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Equipment Design Optimization Based on Digital Twin Under the Framework of Zero-Defect Manufacturing

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Abstract

A digitalized Smart Factory can be considered as a data island. Moreover, engineers have focused on the development of new technologies and techniques not only for transforming information to data but also to achieve efficient data utilization to further optimize manufacturing processes. However, the Zero-Defect Manufacturing concept has emerged, where the main goal is production optimization. The cornerstone in achieving the factories of the future is to further optimize the design of new assets so as they comply with the unique requirements of the customers. Therefore, this paper proposes the conceptualization, design, and initial development of a platform for the utilization of data derived from industrial environments for the optimization of the equipment design. The main aspects of the proposed framework are the data acquisition, data processing and the simulation. The applicability of the proposed framework has been tested in a laboratory-based machine shop utilizing data from a real-life industrial scenario.

Keywords: Digital Twin, Machine Design, Zero-Defect Manufacturing

1. Introduction

The ongoing manufacturing business model demands high product variety, lot-size one production under unpredictable demand as well as tight delivery deadlines. Therefore, the Smart Factories in order to respond to

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unpredictable events and regular changes timely, need to become more flexible and reconfigurable, with the ability to perform high-level tasks without extensive re-programming and with as low as possible, operator intervention. Consequently, the implementation and use of cutting-edge digital technologies in manufacturing is now becoming inevitable. Within this context, the emerging demands for mass customized products can be achieved through digital manufacturing [1]. The backbone technologies of Industry 4.0 and advances in Information Technology, including Internet of Things (IoT), Cyber-Physical-Systems (CPS), Big Data, High-Performance Computing (HPC) and Cloud Computing provide are the cornerstones for the development of Digital Twin (DT) and Artificial Intelligence (AI) applications [6]. As such, the two fundamental principles behind Industry 4.0 are digitalization, and servitization also known as Internet of Services (IoS) [3]. Industrial companies are nowadays acting in Global Production Networks (GPNs) and therefore manufacturing techniques are increasingly becoming digital [4]. While this shift towards digitalization continues, many businesses still struggle to decide what they can do to drive and generate real value on both an organizational and strategic level. The notion of a DT seems to be of particular fascination. As defined in [5], DT is a near-real-time digital image of a physical object or process that contributes to business performance optimization. Additionally, the father of the DT terminology describes the three main parts of a DT model: a) the real object, b) the virtual object and c) the connections of information coupling the virtual with the physical world [6].

In addition to the statements of the previous paragraph, modern manufacturers aim to transition towards smart and sustainable manufacturing business models. As a result, they move towards the Zero-Defect manufacturing (ZDM) paradigm. The benefits of such shift can be summarized at lower costs, lower energy consumption, less material waste, faster delivery times, better production status monitoring, more accurate planning ability and increased output quality [7]. In order to successfully transition towards ZDM, companies must combine and integrate different areas, skills, competencies, collaborative manufacturing, information systems, data from many sensors as well as data analytics [8].

Based on the above-mentioned statements, the motivation for this research work has been formed. Concretely, in this paper, the design and development of a framework for the consideration of customer requirements during the design phase of new manufacturing assets is presented. In an attempt to fully utilize the new technologies introduced in the Industry 4.0 era, the proposed approach relies on the integration of a DT for the simulation of the new design based on historical data gathered from similar machines in already installed and working manufacturing environments.

The remainder of the paper is structured as follows. In Section two the most pertinent literature is presented. Then in Section three, the proposed system architecture is discussed in detail. Next, in Section four the practical implementation steps are analyzed. Then, in Section five the proposed approach is assessed in an experimental scenario and the preliminary results are discussed. Finally, in Section six the paper is concluded, and future research steps are also discussed.

2. State-of-the-Art

There is a plethora of research works related to intelligent and sustainable manufacturing systems, ZDM, circular economy, predictive maintenance, quality control, and DT. Focusing on ZDM, Wang in [9] proposed a series of ideas on how to use product, equipment, and process data in a data mining framework that is used to improve product knowledge and quality. In addition, Teti in [10] presents a compilation of recent research works regarding the integration of multiple sensing systems on machine tools, and the information fusion via Artificial Neural Networks. Further to that the Success Rate (SR) of the developed Neural Networks, has ranged from 80% for the worst-case scenarios up to 100%. In reference [11], the authors have focused on the Beginning of Life of the product and the development of a dynamic Scheduling tool combined with an intelligent Decision Support System (DSS) that takes into consideration the ZDM strategies for eliminating defected parts during production. Lee et al. in reference [12] have analyzed the most recent trends in modern manufacturing based on the utilization of Big Data in an attempt to achieve greater productivity rates. More specifically, their research work is based on the discussion of five areas of Smart Analytics, namely the manager and operator interaction, machine tools fleet, product and process quality, Big Data and Cloud, and sensor and controller networks. Data from sensors are gathered and analyzed by outlining a scalable and generalizable ZDM approach. Next, in two other research works, simulation of maintenance, service and availability is presented [13,14].

Additional technological advances over the past decade relate to software applications enhanced by Augmented (AR) and Virtual Reality (VR), improved interfaces and utilities, and agent-based modeling, indicating the integration of smart components into sophisticated software [15]. In addition, DT approaches also appeared in the literature [16], combining real-time data collection and sophisticated simulation scenarios. The fourth industrial revolution brings manufacturing automation and processes to a new level by integrating and bundling multiple digital technologies [17] under customized and flexible mass production models [18].

Moving on the DT concept, the authors in [19] present a dashboard application that acts as a DT to define calculated values that could have a negative effect on production output by using Key Performance Indicators (KPIs) to produce historical data. In reference [20], the differences of a DT model in a Reconfigurable Manufacturing System (RMS) and the digital thread model in enterprise level are mentioned. Moreover, the authors in [21] proposed a DT model for optimizing the performance and enhancing the machine tool stability. Moreover, Leng et al. in [22] presented a DT-driven Cyber-Physical System (CPS) for optimized control of a smart workshop. Within the same context, Aivaliotis et al. in [23], presented a methodology in order to calculate the Remaining Useful Life (RUL) of machine tools based on the implementation of a DT and physics-based simulation models aiming to create a functioning framework for Predictive Maintenance of manufacturing equipment. Similarly, the authors in [24] presented an interesting framework for Cloud-based manufacturing based on the integration of digital technologies such as DT and Big Data Analytics in an attempt to create a service for on-demand manufacturing processes. Moreover, Nikolakis et al. in [25] focuses on a CPS for enabling human robot collaboration (HRC) based on real-time evaluation of safety distance and a closed-loop control for triggering collision prevention actions.

Besides DT, another important group of technologies for enhancing the performance of manufacturing systems is Artificial Intelligence (AI). Further to that, Machine Learning as a subset of AI, refers to technologies that aim at the extraction of useful insights and enabling a computational system making decisions. This is achieved through a training process with large volumes of data. Towards that end, Alexopoulos et al. in [26] present in their paper the creation of virtual datasets through simulation tools that can facilitate the training of Machine Learning models in a cost and time effective manner. Last, evaluation and reports on the development status of AR technology in recent years and assembly simulation methods based on AR, aiming to provide ideas for Research and Development companies to build AR assembly systems are reviewed in [27].

Thus the trend of digitalizing manufacturing systems establishes a cluster of technologies in the areas of sensing, connectivity, data processing, and decision making. Communication Networks and mechanisms such as the Wireless Sensor Networks (WSN) are important facilitators towards a continuous information flow among the different communication layers [28]. A methodology for machine shop simulation and modelling under the Machine Shop 4.0 framework is presented in [29]. The suggested approach is facilitated through the OPC-UA standard. The outcome is the development of a DT which will contain the Machine Shop 4.0 status in real time. Therefore, efficient decision making can be performed.

Based on the examined literature, it can be safely concluded that under the Industry 4.0 framework, engineers have focused on the utilization of various technologies and techniques for the digitalization of modern manufacturing systems. By extension, numerous research works present methodologies for addressing issues related with the Data Acquisition and Data processing. In terms of simulation, technologies such as Digital Twin, are utilized in all the levels of the production. However, there is still a gap as regards the integration of the above-mentioned technologies for the utilization of data acquired from existing machine tools in combination with the end-user functional requirements, for the design of new machine tools. In order to address this challenge, in this research work, a framework for the design of new manufacturing equipment based on Digital Twins is proposed. Further to that, the proposed framework, also promotes the communication between the clients and the OEMs in an attempt to integrate the former in the design phase.

3. Proposed System Architecture

The proposed approach is based on the development of a Cloud platform for the data acquisition, from the installed Data Acquisition Devices (DAQ) on already installed and operating machines. In addition to that, the Cloud platform will also provide services to the new customers. In Fig. 1, the main components comprising the proposed system architecture are presented. Through the platform a new or existing customer can request to configure a new or existing machine with respect to their unique requirements. Based on the requirements set by the customers, the engineers in the design department of the Original Equipment Manufacturer (OEM), configure the design of the machine. Then in continuation in order to simulate its functioning a DT is created and operates based on the data gathered by the DAQ devices. As soon as the DT provides the results to the engineering department and the engineers optimize their design so as to achieve the best solution.

The DT is created and used for the validation of the design of new machine tools. Two types of data are used to run the DT simulations. At first, historical data that have already been preprocessed and saved in a suitable Cloud database. The use of the historical data is aimed for the training of predictive models for the physical models used in the machine tool DT. From the historical data, two datasets can be created, healthy and faulty, respectively. Then with the utilization of suitable techniques, such as Support Vector Machines (SVM), useful features from the datasets, regarding the working condition of the machine tool can be obtained and automatically classified. These features can be used on the DT of the new design in order to predict its functioning based on the specifications provided by the client/end-user. The second type of data is simulation data. These data are derived from simulation software. More specifically for the individual components which are crucial for the functioning final assembly, such as electric motors, rails, bearings etc. certain simulations are run in order to monitor their behavior under a variety of working conditions. For each of these critical components, in order to generate adequate healthy and faulty datasets, the modelling of faulty situations is required. For instance, in the case of rails, a faulty rail might produce increased frequencies. Therefore, in the DT model of the rails, such frequencies are injected in the model. For that purpose, a detailed 3D model is required, in order to replicate the mechanical properties of the component to the greatest possible degree. In the simulation package-software, it is of great importance to create/place a sufficient number of sensors, i.e. virtual sensors. The purpose of these sensors is to monitor and record data from various aspects of the machine tool. It is stressed that the digital data/simulation data, are welcome since they require less pre-processing, in contrast to the real data, however they require greater computational power. At this point, a trade-off between simulation and real data is needed. Alternatively, it can be expressed as a trade-off between data quality and computational power. However, the recent advances in Information and Communication Technologies (ICT) and the integration of 4G-based technologies, have enabled a considerably bigger volume of data to be processed.

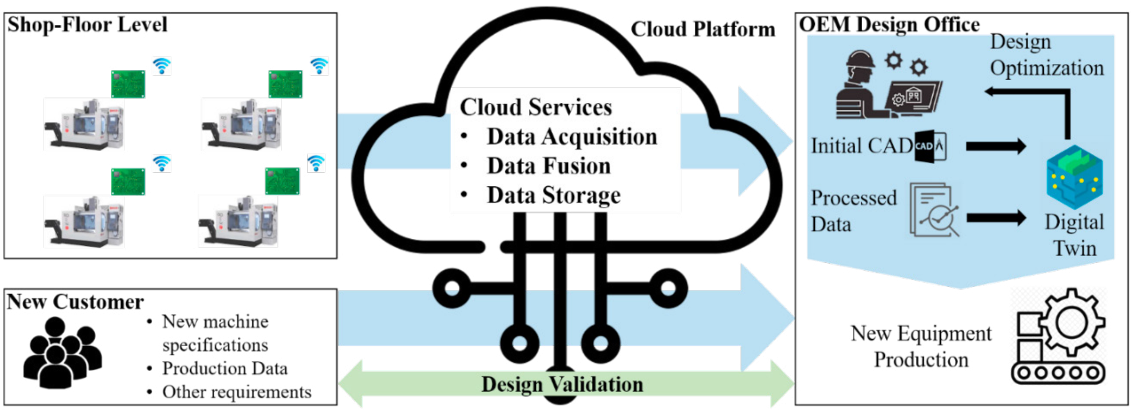

Fig. 1 The proposed system architecture

4. System Implementation

The first step of the practical implementation process involves the detailed design of the components in the Dassault Catia CAD suite [30]. However, in order to cover a wider variety of components, the components have been designed fully parametrically. The 3D CAD designs of the machine tool components are then saved on the Cloud Database, which serves as a CAD repository for future designs. As soon as the 3D CAD designs of the machine components and the final assembly of the new machine tool have been designed in the CAD suite and uploaded to the Cloud, then the model is inserted in the Simulink programming environment. If there are available historical data from other similar machine tools, then these data are downloaded from the Cloud database and inserted in the Simulink model. However, in the case where there are no data available, then the engineer has to generate these data based on the implementation of virtual sensors on the Simulink model. Then, the results from the simulation runs of the DT are exported. If there is need for design optimization, then the design department review the 3D CAD files accordingly and the results are communicated to the client. If the design and the performance of the virtual machine tool, i.e. the DT are satisfactory for the client, then the production of the machine can start, otherwise the machine tool is revised until the desired outcome is achieved. The flowchart of actions within the proposed framework can be displayed in Fig. 2.

Although in an environment such as a machine shop different kinds of machines are used, the types of physical sensors, for the proposed framework, are the same. Therefore, in order to distinguish each machine from the rest, the data island approach has been adopted. By doing so, all the data are gathered, yet they are saved and processed separately, so that the DT gets the correct input. For the establishment of the data islands, on each of the machines to be monitored, a DAQ device is installed along with the sensor configuration, as per the requirements of the engineers. Each of the DAQ devices is also equipped with a wireless network module, which facilitates the communication of the DAQ device to the sensors as well as to a Cloud Database. However, taking into consideration that identical sensors are used over the network, a digital identifier implemented on the firmware of each sensor, is used in order to eliminate the possibility of data overlapping. The same principle has also been implemented on the DAQ devices. Therefore, the created infrastructure, comprises a Wireless Sensor Network (WSN). The infrastructure has been developed so that it is completely wireless, by utilizing the capabilities and the protocols provided by the 4G technology.

The availability of data in modern machine tool, evidently is huge. However, certain devices, for Data Acquisition and communication is highly required. In order to facilitate this process, a custom modular DAQ device is utilized. This device has been designed and developed so that different sensors as well as different sensor configurations can be implemented on a given machine tool. The interval for the DAQ devices has been set to 5 seconds. However, in order to minimize junk data, for the time period a given machine is not operating, the DAQ process is stalled until the machine is turned back on. At this point it is stressed, that this functionality in the current implementation is manually implemented, and in the near future it will be fully automated.

In order to practically implement the framework as discussed in the previous paragraphs, an application has been developed. Through this application the clients can connect to the Cloud platform and visualize the desired machine. Besides the visualization, the clients are also provided with an additional functionality for the formalization of their functional requirements. The resulting requirement form is then automatically communicated to the OEM design department where the reconfiguration of the machine designs takes place.

An equally important aspect of the proposed framework is the security of the WSN. Although the current implementation of the framework is based on the use of a wireless local area network (WLAN), external security breaches can occur. By extension, the framework can be expanded so that it can be operated on a wider network. Therefore, certain security measures are necessary, as data leaks can be proved disastrous for the machine shop.

For the practical implementation of the proposed framework, a variety of tools has been selected. As mentioned in the previous paragraphs, the 3D CAD designs for the machine tool components have been designed with the use of Dassault CATIA CAD suite. For the modelling of the DT, the MathWorks MATLAB programming platform was used. More specifically, the Simulink programming environment was utilized for the modelling of the DTs due to its ability to model multi-domain physical systems with the use of graphical programming. As regards, the processing of the data, the MATLAB platform was used along with the Predictive Maintenance Library. For the data acquisition and the data handling, certain Python scripts were developed, via the Microsoft Visual Studio IDE. Finally for the creation of the frameworks associated Graphical User Interfaces (GUI), the Unity 3D game engine has been utilized. From a hardware point of view, a PC was utilized, equipped with Intel core i7 processor clocked at 3.6GHz, 16 Gb DDR4 RAM memory and an NVIDIA 1060 GPU.

As regards the simulation times, for the extraction of features from the data collected for a ball bearing frequencies, the processing time was recorded at 3 minutes and 47 seconds. The simulation runs for the generation of data from the physical model of the same bearing using the Simulink environment was recorded at 10 minutes and 32 seconds. For the Digital Twin of a complete assembly, combining the simulation of individual components was recorded at approximately 3 hours. Apparently, the simulation times can be further decreased with the use of a more powerful computer.

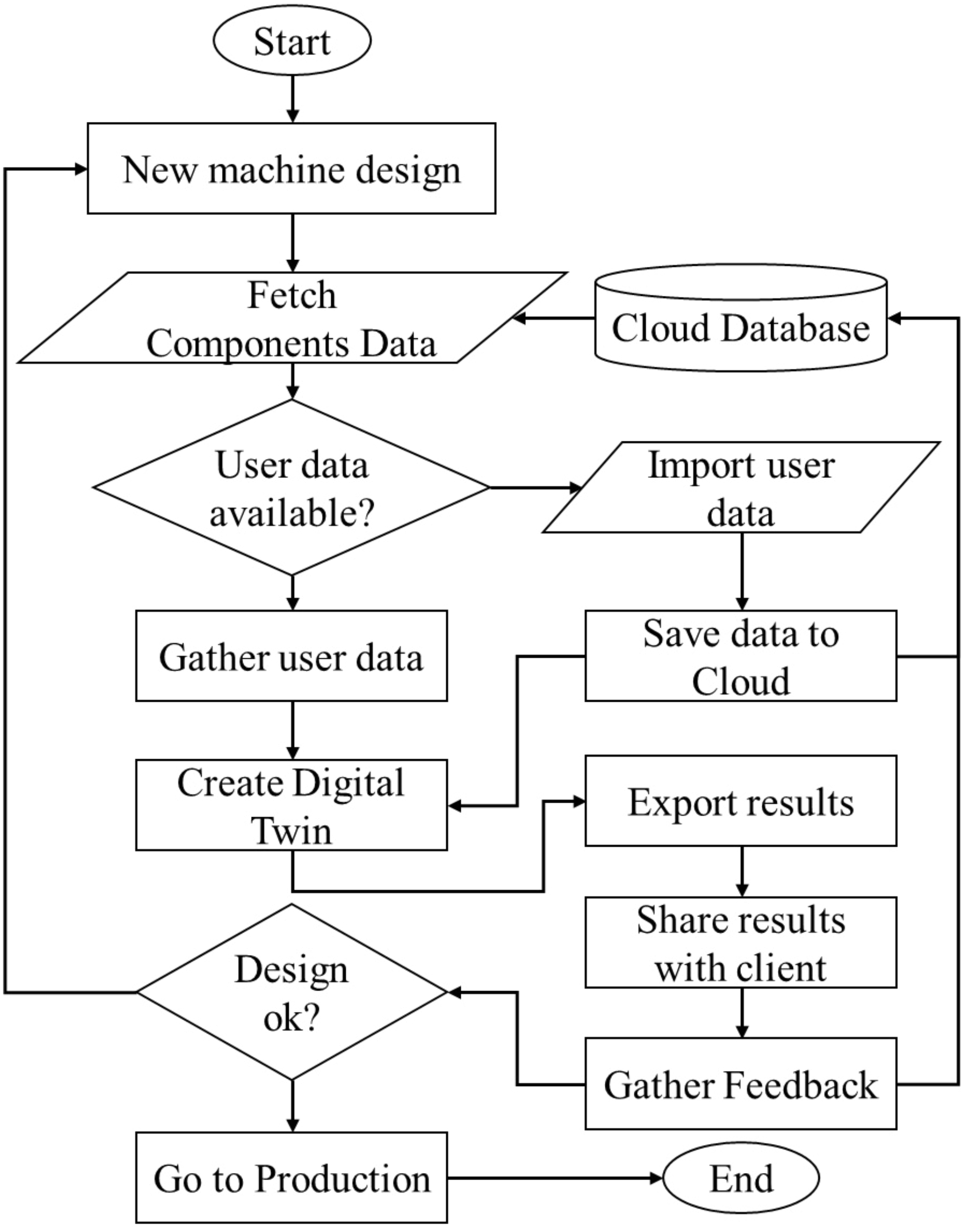

Fig. 2 Flowchart of the proposed system

5. Experimental Case Study

In order to validate the proposed system architecture, a real-life industrial scenario, derived from a bending machine manufacturer will be used as well as a lab-based machine shop. The current situation, in the real-life industrial environment, can be described as follows. The manufacturer offers a wide variety of machines; however, they offer minimal to no customization, thus many clients do not possess a machine tool that covers their needs. Therefore, what is needed, is an advanced communication tool between the OEM and the customer, so that the functional requirements can be successfully communicated to the OEM and then in continuation, the designing department can adapt the initial machine designs to the need of the customer. Although this is an important step, a series of simulation experiments must be undertaken so that the OEM can ensure that the new machine design will perform as per the quality standards of the OEM. Thus, the use of the DT-based framework proposed in the current research work is tested. The goal of the OEM, is to manage and increase their productivity by 4%, maintain the extent of their product line and comply to the customer functional requirements. The OEM foresee that in the near future their company will be able to optimize the R&D division under the ZDM paradigm.

The laboratory-based machine shop was mainly used for initial experimentation and calibration of the system and its sub-systems during the development phase. In addition to that, this provided the opportunity to populate the Cloud Database with 1TB of data, which in turn facilitated the functioning of the DT and the background AI algorithms for the monitoring of the equipment and the prediction of certain values as discussed in the previous paragraphs. In Fig. 3(a), an example design of a CNC milling machine is displayed. The general assembly of the machine as it is resulted from the CAD is presented. Further to that, the engineer can visualize the assembly tree, in order to create the DT and then, adjust its parameters. More specifically, for the creation of the DT, data can be produced either from virtual sensors, or from real sensors installed on existing machines. A series of mechanical models have been implemented for the simulation of the individual components. In the main Graphical User Interface (GUI), where the general assembly of the machine is displayed, user-selected metrics can be constantly monitored. In the case the customer is not satisfied by the performance of the machine, then the engineer can adjust the design of the machine along with the working parameters ,update the DT of the machine and run the simulation again in order to verify/validate the changes in conjunction with the client. An example of this functionality is presented in Fig. 3 (b) and (c), where the GUIs for modifying the parameters of an AC electric motor and a bearing are depicted accordingly.

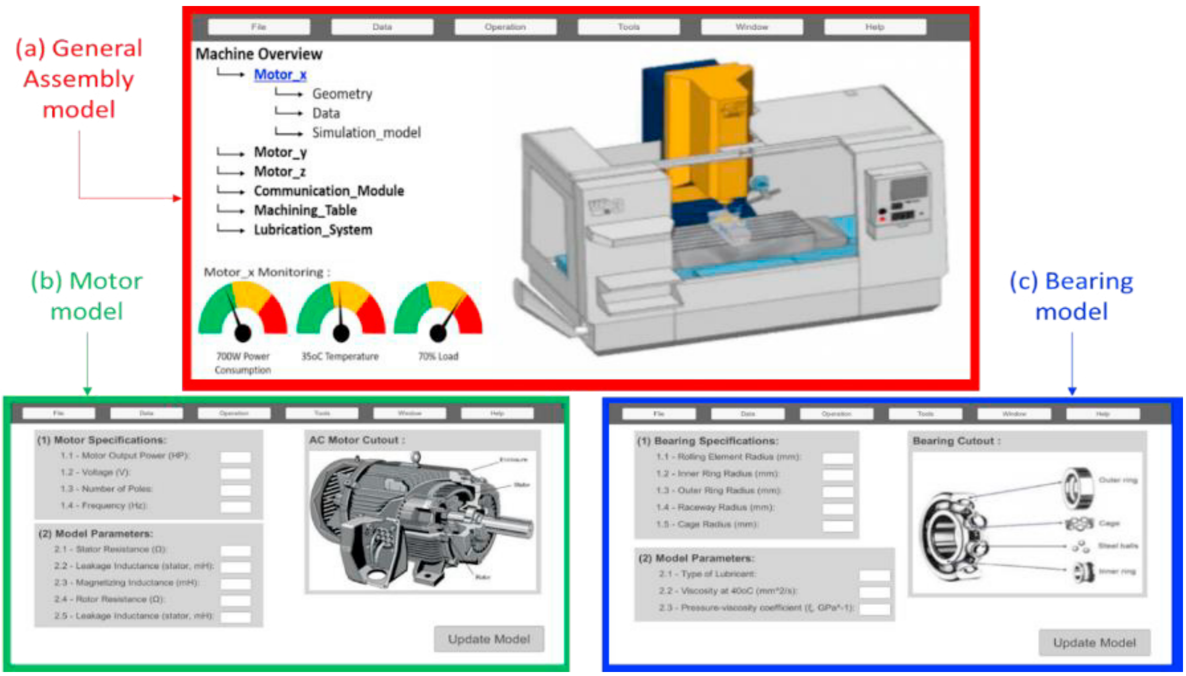

Fig. 3 Screenshots of the developed framework

From the discussions with the industrial case provider for the design and development of a CNC bending machine, the engineering department would need approximately 12 months, in the case of using an older machine design. Concretely in this timeframe, the engineering department would require approximately 7-8 months for the design of the prototype and the rest time for design optimization. However, with the integration of the proposed framework, the engineering department would require considerably less time for the optimization of the machine tool, accounting for approximately 15 days to 1 month. In Fig. 4 (a) and (b) the preliminary results are depicted. An important aspect of the proposed methodology is the integration of the customers in the design phase of the machine tools. More specifically, the industrial partner has expressed their concern as regards the customer satisfaction, which has been calculated by reports at approximately 70%. The customer satisfaction is resulted from the quality of the machine tools, their pricing, the after-sales support, and the features of the machines. according to the industrial partner, the provision of a service for creating engineered-to-order machine tools would have an impact of approximately 9%. Moreover, the provision of a suitable communication tool would facilitate the engineering department to get a better understanding of the customer specific requests upon the design of a new machine tool, thus an increase of 20% in terms of communication is expected.

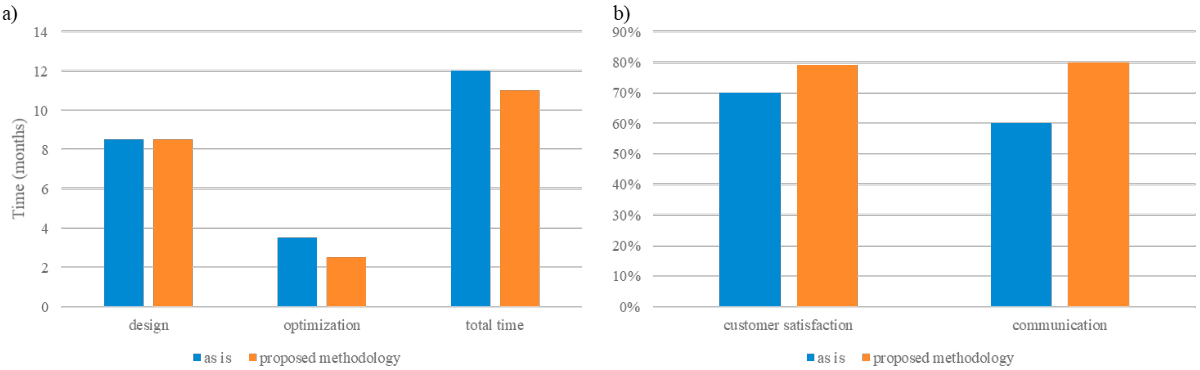

Fig. 4 Preliminary results; a) time to complete design; b) customer satisfaction/communication

6. Conclusions and Outlook

This research work has presented the design and development of a DT-based framework for the optimization of the design phase. The key findings of the research focus on the alternative solutions for the creation of a functional DT, based on the utilization of both real data, gathered from functioning machines, and simulation data, which are generated by simulation models. The implementation of the component models in a structured way, via the GUIs, as they are presented in Fig. 3 (b) and (c), facilitated the engineers into designing a more robust machine as well as to adjust the working parameters of the individual components.

In the future, additional effort will be put on the utilization of simulation networks, so that a cluster of computers can be integrated to this framework, in order to leverage its simulation capabilities and reduce the simulation as much as possible. Besides that, as the framework is implemented, data are constantly being gathered, which provides a great opportunity for revisioning the accuracy of the DT over time, and wherever it is needed to make any required adjustments. Another important aspect that must be covered in the future, is the integration of human DTs in the proposed framework. this functionality will enable the active integration of the end users in the design phase of the manufacturing equipment. For the development of the human DTs, data from the shop-floor technicians as well as working scenarios from their everyday tasks will have to be gathered and processed.

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