ACTA TECHNICA JAURINENSIS
Vol. 16, No. 3, pp. 90-98, 2023
10.14513/actatechjaur.00697

Research Article

Optimizing cutting fluid usage in cutting processes on CNC machines: A conceptual digital twin model for ecological sustainability

Milica Barać[1,*], Nikola Vitković[1], Dragan Marinković[1,2], Predrag Janković[1], Dragan Mišić[1]

[1]Faculty of Mechanical Engineering, University of Niš
Aleksandra Medvedeva 14, 18106 Niš, Serbia
[2]Department of Structural Mechanics and Analysis, Technische Universität Berlin
Country Strasse des 17. Juni 135, 10623 Berlin, Germany
*e-mail: milica.barac@masfak.ni.ac.rs

Submitted: 05/05/2023 Accepted: 27/05/2023 Published online: 14/06/2023

Abstract: The increasing demand for environmentally friendly manufacturing processes has led to the need for optimizing the use of cutting fluids in turning and milling processes. Cutting fluids are commonly used in cutting processes to reduce tool wear and improve cutting performance. However, cutting fluids have a negative impact on environment and human health. This paper proposes a conceptual model of an information system based on digital twin of the production process. This system will enable monitoring of the manufacturing process and provide a decision support system for helping industrial engineers manage its parameters. The model is represented by using SADT (Structured Analysis and Design Technique), and it is presented by using one of the most common problems of optimizing cutting fluid usage in cutting processes on CNC machines from an ecological perspective. The proposed model considers various cutting process parameters (cutting speed, feed rate, depth of cut) and cutting environment factors (cutting process temperature) to determine the optimal cutting fluid flow rate. To optimize the usage of cutting fluid, the smart information system acquires, processes, and stores data from cutting process temperature and cutting fluid flow sensors to establish the correlation between process parameters and sensor data, which is then used to develop a model. The proposed model can be integrated with existing CNC machines to reduce environmental impact while maintaining high productivity. This paper provides a promising approach for optimizing cutting fluid usage in CNC machining processes while promoting ecological sustainability.

Keywords: Cutting fluid optimization; Digital twin; SADT (Structured Analysis and Design Technique); Ecological sustainability; Sensors system

I. INTRODUCTION

Manufacturing industries have been a significant contributor to environmental degradation. The increasing demand for sustainable and eco-friendly manufacturing processes has become a crucial issue in recent years [1]. Machining processes such as turning and milling are widely used in the manufacturing industry. Cutting fluid (CF) is a type of coolant and lubricant designed specifically for metalworking and machining processes [2].

One of the significant challenges in machining processes is the optimization of CF usage. The cutting process heavily relies on CFs as crucial components. CFs are commonly used in turning and milling processes to reduce tool wear and improve cutting performance. During the cutting processes, CFs are vital in ensuring optimal cutting performance, prolonging tool life, preventing workpiece damage, enhancing surface quality, and boosting productivity [3]. However, the CFs usage has adverse effects on the environment, including water pollution, air pollution and the generation of hazardous waste.

CFs are one of the main causes of environmental pollution during the machining [4]. Therefore, the increasing demand for eco-friendly production methods due to environmental concerns has led to a growing interest in developing alternative methods for reducing the CFs usage while maintaining or improving machining performance. Also, CFs usage, in addition to a significant impact on the environment due to their composition and disposal, also leads to potential health risks and economic costs [5]. CF usage accounts for a substantial portion of production costs, averaging up to 17%, with only 6% attributed to the price of the fluid, and the remaining 94% to CF usage costs [6, 7].

The ultimate goal of eliminating CFs is often unattainable due to the stringent requirements of machining operations, making dry machining conditions not always a viable alternative [8]. Due to the adverse effects of CFs, it is essential to minimize their usage in cases where dry machining is not feasible. Minimizing CFs usage contributes to reducing environmental pollution, potential health risks to operators, and economic costs. To reduce the CFs usage and meet the aforementioned objectives, it is imperative to optimize the cutting process while ensuring that desired productivity and the final product quality are not compromised. This implies that the optimal usage of CFs is essentially the minimum amount required to satisfy the necessary surface quality and main machine time [9].

During machining operations, workpiece materials undergo plastic deformation that results in significant thermal stresses on both the cutting tools and workpieces [10]. To reduce the thermal stress that occurs, CFs are used. This means that the CFs usage is closely related to the heat generated in the cutting zone [11]. Therefore, when optimizing CF usage during cutting processes, it is essential to consider the heat generated, which necessitates the use of a temperature measuring sensor. To optimize the CFs usage, data from CF flow sensor and cutting process parameters are essential, in addition to temperature sensor data. Once all necessary data is gathered, filtered, and analysed, it leads to the correlation between the data that is used for developing an optimization model.

The integration of digital technologies into manufacturing processes has revolutionized the way production systems are managed and optimized. One promising approach is the utilization of digital twins. The escalating digitization of various aspects of daily life has resulted in increased opportunities for data acquisition, storage, transfer, and analysis, which has in turn fostered high expectations for the "Digital Twins" concept [12].

This paper introduces a conceptual model of an information system based on digital twin (DT) of manufacturing processes, specifically cutting. The information system is represented by using Structured Analysis and Design Technique (SADT). SADT is a comprehensive systems engineering and software engineering methodology employed for describing systems as a hierarchical arrangement of functions. The hierarchical structure enables the decomposition of the system into smaller parts and thus increases the detail of the system analysis. SADT is a graphical notation that is primarily intended to assist individuals in effectively describing and comprehending complex systems [13]. As the cutting process itself is very complex, SADT represents a good method for creating a conceptual model of an information system based on digital twin (DT) of cutting processes.

This paper presents a conceptual system that builds upon the authors' extensive experience in production engineering and workflow management. The conceptual model developed in this study serves as a crucial initial step in introducing a DT. The authors aim to transfer their knowledge and expertise into a novel workflow that enhances manufacturing processes by harnessing the power of real-time sensor(s) data. Central to this conceptual system is an information system model proposal that facilitates data acquisition and management. In the initial stage, expert knowledge will be leveraged to establish an expert system based on the user-expert experience in the manufacturing process. The main goal is to develop and propose a conceptual model of the intelligent information system that will enable different solutions to improve the manufacturing processes in clean manufacturing, process and product quality. The conceptual model of the information system is general, but to enable a better understanding of its possible applications, the focus will be on optimizing the usage of CFs in cutting processes on CNC machines, considering ecological sustainability.

II. Digital twins

Digital Twins (DTs) are becoming increasingly more important in research and industry as they offer significant benefits in the transition from traditional manufacturing to Smart Factories in line with Industry 4.0. DTs represent a multidisciplinary technology that harnesses the power of models, data, machines, and computers to deliver efficient, real-time, and intelligent services across various domains of smart manufacturing [14]. DTs have been widely adopted in the manufacturing industry to improve production efficiency and reduce costs. In recent years, DTs have been extended to environmental management, with applications in energy management and carbon footprint reduction.

When discussing DTs, it's important to consider their different integration levels: Digital Model (DM), Digital Shadow (DS), and full-fledged Digital Twin (DT) [15]. These levels represent varying degrees of data integration between the physical and virtual counterparts. The DM serves as a foundational virtual representation with geometric and static data. DS act as intermediaries, incorporating static and dynamic data for monitoring and analysis but lacking real-time control. Finally, the DT is a dynamic virtual replica closely mirroring the physical system in real-time, integrating various data sources and enabling real-time monitoring, control, and interaction.

Various definitions of DTs have been proposed by the scientific community with the goal of providing a consistent and comprehensive understanding of their diverse applications [16]. The absence of a universally accepted definition of DTs stems from their wide applicability across diverse industries, the rapidly evolving nature of the field, varying perspectives from different disciplines and communities, and the flexibility in implementation using different technologies and platforms. Overall, DT is a virtual model that replicates the physical characteristics and behaviour of a real-world object or system. They serve as an interface connecting the physical and information worlds [14].

The DT acquires and analyses data from its physical counterpart or other sources, using models and real-time and historical sensor data to assess the current state and predict future behaviour. By processing data, the DT generates recommendations, including optimization suggestions, which can be shared with users or integrated back into the physical system. The DT improves its own models by incorporating current data through a control loop, ensuring continuous refinement and adaptation to environmental changes for optimized results. DTs offer direct support to decision-making processes by providing specific recommendations or even acting autonomously [12]. The paper presents a conceptual model of a smart information system that utilizes a DT for decision-making.

III. SADT METHOD

SADT method is a diagramming technique that provides a graphical notation used in systems engineering for graphical modelling, description, and analysis of the structure of complex systems, their functions, and processes [13]. SADT, which can be applied to various systems comprising different components, enables analysis of their interrelated relationships. It offers a systematic approach to optimize machining processes by examining functions and activities involved. Widely used in software engineering and computer-aided manufacturing systems, SADT diagrams visually represent the system, aiding stakeholders in comprehending its behaviour and structure [13, 17-20].

In SADT, boxes and arrows are used as graphical symbols for constructing diagrams. Boxes represent processes, functions, actions, entities, or activities and contain brief descriptions. In SADT graphical notation, each box in the diagram is labelled in the lower right corner.

Arrows, in SADT graphical notation, have specific meanings:

- Inputs enter from the left, representing necessary data or consumables;
- Outputs exit to the right, indicating resulting data or products;
- Controls enter from the top, representing commands or conditions influencing the activity;
- Mechanisms enter from the bottom, signifying the means, components, or tools used to perform the activity and allocate activities.

SADT hierarchically represents complex systems, ensuring consistency and offering detailed information at each level. Breaking down systems allows analysts to identify issues and areas for improvement. Hierarchical SADT diagrams provide benefits such as clear representation, understanding of component interactions, and a framework for analysis, design, and testing.

IV. RESULTS AND ANALYSIS

The smart information system is a complex system representing a manufacturing environment workflow. The main components, which are the focus of this research, are data processing and decision support system. For data processing, DT is used to represent manufacturing processes and acquire real-time data using IoT, which is Industry 4.0 approach. The Decision Support system is an intelligent part of the information system focused on making decisions that will help industrial engineers resolve complex issues in the manufacturing environment. In the initial stage (concept), the decision support system will enable applying an expert system formed by using specialist knowledge, and an optimization model for finding the optimum of a defined process (CF in this case). Furthermore, machine learning will be applied to predict various solutions when enough sensor data is acquired in future work.

For this research, the information system will be demonstrated by applying SADT conceptual model of the cutting process on a CNC machine to optimize CF usage is hierarchical and consists of several levels of detail. This conceptual smart information system model is based on the authors' extensive experience in production engineering and workflow management. The highest level of the hierarchy depicts the system's overarching objective, which is further decomposed into constituent processes and sub-processes.

At the first level, the context diagram shows the overall smart information system that uses a DT of a process for decision-making. Overall SADT diagram of smart information system and its main inputs, outputs, resources/mechanisms and control elements is shown in **Fig. 1**.

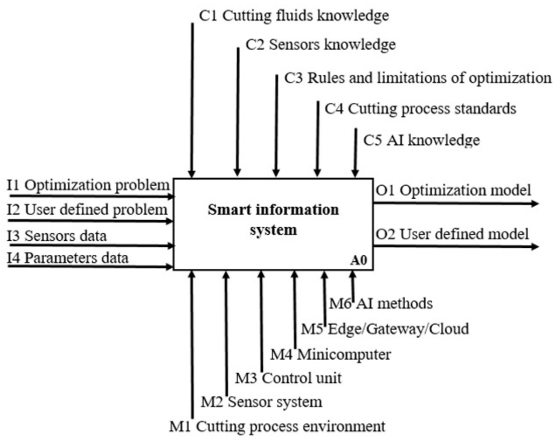

Figure 1. *Smart information system A0 - context diagram*

The system relies on essential data obtained through the use of resources, while considering established standards, rules, limitations and knowledge. In this stage, authors propose a conceptual information system model that utilizes real-time sensor data for data acquisition, serving as an initial step in introducing a DT. The following is a description of the element of the Smart information system for optimizing CF usage in CNC cutting process according to SADT specification.

Main inputs:

- Optimization (I1) and/or User Defined problem (I2) represents the main objective of the system, which is to optimize or to solve the cutting process. In this case, the focus will be on optimizing the usage of CFs, while ensuring that the quality of the final product and productivity are not compromised.
- Sensors data (I3) refers to the data obtained from the temperature and CF flow sensors, which provide information about the cutting process.
- Parameters data (I4) represents the cutting process parameters data, such as cutting speed, feed rate, and depth of cut, which are necessary for optimizing the cutting process.

Main resources/mechanism:

- Cutting process environment (M1) includes the cutting tool, workpiece, CNC machine and operator.
- Sensor system (M2) includes a CF flow sensor and an industrial temperature measurement sensor which gather data from the cutting process.
- Control Unit (M3) provides the necessary data on cutting process parameters such as cutting speed, feed rate and depth of cut.
- Minicomputer (M4) is a small computing device such as Raspberry Pi, Banana Pi, Arduino, or others that can be used to process data locally.
- Edge/Gateway/Cloud (M5) includes Edge, Gateway, and Cloud, and is used to store and analyse data.
- AI methods (M6) include proven techniques like Artificial Neural Network (ANN), Genetic Algorithm (GA), and others that have proven successful in similar optimization problems [21].

Main controls:

- CFs knowledge (C1) involves knowledge about the properties and characteristics of CFs and their effects on the cutting process.
- Sensors knowledge (C2) involves knowledge about the working principles of sensors used in the system.
- Rules and limitations of optimization (C3) involve rules and limitations that need to be considered during the optimization process, such as surface quality and main machine time requirements.
- Cutting process standards (C4) involve adhering to ISO standards and recommendations, such as temperature interval control, which provide guidance for optimization decisions.
- AI knowledge (C5) involves knowledge about applying AI methods to optimize the cutting process.

Main output:

- Optimization (O1) and/or User Defined Model (O2) in this case includes the optimized CF usage and ensures that the cutting process is sustainable, reducing the CF usage while maintaining the required processing quality and productivity. The model provides recommendations on the optimal cutting process parameters that will achieve the desired objective: minimizing CF usage without compromising production quality and productivity. The model should allow taking into account different criteria and different boundary conditions.

The decomposition process starts with the highest level of the SADT diagram, which is the context diagram, and progresses down through successive levels of detail. At the second level, the context diagram is decomposed into major processes with accompanying inputs, outputs, mechanisms, and control elements, with each process represented by a box, as shown in **Fig. 2**. Each process in SADT has its own label in the lower right corner of the box. The main processes represented in this first hierarchical decomposition step of the SADT diagram are Data processing (A1) and Decision support system (A2).

The process A1 - Data processing in the SADT diagram involves several steps to prepare and process the data obtained from the cutting process. During this process, the system acquires necessary data from sensors and control unit. This data is then processed and stored for later use. The purpose of this process is to ensure that the system has access to relevant and accurate data for optimization or

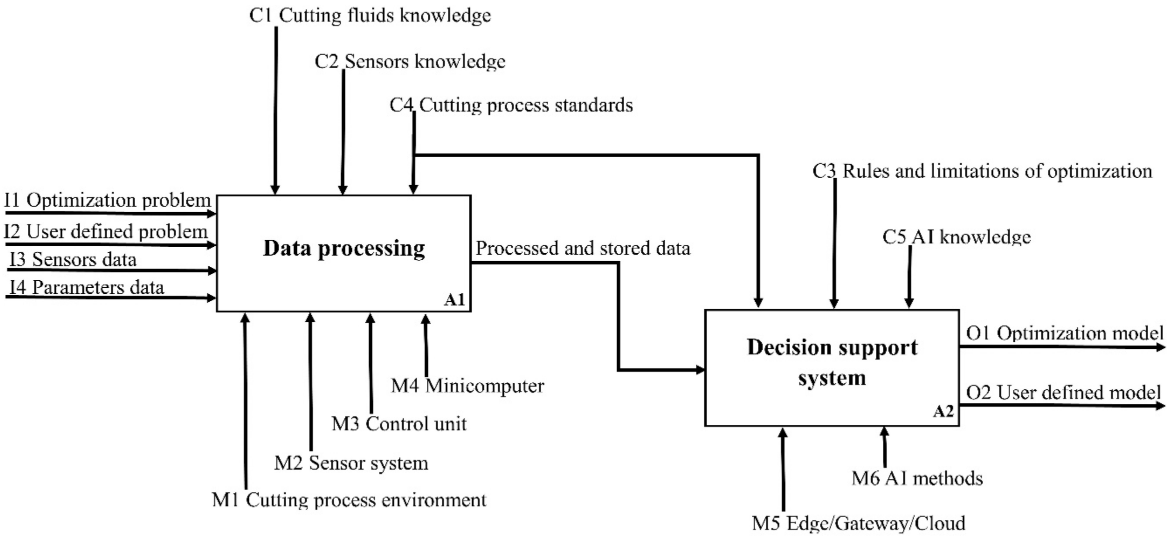

Figure 2. *Main processes of Smart information system – A0*

solving user defined problems. The processed and stored data represent the output of this process.

The process A2 - Decision support system is another main process in the SADT diagram that involves several steps for preparing and analysing the data that have been previously processed and stored locally. The output of the A1 process (processed and stored data) represents the input to this process. As part of this process, the system classifies and stores data on the cloud. Defined correlation between analysed data is used for developing optimization and/or user defined model. The model will be built to satisfy different objective functions and different boundary conditions. The decision support system serves to define optimal process parameters depending on and in accordance with optimization criteria and boundary conditions. Initially, this decision support system (expert system) based on expert knowledge will define a set of rules for analysing data and making preliminary decisions. Therefore, the expert system initially serves for process control and control of the optimization function to define the minimum value of CF usage. The knowledge required for this system will be acquired from specialists in academia and industrial engineering. In this process, depending on the case, optimization can be performed using optimization methods, or prediction can be applied using machine learning methods, or both. As more data is acquired, suitable AI methods will be applied.

Finally, at the third level, each process in the second level is decomposed further into sub-processes. The decomposition of the A1 process is shown on a separate SADT diagram in **Fig. 3**. The process A1 includes three sub-processes: Planning and preparation (A11), Data acquisition and processing (A12) and Data storage (A13). Each sub-process in SADT diagram is represented by a box with associated inputs, outputs, mechanisms and control elements (ICOM box).

The sub-process A11 - Planning and preparation involves defining the objectives, identifying the requirements, and planning the resources needed for data processing. During the planning and preparation sub-process, the system determines the data collection requirements and identifies the necessary sensors and equipment to be used as data sources. The aim of this sub-process is to ensure that data processing is properly planned and prepared before it begins, and that all necessary resources, including hardware and software tools, are available to execute the process efficiently and effectively. The output of this sub-process is a planned and prepared system for collecting the necessary data.

The sub-process A12 - Data acquisition and processing involves obtaining data from two sources and processing it to extract meaningful information. In order to eliminate superfluous data artefacts that are not pertinent to the analysis, such as noise, short circuits, and downtime, the data must undergo pre-processing. The system removes any errors or inconsistencies in the data during this sub-process. The control unit serves as the data source, providing information regarding the cutting process parameters such as cutting speed, feed rate, and depth of cut. The second data source is the sensor system, which includes an industrial temperature measurement sensor and a CF flow sensor. The system converts the raw data into a structured format suitable for storage and further analysis. The sub-process includes data validation, filtering, cleaning, and transformation. The goal is to ensure the collected data is accurate, reliable, and usable for subsequent analysis. The output of this sub-process is the acquired and processed data, which can be used for further analysis.

The sub-process A13 - Data storage involves securely and efficiently storing the processed data. The output of the A12 sub-process (acquired and processed data) serves as the input for this sub-

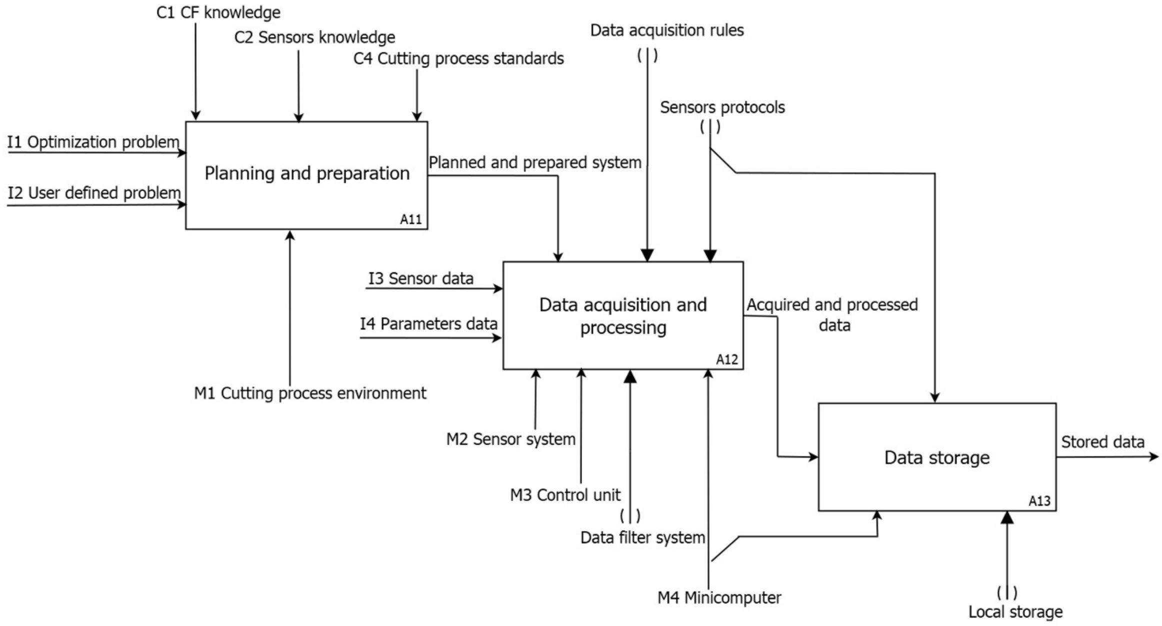

Figure 3. *Sub-processes of Data processing – A2*

process. The sub-process involves storing the acquired and processed data locally on external hard drive. The system ensures that the stored data is organized. This sub-process uses suitable storage techniques and data structures to store data in a structured file format, which can be easily accessed. The sub-process includes a strategy for backup and recovery in case of data loss. The primary purpose of this sub-process is to ensure that the processed data is both accessible and secure. The output of this sub-process is the locally stored data.

The decomposition of the A2 process is shown on SADT diagram in **Fig. 4**. The process A2 includes three sub-processes: Preparation of data for analysis (A21), Data analysis (A22) and Smart model development and application (A23). Each sub-process in SADT diagram is represented by an ICOM box.

The sub-process A21 - Preparation of data for analysis involves preparing the data for subsequent analysis on a cloud-based platform. The output from the main process A1, or more specifically from the sub-process A13 (stored data), represents the input to this sub-process. This sub-process involves receiving data and storing it in the cloud. The sub-process includes cleaning, transforming, and formatting the data to ensure that it is compatible with the cloud platform. Data transfer to the cloud is performed according to protocols and at specific intervals, unless there are any obstacles. If the connection to the cloud is interrupted for any reason, the data is still locally saved within the preceding A13 sub-process. Once the connection is restored, the data is transferred to the cloud. On the cloud, the data is classified, stored, and properly prepared in a suitable organized structure to be analysed. The purpose of this sub-process is to provide logically organized data on the cloud for further analysis. The output from this sub-process is prepared data for analysis.

The sub-process A22 - Data analysis involves analysing the prepared data. The purpose of this sub-process is to identify trends, anomalies, patterns, correlations, and insights within the data. The sub-process includes exploratory data analysis. The output of the A21 sub-process (prepared data) represents the input to this sub-process. This sub-process involves using various data analysis techniques to draw meaningful conclusions from the data. The use of various data analysis techniques allows to analyse large datasets in different ways and thereby identify complex correlations between process parameters. The primary objective of this sub-process is to obtain useful insights that can help optimize and solve problems in the cutting process environment. The output of this sub-process is a defined correlation between data.

The sub-process A23 - Smart model development and application involve the use of an expert system, optimization methods and AI methods, depending on the case and the amount of acquired data. This sub-process generates optimization recommendations or problem solutions that can be directed towards the user or integrated back into the physical system for real-time optimization and management. The goal is to define optimal cutting process parameters depending on various criteria and boundary conditions. In this case, primary objective is to optimize or solve the cutting process by reducing the usage of CF while ensuring that the quality of the final product and productivity are not compromised. The Smart model focuses on making decisions to solve complex challenges in the manufacturing process. Initially, the expert system will be used to

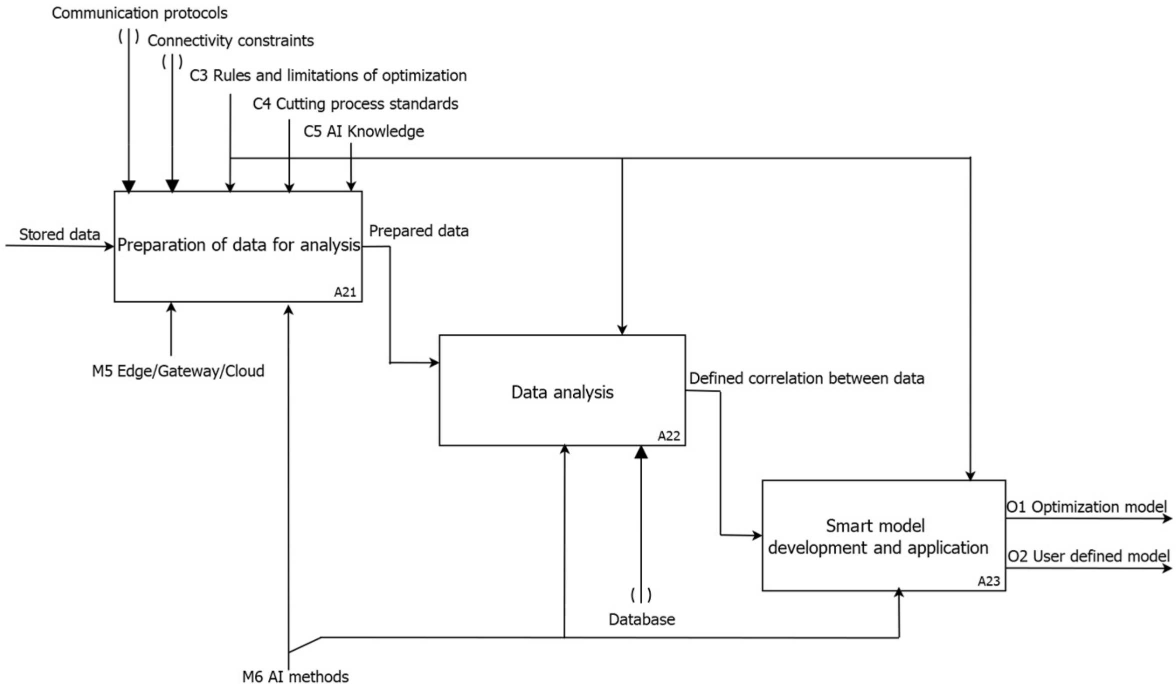

Figure 4. *Sub-processes of Decision support system – A2*

make preliminary decisions using predefined rules based on expert knowledge from academia and industry. Additionally, the optimization model will be applied to determine the optimal parameters for solving the defined optimization problem in the cutting process. As the research progresses, machine learning techniques will be used to predict and explore different solutions as a result of accumulating sufficient sensor data. The aim is to enhance the predictive capabilities of the system and further optimize the decision-making process in the production environment. The system is continuously improved, refining and adapting its own optimization and/or user defined models using an ever-increasing dataset, thereby increasing its maturity over time. The system provides direct support to decision-making processes by offering specific recommendations or even acting autonomously.

V. DISCUSSIONS

The conceptual system is based on the extensive authors experience in the field of production engineering and workflow management. The conceptual model is the first step in introducing DT, which will help authors transfer their knowledge into a novel workflow based on the sensors' real-time data. In this stage, authors propose an information system model that will be used for the data acquisition, and in the initial stage, expert knowledge will be used to form an expert system based on the user (expert) experience in manufacturing process. The conceptual model does not define any specific optimization or machine learning models, yet it presents the manufacturing process management system's overall structure, with the example of CF monitoring.

Initially, in the first stage of the information system application, an expert system (decision support system) will be used to define a set of rules which will be applied for analysing data and making initial decisions. The knowledge will be acquired from specialists from academia and industrial engineers. Then, an adequate AI method(s) will be applied when enough data is acquired, like the ones mentioned in [21]. To conclude, the smart part of the information system will be developed by applying different techniques based on the available data, and it will be a dynamic model, which means it will use various methods to establish adequate decisions. It will be constantly tested by using expert knowledge directly, or by an initially defined decision support system.

In summary, this paper focuses on the concept of an information system model as a foundation for implementing a DT within the manufacturing domain. By combining the authors' expertise, sensor-based real-time data, expert knowledge, and AI methodologies, the conceptual system aims to optimize and solve various optimization and/or user defined problems in manufacturing processes.

VI. CONCLUSIONS

In conclusion, the use of CFs is a major source of environmental pollution and health risks, and reducing their usage is a key priority for manufacturers. In machining processes where dry machining is not applicable, it is necessary to optimize the machining process to minimize the CF usage. That is why the focus is on solving this problem. This paper proposes a conceptual model of an information system based on digital twin (DT) of cutting processes with a focus on optimizing the CFs usage, considering ecological sustainability. The conceptual model proposed in this study was developed using the SADT methodology owing to its hierarchical decomposition. The conceptual system described in this paper is built upon the author's extensive experience in manufacturing engineering and workflow management.

The system aims to leverage digital twin technology and real-time sensor data to improve manufacturing processes. In the first step, data will be acquired, followed by making initial decisions using an expert system or an objective function (optimization). When enough data is acquired, machine learning will be applied to predict different solutions. The smart component of the information system will be dynamically developed using various techniques based on available data, continually tested with expert knowledge or an initially defined decision support system.

The conceptual model is aligned with the vision of cleaner production and sustainable development, and it offers a promising approach for optimizing CF usage in CNC machining processes. Considering that the conceptual model is general, it can also focus on solving other problems and needs of the process. The proposed model can be integrated with existing CNC machines to reduce environmental impact and improve worker safety, while also reducing costs associated with CF usage. Also, with different criteria, boundary conditions and objective functions, the system will be able to adapt and make decisions to solve various optimization and/or user defined problems in manufacturing processes. Overall, this paper highlights the importance of optimizing machining processes in line with environmental protection and demonstrates the potential of optimization models for achieving ecological sustainability in manufacturing.

The authors' global objective is to improve optimization and prediction accuracy using this system, and active efforts to achieve this will be undertaken in the forthcoming period.

Acknowledgement

This research was financially supported by the Ministry of Science, Technological Development and Innovation of the Republic of Serbia (Contract No. 451-03-47/2023-01/ 200109).

AUTHOR CONTRIBUTIONS

M. Barać: Conceptualization, Theoretical analysis, Writing, Review and editing.

N. Vitković: Conceptualization, Theoretical analysis, Review and editing, Supervision.

D. Marinković: Supervision.

P. Janković: Review and editing.

D. Mišić: Theoretical analysis.

Disclosure statement

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

ORCID

Milica Barać https://orcid.org/0000-0002-5355-693X

Nikola Vitković https://orcid.org/0000-0001-6956-8540

Dragan Marinković https://orcid.org/0000-0002-3583-9434

Predrag Janković https://orcid.org/0000-0001-9951-4500

Dragan Mišić https://orcid.org/0000-0001-8765-3204

References

[1] D. Fratila, Environmentally friendly manufacturing processes in the context of transition to sustainable production, Comprehensive Materials Processing 8 (2014) pp. 163-175. https://doi.org/10.1016/B978-0-08-096532-1.00815-3

[2] M. M. Rahman, M. Hassan, M. Abdullah-Al Bari, An optimize system of using cutting fluid in machining operation for light work machine shop, International Journal of Engineering and Applied Sciences 4 (1) (2012) pp. 1-8. https://dergipark.org.tr/tr/download/article-file/217686

[3] S. Debnath, M. M. Reddy, Q. S. Yi, Environmental friendly cutting fluids and cooling techniques in machining: a review, Journal of cleaner production 83 (2014) pp. 33-47. https://doi.org/10.1016/j.jclepro.2014.07.071

[4] X. C. Tan, F. Liu et al., A decision-making framework model of cutting fluid selection for green manufacturing and a case study, Journal of Materials processing technology 129 (1-3) (2002) pp. 467-470. https://doi.org/10.1016/S0924-0136(02)00614-3

[5] A. Alok, S. Kumar, et al., Review on the effect of surface textured tool in the field of machining, Advances in Materials and Processing Technologies (2023) pp. 1-19.

https://doi.org/10.1080/2374068X.2023.2184580

[6] H. J. Heine, Dry Machining: A Promising Option, Foundry management & technology 126 (9) (1998) pp. 50-56.

[7] N. King, L. Keranen, et al., Wet versus dry turning: a comparison of machining costs, product quality, and aerosol formation, SAE Technical Paper (2001) 2001-01-0343. https://doi.org/10.4271/2001-01-0343

[8] E. Benedicto, D. Carou, E. M. Rubio, Technical, economic and environmental review of the lubrication/cooling systems used in machining processes, Procedia engineering 184 (2017) pp. 99-116. https://doi.org/10.1016/j.proeng.2017.04.075

[9] M. Barać, N. Vitković, M. Manić, Conceptual model of an information system for measuring cutting fluid temperature on CNC machines, in: J. Baralić, N. Dučić (Eds.), 38th International Conference of Production Engineering: ICPE-S 2021, University of Kragujevac, Faculty of Technical Sciences Čačak, Serbia, 2021, pp. 68-75. http://spms.fink.rs/doc/2021/Proceedings%20SPMS%202021.pdf

[10] C. G. Yuan, A. Pramanik, et al., Drilling of titanium alloy (Ti6Al4V)–a review, Machining Science and Technology 25 (4) (2021) pp. 637-702. https://doi.org/10.1080/10910344.2021.1925295

[11] T. H. C. Childs, K. Maekawa, P. Maulik, Effects of coolant on temperature distribution in metal machining, Materials science and technology, 4(11), (1988) pp. 1006-1019. https://doi.org/10.1179/mst.1988.4.11.1006

[12] F. Wilking, B. Schleich, S. Wartzack, Digital twins-definitions, classes and business scenarios for different industry sectors, in: Proceedings of the International Conference on Engineering Design (ICED21), Cambridge University Press, Gothenburg, Sweden, 1, 2021, pp. 1293-1302. https://doi.org/10.1017/pds.2021.129

[13] D. A. Marca, C. L. McGowan, SADT: Structured Analysis and Design Technique, McGraw-Hill Book Co., Inc.: New York, 1988.

[14] X. Liu, D. Jiang, et al., A systematic review of digital twin about physical entities, virtual models, twin data, and applications, Advanced Engineering Informatics, 55 (2023) 101876. https://doi.org/10.1016/j.aei.2023.101876

[15] W. Kritzinger, M. Karner, et al., Digital Twin in manufacturing: A categorical literature review and classification, in: M. Macchi, L. Monostori, R. Pinto (Eds.), 16th IFAC Symposium on Information Control Problems in Manufacturing INCOM 2018: IFAC (International Federation of Automatic Control) Proceedings Volume 51 (11), IFAC-PapersOnLine with Elsevier, Bergamo, Italy, 2018, pp. 1016-1022. https://doi.org/10.1016/j.ifacol.2018.08.474

[16] C. Bianconi, A. Bonci, et al., (2020, System thinking approach for digital twin analysis, in: 2020 IEEE International Conference on Engineering, Technology and Innovation (ICE/ITMC), IEEE, Cardiff, UK, 2020, pp. 1-7. https://doi.org/10.1109/ICE%2FITMC49519.2020.9198392

[17] D. T. Ross, K. E. Schoman, Structured Analysis for Requirements Definition, IEEE Transactions on Software Engineering, SE-3 (1) (1977) pp. 6-15. https://doi.org/10.1109/TSE.1977.229899

[18] F. Ahmed, S. Robinson, A. A. Tako, Using the structured analysis and design technique (SADT) in simulation conceptual modelling, in: A. Tolk, S. D. Diallo, I. O. Ryzhov, L. Yilmaz, S. Buckley, J. A. Miller (Eds.), Proceedings of the 2014 winter simulation conference, New York: IEEE, Savannah, GA, USA, 2014, pp. 1038–1049. http://doi.org/10.1109/WSC.2014.7019963

[19] M. E. Dickover, C. L. McGowan, D. T. Ross, Software design using: SADT, in: Proceedings of the 1977 annual conference (ACM '77). Association for Computing Machinery, New York, NY, USA, 1977, pp. 125–133. https://doi.org/10.1145/800179.810192

[20] D. T. Ross, Applications and Extensions of SADT, Computer, 18 (4) (1985) pp. 25-34. https://doi.org/10.1109/MC.1985.1662862

[21] M. Barać, N. Vitković et al., A review of machine learning methods applied in smart machining, in: M. Zdravković, M. Trajanović, Z. Konjović (Eds.), 12th International Conference on Information Society and Technology: ICIST 2022 Proceedings, Information Society of Serbia – ISOS, Belgrade, Serbia, 2022, pp. 244-246. https://www.eventiotic.com/eventiotic/files/Papers/URL/96770bc7-0fd1-442f-95f9-d2e805b598a2.pdf