Energy Visualization and Prediction System for Hot Rolling Line

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ABSTRACT

As we move toward decarbonization, efficient use of energy is increasingly important. In this paper, an energy visualization and prediction system for hot rolling line is described. This system, closely integrated with the process, visualizes energy usage by area, time, and product, allowing identification of wasted energy and initiation of energy improvements. Additionally, it enhances environmental value through emissions and carbon footprint calculations. Also, energy-saving measures using pre-forecast information from a control system are introduced. Power demand modeling approaches are discussed as well. Energy optimization is facilitated by integrating demand forecasting with process control, in collaboration with production and energy management.

Keywords: Hot rolling, Energy saving, Energy prediction, Demand forecast

INTRODUCTION

In the metal industry, minimizing environmental impact by achieving carbon neutrality has become an important issue. It is necessary to further reduce greenhouse gas emissions through energy conservation and to manage energy efficiently. By promptly monitoring and analyzing the production plan, equipment operation status, and power consumption, as well as predicting future power usage, it is possible to enhance energy efficiency, lower costs, and reduce emissions. To achieve this, a prediction system is required that can flexibly adapt to changes in production plans and fluctuations caused by external factors, while collecting real-time data on equipment status and power consumption. In our pursuit of a smart factory, we aim to achieve energy optimization across the entire manufacturing plant (Figure 1). This paper outlines an energy visualization, prediction, and optimization system for the hot rolling line closely linked with the production management and control system.

In a hot rolling line, gas is consumed by the reheating furnace and electricity is used for large motor-driven equipment such as mill stands. The energy visualization system displays product-wise, area-wise and time series energy consumption and greenhouse gas emissions based on control data from the reheating furnace and rolling mill equipment. Through this analysis, inefficient consumption processes can be identified. The next step after visualization and analysis is energy-saving. By utilizing pre-available information calculated by the process control system, the operation of motor-driven equipment, such as pumps, can be optimized, resulting in energy savings. Moreover, by forecasting power demand, it is possible to plan and implement power management strategies such as peak cuts and shifts in power demand. However, the hot strip rolling process is complex, and power consumption varies for each product, making accurate prediction challenging. For power demand prediction, two approaches are described: a method using a statistical model with machine learning based on past records and a method using a detailed physical model of the rolling process. By leveraging real-time predictions and more flexible long-term simulations in cyberspace, operating conditions and production plans can be optimized. A cyber-physical system incorporating process control systems contributes to the optimization of production and energy by coordinating with production and energy management.

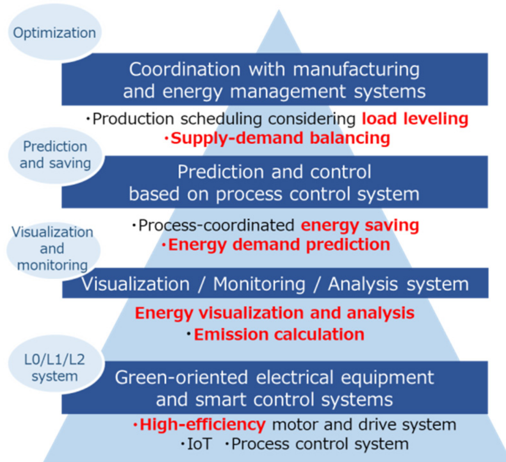


Figure 1. The concept of energy optimization.

VISUALIZATION AND ANALYSIS OF ENERGY CONSUMPTION AND GREENHOUSE GAS EMISSIONS

By visualizing and analyzing energy consumption for each product and process based on control information from each piece of equipment on the production line, it becomes possible to identify inefficient consumption processes. This could contribute to designing energy-saving measures, optimization of equipment operation plans according to fluctuations in power demand, and optimization of power procurement plans. Here, we introduce an example of an energy consumption visualization system.

Energy Visualization and Analysis System

Figure 2 shows an example of the system configuration for visualization and analysis.[1,2] This system connects to control devices such as Distributed Control Systems (DCS) and Programmable Logic Controllers (PLC), enabling the collection of process data and operational data from each device. The system has the following functions: (1) acquisition of historical energy consumption data, (2) calculation of energy intensity per product, (3) calculation of greenhouse gas (GHG) emissions and carbon foot print (CFP), (4) data export functions for more advanced analysis or integration with other systems, and (5) dashboard display.

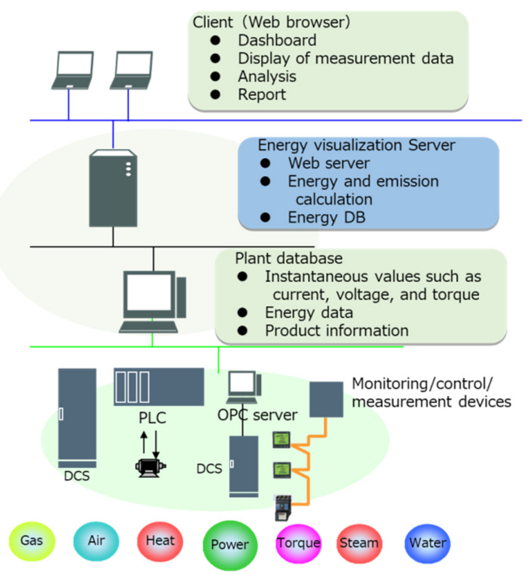


Figure 2. Example of system configuration for energy visualization and analysis.

Additionally, web access from client terminals allows for the monitoring and analysis of energy consumption and greenhouse gas emissions at any time. By graphing the temporal changes in energy intensity, it is possible to identify time periods with decreased energy efficiency, check the energy consumption of each device based on this information, and easily locate areas of inefficient energy consumption (Figure 3). Furthermore, by visualizing the energy used in the production of a single product, the system supports the creation of optimal production plans that match energy consumption with the power supply and demand situation.

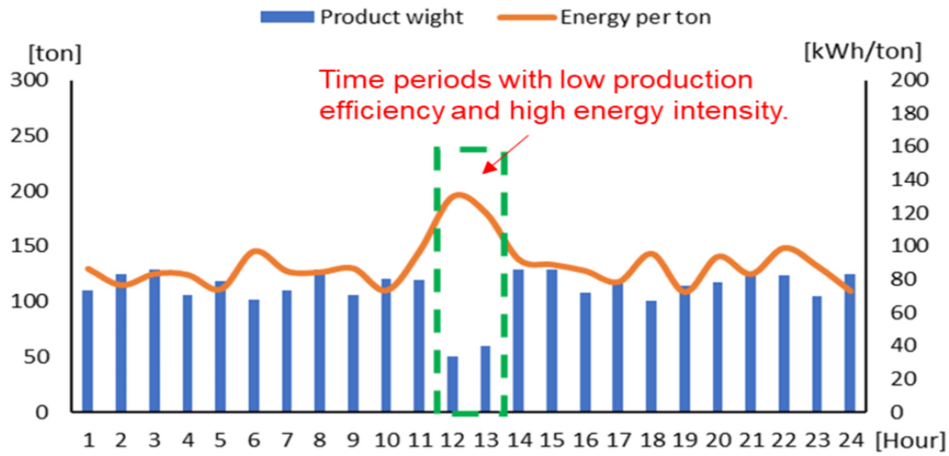


Figure 3. Example of system configuration for energy visualization and analysis.

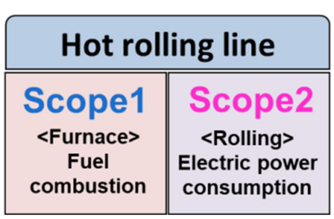
GHG Emissions Calculation

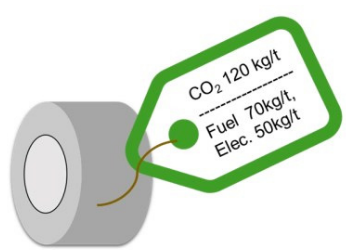
An international standard known as the GHG Protocol,[3] developed by the World Business Council for Sustainable Development (WBCSD) and the World Resources Institute (WRI), has been established to enable companies to calculate and report their GHG emissions. This protocol provides a comprehensive framework for accounting emissions generated throughout the entire value chain, including the procurement of raw materials, manufacturing, logistics, sales, and disposal. Emissions arising from this end-to-end process are referred to as supply chain emissions. The GHG Protocol classifies these supply chain emissions into three categories: Scope 1, Scope 2, and Scope 3. Scope 1 covers direct emissions from sources that are owned or directly controlled by the reporting entity. Scope 2 pertains to indirect emissions resulting from the generation of electricity purchased and consumed by the organization. Scope 3 encompasses all other indirect emissions that occur outside the organization's ownership or control but are associated with its business activities. The basic formula for calculating GHG emissions under the GHG Protocol is:

$$\text{GHG emissions } (CO_2e) = \text{Activity data} \times \text{Emission factor} \quad (1)$$

where "CO_2e (Carbon dioxide equivalent)" is the standard unit used for emissions from various GHGs, "Activity data" refers to the amount of material such as fuel or electricity material used, and "Emission factor" indicates the GHG emissions per unit of activity.

The system described in Figure 2 can calculate GHG emissions categorized under Scope 1 and Scope 2 by monitoring the consumption of energy resources such as electricity, gas, and water. For Scope 3 emissions, estimation is made possible through integration with external entities, enabling the calculation of upstream and downstream supply chain emissions. For example, in hot rolling, the combustion of fuel in the reheating furnace is a major Scope 1 emission source, and the use of electricity in the rolling mill is a major Scope 2 emission source (Figure 4a), and GHG calculations can be conducted using equation (1). In recent years, the importance of calculating carbon footprints (CFP) based on primary data has been increasing, as demonstrated by the development of the Pathfinder Framework by WBCSD,[4] which provides guidance for product-level GHG accounting with greater accuracy and transparency across value chains. The system shown in Figure 2 also calculates the energy intensity for each product, thereby providing product-wise carbon footprint calculations (Figure 4b).





a) Scope 1 and Scope 2 b) CFP of hot rolled coil

Figure 4. Concept of Scope 1 and Scope 2 GHG Emissions and carbon footprint calculations for hot rolling.

EXAMPLE OF ENERGY-SAVING TECHNOLOGIES USING PREDICTIVE CONTROL

For further energy-savings, predictive control using pre-available information can be considered in combination with visualization.[5] As an example of energy-saving solutions using predictive control, power-saving control based on hot rolling process prediction applied to the descaling system pump is discussed below.

Figure 5 shows the general configuration of the machinery and electrical equipment in the hot rolling line. Descaling in the hot rolling mill is a process that blows off the oxide film (scale) formed on the surface of the slab or transfer bar with high-pressure water. A pump supplies high-pressure water through a common pipe to multiple descaler spray headers. Sprays turn on when the slab or transfer bar approaches the header. The flow rate, frequency, and timing of the high-pressure water required for the descaler vary depending on the process and products. The descaler uses large-capacity pumps and motors to instantly discharge sufficient high-pressure water. Optimizing motor operation can be expected to achieve significant power saving. Figure6shows an example of flow rate calculation for high-pressure water required for descaler. The process computer system (L2) calculates the rolling process in advance and predicts the future on/off pattern of the headers. Using this predictive information, the required flow rate and timing are calculated. Pump speed is optimized to minimize power consumption.

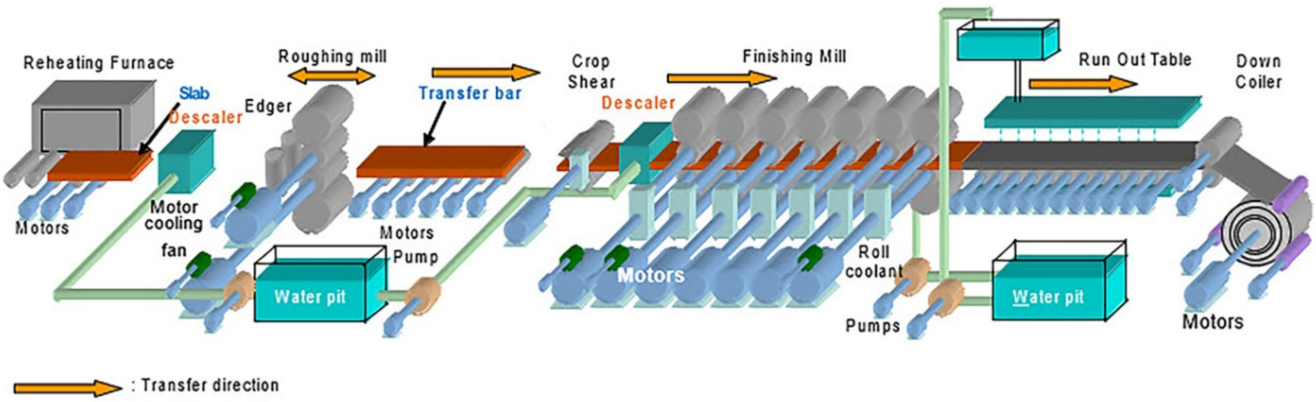


Figure 5. General configuration of machinery and electrical equipment in a hot rolling mill.

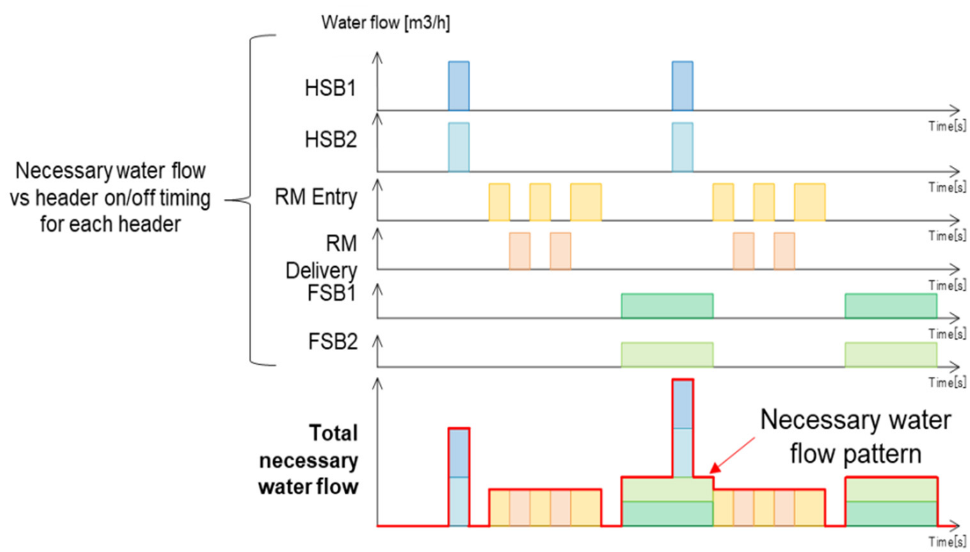


Figure 6. Example of necessary water flow calculation for descaler.

POWER DEMAND PREDICTION

By predicting production line energy consumption, it is possible to formulate and implement power management strategies such as peak cutting and shifting of power demand. However, rolling mill processes are complex, and energy consumption varies for different types of products, making accurate prediction challenging. Two different modeling approaches for power demand prediction are discussed.

Power Demand Prediction by Statistical Model Using Historical Production and Energy Consumption

One of the power prediction approaches involves a statistical model based on historical production and energy consumption. Figure 7 is a schematic representation of statistical model-based power demand prediction.

First, the power consumption for each product is predicted. The product-wise prediction is conducted using a statistical model trained on historical records of product production runs, each comprising product information (e.g., product dimension and material specification) and corresponding actual power consumption and production time. Neural networks are employed. In the prediction phase, the model takes the product information of the planned production as input to predict the power consumption and time required for manufacturing the product. Since actual values are obtained for each production run, the model can be updated through online learning. This prediction can be made for the entire production process simultaneously. However, it is also feasible to forecast for individual processes or specific areas, such as the roughing mill area or finishing mill area. In the case of batch production, such as hot rolling, it is necessary to predict the production intervals, such as furnace discharge pitch, using preceding product data as well.

First, the power consumption for each product is predicted. The product-wise prediction is conducted using a statistical model trained on historical data comprising pairs of production information (e.g., product size and material) and the corresponding actual power and time consumption. As an example of model architecture, neural networks can be employed. In the prediction phase, the model takes the product information of the planned production as input to predict the power consumption and time required for manufacturing the product. Since actual values are obtained for each production, the model can be updated through online learning. This prediction can be made for the entire production process simultaneously. However, it is also feasible to forecast for individual processes or specific areas, such as the roughing mill area or finishing mill area.

Next, the time-series power consumption is predicted by aggregating the product-wise prediction results. The base power consumption by utilities and equipment that operate continuously to maintain and stabilize the production line, which is not necessarily linked to individual products, is considered in the time-series consumption. This prediction also involves modeling and learning using actual power consumption data.

Using neural networks, we attempted to calculate the power consumption for each coil during hot rolling. The evaluation of the mean absolute percentage error (MAPE) showed that the prediction errors for both power consumption and rolling time per coil were less than 3.5 %.

This approach is expected to deliver reliable predictions with relative ease. It is also adaptable to various manufacturing processes and production lines other than hot rolling. It is important to exclude non-stationary data from the actual data for effective training and learning. A challenge arises in responding to operational changes lacking actual data, such as the production of new product types.

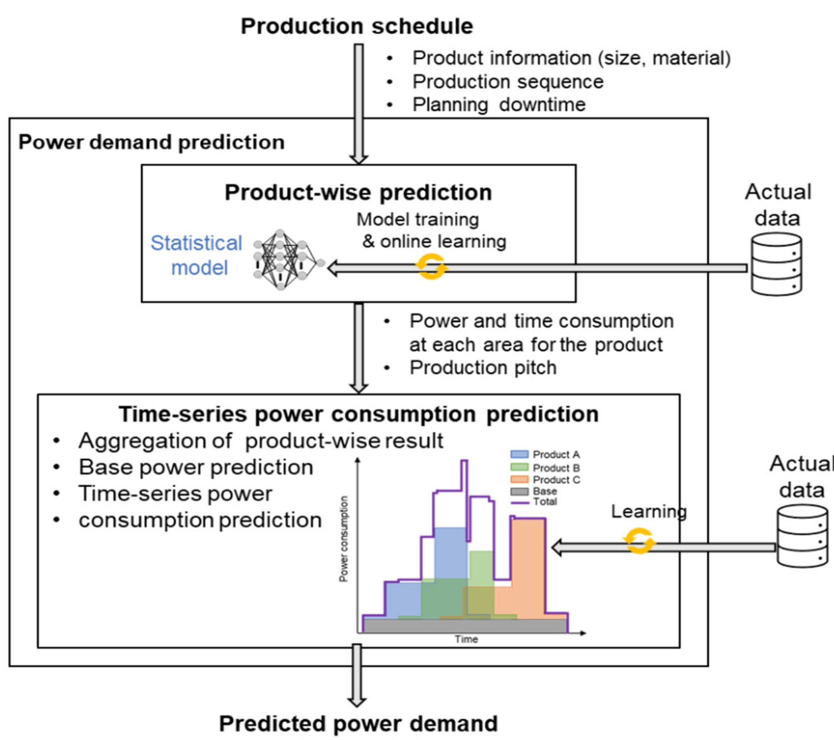


Figure 7. Schematic representation of statistical model-based power demand prediction.

Power Demand Prediction by Physical Model Using Setup Up Calculation

The other approach is physical model-based power demand prediction. The outline of the prediction flow is shown in Figure 8. This approach is characterized by relying on setup calculations, performed by the process computer within the control system for each production coil, as the primary information source. Information necessary for demand prediction, such as product details and the rolling sequence, is obtained from the production management system (L3).

In the rolling setup calculations performed by the process computer (L2), information from the production management system and physical models of the slab and equipment such as rolling mills are used to determine the setup values for each rolling process. The rolling setup values include the reduction amount at each rolling process, known as the pass schedule. They also include the transportation between equipment, and the torque and speed of the main rolling mill. Based on that, the main power consumption per product coil is calculated. By combining the prediction of main power consumption per product with the discharge pitch prediction, base power consumption, and auxiliary power consumption prediction, the power consumption per unit time is predicted.

This approach actively utilizes the rolling setup calculation results from the process computer, enabling smooth integration into existing control systems. Additionally, it has the advantage of being able to respond to operational changes that are not accompanied by actual data, such as the production of new product types. By using detailed setup data based on physical models of each stage of rolling and further improving prediction accuracy through learning based on actual data, this method enhances precision.

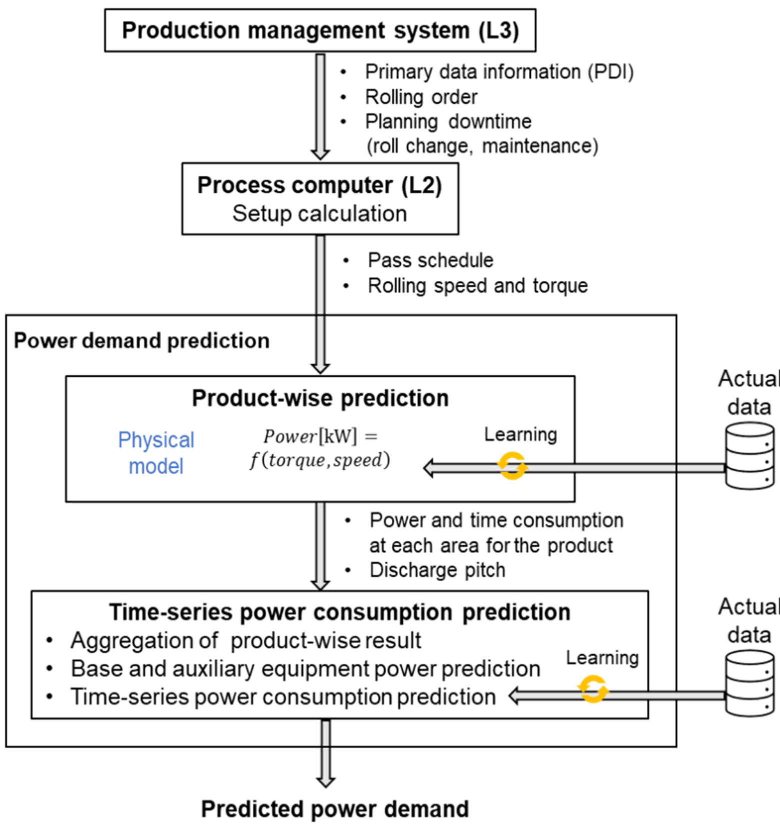
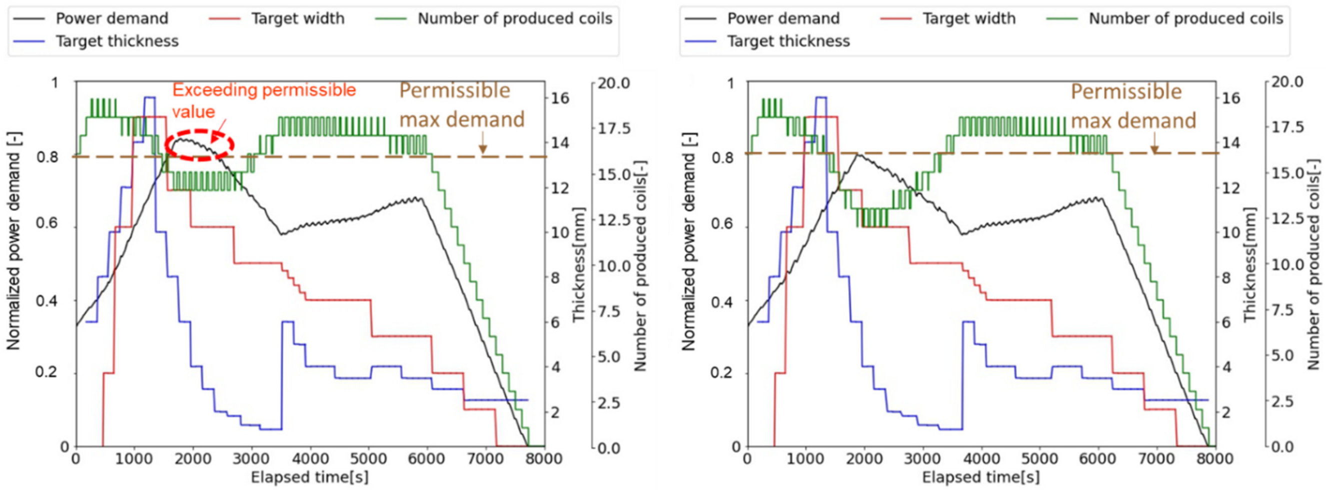


Figure 8. Schematic representation of physical model-based power demand prediction.

An example of physical model-based power demand simulation is shown in Figure 9. In this example, the power demand was normalized to a range of 0 to 1. Optimization was evaluated, assuming that the maximum permissible power consumption per 30 minutes based on the utility power contract is 0.8. In the case of the shortest discharge pitch calculated by mill pacing, demand exceedance was predicted (Figure 9a). To avoid exceeding the permissible value, the discharge pitch of slabs near the predicted time of demand exceedance was adjusted (Figure 9b). By predicting power consumption using physical models and forecasting demand in this manner, optimal energy utilization can be achieved.



a) In the case of the shortest discharge pitch.

b) In the case of adjusting the discharge pitch for peak cut. shortest discharge pitch.

Figure 9. The example of physical model-based power demand simulation.

ENERGY OPTIMIZATION

Thus far in this paper, visualization, energy saving, and energy consumption prediction have been introduced. As a further effort towards decarbonization, it is necessary to develop optimization systems. To achieve optimization of both operations and production, including various energy perspectives such as power consumption, the utilization of cyber-physical systems is beneficial. Figure 10 shows the concept of a cyber-physical system for energy optimization. The system utilizes operation, control, and product performance data gathered by the control systems in the physical space, combined with energy information and statistical data, through digital twins. In digital twins, simulations based on process modeling are conducted to optimize operational conditions and production plan taking forecasted energy demand into account. By reflecting these results in the control systems of the physical space, we can optimize energy utilization throughout the entire manufacturing process.

Figure 11 shows power demand optimization as an example of energy optimization. The physical side predicts and monitors the 30-minute demand for the next few hours. When demand exceedance is predicted, simulations in the cyber space are used to explore operational conditions that can achieve peak shaving without significantly disrupting the production plan. Additionally, it is possible to forecast the power demand for one day or several days based on the production plan in the cyber space. This contributes to optimization through close collaboration between production and energy management, including load leveling by revising the production plan and adjusting energy supply.

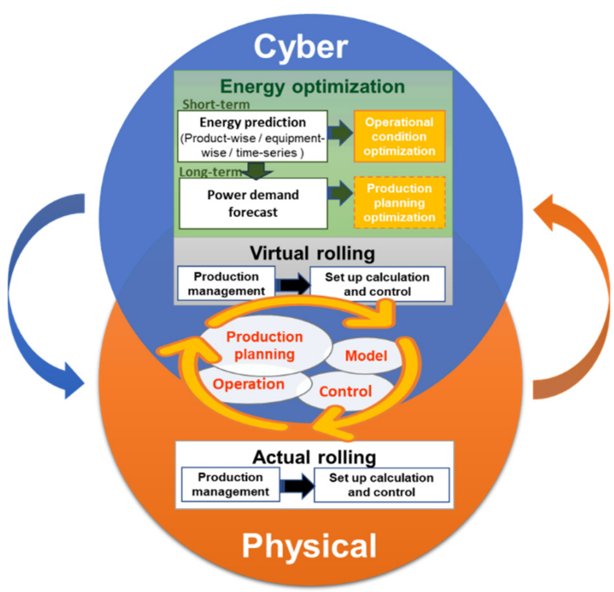


Figure 10. The concept of cyber-physical system for energy optimization.

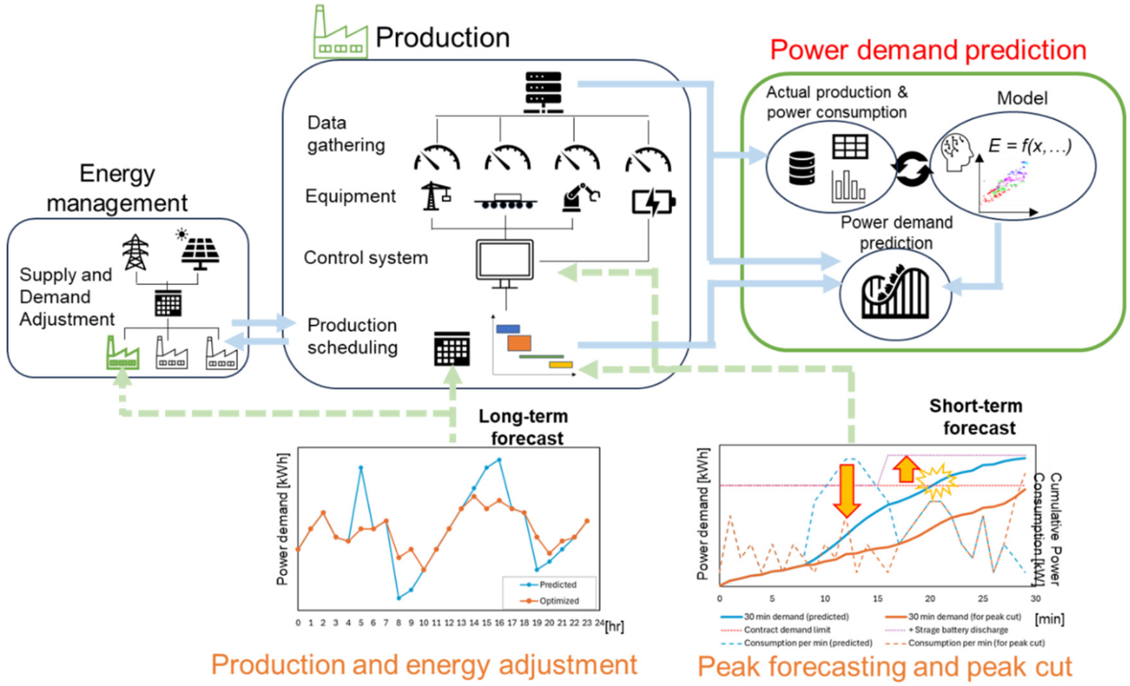


Figure 11. Energy optimization by power demand prediction coordinating with manufacturing and energy management

CONCLUSIONS

In this paper, visualization, energy saving, prediction, and further optimization were described. Through the visualization of energy consumption and emissions, energy savings are expected, along with the building of trust with stakeholders and the enhancement of competitive advantage. The energy forecasting system utilizing process computers combines accuracy and explainability and is also capable of adapting to new processes and products. We plan to further enhance our initiatives for optimal energy utilization in future work.

REFERENCES

1. Y. Osaka, Y. Sakiyama, Z. Lu, H. Imanari, "Intelligent Energy Saving Technology for Hot Rolling", *ROLLING 2016*, 2016.
2. Z. Lu, H. Imanari, S. Shinohara, "All-in-one Energy Saving Solution in Steel Plant", *ESTAD 2019*, 2019
3. *The Greenhouse Gas Protocol: A Corporate Accounting and Reporting Standard*, World Resources Institute & World Business Council for Sustainable Development, 2004.
4. *Pathfinder Framework: Accounting and exchange of product life cycle emissions*, World Business Council for Sustainable Development (WBCSD), 2022.
5. Y. Osaka, H. Imanari, Z. Lu, H. Imanari, S, Shinohara, "Achieving Optimal Energy Savings in Hot Strip Mills with Predictive Solution", *AISTech 2019*, 2019, pp. 2247-2454

