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PROPOSAL FOR AN EXPERT SYSTEM TO AID DECISION-MAKING IN THE DESIGN AND MANAGEMENT OF FLEXIBLE MANUFACTURING SYSTEMS

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Purpose: The objective of this article is to introduce a concept for facilitating decision-making processes in the design and management of flexible manufacturing systems. This concept aims to minimize the risk of either overestimating or underestimating the flexibility and efficiency of production potential.
Design/methodology/approach: The proposal involves the utilization of a hybrid expert system, incorporating a combination of rules, scenarios, and semantic schemes to construct a comprehensive knowledge base. This system also integrates fuzzy logic, artificial neural networks, and agent systems with expert systems.
Findings: The proposed concept of a hybrid expert system allows for the management of flexible manufacturing systems across various levels, including strategic, operational, and technological aspects of production organization and management.
Practical implications: The article has broad applications as it is specifically tailored to address the intricacies of flexible manufacturing systems and expert systems for facilitating decision-making processes within the production context.
Originality/value: Each management level possesses its distinct characteristics, methods, and tools that can be seamlessly integrated through the use of hybrid expert systems.

Category of the paper: Research paper, conceptual paper.

Keywords: Expert systems, flexible manufacturing system, Industry 5.0, production management and engineering.

1. Introduction

The concept of artificial intelligence was first introduced to the scientific community in the mid-1950s by J. McCarthy, who defined it as the endeavor to develop (create) software that enables computers and machines to intelligently process data. Today, artificial intelligence has evolved into an interdisciplinary field. It finds practical application in virtually every area of human activity. Presently, significant research efforts are directed towards achieving autonomy in systems equipped with artificial intelligence. Consequently, a crucial area of scientific work focuses on advancing knowledge in the automation of control and decision-making processes.

The objective of this article is to introduce a concept for an expert system that facilitates decision-making processes by integrating information flow among various modules in the context of computer-integrated manufacturing (CIM) (including the needs of designing and managing flexible manufacturing systems (FMS)) and the production processes implemented with them. The proposed expert system concept encompasses three key management levels within a flexible manufacturing system: strategic, operational, and support and control of manufacturing processes.

The problem addressed in this context revolves around achieving consistent management and decision-making at both the strategic and operational levels, while also considering the management of manufacturing processes in relation to technological processes. The article discusses the challenge of selecting the appropriate method for information processing and constructing the necessary knowledge bases to facilitate optimal decision-making for this specific issue.

For this purpose, the following research questions were formulated:

Can the implementation of a modular hybrid real-time expert system structure enhance the management and decision-making process at the strategic, operational, and technical levels?

Will the integration of modules within an expert real-time system enhance the information flow within its information system and enable better alignment with the requirements of Industry 5.0?

The first section of the article presents a review of the existing literature concerning the evolution of expert systems, focusing on their role in facilitating decision-making processes and the methods utilized for implementing the reasoning process. The subsequent section examines the operation of computer-integrated manufacturing (CIM) in the context of flexible manufacturing systems (FMS). Following these analyses, the article proceeds to introduce the concept of an expert system in its subsequent part.

The concluding section of the paper provides responses to the defined research and design objectives, specifying the tools and decision algorithms that will be integrated into the expert system during its development. The article concludes with a discussion and a summary, presenting concise bullet-pointed conclusions, and offering recommendations for future research.

2. Development of expert systems in the light of supporting decision-making processes (literature analysis)

The rapid advancement of microprocessor systems, specialized neural processors, and the evolution of multi-core systems is driving the progress of information technologies and introducing new challenges for the development of information systems (Qin, Lu, 2021).

In the initial stages of development, expert systems were primarily constructed using languages such as LISP (Steele, 1990) and later Prolog (Clocksin, Mellish, 2003). However, it quickly became evident that establishing a dedicated framework for expert system operations yielded more favorable outcomes. Presently, specialized programming languages like PROLOG, EXYS, OPS5, and CLIPS, well-known and respected in the IT community, are commonly employed (Wakulicz-Deja et al., 2018). Additionally, some general-purpose programming languages such as C, C++, or Java, offer libraries (e.g., Rete++, Jess) that facilitate the development of expert systems. Moreover, there are software programs designed specifically for expert systems, reducing the need for extensive programming, such as EXPERTRule, NEXPERT (Aiken, Liu Sheng, 1990), or the Polish Sphinx program which includes the PC-Shell framework package (Michalik, Simiński, 1998).

For expert systems to effectively carry out their functions, they require a suitable architecture that typically comprises: a knowledge base, an inference module, an explanation module, a control module, a user interface (including communication with the user), and a knowledge acquisition module (Forsyth, 1986). It is important to note that the knowledge within the system does not need to be comprehensive and can be expanded, and sometimes, the solutions provided may exhibit ambiguity. In such cases, the value of the expert system becomes evident (Mulawka, 1996).

The process of acquiring knowledge in expert systems involves data collection and is often one of the most challenging stages in their development. Knowledge is typically transferred by an expert or groups of experts, which underscores the importance of standardization in practice (Cichosz, 2000). This also applies to the automated acquisition of knowledge based on data generated by sensors or other information systems. The unification of acquired knowledge represents a phase of system learning and can be described as the system's effort to enhance the quality of its operations (Linstone, Turoff, 2002). Acquiring knowledge enables the development of rules that represent knowledge for the expert system (Slatter, Norwood, 1987). The rules employed in expert systems are derived from classical methods of logic, and propositional calculus, which is a fundamental branch of formal logic, is utilized to describe the surrounding world (using propositions) that can be either true or false (Ben-Ari, 2006).

Expert systems, equipped with a knowledge base, are capable of performing the reasoning process. Inference is typically accomplished through three primary operations: matching, selection, and activation. Most often, inference is made progressively or regressively, depending on the context of the task being performed (Ligęza, 2005). The utilization of mixed reasoning appears to strike a favorable balance between backward and forward reasoning, mitigating the drawbacks associated with each approach. However, it is important to note that constructing meta-rules can introduce complexities, particularly in terms of comprehensive verification of the inference process and their subsequent updates (Mulawka, 1996). Furthermore, it is worth highlighting the concept of percepts and percept calculus, which arises from building knowledge based on natural language formulations (Sobolewski, 1991). These concepts have also contributed to the development of expert systems in the domain of organizing and structuring knowledge in a classified manner. In many cases, applying the crisp set theory to determine whether an element (object) belongs to a set or not is not always feasible (Skowron et al., 2002). Hence, alternative theories such as Zadeh's fuzzy set theory and the Demster-Shafer belief functions theory are employed (Dempster, 2008). The rough set theory, for example, enables the handling of imprecise data (Stefanowski, 1998). It allows the representation of a vague concept using a pair of precise concepts (the lower and upper approximations of the given concept). This theory is predicated on the idea that, by having information represented by attributes and their values on objects, it becomes possible to establish relationships between objects (Bazan et al., 2004).

It is worth mentioning that the induction of decision rules can also be conducted using methods rooted in rough set theory. Another crucial aspect is the development of algorithms for generating decision rules from decision tables, including the automation of this process (Grzymała-Busse, 1993).

For operational management at the tactical level, a table-based architecture should be considered (Stefanowski, 2001), where, in addition to knowledge in a given field, it is possible to take into account not only domain-specific knowledge but also the inclusion of strategic knowledge *(meta-knowledge)*. In this context, the use of multiple tables with hierarchical information structuring can be advantageous, providing a finer level of detail (Skowron et al., 2002). Decision tables form a decision system closely intertwined with the information system, and the theory of rough sets can be applied to them. A visual representation of an information technology system can be created as a table containing objects and attributes that describe a specific process (Pawlak, 2004). Decision tables can be either deterministic or non-deterministic, involving rules that describe objects that may also be deterministic or not. It is important to note that the use of tables may be constrained by the presence of internal inconsistencies within the rule knowledge base. Decision rules are formulated for both descriptive and classification purposes, establishing a close relationship with decision tables (Stefanowski, 2001).

In the context of describing interactions within complex systems composed of numerous modules, semantic networks, well-constructed frameworks, and appropriately developed scenarios serve as viable alternatives to the rules commonly found in expert systems.

A framework is constructed from slot-cages (slots), which, in turn, are built from cages (fasets). This hierarchical arrangement enables them to adopt the structure of a directed acyclic graph, facilitating the construction of a hierarchical decision-making structure (Wakulicz-Deja et al., 2018).

A semantic network is a collection of interconnected (related) objects with diverse implementations and serves as a graphical representation of logic. The foundation for comprehending the functioning of a semantic network is the associative model of human memory, in which terms are explained using other terms, thus giving rise to a structure of associations that can be closed. The last significant element within the analyzed array of methods and tools used in expert systems is scripts. They are employed to record knowledge regarding stereotypical sequences of events or events occurring within a known context (Rojek, 2017).

In the context of incomplete knowledge characterized by contradictions, inconsistencies, and uncertainty, it becomes necessary to employ fuzzy concepts. What experts find relatively straightforward, which is the formulation of approximate opinions, is challenging in computer modeling (Negnevitsky, 2002). In such situations, approximate (fuzzy) reasoning should be applied. For practical realization of these kinds of issues, the Bayesian network is often used, taking into consideration the certainty factor (CF) method (Dempster, 2008).

Flexible manufacturing systems, during both their design and subsequent operation, can effectively leverage a wide array of artificial intelligence methods, starting from neural networks through fuzzy logic often employed in process automation, and genetic systems, which excel at optimizing manufacturing processes (Barbosa et al., 2015). Nevertheless, the most powerful approach involves the adept integration of artificial intelligence methods into a cohesive inference and data processing system, resulting in the creation of hybrid systems (Shen et al., 2006). These hybrid systems may also incorporate agent systems and classic rule-based expert systems (Zhang et al., 2022).

An analysis of the literature reveals that current solutions exhibit a high level of specialization, primarily stemming from the prevailing technical constraints and emerging theories within a specific phase of knowledge development and the practical feasibility of their implementation. Drawing from this literature review, it becomes evident that there exists a noticeable research gap in the advancement of specialized real-time expert systems that encompass the fusion of aspects related to both strategic and operational management while concurrently conducting real-time analysis of the execution of technological processes and digitally mapping them for the purpose of decision-making across various functional levels.

3. Integration of the manufacturing process in flexible manufacturing systems

The primary issue examined in the article pertains to the integration of decision-making processes across technological, operational, and strategic levels concerning the management of flexible manufacturing systems through the utilization of an integrated expert system (Figure 1).

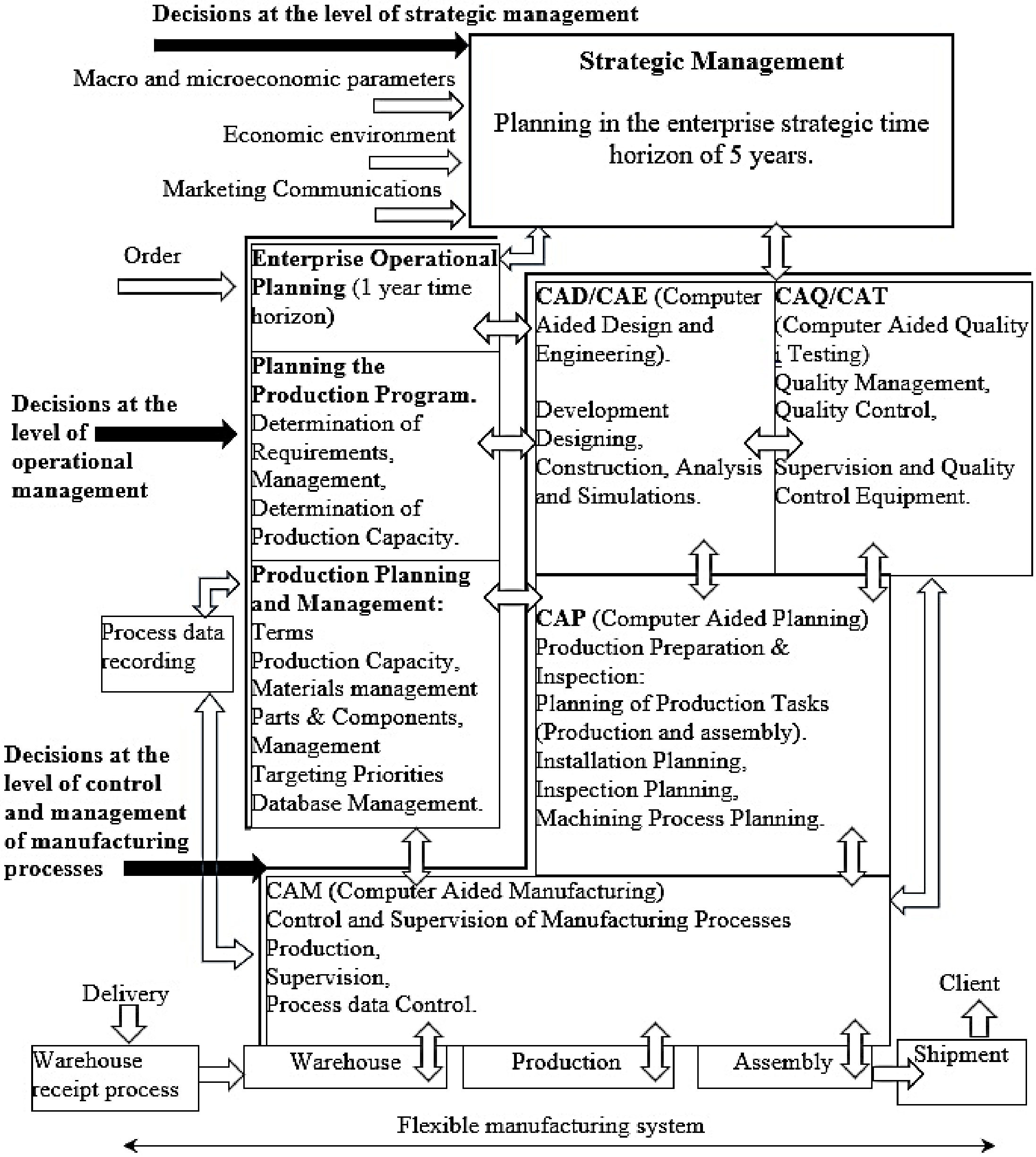

Figure 1. Computer-integrated CIM manufacturing and planning in the enterprise, taking into account three levels of management in a flexible manufacturing system.

Source: Zawadzka, 2007.

Strategic decision-making in the context of a flexible manufacturing system revolves around assessing the declared level of flexibility during its design phase. It is important to note that a flexible manufacturing system is a complex technical system typically comprised of eight functional (infrastructural) subsystems and three flow subsystems. These functional subsystems encompass production, control, transport, manipulation, storage, workshop aids, disposal and delivery, as well as diagnostics and control. The flow subsystems, on the other hand, pertain to the flow of energy, information, and material (Figure 2).

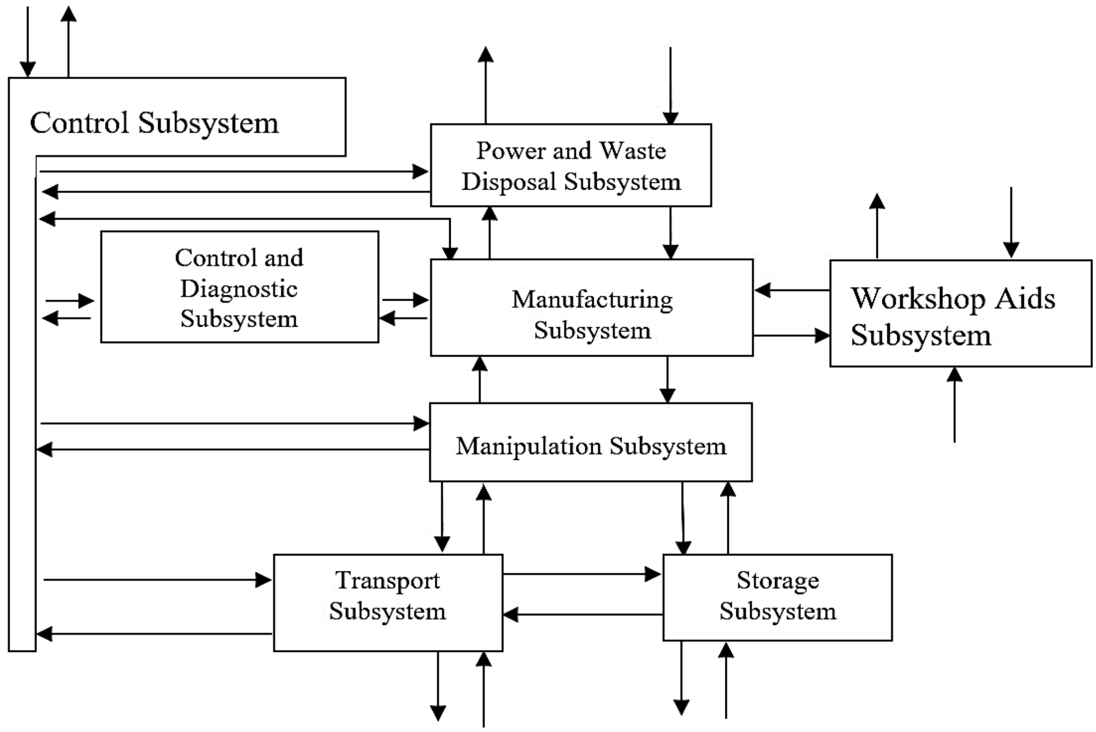

Figure 2. Interaction of subsystems included in the flexible manufacturing system.

Source: Lis et al., 1994.

The costs associated with implementing the system can be substantial, potentially exceeding hundreds of millions of euros. The decisions made regarding the selection of suitable technological and IT infrastructure will play a pivotal role in determining the operational characteristics of the system, as well as the lifespan of its individual subsystems, its adaptability and modernization in relation to both the products being manufactured and the overall production line infrastructure (Figure 3).

To mitigate the risk of overinvestment, the design of a flexible manufacturing system necessitates the incorporation of multiple feedback loops, which are designed to validate the design and detect any errors that may arise during the design phase, encompassing both the product and the required production infrastructure.

The technological efficiency of product construction is significantly influenced by decisions concerning the level of flexibility within the manufacturing system. Consequently, the integration of three key domains (strategic, operational, and technical) has become increasingly pertinent, especially in the context of the ongoing global digital transformation, which facilitates the enhanced integration of these processes.

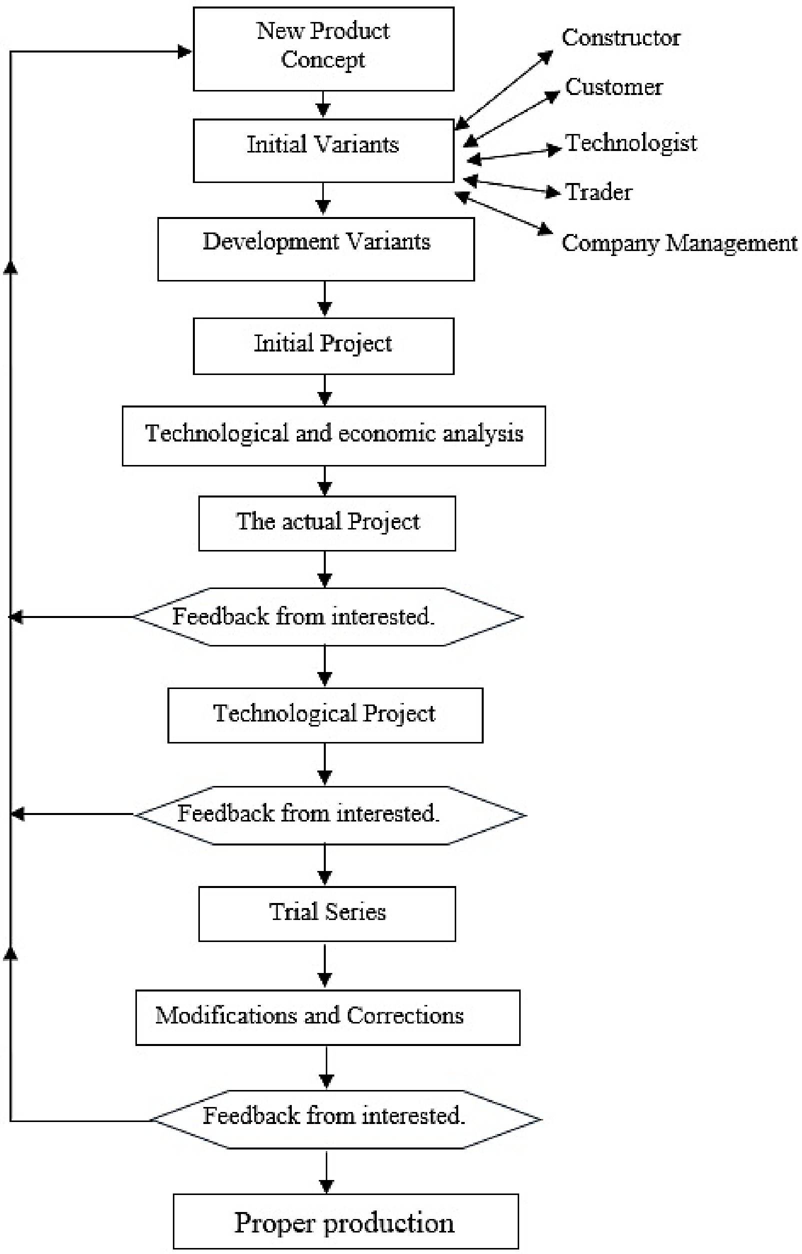

Figure 3. Decision-making algorithm for the degree of automation in the process of preparing the production of a new product using an automated, flexible manufacturing system.

Source: Honczarenko, 2000.

At the strategic level, making decisions necessitates the effective transformation of information into a form that can be characterized as knowledge about the relevant system. This level of knowledge processing represents the highest form of knowledge within the context of flexible manufacturing systems and can be described as wisdom that supports the system's operation. Strategic management frequently focuses on optimizing an enterprise's operation and, in more critical situations, ensuring its survival (Figure 4).

Decisions made at the operational level involve the utilization of knowledge concerning data processing and its application within the production scheduling process in a flexible manufacturing system. This knowledge encompasses the capabilities of the production system, enabling the optimization of resource utilization and the adjustment of the production system to meet customer requirements. Operational management should be closely intertwined with the computer integration of CIM production, with specific focus on the technical aspects of designing and preparing the production process, due to the adaptability of the production process and the system's potential to modify product design, technology, and instrumentation.

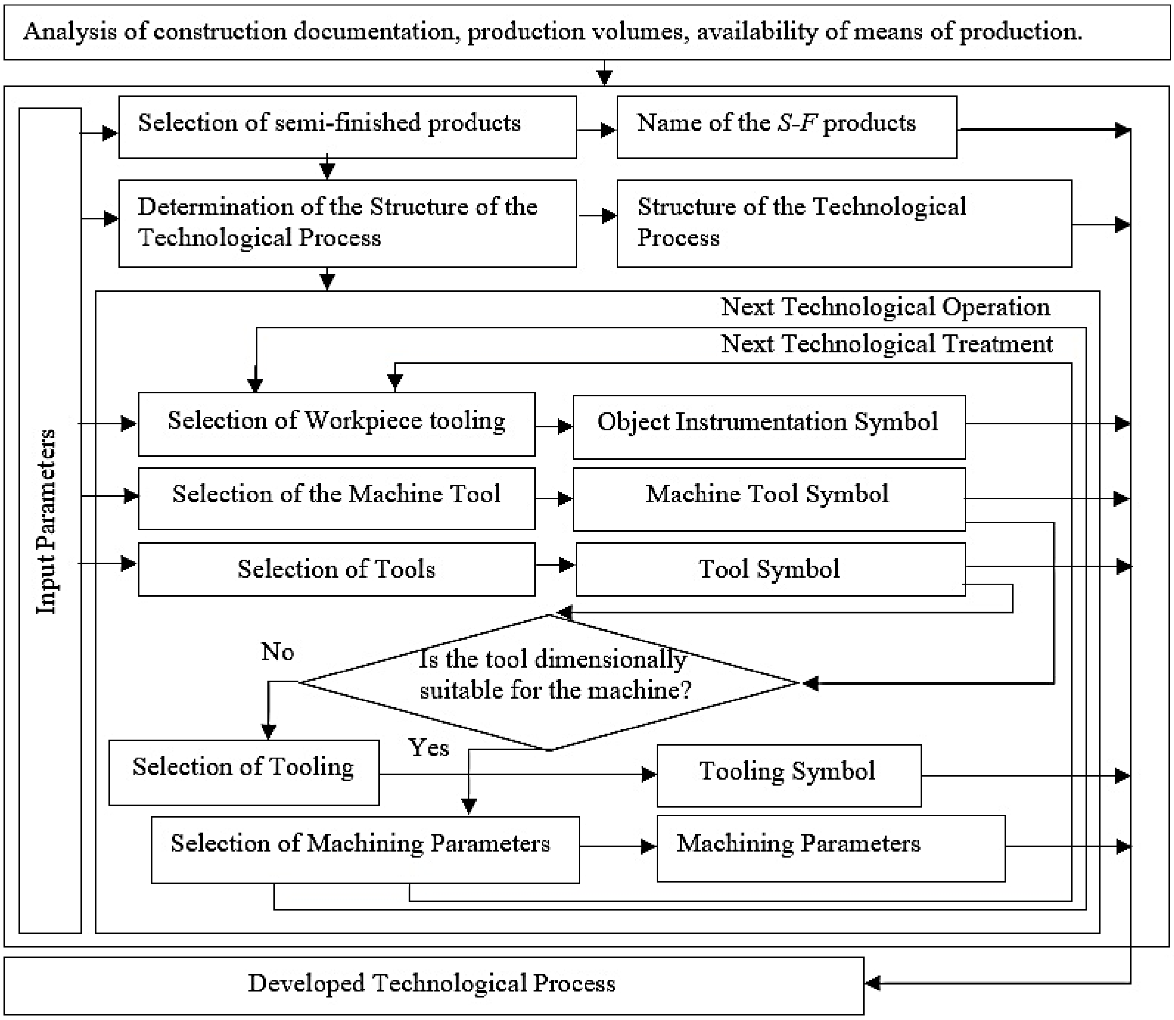

Figure 4. Decisions at the level of implementation of the technological process.

Source: Rojek, 2017.

Information required for decision-making at the technological process level is typically derived from factors such as machining parameters, weight and dimensions of products and components or materials, as well as parameterized to meet the control requirements of CNC devices. The challenge arises from dealing with a considerable number of processes and their high level of flexibility. This can lead to numerous combinations of product types and, consequently, necessitate adaptations in logistics processes for specific groups of technological processes. Moreover, the use of autonomous machining heads and systems supporting the technological process, which intelligently adapt the manufacturing process to dynamically changing conditions within the machining zone in real-time, is becoming increasingly prevalent. Consequently, the execution of the technological process may evolve over time or even be interrupted by the control and diagnostic system should it surpass a critical threshold defining the minimum acceptable process quality.

The presented concept of the expert system was formulated following an analysis of the operation of a flexible manufacturing system. This system is equipped with CNC technological devices for machining and is complemented by supported manipulation subsystems that encompass manipulators, industrial robots, and mobile autonomous transport systems.

4. Proposal for an expert system to support decision-making in the design and operation of flexible manufacturing systems

The integration of manufacturing systems, as presented in part 3, and the intricate interactions among individual systems and subsystems necessitate the development of methods and tools, including the amalgamation of diverse data and information processing techniques in a manner most suitable for the flow of information and the characteristics of technological processes within flexible manufacturing systems. Therefore, based on a review of the literature related to the construction and operation of expert systems, a proposal was made for a hybrid modular system. This system takes into account a range of tools and information processing techniques employed in expert systems and other artificial intelligence systems. It enables the amalgamation of various decision-making levels within a flexible manufacturing system into a unified system (Figure 5).

During the process of building the core knowledge bases for the suggested expert system, it is anticipated that data for generating rules or decision tables will be sourced not only from expert knowledge but also from specialized systems, e.g., fuzzy logic rough sets, neural networks, genetic algorithms, and agent systems. Following the processing and consolidation of this data, it can then be passed on to subsequent tiers of the integrated management system. This approach allows for the efficient management of information flow by leveraging the strengths of the various information processing methods in use while mitigating their individual shortcomings.

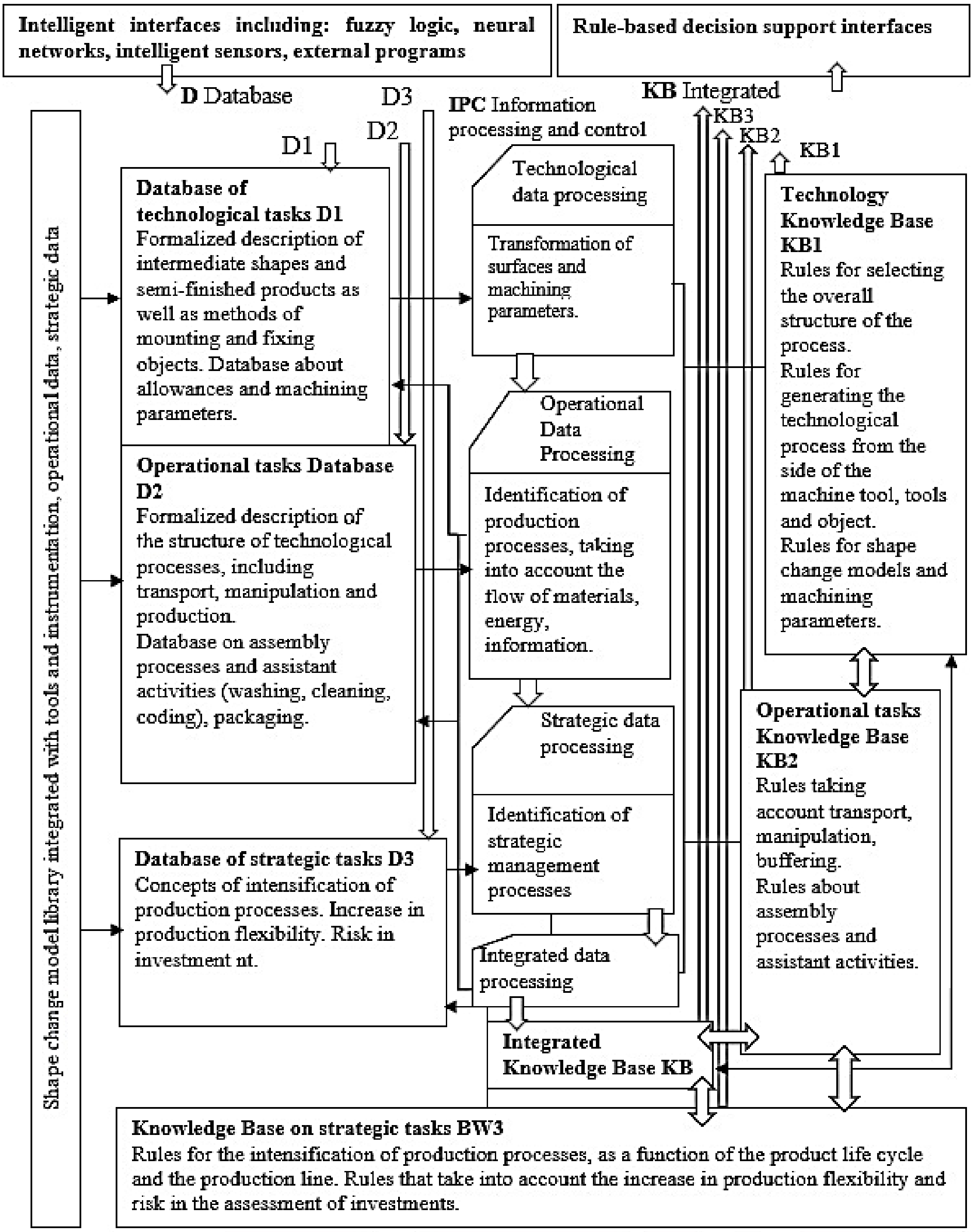

Figure 5. Expert system supporting technological processes based on rules.

The main idea of the proposed expert system is to process information at three levels of its operation (cascade with feedback) (Figure 6).

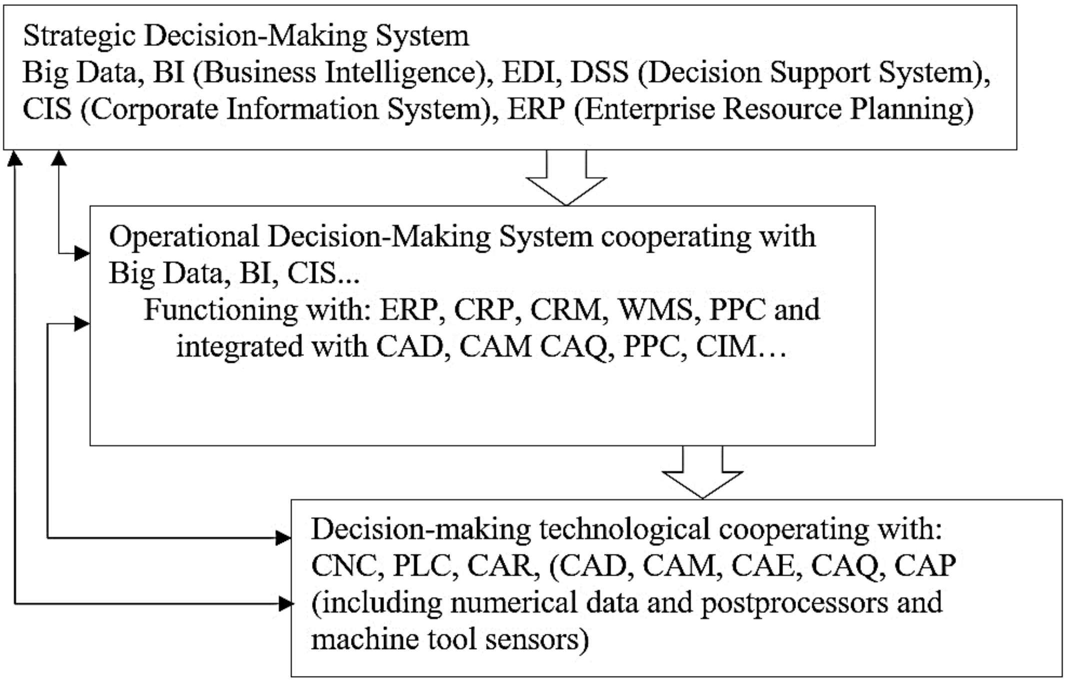

Figure 6. Proposal of an expert system supporting technological processes in accordance with the concept of computer integration of CIM manufacturing.

Consequently, this approach enables the fine-tuning and training of the decision support system's sensitivity at varying stages of information processing, allowing it to be well-suited and adaptable to real-world tasks.

In this scenario, the technical challenge to address involves the integration of information originating from the individual modules within the integrated expert system.

In the context of the technological level for an expert system, it is imperative to identify the critical activities and parameters that the system will execute, as they will define its functional structure. To accomplish this, a framework can be employed, akin to the principles of object-oriented programming in traditional programming (Figure 7).

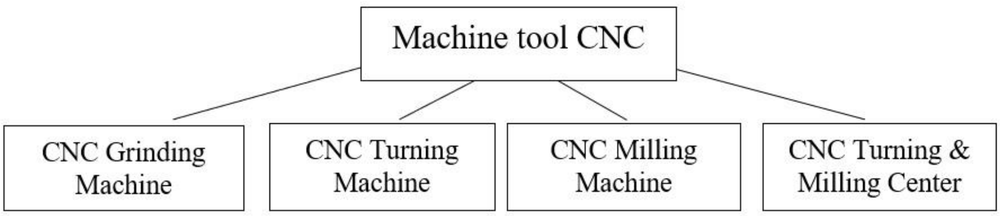

Figure 7. Example of a framework structure in a hierarchical structure for the classification of knowledge in relation to the concept of a CNC machine tool for an expert system.

When delineating the structure of the technological process, it is essential to consider factors such as production volumes, the level of flexibility within production processes, and the structural and technological intricacies of the products, components, and materials that will be incorporated into the production process (Figure 8).

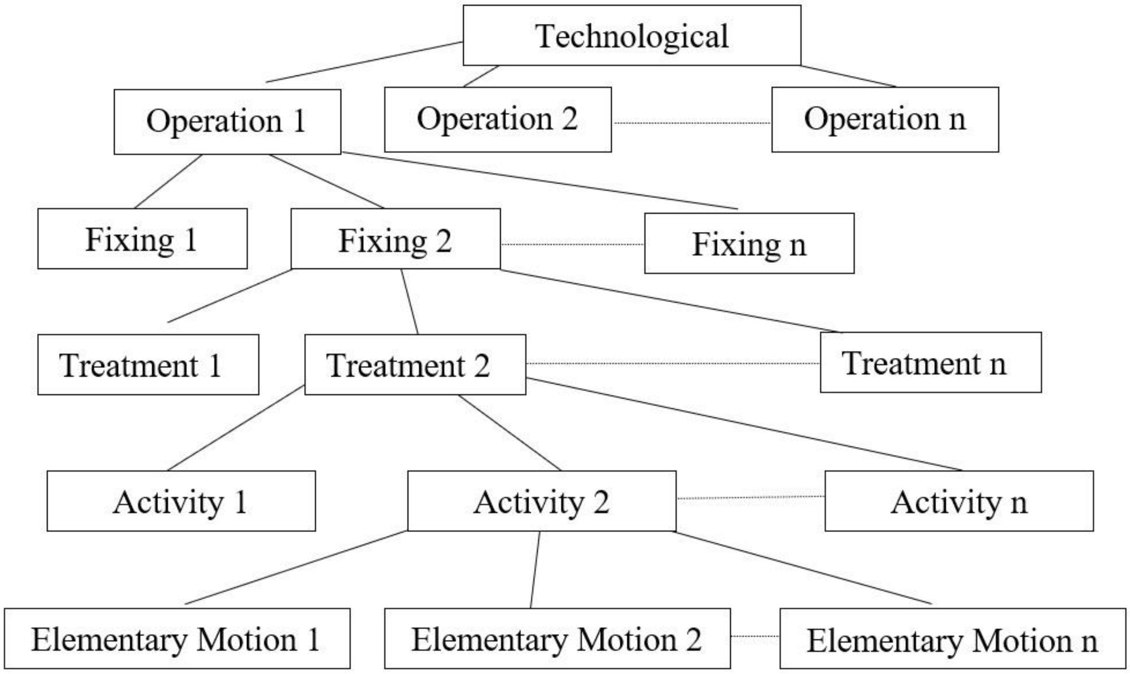

Figure 8. Hierarchical structure of the technological process.

Source: Chlebus et al., 2009.

The management of decision-making processes at the production (technological) level will revolve around the adaptability and interchangeability of technological devices (CNC machine tools) in relation to operational parameters and instrumentation, encompassing components like handles and devices, machining tools, as well as the associated cooling systems and the maintenance of their active surfaces.

At the lowest level of expert system functionality, there should also be a correlation with technological parameters concerning tool allowances, machine tool power, and the physical properties of processed materials, such as hardness and machinability. Technological management level should also consider processing time, which is associated with material characteristics and processing parameters. These aspects need to be linked with the quality of individual operations and treatments. This relationship should account for the requisite surface microstructure parameters (surface topography) and geometric factors like parallelism, perpendicularity, and coaxiality. Decision tables can prove to be valuable in this context, facilitating the establishment of interactions between various components of the technological process (Table 1).

The decision to deploy a CNC machine for a specific process will be influenced not only by the technical specifications of the device but also by factors like its placement and its interaction with other FMS subsystems, such as the kinematic complexity of the manipulation process, transportation distances, methods of buffering and retrieving parts, as well as determining and fixings. For this reason, it is advantageous to employ multiple decision tables that are suitably structured hierarchically. This approach facilitates the acquisition of comprehensive information about the processes and the production system.

Table 1.
Example of the decision board for selecting a CNC machine tool

Number CNC Machine Tool	Characteristics CNC Machine Tool				
	Multi-spindle machine tool over 20 thousand rpm	**More than 20 tools in stock**	**Compatible with a 5-axis robot equipped with <50 mm**	**Mechanical stiffness**	**Decision to use a CNC machine**
1.	Yes	Yes	No	High	**Yes**
2.	No	Yes	No	Low	**No**
3.	Yes	No	Yes	Very high	**Yes**
4.	Yes	No	No	Average	**No**

Note. **Yes** or **No** decision to use a CNC machine.

Source: Own study.

All the mentioned groups of information can be quite easily associated with the costs of implementing the technological process. On this basis, another category of information needed to develop rules describing the implementation of the technological process should be derived from. These include the retooling times of technological devices in relation to both handles and devices, as well as tools defined as cutting blades, and the infrastructure that gives them features that enable them to be used for machining external or internal surfaces.

The formulated rules should also consider the time required for the transportation of materials, components, semi-finished products, and finished products within the storage, manipulation, and transport subsystem. This should encompass the buffering of tools and their transportation within the area of interaction between technological devices and manipulation systems.

In such situations, it is advantageous to employ semantic schemas that facilitate the creation of an information structure capable of forming a suitable knowledge base. This knowledge base will in turn support decision-making tasks in this context (Figure 9).

At the technological and operational levels of the expert system's operation, the primary decision-making activities will revolve around minimizing alterations within the flexible manufacturing system regarding enhancing the rigidity of the tool-machine system, variations in the approach to mounting, diverse methods of executing the transport and manipulation process, and the strategy for cooling the machining zone.

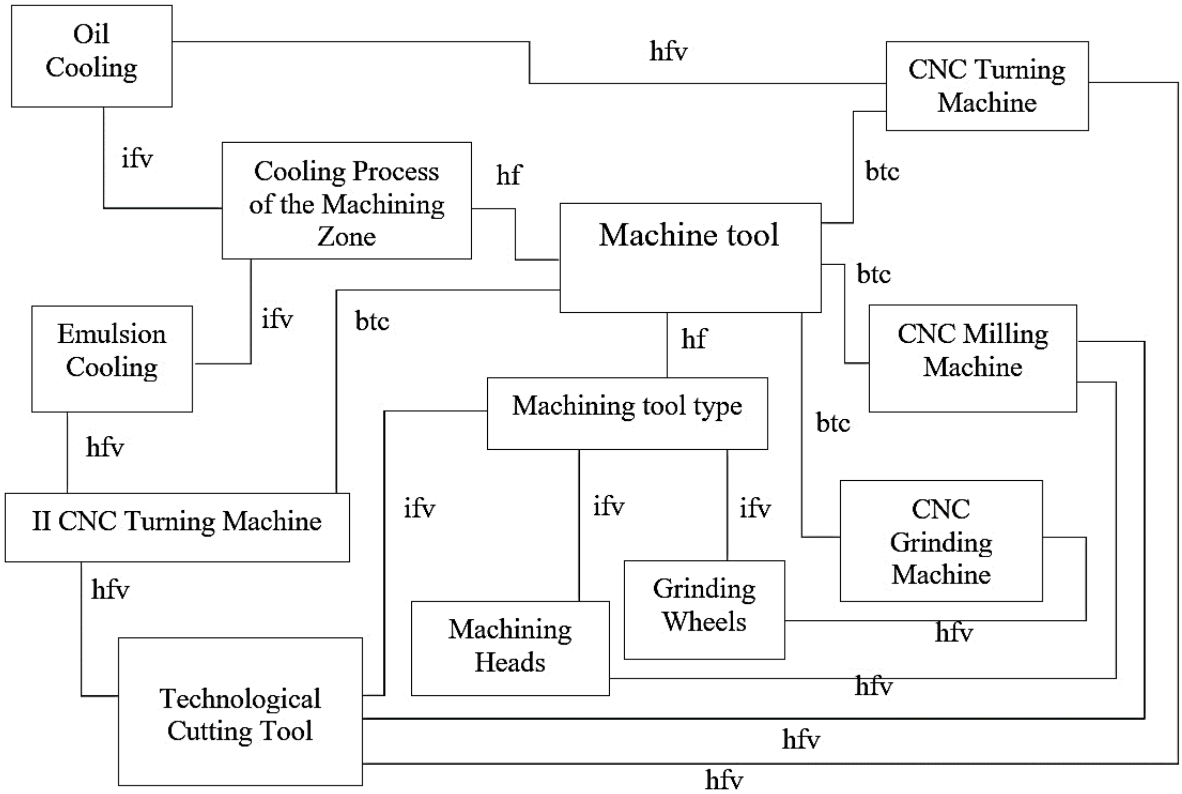

Figure 9. An example of a semantic network of a technological process specifying connections and interactions between individual objects included in it (ifv (is a feature value), btc (belongs to a class), hfv (has a feature value), hf (has a feature).

Any alteration in the system configuration necessitates investing time in retooling and aligning the machining system with the demands of the technological process to uphold the required quality while also considering acceptable process implementation costs. To facilitate the real-time operation of the expert system, it is advisable to incorporate fuzzy sets, which can serve as a tool supporting the operation of rules describing the dependencies of the technological process. Considering the sensors integrated into the equipment of CNC machines, robots, and machining tools for tasks like wear identification, or those employed to automate the operations of machining heads, including the monitoring of force components in the machining zone, it is sensible to introduce agent systems for managing the technical process at this stage. This approach allows for the assessment of the condition of individual devices and the transmission of precise data to the structural framework of the expert system responsible for the real-time technological support of the manufacturing process (Figure 10). In such a scenario, the expert system accurately mirrors the actual flow of information and transforms into a digital representation of the processes transpiring within the flexible production system.

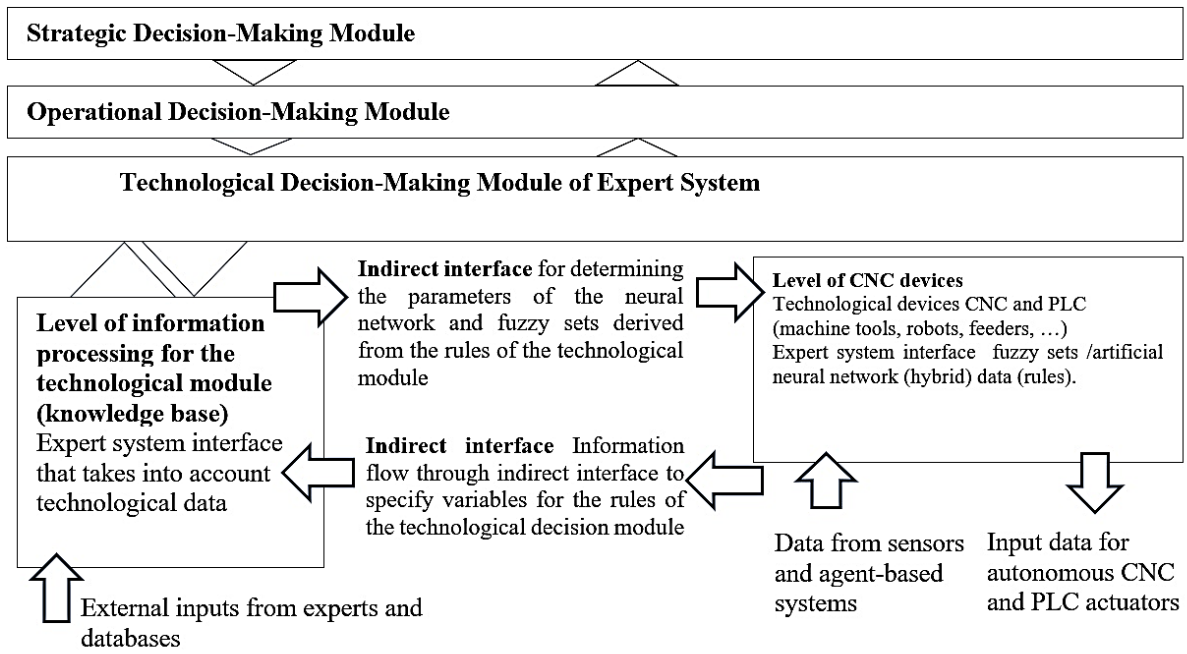

Figure 10. Information flow for the technological level of decision-making and the proposed topography of methods and tools for the decision-making system.

Operational management within a flexible manufacturing system primarily involves the planning of production processes, encompassing production logistics like supply, storage, and transport subsystems. Consequently, in the envisaged hybrid expert system, the adoption of multi-agent systems technology is planned for the operational management level. These agents will be tasked with emulating the self-organization and autonomy of systems in the domain of transport, storage, and supply, with specific focus on internal transportation. The depiction of these processes can also be achieved with the aid of fuzzy sets (including fuzzy logic controllers and neural networks), which are complemented by decision tables and expert system rules. It should be noted that the database for the operational management level and the resulting decisions are derived from the possibility of implementing technological processes, often conditioned by knowledge of mechanics and physical interactions occurring in the interaction with chemical affinity in the tool-workpiece system. Such a knowledge base possesses a distinct nature in contrast to operational management, which is influenced by incoming orders and the flow of information, materials, components, and products, along with the requisite equipment necessary to execute the technological process as a function of time and energy expended (Figure 11).

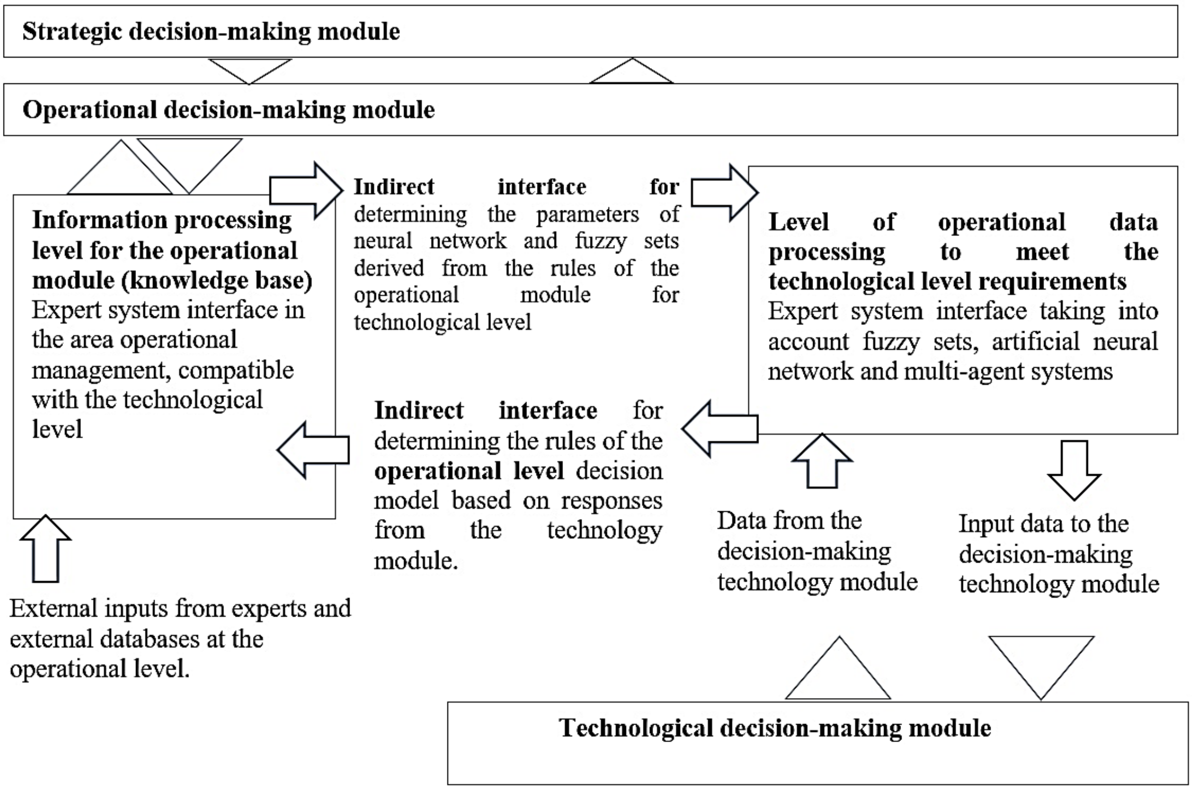

Figure 11. Information flow for the operational level of decision-making and the topography of methods and tools.

The third tier of the hybrid expert system is intended to provide decision support at the strategic level in terms of the design, development, and management of a flexible manufacturing system. It is anticipated that the strategic reasoning subsystem will not only facilitate the external expansion of the knowledge base, which describes the environment of the information system, but will also be closely interrelated with the operational and technological management subsystems.

In the third module of the expert system, economic factors will play a crucial role, with analysis conducted at both regional and global levels. These economic parameters can have an impact on the modification, assessment, and planning of the scale of the production process carried out through a flexible manufacturing system.

Strategic-level decisions can be made through approaches such as backward reasoning, and future scenarios can be constructed based on these decisions. In this context, establishing semantic relationships and employing suitable fuzzy inference in conjunction with neural networks is of significance. However, in this case, their operational model will not focus on the technical aspects of the technological process, as indicated at the technological level of the proposed system. Instead, it will revolve around market observation and economic parameters within a specific economic sector, as well as the analysis of the economic conditions associated with production and investment processes characteristic of a particular type of flexible system (Figure 12).

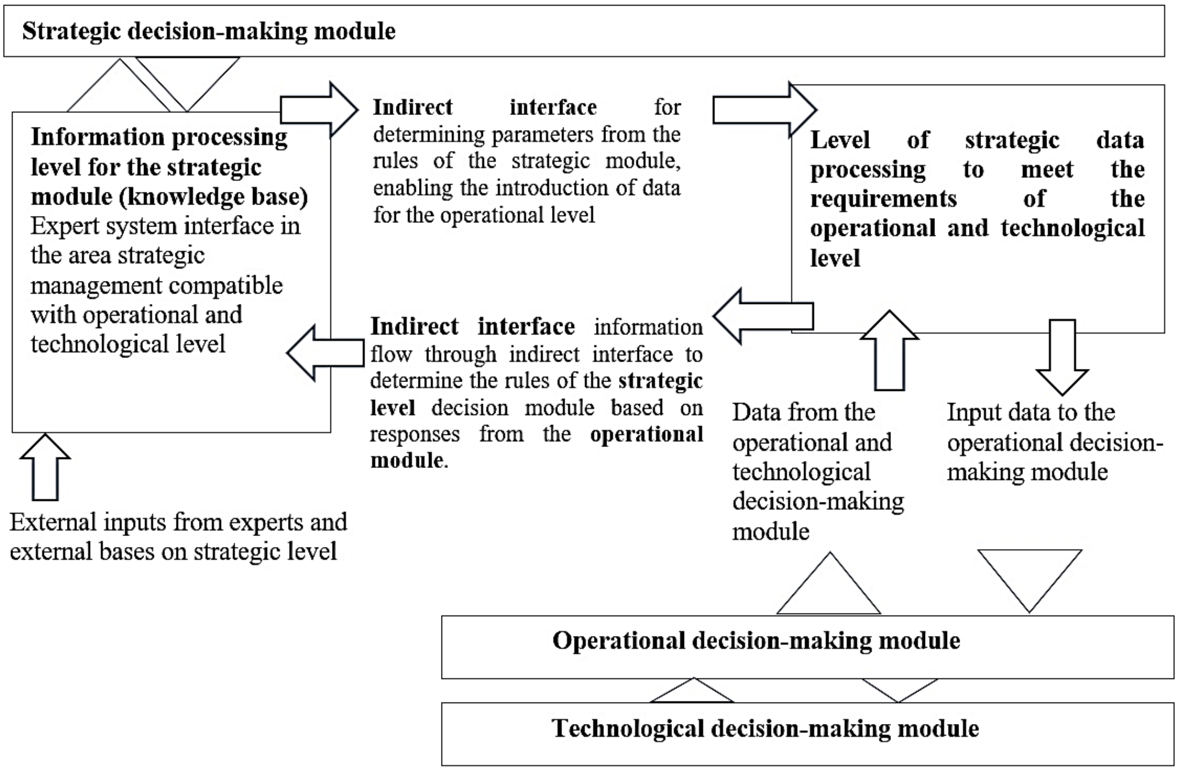

Figure 12. Information flow for the strategic level of decision-making and topography of methods and tools.

Developing a comprehensive decision support system for the design of flexible systems appears advisable, given the substantial business risks associated with managing such systems. The costs associated with designing, implementing, operating, and expanding flexible manufacturing systems underscore the rationale for decision support systems in this domain. Enhancing these systems can be viewed as a purposeful endeavor.

5. Discussion

The proposed configuration of the decision support and management system for a flexible manufacturing system places primary emphasis on the core structure of the rule-based expert system, which should be equipped with specialized modules of the strategic, operational and technological data processing system based on appropriately developed knowledge bases (heterogeneous sources of knowledge) and interfaces enabling integration of individual modules.

In light of the considerations mentioned above, the question raised in the introductory section of the article about whether implementing a modular structure for a hybrid real-time expert system, mapping the structure of a flexible manufacturing system and the interactions within it, can improve the management and decision-making processes at the strategic, operational, and technical levels of a flexible manufacturing system, should be answered affirmatively. The question can be answered positively, since the analysis conducted suggests that the adoption of multi-stage data processing may enable proper scaling and adequate stabilization.

The second question can also be answered in the affirmative. The analysis has demonstrated that the integration of modules in a real-time expert system can enhance the information flow within its information system and align it more effectively with the requisites of Industry 5.0. It appears that the suggested multi-stage integration of subsystems may play a role in stabilizing information flow. Similar to biological structures responsible for cognitive processes and nerve impulse conduction, where information flow is transformed through electrical and chemical interactions within specialized regions of nerve cells. This allows for the appropriate amplification or attenuation of the signal. These biological structures exhibit a degree of autonomy, each assigned to specialized tasks for carrying out specific levels of information processing (e.g., the medulla oblongata). Interactions between systems occur only in specific situations, most commonly during critical moments for the body, such as when balance thresholds are exceeded, for instance, in dangerous situations. Therefore, the article proposes various approaches to processing information that are well-suited to specific tasks.

The article presents a concept for a system that facilitates the decision-making process with regards to designing flexible manufacturing systems and managing production processes, while taking into consideration the intricacies of constructing a flexible system, its operation, and the effectiveness and quality of implemented technological processes. The structure of flexible manufacturing systems and computer-integrated manufacturing was thoroughly examined, leading to the proposal of an integrated approach to management and decision-making, both at the strategic and operational levels, as well as the management of manufacturing processes in relation to technological processes.

The article highlights the importance of structuring information hierarchies to align with the tasks performed in various subsystems and systems, extending all the way to individual CNC devices, robots, and AVG mobile robots. Moreover, when considering the integration of these devices, the knowledge base should encompass sensors and sensor groups, as well as control and diagnostic systems situated within technological devices and PLC controllers responsible for integrating executive devices across production lines and warehouses. This approach enables the creation of a digital representation of the production line within a flexible manufacturing system, complete with interactions and feedback loops within the expert system, essentially forming a mirror image of the FMS information.

6. Conclusions

The concept is tailored to the unique functioning of flexible manufacturing systems and expert systems that provide decision-making support in the production process. Drawing from the research conducted, the following conclusions were derived:

1. The proposed concept of a hybrid expert system holds the potential to aid decision-making in the context of advanced flexible manufacturing system design. It can play a role in cost reduction during design, implementation, and ongoing operation, while minimizing the risk, overinvestment and reversal of all positive aspects of the functioning of flexible production systems.
2. The development of integrators that connect individual management levels through artificial intelligence methods could facilitate the optimal management of such a complex production system. To achieve this, the proposal involves using a hybrid expert system, which includes rules, semantic schemas, decision tables, and tools for implementing fuzzy logic, as well as artificial neural networks and agent systems integrated with expert systems.
3. The costs associated with implementing the technological process can be estimated by leveraging real-time technological data obtained from CNC machine tool controllers and industrial robots. The expert system at the technological level can utilize this data to construct a knowledge base about individual processes over time. Using this foundation, it becomes possible to estimate costs through the use of fuzzy sets and neural networks, without the necessity of simulating all components of the manufacturing process originating from CAM systems. Such an analysis can be conducted at both the technological and operational management levels.
4. Designing virtual manufacturing systems using CAD/CAM systems does not provide a direct answer as to their efficiency and processing time until all technological paths are analyzed, and technological processes are implemented in order to obtain precise information on the time and costs of the process. However, this approach is time-consuming, and the sheer volume of interactions involved makes it practically impossible to conduct a comprehensive analysis.
5. The use of rules in an expert system is comprehensible to a human (expert), allowing them to construct a knowledge representation in the form of a knowledge base. However, the rules have limitations due to the inability to model incomplete knowledge and they do not allow for modeling the full domain and provide automatic reasoning. They also do not allow for backward rule diagnostics. Rule-based reasoning does not always align with the theory of probabilistic reasoning. As a result, relying solely on rule-based expert systems for a complex system like a flexible manufacturing system does not facilitate the integration of its components and consistent real-time data processing.

6. In the analysis of hybrid expert systems, it has been observed that modifying the information flow between different system levels can enhance its stability. Progressing to higher levels of information processing involves translating data that can be adapted. This enables the complex information flow to ascend to broader areas of strategic management while descending to the level of technological decisions with the assistance of rules complemented by fuzzy sets (including hardware-level Fuzzy Logic controllers and neural networks). These can be responsible for identifying specific processes. Agent systems collaborating with sensors, PLC and CNC control systems of technological devices, as well as mobile systems, can facilitate decisions at the operational management level. Importantly, this proposed concept does not exclude expert knowledge; their wisdom can be incorporated into the system through the rules that form the system's overarching structure.
7. It was observed that the configuration of an expert system can function dispersed as a network of individual methods and tools and then, thanks to modern digital transformation possibilities, information can be processed in the system and appropriately unified and transferred for use at subsequent levels, reaching the stage of strategic management.
8. The article is intended for managers and specialists in the fields of management and production engineering, particularly in mechanical engineering and management and quality sciences. The article falls within the domain of technical concepts and a comprehensive analysis of decision support using artificial intelligence methods.

In the subsequent phases of research, the intention is to validate the presented concept by employing actual objects and specific systems and subsystems within a flexible manufacturing system using computer simulations imitating their functioning. The subsequent stage will involve simulating all the subsystems of the flexible manufacturing system as a digital twin, which will be integrated into the expert system. Consequently, this will facilitate correlation research aiming to understand how the digital model of the flexible manufacturing system generates information regarding its status, and how the corresponding integrated expert system identifies responses and formulates decisions to support management processes in the flexible manufacturing system.

Future research will focus on the concept of facilitating the near real-time flow of information between subsystems. The research will revolve around the creation of intermediate interfaces that can parameterize information, making it suitable for further processing. This will enable the development of an automated mechanism for the seamless transfer of information within a modular expert system that replicates the structure of a flexible manufacturing system.

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