configured as follows: The original project involved a large number of input variables, which resulted in performance issues. To address this problem, a two-level hierarchical processing approach was introduced. In the first step, each production order was classified individually, and the statuses were evaluated. Then, the classification of the entire system was performed. The number of rules greatly impacts the computing time, so it was necessary to minimize the number of rules while still classifying the system without ambiguity. During the fuzzy classification process, each rule was evaluated sequentially using the appropriate variables. A rule consisted of NOT, AND, and OR connections, and the variables were inserted into the rule to produce a numeric value between 0 and 1. This value represented the degree of truth or the extent to which a proposition was true.

Some sample rules used in the first pass of fuzzy processing:

1. IF tardiness is small AND machine utilisation rate is big THEN status is normal.
2. IF tardiness is considerable AND machine utilisation rate is big THEN status is deviant.
3. IF quantity is many AND priority is high AND tardiness is considerable THEN category is critical.
4. IF tardiness is considerable AND machine utilisation rate is big THEN status is dangerous.

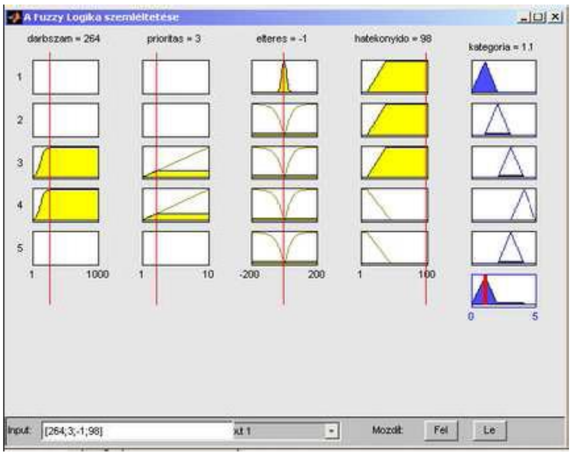

Figure 4. Screenshot of fuzzy classification

In the second processing phase the overall tardiness time was also calculated. The rules used in this phase were as follows:

1. IF status of the ith Product Order POi is normal AND tardiness is negligible THEN status is normal.

2. IF status of POi is deviant AND tardiness is small THEN status is deviant.

3. IF status of POi is critical AND tardiness is observable THEN status is critical.

4. IF status of POi is dangerous AND tardiness is observable THEN status is dangerous

Two kinds of evaluation were applied: the method was tested against the data set used at the learning phase, and then the method was tested against a new data set. (Obviously, fuzzy processing had no learning data set, so that test case was skipped).

BPNN succeeded the learning phase but after certain time it showed no more progress in learning, there was a remaining error. The learning time was considerable.

RBF achieved a very small remaining error and produced better results than BPNN. The learning time was smaller. By increasing the size of the training set the network produced more reliable output.

PNN was characterised by the smaller learning time among the NNs used. By increasing the size of the training set the network produced more reliable output. However, RBF was more reliable.

Fuzzy system was difficult to create good rules. After some experiments the rules were fine tuned. Its performance was behind the NNs. Very likely some more fine tuning is still required.

Some performance data can be found in Table 1.

4. Conclusions and future work

As you can see in Table 1, PNN performed very well on small inputs. However, as the input size was bigger the number of correct classifications decreased. In medium sized problems RBF provided the best result. PNN outperformed other methods in large scale problems. In order to integrate to a MES environment an upcoming task is to execute an Action Generator that selects the suitable actions based on the classification results. This can be achieved through a rule-based system, an expert system, or a neural network. Additionally, the Cockpit Task Management system can also be employed where operators are aided by the classification and other pertinent data.

Table 1. Performance data of NN classifications

Type	Input number	Correct classifications	Goodness (%)
BPNN	100	53	53
RBF	100	23	23
PNN	100	100	100
BPNN	100	51	51
RBF	100	89	89
PNN	400	299	74.7
BPNN	100	52	52
RBF	400	380	95
PNN	800	609	76.1
Fuzzy	100	70	70
Fuzzy	800	544	68

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