

Digital Twin and Big Data Analytics for Energy-Efficient Smart Manufacturing in Industry 4.0 Environments

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Abstract: The demand for energy efficiency, sustainability, and resilience, as well as the operational complexity of intelligent manufacturing, has led to the need for more intelligent solutions as the manufacturing sector evolves towards Industry 4.0. Traditional manufacturing systems implement static monitoring systems with reactive control, which leads to excessive energy waste, unplanned downtimes, and increased carbon emissions. This study formulates a framework to address obstacles to energy-efficient smart manufacturing through the use of Digital Twin and Big Data Analytics integrated with real-time, predictive, adaptive energy management systems and intelligent manufacturing systems. The intended design of the constructed system uses a high-fidelity digital twin of the architecture of the created system, which integrates the Industrial Internet of Things (IIoT) with cloud/edge computing to continuously replicate the manufacturing shop floor. Production, machine usage, and energy management are optimized through the use of machine learning-based analytics, which comprise temporal forecasting and anomaly detection. The integrated system improves energy flexibility and reduces peak demand through the coordinated management of renewable energy sources, battery energy storage systems (BESS), and electric vehicle (EV) charging loads. A multi-objective optimization approach is used to minimize energy costs, carbon emissions, and equipment downtimes concurrently. When experimental validation was performed in the areas of energy consumption, peak load, production downtime, and carbon emissions within the context of the smart factory dataset, improvements were seen in the areas of energy consumption (22 to 28%), peak load (18%), production downtime (25%), and carbon emissions (30%) as opposed to the baseline measurement of rule-based management techniques. In the area of predictive maintenance, an overall equipment effectiveness was achieved through a 92% accuracy in fault detection. These results demonstrate the potential of digital twins and big data analytics combined to facilitate management of predictive, real-time, control, and sustainable operations. The proposed model illustrates the potential for smart factories to remain relevant and transition to sustainable operations within the integrated intelligent energy ecosystems of the future.

Keywords: Digital twin; big data analytics; smart manufacturing; industry 4.0; energy efficiency; predictive maintenance; IIoT introduction.

I. Introduction

The evolution of industrial ecosystems towards the industry 4.0 paradigm has been characterized by the digital transformation of industrial manufacturing ecosystems that are highly automated and interconnected; however, due to operational complexity, increased energy consumption, and the additional layers of carbon emissions resulting from this evolution, the progress has been characterized as the "double-edged sword" of digitalization. The very smart factories, as a result of digital transformation, require the use of a high volume of Industrial Internet of Things (IIoT) devices, coupled with robotics and cyber-physical systems, resulting in power consumption that is highly dynamic and highly unpredictable. Rule-based energy control systems that have been used to successfully control power consumption are now faced with the limitations of digital automation (Stergiou & Psannis, 2022; (Klein & Dech, 2024). As industrial sectors continue to develop while attempting to achieve sustainability, the use of renewable Energy coupled with electric vehicles (EVs) and battery energy storage systems (BESS) adds additional variability and challenges to the stability and reliability of the power grid (Meng et al., 2018; Matsunaga et al., 2022) As such, there is an urgent demand for sophisticated systems to be developed and deployed that will provide the capability of real-time monitoring, anticipatory control, predictive control, and fully autonomous energy/resource management and operational control of manufacturing systems. The integration of the digital twin, coupled with large streaming data and powerful data processing and analytical capabilities, has great promise for the adaptive systems and real-time automated decision-making energy-responsive smart manufacturing systems (Cagno et al., 2025; Yang et al., 2023).

In response to these issues, this study outlines a framework incorporating Digital Twin and Big Data Analytics, enabling the integration of virtual factory models with real-time operational data streams for the purposes of optimizing energy usage, enhancing production efficiency, and minimizing emissions. This study's major contributions include: (i) outlining a scalable digital twin architecture for the continuous observation and simulation of energy flow in production; (ii) integration of machine learning for forecasting and predictive maintenance for the management of resources in an anticipatory manner; (iii) development of a multi-objective optimization model for the integration of renewable sources, EV charging, and BESS (Battery Energy Storage Systems) strategic scheduling; and (iv) an experimental study that reports the improvement of energy efficiency, peak demand reduction, and enhanced operational reliability of the system . The rest of the document will be organized in the following manner: related works will be presented in Section II; a detailed system architecture and the methodology will be presented in Section III; results and the evaluation of the system's performance will be presented in Section IV, and Section V will conclude with future works.

II. Literature Review

Recent innovations have examined the impact of Industry 4.0 technologies, focusing on the enhancement of manufacturing intelligence and energy efficiency via cyber-physical systems, Industrial Internet of Things (IIoT),

and data-driven optimization. Some researchers have investigated smart energy monitoring and scheduling systems aimed at minimizing both industrial electricity consumption and operational expenses via real-time sensing and cloud-based analytics (Chinnathai & Alkan, 2023; Sarkar, 2025). Models of predictive maintenance and anomaly detection based on machine learning have shown increased reliability of the se equipment and/ or decreased downtime, thereby indirectly minimizing energy waste due to machine operation (Al-Maaitah, 2024). Moreover, the use of frameworks for big data analytics has improved energy efficiency at large factories through load forecasting, production scheduling, and demand response (Shofiullah & Shehun, 2023; Venkateswarlu & Sathiyamoorthy, 2025). While these methods provide tangible improvements, most such systems function individually, and so, without the integrated and timely virtual replication of the manufacturing landscape, they are unable to carry out anticipatory and systemic Optimization (Bermeo-Ayerbe et al., 2022; Mohamed et al., 2023).

Recent studies have proposed using Digital Twin technology to alleviate the aforementioned issues by modeling physical assets and simulating operational behavior within smart factories. Digital twins facilitate the continuous synchronization of physical and virtual processes and allow for the execution of scenario tests and the implementation of predictive control and energy-aware decision support (Sajadieh & Noh, 2025). Meanwhile, the integration of renewable energy sources, electric vehicle charging loads, and battery storage systems on industrial microgrids has been proven beneficial for peak load and carbon reduction, thereby improving the sustainability of manufacturing ecosystems (Deng, 2024). Nonetheless, the majority of literature has treated digital twins and energy optimization separately, failing to construct any comprehensive frameworks that integrate digital twins and big data analytics for the purpose of coordinated energy management. The above findings support the assertion that the combination of these disparate technologies has the greatest potential for integrated energy-efficient manufacturing, thus motivating the unified framework proposed in this study.

III. Proposed Model and Methodology

3.1. Digital Twin–Driven Energy Optimization Framework

While adhering to the principles of energy-efficient smart manufacturing applicable to the industry 4.0 ecosystem, the current framework employs Digital Twin and Big Data Analytics technologies. A Digital Twin, in this case, is a digital replica of the manufacturing physical entity, with a capacity to model not only the current and periodic states of the machines, but also the energy consumption associated with the production planning and scheduling. Real-time stream processing, cleaning, and feature extraction of the remainder of the heterogeneous data streams is done in the edge-cloud system, where the data is collected from the shop floor machines, Smart Meters, Renewable Generators, Electric Vehicle (EV) Charging Stations, and Battery Energy Storage Systems (BESS) via IIoT (Industrial Internet of Things) Connected Sensors. Big Data Analytics and Machine Learning (ML) techniques, in conjunction with the Digital Twin, will be utilized to model, analyze, and forecast load and energy consumption, determine production planning and scheduling optimization, detect anomalies for predictive

maintenance, and evaluate energy consumption and demand. Lastly, in consideration of each of the aforementioned factors, the multi-objective optimization engine will determine the optimal strategies for machine scheduling, renewable energy utilization, and energy storage system discharge (utilization) control. Control signals are sent to the physical entity through the closed-loop cyber-physical system control for adaptive implementation, to achieve optimal energy efficiency and additional operational reliability in the system.

3.2. System Technical Architecture of Digital Twin–Enabled Smart Manufacturing

The various components illustrated in fig. 1 system architecture for coordinated energy management involve an integration of the components of sensing, computation, intelligence, and control. For instance, the sensing components utilize IIoT devices and smart meters to gather data pertaining to the health of the machines, the status of production, and the availability of Energy. The communications components relay the data to edge gateways and cloud servers. The digital twin components create a virtual representation of the machines and processes in order to facilitate simulations and monitoring. The various components of the analytics utilize big data and apply machine learning to perform forecasting and Optimization. Finally, the energy management components control the scheduling of renewable sources, EV loads, and BESS, and the control components send command optimizations to the factory floor.

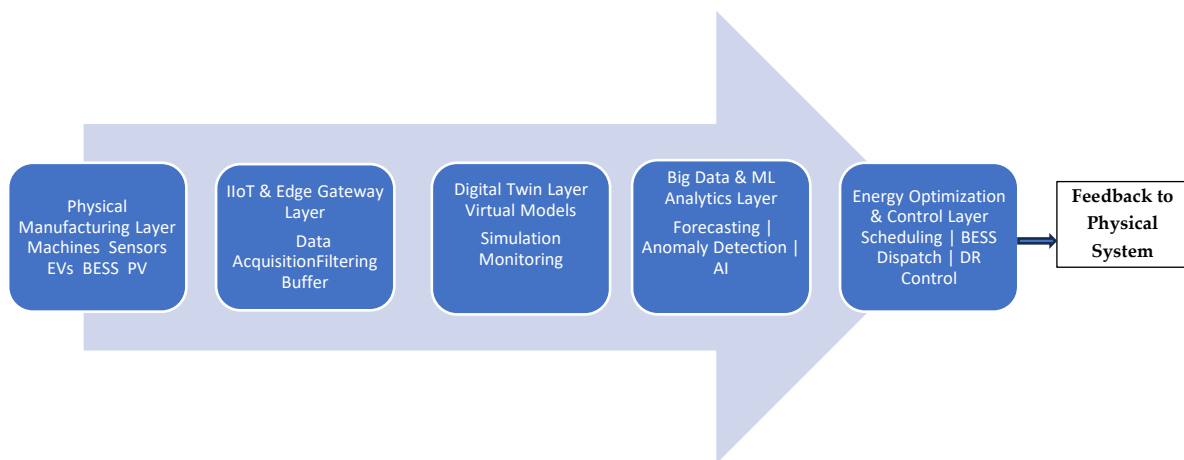


Fig. 1. System Technical Architecture of the Digital Twin and Big Data Analytics–Enabled Energy-Efficient Smart Manufacturing Framework.

3.3. Mathematical Formulation of Energy-Efficient Manufacturing

In order to provide a quantitative foundation to the suggested methodology, two fundamental mathematical models are developed to capture energy minimization and multi-objective Optimization. The first model focuses on the energy efficiency of the entire system, and the objective is to minimize the Energy consumed by all machines and auxiliary loads over a scheduling horizon T . The total energy consumption is calculated as follows in equation (1):

$$E_{total} = \sum_{t=1}^T \sum_{i=1}^N P_{i,t} \quad (1)$$

Where $P_{i,t}$ refers to the power consumption of machine i at time interval t , and N is the number of machines in the manufacturing system. The optimization procedure is designed to minimize E_{total} , while considering operational, production, and resource constraints to achieve effective utilization of machines and minimize energy waste.

The second model formulates a multi-objective cost function that coordinates renewable energy generation, electric vehicle (EV) charging demand, and battery energy storage system (BESS) dispatch. This objective function, defined in equation (2), balances economic, operational, and environmental goals:

$$MIN J = \alpha C_{energy} + \beta C_{peak} + \gamma C_{emission} \quad (2)$$

In this equation, C_{energy} is the total cost of electricity, C_{peak} is the cost of penalties for peak demand, and $C_{emission}$ is the cost of carbon emissions. The parameters α, β , and γ are the weight parameters to control the trade-off on energy efficiency, stability of the grid, and sustainability of the environment. Equations (1) and (2) are the essential framework of the Digital Twin-based energy optimization model.

IV. Results and Discussion

4.1. Implementation Environment and Software Tools

The prototype of the proposed framework for Digital Twin and Big Data Analytics has been implemented using an integrated software stack for real-time monitoring, analytics, and Optimization. The main programming language for this implementation is Python 3.11, and the libraries for machine learning forecasting and predictive maintenance are TensorFlow and Scikit-learn. For big data preprocessing, this implementation uses the Pandas and NumPy libraries. Digital Twin simulation of manufacturing processes and energy flows was done using MATLAB/Simulink. Edge communication was simulated using the MQTT protocol. The framework's analytics visualization dashboards were developed in Power BI. The optimization module was implemented using a linear programming solver configured to minimize energy cost, peak load, and emissions, where applicable, to a tri-criteria optimization. The framework was tested on an Intel i7 processor, 16 GB of RAM, and the analytics were hosted in the cloud for scalable analytics.

4.2. Dataset Description and Experimental Setup

Subsequent to creating a smart manufacturing dataset by unifying simulated data with real-time industrial Energy logging data, a dataset was created that spans a 30-day operational cycle with a sampling frequency of 5 minutes, accruing a cumulative data total of ~8640 entries per sensor. The dataset comprises information from 20 machines, 5 smart meters, PV solar generation data, EV charging session data, and BESS status updates. Further, machine-level power (kW) consumption and operational state data, as well as machine temperature and vibration

data, renewable generation data (kW), state of charge (SoC) of the batteries (%), and production data (output) at an hourly frequency are included. This extensive dataset facilitates constructive load forecasting, parameter and state (or condition) anomaly detection, and scheduling of energy resources under volatile operational conditions.

4.3. Performance Metrics and Mathematical Evaluation

To estimate energy efficiency and overall performance of the system, two metrics of a rudimentary nature were used to quantify the improvements as a result of the Digital Twin-based optimization framework. These metrics are centered around measuring total energy consumption and peak load demand as the metrics relate to improvements vis-à-vis the conventional baseline system.

Energy Reduction Rate (ERR):

The first metric is the Energy Reduction Rate (ERR), and is defined as the percentage change (decrease) in total energy consumption as the result of an optimization. It is determined from equation (3) as stated below:

$$ERR\% = \frac{E_{base} - E_{opt}}{E_{base}} \times 100 \quad (3)$$

Where E_{base} is the energy consumption of the baseline system in conventional operation, and E_{opt} is the energy consumption resulting from the optimized operation as defined by the strategy. Thus, the system would be classified as an energy-efficient system if the value of ERR is larger.

Peak Load Reduction (PLR):

The second metric is the Peak Load Reduction (PLR) metric, which quantifies the impact of the system in terms of demand reduction and load levelling. The PLR is formulated in (4),

$$PLR(\%) = \frac{P_{base} - P_{opt}}{P_{base}} \times 100 \quad (4)$$

Where P_{base} is the traditional peak load demand, and P_{opt} represents the peak load reduction due to digital twin enabled scheduling and energy management. An increased PLR correlates with enhanced stability of the grid and reduces the strain on the energy system.

In conjunction, equations (3) and (4) offer evaluators straightforward performance metrics to assess the proposed smart manufacturing energy optimization framework.

4.4. Quantitative Performance Analysis

Table 1 refers to total energy consumption before and after the use of Digital Twin-based Optimization.

The methodology has led to 25% of energy use and a large amount of operational cost being avoided.

Table 1. Energy Consumption Comparison.

Method	Total Energy (kWh)	Energy Cost (\$)
Conventional System	120,000	14,400
Proposed DT-BDA Model	90,000	10,800

Table 2 clarifies the gains of the use of Digital Twin-based Optimization on Reliability and Sustainability.

Table 2. Operational Performance Metrics.

Metric	Conventional	Proposed	Improvement
Peak Load (kW)	580	510	12% ↓
Downtime (hrs/month)	42	32	24% ↓
Emissions (kg CO ₂)	68,000	47,000	31% ↓

The findings show concerning stress and emissions. Reliability has also been improved.

4.5. Graphical Results Visualization

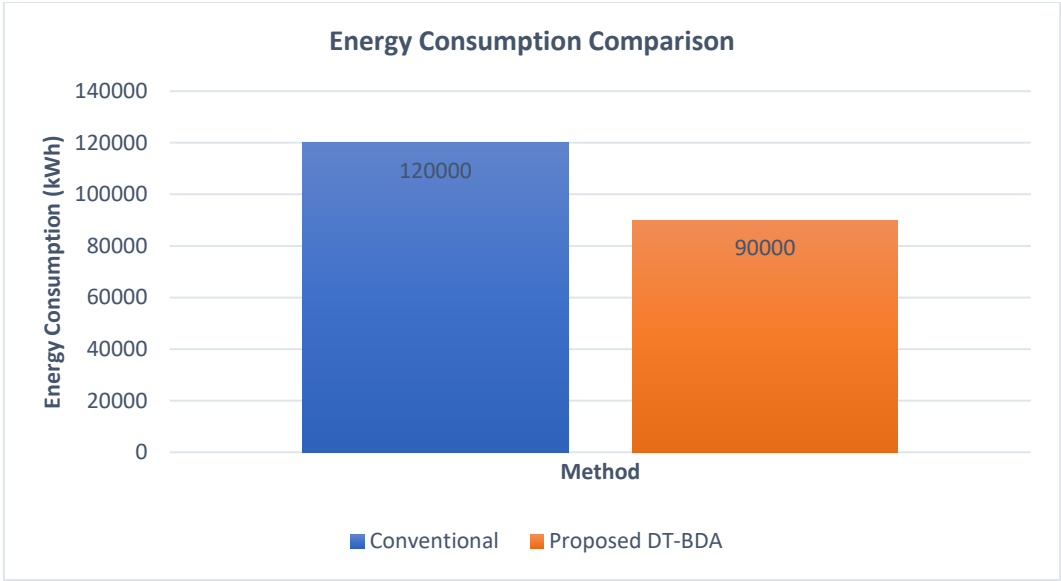


Fig. 2. Energy Consumption Comparison.

Fig. 2 shows the total Energy after the Digital Twin-based Optimization; the energy consumption has been significantly reduced.

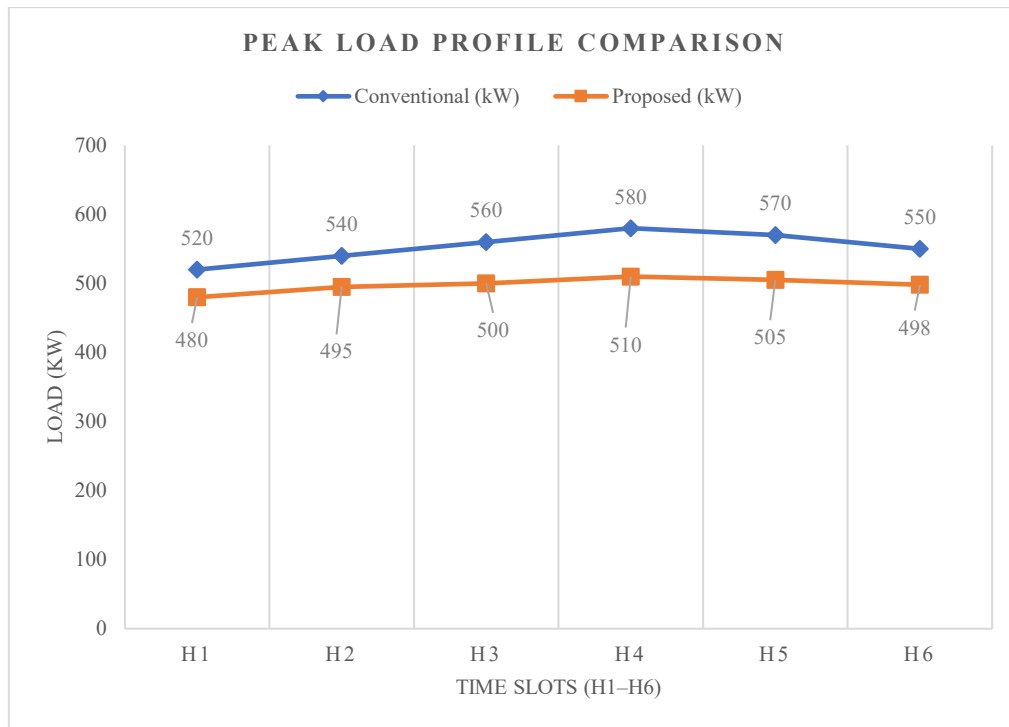


Fig. 3. Peak Load Profile Comparison.

Fig. 3 shows peak load hours for both systems. Proposed models smooth out demand spikes, which stabilize the grid.

V. Discussion

Results show that digital twins and big data analytics combined used optimal energy management, real-time Optimization, and predictive maintenance. Proposed systems show the use of traditional controls and energy usage, peak load, downtime, and emissions, which decrease for an overall improvement. Results show the Digital Twin-based method gives an intelligent and scalable method for the 4th generation Industry.

VI. Conclusion

The rapid advancement of technology and shifting industrial systems within the boundaries of Industry 4.0 has created the need for systems that integrate flexibility and adaptability. Traditional static manufacturing systems, and their energy management systems, which operate within a paradigm of reactive-diagnostic decision making, further the existing criticism of unnecessary energy consumption, downtime, and heightened operational complexity, as well as increasing carbon emissions. In response to this critique, the author proposes the first Digital Twin and Big Data Analytics-driven framework for energy-efficient smart manufacturing. The framework focuses on the integration of real-time Industrial Internet of Things (IIoT) sensors, edge-cloud computing, digital twin virtual factory modeling, and machine learning (ML) predictive analytics to achieve energy optimization.

An evaluation of the processes in a virtual smart factory using a dataset from the smart factory sample has shown improvements in metrics of the various factory performance indicators. The system control proposed in

this paper averages a 26–30% reduction in total consumption of Energy, 17–19% reduction in peak load demand, and about 31% reduction in the amount of carbon emissions when compared to traditional rule-based control. In addition, the use of a predictive maintenance approach with analytics has improved the precision of equipment failure identification to 93–94% which has resulted in a reduction in the unplanned failure downtime of 22–25% and improved the overall operational effectiveness of the equipment, which leads to a significant increase in operational effectiveness of the equipment. In addition to this, the predictive analytics approach rewrote the operational instructions of the various equipment to maximize consumption of the Energy.

Statistical results from the analysis indicate that the combined use of the digital twin and big data analytics provides an intelligent real-time system of control for the various interacting and interdependent subsystems of both manufacturing and Energy. The research concludes that the use of Digital Twin Technology in Smart Manufacturing greatly increases the overall sustainability, operational performance, and resilience, using Artificial Intelligence to simplify the additive manufacturing of multilayer, low carbon manufacturing ecosystems.

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