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Decarbonizing the Industry Sector: Current Status and Future Opportunities of Energy-Aware Production Scheduling

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Abstract: As industries come under growing pressure to minimize carbon emissions without compromising the efficiency of operations, the integration of energy-aware production scheduling with emerging energy markets, renewable energy, and policy mechanisms is critical. This paper identifies critical shortcomings in current academic and industrial approaches—namely, an excessive reliance on deterministic assumptions, a limited focus on dynamic operational realities, and the underutilization of regulatory mechanisms such as carbon trading. We advocate for a paradigm shift to more robust, adaptable, and policy-compliant scheduling systems that provide space for on-site renewable generation, battery energy storage systems (BESSs), demand-response measures, and real-time electricity pricing schemes like time-of-use (TOU) and real-time pricing (RTP). By integrating recent advances and their critical analysis of limitations, we map out a future research agenda for the integration of uncertainty modeling, machine learning, and multi-level optimization with policy compliance. In this paper, we propose the need for joint efforts from researchers, industries, and policymakers to collectively develop industrial scheduling systems that are both technically efficient and adherent to sustainability and regulatory requirements.

Keywords: energy-aware production scheduling; industry decarbonization; renewable integration; demand-response; emission trading

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1. Introduction

The growing emphasis on sustainability and energy efficiency has transformed industrial manufacturing operations. As global energy prices continue to rise and environmental regulations become more stringent, industries are under increasing pressure to optimize their energy consumption and maintain production efficiency. Historically, energy efficiency in the manufacturing sector was largely viewed as an additional expense or afterthought, while throughput, quality, and cost minimization were of greater concern. But the trend has changed over the past few years, with energy-efficient production scheduling becoming a part of industrial competitiveness and sustainability.

Manufacturing industries are increasingly investing in renewable energy sources (RESs) and battery energy storage systems (BESSs) to save on costs, lower carbon emissions, and meet environmental regulations. RESs, like solar, wind, and bioenergy, are clean sources of energy but can cause energy supply uncertainty due to their intermittent nature. This is mitigated by the BESS, which stores surplus energy during high generation periods and releases it during periods of high demand or when RES production tapers off. This integration offers clear advantages in production planning. Industries can reduce energy costs by planning production at times when there is high RES output. The BESS renders

the supply of energy stable, preventing shutdowns and ensuring optimal energy utilization. These systems allow for more dynamic and cost-effective scheduling and enable manufacturers to be less reliant on grid power, making operations both more efficient and sustainable.

Time-of-use (TOU) pricing and demand-response programs are important tools in energy market mechanisms that can have a significant impact on the production scheduling of manufacturing industries. TOU pricing adjusts electricity prices based on the time of day, in a manner that encourages industries to reschedule energy-intensive operations to off-peak hours, thereby reducing costs. To accomplish this, dynamic scheduling systems are required to adjust production plans in real time, optimizing energy usage while keeping the desired output. Demand-response programs provide monetary incentives for manufacturers to curtail or shift their energy usage during peak demand time periods. Participating in these programs allows industries to save money on energy and assist in the stabilization of the power grid. Coupling TOU pricing and demand response with production scheduling allows manufacturers to render production more cost-effective without compromising production efficiency.

Carbon credits enable industries to offset their emissions by buying credits from CO_2 reduction or capture projects to comply with regulation or voluntary sustainability objectives. Scheduling for higher energy efficiency and using low-carbon energy sources can decrease the need for carbon credits, whereas inefficient scheduling can increase their demand. Cost savings can be achieved through better production scheduling by lowering the amount of credit required and enhancing the company's environmental image.

Industries can also utilize green certificates (also known as renewable energy certificates, RECs) [1]. These create economic incentives for industries to utilize renewable energy. The manufacturers can improve their sustainability profile and reap cost savings or regulatory benefits by including these certificates in their production planning process. This not only decreases the consumption of fossil fuels but also enhances the company's market position by aligning with environmental goals, gaining favor with eco-conscious customers, and opening up possible new sources of revenue from the sale of excess certificates.

Lastly, efficient and optimized production scheduling can critically decrease energy costs by minimizing machine idle times and preventing overproduction, ensuring that energy is used only when necessary [2]. It allows for the better coordination of production processes, leading to smoother operations and less energy waste. By balancing workloads, it optimizes equipment usage, thereby reducing the need for energy-intensive setups and reducing peak energy demands. This approach ultimately helps in lowering the overall energy consumption and associated costs in manufacturing operations.

Recent advancements in optimization techniques have greatly enhanced energy-aware production scheduling. Mixed-integer programming (MIP), heuristic algorithms, and hybrid optimization approaches enable producers to trade-off production efficiency and energy conservation. MIP offers exact modeling for scheduling constraints and energy goals and thus is most suitable for well-structured production processes. Yet, since optimal production scheduling is an NP-hard problem, heuristic and metaheuristic methods—such as genetic algorithms, particle swarm optimization, and simulated annealing—were proposed, offering near-optimal solutions in reduced computational times. Hybrid approaches, which blend mathematical programming and heuristics/metaheuristics, try to reap the benefits associated with each optimization approach.

Artificial intelligence (AI), particularly machine learning (ML) and deep learning (DL), has also transformed energy-aware scheduling. ML algorithms learn from extensive production and energy consumption data to predict optimal scheduling policies. These models improve flexibility, allowing production systems to respond dynamically to fluctuations in

energy demand and availability. Deep learning, via neural networks such as convolutional (CNNs) and recurrent networks (RNNs), improves scheduling through the identification of complex patterns in energy consumption. Long short-term memory (LSTM) networks, in particular, improve forecast accuracy, allowing proactive scheduling adaptation. Reinforcement learning (RL) also maximizes scheduling policies for energy conservation while maintaining productivity. Through the integration of AI-based methods and traditional optimization methods, manufacturing industries are able to achieve more intelligent and efficient production planning. Data-driven methodologies enhance predictive capability and decision automation and support sustainable industrial operations for the provision of energy-efficient and high-performance manufacturing systems.

Energy-aware production scheduling is no longer a choice but a requirement for industries to flourish in a rapidly changing energy environment. The confluence of renewable energy penetration, electricity market dynamics, and carbon mitigation policies demands a holistic view of scheduling that balances manufacturing productivity and energy sustainability. This paper elaborates on current developments in energy-aware production scheduling, discussing approaches, challenges, and opportunities that define the frontier of energy-efficient manufacturing.

Figure 1 presents a conceptual overview of the key components and interactions involved in energy-aware production scheduling. The figure emphasizes the interplay between industrial production processes and essential external elements such as the RES, BESS, electricity grid, carbon emission permits, and green certificate trading. Understanding and effectively managing these interactions are critical for optimizing energy efficiency, cost reduction, and regulatory compliance in industrial settings.

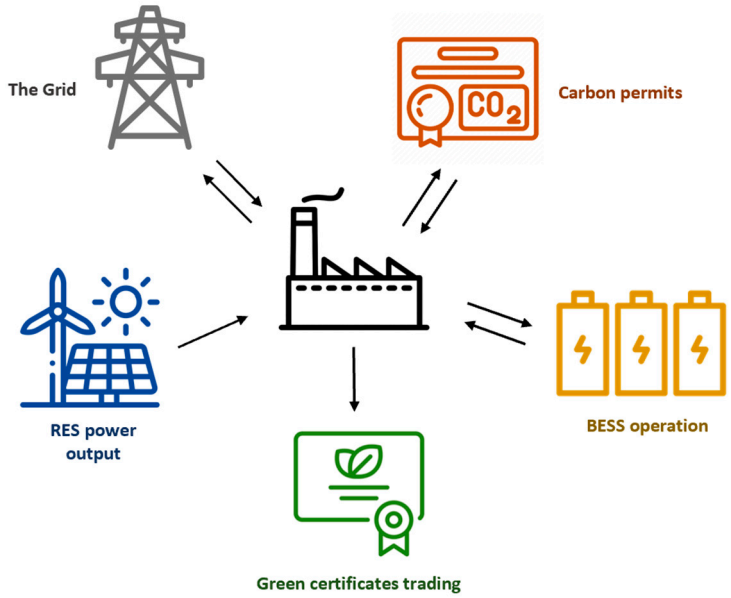

Figure 1. Conceptual framework illustrating key interactions considered in energy-aware production scheduling.

The rest of this paper is structured as follows. Section 2 gives the general literature review of recent research on energy-aware production scheduling, emphasizing methodological developments and application contexts. Section 3 uncovers the current research gaps, while Section 4 proposes a path that academia and industry should follow for the energy-aware production schedule of the future. Finally, Section 5 recapitulates the key findings, emphasizes their implications, and suggests avenues for future research.

2. Literature Review: Current Status

The literature on energy-aware production scheduling includes different methodologies and application domains, the common objective being optimizing energy consumption, reducing production costs, and satisfying sustainability and decarbonization objectives. This section summarizes recent works in a structured manner, dividing them based on their methodologies and thematic integration. Most studies focus on energy-intensive industries, such as manufacturing industries (job shops), metallurgy (copper), petrochemicals, and pulp, where production scheduling plays a significant role in energy and emission optimization.

2.1. Methodological Approaches

A broad array of methodological approaches, ranging from mathematical optimization and metaheuristics to emerging methods, such as machine learning and hybrid methods, have been employed to solve the complex problem of industry decarbonization through efficient production scheduling decisions. These methods are the building blocks for future energy-aware production scheduling research through the provision of an array of tools appropriate for diverse problem sizes, operational requirements, and sustainability targets. This section provides an organized categorization of recent trends in these methodological fields.

2.1.1. Mathematical Optimization

Mathematical optimization methods, particularly mixed-integer linear programming (MILP), mixed-integer nonlinear programming (MINLP), integer linear programming (ILP), linear programming (LP), and constraint programming (CP) are still at the center in tackling energy-aware production scheduling problems. These methods are valued for their capacity to uphold the precise representation of detailed production constraints and energy parameters, ensuring optimal solutions. Their high computational requirements prevents their application, particularly in industrial processes where production is on a large scale, primarily due to the fact that the scheduling problems are NP-hard.

MILP models have been widely used to showcase their versatility across a broad range of applications. Ma et al. [3] developed a MILP model for optimizing the scheduling of coupled production and multi-energy system operation with the particular aim of minimizing the overall operational expenses, including energy purchase and system maintenance expenses. Their method particularly reflects the coupling effect between scheduling decisions and energy storage degradation to allow a realistic representation of operation dynamics. Wang et al. [4] and Xiao et al. [5] used the State-Task Network (STN) structure to model intricate equipment-material interaction and scheduling restrictions, with the goal of reducing electricity costs. Similarly, Fisco-Compte et al. [6] proposed a MILP to include complex operational limitations, such as workforce limitations, at the cost of increased computational complexity. CP was seen by Park & Ham [7] as computationally more efficient than ILP in flexible job-shop scheduling problems with time-of-use electricity pricing. The authors demonstrated the CP's increased computational efficiency over ILP, particularly in handling larger-scale problem instances. Nonetheless, CP's inability to strictly prove optimality in large-scale instances reveals one of the principal trade-offs between computational efficiency and an optimal solution guarantee. Tang et al. [8] introduced a welfare-maximizing multi-period optimal power flow (OPF) approach as an LP formulation to compare demand bidding strategies with traditional demand-response methods for industrial electric loads. Their formulation represents the economic decision-making of industrial plants exactly by formulating electricity demand as production constraints and respective product revenues and attempting to maximize the overall social welfare.

Bi-level and bi-objective optimization frameworks have also been explored to elaborately address complex strategic decision-making. Trevino-Martinez, Sawhney, & Shylo [9] and Trevino-Martinez, Sawhney, & Sims [10] proposed multi-objective MILP models, either sequentially optimizing job sequencing and photovoltaic (PV) system sizing or integrating net metering and energy storage to enhance renewable energy incorporation. Leenders et al. [11] developed a bi-level MILP model to coordinate production scheduling and energy procurement, effectively capturing hierarchical market interactions, although potentially constrained by stable market assumptions. Similarly, Bok et al. [12] employed bi-objective MILP approaches to explicitly identify trade-offs between energy sourcing strategies and production costs under varying carbon emission constraints.

Addressing uncertainty has been tackled through stochastic and robust optimization techniques. Germscheid et al. [13] developed an extended Resource-Task Network (RTN) model to facilitate demand-response scheduling in copper production, taking into account simultaneous involvement in day-ahead (DA) and intraday (ID) electricity markets. They built a two-stage stochastic MILP model, in which DA prices are presumed certain, and ID decisions are formulated after the price uncertainties are determined. Electricity price volatilities were represented through scenarios derived from historical market deviations. Two stochastic optimization problems were examined: expected cost minimization (risk-neutral market participation) and CVaR minimization to approximate risk-averse market participation. The same research group proposed a multi-stage stochastic MILP approach to the simultaneous design and schedule optimization of local renewable electricity supply systems facilitating industrial demand-response market participation [14]. Their methodology considers uncertainty through the detailed scenario analysis of electricity prices, renewable (wind and photovoltaic) generation, and grid emission factors, derived explicitly from historical time-series data. Similarly, Lv et al. [15] introduced a two-stage adaptive robust model to manage uncertainties yet faced practical limitations due to short scheduling horizons and limited scalability. The approach employed both decision-independent uncertainties, which included market demands and renewable energy availability, and decision-dependent uncertainties unique to different carbon emission densities as a function of the production line selection. A novel parametric Column-and-Constraint Generation (C&CG) algorithm was developed to solve the scheduling model robustly. In spite of the methodological accuracy and successful treatment of uncertainties, practical applicability is quite limited by the short planning horizon of one week with hourly resolution and also by the small problem size of just three production lines.

2.1.2. Metaheuristic Approaches

Metaheuristic approaches like genetic algorithms (GAs) and simulated annealing (SA) have become a compelling alternative to mathematical optimization in energy-efficient production scheduling, owing chiefly to their computational efficiency and effectiveness in handling intricate scenarios. The current literature highlights numerous novel applications and methodological improvements aimed at achieving a balance between computational speed and solution quality, especially for large-scale or multi-objective problems for which exact solutions are computationally prohibitive.

The hybridization of metaheuristic techniques is a powerful trend in the literature, as it indeed unites the complementary strengths present in different algorithms. For example, Tian et al. [16] used the Fruit Fly Optimization (FFO) algorithm in combination with SA in their Hybrid Multi-Objective Fruit Fly Optimization (HMOFFO). This hybridized approach significantly enhanced solution diversity and Pareto-optimal solution convergence by combining global search ability with precise local exploitation. Similarly, Geetha et al. [17] combined the Pigeon-Inspired Optimization Algorithm (PIOA) and the Firefly Algorithm

(FA) in a sequential manner and showed improved performance compared to each of the individual methods. However, despite all these enhancements, such hybrid methods can still require tedious parameter tuning while not ensuring optimality.

A few studies have focused on genetic algorithms and evolutionary approaches specifically. Mokhtari-Moghadam et al. [18] proposed an Adjusted Multi-Objective Genetic Algorithm (AMOGA), which managed exploration and exploitation with care and consistently dominated other existing multi-objective genetic algorithms in comparative experiments. Zhao et al. [19] proposed a revised Multi-Objective Evolutionary Algorithm based on decomposition (MOEA/D), which incorporated a Tchebycheff decomposition and a Metropolis acceptance rule to improve convergence and prevent local optima. Though these evolutionary methods dramatically improved solution quality, their performance remains contingent on situation-specific circumstances and meticulous algorithmic tuning.

Iterative and local search-based metaheuristics have been particularly effective. Yağmur & Kesen [20] employed Iterated Local Search (ILS) with a Memetic Algorithm (MA) to address scheduling problems with multiple machines, vehicles, and customer constraints. The study revealed the evident computational benefits of ILS on larger scales. Likewise, Chen et al. [21] tackled mixed-integer quadratic scheduling problems through an MA strengthened by a novel knowledge-driven local search method that significantly enhanced solution convergence rates. Additionally, An et al. [22] examined the simultaneous treatment of production scheduling and strategic maintenance considerations via the use of a Multi-Layer Encoding Genetic Algorithm (MLEGA) to provide effective solutions for intricate, multi-stage scheduling issues with preventive maintenance.

Metaheuristics have also been efficiently utilized to deal with uncertainty in operational environments. Ertem [23] utilized a two-stage stochastic programming methodology combined with a GA, with the particular aim of reducing non-renewable energy costs under uncertainty. Sagar et al. [24] introduced a Whale Optimization Algorithm (WOA) combined with a new machine ON/OFF policy, as well as iterative re-optimization for compliance with carbon footprint constraints. While such frameworks are useful in dealing with uncertainty and enhancing the pragmatic nature of solutions, their iterative nature can interfere with computational responsiveness and efficiency in extremely dynamic environments.

2.1.3. Machine Learning Approaches

Machine learning, and reinforcement learning (RL) in particular, has been growing as a fresh promise for energy-aware production planning, offering algorithms that can be trained from experience and adjust to dynamic, uncertain environments. Such algorithms are good at extracting rich, nonlinear patterns and complementing real-time choices. Though standalone applications are relatively rare, most recent publications integrate ML into general hybrid paradigms in order to compensate for the computation or modeling limitations of traditional optimization techniques.

A recent work by Zhang et al. [25] reformulated a multi-objective scheduling problem—that was initially presented as an MINLP—into a multi-agent Markov game model. Each scheduling goal is represented within a separate agent, and optimization is guided via a Double Dueling Deep Q-Network (D3QN) with Nash equilibrium policies. This approach gives the potential for decentralized learning as well as policy improvement in changing environments. Although this DRL-based approach showed competitive performance against traditional metaheuristics, it also required large training times. Likewise, Wang et al. [26] modeled the scheduling environment as a Markov Decision Process (MDP), where a reinforcement learning agent is trained with the PPO algorithm. The deep neural network-based agent learns to translate system states into optimal scheduling actions through the maximization of cumulative rewards that are associated with energy

efficiency. The model exhibited flexibility and the capacity for real-time learning but was also susceptible to typical DRL pitfalls, such as a sensitivity to reward design and lower learnable policy interpretability. Rui et al. [27] proposed a graph reinforcement learning-based methodology for flexible job-shop scheduling under the industrial demand response. The problem was formulated as a Markov Decision Process, with states represented by a heterogeneous disjunctive graph capturing energy features. A mixed-graph neural network scheduler with attention mechanisms and adaptive greedy sampling was used, and the model was trained using Proximal Policy Optimization to minimize a customized energy efficiency metric.

Rahaman [28] developed an intelligent environmental monitoring system (SEMS) integrating IoT-based sensing and AI-driven analytics to monitor water and air quality in urban areas. The system enables real-time prediction and adaptive action through the integration of sensor data and machine learning techniques with regulatory requirements and sustainable planning. Though intended for environmental application, the approach's methodology—its combination of real-time data streams with predictive learning—offers insights applicable to the construction of adaptive, ML-enhanced scheduling tools.

2.1.4. Hybrid Approaches

Hybrid approaches combining mathematical optimization, metaheuristics, heuristics, simulation, and machine learning have greatly enriched the toolset methodology for energy-aware production scheduling problem solving. Through the utilization of complementary advantages, the hybrid models improve solution quality, computational efficiency, and robustness. The methods often employ machine learning for metaheuristic parameter optimization, complexity reduction, or search space reduction for mathematical optimization methods, thus promoting practical applicability in dynamic and uncertain industrial contexts.

Hybrid methods integrating MILP with heuristic techniques have become extremely popular as a means of enhancing scalability and computational efficiency for energy-aware production scheduling, especially for large-scale or complex industrial systems. These methods preserve the strict modeling capability of MILP yet relax its computational drawbacks using customized heuristic algorithms. Various recent studies have used decomposition-based methods to overcome the scalability drawbacks of MILP. Ghorbanzadeh & Ranjbar [29] suggested dividing the products into groups based on energy consumption and solving a sequence of small MILP subproblems, improving the schedule iteratively. Feng et al. [30] pursued the same philosophy by developing two heuristic frameworks to supplement their MILP model—one starting with batch formation and the other with job-to-machine assignment—both attempting to balance solution speed and energy efficiency. For larger-scale problems, Sel et al. [31] extended the hybridization further by integrating SA with a Fix-and-Optimize approach atop a multi-bucket MILP formulation. Similarly, Jagana et al. [32] incorporated adjustable robust optimization into their MILP formulation to tackle the uncertainties associated with interruptible load commitments. Their two-stage model decouples nominal scheduling decisions from real-time deviations based on actualized reduction requests, introducing robustness at the cost of model complexity.

The integration of MILP and simulation techniques offers a robust and flexible approach to addressing uncertainty and dynamic conditions in energy-aware production planning. Gangwar et al. [33] suggested a simulation-based MILP approach that encompasses ARIMA-based electricity price prediction, Monte Carlo scenario generation, and risk analysis. Forecasted prices feed into a scenario generator to create plausible future trajectories, each of which is treated as a standalone optimization problem. The MILP model,

adapted from an air separation unit case, is solved for each scenario, and the resulting profits are analyzed using risk metrics to assess the economic robustness of scheduling plans. Santecchia et al. [34] also combined MILP and simulation in a prediction-based, rolling-horizon optimization framework. Their discrete-time MILP model is solved for a 24 h horizon and updated every hour for a month of simulation horizon. Monte Carlo techniques are employed to simulate power constraints over a day-ahead scheduling horizon. This specification enables the model to respond dynamically to short-term fluctuations, even though responsiveness can be dampened in very volatile circumstances by the application of approximations within the rolling window. Simulation-based optimization techniques have also been used in environmental monitoring scenarios. For instance, Sofia et al. [35] utilized the Operational Street Pollution Model (OSPM) to optimize the positions and number of air quality stations within a city. The authors modeled PM_{10} concentrations based on traffic and urban background pollution and were thus able to identify optimal sensor locations that can accurately represent pollution levels across different urban locations.

Different solution approaches leveraged the accuracy of mathematical programming while depending on metaheuristics for the effective search of the solution space. Jabeur et al. [36] addressed renewable energy uncertainty using a robust two-stage MILP framework that decouples nominal scheduling and real-time adjustment. For coping with the computational burden of the model, a GA-based decomposition method was proposed, in which the iterative improvement of subproblems was possible. Likewise, Rastgar et al. [37] proposed a multi-objective hybrid flow-shop scheduling with imperfect maintenance. Although the ε-constraint method was employed to optimally solve small-sized instances, hybrid metaheuristics like MOPSO, NSGA-II, and an improved multi-objective harmony search (IMOHS) had to be adopted for large instances. The IMOHS algorithm demonstrated good performance in obtaining Pareto-optimal solutions efficiently.

The integration of ML and MILP models has proven to have growing potential to improve accuracy and responsiveness in the energy-aware scheduling of production, particularly in uncertain contexts. Hybrid strategies tend to use machine learning to predict, classify, or estimate complex relationships and MILP to solve and model the involved scheduling issue. Peerasantikul & Auwatanamongkol [38] compared the models of forecasting—XGBoost, Random Forest, SVR, LSTM, and Ridge Regression—to predict the solar power to be utilized in a MILP-based strategy for scheduling. Utilizing XGBoost, which proved to be the most accurate algorithm, the hybrid strategy supported well-informed scheduling in the presence of the varied availability of solar power. In another energy-forecasting-based study, Shakrina et al. [39] utilized k-means clustering to obtain representative scenarios of the price of electricity to be utilized based on past data and used them to streamline decisions regarding BESS sizing and scheduling. Their approach precomputed the capacity boundaries to constrain the search space, although clustering scenarios can potentially oversimplify dynamic price patterns. Other works utilize machine learning to extract structural details in scheduling. Guo et al. [40] proposed a support vector machine (SVM)-based method to grasp the capacity of the region of production in petrochemical processes. The boundary was embedded into a rolling-horizon MILP strategy through the GPCR strategy, effectively capturing complex constraints while improving computational efficiency. A more tightly coupled ML-MILP integration is found in Jabeur et al. [41], who developed a two-level hybrid model for lot sizing and scheduling in flexible flow lines. The first level applies Q-learning through a multi-agent system to determine optimal machine assignments and sequences, while the second level solves a MILP to optimize lot sizes and inventory flows under TOU pricing. Samouilidou et al. [42] suggested a framework that synergistically combines machine learning approaches with mixed-integer linear program-

ming to optimize scheduling procedures for manufacturing. Using predictive modeling and clustering, the framework identifies patterns in production data, which are then used to guide and optimize the MILP model's scheduling decisions. This shows the potential for combining data-driven insights with traditional optimization techniques for increasing efficiency and responsiveness in cutting-edge industrial applications.

Many strategies utilize ML algorithms to improve metaheuristic performance by refining parameter selection, prediction, or even fitness evaluation while maintaining the flexibility and exploration abilities of evolutionary methods. A key trend is the use of RL to control metaheuristic adaptation. Xu et al. [43] coupled a co-evolutionary algorithm with deep reinforcement learning (DRL), using an Advantage Actor-Critic (A2C) framework to select high-quality solutions and dynamically adapt the search process. The hybrid strategy resulted in excellent solution diversity and an excellent convergence rate but was computationally intensive and required careful tuning. Similarly, Shi et al. [44] coupled a 4 multi-objective evolutionary algorithm (MOEA/D) with a parameter adapting mechanism based on Q-learning to allow the population to dynamically update its search strategy and improve the quality and diversity of the Pareto front obtained. Cui & Yuan [45] utilized an expected SARSA algorithm to adapt key parameters within a GA. The GA was used to solve a MILP scheduling problem and was augmented with learning-based tuning to improve convergence characteristics and overall efficiency. Pereira et al. [46] attempted to refine predictions using an artificial neural network (ANN) to predict aggregated energy consumption, which was in turn utilized to evaluate the members in a GA in order to minimize the makespan.

A few recent studies have explored alternative strategies for energy-aware production scheduling, combining simulation, game theory, model predictive control (MPC), and other techniques. Yang et al. [47] suggested a hybrid MILP-MPC approach that combines the precise power consumption profiles of both industrial equipment and thermostatically controlled loads (TCLs). A generic MILP model, based on the STN framework, captures production constraints, while an MPC framework is employed to dynamically generate optimal schedules. Fu et al. [48] combined simulation with metaheuristic optimization using a hybrid approach that merges a Brain Storm Optimizer (BSO) with a stochastic discrete event simulator. The simulation assesses solution performance under uncertainty, and the BSO uses dual evolutionary mechanisms to enhance both exploration and exploitation. Sun et al. [49] proposed a game-theoretic approach to minimize the makespan and power usage through the formulation of the scheduling problem as a strategic interaction among multiple agents.

An overview of the methodological landscape for energy-aware production scheduling is provided in Table 1, highlighting the diversity of the techniques and approaches used in the recent literature. Note that many studies are marked in more than one column, indicating that they employ hybrid approaches, combining multiple methodological techniques.

Table 1. Summary of methodological approaches used in recent contributions for energy-aware production scheduling.

Literature Contribution	Mathematical Optimization	Heuristics	Metaheuristics	Machine Learning	Other (Simulation/MPC)
Fisco-Compte (2025) [6]	X				
Jagana (2025) [32]	X	X			
Lv (2025) [15]	X				
Rahaman (2025) [28]				X	
Samouilidou (2025) [42]	X			X	

Table 1. *Cont.*

Literature Contribution	Mathematical Optimization	Heuristics	Metaheuristics	Machine Learning	Other (Simulation/MPC)
Xu (2025) [43]				X	
Bok (2024) [12]	X				
Cui (2024) [45]			X	X	
Ertem (2024) [23]			X		
Feng (2024) [30]	X	X			
Fu (2024) [48]			X		
Geetha (2024) [17]			X		
Germscheid (2024) [14]	X				
Guo (2024) [40]	X			X	
Jabeur (2024) [41]				X	
Peerasantikul (2024) [38]	X			X	
Pereira (2024) [46]			X	X	
Rastgar (2024) [37]	X		X		
Rui (2024) [27]				X	
Sel (2024) [31]	X	X			
Shi (2024) [44]			X	X	
Tang (2024) [8]	X				
Tian (2024) [16]			X		
Wang (2024) [4]	X				
Xiao (2024) [5]	X				
Yağmur and Kesen (2024) [20]			X		
Yang (2024) [47]	X				X
Zhao (2024) [19]			X		
An (2023) [22]			X		
Gangwar (2023) [33]	X				X
Germscheid (2023) [13]	X				
Ghorbanzadeh (2023) [29]	X	X			
Jabeur (2023) [36]	X		X		
Leenders (2023) [11]	X				
Mokhtari (2023) [18]			X		
Sagar (2023) [24]			X		
Shakrina (2023) [39]	X				
Sun (2023) [49]					X
Zhang (2023) [25]				X	
Chen (2022) [21]			X		
Ma (2022) [3]	X				
Park et al. (2022) [7]	X				
Santecchia (2022) [34]	X				X

Table 1. *Cont.*

Literature Contribution	Mathematical Optimization	Heuristics	Metaheuristics	Machine Learning	Other (Simulation/MPC)
Trevin-Martinez (2022a) [9]	X				
Trevin-Martinez (2022b) [10]	X				
Wang (2022) [26]				X	
Sofia (2019) [35]					X

2.2. Decision-Making Pillars for Energy-Aware Scheduling

Researchers have explored different decision-making dimensions that influence how energy-aware scheduling is realized. These range from approaches that optimize the production schedule, considering the energy-related parameters of the production process, to formulations that incorporate external incentives, like fluctuating electricity prices or emissions policies, to methods that consider on-site power generation and storage. The following subsections summarize how each of these dimensions has been handled in the recent literature. Notice that Section 2.1 organized the literature based on the methodological approaches employed, whereas Section 2.2 collects the same contributions from the points of view of the decision-making pillars considered. To save repetition, the methodological details already illustrated are not duplicated, but interest is centered on the application context and the specific decisions addressed in each work.

2.2.1. Optimal Production Scheduling for Energy/Emissions Reduction

A large part of the literature contributions concentrates on optimally scheduling production processes for energy and emission reductions. Production efficiency is improved in these solutions through the reduction in idle times, the optimization of production sequence, the reduction in changeovers, and the synchronization of the consumption of resources. By enabling the more efficient use of equipment and production streams, such models reduce the need for utilities such as electricity, steam, heat, and compressed air—thus, both operating costs and carbon emissions. This route is particularly relevant to industries planning to decarbonize regardless of external incentives or the installation of on-site energy resources. The papers included in this section discuss how the intrinsic flexibility of production systems can be utilized to assist low-carbon goals through sophisticated scheduling alone.

Some contributions address job-shop and flow-shop settings where internal scheduling choices directly affect energy and carbon performance. Pereira et al. [46] investigated energy consumption under different batch sizes for a job-shop setting, with implications for the production order quantity on electricity demand. Zhang et al. [25] extended the investigation to a multi-stage flexible job-shop setting in paper production, where steam and electricity are utilized across several stages. Indirect as well as direct energy consumption is considered, bridging energy-conscious operational management and dynamic scheduling. Xu et al. [43] solved a distributed heterogeneous flexible job-shop scheduling problem with several production units of varying capability. By coordinating job assignments across these sites, the study reflects the energy-saving potential of centralized scheduling even under decentralized production. A stochastic open-shop problem that combines open-shop and parallel-machine characteristics, accounting for uncertainty in job processing times, was considered by Fu et al. [48]. Shi et al. [44] and Geetha et al. [17] focused on hybrid flow-shop environments with multiple machines and stages, optimizing job sequencing

to minimize both completion time and energy consumption. The latter work, situated in the Indian furniture manufacturing sector, reported a nearly 10% reduction in the carbon footprint solely through scheduling improvements.

Lot-sizing and scheduling decisions with energy awareness were investigated further by Sel et al. [31], who examined a CNC milling facility with product-dependent machining tools, setup activities, standby power, and auxiliary equipment power. Chen et al. [21] addressed production and outbound logistics, solving production and shipping scheduling on unrelated machines and vehicles with different energy needs in a make-to-order supply chain. Tian et al. [16] tackled energy-efficient remanufacturing through energy and makespan minimization in a closed-loop production process. Zhao et al. [19] achieved reduced energy losses through proper hot-rolling scheduling in a steelmaking process. They focused on synchronizing rolling with casting to prevent reheating cooled ingots. Another team incorporated multi-period tactical planning with strategic choices like the adoption of new processing technologies, delay penalties, and machine-dependent energy consumption [45]. Lastly, Yağmur & Kesen [20] incorporated vehicle routing and scheduling decisions. Their integrated model determines job assignments, machine speed, vehicle assignment, and customer visit sequences, taking into account time windows, load sizes, and machine energy profiles.

Other studies concentrated on real-time and system-level responsiveness. Sun et al. [49] suggested a dynamic energy-efficient integrated planning and scheduling system based on a digital twin to react to interference events (e.g., machine failures). The system reschedules dynamically to attain energy-efficient operations after possible disruptions. Optimal demand management for an actual seat manufacturing factory has been explored [47]. Nonlinear thermal dynamics in temperature control were modeled, and an MPC controller was applied to reduce energy consumption in HVAC-related loads.

2.2.2. Integration of Market and Policy Incentives

In recent years, there has been growing interest in aligning production scheduling with economic and regulatory incentives. Numerous contributions address the integration of such mechanisms, such as time-varying electricity prices, demand-response programs, emissions trading schemes, and carbon taxes, directly into scheduling models. Such external incentives, usually promoted by governments or system operators, introduce both economic motivation and opportunity for the industrial sector to control their energy consumption and environmental footprint. Their combination renders the scheduling problem more challenging, with models needing to trade-off operational efficiency against dynamic price signals, emissions allowances, and regulatory constraints. From the decision-maker's point of view, these models add a wider strategic dimension—changing scheduling from an internal optimization problem to a system-aware decision-making process.

Demand Response

Adjusting production in line with dynamic electricity prices is one key way of reconciling industrial scheduling with decarbonization objectives. The majority of research efforts in this area have considered TOU pricing in the day-ahead market, while others have looked at the more volatile but possibly lucrative RTP seen in balancing markets. The models reschedule energy-consuming activities to lower-cost off-peak times without productivity compromise and are increasingly addressing operational uncertainty and risk.

Park & Ham [7] demonstrated the capability of applying TOU-based scheduling in a flexible job-shop environment by rescheduling job allocations during planned shutdowns, with a total average electricity saving of 6.9%, while not affecting throughput. Similarly, Mokhtari-Moghadam et al. [18] as well as An et al. [22] worked with TOU pricing in hybrid

flow-shop environments, with the consideration of labor limitations, as well as preventive maintenance, respectively, in scheduling productions during off-peak periods. Rui et al. [27] integrated time-of-use price signals in a reconfigurable job-shop scheduling problem for a workshop in China and showed that there was a saving of 14.44% in electricity by optimally allocating jobs and scheduling time-dependent operations. For batch processing, Feng et al. [30] studied the scheduling problem of unrelated parallel batch processing machines. They adapted batch sequencing as well as job allocations into machines based on given TOU windows for electricity savings. Wang et al. [4] also employed a similar strategy in the polysilicon production environment, successfully analyzing the impact of numerous pricing methods as well as production bottlenecks, such as ordering size limitations and storage restrictions. Santecchia et al. [34] proposed a demand-side response approach customized for batch processes by envisioning flexible units as 'equivalent batteries', keeping low-cost power in by-products for future use and incorporating corrective scheduling to counteract unplanned power shortages. Germscheid et al. [13] created a model that concurrently considered intraday market participation alongside the day-ahead market for a copper production facility, comparing risk-averse vs. risk-neutral approaches within price uncertainty. The results showed that more aggressive approaches resulted in larger savings but with a higher risk, while conservative approaches were stable with lower returns. The model also introduced a sequential option to reduce total computational complexity.

Recent studies have more intensely focused on examining RTP and balancing markets. Gangwar et al. [33] incorporated scenario forecasting with risk evaluation in a cryogenic air separation plant, resulting in probabilistic information in terms of the profit margin under RTP. In another study, Xiao et al. [5] analyzed real-time and incentive price impacts on polysilicon manufacturing, determining that dynamic load adjustment can produce substantial cost savings. Jabeur et al. [36] applied this approach to a multi-product manufacturing system that included on-site renewable energy resources and stored inventory, coordinating production schedules with the availability of renewable energy and demand-response signals while also resolving inventory backorders and emissions.

Carbon Pricing and Emissions Trading

A growing subset of the energy-aware scheduling literature incorporates carbon-related policy mechanisms directly related to carbon emissions, such as carbon taxes, emission baselines, and credit trading systems. These mechanisms force researchers to extend traditional scheduling objectives by adding the economic impacts related to the carbon footprint, thus laying a basis for linking industrial operations with sustainability requirements and environmental policies.

Several studies specifically address the integration of carbon pricing into cost-related objectives in the scheduling models. By attaching economic costs to carbon emissions, these models guide production decisions made in pursuit of both emission reduction and energy cost minimization. In flexible manufacturing systems, Sagar et al. [24] incorporated factors related to a carbon tax into tardiness objectives as well as energy objectives. The results show that the use of carbon pricing schemes can lead to emission reduction by more than 20%, in addition to a significant reduction in energy consumption. Likewise, Trevino-Martinez, Sawhney, & Shylo [9] developed a scheduling model for a single machine, taking into account the emissions caused by grid electricity, showcasing the relevance of a carbon tax in carbon-related expenditure modeling as well as strategic planning, thereby informing industry planners with the real-world financial implications of their decisions. Such research emphasizes the role of carbon pricing in planning operations, especially in cases where emissions relate to the condition of the machinery, the setup operations, or the machinery use of energy resources.

Subsequent research explores emissions trading or discusses policy tools involving carbon permits and credit allocations. Fisco-Compte et al. [6] examined a rubber production plant and evaluated the merits of variable-hour carbon taxation in relation to carbon trading options in a multi-machine arrangement subject to shared resources. The study outlines contexts in which real-time pricing performs better when complemented by supplementary carbon credit allocations, thus yielding important observations for policymakers working towards reconciling industrial activities with environmental sustainability. On a related note, Tang et al. [8] developed a demand bidding mechanism that minimizes the cost of production while supporting carbon reduction programs by inducing industrial agents towards higher participation.

Few contributions include emission-oriented objectives in more comprehensive scheduling models. Rastgar et al. [37] combined strategic and tactical decision-making procedures to optimize production, considering emission targets, and Jagana et al. [32] discussed flexible production scheduling under interruptible load contracts. While these models do not explicitly link with emission pricing, they obtain carbon savings through the activation of dynamic energy curtailments and the coordination of load adjustments based on grid limitations.

2.2.3. On-Site Energy Generation and Storage Integration

Another important decision-making dimension is the coordination of the production schedule with the on-site energy generation and storage. Such systems can include renewable energy sources, such as photovoltaic cells or wind power, and waste heat recovery systems, CHP systems, or BESSs. In these cases, the scheduler must manage production flows while simultaneously considering the availability, variability, and storage potential of the energy generated on-site. In some cases, excess energy can be fed back into the grid, thus adding an economic aspect. The main goal in these integrated models is to increase self-sufficiency, reduce the dependence on grid energy, and decrease carbon emissions—elements that are especially relevant for manufacturing businesses located in areas with volatile electricity prices or strict decarbonization requirements. This subsection emphasizes recent developments toward the co-optimization of production practices with on-site energy systems.

Several studies aim to optimally solve the production scheduling problem along with the optimal utilization of renewable energy generation and storage. Peerasantikul & Auwatanamongkol [38] modeled a sand milling facility that reschedules in a manner to maximize solar power utilization, resulting in a solar utilization rate increase from 92.49% to 98.26%, with cost savings of 17%. Trevino-Martinez, Sawhney, & Sims [10] investigated the optimal sizing of the PV and BESS in a plastic injection molding process, indicating cost-effectiveness in the long run compared to grid-only reliance. Ghorbanzadeh & Ranjbar [29] studied the impact of battery capacity, PV panel size, and the planning horizon in flow-shop operations. They showed that increasing the planning horizon has a positive effect on electricity cost improvements; however, diminishing returns are obtained for planning horizons greater than 2.4 days. Ertem [23] tackled the issue of RES uncertainty by utilizing resilient scheduling frameworks, which take advantage of machine speed adaptability in coping with renewable energy variability.

The integration of energy storage and renewable forecasting is explored in contributions such as Shakrina et al. [39], where a BESS sizing strategy for a batch production facility under electricity price uncertainty was set up, and Guo et al. [40], where uncertainty in wind power generation was introduced using a fuzzy modeling approach. Alternative energy source configurations—grid only, grid plus wind, and grid plus wind with BESSs—were examined under uncertain demand and energy supply, showing the value of utilizing agile

configurations. Similarly, Germscheid et al. [14] optimally designed a local generation and storage system for a continuous process environment, underlining the trade-off between significant CAPEX and emission improvements, as well as the trading capacity, when using battery systems. Interestingly, financial and environmental efficiency was influenced more by grid electricity prices and emission factors rather than by self-production.

Other investigations use local non-renewable systems or hybrid configurations. Leenders et al. [11] developed a bi-level scheduling problem where the production system interacts with a lower-level energy system, including CHP and boiler units, supported by gas as well as electricity grids. The investigation considers government subsidies for CHP utilization, demonstrating how energy system characteristics affect production scheduling. Bok et al. [12] demonstrated the replacement of natural gas by coal under different carbon emission levels, examining trade-offs among energy price, environmental sustainability, and greenhouse gas utilization. The model increasingly substitutes energy supplies from natural gas with coal as carbon levels increase, demonstrating the stability of the coal supply under uncertain cost conditions at the expense of increased emissions.

Unified frameworks for production-energy coordination are also emerging. Ma et al. [3] proposed the cooperative optimal control of industrial factories and multi-energy systems (MESs), where the inputs are natural gas and PV power, generating electricity, heat, and refrigeration as outputs. CO_2 recovery and hydrogen production are also integrated in the model, with up to 22% cost savings in energy. Lv et al. [15] integrated low-carbon factory planning with captive power plant operation under uncertainty, where the total energy cost, production cost, and carbon quota trading value were minimized, respectively. Finally, several studies involve the usage of local energy as part of broader multi-objective models. Wang et al. [50] dealt with energy and carbon cost trade-offs in the steel industry, generating Pareto fronts between power acquisition costs and carbon emissions. Jabeur et al. [41] combined on-site energy generation for a lot-sizing and scheduling problem with TOU pricing, considering demand satisfaction, inventory limits, and optimal changeover efficiency.

The reviewed studies are organized in Table 2 based on the decision-making levels they address. This perspective highlights that only a few publications consider optimizing the production schedules while considering the utilization of local energy generation and storage and the exploitation of the market and policy incentives.

Table 2. Categorization of recent publications based on key decision-making pillars in energy-aware production scheduling.

Literature Contribution	Optimal Production Scheduling	On-Site Generation and Storage				Market and Policy Incentives			
		Non-RES	RES	ESS	Sell	Carbon Tax	Carbon Trading	TOU	RTP
Fisco-Compte (2025) [6]							X	X	X
Jagana (2025) [32]						X			
Lv (2025) [15]		X	X	X	X	X		X	
Xu (2025) [43]	X								
Bok (2024) [12]		X				X			
Cui (2024) [45]	X								
Ertem (2024) [23]			X	X					
Feng (2024) [30]								X	
Fu (2024) [48]	X								

Table 2. *Cont.*

Literature Contribution	Optimal Production Scheduling	On-Site Generation and Storage				Market and Policy Incentives			
		Non-RES	RES	ESS	Sell	Carbon Tax	Carbon Trading	TOU	RTP
Geetha (2024) [17]	X								
Germscheid (2024) [14]			X	X	X			X	
Guo (2024) [40]			X	X	X				
Jabeur (2024) [41]			X	X				X	
Peerasantikul (2024) [38]			X					X	
Pereira (2024) [46]	X								
Rastgar (2024) [37]	X					X			
Rui (2024) [27]	X								
Sel (2024) [31]	X								
Shi (2024) [44]	X								
Tang (2024) [8]						X			
Tian (2024) [16]	X								
Wang (2024) [4]								X	
Xiao (2024) [5]								X	X
Yağmur and Kesen (2024) [20]	X								
Yang (2024) [47]	X								
Zhao (2024) [19]	X								
An (2023) [22]	X							X	
Gangwar (2023) [33]								X	
Germscheid (2023) [13]								X	
Ghorbanzadeh (2023) [29]			X	X				X	
Jabeur (2023) [36]		X	X					X	X
Leenders (2023) [11]		X							
Mokhtari (2023) [18]								X	
Sagar (2023) [24]						X	X		
Shakrina (2023) [39]								X	
Sun (2023) [49]	X								
Wang (2023) [50]		X				X		X	
Zhang (2023) [25]	X								
Chen (2022) [21]	X								
Ma (2022) [3]		X	X	X		X		X	
Park (2022) [7]								X	
Santechhia (2022) [34]								X	
Trevino-Martinez (2022a) [9]						X		X	
Trevino-Martinez (2022b) [10]			X	X	X			X	
Wang (2022) [26]	X						X	X	X

3. Challenges and Research Gaps

While the body of literature on energy-aware production scheduling has evolved at a rapid rate over the past few years, several critical challenges continue to hamper its practical applicability and implementation in real-world industrial settings. Such challenges are not merely technical in nature but are also conceptual and systemic and emerge from limitations in modeling paradigms, technology integration, market congruence, and cross-disciplinary collaboration. A more holistic and realistic strategy is necessary to move forward from theoretical optimization models to workable tools facilitating industrial decarbonization at scale.

3.1. Modeling Limitations

One of the key features of the majority of the existing work is that it tends to be based on deterministic models, with the supposition of the complete knowledge of future system states. Electricity prices, renewable power output, and electricity demand are typically assumed to be known and constant over the optimization horizon. In practice, these assumptions do not hold frequently. Power generation from renewables, such as solar power and wind, is weather-dependent and stochastic in nature. Market prices can fluctuate significantly, especially in real-time, and operational breakdowns such as machine failures or supply chain disruptions introduce another source of uncertainty into the production system. These realities call for the development of scheduling models that explicitly incorporate uncertainty, using stochastic programming, robust optimization, or hybrid approaches that blend optimization with real-time learning and forecasting. For example, robust optimization methods can provide solutions that hedge against worst-case scenarios, while probabilistic approaches can optimize expected performance under known distributions. Yet, such methods are still relatively underused in energy-aware scheduling. Even among the studies that address uncertainty, most are limited to narrow domains, simplistic assumptions, or small-scale case studies.

The requirement for long-term planning introduces an additional layer of complication. While TOU pricing is usually possible for the upcoming day, scheduling decisions tend to span longer horizons—e.g., weekly or monthly planning intervals—particularly when they are related to maintenance cycles, production campaigns, or inventory buildups. In these situations, dependence on accurate forecasts becomes paramount. Among the promising directions is the application of rolling-horizon methods, in which a longer-term plan is repeatedly revised as more precise information becomes available. Such a replanning strategy more accurately reflects industrial decision-making procedures in a dynamic way and enables an adaptive response to evolving market and operational conditions. However, despite their conceptual appeal, rolling-horizon models with long planning horizons that tackle forecast uncertainty remain largely unformalized in the current literature. We consider this an essential topic for future research, in which both new model formulations and case studies would be beneficial to bridge the gap between theoretical development and industrial practice.

3.2. Scalability and Industrial Applications

Another research gap is the disparity between the simplicity of most academic models and the complexity of actual industrial systems. Most research concentrates on idealized settings, dealing with single-machine systems, identical parallel machines, or simple job-shop setups. Such simplifications are helpful in methodology development but do not reflect the richness of real production settings, with multi-stage processes, intermediate inventories, departmental synchronization, and heterogeneous equipment with special operating constraints. In practice, manufacturers must contend with perishable products, product quality

deterioration, machine state variation, and demanding delivery times. Scheduling under these conditions often entails process-dependent constraints such as cleaning, batching, tool switching, and interoperation dependencies. Along with these built-in complexities, real industrial scheduling must also be able to handle multi-dimensional constraints such as logistics coordination, product quality inspection, multi-site resource balancing, and preventive or predictive maintenance. But there are a few studies published that tackle these characteristics in detailed case studies, and most benchmarks continue to depend on highly simplified and small-scale examples. Therefore, the transferability and robustness of current scheduling techniques to real industrial environments are still limited. Additionally, the majority of the existing scheduling methods are based on discrete-time formulations, specifically in MILP-based formulations. The choice of this modeling approach is effective in representing time-dependent variables, e.g., electricity price variability along a specified horizon. However, discrete-time models are susceptible to computational scalability problems and a compromise on temporal accuracy, especially if high time granularity is required. These restrictions can have a major impact on the feasibility of employing such models for large-scale, real-world industrial settings. To facilitate accurate and large-scale scheduling, further effort must be placed on the development of continuous-time modeling frameworks, e.g., those relying on flexible time grids or precedence-based representations. Such frameworks provide improved accuracy in process dynamics and are better suited for complicated, dynamic, and data-rich industrial settings.

There have been few attempts to address these challenges via large-scale industrial case studies, and even fewer have directly collaborated with manufacturing firms to test and refine their models. Addressing this gap requires not only algorithmic advances but also closer collaboration between industry and academia, capable of co-developing solutions that are both technically sound and operationally viable.

3.3. Integration of Multiple Decision Pillars Within a Unified Framework

The majority of research contributions are limited in their scope, addressing a single or only a few decision pillars in isolation. Models, for example, might include on-site renewable generation but neglect energy storage or account for TOU pricing but not real-time pricing. Even fewer account for carbon taxation, emissions trading, or regulatory caps in conjunction with operational scheduling. Furthermore, there is little integration with other enterprise operations. Production scheduling is tightly connected with logistics, inventory management, vehicle routing, and supply chain coordination. For instance, electric delivery trucks can also serve as mobile energy storage assets, yet their scheduling requirements may interfere with production and charging demands. Maintenance planning and labor availability are also constraints and opportunities that are typically not included in the current literature. Future work must prioritize the creation of integrated frameworks, consolidating these various pieces within a single optimization model. Such frameworks must include production decision-making, energy purchasing, market involvement, regulatory compliance, and supply chain concerns so that they are fully engaged and are accounted for simultaneously. Only the systems perspective enables trade-offs and synergies that single-domain models overlook to be captured.

3.4. Forecasting, Real-Time Data Integration, and System Connectivity

Forecasting and data integration are the cornerstone of any adaptive or real-time scheduling system yet are underdeveloped in the majority of the literature. The accurate forecasting of electricity prices, renewable generation [51,52], and production demand is crucial to make properly informed scheduling decisions, particularly in 15 min settlement and dynamic pricing markets. ML and DL provide effective ways of building predictive

models from historical data. Specifically, the time-series prediction of solar irradiance, wind speeds, and electricity prices can be enhanced using RNNs, attention-based models, or hybrid statistical-ML models. Though a possibility, there are limited scheduling models that explicitly include forecasting modules within their optimization algorithms.

More critically, the infrastructure for linking real-time data streams with scheduling decisions is typically not present. Modern industrial facilities are becoming ever more equipped with sensors, IoT devices, and MESs that generate vast volumes of operational data. But such data is rarely leveraged for adaptive scheduling, primarily because there is typically no integration between IT systems, energy management systems, and optimization solutions. One of the directions for promising research is creating cyber-physical manufacturing systems (CPPSs) that integrate real-time monitoring, predictive analytics, and adaptive control. Such systems have the potential to modify schedules online at times based on streaming data, enabling reactive behavior and system resilience. The achievement of such a vision demands online optimization, incorporation with machine learning, as well as dependable communication protocols to industrial control systems.

3.5. Regulatory-Policy Integration and Multi-Objective Trade-Offs

Industrial scheduling is inherently a multi-objective problem. Not only do producers aim to reduce energy expenses but they also need to trade-off other objectives like makespan, on-time delivery, equipment use, emissions reduction, and labor contentment. Trade-offs among these objectives are generally unavoidable. For example, shifting production to off-peak times can reduce energy expenses but create longer lead times or greater labor needs. Most existing models focus on single-objective formulations to minimize electricity costs or emissions, thus neglecting to model such intricate interactions. There is an increasing demand for multi-objective optimization models that provide Pareto-efficient solutions and facilitate informed trade-off analysis. The models must also incorporate indirect returns—reputational gains, risk mitigation, and long-term sustainability—in addition to direct financial returns. In addition, regulatory contexts and policy changes must be dynamically modeled so that decision-makers can examine "what-if" scenarios and respond to changing policy contexts. Finally, the formulation of such overall models will necessitate interdisciplinary cooperation, spanning operations research, energy systems, economics, and industrial engineering. In the absence of such integration, the promise of energy-aware production scheduling in enabling real-world decarbonization will remain mostly theoretical.

3.6. Strategic Prioritization for Industrial Implementation

Although all five challenges introduced here are significant to advancing the frontiers of energy-aware production scheduling, their relative importance in terms of practical significance differs. The first three—modeling limitations (Section 3.1), scalability and industrial applications (Section 3.2), and the lack of unifying frameworks (Section 3.3)—currently form the core of research agendas. These are most vital to enabling actual implementation, particularly by managing uncertainty, allowing the consideration of large-scale problems, and coupling the interdependent levels of decision-making across energy, manufacturing, and policy domains. Real-time connectivity and forecasting (Section 3.4) is next in priority, as it allows the needed digital basis and adaptability through cyber-physical production systems. Regulatory-policy integration and multi-objective trade-offs (Section 3.5) are, while extremely important, best dealt with after having robust and scalable optimization models. However, development in all these areas must occur to achieve the full potential of intelligent and sustainable industrial scheduling systems.

4. Designing the Future of Energy-Aware Production Scheduling

To unlock the full potential of energy-aware production scheduling in the interest of industrial decarbonization, a paradigm shift is needed—one that goes beyond fragmented, static, and oversimplified models towards an integrated, adaptive, and sustainability-driven approach. Future production scheduling needs to account for the growing complexity of industrial systems, energy market uncertainty, and escalating regulatory and societal pressure for reducing the environmental footprint. Proactive collaboration among academia, industry, and government—aligned with the Triple Helix model—is essential to accelerate this transition. Universities can drive methodological advances, industries can operationalize innovative solutions, and governments can foster enabling policy frameworks. Embedding this synergy into scheduling research and deployment will be key to impactful, scalable decarbonization. Our study's unique contribution lies in systematically linking this collaboration to operational-level production scheduling practices that explicitly incorporate renewable energy integration and carbon mitigation policies. We articulate a novel interdisciplinary approach that connects policy frameworks, technological solutions (RES and BES), and industrial scheduling models, thereby bridging the gap between high-level collaboration and practical implementation in production systems. We provide the framework for this vision in this section, grounded in the constraints we delineated above and motivated by encouraging developments in forecasting, optimization, and digital technologies.

4.1. From Fragmented Models to Unified, System-Level Optimization

The upcoming generation of scheduling systems has to combine all the major pillars of energy-efficient production: on-site renewable energy sources (RESs), battery energy storage systems (BESSs), time-of-use (TOU) and real-time electricity pricing (RTP), demand side management (DMS), and sustainability policies such as carbon trading and green certificates. All these features no longer have to be addressed separately. Instead, they need to be modeled as the interdependent components of a combined system in which scheduling decisions simultaneously affect, and are affected by, energy resource availability, market prices, and policy constraints. Towards this, scheduling models must move beyond standalone implementations and towards full integration, where energy market participation, on-site energy assets, and policy levers have common representation within an integrated optimization framework. Several contributions already show how dynamic electricity pricing, in the form of RTP and TOU tariffs, can be integrated into production scheduling to offer decision support for grid consumption, energy storage management, or surplus power dispatch. Likewise, carbon pricing schemes, emissions trading, and sustainability constraints have been incorporated in some state-of-the-art models to influence energy procurement and job scheduling. However, the simultaneous and synergistic integration of all of these pillars—coupling dynamic pricing schemes, local renewable generation, storage facilities, demand-response involvement, and regulatory constraints—into one unifying model remains scarce. It is this system-level viewpoint that future work must converge on to transition from component-level optimization to holistic, energy-aware scheduling solutions.

Beyond energy and emissions, scheduling must also be linked to the broader enterprise-wide decisions that overlap logistics, vehicle routing, inventory management, and maintenance planning. Industrial systems do not exist in isolation; what is performed on the production floor has an immediate effect on downstream distribution schedules, storage requirements, and departmental resource allocation. A true system-level perspective must recognize these interdependencies and provide a way of optimizing global performance—not just localized energy consumption or cost. An example is the integration

of energy-aware production scheduling and vehicle routing issues (VRPs), particularly when firms use electric vehicle (EV) fleets. Here, charging vehicles is part of the energy strategy. EV charging time, place, and quantity need to be synchronized with production schedules and the energy market (e.g., TOU and RTP signals) to prevent peak load, reduce cost, and have vehicles ready for timely dispatch. This is a multivariate optimization problem in which production tasks, energy purchasing, and transport planning need to be optimized together in concert. These scenarios pose potentially conflicting objectives—for instance, charging vehicles during the periods of lowest electricity cost may conflict with production schedules or strain local energy capacity. Such trade-offs are dealt with by model architectures capable of capturing cross-functional constraints, dynamic decision horizons, and interactions across a number of resources. In addition, it creates new opportunities for the application of EVs not just as transport assets but also as on-the-move storage devices, with the potential to engage in demand-response programs or grid services.

Apart from intra-factory coordination, the upcoming scheduling systems must also consider the synergistic advantages of cross-factory cooperation, especially in industrial symbiosis. In these systems, groups of factories or manufacturing plants—typically in the same industrial complex or area—share energy facilities, storage facilities, or even elastic loads so that as a group, they can improve energy efficiency as well as lower emissions. For example, excess energy produced on-site by one plant could be directed to a nearby facility that is experiencing a deficit, or runs could be staggered to reduce peak combined load profiles over a local grid.

For this degree of coordination to take place, scheduling systems in the future need to develop from standalone optimization techniques to enterprise-scale, interoperable decision systems that can handle the growing complexity of decarbonized industrial clusters. Beyond this, an important future direction lies in extending such systems to support multi-stakeholder coordination, not only between industrial sites but also involving external actors, such as utilities, regulators, and energy suppliers. Formalizing these interactions through game-theoretic or contract-theoretic models could enable collaborative decision-making within industrial symbiosis ecosystems, aligning economic incentives with decarbonization goals.

4.2. Modeling Perspectives

Industrial scheduling involves the consideration of multiple competing objectives, e.g., energy cost minimization, makespan minimization, and throughput maximization. Effective sustainable scheduling systems must handle such trade-offs explicitly and efficiently. Future research should focus on developing multi-objective optimization models that produce Pareto-optimal schedules, thereby offering decision-makers different alternatives adhering to different priorities. These models are particularly adept at balancing economic benefits, e.g., real-time pricing profits or carbon credits) against quantity and quality targets. Secondly, sustainability needs to be a design requirement and not simply an optimization objective, pushing systems towards long-term decarbonization and resilience as opposed to short-term cost-effectiveness.

However, multi-objective models pose serious computational challenges due to their increased complexity. Surpassing these methodological limitations requires new solutions with the potential to effectively manage computational resources without sacrificing solution quality. Hybrid methods should be the priority going forward, given their potential to consolidate the complementary strengths of alternative approaches. The integration of ML techniques and MILP, in particular, appears very promising. MILP formulations ensure solution optimality by rigorously accounting for constraints and objectives, whereas ML has the potential to significantly enhance computational tractability by effectively pruning

the search space. By leveraging data-driven knowledge, ML can propel MILP to highly prospective regions in the solution space with significantly less computational effort.

4.3. Leveraging Forecasting and Real-Time Adaptation

Flexibility is at the core of the suggested framework, which demands a close integration of cutting-edge forecasting methods and real-time data feeds. Accurate forecasting is not a supporting task—it is at the heart of enabling proactive, cost-saving, and sustainable decision-making in energy-aware production scheduling. Three key parameters at the focal point of this problem are electricity prices, renewable energy generation, and industrial energy demand. Electricity price forecasting is important in systems engaged in day-ahead and intraday markets, where prices are updated hourly or even every fifteen minutes. With access to timely price forecasts, companies can schedule energy-intensive operations for low-tariff periods or strategically participate in real-time operations to gain higher cost savings. Also important is the prediction of renewable generation, especially from on-site resources like solar and wind systems. While solar power can reliably be forecasted with acceptable precision from irradiance forecasts, wind generation is far more challenging to model because of high temporal and spatial variability. For wind energy or hybrid renewable setups that plants rely on, the production forecasts' uncertainty can significantly affect scheduling flexibility and energy availability, emphasizing the need for probabilistic or ensemble forecasting techniques. Left relatively uncared for in the literature thus far—but no less important—is the prediction of industrial energy use. The power consumption of equipment in actual industrial environments is often condition-dependent and non-stationary. It may change with the task being undertaken, the characteristics of the material involved, the current state of the machine, and particular manufacturing operations like retooling or cleaning. Classical scheduling models have a tendency to employ average consumption values from manufacturers, which may be inaccurate and produce poor or infeasible schedules. More realistic models ought to include data-driven energy demand estimators, which are trained on real-time and historical data gathered through IoT sensors and manufacturing execution systems. Such estimators are required to learn dynamically in order to reflect the actual energy footprint of activities in changing conditions.

Yet, forecasting is only part of the struggle. Schedules also need to be adjustable dynamically to react to the deviations from anticipated circumstances or to fresh market indicators. This involves formulating reactive and online scheduling algorithms that change operational strategies continuously as new data emerges. One way of performing this is by employing a rolling-horizon algorithm, in which the schedule is created for a longer horizon—e.g., a whole production week—but with different levels of confidence. In this arrangement, the initial portion of the horizon (e.g., the ensuing 24 h) is based on high-confidence inputs, i.e., TOU electricity prices on the day-ahead market. The subsequent days are calculated from the forecasted values of electricity price, renewable generation, and demand, for which the confidence of the forecast generally diminishes with time. The re-optimization of the schedule occurs daily or continuously as new parameters are updated with actual data. This replanning feature echoes the ways in which real-life industrial processes evolve and allows a dynamic reaction to a shift in market price, renewables availability, or production parameters.

Figure 2 illustrates the methodological framework proposed, structured around two primary levels: the forecasting and optimization levels. At the forecasting level, key inputs, such as energy demand, electricity price, renewable energy source output, and production demand forecasts, are automatically obtained via data pipelines. These forecasts feed into the optimization level, where a hybrid optimization approach integrates these predictions to derive optimal decisions regarding energy-aware production scheduling, renewable

energy integration, and battery energy storage system operation. This structured approach allows the model to effectively handle uncertainties and optimize performance across multiple operational dimensions. Although this framework remains at a conceptual stage in the current study, we envision its implementation and validation in future research, ideally through pilot case studies or simulation-based experiments in collaboration with industrial partners.

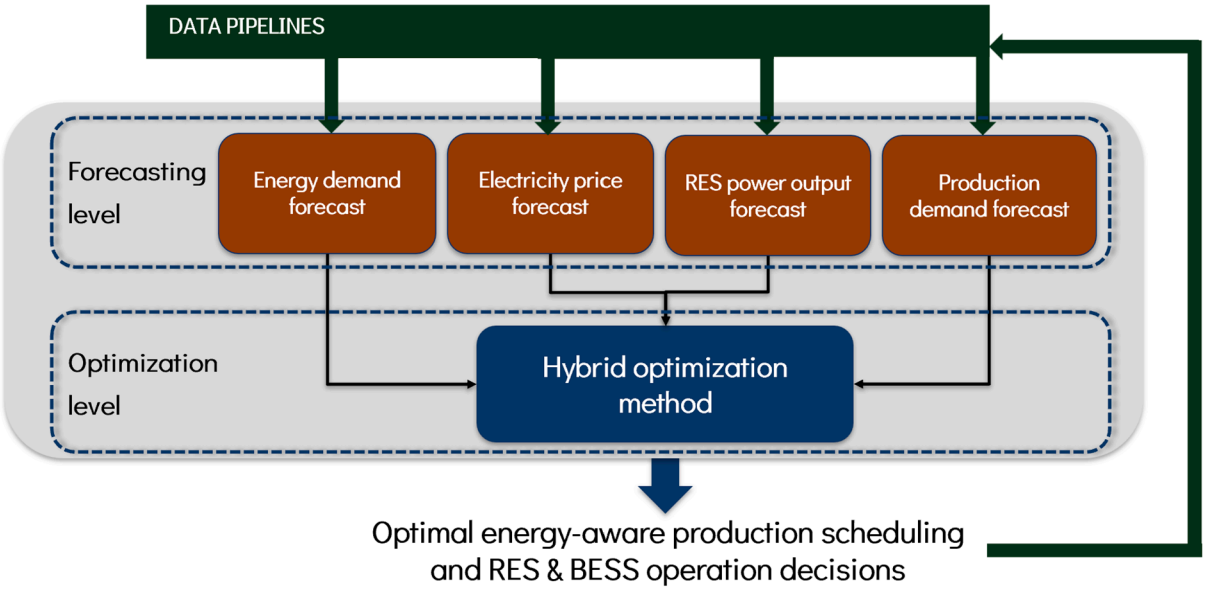

Figure 2. Overview of the proposed methodological framework combining forecasting and hybrid optimization for energy-aware production scheduling.

To enable this degree of responsiveness, scheduling systems need to be underpinned by control mechanisms based on feedback, with the ability to track real-time deviations and initiate corrective actions. Approaches like digital twins—the real-time simulation of physical system dynamics—and reinforcement learning algorithms that adapt policies based on observed effects can be a crucial enabler in this regard. They not only facilitate predictive and prescriptive changes but also assist in accounting for process dynamics, equipment conditions, and unplanned events. These elements come together to form the basis of an adaptive scheduling system: one that schedules in advance based on the best predictions available, tracks in real time, and responds with agility as conditions evolve.

4.4. Embedding Intelligence and Interconnectivity

To achieve the level of responsiveness and sophistication noted herein, the scheduling systems need to be smarter and more networked. Technologies from Industry 4.0, including industrial IoT, cyber-physical systems (CPSs), and cloud-based systems, provide the technological foundation for such an upgrade. The scheduling framework needs to incorporate real-time automated machine, smart meter, and production line data feeds to properly estimate machine status and energy demand. There should be learning algorithms that adapt where these data streams drive the models for energy consumption and become more accurate with time, with resulting predictions and schedules being similarly more dependable. Real-time monitoring, automated decision streams, and interfaces to enterprise resource planning (ERP) and MESs will be needed to facilitate close communication between the controls and the optimization engines. Additionally, the growing ability to process large amounts of industrial data opens up the possibility of leveraging data-driven control approaches. For instance, real load profiles can be applied in bottleneck forecasting or DR opportunity identification, and historical energy consumption patterns can be used

in predictive maintenance or work scheduling. Not only do these enhance operational efficiency but also system resilience and agility.

To realize this vision in practice, we propose a CPPS architecture of a layered cyber-physical production system that integrates real-time sensing, data processing, forecasting, optimization, and control. The architecture includes the following:

(i) a data acquisition layer connecting machines, smart meters, and sensors via industrial IoT networks;

(ii) a communication layer based on protocols such as OPC UA or MQTT, providing efficient, secure data exchange;

(iii) a data processing and analytics layer, in which forecasting algorithms operate;

(iv) an optimization and decision layer, responsible for adaptive scheduling;

(v) a control and interface layer, integrating MES, ERP, and plant control systems to execute decisions in real-time.

This multi-layer design supports real-time responsiveness, data-driven adaptation, and seamless IT-OT integration, transcending current limitations in industrial scheduling systems. This design concept may serve as a reference for the upcoming deployments of integrated energy-aware scheduling systems and guide academic prototypes and industrial pilot systems accordingly.

4.5. Enabling Cross-Disciplinary and Collaborative Innovation

Realizing this vision will necessitate an interdisciplinary R&D community that transcends conventional disciplinary borders. Operations researchers, computer scientists, control engineers, energy economists, and industrial practitioners will have to collaborate to co-design theoretically sound and operationally feasible solutions. Academic studies need to go beyond stylized problem formulations and join with industry partners in experimenting with solutions on actual systems. This involves applying scheduling models to pilot projects, creating open-access datasets and benchmarks, and verifying outcomes under realistic operational constraints. Similarly, industries need to see the strategic importance of energy-aware scheduling—not merely as a cost-reduction strategy but as a means to regulatory compliance, reputation capital, and ultimate competitiveness. In parallel, regulators and policymakers also need to enable market frameworks, pricing mechanisms, and incentive structures in accordance with industrial flexibility and sustainability. Energy efficiency scheduling will be most effective if complemented by policies that encourage load shifting, facilitate entry into ancillary service markets, and internalize the carbon externality of emissions.

4.6. Industry Initiatives and Challenges in Developing Countries

Many industries worldwide have initiated efforts toward decarbonization, including the adoption of renewable energy sources, the deployment of battery energy storage systems, and adherence to carbon mitigation policies and green certification programs. These initiatives are particularly prominent in developed economies where resources and regulatory frameworks support their implementation. In contrast, industries in developing countries often encounter significant challenges, such as the high costs and administrative burdens associated with obtaining sustainable certifications, limited access to financing, and infrastructural constraints. These factors can impede the widespread adoption of decarbonization measures and highlight the need for tailored strategies that consider local economic and regulatory contexts. The future design of energy-aware production scheduling frameworks should therefore incorporate flexibility and adaptability to accommodate such regional disparities, enabling scalable and context-specific solutions that support decarbonization efforts globally.

5. Conclusions and Future Directions

This work has charted the state of the art of energy-aware production scheduling, assessing methodological innovation, practice uptake, and persistent challenges. Although the literature demonstrates considerable progress on optimization methodologies, renewable integration, and demand-response interaction, it is still limited by fragmented methodologies, simplifying assumptions, and a lack of system-wide integration. To be successful in facilitating industrial decarbonization, the scheduling systems of the next generation need to overcome these limitations through integrated design, real-time responsiveness, and cross-disciplinary collaboration. One of the principal findings of this analysis is the necessity to unify disjointed operational and energy-related decisions within a single adaptive framework. Scheduling needs to be transformed into an enterprise-wide, data-driven activity that aligns production with energy markets, regulatory frameworks, and sustainability objectives, rather than an isolated activity. This involves introducing on-site renewable energy facilities, utilizing flexible energy storage, engaging in dynamic pricing schemes, and aligning with emission reduction policies and sustainability regulations. In addition, scheduling decisions must increasingly factor in extended domains of operation, including the logistics, maintenance, and use of electric vehicle fleets as flexible energy resources. Their representation will require robust forecasting models for electricity prices, renewable output (wind especially), and machine-level energy requirements—each posing its own data issues and model uncertainties. Rolling-horizon techniques, supported by real-time monitoring and feedback, present a viable compromise between short-term precision and long-term adaptability. Digital twins, industrial Internet of Things, and cloud-accessible cyber-physical systems are the technologies that will bridge planning and execution. Going forward, several key research directions emerge. New models must better capture real-world variability and scale, through stochastic or robust formulations informed by actual industrial data. Integrated frameworks must be formulated that explicitly balance multi-objective trade-offs in support of not only cost-effectiveness but also emissions reduction, operational flexibility, and labor considerations. Moreover, there needs to be more active collaboration between industry and academia to validate approaches and develop viable implementation strategies. To this end, pilot studies involving on-site renewable generation, battery energy storage systems (BESSs), demand-response mechanisms, and real-time electricity pricing schemes (e.g., TOU and RTP) would be essential to bridge theoretical advances with practical feasibility. Lastly, policy coordination will be essential to rendering scheduling tools not just technologically viable but economically and environmentally effective. In conclusion, energy-aware production scheduling is where digitalization meets industrial sustainability. Integration, flexibility, and collaboration are keys to the next generation of research being able to deliver not only more efficient plants but also smarter, greener, and more sustainable industrial systems.

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