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Digital Twin based What-if Simulation for Energy Management

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Abstract—**The manufacturing sector is one of the largest energy consumers in the industrial world, being the energy consumption by the shop-floor equipment, e.g., robots, machines and AGVs (Autonomous Guided Vehicles), a major issue. The combination of energy-efficient technologies with intelligent and digital technologies can reduce energy consumption. The application of the digital twin concept in the energy efficiency field is a promising research topic, taking advantage of the Industry 4.0 technological developments. This paper presents a digital twin architecture for energy optimisation in manufacturing systems, particularly based on a what-if simulation model. The applicability of the proposed what-if simulation model within the digital twin is presented to promote the efficient energy management of AGVs in a battery pack assembly line case study.**

Keywords: Digital Twin, What-if simulation, Energy Efficiency.

I. Introduction

Today's manufacturing industry is under unprecedented pressure to reduce energy consumption and increase productivity in response to governmental ambitions to achieve Net Zero around mid-century [1]. According to [2], in 2019, the industrial sector that includes refining, mining, manufacturing, agriculture and construction, is responsible for more than 50% of the energy consumption worldwide and is expected to remain the largest energy consumer until 2040. As reported in [3], one of the main problems in the manufacturing sector is the significant amount of energy consumed by the shop-floor equipment, e.g. machines, robots and autonomous guided vehicles (AGVs). In this sector, it is essential to understand how energy is being used at every stage of the manufacturing process to optimise processes and, consequently, reduce energy consumption [1]. According to [4], the combination of energy-efficient technologies and intelligent technologies has the potential to reduce energy consumption by 50%, since with operational improvements it is only possible to achieve a 10-20% reduction. For the AGVs used in manufacturing systems, energy efficiency management technologies are an important aspect that contributes to reducing energy consumption and improving their availability due to reduced docking time for battery recharging. This represents savings in energy consumption, production and operational costs.

The information and communication technologies (ICT) are considered a significant enabler for energy efficiency and management in the manufacturing sector [1]. Through Industry 4.0, the implementation of ICT technologies, e.g., internet-of-things (IoT), big data, artificial intelligence (AI) and cloud computing, in manufacturing has become a reality. The integration of physical and virtual worlds, promoted by the use of cyber-physical systems (CPS) [5], raises the use of the digital twin concept. This is a near-real-time virtual model of a physical entity, e.g., system, process, equipment, component or product, with a potential to perform continuous analysis, monitoring, control and decision support.

Few studies are using digital twin in energy efficiency in the manufacturing sector. However, with the current digitisation level, it is possible to perform energy monitoring, analysis, control and optimisation, in a real-time manner. In order to achieve the level of energy efficiency required by manufacturing systems, energy consumption should be measured and analysed in real-time to derive knowledge and patterns for each part of the manufacturing system [6]. The digital twin fits the requirement of performing energy management in manufacturing, assuming one prominent research area [7], [8], [9]. The main contribution of this paper is the development of a generic digital twin architecture for the energy efficiency management, introducing a what-if simulation model that contributes to the near real-time decision support based on the user trust level. For this purpose, this paper provides an application of digital twin in the energy efficiency area in the manufacturing sector. The proposed digital twin based on what-if simulation is applied to a battery pack assembly line case study that uses AGVs to transport parts along the line. The what-if simulation is used to determine the best battery charging profile to be used by AGVs, considering the throughput and their charging times. The results revealed the potential benefits of using what-if simulation with digital twin.

The rest of the paper is organised as follows. Section II provides a review of the digital twin concept for energy management. Section III presents the digital twin architecture and the what-if simulation model. Section IV presents the case study and the implementation of the proposed approach and discusses the preliminary results. Finally, Section V rounds up the paper with conclusions and points out the future work.

II. Digital Twin for Energy Management

The digital twin concept for energy management is mostly applied in two main areas, namely manufacturing and smart cities. A literature review was performed based on the study and application of the digital twin applied for energy management. In 2016 [10] SIEMENS published a patent application in which the main goal was to use digital twin for energy-efficient asset maintenance and improve product quality. The authors of [11] proposed using the digital twin for performing energy optimisation in an SMT-PCB assembly line. For this, an IoT network was deployed, collecting data from the line, and a virtual model was developed using discrete event simulation (DES) software, for performing what-if analysis to identify optimisation actions to the system's energy efficiency.

The authors of [3] proposed applying the digital twin for equipment energy consumption management to improve energy-efficiency. The authors proposed a framework and guidelines to use the digital twin to improve and optimise energy consumption. According to [1], energy consumption in one of the significant problems associated with the manufacturing sector. Based on this fact, the authors performed a review of methodologies and frameworks for analysing energy consumption at the machine level using DES. In [12], the authors reviewed digital twin applications in the manufacturing area and developed a digital twin for energy consumption monitoring for an assembly line. The authors in [13] presented a generic architecture based on energy-aware digital twins for energy efficiency in manufacturing. In [14], the authors propose a digital twin-driven approach towards smart manufacturing to reduce energy consumption, demonstrating its validity in a robotic cell. In [8], a categorical review on recent papers about digital twin was performed. This review divided its research into three main research areas, manufacturing, smart cities and healthcare. According to this study, one of the key enablers of the digital twin adoption by the manufacturing domain was the extensive work done in connectivity and the digital twin's embedded capability to perform near real-time simulation. Most of the digital twin research conducted today is in the manufacturing domain, can be divided into four subareas, i.e., smart manufacturing, simulation and AI, system design and development, and energy-efficient manufacturing.

Considering the literature review, it was possible to conclude that applying the digital twin concept for performing energy efficiency in the manufacturing domain has significant potential. Although there are already some scientific publications, it is important to keep exploring this field, by creating new or improving existing architectures and frameworks since energy efficiency is gaining such a critical weight in the manufacturing sector's future. Another future challenge is the integration of AI techniques with simulation in the decision support cycle offered by the digital twin. Lastly, is the development of a digital twin with end-user engagement and with the use of the user trust in the decision making cycle [15].

III. Digital Twin Architecture and What-if Model

In this section are going to be presented the developed digital twin architecture and what-if simulation model.

A. Digital Twin Architecture

In the manufacturing sector, shop-floor equipment is responsible for the vast majority of energy consumption of a factory. With the implementation of digital technologies, i.e. digital twin, and strategies to optimise resources, it will be possible to perform efficient energy management. Figure 1 illustrates the proposed digital twin architecture, that is based on a generic architecture for decision support previously published [16].

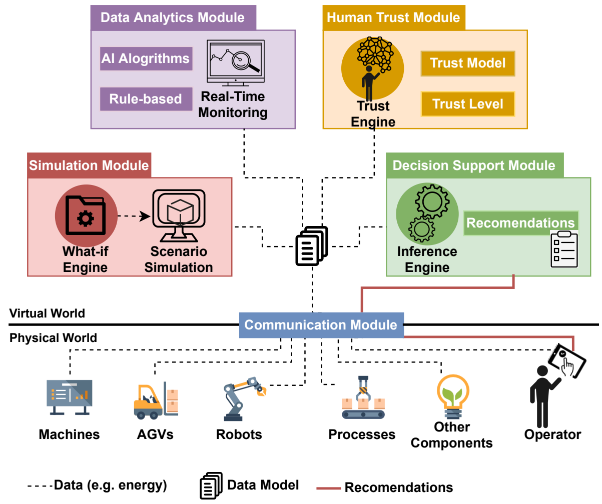

Figure 1: Digital Twin generic architecture.

The architecture comprehends two dimensions, the physical world and the virtual world. In the case of the first dimension, physical world, this can be represented by a machine, a robot, an AGV or the conjugation of elements and processes on the shop-floor depending on the digitalisation level and the purpose of the digital twin; in the case of the virtual world dimension, is built upon five modules, the ***Communication Module***, ***Simulation Module***, ***Data Analytics Module***, ***Decision Support Module*** and ***Human Trust Module***.

The ***Communication Module*** has the primary objective of establishing communication between the physical and virtual world and vice-versa and allowing data exchange between the virtual modules that constitute the digital twin architecture. This module comprehends the utilisation of a data model, responsible for organising in a standardised manner the different types of data being exchanged and utilising standard industrial communication protocols (e.g. OPC-UA, Modbus, or EtherNet/IP). The ***Simulation Module*** is responsible for running different simulation scenarios of the virtual copy of the physical world entities or system, which can serve as validation, evaluation and verification tool. Inside this module, there is a what-if engine, responsible for creating various testing scenarios, where different parameters and configurations can be established and tested by applying them to the simulation model of the physical system.

In the ***Data Analytics Module***, two main actions are performed, real-time monitoring and prediction. The real-time data is collected from the physical system is subjected to rule-based monitoring. AI algorithms (e.g., machine learning) are applied to historical data collected from the system to perform predictions. The ***Decision Support Module*** aims to support operators in the physical world in the decision-making cycle (strategic and/or operational), including the human operator as Human-in-the-Mesh (HiTM) and Human-in-the-Loop (HiTL). The decision support works by providing recommendations through the use of a knowledge-based inference engine.

Lastly, the ***Human Trust Module*** is responsible for assessing the trust level of the human operator in the digital twin for determining the level of implementation of the recommendations into the physical world. The trust level will be determined by a trust engine that uses previously defined trust models and AI algorithms (e.g. reinforcement learning) to determine the trust level for a particular type of recommendations. The system's trust level will be determined based on the established trust model and the current trust level.

B. What-if Simulation Model

An important aspect of the digital twin is decision-makers' support, promoting informed decisions in a near real-time manner. With the integration of what-if simulation into the digital twin, users can have a broader view of what can happen to the physical system. According to [17], what-if analysis can be defined as a *"data-intensive simulation whose goal is to inspect the behaviour of a complex system under a given hypothesis called scenarios"*. The what-if analysis has the main purpose of simulating and inspecting the behaviour of a system. Figure 2 illustrates the proposed what-if model.

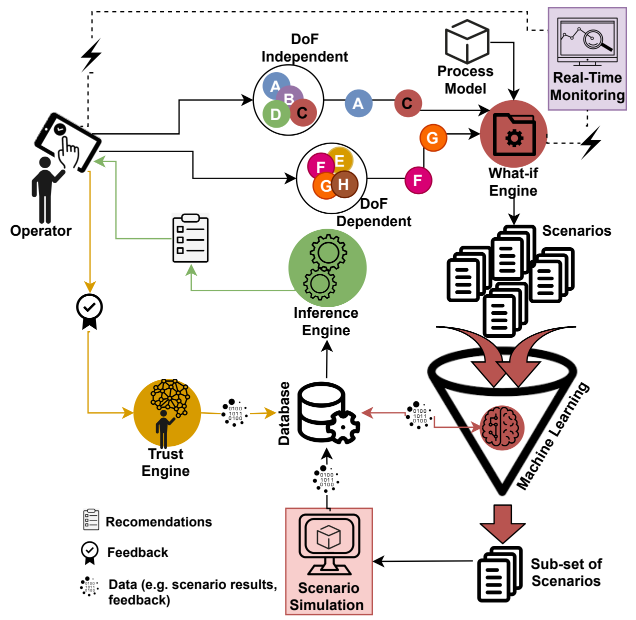

Figure 2: What-if simulation model.

According to the digital twin architecture, the ***Data Analytics Module*** is always performing real-time monitoring over the physical system's data. Considering the collected data, e.g., if it leaves the established limits or if a new order enters the system with new product demand, this module sends a trigger to the operator. The operator then selects the degrees of freedom (DoF), which represent the variables of the system that can be adjusted for its operation, and builds the DES model for the problem in question. Apart from this, the function of real-time monitoring can act in the background sending triggers directly to the what-if engine, exploring other promising scenarios.

The DoF of the physical system can be classified into two categories, independent and dependent. The independent DoF can be defined as independent variables of a physical system, which do not depend on other variables (e.g., shift duration, number of AGVs). The dependent DoF are known as the dependent variables of the physical system (e.g., throughput of the system), whose calculation is dependent on independent variables. The DoFs defined by the operator are sent to the what-if engine, in the ***Simulation Module***, where all scenarios are created based on the exploration of all possibilities combining all the different DoFs.

Following this, the set scenarios' reduction will be performed if there is already historical data on the problem in question. This will be performed by the application of AI algorithms, e.g., reinforcement learning algorithms. This reduction is based on historical knowledge acquired during similar what-if simulations, including past scenarios performance scores and the user's trust level in the recommend scenarios. This will result in performing a faster analysis performing simulation only on the most promising scenarios.

The sub-set of the most promising scenarios are then simulated using the developed model in simulation software. The achieved results are saved into a database and passed to an inference engine present in the ***Decision Support Module***. In the inference engine, the results are compared, and the optimal set of DoFs is defined. The optimal set of DoFs can be defined as the DoFs that best optimise the physical system taking into account a defined performance score. After this, the engine can produce the optimal DoFs and recommendations for the physical system. These recommendations are sent to the decision-maker, which interprets and defines the user's trust level in the recommendation. The trust level is sent back as feedback from the user to the trust engine, present in the ***Human Trust Module***, and saved in the database.

One possible application of what-if simulation can be the determination of the optimal number of AGVs for a production line. The operator would use the what-if simulation system for assessing the various possibilities, defining as the independent DoF, e.g., number of AGVs, and the dependent DoF, e.g., throughput. These variables are then fed into the what-if engine, which builds all of the possible scenarios. Assuming no historical information about the problem in question, all the scenarios will be simulated, and the results are sent to the inference engine. The system recommends to the operator the optimal number of AGVs.

IV. Experimental Validation

This section presents the initial developments of the proposed what-if simulation model for a case study. The proposed case study's main goal is to realise efficient energy management of AGVs batteries in a battery pack assembly line.

A. Description of the Case Study

The case study is a battery pack assembly line composed of robots, pick and place units, conveyors, manual workstations and AGVs. This assembly line, called IML (Integrated Manufacturing & Logistics), is installed at WMG, University of Warwick. IML is primarily used for demonstrations and research purposes. The main product assembled on this system is an automotive battery pack, which conjugates industry-standards battery cells and custom-containment modules. Figure 3 shows the schema and respective DES model.

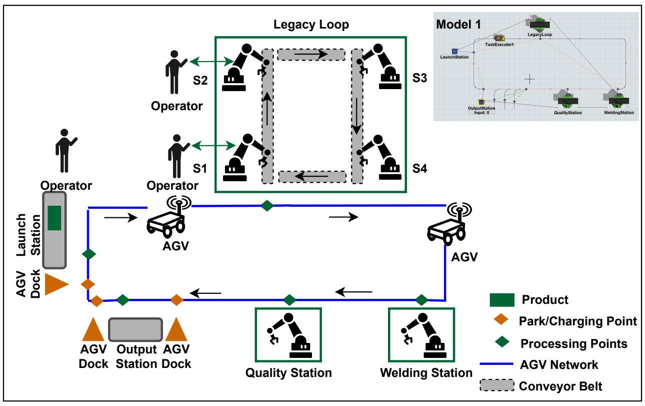

Figure 3: Assembly line schema and model [18].

The assembly line consists of two complete manual stations, a legacy loop (containing conveyor system, two robots and two pick and place units), two stand-alone stations, two AGVs and three trolleys with conveyors. The manual stations are the launch and disassembly stations; the launch station is responsible for initiating the assembly process through the interaction between the human operator and the manufacturing executing system (MES) of the assembly system. The legacy loop has two robot stations, responsible for feeding the battery modules with cells, and two pick and place units, which brings together modules transforming them into packs. The robot stations are manually fed with battery cells. Inside the legacy loop, the battery modules are moved through the use of conveyor belts. The stand-alone stations are simulating laser welding and camera-based inspection processes. Finally, the AGVs are responsible for connecting all the stations, transporting the battery packs using conveyor trolleys.

The assembly line's task sequence is as follows: the operator gives the starting order of the requested assembly product to the MES, calling the AGV for transporting the correspondent battery module components. The AGV travels to the legacy loop, where the conveyor trolley feeds the legacy loop stations. The robot stations fill the modules with battery cells, followed by the pick and place stations that assemble various modules to build battery pack. After the battery pack is assembled, it is transported on a trolley to the stand-alone welding station and inspection station. Lastly, the battery pack is returned to the disassembly station.

For this case study, the work is going to focus on energy management of AGVs, paying close attention to how variables as throughput, battery recharge threshold (i.e. the % of battery necessary to send the AGV to a charging point), and battery resume threshold (i.e. the % of battery necessary to reach while charging to send the AGV back to work), can influence the energy efficiency and which combination leads to the optimal working configuration. For the assessment of the energy parameters related to the AGVs, the following characteristics have been taken in consideration; the physical system makes use of two MiR100 AGVs, which has an average of 10 hours running time (or 20 km), being able to reach a maximum speed of 1.5 m/s forward and 0.3 m/s backwards. In terms of power, the AGV is powered by a battery (Li-NMC, 24V, 40Ah), which can be charged at docking stations, taking 4.5 hours to be fully charged.

B. Experimental Implementation

The DES model of the physical system, previously described, was developed using the FlexSim software (see Figure 3). In this model, triggers were created for retrieving pre-determined data (e.g., throughput, recharge and resume threshold), machine states (i.e. idle and processing) and AGV states/time (i.e. idle, charging, travelling loaded and unloaded, blocked) from the simulations.

A database infrastructure using SQLite3 was developed to save the scenarios' data and the results from the simulation process. An user interface was developed using the Node-RED software, which also plays the role of an intermediary between the FlexSim package and the database. Figure 4 illustrates the Node-RED dashboard.

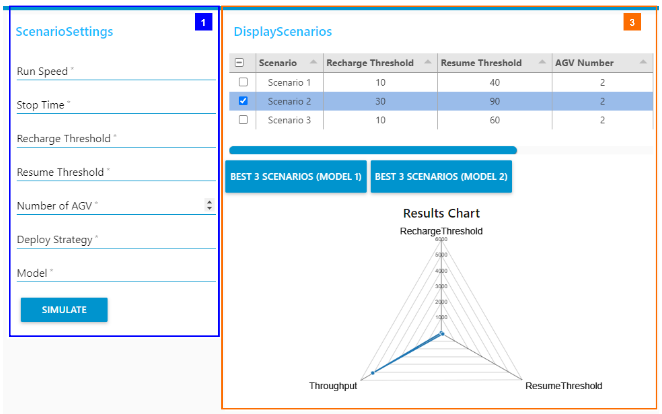

Figure 4: Node-RED dashboard.

In the *Scenario Settings* part of the dashboard, labelled number 1, it is possible to introduce values for the scenario parameters also know as DoF, such as *Run Speed* (i.e., the speed that the simulation software is going to run the scenario), *Stop Time* (i.e., physical time which the software is going to simulate), *Recharge Threshold* (i.e., % of battery level to the AGV going to the recharging station), *Resume Threshold* (i.e., % of battery necessary for the AGV return to the transport), *Number of AGVs* (i.e., are the number of AGVs present in the model), *Deploy Strategy* (i.e., strategy followed by the AGVs during the production process, e.g., whether the AGV waits for the machines were just unloaded the product to finish processing, or if the AGVs unloads the product and keeps travelling for the next job) and *Model* (i.e., DES base models available of the physical system). The DoF values must follow certain limits defined according to the limits of the model built in FlexSim. If the introduced values are out of bounds, a pop-up message is showed with a respective error message. By pushing the *SIMULATE* button, a connection to FlexSim is established, and the scenario simulation is performed. In the *Display Scenarios* part of the dashboard, identified with the number 3, it is possible to compare the best-recommended scenarios in the format of a table and/or a spider chart. In the spider chart, it is possible to dynamically present the different scenarios by selecting the table's scenario. The best-recommended scenarios are the simulated scenarios that reach the success level of the key performance indicators (KPIs).

The dashboard's development code is presented in Figure 5, which is divided into three parts. The part labelled as 1 refers to the input of the scenarios DoF and the *SIMULATE* button. This button works as a trigger for executing a batch file responsible for launching the scenarios' simulation in the background. The code labelled as 2 is responsible for transforming data related to scenarios DoF and the simulations' results. After the data transformation, SQL queries were made, and the data was sent to the database.

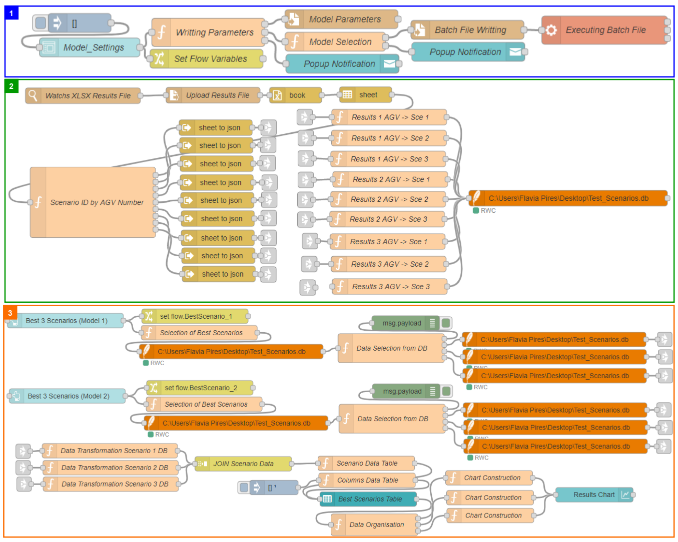

Figure 5: Node-RED code.

Finally, the code labelled as 3 is related to displaying the best-recommended scenarios, allowing the comparison in terms of throughput of the system, the resume and the recharge threshold, the number of AGVs and the deploy strategy. These SQL queries were performed, and the data was organised to present the results in a table and a spider chart.

C. Experimental Results

The case study comprised one legacy loop and two stand-alone stations in the DES model. Table I presents the definition of the DoFs used in this work, including the minimum and maximum limit and the increment (user-defined values). In this case, the number of AGVs can vary between 1 and 3, the recharge threshold varying from 10 to 80% with an increment of 10%, the resume threshold varying from 30 to 90% also with an increment of 10%, and two deploy strategies ("deploy" and "wait") for the AGVs are considered.

Table I: Characterisation of the DoFs.

DoF	Minimum	Maximum	Increment
Recharge Threshold (REC)	10%	80%	10%
Resume Threshold (RES)	30%	90%	10%
Nº of AGVs	1	3	1
Deploy Strategy (DS)	"deploy" (1)	"wait" (2)	–

Considering these DoFs, 210 scenarios were created corresponding to all alternative configurations that should be simulated (note that in an eligible scenario, the recharge threshold must be smaller than the resume threshold). This batch of scenarios was simulated using the FlexSim software package during 14,32 hours, with each scenario being simulated for one week (7 days) time horizon. The achieved results from the simulation of each scenario, namely the throughput and the charging time, were stored in the database. Note that the AGVs in the virtual model were defined according to the real AGVs, being its initial percentage of battery is 100%.

The selection of the best scenario was made through the following performance score equation,

$$Score = Throughput \times Part_V - Charging_T \times C_{Kwh} \quad (1)$$

where the $Throughput$ is the total number of produced battery packs, $Part_V$ is the final sale value of the battery pack (in this case 2€each without considering the costs associated with the charging the AGVs), $Charging_T$ is the time in hours in which the AGVs wherein a charging state and, finally, C_{Kwh} is the cost of the Kwh for industrial consumers (e.g. in the U.K. 0,1968€[1]). Table II presents the five best-recommended scenarios provided by the what-if simulation process.

Table II: Recommended scenarios from what-if simulation.

Scenario Characterisation				Throughput	Charging Time	Score
REC	RES	AGV	DS			
10%	40%	2	2	5098	73,1h	10181,6
30%	90%	2	2	5097	74,7h	10179,3
10%	60%	2	2	5089	72,7h	10163,7
20%	80%	2	2	5080	74,2h	10145,4
40%	90%	2	2	5079	74,3h	10143,4

The best-recommended scenario provided by the what-if simulation, and considering the throughput and the charging

[1]https://www.pordata.pt/Europa/Pre%C3%A7os+da+electricidade+para+utilizadores+dom%C3%A9sticos+e+industriais+(Euro+ECU)-1477

time, was the configuration with a recharge threshold of 10%, a resume threshold of 40% and 2 AGVs present in the system following the deploy strategy of "wait". When comparing the second scenario with the best one, this is very close in terms of throughput but the fact that the AGVs spend more time charging the performance score reflects that, being slightly lower. The third scenario has the lowest charging time, but the throughput was not sufficient to overthrow the best scenario. Lastly, the fourth and fifth scenarios had higher charging times and consequently, more costs.

At this point, the operator should make a decision based on these recommendations, but also considering his trust in the recommendation system and his context aware and experience about the physical system. The decision taken by the operator will be used in a next iteration to adjust the trust level that will affect the recommendation of the best scenarios.

In this work, the entire space of scenarios, totalling 210 scenarios and 14,32 hours of simulation, were simulated requiring great computational power. These numbers can exponentially increase if the simulation model's complexity increases, clearly affecting the decision-support process's efficiency and responsiveness. These observations clearly show the need to reduce the simulation time and the set of scenarios. In the future are going to be applied AI-based techniques for reducing the scenario space. These techniques will use the knowledge acquired from the previous simulations and the operators' trust level feedback. The simulation time reduction can also be achieved by simulating several scenarios in parallel, e.g., using a multi-agent system (MAS), where each agent is responsible for managing the simulation of its scenario.

Additionally, the best-recommended scenarios were chosen based on a performance score equation, which was calculated based on the throughput and charging time parameters. In the future system, more elaborated recommendation services should be considered, namely using Machine Learning (ML) techniques that consider quantitative and qualitative parameters, the user profile and the historical decision record.

V. Conclusions and Future Work

Today's energy demands in the manufacturing sector are significantly raised, with a need to implement technologies that can intelligently enable and manage energy efficiency, such as using a digital twin concept. Efforts have been made to apply the concept in the energy efficiency area. In this paper, a new digital twin architecture and what-if simulation approach are proposed. The paper presents the proposed architecture and the initial developments for the digital twin based what-if simulation. The developed infrastructure includes a simulation software, a user interface and a database. In order to assess the applicability and performance, a case study was conducted on a battery assembly line. Although some improvements are still necessary, these initial tests revealed the potential of applying the presented approach to reduce energy consumption.

As future work, the case study will be further developed increasing its complexity and adding more elements to get it closer to a real system (e.g. more products, demand schedule, human operators, working schedule, maintenance, faults). The what-if infrastructure is going to be further developed, including the scenario space reduction using AI-based techniques, the integration of MAS for the parallel simulation of scenarios, and the enhancement of the recommendation service based on ML techniques and the users' trust level.

Acknowledgement

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