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TOWARDS THE DIGITAL MODEL OF TOOL LIFECYCLE MANAGEMENT IN SHEET METAL FORMING

Sheet metal forming is a critical process in the manufacturing industry, which involves shaping sheet metal into desired configurations and structures. The use of digital tools in the lifecycle management of sheet metal forming tools has become increasingly important to ensure the efficiency and effectiveness of the process. The digital model of tool lifecycle management (TLM) in sheet metal forming provides a complete approach to manage the entire lifecycle of tools used in sheet metal forming. It enables optimization of tool design, simulation of the tooling process, real-time monitoring of tool conditions, and retirement and replacement of tools. This approach improves efficiency, reduces costs, and ensures optimal performance in sheet metal forming. The paper presents an elaborate analysis of the development of TLM models concerning the progress in ICT modelling and its implementation in the field of sheet metal forming. Furthermore, the paper includes an exemplary TLM model for an industrial enterprise.

1. INTRODUCTORY NOTES

With the Industry 4.0 model, smart manufacturing enables many advantages for the metal industry. One of the most significant benefits is the quick adaptation of manufacturing to customer demands, with better productivity, efficiency, and quality [1]. When implemented correctly, smart manufacturing (SM) increases the ability to monitor the entire manufacturing process and adapt it to achieve optimized production throughout. The workshop (WS) in our example uses Manufacturing Execution System (MES), a real-time system that integrates data from multiple sources to monitor and control the manufacturing process. MES plays a vital role in SM by collecting and analysing production data from various equipment and sensors, automated operations, and manual processes, delivering this information to all manufacturing stakeholders and providing real-time status updates.

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MES is the basis for online management according to the Industry 4.0 model in real manufacturing in the plant. On the other hand, it integrates all digital product models and forms the hub of the engineering (CAD/CAPP/CAM/CAI) and business (CRM/SCM/ERP) planning functions from which the manufacturing management model in WS (MES) grows [2]. Conducted research on the practice of Industry 4.0 showed that the application of MES management modelling agents is not adequate for industrial application. Therefore, the software-defined control (SDC) model [3] is proposed as adequate at this time. It is also important to point out that it is compatible with ISA-95, where MES and Enterprise Resources Planning (ERP) are mutually integrated and logically centralized. This approach was also used in our TLM model, in this paper.

This paper comprises of the following aspects: (a) the introduction provides a fundamental overview of SM, which includes the TLM model as an integral part, (b) the second part meticulously demonstrates the impact of ICT development on research, development, and industrial application of sheet metal processing tools, from the mid-1980s to date, (c) the following section elaborates on the developed and applied TLM model in an industrial company, as part of an applied project on digitization of manufacturing based on Industry 4.0, and (d) finally, future directions for research and development of this TLM model for the industry are provided.

2. ANALYSIS OF RESEARCH AND APPLICATION OF ICT MODELS IN LIFECYCLE OF SHEET METAL FORMING TOOLS – LITERATURE REVIEW

The analysis of the state of development of research and application of tools for sheet metal, primarily those for blanking, bending and deep drawing, is carried out in this paper along two axes:

a) development and application of ICT technologies in the planning of the technological process of sheet metal processing and the exploitation of tools in production, by monitoring the necessary parameters:
    a. until 2010 (Industry 3.0),
    b. from 2010 to 2020 (Industry 4.0), and
    c. after 2020 (Industry 5.0).

Another axes of analysis is their lifespan:

a) design (according to the parts that will be made on them). For these reasons, this paper analyses different approaches to planning technological processes with plastic deformation, and
b) production and operation, following especially the processes that take place on them.

According to these approaches, an analysis of their development and application from the mid-nineties of the last century to the present day was carried out. In this way, the global trends of future development in this area. As our contribution to this analysis, in the second part of this paper, an industrial example of the TLM model for tableware production is given, which includes the elements of I 3.0 and I 4.0 with the prospect of applying the I 5.0 model.

2.1. THE PRE-2010 LIFECYCLE OF SHEET METAL FORMING TOOLS DURING THE ERA OF INDUSTRIAL REVOLUTION 3.0

The first period of analysis refers to the period of the twentieth century, the last two decades, as well as the first decade of the twenty-first century, which is characterized by intensive development and application of ICT technologies in production. This period is known as Industry 3.0, and it meant computerization in production, through the creation of "automation islands", which solved certain segments of business and production.

The feature approach in forming dies, the objective is quickly and efficiently machine prototype dies for stamping the first part [4]. This approach is based on defining characteristic morphologies of the forming dies, and the definition of the geometrical model of each feature, using the concepts of "concave" and "convex", Table 1.

Table 1. Comprehensive Analysis of Research and Application of ICT Models in the Pre-2010 Lifecycle of Sheet Metal Forming Tools during the Era of Industrial Revolution 3.0

Input Mechanism (model)	ICT application model (AI Techniques)	Output data (solution)	References
CAD/CAM experimental station.	Feature modelling.	Rapid and high-quality manufacturing of prototype dies.	[4] (1993)
Numerical tool model.	Simulation.	Reliable operation of the tool.	[5] (1996)
Tool life prediction and management (TLPM).	Regression analysis.	Sheet metal tool life.	[6] (1996)
Predictive tools, intelligent design strategies, and local adaptive control systems.	Simulation.	The controllability and flexibility of stamping dies design.	[7] (2001)
Knowledge and experience about the process.	Expert system and Fuzzy logic	Intelligent control of the blanking process.	[8] (2008)
The multi sensor approach (force and acoustic sensors and intelligent camera).	Camera DTSO with a CMOS sensor, FPGAs, RAMs, and a USB 2.0 connection.	The artificial vision system design.	[9] (2008)
SMAs in forming tools to improve control of the material deformation process.	SMAs shape memory properties.	Driven by innovation in tool structure design.	[10] (2006)
Artificial vision and ANN with fuzzy logic-based automatic process control.	ANN and Fuzzy logic.	Real-time adjustments and compensating for any variations in the material properties.	[11] (2005)
A thermo mechanical stress analysis of a superplastic forming (SPF) tool during the entire forming process.	Simulation by FEM.	Residual stress and distortion accumulate as the loading cycle progresses.	[12] (2005)
EMD to extract the main features of the strain signals.	Learning vector quantization (LVQ).	Hilbert marginal spectrum, which defines fault of the sheet metal stamping process.	[13] (2007)
Force pressure and material parameters.	FEM model for tool wear.	Reduce tool wear and increase tool life.	[14] (2004)
On-line measurement deep drawing process with FEM simulation.	FEM and Fuzzy controller.	The controlled variable for closed-loop control of deep drawing processes.	[15] (2003) [16] (2002)
The integrated sensing technique quantifies process variations and provides a reference base for process control to ensure product quality.	The thin-plate spline (TPS) method.	The on-line observability of the stamping process and ensuring part quality.	[17] (2009) [18] (2007) [19] (1989)
CAD model of parts for FME analysis of die tool.	ES for Computer Aided Process Planning (CAPP) of Die Design.	The integrated process simulation and die design system.	[20] (2008)

Deep analysis of influence factors on tool die life.	Knowledge based system (KBS).	Tool life prediction for sheet metal working.	[21] (1992) [22] (1991)
CAD model of part.	FME analysis of sheet metal deformation.	Used in the automotive industry.	[23] (2001) [24] (2000)
CAD model of part.	AI Applications to Metal Stamping Die Design.	Support for engineers and designers in making decisions.	[25] (2010)
Methods and techniques for tool repair.	Simulation.	Knowledge of the advantages and limitations of various repairing options.	[26] (2013)
Model of the part that will be produced in the tool.	FEM simulation and ANN	FEM simulation to create training cases for ANN(s) and predict the performance tool of the design.	[27] (2008)
Indicate problems such as die wear, material flow problems or improper lubrication.	Vector regression (SVR) to detect deviations from expected process outputs.	Detecting abnormal thermal patterns in the dies during the stamping process.	[28] (2005)
Determines whether a given part can be produced using stamping technology.	KBS for stamping process.	The knowledge-based system enables stamping process planning.	[29] (2006)
A methodology for analysing the roughness of the formed pieces as a measure of tool wear.	Roughness parameters as tool wear form.	The scatter in the friction coefficients caused by wear was quantified.	[30] (2001)
CAD model part.	KBS for process-planning of deep-drawing.	The optimization of deep-drawing operations.	[31] (1986)
Influence parameters: surface preparation, tool geometry and the material of the tool.	Simulation.	Optimizing production processes.	[32] (2011) [33] (2008)
CAD model part.	KBS in sheet metal stamping.	The reasoning logic scheme.	[34] (2013)
Data and knowledge of CAD models.	KB CAPP model for sheet metal components.	Data and knowledge of CAPP model integrated.	[35] (2013) [36] (2004)
CAD/CAM model for tools.	CAI model for tool.	CMM inspection of tools.	[37] (2000)
CAD/CAE/CAM system.	The digitized-die forming (DDF) technology	Model of final part.	[38] (2007)
KBS has a module (symbolic module) and a process-modelling analysis module (numeric module).	KBS for axisymmetric sheet metal.	Generate initial-guess process sequences.	[39] (1991)
Customer request for product (tool)	Platform for product design with user interface.	Tool solution (technical drawing and EBOM).	[40] (2005)
FME model.	Simulation of sheet metal forming.	Optimum solution for each case.	[41] (2000)
Integrated process simulation and die design system.	FME and CAPP for sheet metal.	FEM analysis and manufacturing plan.	[42] (2013) [43] (2005)
Using the CBR methodology to plan stamping processes and design stamping dies.	KBS for process planning and die design in the automotive industry.	Adapt existing designs or generate new designs based on stamping knowledge.	[44] (2010)
Integrate CAD with FEA, and ANN.	Hybrid intelligent systems (FME and ANN) process planning and die design.	Process plan for die.	[45] (2000)
Meta modelling techniques.	Integrating support vector regression (SVR), design of experiment (DOE) and FME.	The optimization of sheet forming design.	[46] (2010)

The problem of errors in the shape of parts caused by improper operation of some elements (for example, return spring) is a very common defect in sheet metal processing processes. In [5], a model for numerical tool design was developed and applied, where the accuracy of tool operation became absolute. New approach to tool life prediction and management (TLPM) [6], where integrating theoretical predictions with real-time data-driven modifications, this approach can help manufacturers optimize their tooling processes and improve efficiency in the production process. The use of advanced predictive tools, intelligent design strategies, and local adaptive control systems allows for increased controllability and flexibility of stamping dies, which ultimately leads to higher quality and cost-effectiveness of the final product (sheet metal part) [7]. The intelligent control system based on expert systems, has been developed to emulate the decisions that expert operators make but in a faster and more reliable manner. The developed intelligent control system has been installed in a blanking facility, and very good results have been achieved [8]. The multi sensor approach using artificial vision will improve fault detection robustness, leading to a zero-defect forming control system that minimizes costs and maximizes the throughput of parts [9]. Innovative tool structures/systems can be categorized into three groups: conventional geometric design modifications, unconventional geometric design modifications, and hybrid modifications. A new forming tool concept was introduced that involves the use of shape memory alloys (SMAs) integrated into the tool structure [10]. To improve reliability and avoid production breakdowns, an integrated automatic control system has two parts: (a) the diagnosis and prediction system uses by sensors, artificial vision, and neural networks to identify any deviations in the sheet metal stamping processes and predict the likely results, and (b) the automatic control system, which is based on fuzzy logic [11]. The numerical simulation can be used to compare various materials that can be used to manufacture the forming tool, and selection of the most suitable material based on its thermo-mechanical properties and cost-effectiveness [12]. Empirical mode decomposition (EMD) to extract the main features of the strain signals into intrinsic mode functions (IMF) [13]. The signal energy and the Hilbert marginal spectrum, which reflects the working condition and the fault pattern of the sheet metal stamping process. Developed is a finite element model for the numerical prediction of die wear tool, which allows for the evaluation of its life, which is a function of the force pressure and some material parameters [14]. The new optical sensor, contact-free recording of the material flow to predict faults that occur during the deep drawing processes, such as cracks, which can ultimately improve the quality of the finished product [15,16]. Used are two sensing methods that create a tooling-integrated sensing system: mutual inductance-based displacement measurement for sheet draw-in and distributed contact pressure measurement at the tool- workpiece interface [17–19]. The force sensor data were numerically interpolated to form the contact pressure distribution across the tool- workpiece interface using the thin-plate spline method. Example of integrated solutions for both process planning and die design engineers in the automotive industry by ES [20]. Tools form the critical interface between machines and workpieces during the process of sheet metal working. Successful tool design and manufacturing techniques and emphasizes the importance of a knowledge-based approach that combines computer-aided techniques with human experience in predicting tool life [21, 22]. There is intense information exchange between the people working with sheet metal forming simulation, Finite Element (FE) specialists, and the people working with the die design (process engineer) [23, 24]. AI techniques developed and applied in stamping die design are: expert system (ES), knowledge-based system (KBS), neural network (NN), fuzzy logic (FL), agent-based system (ABS), rule-based system (RBS), analytical hierarchy process (AHP), object oriented techniques (OOT), and case-based reasoning (CBR) [25]. Failure analysis of dies and molds are crucial to understand the causes of failures during operations, which can include high thermal shocks, mechanical strain, cyclic loading, corrosion, and other factors. These failures can result in heat checking, wear, plastic deformation, and fatigue [26]. The traditional die design and development, design is usually based on heuristics and experiences. In [27] an integrated methodology based on FEM simulation and artificial neural networks (ANN) was given to approximate the functions of design parameters and evaluate the performance of designs to identify optimal designs. The sheet metal stamping process is a widely used manufacturing process, but it involves complex interactions between the press, dies, material, and forming process. Despite advanced technologies like vector regression (SVR) and computer control, malfunctions can still occur, making condition monitoring and fault diagnosis important [28]. The knowledge-based framework includes a knowledge base, reasoning engine, and user interface. The knowledge base contains domain-specific knowledge related to stamping, including design rules, material properties, and process constraints [29]. Observations of the formed pieces and wear of the AISI M2 tool steel were used to predict the tool wear when roughness parameters exceed fixed criteria. The application of this methodology allows for the lifetime of the tool to be predicted before any workpiece is formed, providing a proactive approach to tool replacement or polishing [30]. The model provides a structured approach to deep-drawing axisymmetrical parts that can be readily utilized by an automated process-planning procedure [31]. Paper [32, 33] explores the factors that affect the wear and life length of production equipment for sheet metal forming operations, which is largely dependent on the wear of the tools that are in direct contact with the sheet. KBS in sheet metal workings, the analysis covers different stamping phases, including stamped part design, stamping process planning, die structure planning and manufacturing (with a focus on progressive die designs), and strip layout planning [34]. KBS increase accuracy and consistency in the decision-making process, leading to enhanced product quality and reduced production costs. Data and knowledge modelling for the integration of CAD (design) and CAPP (process planning) activities for sheet metal components [35, 36], as a framework that aims to bridge the gap between data and knowledge models and establish a common foundation for integration between the two domains. The quality control loop, as a CAI model, emphasizes the importance of limiting the measurement and feedback to selected areas in order to minimize cost and time, and improve the quality tool [37]. Varying deformation path DDF allows for the manufacture of sheet parts along an optimal forming path, which can achieve large deformation for materials with poor formability [38]. The closed-loop forming system has been developed by combining DDF with a rapid 3D-shape measurement system to compensate for material spring back and improve dimensional accuracy. In [39] presents a tool called the "product audit" that enables a design team to evaluate their products against a range of criteria, with the aim of identifying areas for improvement, with a case study of a tool for stamping process. In the past decade or so, Computer Aided Process Planning (CAPP) and Die Design have become essential engineering tools in the field of sheet metal forming, particularly in the automotive industry

[40]. In [41] it identifies the basic requirements of simulation tools and discusses various methodologies, with a focus on static explicit and dynamic implicit finite element procedures. These tools have gained significance parallel to the rapid development of Finite Element Modeling (FEM) [42, 43]. The paper [44] has key innovations in the integration of case-based reasoning (CBR) into the regular process planning and die design processes to generate a hybrid KBE system. In [45] ANNs are trained from finite element analysis (FEA) results for a generic set of component geometries, process conditions, and material properties. The final die design validation is carried out by FEA. The meta model-based optimization method by integrating support vector regression (SVR) and an intelligent sampling strategy in order to optimize sheet forming design, was given in [46].

The performed analysis allows us to define the following conclusions: (a) a period of about three decades enabled the development and industrial application of a large number of AI tools and techniques, and (b) all this was the basis for the development of ideas and the definition of the Industry 4.0 model, which will be the subject of analysis in the next point of this paper.

2.2. THE 2010-2020 LIFECYCLE OF SHEET METAL FORMING TOOLS DURING THE ERA OF INDUSTRIAL REVOLUTION 4.0

Industry 4.0 is an advanced model of automation of technological systems based on the networking (IoT) of production technology entities (CPS), with the use of clod computing and optimization of large amounts of data (BDA analysis). All technological processes are monitored online and decisions are made by AI/ML systems, while humans are informed about it or just monitor them. Of course, this is all that has been said before, at the moment it is true for pilot plants and research centres, and the widest industrial application goes towards this model, through the application, step by step, of certain elements of Industry 4.0, of which there are currently 48. And tools for sheet metal processing are part of this concept, and for that reason, an analysis of its application in this area is carried out in the following text.

The review highlights advances in tool materials, such as high-speed steels and polycrystalline diamond, as well as advanced fabrication processes that enable the production of complex geometries and surface textures. Sensing and data analytics techniques for tool monitoring and predictive maintenance are given in [47], Table 1.

Table 2. Comprehensive Analysis of Research and Application of ICT Models in the 2010-2020. Lifecycle of Sheet Metal Forming Tools during the Era of Industrial Revolution 4.0

Input Mechanism (model)	ICT application model (Elements of I 4.0)	Output data (solution)	References
Sensing and data analytics (BDA)	Smart product.	Smart tooling for metal forming including sheet tools.	[47] (2019).
Online monitoring of forces and deformations.	The monitoring and analysis of process (BDA).	Improve the safety, reliability, and performance of sheet tools.	[48] (2014).
Online monitoring of process (die).	IoT (health of sheet tools -BDA).	Sheet tools predictive maintenance.	[49] (2020).

Point topology mappings of products.	3D simulation.	The computed 3D product geometry with very high accuracy.	[50] (2014).
Advanced remanufacturing practices.	Simulation.	Remanufactured dies and molds.	[51] (2014).
Effective approach for monitoring the health condition of punching processes.	On line the wavelet energy distribution.	Punching sheet metal fabricating process.	[52] (2018).
The system consists of three main agents.	Multi-agent technology.	Simulation model based on real-world data for toll management.	[53] (2010).
The sensing points through the construction of continuous CPD maps.	3D simulation.	Determining the contact pressure distribution (CPD).	[54] (2010).
Sensors for online process monitoring.	3D simulation and BDA.	Closed-loop control systems accuracy of metal forming processes.	[55] (2016).
Industry 4.0 technologies in the metal forming industry.	CPS, IoT , DT, BDA and CC.	Improve the efficiency and accuracy of processes.	[56] (2022). [57] (2021). [58] (2020).
Achieving flexibility in metal forming processes.	CPS and IoT	The use of flexible dies, adjustable forming parameters, and adaptive tooling systems.	[59] (2018).
Sustainability evaluation framework.	Industry 4.0 technologies.	Each technology to be evaluated as variable influence on sustainability.	[60] (2020).
The latest sensing technologies used in metal forming processes.	AI/ML and IoT.	On line monitoring process (SCADA support).	[61] (2019).
Remote monitoring and decision making.	SCADA, Cloud computing and BDA.	Online monitoring and process improvement.	[62] (2019).
Monitor and control of CPS for sheet metal processing.	Digital Twin and FEM.	Learning factory.	[63] (2020).
Using sensors and control systems to monitor and adjust the press parameters in real-time.	CPS and IoT.	Digital manufacturing system for sheet metal processing.	[64] (2018).
Flexible and adaptable platform for future manufacturing systems.	Cloud manufacturing.	Intelligent factories and smart manufacturing.	[65] (2016).
Planning and control in SM.	Machine Learning (ML) methods.	Smart manufacturing (SM).	[66] (2020).
Advanced design of sheet metal tools.	Cloud based design.	Digital manufacturing.	[67] (2015).
Process control to improve the quality of stamping parts.	CPS and IoT.	Online scanning.	[68] (2016).
Industry 5.0 .	BDA, Synthetic biology.	Bioengineering will drive innovation, similar to how digitalization is driving innovation today.	[69] (2016).
Complex sheet metal parts.	Non-uniform rational B-spline mesh surface.	Intelligent design method for stamping dies of complex automotive parts.	[70] (2020).
3D part model.	ANN modelling.	Increase the lifespan of sheet metal processing tools.	[71] (2017).
3D part model.	FEM analysis.	Shape and form of part.	[72] (2015).
Stamping Tools for Sheet Metal Forming Future Research Directions	Advanced design and sensor technology.	New concept of Stamping Tools for Sheet Metal Forming.	[73] (2020).
Key components of DTs: sensors and data acquisition, data processing and analytics, modelling and simulation, and visualization and decision-making.	Digital twin for sheet metal processing.	Integrated the physical and cyber aspects of a system.	[74] (2021). [75] (2019).

Knowledge obtained through process simulations.	Industry 4.0 application in the real sheet metal forming process.	On-line measured data into process simulation.	[76] (2019).
Platform for data-driven decision making.	Collaborative monitoring and control system to enhance production process performance.	Real-time production data to enable effective control.	[77] (2020).
Hybrid Machining Processes - the significant increase of process capacity and efficiency.	Advanced manufacturing.	Sheet metal tools.	[78] (2021).
Definition of critical parameters and topology optimization.	FEM simulation.	Enhancing die tool shapes.	[79] (2019).
	CPS - 2M Communication.	IMS	[80] (2018).
3D model of parts.	AM technology for sheet metal forming.	AM technology has the potential to revolutionize sheet metal forming for low quantity production in the automotive industry.	[81] (2019).
Knowledge base of advanced material and friction models.	The KBS-FEM simulation by cloud.	Sheet metal forming processes of aluminum alloy.	[82] (2016). [83] (2019).
3D model of part.	KBS and ANN.	The production of arbitrary individualized sheet metal parts.	[84] (2015).
Cloud-based genetic algorithm-based scheduling application.	Cloud-based production scheduling system.	Cloud manufacturing for the sheet metal manufacturing industry.	[85] (2018).
3D CAD files.	Modelling.	Sheet metal fabrication.	[86] (2023).
Manufacturing process for sheet metal forming.	Learning by experience.	Application of new optimization algorithm of the draw bead restraining force (DBRF).	[87] (2016).

Sensory fasteners provide a unique solution for monitoring mechanical loads and pretensioning forces in various fields of technology, including sheet tools [48]. The integration of elementary sensors into the metallic fastener structure during manufacture results in an assembly of supporting structure and sensor that shows a highly reproductive and sensitive interaction between its mechanical and electrical properties. By model of IoT to improve and apply predictive maintenance in sheet tools [49]. E-DA-3D method is an enhanced numerical approach for designing forming tools in three-dimensional [50]. The paper [51] provides a comprehensive review of advanced remanufacturing practices in the die and mold industry and explores the potential benefits of these practices. In [52] proposes a method of monitoring the punching process using piezoelectric strain sensors to measure the press column's surface strain in response to the stamping force. The approach involves a feature extraction method based on the wavelet transform. The agent model communicates and negotiates among themselves to acquire the required sheet tools at the most competitive price and within the required delivery time [53]. A new method is proposed for determining the contact pressure distribution (CPD) between the tool and the work piece in sheet metal forming processes, using the Thin Plate Spline (TPS) surface generation method, which creates temporal snapshots [54]. Closed-loop control allows for more precise process control, reducing the variability in product properties and improving the quality of the finished product of different sheet forming processes [55]. Industry 4.0 technologies have the potential to improve every stage of the metal forming process, from supply chains and raw material provision to tool design and manufacture, forming operations, energy consumption, cost, quality control, and customer services [56, 57, 58]. Flexibility in the manufacturing environment can be achieved through the use of modular and reconfigurable manufacturing systems, as well as the integration of Industry 4.0 technologies, such as cyber-physical systems and the Industrial Internet of Things (IoT) [59]. The study [60] focuses on examining Industry 4.0 technologies in terms of their application and sustainability implications. The latest sensing technologies used in metal forming processes was given in [61]. The Industry 4.0 concepts and associated sensors and data analytics have the potential to revolutionize the metal forming industry by improving the quality, reducing costs, and increasing flexibility [62]. The paper [63] gives some results of the implementation of Digital Shadows and Digital Twins in the learning factory, supported by FEM analysis. By utilizing servo press systems as CPS and the IoT, manufacturers can improve productivity, product quality, and efficiency while reducing costs and waste [64]. Cloud-Based Manufacturing as one Industry 4.0 pillar by providing agility, flexibility, and adaptability while reducing the challenges associated with complexity [65]. ML methods are applied in manufacturing process planning and control, predictive maintenance, quality control, in situ process control and optimization, logistics, robotics, shop-floor, etc. [66]. The paper [67] shows that cloud-based design and manufacturing is a new and emerging paradigm that has the potential to revolutionize sheet metal tool design. In recent years, the increasing complexity of car body part designs has posed significant challenges for achieving stable forming processes. Piezoelectric actuators have emerged as an effective means of controlling the material flow during the stamping process [68]. Bionics, the imitation or abstraction of natural inventions, and synthetic biology are expected to have a significant impact on engineering development and industry [69]. Current projects in bionics include code engineering, artificial DNA, signalling molecules, and biological circuitry. In [70] was presented an intelligent design method based on parameters aimed at addressing the problem related to curve offset and surface construction. The decision support system based on artificial neural networks to analyse the data obtained from mechanism thermo-mechanical fatigue of sheet metal [71]. FEM simulation presents an excellent approach for predicting the outcome of sheet metal forming processes accurately, thereby improving the efficiency of the process, quality of parts and cost savings [72]. In paper [72] presents the results of a study on progressive stamping tool design. DTs and their major applications in industry (including sheet metal forming), including real-time monitoring, predictive maintenance, and product design and optimization [74, 75]. In [76] was given a hybrid data- and model-based approach, as part of Industry 4.0 concept, that uses reduced process models derived from process simulations, combined with manufacturing data, to capture deviations present in the real sheet metal forming process and incorporate enhanced process knowledge derived from the simulations. To successfully predict and control the outcome of the sheet metal forming process, it is necessary to have a holistic understanding of the product/process parameter influences on output quality [77]. The combination of different physico-chemical phenomena significantly improves manufacturing processes and creates new opportunities concerning sustainable manufacturing and Industry 4.0, including manufacturing of sheet metal tools. Industry 4.0 combines information technology with computer-controlled machines in an online network, allowing for process optimization in real-time [78]. This paper focuses on the use of FEM to optimize die tool geometry for sheet metal forming processes [79]. The system architecture and the networking technique of the system are illustrated in [80] through a case study on a precision mold making system, where we have had that about 40% of mold production time could be shortened.

Additively manufactured forming tools offer a range of potential benefits for prototype construction and small-scale manufacturing, including increased flexibility, faster production, and improved performance [81]. The results show that KBS-FEM simulation by cloud, improves the accuracy of the predictions while significantly reducing the computational time required to run the simulations, about 40% [82, 83]. The knowledge-based system that employs neural networks in forming methods to provide manufacturing strategies for customized sheet metal components was given in [84]. Cloud manufacturing is a novel concept that utilizes centralized cloud computing to support a distributed and collaborative sheet metal manufacturing environment [85]. Sheet metal fabrication is a versatile and widely used manufacturing process, the use of 3D CAD files allows for precise control of machines, resulting in consistent and accurate parts [86]. In [87] he proposes a new intelligent optimization method for sheet metal forming processes based on an iterative learning control model.

And the analysis of the application of the elements of Industry 4.0 in the application of sheet metal tools allows us to define the following conclusions: (a) the application of this concept in this area (sheet metal tools) must be seen as part of its application in the manufacturing industry, which is in a broad sweep, and (b) as well as production, the following elements of Industry 4.0 are most represented in this area, namely: IoT, BDA, AI/ML and Simulation.

2.3. THE POST-2020 LIFECYCLE OF SHEET METAL FORMING TOOLS DURING THE ADVANCEMENTS OF INDUSTRIAL REVOLUTION 5.0

The first decade of the Industry 4.0 concept in the world ended with a mature model of its application in the most developed countries, as an advanced model of automation of technological systems. During the mentioned period, significant changes of a political nature took place in the world, from the disruption of global supply chains to climate change, which caused new thinking about the next stage of development of technological systems. It is defined as Industry 5.0, which basically has the model of Industry 4.0, with special emphasis on: ecology and resource management (sustainable development and circular economy), deepened application of AI (deep ML) and sensible collaboration between man and machine (collaborative robots).

In the rest of this text, a detailed analysis of this concept is given, with a focus on application in the use of sheet metal processing tools.

The reliability of engineered systems is of utmost importance in different industries, for improving reliability, efficient and effective system health monitoring methods of analysing massive amounts of machinery data to detect anomalies and perform diagnosis and prognosis [88], table 3.

Table 3. Thorough Analysis of Research and Application of ICT Models in the Post -2020 Lifecycle of Sheet Metal Forming Tools during the Advancements of Industrial Revolution 5.0.

Input Mechanism (model)	**ICT application model (Elements of I 5.0 AI/ML Deep) Techniques**	**Output data (solution)**	**References**
Deep learning-based models for PHM frameworks.	Deep learning.	Prognostics and Health Management (PHM) machines and processes.	[88] (2020).
Using fusion sensors methods, modern data acquisition systems, virtual simulation.	Machine learning and IoT .	Big data handling, model generalization, and cloud computing latency.	[89] (2023).
Stamping and deep drawing.	Deep learning.	Deep learning model recursively predicts the forming parameters.	[90] (2022).
Industry 5.0 will create a new form of industrialization that is sustainable, efficient, and people-centric.	Industry 5.0.	The sustainability trilemma: to balance economic growth, social development, and environmental sustainability.	[91] (2020). [92] (2020).
Used mathematical, experimental, and simulation software techniques for metal forming.	Smart metal forming.	Optimizing productivity, quality, and economic feasibility.	[93] (2021).
3D model of part.	Scalar-based machine learning methods (SBMLMs).	Metal forming simulations.	[94] (2022).
RAMI 4.0 model.	Big data.	Driver for decision-making support, process optimization, and operational efficiency.	[95] (2021).
Using ML methods: supervised, semi-supervised learning, unsupervised and reinforcement methods.	Machine learning.	ML application roadmap for the manufacturing industry.	[96] (2023). [97] (2022).
The OSM process uses Material Discontinuities (MD).	Life Cycle Analysis (LCA).	OSM requires less energy and produces fewer emissions than the stamping process.	[98] (2023).
Convergence of physical and digital systems.	Industry 4.0/5.0.	The intelligent factory.	[99] (2021).
Knowledge of the interdependencies between the forming tool and machine.	Cognitive production.	Improve process transparency and ensure high-quality formed parts.	[100] (2022).
Sustainable and resilient manufacturing industry.	Manufacturing as Sustainable Future.	The SMART Manufacturing Scenarios.	[101] (2013).
Sheet metal forming force online monitoring.	BDA analysis / ML.	Effective in identifying wear growth.	[102] (2022). [103] (2022). [104] (2023).
Large database of existing sheet metal parts.	Machine learning.	Manufacturable and cost-effective parts.	[105] (2023).
Laser, CVD and PVD techniques.	Advanced technology.	Increase tool durability.	[106] (2023).
Accurate and efficient FEM, optimization of tooling design and materials.	Virtual and physical prototyping.	Formability of sheet metals of lightweight metallic materials.	[107] (2023).
Developing non-conventional methods to form lightweight materials.	Innovations in SMF.	Evaluating the ecological convenience of SMF processes.	[108] (2020).
Data initially obtained comprises about 5000 materials and more than 350 properties.	ANN and ML.	Characterization of aluminum alloys.	[109] (2021).
ANN solutions are collected from numerical simulation using the FEM method.	Machine learning.	Predicting material properties and controlling sheet metal forming processes.	[110] (2021).

The tool condition monitoring (TCM) systems in the context of autonomous and self-adaptive industrial sheet metal manufacturing, play a critical role in detecting signs of tool failures and estimating tool life [89]. The deep learning model recursively predicts the forming parameters, namely punch location and punch stroke, for each deformation step, which yields the optimal tool path [90]. The prospective technologies of Industry 5.0 include augmented reality, collaborative robots, and block chain technology, which will transform the manufacturing process, enabling greater flexibility, customization, and real-time communication with customers [91, 92]. Smart and sustainable manufacturing processes (including sheet metal forming) like Industry 4.0/5.0 is to become more competitive, adopt customization, and ensure sustainability [93]. The optimization of metal forming processes has become increasingly important in recent years, using for example image-based machine learning methods (IBMLMs) [94]. Innovative approach for digitizing the value chain for sheet metal processing, using the RAMI 4.0 model [95]. Paper [96] presents two dimensions for formulating ML tasks: "Four-Know" (Know-what, Know-why, Know-when, Know-how) and "Four-Level" (Product, Process, Machine, System). In manufacturing, machine learning can be applied to optimize production processes, reduce downtime, and improve product quality [97]. In [98] focuses on the cradle-to-gate Life Cycle Analysis (LCA) of the Origami-based Sheet Metal (OSM) folding process to determine its sustainability. The intelligent factory is the ultimate goal of Industry 4.0/5.0, where all aspects of production are connected, transparent, and optimized, leading to significant improvements in productivity, quality, sustainability, and cost-effectiveness [99]. The paper discusses the need for cognitive production systems to ensure high reproducibility and quality in forming processes [100]. Emphasizes understanding the interdependencies between the forming tool and machine to improve process transparency and ensure high-quality formed parts. The SMART Manufacturing Scenarios provide a framework for stakeholders to work towards a sustainable and resilient future for the industry [101]. This paper [102] discusses the use of sensors to monitor the forming or stamping process in sheet metal forming. Therefore sensors are used to detect auxiliary quantities such as acoustic emission and force, which relate to the physical quantities of interest. The sheet metal forming industry by enabling early detection of wear and reducing the risk of tool failure and poor workpiece quality [103, 104]. In [105] was given a model which uses a combination of machine learning, computational design, and optimization techniques to generate manufacturable sheet metal parts. Coatings used different techniques such as laser, chemical vapor deposition (CVD), and physical vapor deposition (PVD), which significantly increase tool life by providing wear resistance, reduced friction, and improved surface finish in the process of sheet metal forming [106]. Sheet metal forming (SMF) is a critical technology for manufacturing lightweight, thin-walled, complex-shaped components, and numerical simulation and theoretical modelling have been increasingly used to enhance the performance of new SMF technologies [107]. Recent innovations in SMF focus on improving material formability, producing complex-shaped parts with good surface quality, reducing production time and environmental impact, and creating more efficient manufacturing processes [108]. The paper [109] presents a methodology for optimizing a multilayer neural network using machine learning techniques to predict the mechanical properties of wrought aluminum alloys, which is essential for optimizing metal forming processes. Manufacturing processes and sheet metal forming seek to improve efficiency and control of processing and material characterization parameters by machine learning modelling through artificial neural networks (ANNs) [110]. Annals for the last decades of the origin and development of the concept of Industry 5.0, show us that it is in its infancy of application, without clear contours and models in the industry, including sheet metal processing tools. Even more, it would rather be said that the application of the concept of Industry continues more and more 4.0, as shown by the detailed analysis in Table 3.

3. DIGITAL MODEL OF THE XYZ COMPANY

The digitization of the business and manufacturing system of the company XYZ, which produces dishes and household appliances, has been implemented for two decades. “Islands” of automation, business and engineering development activities were created, which are now being integrated according to the Industry 4.0 concept into the cloud model (CM) of digital manufacturing, Fig. 1 [111].

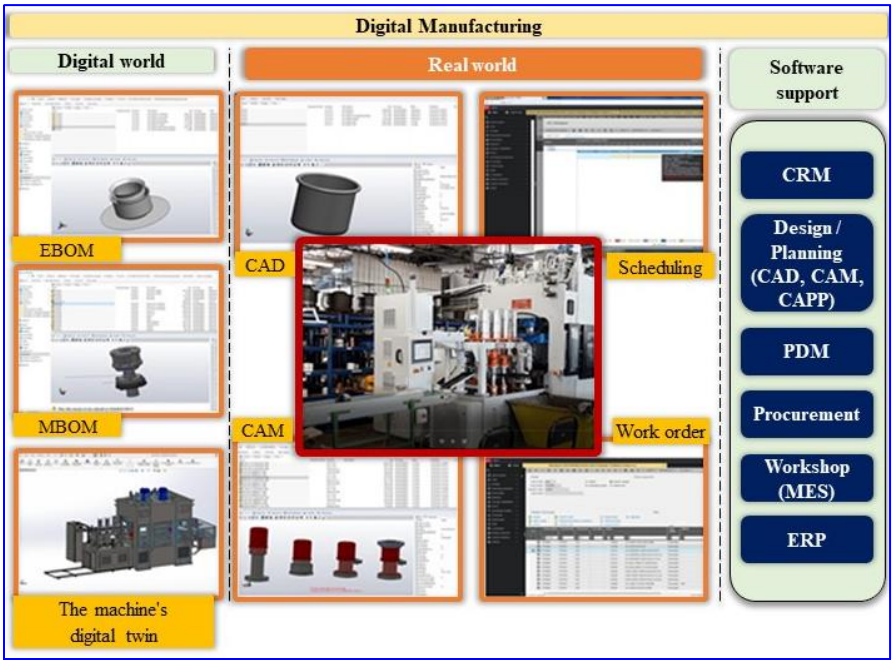


Fig. 1. Digital model of XYZ company

The developed and applied model of digital manufacturing in this company has a unique database (knowledge) about all entities of business, updated on a daily basis (some of them online) - with the latest (current) versions of products and the history of their changes [111]. Some of them are up-to-date online, such as the MES subsystem of the work order (WO) management, for the plastic deformation WS and the three CPS (photo from Fig. 1, one of them), which now represent the “islands” of Industry 4.0 in manufacturing and the digital manufacturing model of this company [53].

How does the formation of digital chains for a product in this organization begin, and how is it further formed [111] ? It starts from the request for a customer's offer, for the product (dishes), which is generated in the CRM (customer relationship management) module, which, after acceptance by the customer, is translated into a request for manufacturing and planned purchase orders for materials, which are generated through business information system (CRM module (order / delivery note that is created directly in ERP). Thus it becomes part of the system of a single database (DB), so the designer of the product (dishes) based on the standard parameters of the dimensions, automatically generates a typical CAD model (3D model of the part, component (structural, quantitative, modular)). In the next phase, the manufacturing designer generates a typical CAPP technology for the CAD model, which includes: the sequence of manufacturing operations + **extraction tool** + machine tools (3D machine tools model - digital twin). From this moment on to the stage the TLM model steps in, which will be explained in the next chapter. After the CAPP (manufacturing plan) documentation, the system generates the CAQ (quality control plan for the part, as part of the ISO 9001 model) in the next phase. In the next step, ERP forms a set of work orders (WO): degreasing sheet, enamelling sheet, manufacturing sheet (CAM), quality control sheet (QA) in the WS, calculates costs in the WS, forms a packing list, gives and final product control plan. After this, using the SCM (supply chain management) module, procurement is defined and of the quality control plan of incoming materials and raw materials and thus forms an essential system of digital model of the chain for the product to be manufactured in the planned quantity with a hyphenated deadline (scheduling), which is included in the unique system of classification of business entities. The PDM system is now in full use, and it is located on the cloud, and now it is being extended to the PLM system, which would move from the product level (entity of dishes or tools) to the digital level of the manufacturing program (types of dishes and tools for them), also on the cloud. Ensuring traceability and tracing errors is done backwards, through the delivery request and the work order (WO), through ERP, because in it they are connected across levels (higher and lower). The MES system works online, because a digital manufacturing monitoring chain is provided, using IoT and the WO application. This means that the ERP system is also monitored online, and then the business plan is created on an annual basis, the production and delivery plan on a monthly basis, and the term production plan on a weekly/daily basis.

4. TOOLS MANAGEMENT MODEL IN THE COMPANY XYZ

When we analyse industrial production, where tools are used, we can say that the integrated process of management of tools in their life cycle, tool lifecycle management (TLM) represents a set of activities in the organization that include: defining tool needs (CRM/ CAD/CAPP/ERP), procurement (SCM) or tool production (CAM/ERP/MES), tool use and maintenance (ERP/MES) and decommissioning (PDM/PLM). For these reasons, the TLM model must have key connections with ERP, PLM and MES models in the organization [4], which also applies to our model, which is presented in this paper. So it is important to note here that in this concept (TLM), the tool is viewed as a product and as an entity for the production of other products, so this should always be taken into account.

In its manufacturing process, this company uses more than four thousand tools for sheet metal forming for the following operations: blanking, bending and deep drawing. More than 80% of these tools are used for bending and deep drawing, the dominant operations in dishes manufacturing. The tools are manufactured in the tool workshop, and all activities related to them are part of the digital model of this company from Fig. 1, and with the toll lifecycle management (TLM) subsystem, Fig. 2.

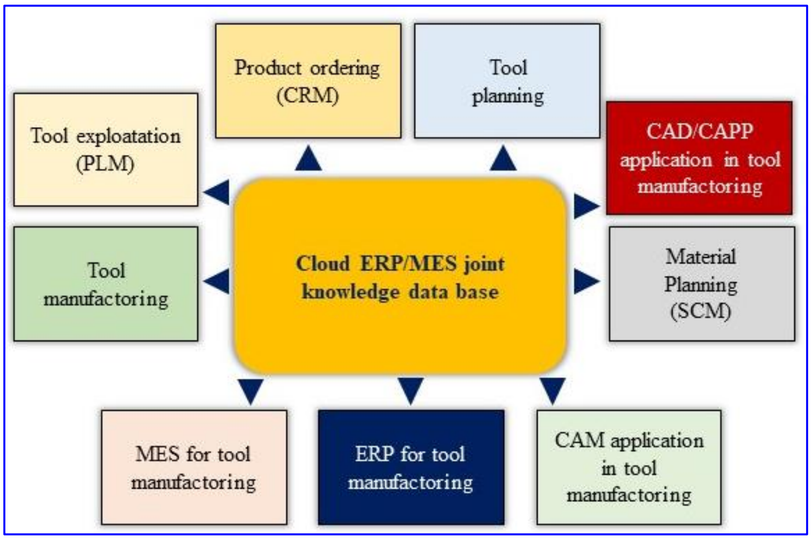
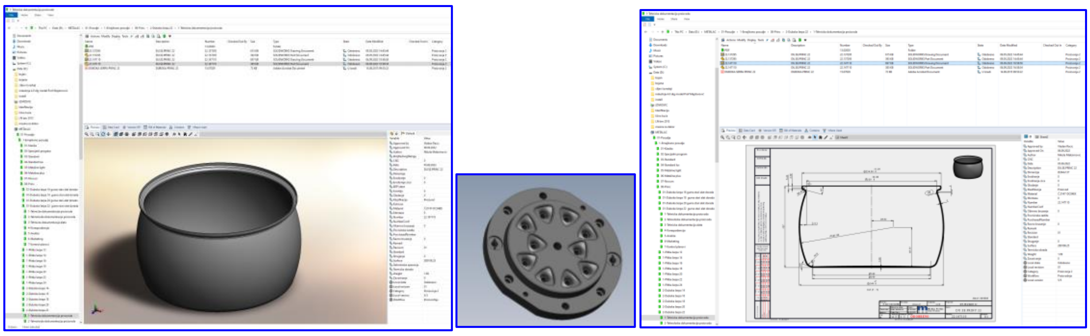


Fig. 2. TLM model in Company XYZ

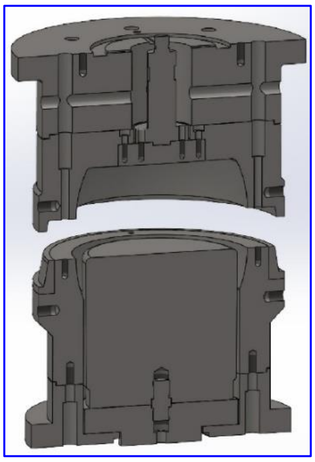
The creation of 3D models and tool drawings is done according to the 3D model of the dishes product, and after accepting the customer's request for the product, if such a tool does not exist. The manufacturing of tools is carried out using cutting technologies, in the tool workshop. Prototyping of the matrix is done by 3D printing, and checking of shape, dimensions and tolerances is done through 3D simulations, using digital twin. Solid works (CAD) and PDM are used for tool design, along with the generation of a 3D model, its monitoring and verification of changes, Fig. 3.

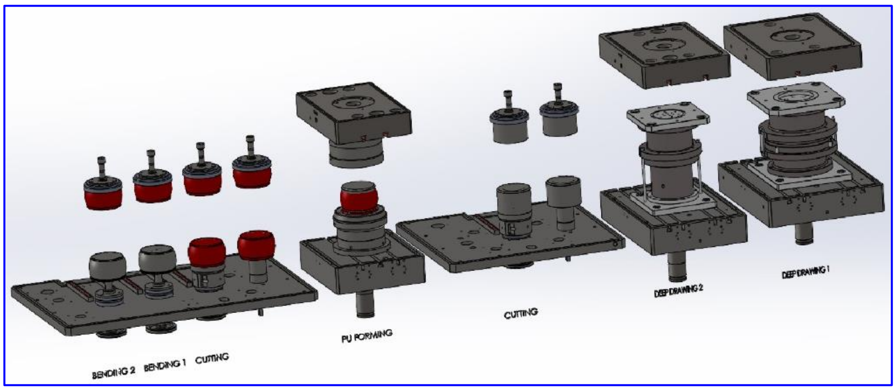


a) Model 22.14710 deep pot prince 22 b) c) Model 22.14710 deep pot prince 22 drawing

Fig. 3. Model of the dishware part (a), model of the bottom plate (matrix) of the tool (b) and drawing of the dishware part (c)

The engineering activities of designing tools for sheet metal processing are completed with a set of models from Fig. 3: the part that will be made in it with its drawing and the bottom plate (matrix) of the tool for this part of the dishes, on the basis of which the macro model of the tool is defined, according to the geometric shape part and the type of material from which the part is made, thus completing the first step in the TLM model, product ordering / tool planning, Fig. 4.

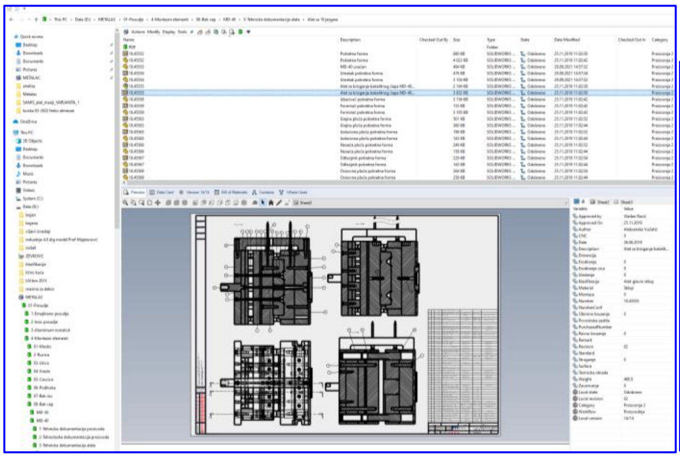




a) b) Order of operations for shaping the product deep pot prince 22 cm

Fig. 4. CAD model of the tool (a) with stages of operations on the CPS (b)

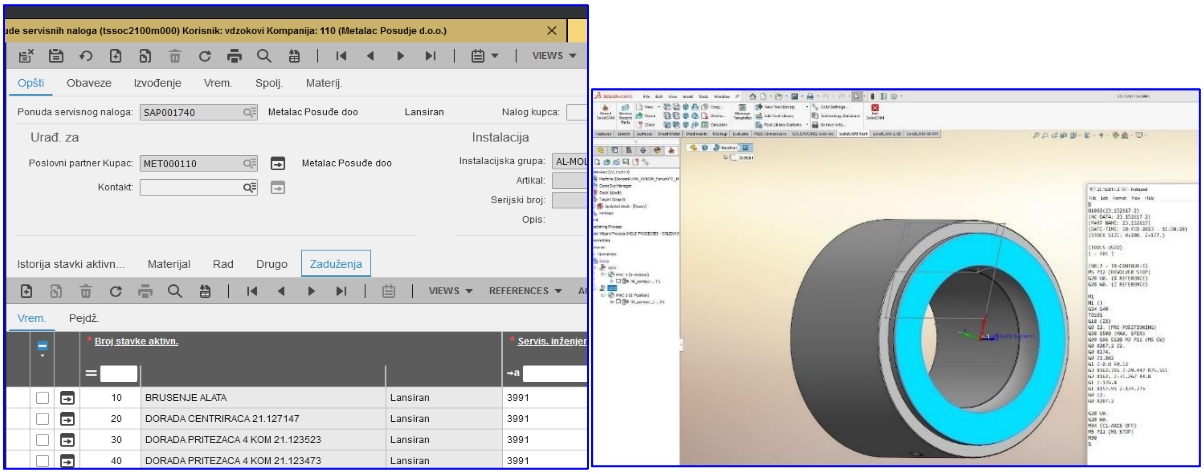
Tool engineering design (CAD/PDM), is the next step in the TLM model, where using standard tool parts, such as: steel plates, guides, pins, screws, punches, slides, insulating plates, heaters, Fig. 5a. The output from the design are the 3D models of the tool and the necessary technical drawings of the tool, as well as the structural component of the tool (EBOM), Fig. 5b.



a) Assembly drawing of the bakelite cap injection moulding tool for the previously mentioned product with the BOM in the table b) BOM a in ERP

Fig. 5. Model of the tool (a) and BOM of the sheet metal processing tool (b)

At this level, we get all the geometric models, shapes and tolerances of the tool and its components, for which technology design (CAPP/CAM) is performed. This is done in the tool workshop technology office, Fig. 6. This is how the technological component of the tool (MBOM), CAPP, Fig. 6a and the CAM model for the tool (components), picture 6b, is created.

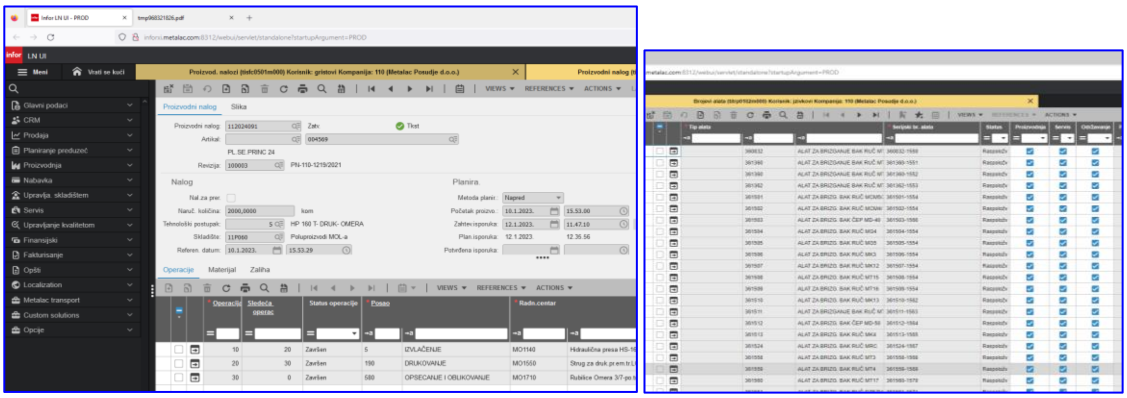


a) CAPP of the lower part of the form of the tool for shaping with rubber deep pot prince 22 cm

b) CAPP simulation on a CNC lathe, Solid-Works-CAM

Fig. 6. Technological procedure of tool making – manufacturing operations plan (CAPP) (a) and CAM model (b)

The next stage is the creation of a work order (WO) for the manufacturing of tools, which with the generated data on the prices of materials and the time required for the manufacturing of tools, total costs and manufacturing time, form the basis for defining the schedule of its manufacturing (ERP scheduling), Fig. 7. In this way, together with the CAM information, the work order (WO) for tool manufacturing is completed.



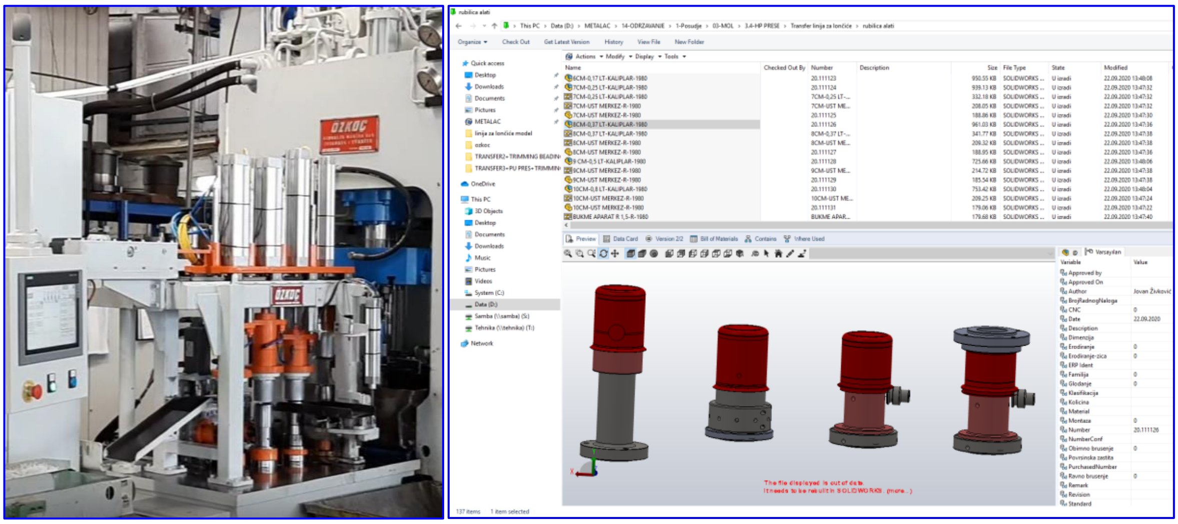
a) Part of the CAPP model for deep pans prince 22 cm

b) Bill of tool for CAPP deep pots prince 22 cm

Fig. 7. Tool manufacturing work order (a) and tool manufacturing schedule (b)

After manufacturing, the final control of all entities of the tool is carried out, as well as its assembly. After that, the tool is assigned an identification-classification number, the service life is prescribed and the maintenance technology of the tool is defined, using a QR code. All electronic documentation according to the ISO 9001 model (design and development) is generated on the cloud, and then the tool box is opened in electronic form and the operation phase begins, with online monitoring of the operation of the tools through the MES and ERP models of dishes manufacturing. Then, in the mechanical technologies of tableware production, the tool is connected to the operations of technological processes of dishes manufacturing (CAPP), through the tools module in ERP. The lifetime of the tool, the period of inspection and maintenance of the tool is given based on the number of pieces made in it, using information from completed work orders for manufacturing (WO). When the tool requires subsequent maintenance interventions, a service order is opened in the tool workshop (initiated by manufacturing) for finishing, tool sharpening or repairs. In this way, tool maintenance costs are monitored individually (per tool), grouped (types of tools) or per plant (manufacturing of dishes).

This factory has three automatic machines for dishes making in its WS that work autonomously, as a CPS in a CM environment. These three machines (CPS) increased the productivity of tableware manufacturing several times, and brought the quality of the products on them to "zero defect". Figure 8 shows one CPS in operation, with four dishes making operations in the tool used on it.



a) photo of CPS in working for a deep pot prince 22 cm

b) set of tools in the order of operations shown as 3D models

Fig. 8. CPS in a dishes making operations in WS (a) and a model of the tools used on it (b)

The presented TLM model (Fig. 2) gives us, at the beginning of the application (Request for a new product), the real state of the tool and its components, with the traceability of all changes and refinements, with the last valid states of the tool. The digital manufacturing model (Fig. 1) made it possible to define all parts of the tool from the 3D model of its components (designed according to the model of the dishes), with manufacturing technologies obtained directly through the CAM modules of the machine tools in the tool workshop. In this way, the fastest delivery of dishes for customers (CRM), managing the costs of tools in their lifetime while ensuring high quality of the product (dishes) is ensured.

By connecting the TLM module to the ERP dishes model, tool monitoring is achieved through: the number of pieces made on it, tool maintenance costs, reaching the tool life (planned/achieved) and planning the manufacturing of new tools (expired life of existing tools).

The presented TLM concept in this organization enabled the implementation of the following: (a) reduction of tool costs (26%) and increase of manufacturing quality (costs of scrap reduced by 80%, and (b) digitization of this segment of the company's business, with elements of Industry 4.0.

5. CONCLUSIONS AND FUTURE RESEARCH

Digitization is applied in all business segments (engineering and business part) in this organization. The implementation of projects for the application of Industry 4.0 elements in business-manufacturing and technological units is underway, namely [111, 112]: (a) CPS and digital model (twin off-line), Fig. 9, (b) BDA analysis , for the area maintenance and operation of tools, Fig. 9 and (c) the same alloy for optimizing the technology of tool making, as well as dishes (especially the thickness of the enamel on the bottom of the dish, depending on the purpose of the dishes).

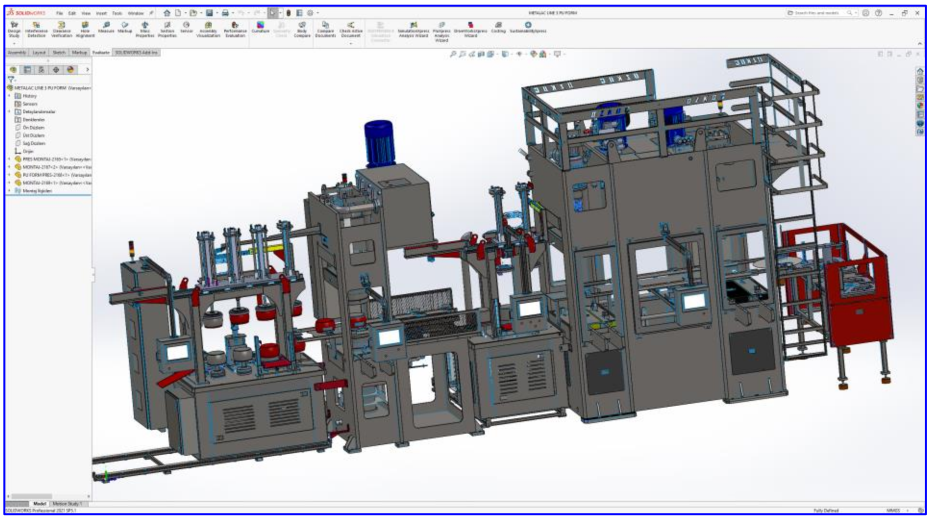


Fig. 9. Digital model (twin off-line) of CPS for manufacturing of deep pot prince 22 cm

Particularly important is the online work order (WO) management project using IoT [111, 112], which is now being implemented and represents a further improvement of the digital ERP model in the manufacturing of dishes and tools.

The presented structure from Fig. 10 represents the architecture of services for cloud computing (CM), with which applications are managed through data centres, and supports all platforms: SaaS, PaaS and IaaS. The goal is to go towards the models, which are shown in [113, 114], in order to realize the concept of smart manufacturing [1].

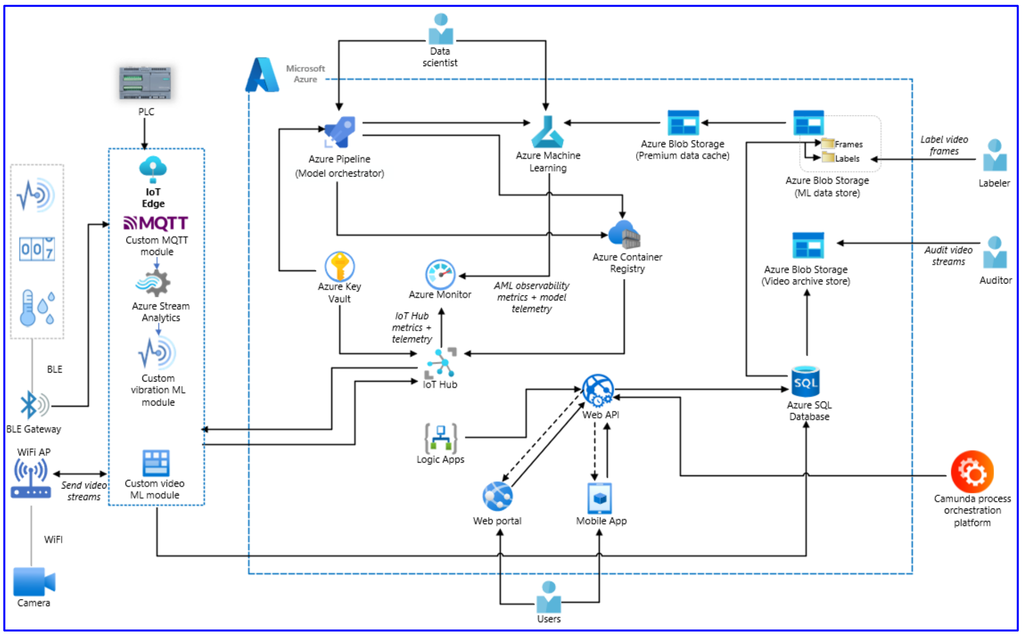


Fig. 10. Company XYZ solution architecture for ERP online model [112]

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