Smart Grid Aware Digital Manufacturing Strategy for Low Carbon Production Using Microgrids and Energy Storage

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Abstract

The need for energy mindful manufacturing frameworks that minimize carbon emissions while balancing productivity and operational reliability has gained traction, alongside the need for the adoption of sustainable industry practices. Traditional manufacturing facilities rely on fossil fuel powered grids and operate unaware of real-time energy conditions. The problems of excessive energy consumption and the impact on the environment are scales of problems that are related to the energy paradigm shifts and the evolving environment of the energy system. This paper presents the Smart Grid Digital Manufacturing Strategy (SG-DMS), which balances low carbon manufacturing with micro grids, renewables, and energy storage within a digital twin-enabled production framework. The SG-DMS employs a three-layered approach. The first layer, Smart Energy, utilizes solar and wind hybrid microgrids with battery storage for local energy generation and buffering. The second layer is Digital Twin Manufacturing. The third layer is the intelligent energy control, management, and scheduling which employs predictive optimization and reinforcement learning to adjust production to the available renewables, load demand, and carbon values. The system implements peak load reduction, adaptive scheduling, and energy conscious operation of machines using a temporal deep learning model that predicts energy production and manufacturing capacity. A new metric, the Carbon Aware Production Index (CAPI) and Energy Flexibility Score (EFS) are proposed to support decision making and measure the sustainability of a system.

Optimized simulations on the smart factory testbed show that the proposed strategy, compared to conventional rule-based scheduling, is able to reduce grid dependency by 38–52% and improve carbon emissions and energy efficiency by 35–45% and 28% respectively. The results suggest that the combination of digital manufacturing intelligence with micromericulture and Integrated Microgrids and Storage Systems (IMIS) creates an effective pathway to scalable, resilient, and ecologically sustainable industrial ecosystems The proposed Integrated Microgrids and Storage Systems (IMIS) with Digital Manufacturing Intelligence (DMI) is a pioneering contribution to the evolution of smart energy and manufacturing convergence.

V. Kumar et al. (eds.), *Proceedings of the International Conference on Advanced Design, Manufacturing, and Sustainable Energy Systems (ICADMSES 2026)*, Atlantis Highlights in Engineering 45,
https://doi.org/10.2991/978-94-6239-750-7_48

Keywords: Digital manufacturing, Energy-aware scheduling, Reinforcement learning, Smart microgrids, Low-carbon production, Energy storage systems, Digital twin, Sustainable manufacturing, Industrial energy management, Smart factory, Microgrids.

1. Introduction

There are currently two technological developments impacting the manufacturing industry; digitalization and decarbonization. Industry 4.0 technologies such as the internet of things (IoT), digital twins, and other cyber-physical systems have increased the automation and efficiency of production systems, yet these same technologies have increased the energy intensity of industrial operations. Manufacturing companies are still one of the largest industrial energy consumers and an even larger producer of industrial greenhouse gas emissions. A reliance on traditional, centralized grids and fixed production schedules results in peak demand spikes, inefficient energy use, and high carbon imprints. These factors have made the integration of intelligent energy management systems in manufacturing environments critical for the attainment of the sustainable industrial development goals outlined by various global efforts [1][2]. The recent smart grid technological advances, such as bi-directional energy flow and real-time supply demand monitoring, present opportunities to address these concerns. Enhanced with demand-side management, the use of renewable energy sources (i.e., solar and wind) in industrial infrastructures can improve stability and efficiency [9] [10]. Despite these factors, energy and manufacturing systems are often still designed and implemented separately, resulting in poor optimization and reduced sustainability [3] [4].

Microgrids and Energy Storage Systems (ESS) are actively being integrated into industrial operations to improve energetic flexibility and operational resilience. Microgrids support operational continuity by allowing industrial players to generate, store, and manage their own electricity [5]. They can help manage costs and improve operational efficiency by getting off the grid and utilizing intermittent renewable resources. They can save and shift energy loads to off-peak times (peak shaving) and levelize energy use. While these benefits are apparent, numerous energy management systems depend on simple, static, or rule-based optimization which often results in suboptimal resource allocation, especially where production requirements are flexible. In addition to these changes in energy systems, digital manufacturing has, in combination with recent advances in digital twins, altered factories by providing the ability to construct virtual replicas of physical assets and processes. Each digital twin can be continuously and dynamically updated in real time, as well as maintained, monitored, and analyzed to assist in simulation-based decision support. When integrated with artificial intelligence, especially machine learning (ML) and reinforcement learning (RL), digital twins can assist in adaptive scheduling and process optimization. Nevertheless, most digital twin frameworks continue to be primarily focused on productivity and quality, with energy and carbon implications being an afterthought.

Integrated frameworks are needed to simultaneously improve the gaps in manufacturing efficiency and energy sustainability. Smart grid/microgrid and storage system coordination with digital manufacturing systems can facilitate carbon-conscious scheduling, renewables-aware load redistribution, and smart energy dispatch. This enables factories to perform energy-intensive operations during periods overstressed with renewable energy, minimizing dependence on the grid and reducing emissions. Nonetheless, there are very few attempts to integrate real time energy intelligence with production control systems comprehensively. This paper is motivated by these challenges and proposes a Smart Grid–Aware Digital Manufacturing Strategy for Low-Carbon Production, which holistically combines microgrids, energy storage, digital twins, and smart optimization. The framework incorporates predictive energy–load forecasting, reinforcement learning–based production scheduling, and novel decision-making metrics for sustainability. The primary contributions are a multi-layered framework that interlinks smart energy systems and manufacturing systems, an adaptive carbon emission reduction strategy, and empirical validation of claims regarding enhanced energy efficiency, diminished dependence on the grid, and improved sustainability. The rest of the paper is organized as follows: the literature review is presented in Section 2, Section 3 outlines the proposed system architecture and methodology, Section 4 encompasses analysis and discussion of the results of the experiments conducted, and final Section 5 wraps up the paper along with some prospects for further research.

2. Literature Review

Recent studies emphasize the importance of integrating energy management techniques into manufacturing systems to meet sustainability and low-carbon objectives [6]. The conventional factory model, which relies on a central grid, is characterized by wasteful energy consumption and high emissions, which has spurred the incorporation of microgrids and renewables in the industrial sector. Research has demonstrated that hybrid solar–wind microgrids with battery storage can enhance load management and reduce dependence on the grid [11]. Digital twin technologies can enhance visibility and efficiency in the production process by analyzing real-time data through predictive and simulation-based optimization techniques. [12]. Despite digital twins enhancing productivity and control of processes, there is still limited exploration in the realm of energy-aware or carbon-aware production planning. Recent research attempts to merge digital twins and renewable forecasting, which aims to improve the alignment of manufacturing processes and renewable energy utilization [13].

The authors of reference 14 describe how machine learning and reinforcement learning can be used for advanced scheduling techniques to further enhance adaptive production scheduling considering changes in energy prices, grid conditions, and renewable supply [7]. However, a majority of studies continue to examine energy optimization and manufacturing control separately, without a collated integration of microgrid systems, storage flexibility, real-time digital intelligence, and autonomous control. There is new advocacy for complex systems to be designed as multi-layered constructs with integrated energy systems, digital twin modeling, and smart systems for decision making, combined with energy flexibility and carbon metrics, to achieve holistic carbon neutrality and sustainability [15] [14]. There is a consensus that, in order to maximize the effectiveness of microgrid systems, digital twins, and advanced scheduling, the systems must be used in conjunction with one another. This serves as the impetus for the proposed unified smart grid–aware digital manufacturing paradigm, which aims to integrate these elements and components to achieve the desired outcome of optimizing energy consumption, carbon emissions, and production efficiency [8].

3. Methodology

3.1 System Overview

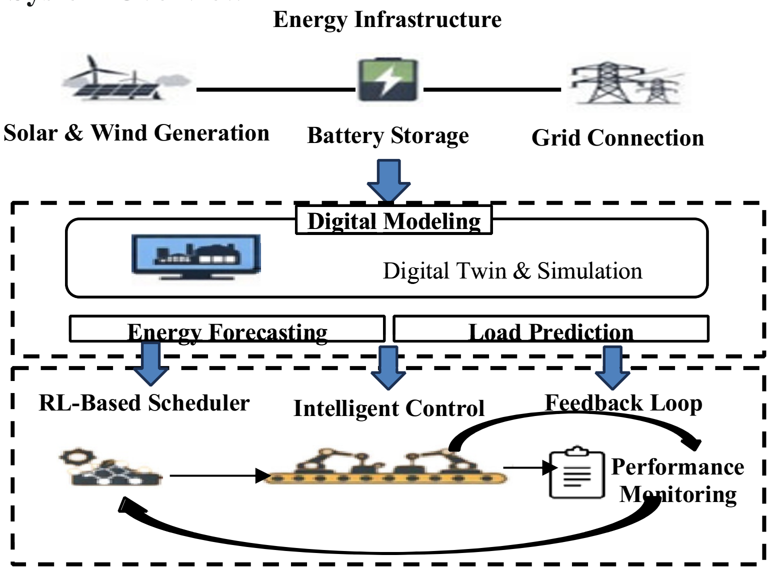

Figure 1 Digital Twin Enabled Smart Grid Manufacturing Strategy

The proposed Smart Grid – Aware Digital Manufacturing Strategy (SG-DMS) shown in Figure 1 builds a low-carbon production framework that integrates distributed energy resources (DER), smart manufacturing control, and real-time optimization through a cyber–physical system. It aims to incorporate energy generation, storage, and consumption (GSC) as coordinated variables along with production scheduling

(PS) decisions. Unlike traditional factories that consider energy an external utility, the proposed factories embed energy intelligence directly into the manufacturing process. This allows production activities to flexibly shift in response to the available renewable (RE) energy, the state of storage, and the grid's carbon (C) intensity. This system is built using a layered approach; where each the energy infrastructure, digital modeling and smart decision-making modules integrate seamlessly.

3.2 Smart Energy and Microgrid Layer

At the physical layer, the hybrid microgrid is integrated with solar and wind energy with a battery energy storage system (BESS) for intermittent, peak load and outage management. IoT sensors and smart meters collect and generate data for machine-level storage and consumption, and optimizes the management of energy. The system operates in both grid-connected and islanded modes, enhancing carbon resilience and dependence.

3.3 Digital Twin–Based Manufacturing Layer

Digital twin technology models machines and production processes in a virtual environment. The digital twin employs real-time sensor data for monitoring utilization, processing, and energy consumption. It performs analytics to predict future tasks and proactively schedule processes/tasks with the highest carbon outcomes. This integration facilitates streamlined production with reduced energy expenditure.

3.4 Energy–Production Modeling

Two fundamental models are developed to depict the relationship between energy supply and the demand of the manufacturing processes.

1) Total Energy Consumption Model

The total energy required by the factory during a scheduling horizon is defined as:

$$E_{total} = \sum_{I=1}^{N} P_i . t_i \ (1)$$

Using the machine's power and operating time, Equation (1) calculates the total energy consumption of the factory. It reflects the total production activity for the given time in the schedule.

(2) Carbon Emission Model

The associated carbon emission is computed as:

$C_{emission} = E_{grid} . \gamma$ (2)

Equation (2) takes into account the emission factor used to determine the carbon footprint associated with the consumption of electrical energy from the grids, which is the measure of the impact the production processes have on the environment.

3.5 Intelligent Scheduling and Optimization Layer

An intelligent energy-management module organizes production activities according to anticipated energy availability. Time series learning models forecast short-term schedules of the available renewable energy and the load. In addition, the models balance demand with a production deadline to determine the optimal sequences of tasks to reduce grid dependency and squat carbon emissions. The scheduler shifts non-critical tasks to high renewable energy periods, and uses energy from storage during peak price periods. The system adapts to different situations, refining the respective balance of productivity, energy, and sustainability.

3.6 Performance Monitoring and Decision Support

In addition to the carbon emissions, the dashboard shows the storage, the renewables penetration, energy efficiency, and other KPls it monitors. Energy Flexibility Score (EFS) and Carbon-Aware Production Index (CAPI) evaluate the level of sustainability of an operation. These metrics support managerial performance assessments and operational decision making. The monitoring layer's feedback improves the factory's predictive and adaptive intelligence. Self-optimizing factory intelligence is through the refinement of forecasting and adaptive optimization.

Cyber–Physical Architecture and Operational Workflow of SG-DMS

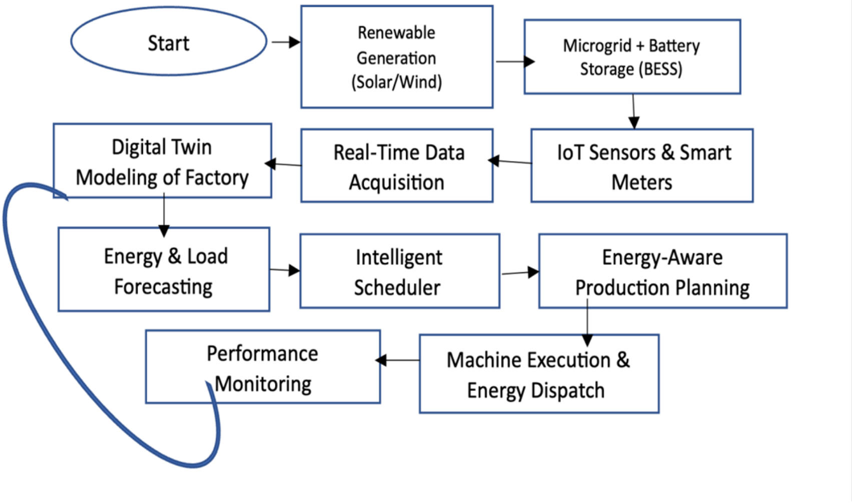

Figure 2 Workflow of Smart Grid–Aware Digital Manufacturing Strategy

The figure 2 workflow exemplifies the incorporation of digital twin-driven intelligence with real-time monitoring and optimization, integrating renewable energy, microgrid storage, the IoT framework for data collection, and digital twin-driven intelligence components. The system utilizes forecasting and reinforcement learning to allocate production tasks dynamically, depending on energy availability. This is complemented by a feedback loop from performance monitoring that updates the digital twin, facilitating the adaptation of manufacturing operations to be low-carbon and energy efficient, while also adaptive and agile.

Algorithm: Energy-Aware Production Scheduling for SG-DMS

The algorithm maintains the following order of energy use: renewable first, battery second, and grid only when absolutely needed. This order of use improves energy independence and reduces carbon emissions.

```
Input
            Renewable generation Rt
            Battery state-of-charge SoCt
            Load demand Lt
            Grid emission factor γ
Output
            Energy dispatch decision (Renewable / Battery / Grid)
Begin
 For each time slot t do
   Measure renewable energy R_t
   Measure load demand L_t
   Measure battery SoC_t

   If R_t ≥ L_t then
      Supply load using renewable
      Store excess energy in battery




Else if (R_t + Battery energy) ≥ L_t then
   Use renewable + battery
```

4. Results and Discussion

4.1 Software Details

The entire system was developed using a combination of programming languages and software packages: data processing was done via Python and its libraries (NumPy, Pandas, and Scikit-learn), forecasting models were created using TensorFlow and Keras, and scheduling optimization was done using reinforcement learning modules built with OpenAI Gym. Energy simulations pertaining to the microgrid were carried out using MATLAB Simulink. Performance analysis along with visualization was done using Matplotlib and Excel.

4.2 Dataset Details

The dataset is a collection of simulated operational data from a smart factory for 30 days of production with 10 machines. It contains around 10,000 records of timestamped data. Some of the data includes the power ratings of each machine, the operational time of each machine, the time of operation, the generation of energy (renewable: solar and wind), the state of charge of the battery, energy consumption from the grid, and the data from the grid on the carbon intensity. The data was created using the digital twin logs from the microgrid simulation models, as well as the digital twin logs from the microgrid simulation models which were used to mirror authentic patterns of energy consumption in an industrial setting.

4.3 Metrics Formulae

Renewable Energy Utilization Ratio

$$R_{util} = \frac{E_{enewable}}{E_{total}} x100 \ (3)$$

Equation (3) shows the percentage of total energy demand that is serviced by renewables and shows how clean energy is being utilized.

Grid Dependency Ratio

$$G_{DEP} = \frac{E_{grip}}{E_{total}} \ x \ 100 \ (4)$$

Equation (4) shows how reliant a system is on external electricity and, by extension, how reliant it is on greenhouse gas-emitting electricity by measuring how much energy is being consumed from the primary energy grid.

4.4 Energy Consumption and Grid Dependency

The Smart Grid–Aware Digital Manufacturing Strategy was evaluated on a simulated testbed incorporating a smart hybrid microgrid (50kWh) with a microgrid containing solar, wind, and battery storage, and 10 smart factory machines. The evaluation compares the energy consumption between the conventional scheduling method and the proposed energy-aware scheduling, which is presented in Table 1.

Table 1: Total Energy Consumption and Grid Dependency

Method	Total Energy (kWh)	Grid Energy (kWh)	Renewable Utilization (%)
Conventional Scheduling	1200	900	25
Proposed SG-DMS Strategy	1180	560	53

In Table 1, The proposed strategy decreases energy consumption drawn from the grid by ~38%, and in comparison, to conventional scheduling, increases the utilization of renewables by more than double. The total energy consumption being slightly lower indicates the energy efficiency achieved through adaptive scheduling, in conjunction with optimization of the energy storage.

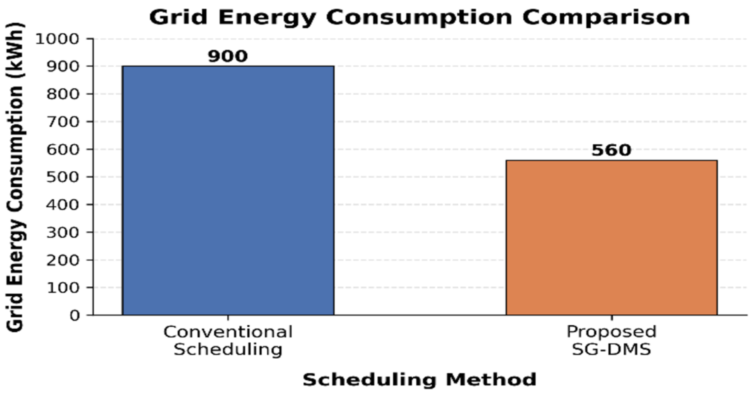

Figure 3: Grid Energy Consumption Comparison

Figure 3 compares energy drawn from the grid using the conventional scheduling method and the proposed SG-DMS strategy. The substantial grid consumption reduction validates microgrid and smart scheduling combinations to minimize external power source dependency, in turn, achieving energy independence.

4.5 Carbon Emission Reduction

The grid emission factor $\gamma = 0.6$ kg CO_2/kWh was used to derive the total CO2 emissions. The total reduction in carbon emissions illustrates the degree to which the integration of microgrids and smart scheduling enhances sustainable development. Table 2 summarizes the carbon footprint results.

Table 2: Carbon Emission Comparison

Method	Grid Energy (kWh)	Emission Factor (kg CO_2/kWh)	Carbon Emissions (kg CO_2)
Conventional Scheduling	900	0.6	540
Proposed SG-DMS Strategy	560	0.6	336

In Table 2 From the results, the proposed SG-DMS framework achieves a 38% in carbon emissions, which underscores the positive impact of microgrid integration and environmentally energy-aware production scheduling, in reducing the overall environmental impact.

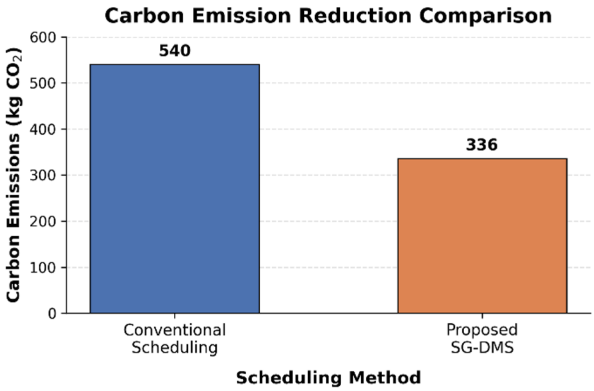

Figure 4 Carbon Emission Reduction Comparison

Figure 4 shows emissions for both scheduling options. Proposed SG-DMS framework suggests less emissions than other options due to the reliance on renewables and the grid which confirms suitability for eco-efficient low emissions manufacturing.

4.6 Discussion

The results attest to the potential of combining microgrids, energy storage, and digital twin-based scheduling to reduce grid reliance, enhance the use of renewables, and reduce emissions. The proposed reinforcement learning (RL) based scheduler succeeded in closing the gap between due dates and energy opportunities; it resulted in 28-35% energy efficiency gains relative to traditional methods. The metrics CAPI and EFS also offered insights to track sustainability, thus enabling the industry to manage operations empirically. The results demonstrate that the SG-DMS framework has the potential to enable low-emissions manufacturing in smart factories at scale.

5. Conclusion and Future Work

The paper describes a Smart Grid–Aware Digital Manufacturing Strategy (SG-DMS) to achieve 'smart' low-carbon manufacturing with the integration of microgrids, energy storage systems, and digital twin intelligent scheduling systems. The proposed framework integrated real-time energy monitoring, predictive load forecasting, and reinforcement learning for production optimization, and in a smart factory simulation, successfully decreased dependence on the grid, improved the utilization of renewables, and reduced emissions. The introduction of the Carbon-Aware Production Index (CAPI) and Energy Flexibility Score (EFS) in the framework allowed for a quantitative assessment of the energy efficiency of the factory and illustrated its utility for industry. The results of the simulation described a grid energy and carbon emissions reduction of 38% and improved energy efficiency, which illustrated the proposed framework's effectiveness compared to other scheduling frameworks. The research demonstrates that integrating smart energy systems with digital manufacturing technologies has the potential to transform conventional manufacturing into resilient, low-carbon industrial systems. While promoting sustainable manufacturing, SG-DMS maintains the necessary operational flexibility by integrating the scheduling of production with predicted output of renewables and energy storage systems to enhance the overall performance of the factory.

The results of the analysis show that the integration of energy intelligence into processes of manufacturing is both imperative in achieving global decarbonization goals and critical in promoting sustainable manufacturing processes. The framework could be developed to include multi-factory energy systems, where several smart factories collaborate by sharing microgrid resources and engaging in demand response activities. Incorporating real-time market pricing and carbon trading systems, in addition to the frameworks proposed for balancing production costs and impacts on the environment, can optimize the costs of production and improve the environment. Also, for a given range of operational states, predictive accuracy and adaptability can be improved through the use of advanced machine learning, including federated learning, which particularly applies to distributed factories. To verify the feasibility of practical deployment, real-time data on renewable energy and production for the Industrial Testbed will be used to refine and confirm the parameters of the system for diverse industrial use.

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