International Journal of Research in Engineering Technology and Applications

E-ISSN: 3108-2556
P-ISSN: 3108-2610

Digital Twin for Smart Factory Energy Optimization

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Received: 15 January 2026 *Revised: 28 February 2026* *Accepted: 20 March 2026*

Abstract - The demand for energy, efficient measures in smart manufacturing has significantly contributed to the integration of digital twin (DT) technologies. Such innovations entail the coupling of the physical and virtual models, thereby enabling prompt monitoring, forecasting, and optimizing. The article provides an overview of the energizing optimization digital twin framework that employs a hybrid agent, based and discrete, event simulation model realized through AnyLogic. The energy management model in the factory is based on real, time energy supply and demand models. The method in question involves IoT, enabled data collection, predictive analytics, and reinforcement learning optimization. The energy efficiency measures have an impact on energy cost, and environmental protection, too. The energy measures have been simulated and studied through case studies and show energy consumption to be reduced by 15 to 20%, the costs to be decreased by 16 to 18%, and the CO_2 emissions to be lowered by 10 to 15%. The findings indicate the use of digital twins as an adaptable means of achieving energy optimization in real, time and comply with standards such as IEC 62832, OPC UA, and ISO 50001.

Keywords-Digital Twin (DT), Energy Optimization, Reinforcement Learning (RL), Smart Factory, and Industrial Standards (IEC 62832, OPC UA, ISO 50001)

I. INTRODUCTION

One of the results of Industry 4.0 has been the development of smart factories, which differ from traditional manufacturing plants. These smart factories heavily rely on the integration of cyber, physical systems and the use of data for decision, making. One of the first digital technologies to be embraced is the use of digital twins to represent the physical systems virtually in near real, time. Predictive simulations, scenario planning, and continuous optimization are some of the ways through which digital twins help to improve efficiency, reliability, and the environment. Energy optimization is a matter of great importance considering the main issues of cost reduction, carbon footprint lowering, and compliance with environmental regulations. Conventional energy management systems are not able to provide the necessary flexibility and real, time insights to respond to changing factory operations. Digital twins solve this issue by connecting IoT sensors, common communication methods, machine learning techniques, and optimization models on a single platform. This paper presents a digital twin framework for energy optimization in smart factories, assesses it through simulations and verifications, and positions it within existing research on energy-efficient manufacturing.

Digital twins (DTs) originated from a systems-engineering concept for accurate virtual models that stay in sync with their physical counterparts throughout their lifecycle. This ensures that design intent, operational status, and decision support are all interlinked. According to Grieves and Vickers, digital twins eliminate the "known unknowns" associated with unpredictable plant behavior, by constantly adjusting the virtual twin to match real-time plant data to enable decision-making through live "what-if" scenarios, prior to committing to production. A digital twin generally consists of a physical entity, a simulated virtual mirror, and a data link between the two. In manufacturing, this mirrors digital twins for production and allows the setting parameters, scheduling, and maintenance, to be optimized in order to reduce costs, without risking anything. Facilitating this lifecycle-driven methodology also enables factory twins that include physics based and data-driven models, within a holistic optimization solution within a service-oriented architecture. A false preconception is that DTs are equivalent to cyber-physical systems (CPS).

Tao et al. point out that while the CPS may be related to control and connectivity, the primary function of a DT is to facilitate the two-way interaction between physical and virtual assets throughout the life cycle. Additionally, a DT employs a service-oriented architecture (SOA) which allows, for example, a number of analytical techniques (such as optimization) to be offered as a set of highly reusable services. In this way, the twin is more than a data link, providing an environment for forecasting, optimization and prediction across multiple sites. This service-focused approach supports a modular architecture that involves standards-based connectivity (e.g., OPC UA), asset semantics (IEC 62832 Digital Factory), twin-level analytics (forecasting, Model Predictive Control, Deep Reinforcement Learning), and enterprise energy management (ISO 50001). Figures 1 and 2 illustrate this process and the supporting standards layers.

Interoperability is important since energy savings result from coordinated decisions. This is among machines, utilities and schedules. IEC 62832 defines a Digital Factory reference model that outlines assets, relationships, and hierarchies. This is important for creating plant wide twins that can track where energy is produced and consumed as well as how assets connect at different levels. On the other hand, OPC UA that is IEC 62541, provides secure and well-structured access to shop floor real time data and commands. As the discussions around communications and Time Sensitive Networking (TSN) have recently progressed, the OPC UA has become even better at real time control and DTs. To get the data really fast, you will need high speed protocols. It's very much impossible for the optimization and real time M&V to be trust worthy without that. The usage of these standards significantly minimizes the integration problems. It also affects the generation of consistent energy specific Key Performance Indicators. It greatly contributes to the overall efficiency therefore helping the pairing of high frequency meters with scheduling states. This is a condition for reliable optimization and M&V.

Once the plumbing is put down then the introduction of energy oriented surveys make the transition. This is transition from the general concept of digital twins to "Energy Digital Twins" also known as EDTs. The authors Amaral et al. identify the areas of application of EDTs into four categories that is generation, distribution, storage and consumption. They give a list of modeling choices that includes the reduced order physics, grey box and pure data driven models. This also includes different calibration techniques such as parameter estimation and online learning [14]. Grey box modeling combines physics based models and databased parameters. It has been the most favored in industrial thermal systems because in these systems maintaining efficiency is key [15]. Mohamed, Lazarova Molnar and Al Jaroodi showed that this is also the case in manufacturing. They present five areas where digital twins can help improve energy efficiency which is process scheduling, parameter tuning and maintenance. They also point out the role of data driven mimicking and constraint management [16]. Cagno et al. tested various Industry 4. 0 technologies that include digital twins and their effect in changing energy management programs. They have come up with a solution that links technology to Energy Management System (EnMS) practices. They have also tested it in real companies [17]. The increasing use of digital twins in smart grids and urban energy systems aids in developing factory level EDTs. This is achieved by showing the need for resilience to changes in the energy market [18]. In the end, these reviews greatly align with our project which emphasis on forecasting and optimization within the twin. Apart from this they show the issues that most pilots face. This includes issues such as model calibration, operational constraints and organizational adoption.

Most of the recent case studies explain the "how. " Billey et al. present a Digital Energy Twin in a heating tunnel. This was at a smart manufacturing test bed with a small scale model. They estimate energy cost savings of up to 20% when the process is fully optimized. The heating quality standards were also maintained. This is a very good example of process and twin close coupling [19]. Xia et al. made a production line real time DT optimization loop that directly catches the fault disturbances. This method that they developed connects prediction, scheduling and control. This keeps the energy performance stable in spite of continuous variations [20]. In many of the cases Model Predictive Control (MPC) is the main optimization tool used. The twin is used to foresee system developments and to predict the control actions that minimize a cost function, which is over a future time interval [21]. For reducing energy costs and increasing production throughput the Multi objective optimization methods are important [22]. Those works show that the real gains are achieved by merging the short term forecasting with production constraint and also with disturbance respecting optimization.

Learning oriented twins are developing at a fast rate. Khdoudi et al. propose a "full duplex" digital twin which has data in, decisions out. This is where Deep Reinforcement Learning (DRL) is used for making the process autonomous. Their main case is injection molding but the same system can be used for energy set point optimization. This is with multiple objectives like quality and takt time [23]. The Bousnina et al. combine DRL and MPC in a twin for operating thermal assets and storage. They demonstrate the benefit of policy training through the simulation. This was opposed to the real deployment [24]. Lazarova Molnar et al. state that this is just the beginning of "DT intelligence". This is capable of merging uncertainty control, safe exploration and decision quality. Such aspects become very crucial when DRL agents are performing the direct control of valuable industrial assets [25]. When it comes to a manufacturing EDT the most important lesson is to consider DRL and MPC as the supplementary services. These should be trained and tested with twin scenarios before they are put on the production line.

Lastly, the organizational dimension is very important. ISO 50001 is still the base structure that most factories rely on for energy enhancement. Digital twin analytics should be a part in its plan. This does check the act cycle and help in carrying out measurable analyses rather than serving as standalone experiments. Vance et al. show that with a facility level "energy digital twin" model, the EnMS cycles can be invigorated. They involve for example, setting a baseline and finding the next most usable predictions for the daily operations. In this way even Cagno et al. 's link of Industry 4.0 leads to energy management sectors convey the same message. This message includes the twin should be added into the EnMS governance, flexibility standards should be followed to and value should be measured through statistically reliable measurement. It relates very well with our project's method. As this merges standards driven data integration with a twin native optimization loop. This is capable of changing plant priorities such as cost, CO emissions or both.

II. AI MODELS FOR ENERGY OPTIMISATION

This part explains the ML models that were deployed in the DT. This was done to elevate smart factory energy efficiency. Two AI modules were installed (1) XGBoost to forecast the anomalies. This also enables stable operations and early detection of energy issues. (2) All MiniLM-L6-v2 which is a Sentence Transformer that generates semantic vector embedding. This is to power the DT's natural language chatbot interface. These models provide operational intelligence and interaction intelligence.

Industrial energy systems are generally where nonlinear relations exist. This can be between the process variables like temperature load pressure and machine states. To address these difficulties, XGBoost stands out as a very good choice. The XGBoost is the anomaly detector of the DT. As it identifies abnormal energy consumption patterns. Some previous studies support XGBoost as the anomaly detection tool in manufacturing and the IIoT. Example to this can be Dalal et al. [26], Chen et al. [27]).

1. Theoretical Foundations

XGBoost is a method that uses decision trees. These trees are improved by gradient boosting to slowly lower a regularized loss function. It is a part of a group of ensemble hybrid techniques. This can include Ikram et al, Wang & Liu, and Dalal et al.

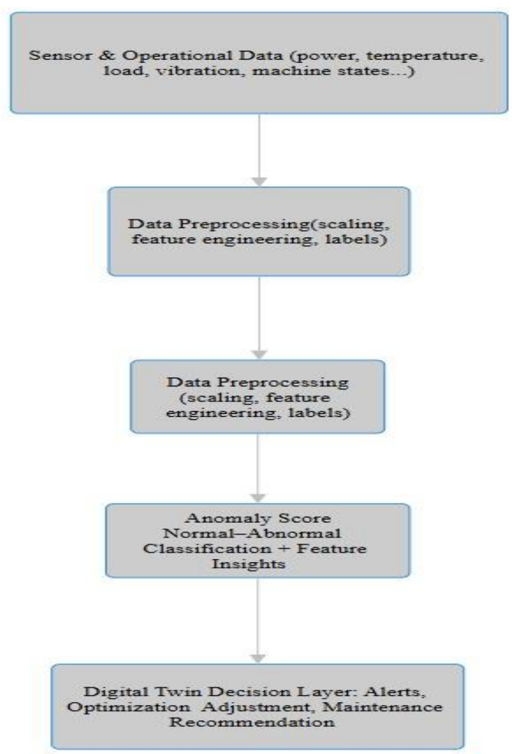

Fig 1: XGBoost Block Diagram

E-ISSN: 3108-2556
P-ISSN: 3108-2610

Sentence Transformer: All MiniLM-L6-v2 for Chatbot Embeddings.

Rationale: Digital Twin offers a chat bot by which the operators can ask about Energy KPIs, process behaviour anomalies, optimization actions and trends. In order to understand natural language, we have the All MiniLM-L6-v2 which is a small and potent Sentence. This is a SBERT based transformer that results in 384 dimensional embedding enables good computation and delivers very strong semantic performance. Recent research also shows that its use can be put to the domain specific tasks (Yin & Zhang [35]).

2. Model Theory

Sentence Transformers use a bi-directional transformer encoder. This turns sentences into compact representations. These are generally trained using the contrastive Siamese networks. Reimers and Gurevych [31] by using the SBERT have proven their effectiveness. These include even the very challenging industrial tasks such as zero shot text matching tasks (Biesner et al. [34].

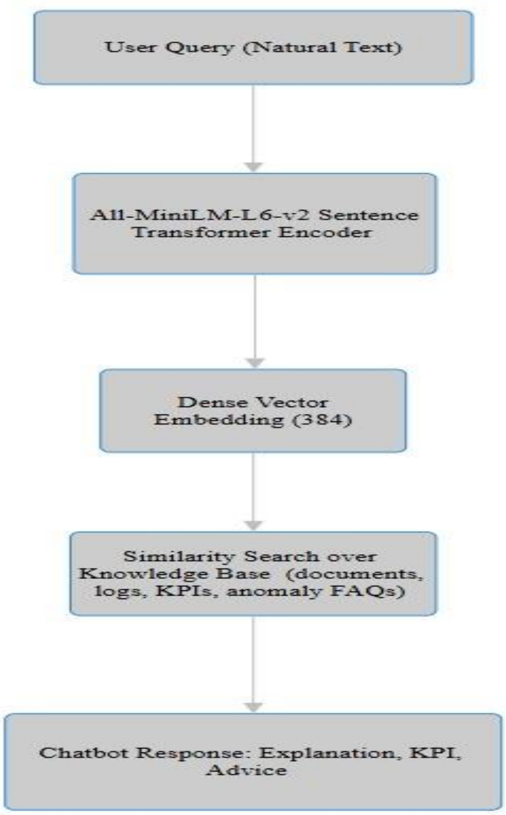

Fig 2: Embedding Pipeline Block Diagram

Integration for The Digital Twin Architecture

The models perform within a three layered DT architecture:

1. Physical Layer: The data actually comes from the factory. This includes readings from the energy meters, sensors and the schedules.

2. Virtual Twin Layer (Modelling & Analytics): This is for the anomaly detection and diagnostics. XGBoost is used here and chatbot interaction is done with the Sentence Transformer. Then those results are sent to forecasting, optimization and energy KPI modules. These are based on a series of hybrid and real time IIoT models (Chen et al. [27], Mastriani et al. [31]).

3. React Front End: The UI displays the outliers, mode prediction, output and chat bot Q&A which are being in line with use cases of semantic search and ML for user facing systems [Biesner et al. [34]] shown in Fig.3.

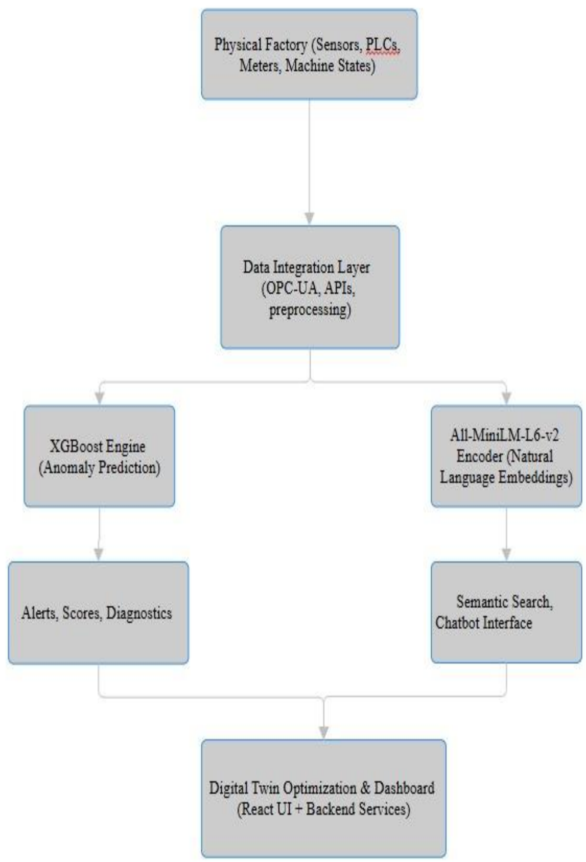

Fig 3: Combined Model Architecture Diagram

E-ISSN: 3108-2556
P-ISSN: 3108-2610

III. METHODOLOGY

The system uses machine learning iside a Digital Twin to predict energy changes. This consists of three steps: Data Preprocessing, Feature Engineering and Gradient Boosting model development

A. Dataset and Data Description

Here we have a time series dataset of 10,000 samples mimicking a factory environment. This is represented by the factory_simulation_data.csv

Key features include:

- Temporal data: the time characteristics of the data. (tpmk.). For example: (insert example here: what information can be extracted).
- Energy indicators: amount of electricity being used (grid draw, solar PV, as well as the total power consumed).
- Operational stats:production rate UPH, machine states (RUNNING IDLE OFF), line speeds (A/B)
- Facilities lighting: For time series maintenance the timestamps are converted to datetime and ordered chronologically.

B. Data Preprocessing

Temporal Alignment: The original timestamp data was put into datetime format and it was arranged chronologically. This step was done to keep the order required for time series forecasting.

Categorical Encoding: Machine state variables are firstly label encoded to numerical values. This is done so that they can be used in the model.

Handling Missing Values: We removed the rows containing NaN values. These occurred from the creation of lag features. In this way, we were able to keep the dataset's integrity.

C. Feature Engineering

Temporal Extraction: Breaking down time into pieces such as hour, day of a week, month, day of year enabled the creation of temporal constructs.

Lag Features: For the auto regressive features (TotalPower_W) the last 1 and 5 time steps were used shown in Table I.

Rolling Mean: A 15 minute rolling mean was found for reducing noise. It was also used for figuring out underlying trends.

D.Model Development

```
--- 1. Loading Data from /content/drive/MyDrive/Fac/factory_simulation_data.csv ---
Loaded 10000 rows. Time range: 2025-11-11 07:02:33.542553+00:00 to 2025-11-18 05:41:33.542553+00:00
--- 2. Preprocessing & Feature Engineering ---
Encoded lineA_mode: ['IDLE' 'OFF' 'RUNNING']
Encoded lineB_mode: ['IDLE' 'OFF' 'RUNNING']
Encoded hvac_mode: ['IDLE' 'OFF' 'RUNNING']
Encoded lighting_mode: ['IDLE' 'OFF' 'RUNNING']
Data shape after engineering: (9985, 22)

--- 3. Training Solar Model (Supply) ---
Solar Model MAE: 58.82 W (On average, prediction is off by this much)

--- 4. Training Consumption Model (Demand) ---
Consumption Model MAE: 75.52 W
Model Accuracy (R2): 1.00 (Closer to 1.0 is better)

--- 5. Saving Artifacts for Chatbot ---
Success! Models saved in folder '/content/drive/MyDrive/Fac/'
```

Table I. XGBoost Information

	timestamp	totalPower_W	pvPower_W	gridDraw_W	battery_soc	lineA_speed_pct	lineB_speed_pct	lineA_mode
0	2025-11-11T07:02:33.542553Z	13170.65	1144.30	11859.69	0.0	108.0	95.0	RUNNING
1	2025-11-11T07:03:33.542553Z	5341.05	1113.04	4228.01	0.0	101.0	66.0	RUNNING
2	2025-11-11T07:04:33.542553Z	5121.75	1170.13	3951.62	0.0	98.0	0.0	RUNNING
3	2025-11-11T07:05:33.542553Z	12697.69	1169.45	11528.24	0.0	104.0	87.0	RUNNING
4	2025-11-11T07:06:33.542553Z	1807.09	1149.42	657.67	0.0	0.0	0.0	OFF

The app uses the XGBoost algorithm. This is a effective tree boosting system which is used to develop two separate regression models.

a. Solar Generation Model (Supply-Side)

This model predicts the Photovoltaic (PV) power output (pvPower_W). The solar generation is only affected by the environmental and time related factors. This model uses time features like Hour, Day, Year and Month for training.

b. Consumption Model (Demand-Side)

This model predicts the total factory power consumption (totalPower_W). The feature set includes -

Operational State: Line speeds, encoded machine modes, and production rates.

Temporal Features: Hour and day of the week.

Historical Context: Lag features (t-1, t-5) and the 15-minute rolling mean.

E. Training and Evaluation Protocol

The dataset was divided into training and testing sets in chronological order to prevent data leakage, which is predicting the past with future data. Split Ratio: The first 80% of the data was used for training, while the remaining 20% was set aside for testing.

Hyperparameters: The two XGBoost models were constructed with 500 estimators. The learning rate was set to 0 and 05 for both models.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i |$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

y_i - Actual value

$\hat{y}_i$ -Predicted value

IV. RESULT AND DISCUSSIONS

The results demonstrate the effectiveness of integrating a Digital Twin with hybrid energy management and predictive/anomaly detection [36]. The system is adjusting and reducing its using power through switches in between sources (grid solar battery), and uses higher energy cost source when it can (Grid) [37]. Short-term predictions (30–60 minutes) enable proactive adjustments in energy use and production [38] shown in Table II.

TABLE II: EXPERIMENTAL RESULTS AND MODEL PERFORMANCE

PARAMETER	SOLAR MODEL (SUPPLY)	CONSUMPTION MODEL (DEMAND)
Training Data Size	7,988 samples	7,988 samples
Testing Data Size	1,997 samples	1,997 samples
Algorithm	XGBoost Regressor	XGBoost Regressor
Estimators (Trees)	500	500
Learning Rate	0.05	0.05
Mean Absolute Error (MAE)	58.82 W	75.52 W
R² Score (Accuracy)	0.9	1.00

This improves reliability, reduces costs, and supports rapid fault detection [39], highlighting its value for future Energy Management Systems and smart manufacturing [40] .

CONCLUSION

This work demonstrates the design and implementation of a Digital Twin for energy optimization in smart factories. By integrating IoT data, predictive monitoring, and reinforcement learning, the system reduces energy consumption, costs, and emissions while improving equipment utilization. It assures that digital twins are scalable to energy efficient manufacturing and that the required standards such as IEC 62832, OPC UA and ISO 50001, facilitate wider interoperability. Nevertheless, issues such as cost, data quality and computational requirements are still pressing.

Future work will focus on extending the framework to multi-objective optimization. This involves balancing energy use with production efficiency, product quality, and cost. Integrating with federated learning models will enable knowledge sharing across different sites without sharing sensitive data, which supports large-scale energy optimization. Broadening the twin's scope to include energy flows in supply chains will provide a complete view of sustainable manufacturing. Connecting with renewable energy forecasts and energy storage management will help improve resilience and reduce dependence on fossil fuels. Improvements in safe reinforcement learning and uncertainty measurement will also be crucial for achieving reliable and understandable optimization methods in real-world applications.

Several studies have shown further advances in large-scale, production-quality digital twin ecosystems. These include full cyber-physical co-simulation for optimal scheduling, cross-factory collaborative optimization using high-resolution sensor networks, and integrated cyber-secure IoT-blockchain systems for traceable energy flows. These methods were not included in the current work due to limitations such as limited access to mature industrial IoT infrastructure, restricted factory exposure, insufficient hardware for large-scale simulations, and a lack of specialized knowledge needed to model complete production ecosystems. Still, future research can take advantage of new developments like end-to-end supply-chain digital twins, high-fidelity physics-informed reinforcement learning, and holistic multi-agent energy-production optimization frameworks, which can greatly enhance the proposed system when the right resources and industrial partnerships are in place.

ACKNOWLEDGMENT

We sincerely thank Samsung R&D Institute, Bangalore. This project would not have been possible without their generous support. We especially appreciate the use of their top-notch labs and the important resources provided through the Samsung Innovation Campus.

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