XAI-Powered Digital Twin for Industrial Energy Prediction and Optimization

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***Abstract*—This paper presents Energy-Twin, a system that integrates Digital Twin (DT) technology with Explainable Artificial Intelligence (XAI) to enable real-time energy prediction and optimization in industrial manufacturing. Leveraging data from the Gumi Industrial Complex, the framework synchronizes physical operations with their digital counterparts for continuous monitoring and simulation. A hybrid deep learning model—comprising CNN, GRU, and BiLSTM layers—captures spatial-temporal patterns in energy usage to enhance forecasting accuracy. The DT module enables adaptive scenario testing, while XAI ensures transparency and operator trust. Experimental results show a high prediction accuracy of 99.55% with minimal computational cost, positioning Energy-Twin as a scalable solution for energy-efficient manufacturing in Industry 5.0 environments.**

***Index Terms*—Digital twins (DT), explainable artificial intelligence (XAI), energy consumption, and smart manufacturing.**

I. Introduction

As Industry 4.0 advances toward Industry 5.0, intelligent systems are reshaping manufacturing into cyber-physical, data-driven ecosystems. A persistent challenge in these environments is the efficient management of energy consumption, particularly in large-scale industrial zones like the Gumi Industrial Complex, where energy usage directly affects cost, reliability, and sustainability [1], [2]. Conventional rule-based systems and isolated monitoring methods fail to capture the complex spatiotemporal patterns of industrial energy use. Recent deep learning approaches—such as CNN-LSTM [3] and SVM-based models [4]—have improved forecasting, but they often lack interpretability and require substantial computational resources, limiting their applicability in real-time or edge settings. Moreover, the absence of real-time interaction between physical operations and predictive models hinders proactive adjustments and anomaly detection. These gaps call for solutions that are not only accurate and efficient but also explainable and responsive to live industrial conditions. To overcome these limitations, this paper proposes Energy-Twin, a real-time, XAI-integrated Digital Twin framework for energy prediction and optimization. It employs a lightweight CNN-GRU-BiLSTM architecture to model spatial-temporal energy patterns while synchronizing with live system data for dynamic simulation and control.

The major contributions of this paper are summarized as follows:

- We propose an XAI-integrated Digital Twin framework that enables real-time, transparent, and adaptive energy optimization in smart manufacturing environments.
- The system achieves high prediction accuracy (99.55%) while remaining lightweight enough for edge deployment, thus addressing the challenge of scalability in industrial applications.
- We validate the model using real-world data from the Gumi Industrial Complex, demonstrating its practical relevance and scalability across different facility types.
- Finally, the integration of XAI enhances trust and usability by offering interpretable insights, allowing human operators to understand and act on the system's recommendations.

By aligning high-performance prediction with explainability, Energy-Twin supports the vision of Industry 5.0—where automation meets transparency in human-centric, sustainable manufacturing systems.

II. Proposed Methodology

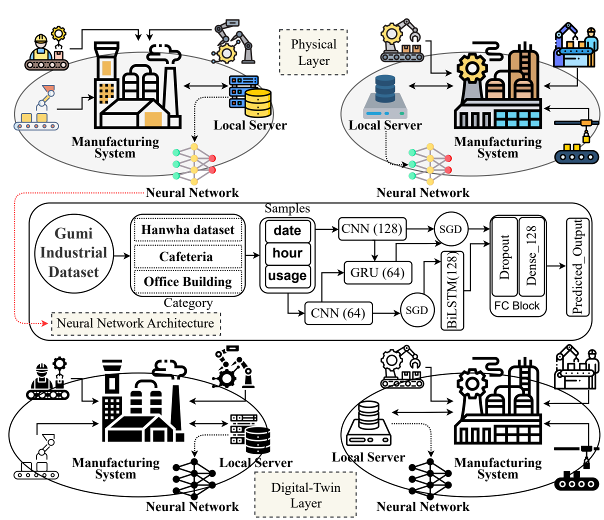

Fig. 1: Proposed Energy-Twin Framework

The proposed system, illustrated in Figure. 1, integrates a Digital Twin (DT) layer with a hybrid deep learning architecture to achieve real-time energy prediction and optimization.

The physical layer utilizes real-time data from the Gumi Industrial Dataset, covering diverse facility types (e.g., cafeterias, office buildings), and processes this data locally at each site through lightweight edge servers.

Each local server employs a hybrid neural network composed of CNN, GRU, and BiLSTM layers. The CNN blocks (128 and 64 filters) extract local spatial features from inputs such as date, hour, and energy usage, while the GRU (64 units) and BiLSTM (128 units) layers model sequential dependencies. A dense layer (128 units) followed by dropout reduces overfitting and enhances generalization. The output layer generates energy consumption forecasts, optimized via Stochastic Gradient Descent (SGD) for fast convergence and robustness against local minima.

The Digital Twin layer synchronizes real-time physical system data with its virtual representation. Using predicted energy usage, it performs live simulations to identify optimal operational settings and detect anomalies through deviations between predicted and actual consumption. This enables adaptive scheduling, load balancing, and continuous optimization. Additionally, the integration of Explainable AI (XAI)—through techniques such as SHAP—ensures transparency, allowing system operators to interpret model decisions and gain trust in the system.

By combining predictive accuracy with interpretability and edge compatibility, the proposed methodology addresses the limitations of previous works [3]–[6] and contributes toward a practical, scalable energy optimization solution for Industry 5.0 environments.

III. Result Analysis

TABLE I: Comparison of the Proposed Energy-Twin with Existing Energy Prediction Models.

Model	Accuracy (%)	MAPE (%)	No. of Trainable Parameter	Model size (MB)
CNN-BiLSTM [3]	78.72	21.28	189,953	7.25
CNN-GRU [5]	98.32	1.68	2,075,259	19.08
CNN- BDLSTM [6]	98.42	1.58	2,065,259	1.56
SVM [4]	97.24	2.76	18,628	3.825
Energy-Twin	**99.55**	**0.45**	**289,601**	**1.1**

The Table I compares the proposed Energy-Twin model with existing energy prediction models based on accuracy, mean absolute percentage error (MAPE), number of trainable parameters, and model size. Energy-Twin outperforms all other models with an accuracy of 99.55% and a MAPE of 0.45%, demonstrating its superior predictive performance. It also has significantly fewer trainable parameters (289,601) and a smaller model size (1.1 MB) compared to other high-performing models like CNN-BDLSTM and CNN-GRU, which have over 2 million parameters and much larger model sizes. This indicates that Energy-Twin is not only more accurate but also more efficient in terms of computational resources. It is also possible to use the proposed model with any edge devices. Other models, like SVM, achieve good results in accuracy (97.24%) and MAPE (2.76%) but have fewer trainable parameters and smaller model sizes, making them less effective than Energy-Twin for complex scenarios.

IV. Conclusion and Future Work

The Energy-Twin model offers an advanced solution for enhancing energy efficiency in energy-intensive sectors by integrating DTs with AI techniques like CNN, GRU, and BiLSTM. Its real-time monitoring, predictive analysis, and optimization capabilities make it ideal for smart manufacturing, where reducing energy usage is crucial for minimizing costs and environmental impact. The model is adaptable to semiconductor manufacturing, automotive production, and chemical processing, which involve complex processes with high energy demands. By detecting inefficiencies, forecasting energy patterns, and providing actionable insights, Energy-Twin enables real-time adjustments to improve energy management. Additionally, facilities like data centers can leverage the model to achieve better energy sustainability. With explainable AI, the model ensures transparency in decision-making, making it a reliable tool for industries aiming for greater energy efficiency and operational resilience.

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