

Machine Learning–Based Demand Side Management for Industrial Load Scheduling with Solar Energy Integration

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Abstract: - As the effects of volatile electricity prices, network constraints, and the growing use of renewable energy sources on industrial facilities become more significant, the traditional load scheduling approach that uses fixed operating plans is being challenged, and this has led to reconsideration of how load scheduling is managed in light of the convergence and interplay of these factors. Conventional methods fail to take into account hourly price fluctuations and the time-dependent availability of solar energy, leading to unnecessary operational costs and inefficient energy use in many instances. This work introduces a demand-side management framework that integrates machine learning with a practical load scheduling strategy for industrial applications. The study employs a Random Forest-based classification model to predict hourly operating decisions for seven industrial loads based on temporal variables, electricity tariffs, photovoltaic generation, and operational constraints. The model is trained on a synthetic but realistic dataset for a medium-scale industrial facility with an 80-kWp rooftop photovoltaic system. Based on these three objectives, a greedy multi-objective scheduling algorithm is then developed for minimizing peak-hour operation (to avoid this), maximizing use of available solar generation, while balancing shift operations as evenly as possible. The simulation results show that with the proposed approach, annual electricity costs can be reduced by 11.7%, the amount of time operating during peak hours could be cut down by 95.6%, and usage would increase from currently using about 42.3% to approximately 70%, while total operational hours or energy consumption remain constant. The findings indicate that effective industrial demand-side management can be attained by employing machine learning techniques that are straightforward and interpretable, in conjunction with domain-specific scheduling logic.

Key-Words: - Demand Side Management, Industrial Load Scheduling, Machine Learning, Random Forest, Solar Energy Integration, Energy Cost Optimization

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1 Introduction

The electrical usage by all types of industry accounts for an enormous portion of total worldwide energy consumption as well as being a significant factor in the behavior of modern power systems. With expanding industrial activity and higher costs of electricity combined with escalating peak-demand charges, economic and operating pressure upon these facilities has skyrocketed. Traditional industrial load scheduling is based on static, production-based operating plans, which do not consider the fluctuating prices of electricity, grid congestion, or renewable energy supply. This leads to many industrial facilities incurring unnecessary energy costs, increased risk at peak hours, and poor energy resource management [1], [2].

There has been considerable interest in demand-side management (DSM) as a means to improve

electricity consumption patterns at the client level, especially among large energy consumers such as industrial facilities, so that the timing of electricity use can be changed rather than reducing total consumption, which would allow greater price sensitivity and responsiveness to operating conditions of electricity systems, while avoiding disruption of production processes. Load shifting, peak clipping, and valley filling are common DSM strategies.

There is a large body of research that has shown that properly implemented DSM programs can result in significant savings in operating costs, while at the same time improving grid reliability and reducing peak demand. These benefits are particularly relevant in industrial settings, where industrial equipment has high power ratings and

peak demand charges can have a significant impact on the overall electricity bill [3], [4].

As renewable energy sources are increasingly integrated into power systems, particularly solar photovoltaics, DSM becomes even more important. Results have shown that industrial facilities with on-site photovoltaic (PV) generation systems can reduce their grid electricity demand, and hence reduce the corresponding environmental emissions, but the overall benefits of solar energy integration depend on the alignment of load operation with generation profiles, since solar energy production is inherently intermittent and non-dispatchable.

However, when industrial loads are scheduled regardless of available solar, a significant portion of locally generated energy can be wasted or exported to the grid at a low economic value, while still paying for expensive grid electricity during peak periods [5], [6], [7]. Therefore, coordinating the operation of industrial loads with renewable energy availability has become an important topic of research in smart grids and industrial energy management.

New developments in AI and ML have opened up new possibilities to improve the effectiveness of demand-side management and load scheduling, and results from using data-driven methods have shown improved performance over rule-based methods in areas such as forecasting demand for electricity, characterizing loads, and making automated scheduling decisions, especially in complex operating environments.

Among these methodological options, ensemble learning techniques have proved to be particularly effective when applied to the structured tabular datasets that are characteristic of industrial energy systems, particularly random forest models, which are able to capture nonlinear relationships while remaining relatively straightforward to train and interpret, making them well suited to practical industrial applications [8], [9].

However, despite the extensive research on DSM, many of the existing frameworks are still hampered by practical limitations, including the fact that many are based on complex optimization algorithms or deep learning and reinforcement learning models that require large volumes of data, specialized hardware, and a significant amount of tuning effort, which makes their practical implementation in real-time industrial environments challenging [10], [11].

Inspired by these gaps, this paper presents an artificial intelligence (AI)-based demand-side management framework for industrial facilities that integrates machine learning-assisted operational

prediction and a practical scheduling strategy. A Random Forest classification model is used to identify the most suitable operating states for industrial loads based on temporal, economic, and renewable energy features. The predicted states are then executed by a multi-objective greedy scheduling algorithm that explicitly considers peak-hour avoidance, renewable energy utilization, and shift-balancing constraints. The underlying principles of simplicity, interpretability, and scalability are the guiding principles of the proposed framework to provide measurable economic and operational benefits.

2 Problem Formulation

Industrial load scheduling in contemporary power systems can be expressed as a constrained optimization problem in which the operating patterns of multiple electrical loads must satisfy production requirements while minimizing energy-related costs. In contrast to residential or commercial customers, industrial facilities typically involve large power demands, predefined working shifts, and strict process continuity constraints. These characteristics significantly limit scheduling flexibility and require careful consideration of operating rules. As a result, effective industrial load scheduling must explicitly account for time-dependent electricity prices, renewable energy availability, and operational constraints specific to industrial environments [3].

The study considers an industrial facility that consists of several electrical loads operating within a shared production environment

$$L=\{1,2,...,l\} \quad (1)$$

The system operates within a discrete time horizon that is divided into hourly intervals

$$H=\{1,2,...,T\} \quad (2)$$

The scheduling horizon corresponds to a full year, with, $T=24 \times 365$ hourly intervals. Each load $l \in L$ is defined by its rated power P_l (kW) and a specified daily operating duration H_l (hours), which must be met continuously in order to maintain production output.

2.1 Decision Variables

The operational state of each load is represented by a binary decision variable:

$$x_{l,t} = \begin{cases} 1, & \text{If load } l \text{ operates at hour } t \\ 0, & \text{Otherwise} \end{cases} \quad (3)$$

This binary representation of load operation allows the scheduling task to be naturally expressed as a supervised classification problem, where each decision corresponds to whether a load operates during a given hour. When combined with an optimization layer, this approach follows recent data-driven demand side management methodologies that leverage machine learning to support operational decision-making [5], [7].

2.2 Objective Function

The primary objective of the scheduling problem is to minimize the total electricity cost incurred over the scheduling horizon. The total cost is computed as the sum of hourly energy costs across all loads:

$$C_{total} = \sum_{t=1}^T \sum_{l=1}^L P_l * x_{l,t} * \pi_t \quad (4)$$

where:

π_t is the electricity price (€/kWh) at hour t ,

$P_l \cdot x_{l,t}$ represents the power consumption of load l at hour t .

This objective function focuses directly on minimizing total electricity expenditure over the scheduling horizon by aggregating hourly energy costs across all industrial loads. Such a formulation is consistent with commonly adopted demand side management and industrial energy optimization models, where electricity cost reduction is a primary operational objective [1], [3].

2.3 Operational Constraints

A variety of practical constraints are imposed on the problem of load scheduling, reflecting the realities of industrial operations, and ensuring that optimized schedules are still viable in the context of production, labor continuity, and process continuity, therefore precluding solutions that might be mathematically optimal, but not practical in industrial settings.

2.3.1 Daily Operating Time Constraint

Each load must operate for a predefined number of hours per working day:

$$\sum_{t \in D_d} x_{l,t} = H_l \quad \forall l \in L, \forall d \in D \quad (5)$$

where D_d represents the set of hours belonging to day d . This constraint guarantees that each industrial load operates for its required duration on every working day, thereby preserving production output. Any reduction in electricity cost is therefore achieved by shifting operating hours within the day rather than by shortening operating time or reducing

energy consumption, which is consistent with industrial DSM principles [12].

2.3.2 Consecutive Operation Constraint

Industrial processes typically require continuous operation once started. Therefore, the operating hours of each load must form a contiguous block:

$$x_{l,t} + x_{l,t+1} + \dots + x_{l,t+H_l-1} \leq H_l \quad (6)$$

This constraint enforces continuous operation once a load is activated, preventing fragmented or intermittent scheduling patterns. Such continuity is essential in industrial processes where frequent start-stop cycles may lead to equipment wear, efficiency losses, or production disruptions [10].

2.3.3 Shift and Working-Hour Constraints

Load operation is restricted to predefined working shifts:

$$x_{l,t} = 0 \quad \forall t \notin \{08:00-16:00, 16:00-24:00\} \quad (7)$$

and only on working days. Restricting load operation to predefined working shifts and designated working days reflects common industrial labor arrangements and operational practices. Incorporating these limits ensures that scheduling decisions remain compatible with workforce availability and established production routines, as adopted in earlier industrial DSM studies [3], [11].

2.3.4 Peak-Hour Avoidance Constraint

To reduce exposure to high electricity prices and grid stress, peak hours (typically 18:00–20:00) are penalized or restricted, especially for high-power loads:

$$x_{l,t} = 0 \quad \forall t \in H_{peak}, \forall l \in L_{heavy} \quad (8)$$

where L_{heavy} denotes the subset of high-power loads. The peak-hour constraint aims to reduce exposure to periods associated with high electricity prices and increased grid stress. By discouraging or prohibiting the operation of high-power loads during peak hours, this constraint supports peak-shaving objectives and aligns with demand response strategies commonly discussed in DSM literature [4], [6].

2.4 Renewable Energy Integration

An on-site photovoltaic system provides a time-dependent solar power output S_t (kW). While solar generation does not alter production requirements, it influences optimal scheduling by incentivizing operation during daylight hours:

$$P_l * x_{l,t} \leq P_l * S_t \quad (9)$$

Although on-site photovoltaic generation does not alter industrial production requirements, it plays an important role in influencing optimal load scheduling. By encouraging operation during hours of higher solar output, this constraint promotes improved utilization of locally available renewable energy while maintaining compliance with operational limits [5], [7].

2.5 Problem Characteristics

The resulting scheduling problem involves binary decision variables, time-coupled constraints, and multiple operational requirements, making it challenging to solve using conventional deterministic optimization techniques, especially over long-time horizons. To overcome these limitations, the proposed framework separates the problem into two complementary components: a machine learning-based prediction stage that identifies favorable operating periods, and a constraint-aware greedy scheduling strategy that constructs feasible daily schedules. This hybrid formulation achieves a balance between computational efficiency and solution quality, in line with recent advances in industrial demand side management research [8], [9].

3 Problem Solution

This work tackles the industrial load scheduling problem presented in Section 2 with a hybrid solution strategy that combines data-driven prediction with rule-based scheduling logic, the goal being to minimize electricity costs while satisfying production requirements, operational feasibility, and grid-related constraints. The proposed approach avoids relying on a single optimization technique and instead opts for a strategy that compartmentalizes decision-making into a set of interconnected stages to strike a balance between flexibility and practicality. This compartmentalization aims to achieve a balanced synergy between flexibility and practicality.

The proposed framework is structured around two interacting layers. The first layer focuses on predicting favorable operating states using a machine learning model, while the second layer converts these predictions into feasible industrial schedules through a constraint-aware greedy algorithm. This layered design simplifies the overall scheduling task by delegating pattern recognition to the learning model and constraint enforcement to a deterministic scheduling procedure. As a result, complex scheduling decisions can be implemented

efficiently without sacrificing transparency or scalability [7], [8].

3.1 Machine Learning-Based Load State Prediction

In the first stage, the scheduling decision for each industrial load is formulated as a supervised binary classification task. The objective of this stage is to determine whether a specific load should operate during a particular hour based on contextual information describing time, price conditions, and renewable energy availability. Framing the problem in this manner allows historical and simulated data to be used effectively for learning operational preferences.

For each load l and hour t , the classifier learns the mapping:

$$\hat{x}_{l,t} = f(X_{l,t}) \quad (10)$$

where:

- $\hat{x}_{l,t} \in \{0,1\}$ is the predicted operational state,
- $f(\cdot)$ denotes the trained Random Forest model,
- $X_{l,t}$ is a feature vector containing temporal, economic, and renewable energy variables.

The selected features include hour of day, day type (working or non-working), shift indicator, electricity price, peak-hour flag, and photovoltaic availability. Electrical measurements such as power and voltage are excluded to avoid target leakage and to ensure generalization [5], [7].

Random Forest is chosen due to its strong performance on structured tabular data, robustness to noise, ability to model nonlinear dependencies, and low computational requirements. These characteristics are particularly suitable for industrial energy management applications that require reliable predictions with limited tuning effort [8], [9].

The output of the present stage provides a feasible operational preference map, indicating hours of operation based on learned patterns as opposed to rigid rules.

3.2 Multi-Objective Scheduling Strategy

Although the machine learning model identifies favorable operating periods, its predictions alone do not ensure compliance with industrial constraints such as continuous operation, shift limitations, or peak-hour restrictions. Therefore, a second optimization stage is introduced to convert predicted preferences into implementable schedules that satisfy all operational requirements.

3.2.1 Load Classification

Loads are classified according to their rated power:

- Heavy loads (high power demand),
- Medium loads, and
- Light loads (lower power demand).

This classification enables differentiated peak-hour handling, since high-power loads contribute disproportionately to peak demand and electricity costs [3], [4].

3.2.2 Multi-Objective Scoring Function

Each candidate operating hour t for load l on day d is evaluated using a weighted scoring function:

$$S_{l,t} = \omega_1 C_t + \omega_2 R_t + \omega_3 P_{l,t} + \omega_4 B_t \quad (11)$$

where:

- C_t represents the normalized electricity price component,
- R_t reflects renewable (solar) availability,
- $P_{l,t}$ is a peak-hour penalty depending on load category,
- B_t is a shift-balancing term,
- ω_i are weighting coefficients selected according to operational priorities.

Peak-hour penalties are applied hierarchically:

$$P_{l,t} = \begin{cases} -\gamma_H, & \text{heavy load during peak hour} \\ -\gamma_M, & \text{medium load during peak hour} \\ -\gamma_L, & \text{light load during peak hour} \end{cases} \quad (12)$$

with $\gamma_H \gg \gamma_M > \gamma_L$, enforcing strict peak avoidance for high-power loads while preserving flexibility for lighter loads [1], [3].

$$R_t = \frac{S_t}{S_{max}} \quad (13)$$

encouraging operation during periods of high photovoltaic generation [7].

3.2.3 Greedy Scheduling Algorithm

Using the scoring function, a greedy algorithm schedules loads sequentially in descending order of rated power. For each load, all feasible consecutive hour blocks that satisfy operational constraints are evaluated, and the block with the highest cumulative score is selected.

Algorithm 1: Greedy Industrial Load Scheduling

- 1) Sort loads by decreasing rated power
- 2) For each load l :
 - a. Enumerate all feasible consecutive time blocks of length H_l
 - b. Discard blocks violating shift or peak-hour constraints

- c. Compute total score using Eq. (11)
- d. Select block with maximum score
- 3) Update shift usage and repeat for remaining loads

This greedy approach is computationally efficient and well-suited for long-horizon industrial scheduling problems where exact optimization may be impractical [9], [13].

3.3 Discussion of Solution Characteristics

The proposed solution strategy offers several key advantages:

- Production preservation: Operating hours are fixed, and only their timing is optimized.
- Peak demand mitigation: Hierarchical penalties ensure heavy loads fully avoid peak hours [4], [6].
- Renewable energy utilization: Solar-aware scoring significantly increases PV self-consumption [5], [7].
- Scalability: The greedy strategy allows rapid scheduling even for extended time horizons.
- Practicality: No advanced solvers or specialized hardware are required.

By integrating machine learning with domain-specific scheduling logic, the proposed framework achieves a balance between optimization performance and real-world feasibility, aligning with best practices in industrial demand side management [8], [9].

4 Results and Discussion

This section evaluates the performance of the proposed AI-based demand side management framework by comparing the optimized load scheduling results with a conventional baseline schedule. The analysis focuses on three key performance dimensions: economic impact, peak-hour mitigation, and renewable energy utilization. All results are obtained using the same production requirements and total operating hours to ensure a fair comparison.

4.1 Performance of the Machine Learning Model

The Random Forest classifier demonstrated strong predictive capability in identifying feasible operating hours for industrial loads under varying temporal, economic, and renewable conditions. An

independent test dataset comprising 24,596 hourly records was utilized in the evaluation process.

Table 1 presents a synopsis of the classification performance metrics.

Table 1. The Random Forest Model's Performance in Classifications

Metric	Value (%)
Accuracy	95.63
Precision	78.70
Recall	98.01
F1-Score	87.30
ROC-AUC	98.74

Source: create by the author

In particular, its high recall value (98.01%) is particularly important for industrial applications, where almost all of the required operating hours can be identified so that the scheduling algorithm can minimize cost and peak times. The ROC- AUC value near one verifies that the decision boundaries between operating and non- operating states are very clear.

4.2 Baseline Scheduling Performance

Conventional industrial operation is exemplified by the baseline schedule, wherein loads are randomly allocated within permissible shifts, without taking into account price variations in electricity, periods of peak demand, or the availability of renewable energy.

As illustrated in Table 2, the baseline annual performance metrics have been met.

Table 2. Baseline Scheduling Performance

Metric	Value
Total Annual Cost	€19,629.39
Total Operating Hours	5,024 h
Peak Operating Hours	1,118 h
Peak Hour Cost	€ 3,747.58
Peak Cost Share	19.1%
Solar Energy Utilization	42.3 %

Source: create by the author

Interestingly, peak hours, which are defined here as the hours from 6 pm to 8 pm, are only 12.5% of the daily time window but are responsible for nearly one-fifth of the total energy usage, illustrating the inefficiency of static scheduling and the need for intelligent demand-side management. The load profile at the beginning of the time series, as shown in Figure 1, demonstrates high activity during peak

pricing times and no correlation with solar availability.

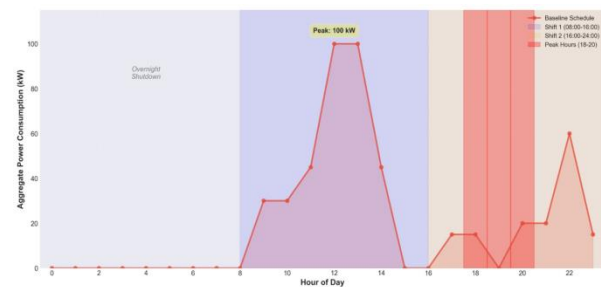


Fig. 1: Representative Aggregate Load Profile (Baseline Schedule)

Source: create by the author

4.3 Optimized Scheduling Results

The proposed AI-based scheduling framework was applied to the same operating requirements using the machine learning prediction layer and the greedy optimization strategy described in Section 3.

Table 3 compares the baseline and optimized annual performance.

Table 3. Baseline vs. Optimized Scheduling Performance

Metric	Baseline	Optimized	Improvement
Total Annual Cost	€19,629	€17,336	-11.7%
Peak Operating Hours	1,118 h	49 h	-95.6%
Peak Hour Cost	€ 3,747	€ 187.41	-95.0%
Average Hourly Cost	€ 3.91	€ 3.45	-11.8%
Solar Utilization	42.3 %	~70%	+27.7 pp
Total Operating Hours	5,024 h	5,024 h	0%

Source: create by the author

The optimal scheduling reduced the total electricity cost by 11.7% compared with the baseline strategy, and this improvement is mainly achieved by cutting down the operation during peak price periods by 95.6%, with the same total number of hours of operation, which indicates that the cost saving is purely from temporal rescheduling and not from load curtailment or reduced production.

4.4 Load-Level Analysis

To gain further insight into the behavior of individual loads, the optimization results were analyzed according to load category. Load-specific cost outcomes are summarized in Table 4.

Table 4. Load-Level Cost Optimization Results

Load	Category	Annual Cost Before (€)	Annual Cost After (€)	Savings (%)
Load 1 (45 kW)	Heavy	6,443	6,326	1.8
Load 3 (55 kW)	Heavy	3,853	3,540	8.1
Load 2 (30 kW)	Medium	2,120	1,978	6.7
Load 4 (25 kW)	Medium	1,186	843	29.0
Load 5 (20 kW)	Light	3,050	2,401	21.3
Load 6 (15 kW)	Light	1,496	1,130	24.5
Load 7 (15 kW)	Light	1,48	1,118	24.5

Source: create by the author

These results demonstrate that the heavy loads completely avoid peak-hour operation, thus verifying the effectiveness of the hierarchical peak-hour penalty mechanism used in the scheduling strategy, while the medium and light loads offer a limited flexibility during peak hours but contribute significantly to cost reduction; therefore, the proposed approach benefits all load categories rather than just the high-power equipment.

4.5 Peak Demand and Grid Impact

The proposed DSM approach is essential for peak demand mitigation, and optimized schedules result in significant reductions of maximum and average peak demand, and the elimination of all heavy loads from peak hour operation as shown by the peak load duration curves in Figure 2, which would reduce stress on the electrical grid and improve compatibility with demand response and grid support programs, which are becoming more critical in modern power systems.

4.6 Solar Energy Utilization and Temporal Redistribution

The optimized schedule significantly improves alignment between load operation and photovoltaic generation.

Key results:

- Solar utilization increased from 42.3% to approximately 70%
- Operations shifted toward daylight hours (11:00–15:00)
- Shift 1 share increased to 57.8%, reflecting optimal solar-price alignment

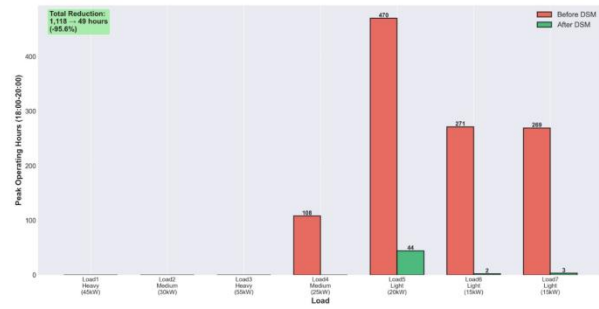


Fig. 2: Peak Load Duration Curve (Before and After DSM)

Source: create by the author

Figure 3 shows the redistribution of load operation across the day.

This redistribution confirms that the algorithm achieves cost savings through intelligent temporal shifting rather than operational reduction, preserving both productivity and energy efficiency.

4.7 Discussion

The results demonstrate that combining machine learning-based operational prediction with a practical scheduling strategy can deliver substantial benefits in industrial energy management. Compared to rule-based or static scheduling, the proposed framework achieves superior peak mitigation and cost reduction with minimal computational complexity.

Unlike deep learning or reinforcement learning approaches that require extensive training data and hardware resources, the proposed Random Forest and greedy scheduling combination provides a deployable, explainable, and scalable solution. The results indicate that intelligent DSM does not require overly complex algorithms to achieve meaningful improvements, provided that domain-specific constraints and objectives are carefully integrated.

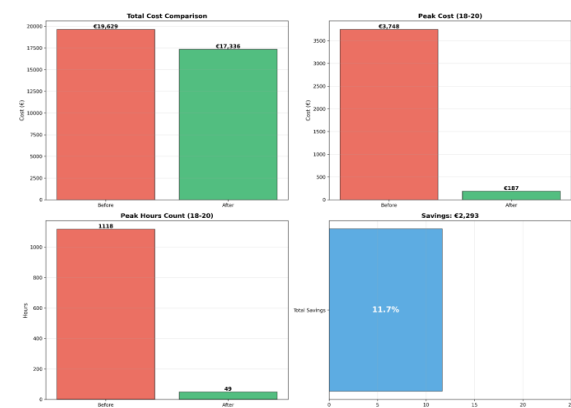


Fig. 3: Hourly Load Distribution After Optimization

Source: create by the author

5 Conclusion

This paper presented an AI-based demand side management framework for industrial facilities that combines machine learning–assisted operational prediction with a practical scheduling optimization strategy. A Random Forest classifier was used to identify feasible operating periods for industrial loads based on temporal, economic, and solar generation features, while a greedy multi- objective scheduling algorithm translated these predictions into implementable load schedules.

Based on an industrial case study, it is shown that the proposed approach would reduce annual electricity costs by 11.7% and reduce peak-hour operations by 95.6% while increasing the use of solar energy to a level of about 70%, all without sacrificing overall operating hours or annual energy consumption, thereby meeting production needs.

The results indicate that effective industrial energy management does not require highly complex optimization models or extensive computational resources. Instead, meaningful economic and operational benefits can be obtained by combining accessible machine learning techniques with scheduling strategies that explicitly account for industrial constraints and renewable energy availability.

Future work will focus on real- time implementation, integration of energy storage systems, and extension to dynamic production environments.

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