Data-Driven Extraction of Simulation Models for Energy-Oriented Digital Twins of Manufacturing Systems: An Illustrative Case Study

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Karlsruhe Institute of Technology
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DATA-DRIVEN EXTRACTION OF SIMULATION MODELS FOR ENERGY-ORIENTED DIGITAL TWINS OF MANUFACTURING SYSTEMS: AN ILLUSTRATIVE CASE STUDY

Atieh Khodadadi[1], and Sanja Lazarova-Molnar[1,2]

[1]Institute AIFB, Karlsruhe Institute of Technology, Karlsruhe, GERMANY
[2]The Maersk Mc-Kinney Moller Institute, University of Southern Denmark, Odense, DENMARK

ABSTRACT

Manufacturing systems, as significant energy consumers and potential contributors to energy efficiency optimization, play an important role in addressing global energy challenges. Digital Twins utilize available data from smart manufacturing systems to effectively understand and replicate systems' energy-related behaviors. Digital Twins facilitate detailed systems analysis and enable decision support for optimizing energy efficiency through performing relevant "what-if" scenario analyses. In this paper, we propose a methodology for data-driven extraction of simulation models for Energy-Oriented Digital Twins of smart manufacturing systems. Through a case study of a data-driven Energy-Oriented Digital Twin for an assembly process of a quadcopter drone part, we illustrate our initial methodology and the related data requirements. Our case study helps comprehend the complexity of extracting Energy-Oriented Digital Twins in smart manufacturing systems, offering insights into the integration of production and energy-related processes and behaviors of the system.

1   INTRODUCTION

Rapid global economic growth and population increases are driving a significant surge in energy demand, which is projected to potentially double by 2050, leading to concerns about energy supply and resource reduction (Khan et al. 2021). CO_2 and other greenhouse gas emissions are also driving climate change, necessitating immediate action to reduce their impact (Keiner et al. 2023). The industrial sector, accounting for more than 30% of global greenhouse gas emissions, is under significant pressure to minimize its environmental footprint (Mallapaty 2020). Consequently, several countries are targeting 'net zero' carbon emissions by enforcing strict controls on industrial systems. The shift towards greener operations, coupled with the surge in consumer demand, is leading to increased manufacturing expenses and impacting competitiveness, highlighting the urgent need for advanced energy-saving technologies, and establishing a low-carbon energy infrastructure. In this context, Digital Twin (DT) technology stands out as a key enabler, offering a promising solution to enhance energy efficiency in manufacturing by optimally aligning plant operations and assets to tackle energy-emission challenges (Do Amaral et al. 2023).

A DT is a virtual model that replicates and simulates the behavior of a physical system. A DT is defined as a virtual representation or model that mirrors a physical object, where both entities are linked through the real-time exchange of data (Singh et al. 2021). Smart Manufacturing Systems (SMS) are advanced, fully integrated, and collaborative systems that deliver real-time responses to meet the demands and conditions of the industry, supply chains, and customer needs (Kusiak 2023). The term "energy-oriented" refers to approaches, strategies, or systems that emphasize efficient energy utilization. Implementing Energy-Oriented DTs (EODTs) in SMSs to evaluate energy utilization and enhance energy efficiency facilitates the identification of significant energy consumers, supports process improvements, and leads to cost reductions (Billey and Wuest 2024). While a standard DT can track energy consumption by monitoring the necessary variables, an EODT specifically simulates, analyzes, and supports decision-making to optimize energy use and sustainability, providing targeted insights and actionable strategies for energy efficiency improvements.

Even with the broad application of DTs in diverse domains of manufacturing systems, the adoption of DTs for improving energy efficiency in the manufacturing industry is still notably limited. In this paper, we explore the methodology for developing EODTs for SMSs, and through a case study, we explain DT's model extraction methodology and DT's potential to optimize energy efficiency in SMS.

We structured the paper as follows: In Section 2, we discuss the concept of DT and its role in enhancing energy efficiency in SMSs, with an overview of relevant research. In Section 3, we outline an initial methodology for extracting EODTs. In Section 4, we present a case study to illustrate the requirements, implementation process, and outcomes of EODTs in smart manufacturing systems. Finally, in Section 5, we summarize our findings and provide insights into potential future advancements in EODT for SMSs.

2 BACKGROUND AND RELATED WORK

In this section, we provide an overview of DTs for SMSs, followed by a discussion on the significance of energy efficiency in SMS. In the final subsection, we summarize existing research on the use of modeling, simulation, and DTs for enhancing energy efficiency in manufacturing processes.

2.1 Digital Twins for Smart Manufacturing Systems

The origins of DTs can be traced back to Grieves and Vickers (2017) formal introduction to the concept of DTs, at a conference organized by the Society of Manufacturing Engineers. Grieves outlined the foundational framework that consists of three main components: the physical entity in the real world, its digital counterpart, and the data and information connections that facilitate interactions between the physical and virtual realms. The term "Digital Twin" was first used in the work of Hernández and Hernández (1997), where DT was applied to iterative changes in the design of urban road networks. The continuous updating feature of DTs allows us to test various "what-if" scenarios, aiding in outcome prediction and decision-making support. Furthermore, the International Organization for Standardization has introduced a framework for DT manufacturing. ISO 23247 aims to establish a universal language and structure for the development of DTs within the industry (ISO 23247-1 2021).

Data-driven solutions, which utilize data analysis and interpretation to inform decision-making, offer an opportunity for manufacturing systems as an effective way to address challenges, including rapidly changing demands and the need to reduce time to market. Consequently, the adoption of data-driven technology is increasingly employed as an approach to developing DTs in process industries (He et al. 2019). DTs have demonstrated substantial potential across various domains, attracting significant interest from both the industrial sector and academic communities (Liu et al. 2021). DTs can be applied to various industry domains, such as training employees (Kaarlela et al. 2020), real-time monitoring (Li et al. 2023), fault detection (Kumbhar et al. 2023), and maintenance prediction (Zhong et al. 2023).

2.2 Energy Efficiency in Manufacturing Systems

Over the last three decades, researchers and policymakers have paid close attention to the relationship between energy demand and environmental impact (Hussain and Zhou 2022). Energy performance stands as a crucial component of policies aimed at securing inclusive and sustainable economic growth worldwide (Ahmad and Zhang 2020). Energy efficiency represents the ratio of performance, goods, or services output to the necessary energy input (Lovins 2004). In manufacturing, energy efficiency focuses on optimizing the ratio of production output to the total energy consumption (Patterson 1996).

Manufacturing processes encompass a range of inputs and outputs. Inputs include production components such as raw materials and energy, whereas outputs include the manufactured products and waste generated (Mohamed et al. 2019). Energy waste may occur due to heat loss, inefficient usage, or inappropriate arrangements of machinery. Optimizing energy consumption in non-value-adding production phases is crucial for reducing overall consumption, targeting periods where energy is used without contributing to product creation, such as the idle state of a machine (Römer and Römer 2021).

To optimize production, continuous monitoring of operational parameters is crucial for improving resource efficiency, output quality, and energy consumption through data-driven insights and iterative improvements. In the context of SMSs, key enabling technologies encompass the Internet of Things (IoT) (Ryalat et al. 2023), Cyber-Physical Systems (CPS), cloud computing, artificial intelligence (AI) (Liagkou et al. 2021), and big data analytics (Liagkou et al. 2021). A study by the Institute for Mechanical Systems Engineering and Structural Durability (IMAB) at Clausthal University of Technology, based on a VDMA survey, highlights the significant advantages of SMSs (Lentes and Dangelmaier 2013). According to IMAB assessments, the benefits of utilizing data in SMS include a 70% reduction in planning errors, 30% less planning time, 15% in change costs reduction, and savings of 3-5% in total manufacturing costs, underlining the primary advantage of enhanced planning quality and error prevention.

2.3 Modeling, Simulation, and Digital Twins for Energy Efficiency in Manufacturing Systems

Despite the vast use of DTs in various aspects of SMSs, research in the field of EODT in SMS is limited. As a result, we performed a literature review on the application of DTs and simulation to enhance energy efficiency in SMSs. To enhance energy efficiency in SMSs, it is critical to both understand the dynamic interconnections across the system and closely analyze the energy consumption behaviors of each component. Additionally, evaluating key metrics such as output, time, quality, and costs is essential for a holistic approach to improving efficiency (Wenzel et al. 2023).

Simulation models can generally be developed using one of four main approaches: discrete-event simulation (DES), continuous simulation, also referred to as system dynamics (SD), agent-based simulation (ABS), and hybrid simulation (HS). Each paradigm has its own strengths and application areas, and offers unique insights, especially for enhancing energy efficiency in manufacturing. In DES models, the state of the system is considered to change only at discrete points in time, triggered by events. In contrast to DES, in SD the state of the system is considered to change continuously over time (Banks and Carson 1986). ABS concentrates on a system's active parts, describing them as agents, each with their own behaviors (Parv et al. 2019). HS models systems with mixed continuous/discrete behavior (Mosterman 1999).

From existing literature, we observed that DES and HS provide valuable tools for modeling and analyzing different energy-related aspects of an SMS. Based on literature, there is three main strategies for integrating energy-related behaviors of manufacturing systems in DES simulations (Herrmann et al. 2011). Strategy A employs external energy analysis, utilizing production data from the simulation environment for energy demand calculations, offering an approach where energy needs are assessed separately. Strategy B integrates production simulation with other modules, such as technical building services (TBS), either within one software suite or through the combination of multiple tools, for a more comprehensive analysis. Strategy C embeds energy considerations directly into the simulation environment itself, creating a unified, seamless approach for energy efficiency analysis within manufacturing systems.

In the following, we list relevant approaches of the different simulation strategies, used for enhancing energy efficiency in SMSs. Ghani et al. (2012) implemented strategy A in the automotive sector, focusing on comprehensive energy analysis and optimizing design processes to minimize time and costs. The study offers insights to identify and reduce energy use in idle processes, supporting sustainable resource management and cost-effective product development.

Sobottka et al. (2020) developed and evaluated a model based on strategy B for a metal casting manufacturer in Austria, integrating DES and SD models into an HS method for multi-criteria optimization. Results indicate a potential of ca. 10% in global optimization, improving cost and energy efficiency, with an additional 6% in energy savings. Using the same simulation paradigm, Schönemann et al. (2019) created a hybrid agent-based simulation model for battery factory systems, improving energy efficiency and reducing environmental impact. Schönemann et al.'s work enhances energy efficiency, environmental impacts, and costs by deriving alternative strategies in the production of lithium-ion battery cells.

To study the feasibility of the third strategy C, Dér et al. (2022) developed a DES framework to evaluate the environmental impact of manufacturing fiber-reinforced automotive parts, analyzing energy use at each

process step to create load profiles. The authors identified that the top five process steps accounted for about 80% of energy intensity. Dér et al. further revealed through simulation that increasing processing rates by 5% in bottleneck areas could eliminate the need for an additional machine, thereby reducing total energy demand. Similarly, Kesharia et al. (2018) presented a DES to explore energy efficiency in the pulp and paper industry, implementing strategies to improve energy use and production flow in two scenarios, enhancing both energy and operational efficiency.

3   ENERGY-ORIENTED DIGITAL TWINS

An EODT is a virtual model designed particularly to simulate, analyze, and optimize the energy consumption behavior and possibly, sustainability of systems, such as SMS. EODTs leverage real-time data and predictive analytics to identify energy-saving opportunities and reduce carbon footprints, making DTs an essential tool for achieving energy efficiency and sustainability goals in the industrial sector. In this section, we introduce an initial methodology for extracting EODTs. We examine the key elements of an EODT for an SMS, as well as the essential data requirements to capture manufacturing processes' energy dynamics accurately. We then explore model extraction processes, utilizing data- and process-mining (PM) techniques. Lastly, we discuss the methodology for model validation of EODTs.

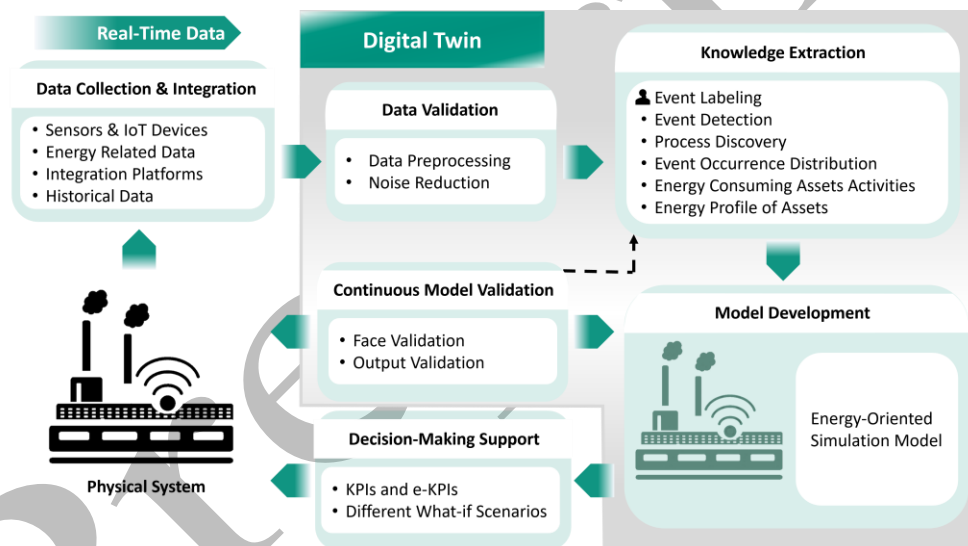### 3.1   Key Elements of Energy-oriented Digital Twins of Manufacturing Systems

Figure 1: Framework for the energy-oriented data-driven Digital Twin.

As we illustrate in Figure 1, three key elements that enable a data-driven DT for an SMS include the physical entity, data-driven simulation model, and data flow between these two elements. The physical system (SMS) that generates large-scale data, such as event logs from different sources, including IoT technology, focuses on capturing energy-related information, such as energy consumption over time. The extracted data, integrated from various sources, creates a comprehensive, accurate, and current dataset that also serves as a historical record. In the data validation step, we validate the data to ensure it is free from problems such as noise and missing values (Koschmider et al. 2021). The validated data is a foundation for reliable knowledge extraction. In the next step, knowledge extraction involves pulling insights from validated data, focusing on several critical processes. Event detection in an SMS is crucial for the construction of DES models. Experts pinpoint events in unlabeled event logs, and further ML techniques, such as classification (Morariu et al. 2020) and clustering (Landauer et al. 2020), can be used for automatically detecting events. Next, we extract the process flows with the help of the PM of the event logs. In the context of knowledge

extraction, data analysis facilitates the uncovering of process insights, such as the distribution of timed transitions, as well as energy-specific knowledge, for example, Energy Consumption Profiles (ECP). From the knowledge extraction, we achieve a unified process model that integrates both product and energy-focused processes. Discovered process flows can be described and analyzed using modeling languages or specifications, such as Petri nets (Murata 1989). The next critical step in our proposed framework is creating an energy-oriented, data-driven simulation model based on the extracted model. This simulation model automatically updates to mirror changes in the SMS (Friederich et al. 2022). The continuous validation ensures accurate models that support effective energy-focused decision-making. Finally, the validated DT turns into a valuable resource for executing various "what-if" scenarios, leading to the development of a decision support system focused on energy optimization.

3.2 Data Requirements

Next, we identify the essential data requirements for enabling EODTs in SMSs. Given the discrete operational nature of manufacturing systems, the collection of event and state logs is a standard practice. Although DES is widely researched and frequently used in SMSs, applying DES to assess energy aspects of systems is a relatively recent development that has become increasingly significant (Wenzel et al. 2023). In our previous study (Khodadadi and Lazarova-Molnar 2023), we identified the necessary data for creating EODTs in SMSs. We described the corresponding event and state log structures, required for gathering information on energy consumption and operational states of SMSs for analysis and improvement of SMSs energy efficiency. Event logs should be collected from each asset in the manufacturing system and the production line of interest, along with a state log from the production line of interest.

The event log structure comprises several key components that capture the dynamics of energy consumption and task management. Each event is marked with a Timestamp (TS), indicating the exact time the event occurred, a Task Identifier (ID) for tracking and identification of each event, and an 'Event' field that details the action occurring at the time of logging. The Energy Stamp (ES) captures the energy consumption of each asset for each activity in the meantime of event occurrence. Each piece of equipment within the system is uniquely identified in the 'Asset' field, and the Power Type (P) field indicates the source of energy, such as battery, grid, or solar, which is essential for further energy analysis and optimization.

The state log complements the event log by tracking the status of assets over time. The state log includes a Timestamp (TS), 'Asset' as a unique identifier for each piece of energy-consuming equipment, and 'State' field to identify the asset's current operational state. This structured approach to data logging is vital for detailed analysis of a system's energy bottleneck and for driving improvements in operational efficiency.

3.3 Energy-oriented Model Extraction

In the following, we describe the methodology for extracting a data-driven EODT from an SMS. The extraction process captures event and state logs from the original model, encompassing all relevant activities and energy consumption patterns. We process the extracted logs using PM techniques to identify the underlying process flows. The extracted flows are integrated to create a comprehensive energy-oriented model, represented as an SPN, which is then simulated. In Algorithm 1, we outline the systematic approach for extracting a comprehensive model from event and state logs. Collected data is first subject to a data validation phase, which includes cleaning and preprocessing tasks such as removing incomplete event records. Subsequently, we implement PM techniques to extract individual process flows from the production line and each asset's event log. These process flows are then integrated, combining the basic production flow with the asset's process flows in overlapping processes, such as places where assets are involved in the production process. Moreover, we transform asset flows into iterative loops to signify repeated utilization. The final process flow integrates both time-oriented and energy-oriented process flows.

The underlying extracted model is a Stochastic Petri Net (SPN), which is characterized by incorporating two distinct node varieties, named places, and transitions, with connections that extend from a place to a transition or vice versa (Murata 1989). The changes within a Petri net are driven by the movement of tokens

from one place to another via transitions representing the execution of operations or events, altering the system's state accordingly. SPNs distinguish between two categories of transitions: timed and immediate transitions. To effectively implement the SPN model, it is essential to detail the attributes of each transition, such as the distribution of timed transitions and the weights of immediate transition outputs.

After PM, we apply data mining in four steps. First, we extract probability time distributions for timed transitions (Friederich et al. 2022). For start events, such as new orders, we employ a modest input dataset of the original model (a simulation model showcasing a manufacturing system used as a case study), while for other timed transitions, we utilize the whole dataset. Second, for immediate transitions with multiple outputs, we determine each event's occurrence weight. The third task involves calculating each asset's energy consumption profile from its event log. To achieve the ECPs of the asset, we calculate the energy consumed between the beginning and end of activity with the same ID, dividing by the activity's duration, as outlined in Equation (1), expressed in the power per unit of time, where n represents the number of IDs, E_i denotes the energy consumed for the activity, and T_i is the time duration of each activity. The average energy consumed for all identical activities is considered the energy consumption rate for that activity, which, within our extracted process flow, denotes the energy rate for transitions. The fourth task aims to identify and analyze special energy-related behaviors of assets, for instance, the charging threshold for battery-operated assets. We can identify special energy-related behaviors from each asset's event log.

$$ECP = \frac{1}{n}\sum_{i=1}^{n}(\frac{E_i}{T_i}) \tag{1}$$

The final step of our methodology is the integration of the extracted ECP, and process flows with their distributions into an energy-enriched process flow. This model comprehensively extracts the EODT, detailing both the operational processes and the associated energy consumption patterns of the system.

Algorithm 1: Extraction of Energy-Oriented Digital Twin model.

```
Input:   energy-oriented_event_log
Output: energy_featured_model
Procedure:
1.  Data Preprocessing
    •   Remove noise and incomplete events.
2.  Process Mining
    •   For each event log, extract the individual process flows.
    •   Synthesize the production line and each asset's process flows into a unified process flow
        model by:
        - identifying and aligning overlapping processes.
        - converting asset flows into iterative loops, indicating repeated asset utilization.
3.  Data Mining
    •   Timed Transitions
        - Calculate durations between the start and end of the same activities based on
        individual event identifiers.
        - Apply statistical analysis to find the best-fitting probability distribution.
    •   Immediate Transitions
        - Determine the probability of occurrence for each event by dividing the count of
        specific event occurrences by the total count of all linked places' events.
    •   Energy Consumption Profile extraction
        - From each asset's event log aggregate activities and compute:
            - energy consumed and the duration until the subsequent event.
            - calculate the mean of energy consumption rate per unit of time per each activity.
    •   Energy-Related Behaviors of Assets
        - Identify and analyze specific or unusual energy consumption patterns and behaviors of
        assets that deviate from the norm such as activities that are not included in the
        production process.
4.  Integration of Process and Energy Data
    •   Merge the detailed process flows with the extracted energy profiles to construct the
        "energy_featured_model".
```

3.4   Model Validation

Validation is the process of ensuring that a simulation model accurately reflects real-world behaviors sufficiently for informed decision-making. The model validation process follows a two-step approach: first, developing a model with high face validity; second, assessing the simulation's output quality (Kleijnen 1995). Face validity is assessed by presenting the model's outputs to both users and experts familiar with the system, ensuring the outputs reflect realism. To further validate the extracted model, we directly compare its outputs with data from the original model. The comparison utilizes Key Performance Indicators (KPIs) that are pivotal in the validation process of data-driven EODT models (Friederich 2023). These KPIs and Energy KPIs include production volume, which measures the total number of production orders completed in a set period, throughput, which indicates the portion of the output to production orders (input), overall energy consumption, which tracks total energy used through the manufacturing process over time, and energy consumption per asset which monitors energy usage by each asset over time.

The validation frequency indicates how often we assess the validity of our data-driven model against the real-world system. For this, we compute a 95% confidence interval using the t-distribution for both the original and the extracted models. We then examine the extent of overlap between these confidence intervals. An overlap indicates that the means of the observed and simulated data sets are not significantly different, affirming the model's validity. Comparing these results allows us to demonstrate the effectiveness of our approach in applying the model in different "what-if" scenarios to improve energy efficiency in SMS.

4   CASE STUDY

To demonstrate the process of extracting underlying models of EODT for SMS, we designed a case study based on a previous study presented in (Friederich et al. 2022). In our case study, we use a DES simulation model of a system using the "c-paradigm" (Herrmann et al. 2011), which includes energy evaluation in a program. We use our model which we term as the *original model* to generate data that we then use to (re-)discover the underlying energy-oriented model. We, first, outline the case study system, followed by identifying the necessary data for extracting EODT's underlying model. Next, we elaborate on the process of extracting the data-driven DT model. Subsequently, we detail the methodology to validate the extracted EODT's model with the original model. Finally, to illustrate its applicability, we use the validated model in "what-if" simulation scenarios for energy efficiency improvement of the SMS.

4.1   Case Study Model Description

Our case study production line assembles a vital component of a quadcopter drone, consisting of a rotor, motor, and chassis. We operate two production lines that, while identical in assets, each exhibit unique energy consumption patterns. The production line is equipped with five key assets: a warehouse with automated order picking and admission, two Automated Guided Vehicles (AGVs) for loading, transporting, and unloading items, and two assembly cobots, designed for assembly tasks.

Each production line follows the same process but operates independently with its own set of AGVs and cobots. The production process is initiated when a user places an order. The warehouse then prepares the necessary parts. An order has a 50% chance of being assigned to either Line 1 or Line 2. The assigned line's AGV transports the parts to the line's cobot assembly area. Here, the cobot assembles the parts and returns the finished product. Finally, the warehouse stores the finished product, and notifies the user.

In terms of energy usage, Line 1 features an AGV with a low ECP and a cobot with a high ECP. Conversely, Line 2's AGV has a high ECP, while its cobot has a low ECP. Each AGV operates with different ECP rates based on its activity, including idle, loading, unloading, and moving with or without production parts. AGVs are battery-powered, while cobots are connected to the grid for their power supply. AGVs receive an alert to proceed to the charging station when their battery level drops to a specified threshold, set at 30%. AGVs utilize an inductive charging system located at the loading and unloading areas for this process. The time required to fully charge an AGV depends on its current battery level and charging

rate, set at 1.5% per minute. Cobots have two energy states: idle and active, ensuring efficient energy use throughout the production process.

4.2   Data Requirements

In this subsection, we outline the data requirements to extract the energy-oriented (EO) model of our case study. For this purpose, we require two types of logs: event logs and state logs. We require event logs for the entire production process as well as for each energy-consuming asset. To extract the event log from each asset, it is essential to identify all activities of the asset, encompassing both non-value and value-adding processes. For instance, in our case study, we maintain event logs for the entire production system, from the placement of a new order to the end of production.

State logs are implemented to extract the utility of each asset, aiming to identify non-value-adding states. This analysis enables us to pinpoint areas within the SMS states that offer opportunities for enhancement. Consequently, we gather event and state logs, yielding a total of five event logs and one state log. Table 1 and Table 2 showcase a subset of the event and state logs related to the production line. The data extracted from the system covers a 24-hour operation period of the production line, with each data point recording time details down to the second.

Table 1: Energy-oriented event log excerpt.

Time Stamp	ID	Asset	Energy Stamp	Power Type	Event
00:07:00	531	NA	NA	NA	New Order
00:07:00	531	NA	NA	NA	Direct to Line1
00:07:01	531	AGV1	68.51	Battery	Seize AGV1 Begin
00:08:21	531	AGV1	67.94	Battery	Seize AGV1 End
…	…	…	…	…	…

Table 2: Energy-oriented state log excerpt.

TS	Asset	State
00:07:01	AGV1	Active
00:09:43	AGV2	Idle
00:09:43	AGV2	Active
00:12:32	Cobot1	Idle
…	…	…

4.3   Energy-Oriented Model (Digital Twin) Extraction

In the following, we explain the methods, applications, and tools utilized to extract the EODT model of our case study. To ensure data validity, we eliminate unfinished processes during the validation phase, preventing the misidentification of incorrect endpoints in process mining (PM). We employ the PM4Py (Berti et al. 2023), a PM library, to extract the process flow from each event log of each asset and the entire production line, resulting in five distinct processing models. At this stage, our objective is to merge processes that occur at the same places, thereby capturing a unified process flow of the entire system.

We apply data mining techniques to analyze the distribution of timed processes and extract the weight of immediate transitions with two or more output places, as demonstrated in our case study for the new order's line assignment. We use SciPy (Virtanen et al. 2020) to identify the best-fitting probability distributions for the timed transitions on the event logs of 100 runs of the original model. We examine the logs of each asset to determine the ECP for each one. To calculate the ECP of each asset, we use Equation (1), as outlined in our methodology. Additionally, we assess the rate at which AGV batteries charge by dividing the required charging percentage by the duration of charging.

In Figure 2, we present the final extracted Petri net of the case study system, integrating energy-related information with the traditional Petri net components. Our Petri net includes specific transitions and places, such as energy places that record the energy consumption by assets, whether from a battery or the grid. The energy value at these places can be altered through timed or immediate transitions, based on the principle that the energy added to each energy place is the product of the transition's time duration and the ECP rate of the transition. Each asset's place is considered an idle state, assuming that when the asset's token is in its place, it is in an idle state. As soon as the asset moves, the energy consumption of the idle state is added to its energy place, considering the duration from when the token is in the idle place until it departs, noting that immediate transitions do not have a time duration. Whenever an AGV is in an idle state and a new
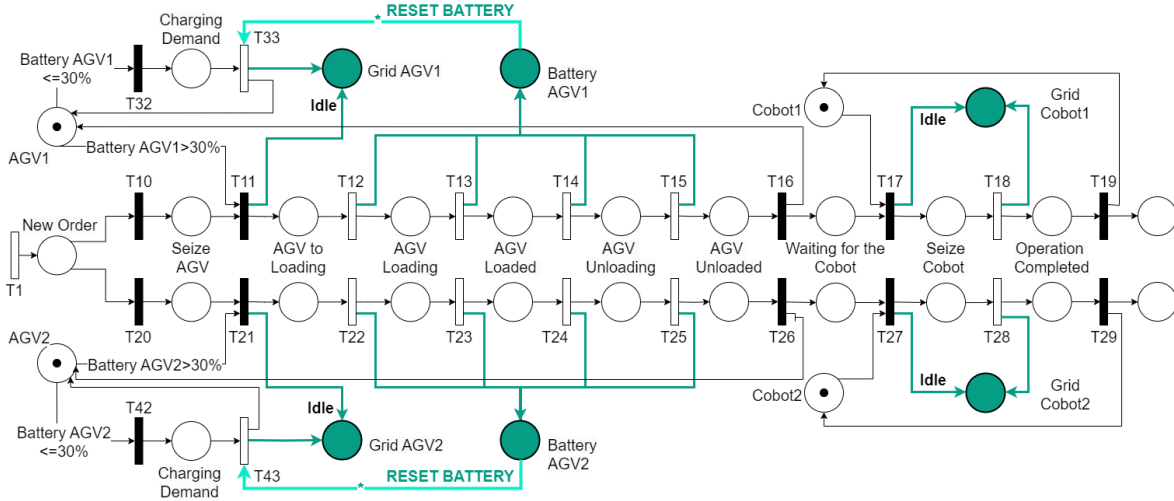
Figure 2: Petri net of the case study using event logs.

order is placed, we evaluate if the AGV's battery level exceeds the 30% threshold required to proceed with the transport process, or if it necessitates charging. The duration of the transition to fully charge the AGV's battery is defined by equation (2), expressed in units of time, where E_c represents the current battery level, and R_{ch} represents the AGV charging rate. Once the AGV reaches full charge, its battery energy level is restored to full capacity. Next, we used PySPN (Friederich and Lazarova-Molnar 2023), a Python library for modeling and simulation of stochastic Petri nets (SPN), and extended it with elements to capture energy-related dynamics.

$$T_{ch} = \frac{100 - E_C}{R_{ch}} \qquad (2)$$

4.4   Case Study Model Validation

To validate the model, we compare the outputs of the original model with the outputs from the extracted simulation model. We began with face validity assessments, which demonstrated that the Petri net extracted from the simulation model accurately reflected the real system. Subsequent validation involved checking for overlap of 95% confidence intervals for KPIs after 100 independent replications. The validation KPIs include production volume, throughput, overall energy consumption, and energy consumption per asset. In Figure 3, we present a comparison of throughput and total energy consumption, demonstrating a reasonable match between our extracted and original models.

4.5   What-If Scenarios

Based on the extracted model, we aim to optimize the energy efficiency of the system through a "what-if" scenario. Analysis of the cobots' extracted state log revealed a substantial duration of idle states. Therefore, we proposed an improvement strategy where cobots are programmed to shut down after a 30-second
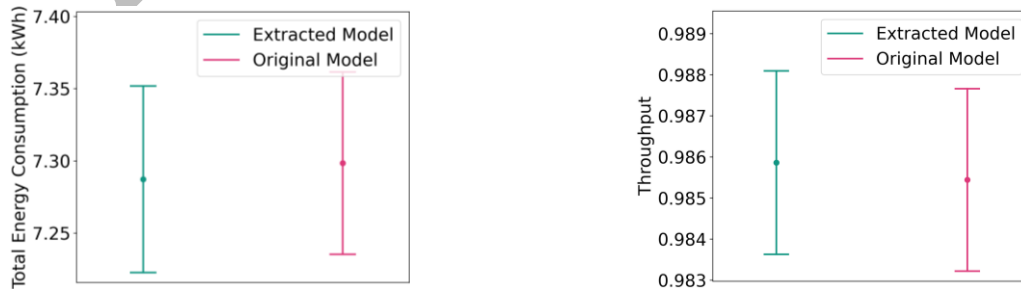

Figure 3: KPIs' 95% confidence intervals from simulating 100 independent replications.

inactivity period during the production cycle. This strategy defines "turned off" and "startup" as distinct energy consumption profiles. In the "turned off" state, cobots consume zero energy, whereas the "startup" phase initiates when AGVs begin the unloading of parts, prompting cobots to activate. The "startup" state is characterized by a higher energy consumption rate over a duration of 20 seconds. We conducted a comparative analysis of energy utilization between the original system and the system post-scenario implementation, maintaining an equal product output rate. As shown in Figure 4, using this strategy for both cobots resulted in a notable reduction in energy consumption, averaging a decrease of 25%. Additionally, we present a comparison of the total energy consumption of the SMS in its baseline configuration and with the scenario implementation. The analysis reveals that, with the application of our proposed strategy, the total energy consumption of the SMS exhibits an overall improvement of 11% in energy efficiency. This enhancement further validates the significance of our optimization approach in contributing to more energy-efficient scenarios using DTs in manufacturing systems.
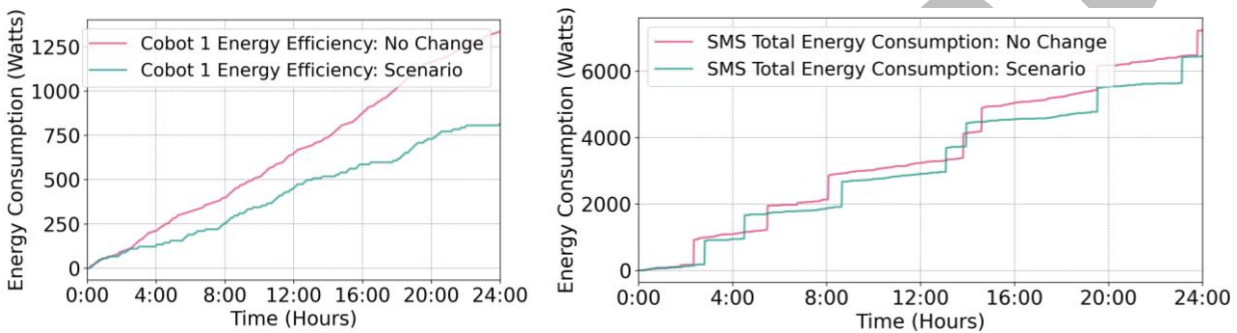

Figure 4: Comparative energy consumption of one cobot and total energy consumption over 24 hours.

5   SUMMARY AND OUTLOOK

The rapid expansion of the global economy and the growing world population have significantly increased energy demand, raising concerns about energy supply limitation, resource depletion, and environmental impacts. The necessity for low-carbon operations, rising production costs, and the quest for competitive advantage underscore the importance of advanced energy-saving technologies and the establishment of a sustainable energy ecosystem. In this context, leveraging Industry 4.0 technologies, DTs stand out as a promising tool for optimizing energy efficiency and reducing carbon footprint in SMSs. Our research explores a foundational methodology and essential requirements for extracting data-driven EODTs for SMSs. Through a detailed case study, we demonstrated the effectiveness of our proposed methodology in extracting a DT model that accurately captures both production and energy consumption behaviors. Additionally, we conducted validation of the extracted simulation method to ensure the robustness of our methodology. Subsequently, we applied our extracted EODT to a practical scenario, where we achieved an 11% reduction in energy consumption within the production line of interest, illustrating the potential benefits of integrating data-driven EODTs for energy optimization in SMSs. For our future work, we aim to tackle the following challenges for advancement:

- Complex Systems Expansion: The approach will be extended to include systems with various energy-consuming assets and distinct ECPs, requiring advanced modeling techniques to capture diverse energy dynamics accurately.
- Renewable Energy Integration: This challenge includes integrating renewable energy systems, like solar power while managing weather-related uncertainties. We aim to develop predictive models to forecast energy availability and optimize usage, ensuring manufacturing efficiency.
- Automation for Model Extraction: This challenge is aimed at fully automated model extraction. This effort will boost the system's adaptability to changes, securing continuous energy optimization.

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AUTHOR BIOGRAPHIES

ATIEH KHODADADI is a Ph.D. student at the Institute of Applied Informatics and Formal Description Methods, Karlsruhe Institute of Technology, Germany. Her research concentrates on using Digital Twins to improve energy efficiency in manufacturing systems, specifically through energy, modeling and simulation, and data analysis. Her email address is atieh.khodadadi@kit.edu.

SANJA LAZAROVA-MOLNAR holds professorships at the Karlsruhe Institute of Technology and the University of Southern Denmark. Her research spans data-driven simulation, digital twins, and cyber-physical systems modeling, focusing on reliability and energy efficiency. She actively develops methodologies to optimize complex systems using these technologies. Leading several European and national projects on digital twins and data-driven simulation, she also holds leadership roles in IEEE and The Society for Modeling & Simulation International (SCS). Additionally, she served as a Proceedings Editor for the Winter Simulation Conference in 2019 and 2020 and as an associate editor of SIMULATION: Transactions of The Society for Modeling and Simulation International. Her email address is sanja.lazarova-molnar@kit.edu.