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Concept of hybrid-modelled digital twins for energy optimisation and flexible manufacturing systems for SMEs

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Abstract

Digital twins (DTs) are virtual representations that reproduce the behaviour and characteristics of real manufacturing systems dynamically and in detail by combining information from different data sources. The behaviour is usually represented and digitally mapped by several models at different manufacturing levels, e.g. factory, machine, or process level. Both data-driven and physics-based digital modelling approaches can be used to monitor, analyse, and predict aspects of the corresponding manufacturing system in real time to interact with them and control them optimally. This paper presents a concept for hybrid DTs by intertwining different DT models for energy optimisation and improving the flexibility of manufacturing systems. The approach is based on the Asset Administration Shell (AAS) standard to create Industry 4.0-compliant DTs tailored for small and medium-sized enterprises (SMEs). The concept is applied to a real-world use case in the electronics industry that mainly consists of automated Surface Mount Technology (SMT) Printed-Circuit Boards (PCB) assembly lines.

Keywords: Hybrid Digital Twin, Asset Administration Shell, Manufacturing, Energy Optimisation

1. Introduction

Factors such as rising energy prices, legal environment constraints and an increasing social interest in sustainable and environmental aspects motivate energy-intensive industrial sectors to become more energy efficient and establish energy management systems within the manufacturing systems [1]. To reduce overall energy consumption and respond flexibly to the fluctuating production of renewable energies, such systems must overcome various challenges at all levels of production, from increasing energy efficiency at the asset level to energy-optimised production planning at the factory level [2]. Digital twins, which are a virtual representation of a physical system and reflect its state and behaviour in real-time by linking different data and information sources, are suitable for solving these challenges by monitoring, analysing, simulating, and predicting aspects of the corresponding manufacturing system to drive real-world decisions [3]. Both physics-based and data-driven modelling approaches are suitable for such an implementation. Thereby, hybrid digital twins are becoming increasingly popular. They combine both modelling techniques and offer greater accuracy and decision-making capabilities that are particularly valuable for prognosis [4]. The hybrid approach leverages the strengths of each modelling technique to gain more comprehensive insights and facilitate sustainable energy management in manufacturing systems, which promises a high potential to reduce energy costs significantly. The integration of such digital twin technologies into current manufacturing systems poses major challenges for SMEs, as they face high technical barriers, scalability issues and significant investment and operational costs. These hurdles underscore the urgent need to make digital twin technologies

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accessible and viable for SMEs, considering their limited financial resources, expertise, and outdated systems [5].

This paper presents a concept for a lightweight digital twin that uses a hybrid modelling approach and can be applied at different manufacturing system levels, with a specific focus on addressing the needs and challenges of SMEs. Physics-based models and data-driven models are merged to overcome the challenges of both modelling techniques of a digital twin and enable more energy-efficient and flexible manufacturing. The paper is structured as follows: Section 2 provides a comprehensive overview of the technologies and discusses the challenges in realising a hybrid digital twin (DT) within manufacturing SMEs. The state of the art in modelling techniques is summarised, taking both approaches into account. To achieve standardisation, the concept of asset administration shells is presented and adopted to use it within Microsoft Azure. Considering the state of the art, an architecture for a lightweight hybrid DT, specifically tailored to the requirements of SMEs, focusing on energy optimisation and the integration of the energy factor in decision-making is proposed (Section 3). Section 4 shows how the proposed concept can be applied to a real use case from the electronics industry, specifically for PCB manufacturing with SMT lines, highlighting its practical relevance for SMEs. The paper concludes with section 5, which gives an outlook on future research directions.

2. State of the art

2.1. Digital Twins

According to the Industrial Digital Twin Association (IDTA) [5], a digital twin is defined as the digital replica of an asset, process or system that maps its state and behaviour of the real world in the digital world. Key elements of a digital twin include its attributes that describe its characteristics, models that define, predict, and simulate its behaviour and services that enable interaction with external services [3]. The main objective of a digital twin within a manufacturing system is to eliminate data silos by combining and integrating isolated data sources and models in a semantically consistent way to provide an integrated, unified view of data and information to support decision-making or enable self-controlled closed loops [7]. Therefore, DTs are based on linking operational data originating from sensors or IoT devices, information data originating from Manufacturing Execution Systems (MES) or Enterprise Resource Planning (ERP) systems and digital, application-specific models. This enables the models used to process real-time data to carry out simulations considering the current status of the production system [8]. Within the manufacturing system, DT can be employed at micro and macro levels [9]. At the factory level, for example, digital twins are used to monitor the physical properties and characteristics of the manufacturing system, including energy value stream relevant features [10] such as energy consumption or error rates. At the process level, digital twins can be used to monitor production processes under DIN 8580, such as cutting or joining, which also includes soldering. At the machine level, digital twins are used to monitor machine tools, components and measuring devices. As mentioned above, models play a fundamental role in the use of DTs in manufacturing systems. In addition to traditionally used physics-based simulation models, data-driven models are increasingly being used with current advances in Machine Learning (ML). Both types of models offer complementary advantages, which is why they are increasingly being used as hybrid models within DTs.

2.2. Hybrid-Modelling

As already described, a distinction is mainly made between physical simulation models and data-driven models. Physic-based models follow the white-box principle and describe a phenomenon of a real manufacturing system based on known prior knowledge (such as physical equations or physically based relations). For the simulation to represent the physical counterpart in the best possible way, specific information about the real manufacturing system based on expert knowledge is required for the description of its physical state [9]. Therefore, task-specific simulations are performed with input data from multiple sources to account for the boundary conditions of the simulation and provide accurate predictions Examples of physics-based models within MS are finite elements method (FEM) [11], energy simulations [2] and value stream mapping (VSM) [12]. Examples include FEMs for modelling a production process such as soldering and the optimisation of its manufacturing parameters as well as synchronised VSM with the real system for discrete event simulations.

In contrast, data-driven models follow a black-box principle, where only the input and output of the model are viewed, without knowing in detail how the model obtains its results. They consist of computational algorithms that process large amounts of data and apply techniques such as data mining, machine learning or deep learning to extract insights from historical data and apply them to incoming real-time data [4]. Within manufacturing systems, data-driven models have a wider range of applications as little to no specific expertise is required for modelling. The aim is to gain insights from mainly high-frequency data, such as OT from sensors or machines, to enable e.g. classification of manufactured parts (process), predictive maintenance (machine level) or production scheduling based on manufacturing process (factory) predictions [4].

To gain a comprehensive understanding of the manufacturing system, multiple models and data need to work together. A hybrid digital twin (DT) combines information from isolated DT models to identify and communicate less optimal behaviour at an early stage. This fusion of physics-based simulation and data-driven modelling techniques makes it possible to leverage the advantages of both approaches. The hybrid approach, following the grey box principle, integrates the proven expertise from physical simulations into data-driven models. This results in more accurate predictions and a better understanding of the past and future of a modelled manufacturing system element [3][9]. A typical combination could be the use of a simulation model to generate training data for machine learning models if not enough training data/parameters are available.

2.3. Standardisation based on Asset Administration Shell

As mentioned above, DTs consist of models and attributes that describe the characteristics of the real object in the digital world. In the world of Industry 4.0, each asset is assigned an Asset Administration Shell (AAS). The AAS consists of several sub-models (SM) in which all information and functions of a specific asset - including its characteristics, properties, status, parameters, measurement data and capabilities - are described in UML in a standardised, technology-neutral way. It enables the use of various communication channels and applications and serves as a link between I4.0 objects and the networked, digital and distributed world [13]. It facilitates uniform access to information and functions to promote interoperability between the applications of a manufacturing company. Through a standardised API, data from assets with proprietary communication interfaces can be retrieved as an AAS. The physical positioning of AASs can be at different levels of the factory hierarchy [14]. AASs thus offer the opportunity to make data discoverable and identifiable, to enable access through standardised APIs and to form a digital basis for future autonomous systems. A powerful key concept of the AAS metamodel is that all relevant information is provided by sub-models. The used sub-models within the metamodel of the AAS are each adapted to the functionality of the represented device. There are already various e-class standardised templates for this [3]. The AAS approach for standardisation can also be applied to other technologies. For example, Mayrbäurl et al. [15] tested and implemented the applicability of the AAS as the basis for building an ontology for Smart Manufacturing in Microsoft's open standard for describing models of device and logical DTs, the Digital Twin Definition Language (DTDL).

2.4. Research Gap

In the literature, several research can be found on DT technologies, the different modelling approaches or the use or adaption of AAS. Helal et al. [16] provide a holistic overview of approaches for comparing available open-source and proprietary technologies and methods, their characteristics and their integration and combination possibilities. Kasilingam et al. [17] provide a high-level overview of hybrid modelling in manufacturing. The literature review focuses on the clear combination of physics-based and data-driven modelling in the manufacturing context. Karanjkar et al. [18] presented a discrete-event digital twin to improve the energy efficiency of an SMT PCB assembly line and evaluated the impact of buffer storage using simulations of the digital twin. Data-driven or hybrid approaches and other implementation levels were not considered.

Langlotz et al. [2] provide an assessment table to describe data-driven and physics-based models and their inputs, outputs and other requirements to support the implementation of hybrid models in manufacturing systems and their application for energy management. This table allows users to get an overview of the requirements for implementing a hybrid model. However, it should be noted that this work does not provide a detailed analysis of the challenges faced and standardisation approaches and applicability to all levels of manufacturing are not considered in detail. The research of Wagner et al. [4] focuses on the development of a conceptual framework that guides the implementation of hybrid models in industrial settings where limited model input environments need to be dealt with. Contains the steps to be implemented but does not consider the combination of models of different manufacturing levels, system architectures, standardisation, or their use for more sustainable manufacturing. Jacoby et al. [3] present an architecture approach to realise a hybrid DT based on AAS to generate data for training ML models using simulation in case the data is not available/reliable or the models are not precise. The approach is evaluated on asset level considering a use case of the process industry.

However, most studies focus on specific aspects without considering the challenges and standardization needs of SMEs. SMEs face difficulties due to the high technical barriers, scalability issues, and significant costs associated with implementing DT technologies into their existing production systems [5].

What is lacking in the literature is a comprehensive exploration of the challenges and standardization approaches related to the integration of hybrid models across different manufacturing stages that are specifically tailored to the needs and constraints of SMEs. Considering the hurdles SMEs face when adopting digital twin technologies, there is an urgent need to develop a concept for hybrid DT models based on a standardized approach that removes the technical and financial hurdles and provides SMEs with the necessary tools to achieve sustainable and flexible production processes and remain competitive in the market.

3. Approach to lightweight hybrid modelled DT

The following section presents a concept of what the architecture of hybrid DTs should look like to meet the requirements of standardisation and enable hybrid-modelled applications for energy optimisation and improved flexibility of the production system. Based on Jacoby et al. [3], the approach should fulfil the following requirements:

- Interoperability: requires standards for the DT metamodel.
- Interoperability/Extensibility within DT: DT must enable problem-specific application development and a combination of modelling approaches.
- Interoperability within MS: DT should enable the development of applications for all manufacturing levels (factory, process, asset).
- Extensible: DT should handle different types of modelling techniques (using external simulation tools

To fulfil the requirements and describe the different levels of the manufacturing system with its properties in the best possible way, it is necessary to combine several data sources and models into a manufacturing ontology (e.g. according to ISA 95). The general architecture for the realisation is presented in Figure 1. The illustration shows a modified layer concept from RAMI 4.0 [19] for energy-efficient manufacturing and follows the approach presented by Cavalieri and Salafia [20] and the AAS [6], and the ontology that is used by Microsoft Azure Digital Twins [15]. It highlights the several data streams and relationships between different components. From a high-level point of view, the presented general approach can be divided into three sections – a connection layer, an operation layer, and an application layer.

The connection layer maps the connection of the various real physical devices and enables DT to access the various data sources. This includes the connection of sensors or machines through to the connection to higher-level systems such as ERP or MES. The operational level in the architecture of hybrid digital twins plays a central role in the representation of assets, process information and relationships in production. The modelling is based on the AAS approach for the standardized representation of assets. This enables the use of various standardized submodels to accurately describe the characteristics and functions of the assets. Information from various sources, including sensors and higher-level systems such as MES, is integrated to ensure a comprehensive digital representation of the assets. The individual systems are then assigned to the relevant process step. In summary, this layer enables the correlation of multiple data streams and standardizes the information for the development of specific applications. Implementing this approach via a cloud service such as Azure Digital Twins offers SMEs an efficient way to adapt and implement these AAS principles and reduces the hurdle to start digitization.

The created manufacturing ontology serves as a data source for the development of problem-specific applications such as visualisation and monitoring, prediction, or simulation at various application levels, visualised within the application layer. With the help of appropriate query commands, the required data can be retrieved from the DT and used as input for models or simulations. These can be executed either internally or in an external environment, with cloud providers such as Azure benefiting from a range of additional services that enable the creation of such applications in the same environment. Bidirectional data transfer allows the models developed within the application to be updated with DT changes or new simulated or predicted properties to be returned to the DT for use in other applications or for direct control, e.g. by adjusting configuration parameters. The implementation of energy-efficient production is achieved by combining different models. On the one hand, a data-driven machine learning model is used to predict the internal power generation of the photovoltaic (PV) system. On the other hand, an energy value stream simulation is used to predict the internal power consumption of production. Together with an external electricity price forecast, the simulated and predicted values are used as input for a decision-making tool, which optimizes the detailed planning of production based on these predictions.

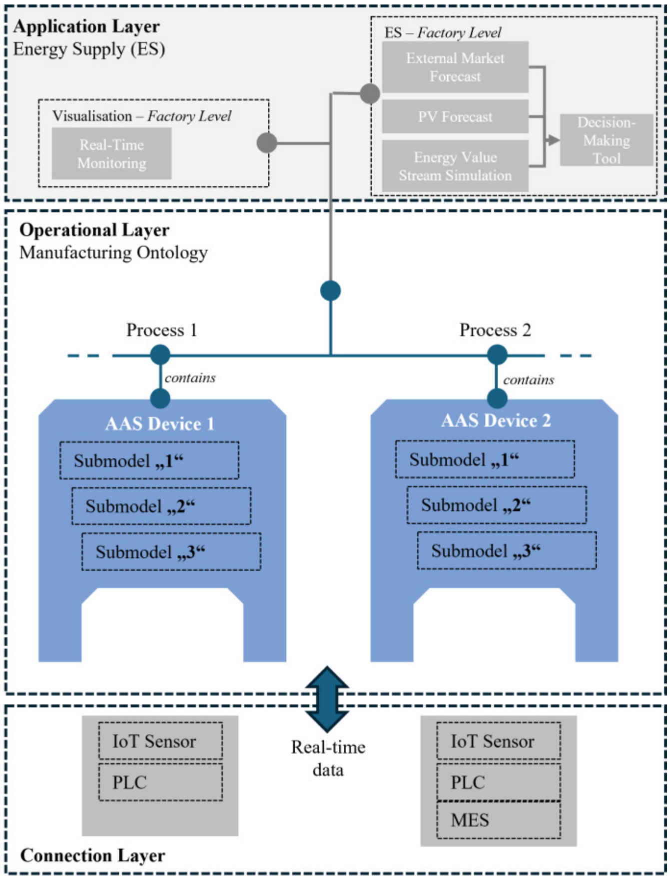

Fig. 1. RAMI 4.0: Modified layer concept:for energy-efficient manufacturing

With the help of the layer concept presented in Figure 1, hybrid DTs can be developed to enable energy-efficient manufacturing considering different production stages. The layer concept presented is validated and applied to a real use case of an SME in electronics manufacturing to improve the flexibility of the MS and optimise energy consumption.

4. Use-case: Energy optimisation at factory level

Given rising energy prices and the increasing social interest in sustainability, it makes sense to make manufacturing systems more flexible and to increase energy efficiency and the use of self-generated energy. Therefore, the presented use case aims to develop a hybrid DT application at the factory level to reduce the energy costs of a factory and increase the penetration of renewable energy using the explored DT approach. For this purpose, a real manufacturing system of an SME is considered, which consists of several identical SMT lines for PCB production and an installed PV system on the manufacturing side. Since the reflow oven with its various heating and cooling zones is the main power consumer within the manufacturing process, only this is considered to simplify the logic.

The relevant properties for describing the characteristics of the SMT soldering units and the PV system are described below. To achieve standardisation, the layer concept presented in section 3 is used. The physical assets are characterised using models and sub-models and linked to a manufacturing

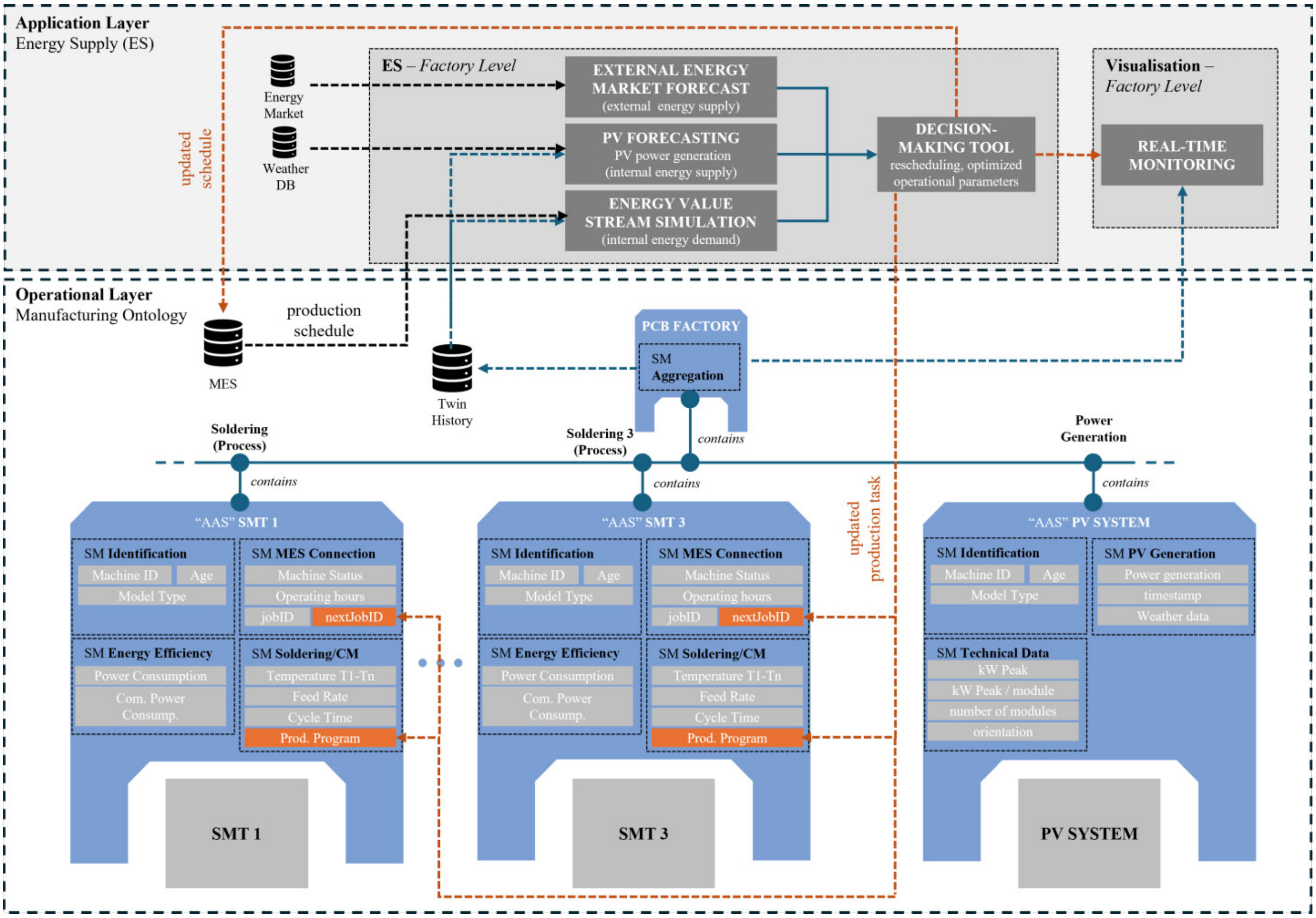

Fig. 2. Use-Case: Layer concept and application for energy-efficient PCB manufacturing

ontology. The implementation is done with Azure Digital Twins (ADT) and other Azure services that access the ADT service endpoint.

To describe the SMT soldering unit, the sub-models SM identification, MES connection, energy efficiency and soldering are used. As the lines are identical, these sub-models can be reused to describe the other SMT soldering units. The SM identification is used to recognise and distinguish the individual machines and contains properties such as machine ID, model type and age. The SM MES Connection indicates the status of the machine, i.e. whether the machine is producing, ready for production, has a fault or is being serviced. It contains, for example, the properties' production status, operating hours, current job ID and the planned runtime of the job. Factors that influence the status of the machine are not mapped in this SM. The SM energy efficiency specifies the details of the energy consumption. It contains measured values for properties such as the electricity consumption, the integrated electricity consumption over time (e.g. since the start of the current job) and the cumulative start date. The SM Soldering contains a range of functions to describe, start, end, or simulate the soldering process. This includes properties such as the feed rate of the conveyor belt, the planned and actual cycle time per panel (via timestamps), the temperature T_1 -T_n per heating or cooling zone, the start of the job, the selected production program or the workpiece served.

The PV system, which is modelled using SMs for identification, technical data, and PV generation, is also located within the production ontology. The SM identification contains the model type, an ID, and the age of the system. The SM technical data contains the technical system details, installed kW peak, kW peak per module, number of modules, orientation & angle. The SM for PV generation specifies the details of energy generation, via properties such as current generation in kW, timestamp, and associated environmental features. The problem-specific application is created based on the described manufacturing ontology. Only the properties required for the model are retrieved from the ontology. To solve the described problem at the factory level, a hybrid approach consisting of physics-based simulation and data-driven prediction is required. The data-driven model aspires to predict the power generation of the installed PV system. Therefore, the recorded historical data of the power generation and the corresponding surrounding weather conditions is needed. Then, the trained ML algorithm is applied to an external weather forecast for time-series forecasting to predict the power generation of the PV system (internal energy supply).

The physics-based model is used to simulate the energy consumption (internal energy demand) of the manufacturing system. The physics-based model aims to calculate the runtime and the expected power consumption per order. Determining these new parameters requires the current production plan from the MES, which contains the details of the orders and the planned resources, as well as the measured and characterising properties of the DT for the respective SMT soldering units as model input. The simulated output contains information regarding the energy consumption and the expected runtime per order, depending on the selected resource respectively SMT unit for manufacturing.

The task of the hybrid model is to combine the output of both models and enable better decision-making. The required input consists of the output of the two models described above, in this case, the prediction of the generated electricity from the PV system and the simulated parameters, which include the energy consumption and the runtime per order concerning the selected SMT soldering unit. As a third input, the decision model receives an external market forecast (external energy supply). The aim is to adapt the energy consumption to the company's power generation to minimise electricity costs and maximise the proportion of renewable energy used. The result of the model is an adjusted production schedule that recalculates the start time and the selected resource to manufacture each order.

Figure 2 shows an overview of the PCB manufacturing use case of an SME, including the required components, properties, and their interaction. The status of the individual machines/systems is monitored via sensors and the integration of PLC and MES data. It is represented by high-frequency (e.g. time-series measurements) and low-frequency data (e.g. reported start and end time of an order). The data originating from different data sources is standardised using a predefined metamodel that describes the properties of the counterpart. The data can be used directly for monitoring or as input for the hybrid model to optimise the energy supply (ES). The data from the various data streams bundled in the manufacturing ontology provides general information about the current process and the status of the manufacturing system. The schematic data is stored in a database to enable data-driven decisions based on historical data.

The figure also shows an example of how independent physics-based and data-driven models can be combined into a hybrid application to solve complex issues such as the optimisation of the production schedule based on energy parameters. It also shows how the results of the hybrid model can be used to directly interact with the assets, e.g. to automatically adjust the next scheduled job ID and the corresponding production program based on the model output.

5. Conclusion and Outlook

In this paper, an innovative approach to applying digital twins in manufacturing systems is presented, focusing on two key areas. First, a standardised metamodel for data acquisition is being developed that reflects the entire manufacturing environment in a manufacturing ontology and facilitates the transfer of asset data structures across different parts of the production system by adapting AAS-based sub-models within a cloud service like ADT. This standardised approach simplifies the integration of new assets and applications at different manufacturing levels and increases the flexibility and scalability of DT. It also provides an access point for the development of problem-specific applications through which the various data streams of the production system can be accessed in a bundled manner.

Using cloud providers such as Microsoft Azure to implement the operational and application layer as a service on a subscription basis offers a cost-effective and scalable option for small and medium-sized manufacturing companies. It lowers the barrier to the adoption of new technologies and removes the need for significant upfront investment in technical infrastructure and expertise, enabling SMEs to harness the power of hybrid DTs while leaving the technical complexity to the service provider.

Secondly, the combination of different modelling technologies into a hybrid DT at factory level is proposed to optimize the energy efficiency of production. Based on the simulation of the energy value stream, prediction of PV power generation and prediction of the electricity market, an approach is proposed to make production planning more flexible and manufacturing more sustainable. The aim is to maximize the use of renewable energy and self-generated electricity and reduce overall energy costs. The performance of the presented application to improve the energy efficiency of manufacturing SMEs still needs to be validated during the running process over a longer period.

Outlooking future research, the applicability of the presented layer concept for different MS levels and use cases should be evaluated in more in-depth. Studies could focus on how the ontology can be used to combine multiple models across different manufacturing levels to account for their mutual influence and achieve a superior optimum. In addition, studies could investigate the addition of technologies such as battery storage to improve overall energy efficiency and optimize the control of the MS system. Furthermore, the applicability and benefits of the proposed layer concept and the presented energy supply application to SMEs in different sectors (with high or low energy-consuming processes) can be evaluated.

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