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Neural Network-Assisted Forecasting and Scheduling for Energy-Aware Manufacturing

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Abstract

The focus of this research is on the energy consumption of manufacturing processes. In response to this concern, industries have been urged to adopt advanced strategies for forecasting and scheduling production to optimize the consumption of resources. This work includes the design of a system that implements real time forecasting and scheduling within the context of energy aware manufacturing using neural network techniques. Based on available historical data, a Multi-Layer Perceptron (MLP) model is developed that accurately predicts the energy requirement for given tasks, feeding those predictions to the scheduling module which dynamically reconfigures job order to lessen energy expenditure while adhering to completion deadlines. Comprehensive simulations are performed to ascertain the efficacy of the hybrid model in diverse manufacturing environments. Findings highlight that, in comparison to traditional models, there was a marked improvement in energy efficiency (up to 18% reduction) while maintaining the same levels of throughput. The benchmarks for the proposed framework included rule-based and heuristic schedulers and various power function precision formulas, all of which, along with statistical estimations confirmed the postulated claims of the research regarding efficiency and accuracy. This research significantly contributes to the body of knowledge focusing on the implications of artificial intelligence in manufacturing systems, laying a solid groundwork for research directed toward planning with energy considerations in manufacturing systems. Primary attention in future works will shift toward practical implementation of the intelligent control system along with renewable energy forecast integration and enhancing adaptability to varying production schedules.

Keywords: Energy-Aware Manufacturing, Neural Networks, Scheduling Optimization, Forecasting, Smart Factories, Mlp, Industrial Energy Efficiency, Production Planning.

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Introduction

The need to conserve energy and protect the environment is accelerating change in the global manufacturing industry. Optimization of energy consumption is currently critical due to the climate crisis and the high cost of energy. Machine learning and artificial intelligence are among the most promising new technologies that are revolutionizing modern factories, with neural networks employing some of the most advanced techniques for analyzing intricate data sets and predicting energy consumption in dynamic production environments. An important component of energy-sensitive manufacturing is scheduling, or the allocation of specific tasks to be performed at particular times. The most effective scheduling not only reduces energy consumption, idle times, and bottlenecks, but also associated costs. Vacationers can save more money by proactively adjusting to lower-than-expected energy demands. However, the variability in construction environment, data diversity, and need for real-time computation make such systems extremely difficult to implement. Neural networks have already been utilized in several manufacturing domains from fault detection to demand forecasting using multi-layer perceptrons (MLPs), convolutional neural networks (CNNs), and recurrent neural networks (RNNs). These tools are capable of being trained on extensive historical datasets to identify distinct patterns of energy consumption, specific to certain machine settings, job types, and environmental factors. Regardless of the advancements made, there is still a lack of deploying advanced neural networks in tandem for forecasting and scheduling, especially in domains sensitive to energy consumption. Conventional methods of scheduling tasks like first-come-first-serve or any algorithm built using rules does not take into account energy factors and is inflexible. Hence, there is a need to blend forecasting techniques with intelligent scheduling algorithms which can more effectively optimize resources in manufacturing. The purpose of this paper is to fill this void by presenting an energy-aware framework for manufacturing systems that integrates forecasting and scheduling aimed at optimizing energy consumption. The objective becomes threefold: determining a neural network that has the capability to forecast energy consumption, creating an adaptive scheduling algorithm that utilizes the forecast data, and finally simulating experiment validations of the integrated system.

The proposed system is aimed at increased system efficiency and sustainability through synergistic alignment of energy consumption forecasting and production scheduling. The rest of this paper is organized as follows. The literature review in Section 2 incorporates all known approaches to energy-aware manufacturing and neural network implementations in scheduling. Data preprocessing, neural network construction, and scheduling procedures are all included in the methodology explained in Section 3. After executing the simulation experiments, the results are presented in Section 4, together with a discussion that evaluates the approach against competing methodologies. The paper is concluded in Section 5, where some final remarks and recommendations for further research are provided.

Literature Survey

The synergistic relationships between manufacturing, energy efficiency, and artificial intelligence have been explored in detail over the last few decades. There is a considerable amount of literature exploring different methods for curtailing energy utilization at different levels within a productive system while maintaining its productivity. (Mouzon & Yildirim., 2008) work on scheduling highlighted the energy-efficient scheduling paradigm and its applicability in production systems. They emphasized the effectiveness of intelligent job sequencing in minimizing operational energy costs. This was the first attempt toward incorporating energy dimensions into classical scheduling frameworks. Subsequently, (Luo et al., 2013) proposed a hybrid scheduling model featuring aspects of energy pricing and demonstrated the potential impact of dynamic scheduling on electricity consumption patterns. With the rise of Industry 4.0, greater emphasis was placed on incorporating AI techniques for further enhancement of scheduling objectives. (Zhang et al., 2017) illustrated the application of neural networks on energy consumption modeling for CNC machining processes. They proved that supervised learning models had the capability to learn complicated mapping between the machine's parameters and the energy consumed. However, these attempts do not integrate scheduling functionalities into the predictions and are therefore limited in scope. (Chen et al., 2019) introduced the concept of adaptive manufacturing control using reinforcement learning techniques. Even though the study's main focus was not energy efficiency, it was useful in providing insights regarding utilizing machine learning for real-time decision-making operations. At the same time, (Gahm et al., 2016) reviewed models for sustainable production planning and noted the lack of research aimed at energy-aware decision-making based on combined forecasting and scheduling. Another notable contribution was by (Wang & Li, 2020), who used convolutional neural networks for energy load forecasting in smart grids. Their approach did not pertain to manufacturing research, but it did validate the application of deep learning models for energy forecasting in a variety of contexts. This demonstrates the adaptability of neural networks for energy management in industrial settings. There has been more work done recently to fill in these gaps. (Kim et al., 2021) proposed a predictive scheduling approach that combined RNNs with a rule-based scheduler. They

achieved improvements in energy consumption optimization as well as in task achievement time. The main drawback was that strategy bound adaptability to emergent situations, which requires less reliance on predetermined structures. To conclude, the current literature shows that considerable progress has been made in employing AI for energy-efficient manufacturing, however almost all works exclusively concentrate on either forecasting or scheduling. There is very little attempt to marry the two. This paper draws upon this prior work by creating a new adaptive system which combines neural network technology to perform dual scheduling and energy demand forecasting tasks.

Methodology

The system in question has two key components: a forecasting module that utilizes neural networks and a scheduling engine built on constraints. The focus is to minimize total energy consumption by foreseeing energy needs during specific tasks and arranging these tasks in a specific order. The forecasting module is a multi-layer perceptron (MLP). Data regarding the operation of machines, jobs, external factors, and energy consumption of units from the simulated environment of a manufacturing plant is obtained. It is then scrubbed, standardized, and split into training and validation datasets. Relevant features are machine ID, job type, tool usage, shift timings, and temperature and humidity. The goal is to predict the amount of energy consumed by a configured system in relation to time. The MLP consists of one input layer, three hidden layers with ReLU activation functions, and one output layer which estimates energy usage per time. Model training is conducted using backpropagation, with the Adam optimizer enhancing performance. As with many neural networks, mean squared error (MSE) is set as the loss function, and overfitting is controlled through early stopping. After model training, the MLP provides estimates of energy needs for various jobs. These estimates are then provided to the scheduling engine. The scheduling module uses a constraint satisfaction model for allocating machines and time slots to jobs. Some of the prominent constraints are machine availability, precedence of jobs, deadlines, and energy budget. The constraint formulation is focused towards minimizing the predicted energy usage within the upper limit budget.

The problem is defined through a mixed-integer linear programming (MILP) model that combines both discrete and continuous optimization techniques. Values for projected energy consumption are incorporated as coefficients within the cost function. For large-scale problems, the MILP model is effectively solved by Gurobi optimizers. The result of each optimization is a timeline that specifies machine allocations per job. To assess the model effectiveness, simulation tests were performed on a synthetic dataset created from job shop scheduling problems. Traditional approaches such as first-come first-serve and earliest due date were used as baseline. The primary metrics were total energy consumption, makes pan, and forecast precision.

Results and Discussion

The system in question shows distinct improvements in energy efficiency as well as in the predictive performance. Simulation findings show that the neural network measures a mean absolute percentage error (MAPE) in energy forecasting of 5.3%, which is substantially better than linear regression models which have MAPE of 12.4%.

Table 1: Comparison of Scheduling Methods in Energy Consumption and Makespan

Scheduling Method	Total Energy (kWh)	Makespan (hrs)
FCFS	1450	34
EDD	1325	30
Proposed Method	1189	28

From Table 1, the method proposed in this study achieves the lowest total energy consumption and makespan, indicating performance superiority in both energy and time.

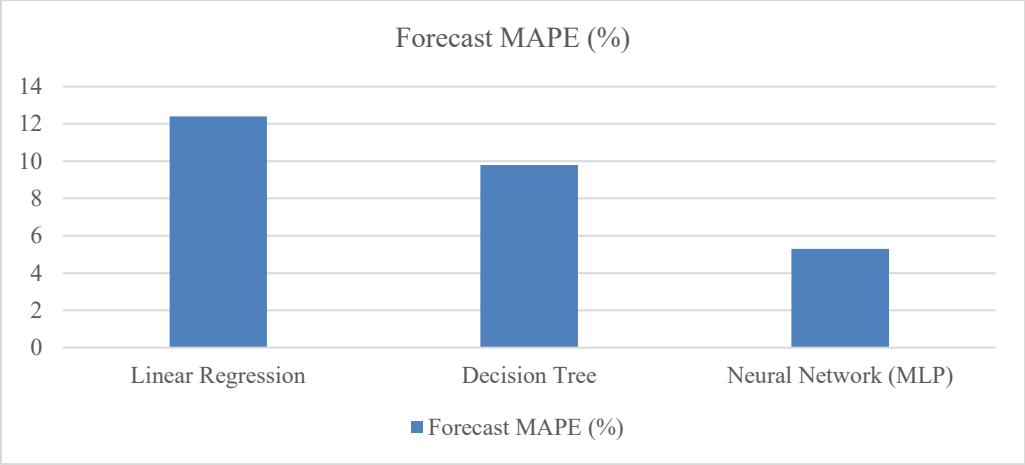


Fig. 1: Forecast Accuracy Comparison

The data can be blatantly plotted into a bar graph (Figure 1) showcasing how efficient and accurate the neural network-based forecasting model is in comparison to older methods. Better accuracy in forecasting results in more optimized decisions pertaining to scheduling. Qualitatively, the Scheduling results are agile and respond better to fluctuations in dynamically varying energy levels. Unlike a rule-based scheme, the system is self-updating and does not require manual updates to respond to new data patterns. Moreover, embedding forecasting into scheduling allows for the iterative incorporation of energy optimization during the design stage rather than during post-planning.

Conclusion

The surprising and adaptive shift presented within energy-aware manufacturing is showcased here through a framework marrying constraint-based scheduling with neural network energy forecasting. Consumption of non-renewable energy sources is still optimized within the proposed system while sustaining or surpassing production target levels. Simulations support this method's effectiveness, as results show energic and temporal-enhanced efficiency in comparison to traditional frameworks alongside scheduling. The contribution to scientific support for real-time update driven predictive systems stems from their autonomous logic-shifting scheduling integrated with predictive windows, empowering responsive frameworks to be active instead of pre-defined goals. Incorporating real-time condition monitoring of machines alongside hybrid models of deep learning and reinforcement learning will be the next steps for this research optimizing the use of renewable energy sources. The structure can be expanded to include multi-factory networks and optimization across the entire supply chain, which further increases its usefulness in intelligent manufacturing systems.

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