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A CONCEPTUAL MODEL FOR COGNITIVE MANAGEMENT OF MANUFACTURING SYSTEMS TO INCREASE COMPETITIVENESS

Assoc. prof. Luiza DASCHIEVICI
Assoc. prof. Daniela GHELASE
"Dunarea de Jos" University of Galati,
Galati, Romania

ABSTRACT

The competitiveness of manufacturing systems is increasingly influenced by their ability to dynamically adapt to demand variations, economic constraints, and operational conditions. Classical manufacturing management approaches, based on static strategies or local optimizations, are often insufficient to meet these requirements in a dynamic industrial environment. In this context, the paper proposes a conceptual framework for cognitive management of manufacturing systems, based on a cyclic cognitive loop, which integrates continuous perception of the system state, performance analysis, decision mechanisms, and adaptive feedback. The cognitive loop is formulated by correlating the principles of cognitive engineering with machine learning techniques, with the explicit objective of maintaining and improving the competitiveness of the manufacturing system. The novelty of the paper consists in the structuring of a cognitive loop dedicated to competitive management, in which decisions to adapt manufacturing processes are guided by a quantifiable economic indicator, expressed by the unit cost of production. Unlike existing approaches oriented mainly towards digitalization and connectivity, the proposed framework emphasizes the cognitive autonomy of the manufacturing system and the direct link between cognitive mechanisms and economic performance.

The paper has a conceptual and methodological character, providing a theoretical basis for further developments regarding mathematical modeling, experimental validation, and industrial implementation of the proposed cognitive loop.

KEYWORDS: cognitive engineering, cognitive management, manufacturing systems, competitiveness, cognitive loop, machine learning.

1. INTRODUCTION

Increasing the competitiveness of manufacturing systems is one of the major challenges of the contemporary industrial environment, characterized by rapid variations in demand, short product life cycles, and constant pressures on production costs.

In the specialized literature, competitiveness is frequently associated with the ability of manufacturing systems to provide products at low costs, with high flexibility and adequate levels of quality [1]; [2]. In this context, manufacturing systems are forced to continuously adapt their structure, operating parameters, and management strategies to effectively respond to these dynamic demands.

Traditional manufacturing management approaches are generally based on deterministic models, static scheduling, or local optimizations defined in advance of the production process. While these methods can be effective in stable environments, they become limiting in situations characterized by uncertainty, variability, and frequent changes in demand. Such limitations are highlighted in numerous studies in the field of operations management, which emphasize the difficulty of maintaining overall performance in the absence of adaptive mechanisms [2].

An important research direction in recent decades is represented by the concepts of Industry 4.0 and smart manufacturing, which promote digitalization, connectivity, and integration of cyber-physical systems in manufacturing.

Architectures based on cyber-physical systems allow the collection and processing of large volumes of data from production processes, providing the premises for improving operational performance [3], [4]. However, numerous authors emphasize that digitalization and connectivity, in the absence of advanced decision-making mechanisms, do not automatically lead to truly autonomous or adaptive manufacturing systems [5].

In this context, cognitive engineering provides an appropriate theoretical framework for addressing the problems of managing complex systems. Originating from cognitive science and the study of socio-technical systems, cognitive engineering analyzes the processes of perception, decision, and action in dynamic systems, emphasizing the interaction between humans, technology, and the environment. These principles have been successfully used in areas such as aviation, energy or autonomous systems, but their systematic application in manufacturing management is still under development.

A key component of cognitive systems is situation awareness, defined as the ability to perceive relevant elements of the environment, interpret them, and anticipate their evolution [6]. Translated into manufacturing, this capability involves continuous monitoring of the system's state, performance evaluation, and real-time adaptation of management decisions.

The integration of machine learning and artificial intelligence techniques provides the necessary support for the implementation of these cognitive mechanisms.

Recent studies in the field of cognitive manufacturing highlight the potential of machine learning in identifying complex relationships between technological parameters, process performance, and economic outcomes. However, the specialized literature indicates the lack of clear conceptual frameworks that integrate these techniques into a coherent model of cognitive management explicitly oriented towards competitiveness.

Based on these considerations, this paper proposes a conceptual model of cognitive management of manufacturing systems for increasing competitiveness. These are based on the formulation of a cognitive loop that integrates the perception of the system state, performance analysis, decision mechanisms, and adaptive feedback.

Competitiveness is approached from an economic perspective by using a quantifiable indicator, which allows the direct correlation of cognitive decisions with the overall performance of the manufacturing system. The paper has a conceptual and methodological character, having as its main objective the formulation and theoretical substantiation of the proposed cognitive loop. Experimental validation and industrial implementation of the model constitute future research directions, which will be addressed in subsequent papers.

2. THEORETICAL FOUNDATIONS OF COGNITIVE MANAGEMENT IN MANUFACTURING SYSTEMS

2.1 COGNITIVE ENGINEERING AND MANAGEMENT OF COMPLEX SYSTEMS

Cognitive engineering is an interdisciplinary field located at the intersection of cognitive sciences, engineering, and the study of socio-technical systems, with the main objective of modeling and supporting the processes of perception, decision, and action in complex and dynamic systems.

Unlike classical engineering approaches, which predominantly treat systems from a structural or functional perspective, cognitive engineering emphasizes information processing and decision-making mechanisms that govern the behavior of the system [7].

One of the fundamental concepts of cognitive engineering is the Skills–Rules–Knowledge (SRK) model, which describes different levels of cognitive control depending on the complexity of the situation and the system's degree of familiarity. This model highlights the fact that, in dynamic and unpredictable situations, decisions can no longer be solely based on predefined rules but require higher-level cognitive processes based on interpretation and learning [7]. This observation is particularly relevant for modern manufacturing systems, characterized by frequent demand variations and operational disruptions.

Extending these ideas, the concept of Joint Cognitive Systems emphasizes that the overall performance of a system results from the interaction between human and technological components, with intelligence emerging from the way information is perceived, interpreted, and used across the system [8]. Applying this concept to manufacturing leads to a reconsideration of the role of automated systems, which are no longer solely viewed as executors of predetermined commands but as active participants in the decision-making process.

A central element of cognitive engineering is situation awareness, defined as the ability of a system to perceive relevant elements of the environment, understand their meaning, and anticipate their evolution [9].

In the case of manufacturing systems, this capability involves continuous monitoring of equipment status, production flows, and performance indicators, constituting the premise for making effective adaptive decisions.

The principles of cognitive engineering were later used in the development of autonomous and self-adaptive systems, culminating in the formulation of decision-making loops of the perception–decision–action type. A representative example is the autonomic computing paradigm, which introduces the MAPE-K (Monitor–Analyze–Plan–Execute–Knowledge) loop as a generic mechanism for adapting complex systems [10]. This loop provides a general conceptual framework for implementing autonomy, but requires customization depending on the application domain.

In the context of manufacturing systems, the complexity of technological processes, the interdependence of resources, and economic objectives require the adaptation of these general concepts to specific requirements.

Cognitive management of manufacturing involves not only reacting to current events, but also learning from previous experience, anticipating future developments, and correlating operational decisions with the competitiveness objectives of the system. Thus, cognitive engineering provides the theoretical foundation necessary for the development of management models capable of overcoming the limitations of traditional approaches.

Therefore, the application of cognitive engineering principles to the management of manufacturing systems represents an essential step towards the development of adaptive, autonomous, and economically performance-oriented systems.

These theoretical considerations constitute the basis for the introduction, in the following chapters, of the concept of a cognitive loop dedicated to the competitive management of manufacturing systems.

2.2 MANUFACTURING SYSTEMS MANAGEMENT AND THE ROLE OF MACHINE LEARNING

Manufacturing systems management has evolved significantly from classical approaches based on deterministic planning and hierarchical control to distributed and adaptive models. Traditionally, manufacturing systems have been managed through offline planning strategies, followed by rigid execution of previously established plans. These approaches assume a high degree of stability of the production environment and low variability of demand, conditions that are increasingly rarely met in the current industrial context [2].

The literature highlights that the performance of manufacturing systems is strongly influenced by their ability to react quickly to disturbances, such as demand variations, resource unavailability, or changes in product specifications [11]. In the absence of adaptive mechanisms, these disturbances lead to increased production costs, decreased productivity, and diminished overall competitiveness of the system.

In this context, the concepts of flexible manufacturing systems and reconfigurable manufacturing systems have been introduced to increase the structural adaptability of manufacturing. However, structural flexibility is not enough in the absence of management mechanisms capable of efficiently exploiting this flexibility through informed and adaptive decisions [11]. Thus, the management problem can no longer be treated exclusively at the technological level, but requires the integration of advanced analysis and decision-making mechanisms.

The development of digital technologies and cyber-physical systems has allowed the real-time collection of large volumes of data from manufacturing processes. Industry 4.0 architectures facilitate the monitoring of equipment status, production flows, and performance indicators, creating the prerequisites for process optimization [3]. However, numerous studies emphasize that the mere availability of data does not automatically lead to improved performance in the absence of effective interpretation and decision-making mechanisms [4].

In this context, machine learning plays an essential role in transforming raw data into useful knowledge for managing manufacturing systems. Machine learning techniques allow the identification of nonlinear relationships between process parameters, operating conditions, and the results obtained, relationships that are difficult to model using classical analytical methods. Their applications include process performance prediction, anomaly detection, optimization of technological parameters, and decision support [4].

In recent literature, these directions are brought together under the concept of cognitive manufacturing, which proposes manufacturing systems capable of learning from data, adapting to changing conditions, and making autonomous decisions in order to improve overall performance. However, most works focus on specific applications of machine learning, without integrating these techniques into a unitary framework of cognitive management explicitly oriented towards economic competitiveness.

Furthermore, decisions supported by machine learning are often evaluated solely from a technological perspective, such as reducing process times or increasing resource utilization, without being directly correlated with relevant economic indicators. This approach limits the real impact of intelligent techniques on the competitiveness of manufacturing systems.

Therefore, the need for a cognitive management model that integrates machine learning techniques into a coherent decision-making structure, capable of correlating the adaptation of manufacturing processes with the economic objectives of the system, is outlined. These considerations constitute the premise for introducing, in the next chapter, a conceptual model based on a cognitive loop, dedicated to the competitive management of manufacturing systems.

3. CONCEPTUAL MODEL OF COGNITIVE MANAGEMENT OF MANUFACTURING SYSTEMS

3.1 ASSUMPTIONS AND OBJECTIVES OF THE PROPOSED MODEL

The conceptual model of cognitive management proposed in this paper has as its main objective the increase of the competitiveness of manufacturing systems by continuously adapting the management decisions to the dynamics of the operational environment. In this sense, the model is formulated at a level of abstraction that allows its generalization to different types of discrete manufacturing systems, without being limited to a specific technological configuration.

The development of the model is based on a set of fundamental assumptions necessary to delimit the scope of applicability and to ensure conceptual coherence.

Based on the theoretical foundations presented in Section 2 and the current trends in cognitive manufacturing systems, the following working hypotheses are formulated for the proposed conceptual model.

The first assumption considers the manufacturing system as a complex and dynamic system, characterized by interdependencies between resources, processes, and production flows. The overall behavior of the system cannot be deduced exclusively from the analysis of individual components, but results from their interaction, under conditions of variability of demand and operating environment [11], [9].

The second hypothesis assumes the existence of a data acquisition mechanism that allows continuous monitoring of the state of the manufacturing system. This includes information on the state of equipment, technological process parameters, production times, and economic performance indicators. The hypothesis is compatible with modern Industry 4.0 architectures, based on cyber-physical systems and digital infrastructures.

The third hypothesis concerns the possibility of using machine learning techniques to analyze collected data and support the decision-making process. It is believed that these techniques can identify relevant relationships between process parameters and system performance, facilitating the adaptation of management decisions in real or near real-time [4]. The model does not impose a specific type of machine learning algorithm, maintaining a general and extensible character.

The fourth hypothesis assumes the existence of a quantifiable competitiveness indicator, used as the main criterion for evaluating the overall performance of the manufacturing system. Within this model, competitiveness is approached from an economic perspective, through indicators such as unit production cost, which allow for the direct correlation of management decisions with the strategic objectives of the system [2].

Based on these assumptions, the objectives of the conceptual model can be formulated as follows. The first objective is to define a cognitive management structure that integrates system state perception, performance analysis, and decision-making in a coherent framework. The second objective aims to achieve a continuous adaptation mechanism, through which the operating parameters of the manufacturing system are adjusted according to the evolution of demand and historical performance.

A third objective is to explicitly correlate the decision-making process with the competitiveness indicator, so that cognitive decisions are oriented not only towards local optimization of processes, but towards improving the overall performance of the system. In this sense, the proposed model aims to overcome traditional management approaches, which treat technological and economic performance as separate objectives.

Finally, the conceptual model is designed as a theoretical basis for further developments, including the mathematical formulation of the decision-making process, experimental validation, and industrial implementation. These steps are considered future research directions, and the present work focuses on clarifying the cognitive structure and fundamental driving mechanisms.

3.2 COGNITIVE MANAGEMENT LOOP FOR INCREASING THE COMPETITIVENESS OF MANUFACTURING SYSTEMS

The central element of the proposed conceptual model is the cognitive leadership loop, which allows manufacturing systems to continuously adapt to changes in operational conditions and market requirements, with the explicit objective of increasing competitiveness.

The structure of the cognitive management loop is illustrated in Figure 1, which presents a cyclical framework that integrates perception, competitiveness assessment, decision-making, and learning in the management of manufacturing systems.

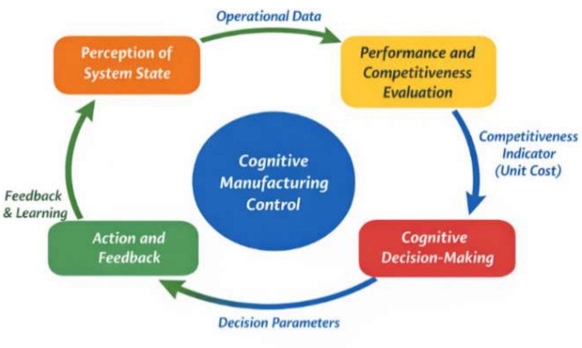

Fig. 1 Cognitive control loop for enhancing the competitiveness of manufacturing systems

Figure 1 highlights that management oriented towards competitiveness is not a linear process, but an iterative and adaptive one, in which the behavior of the system evolves over time based on feedback and accumulated knowledge.

The cognitive management loop consists of four interconnected stages. The loop begins with the System State Perception stage, in which operational, technological, and economic data are continuously obtained from the manufacturing system. This data may include equipment status, processing times, failure rates, energy consumption, and costs associated with technological operations. This stage provides situational awareness by building an abstract representation of the current state of the system, including machine performance, production rates, resource utilization, and cost indicators.

In the proposed model, perception is not limited to simple data acquisition, but involves a cognitive representation of the system state, in the form of a state vector relevant to the decision-making process. This representation allows for the reduction of information complexity and the provision of synthetic information, oriented towards performance and competitiveness, to the decision-making level.

In the second stage, Performance and Competitiveness Evaluation, the perceived state of the system is analyzed in relation to pre-established competitiveness criteria. In the proposed model, competitiveness is mainly associated with the unit cost of the product, which constitutes an overall indicator that reflects both the efficiency of the manufacturing process and economic performance. This stage allows the identification of deviations from the target levels of competitiveness.

Competitiveness assessment involves correlating technological parameters with economic outcomes, allowing the identification of situations in which system performance deviates from established strategic objectives. This stage plays a critical role in the cognitive loop, as it provides the main criterion on the basis of which adaptation decisions are generated.

The third stage, Cognitive Decision Making, represents the adaptive core of the loop. Based on learning mechanisms and accumulated operational experience, the system determines appropriate management actions, such as adjusting process parameters, production planning strategies, or resource allocation policies. Decisions are generated dynamically, without relying solely on static rules, allowing the system to respond effectively to variability and uncertainty.

The decision-making process represents the actual cognitive component of the loop. Within the conceptual model, it is supported by machine learning techniques, capable of analyzing historical and current data of the system and identifying relevant relationships between process parameters and the level of competitiveness [8], [9].

The cognitive decision is not formulated as a fixed rule, but as a result of the learning process, which allows for continuous adjustment of management strategies. This approach differentiates the proposed model from classical management systems, based on static rules or local optimizations, and gives the system the ability to adapt under conditions of uncertainty and variability.

The loop closes with the Action and Feedback stage, where selected decisions are implemented in the manufacturing system and their outcomes are constantly monitored. The resulting feedback is fed back into the Perception stage, allowing for continuous learning and progressive refinement of decision-making mechanisms.

Feedback plays an essential role in the continuous learning process, allowing the updating of decision models and the progressive improvement of the system's performance. In this way, the cognitive loop ensures not only the reaction to changes but also the accumulation of operational knowledge, which contributes to maintaining and increasing long-term competitiveness.

By integrating these four stages into a closed management structure, the cognitive loop establishes a direct link between operational data, competitiveness objectives, and adaptive leadership actions. Unlike traditional approaches to manufacturing systems leadership, which are often reactive or locally optimized, the proposed loop supports continuous adaptation geared toward global competitiveness.

In the context of this paper, the cognitive loop illustrated in Figure 1 represents the main conceptual contribution and provides the foundation for future developments, including mathematical modeling, simulation analysis, and applications in smart manufacturing environments and Industry 4.0.

Figure 1 presents the conceptual architecture of the cognitive loop driving the manufacturing system, highlighting the cyclical nature of the decision-making process and the role of feedback in the continuous adjustment of operating parameters.

In conclusion, by introducing the cognitive management loop, the proposed conceptual model offers an integrative approach to the decision-making process in manufacturing systems, combining perception, competitiveness assessment, decision, and learning in a unitary framework. The novelty consists in the explication of this mechanism at a conceptual level, as a foundation for further mathematical and experimental developments.

4. CONCLUSIONS

The paper proposed a conceptual model of cognitive management of manufacturing systems, oriented towards increasing competitiveness through continuous adaptation and learning. The central element of the contribution is the representation of a cognitive management loop that integrates the perception of the system state, the assessment of economic performance, adaptive decision-making, and feedback mechanisms.

The model highlights the role of competitiveness indicators, especially the unit cost of the product, as a link between the operational level and the strategic objectives of the organization. By integrating learning mechanisms, cognitive management goes beyond traditional reactive approaches and allows for dynamic adjustment of system parameters under conditions of variability and uncertainty.

The conceptual nature of the paper provides a theoretical framework for further developments, such as mathematical modeling, simulation validation, or implementation in specific industrial contexts. Therefore, the proposed cognitive loop constitutes a basis for the design of manufacturing systems strategically oriented towards maintaining and improving competitiveness.

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