Renewable energy management in industry using AI and system simulation

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Abstract

Artificial intelligence (AI) prediction techniques have attracted much attention due to their ability to learn and model complex and unstructured datasets. However, their effectiveness is highly dependent on the availability of sufficient and high-quality data, which is often limited or unavailable in many industrial environments. This study presents an integrated framework that combines AI forecasting techniques with discrete-event system simulation (DESS) to address the challenges of data scarcity, particularly in the context of renewable energy management. The proposed approach uses DESS to generate synthetic datasets suitable for training AI models when real-world data is insufficient or incomplete. The results demonstrate that the proposed framework can be a powerful tool, enabling the optimal management of renewable energy systems through increasingly accurate predictions using AI techniques, even in data-limited environments, which are particularly common in industrial applications.

Keywords

artificial intelligence, discrete event system simulation, energy management, renewable energy

1. Introduction

In recent years, there have been significant and rapid advances in the adoption and utilization of renewable energy, particularly wind and solar energy [1]. Utilizing these sources, especially photovoltaic (PV) panels and wind turbines (WT), is challenging due to their dependence on weather conditions and daily solar cycles [2]. Accurate prediction of renewable energy production, particularly through the use of artificial intelligence (AI) techniques, is crucial for overcoming these challenges [3]. The integration of battery energy storage systems (BESS) into renewable energy systems mitigates the effects of renewable energy variability [4]. A wide range of AI prediction models have been employed, including artificial neural networks (ANN) [5], extreme gradient boosting (XGBoost) [6], deep neural networks (DNN) [7], long short-term memory (LSTM) [8], and other deep learning techniques [9].

The predictive power of AI techniques is highly dependent on the quantity and quality of training data. However, obtaining sufficient and suitable datasets in industrial environments is difficult. Operational changes, equipment upgrades, and a lack of historical records can all contribute to data scarcity in industrial environments [10, 11]. To address this challenge, discrete-event system simulation (DESS) has been considered a practical approach. DESS is particularly used in simulating manufacturing and industrial systems [12, 13]. DESS can generate synthetic datasets that reflect real system processes [14]. Recent research highlights the powerful synergy achieved by integrating DESS with AI. Synthetic data generated from a simulation model can significantly enhance the training and performance of AI techniques, particularly in industrial environments where real-world data is limited or incomplete [15, 16].

The primary objective of this study is to utilize data from simulation models to train AI prediction techniques, particularly when experimental data are incomplete or unavailable. The contribution and novelty of this research are summarized as follows:

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- A novel framework is developed to integrate AI prediction techniques with Discrete Event System Simulation (DESS) and overcome the challenge of data scarcity in renewable energy-based industrial systems.
- AI prediction techniques are trained to accurately predict energy consumption in complex industrial environments, utilizing synthetic datasets generated from a simulation model.

The remainder of the paper is organized as follows: Section 2 outlines the materials and methods used in this study. Section 3 presents the results and discussion. Section 4 details the computational experiment, and Section 5 provides the conclusions.

2. Materials and methods

This section outlines the general model and methodological flowchart of the study. The primary goal is to utilize DESS to generate a tailored and sufficient amount of specific data for training AI prediction models, particularly in cases where empirical data are scarce or unavailable. The case study focuses on a steel complex that primarily relies on the external power grid to meet its electricity needs.

In contrast, an on-site PV system supplies a portion of its energy. While historical time-series data on PV output are available for training AI techniques, a significant challenge arises due to the absence of energy consumption data. This data shortage is exacerbated by planned product line revisions, which will also change consumption patterns. As these revisions have not yet been implemented, no real data exists to reflect the modification of energy consumption. To overcome this limitation, this study utilizes DESS to simulate the operational behavior of both the current and modified production lines, subsequently generating synthetic consumption data aligned with the new configuration. This simulated data serves as the basis for training AI models that aim to predict future energy consumption. An overview of the general framework and its components is illustrated in Figure. 1.

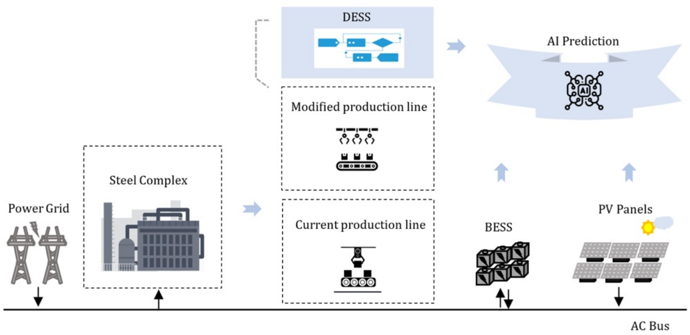

Figure 1: The overview of the general model.

Figure. 2 presents the methodological flowchart developed and implemented in this study. The process begins with the construction of simulation models for both the current and modified production lines of the industrial system. A two-step quality assurance procedure, including verification and validation, is applied following model development. If the model fails to meet the required standards at either stage, it is revised before re-execution. Once the simulation model is verified and validated, it generates synthetic data on energy consumption. Concurrently, historical time-series data on PV power generation are prepared for analysis. Two AI prediction techniques (XGBoost and LSTM) are then employed to forecast both energy consumption (based on simulated data) and PV output (based on time-series data). The performance of these prediction techniques is evaluated using relevant metrics, allowing for the selection of the most accurate method for each dataset. The final stage of the process integrates the optimal prediction outputs into a broader energy management framework for enhanced efficiency.

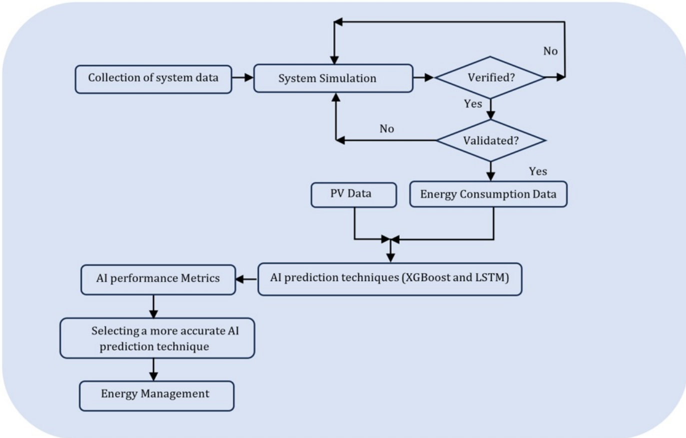

Figure 2: The methodological flowchart.

3. Results and Discussion

This section presents the simulation of a hot-rolled production line designed for manufacturing steel coils. Hot rolling is a highly energy-intensive process in steel production, making it a critical factor in production planning and energy efficiency strategies in steel plants [17, 18]. Figure 3 illustrates the general process flow of hot rolling production.

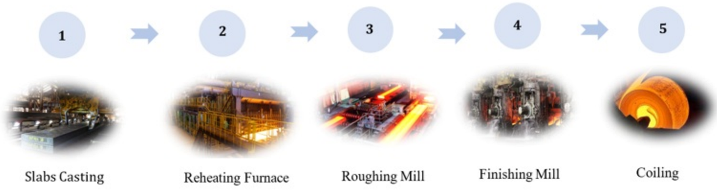

Figure 3: Process flow diagram of the hot rolling production procedure [18].

Time data for each of the five primary process stages (main events of the system) were collected based on the defined steps of the hot rolling production line. Subsequently, the most appropriate statistical distributions were identified to accurately represent the data associated with each event. The Input Analyzer tool of Arena v15 software was used to test multiple distributions and rank them based on goodness-of-fit criteria. For example, as shown in Figure 4, the time data for the *roughing mill* was best modeled by a normal distribution (NORM(149, 5.61)), as it provided the best fit among all tested alternatives.

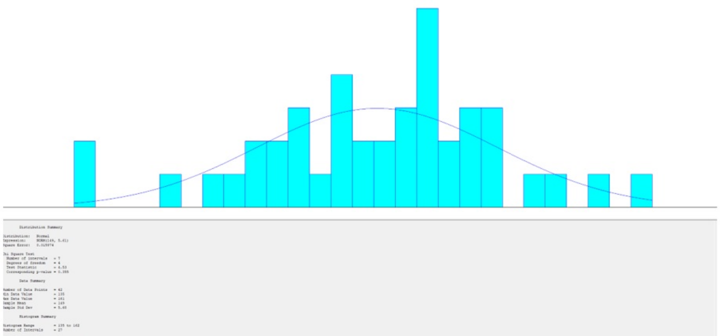

Figure 4: The best-fitted statistical distribution for the roughing mill data set.

A similar process was carried out for the remaining stages of the production line. The production line was then simulated using Arena v15 software [19]. Figure 5 provides an overview of the simulated hot rolling production line model.

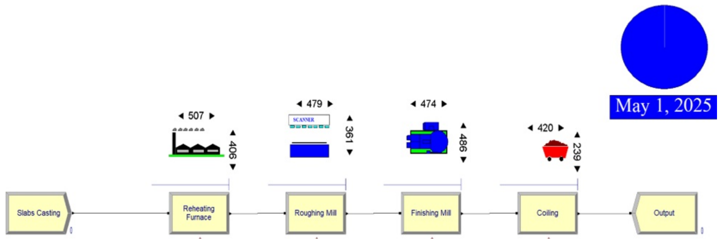

Figure 5: The simulated model of the hot rolling production line.

Following successful verification and validation of the simulated model, its output data can be utilized to estimate total energy consumption in the production line at any given time. Analyzing the status of each of the five main process steps of the hot rolling production line at specific time points during the simulation run generates a time series of energy consumption, providing a precise representation of energy consumption patterns.

4. Computational experiment

This section presents the results of XGBoost and LSTM techniques for prediction on two datasets: synthetic data of energy consumption from the simulation of a production line, and a time series dataset of PV panel generation. Data analysis was performed using Python in the Jupyter extension of Visual Studio Code.

Considering the opinions and decisions of the steel complex management, an additional reheating furnace was installed on the production line, and the line was modified accordingly. Based on this, a modified simulation model of the production line was developed. Figure 6 presents an overview of the modified simulated hot-rolling production line. The development of this simulation model follows the methodology mentioned in the previous section. The modified simulation model was verified and validated to ensure it ran without errors or logical inconsistencies. Using the simulation model for one year, synthetic hourly energy consumption data (in megawatts) for the modified production line were extracted. The resulting dataset, structured as a time series, provides energy consumption records for each hour. For this dataset, 70% of the data was allocated for training and 30% for testing. We employed XGBoost and LSTM techniques to perform predictions on the dataset.

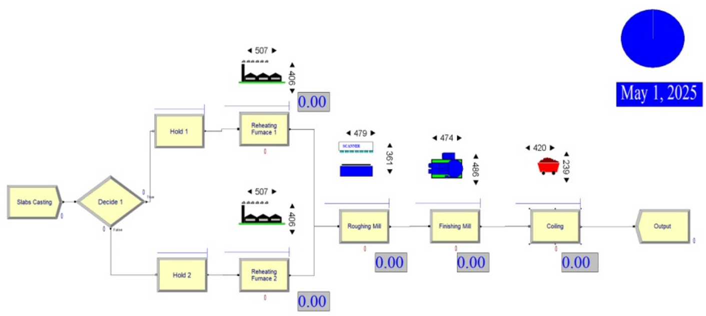

Figure 6: The modified simulated model of the hot rolling production line.

Table 1 shows the results of the prediction performance metrics for these AI techniques. The lower values of MAE, MSE, and RMSE indicate a better fit between the predicted data by the AI technique and the actual data. The results show that the LSTM technique outperformed XGBoost.

The PV panel dataset records the output power in kilowatts (kW), representing system performance. Structured as a time series, it captures hourly data over a five-year period (2019–2023) [20]. We allocated 70% of the dataset for training and reserved the remaining 30% for testing.

Table 1
Results of performance criteria in predicting energy consumption

AI Model	MAE	MSE	RMSE
XGBoost	3672.7234	20478144.0	4525.2783
LSTM	2760.7234	11926939.0	3453.5400

Table 2 shows the results of the prediction performance metrics. The results indicate that the XGBoost technique outperforms LSTM in two key performance metrics: Mean Squared Error (MSE) and Root Mean Squared Error (RMSE). In terms of Mean Absolute Error (MAE), the LSTM technique outperforms XGBoost.

Table 2
Results of performance criteria in predicting energy consumption

AI Model	MAE	MSE	RMSE
XGBoost	14.6637	524.6783	22.9059
LSTM	14.0474	623.7130	24.9742

5. Conclusion

AI techniques require large amounts of data to make accurate predictions, which may be scarce or inaccessible. This is a significant challenge, especially when applying these techniques in industries. To address this challenge, this study uses Discrete Event System Simulation (DESS) to generate synthetic data for training AI models. We propose a framework for using DESS to generate sufficient synthetic data that enables more accurate predictions, especially in renewable energy-based industrial systems. The proposed framework enables the generation of synthetic but operationally accurate datasets in data-poor environments, a common scenario in many industrial systems. This study utilizes the proposed framework to predict synthetic energy consumption datasets from a simulated hot rolling production line in a steel complex. The results show that DESS can effectively generate synthetic, reliable data to improve AI predictions. The proposed framework is generalizable and can be adapted to other industrial systems.

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Declaration on Generative AI

During the preparation of this work, the authors used Grammarly in order to: Grammar and spelling check and reword. After using this service, the authors reviewed and edited the content as needed and take full responsibility for the publication’s content.

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