Towards adaptive sustainable scheduling within lithium-ion battery production

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1 An introduction to adaptive scheduling

The rapid electrification of mobility and renewable energy integration have placed unprecedented demand on the large-scale production of lithium-ion batteries. Within this complex landscape, BATTwin[1] aims to revolutionize the battery manufacturing industry by developing a Digital Twin Platform that supports a digitally enhanced, zero-defect approach. The project emphasizes knowledge-based and explainable decision-making, scalability across production volumes, and robustness across battery chemistries. Among these challenges, the Flexible Job Shop Scheduling Problem (FJSP) stands out as a core decision-making task. Modern factories no longer seek only to minimize makespan; they must also ensure quality assurance, resource efficiency, and sustainability. The integration of digital twin feedback into scheduling optimization allows production systems to adapt dynamically to deviations, equipment conditions, or operator performance. This coupling transforms scheduling from a static pre-planning exercise into an adaptive decision process driven by continuously updated process knowledge [1] [2].

Therefore, in this paper, we address the integrated challenge of incorporating a digital twin into a quality- and energy-aware flexible job shop scheduling framework with operator allocation constraints, aiming to evaluate its ability to balance performance, quality, and sustainability within modern, data-enhanced manufacturing environments. More scientifically, this paper seeks to answer the following questions: What specific insights can the digital twin model provide? What measurable improvements can be expected from its integration? And how should its real-time feedback be systematically embedded within the optimization model to establish a closed-loop, adaptive decision-making system?

2 Adaptive scheduling framework description and application

In modern era, Digital twin models can capture complex, nonlinear dependencies between scheduling decisions and production outcomes, allowing systems to predict how sequences of operations, machine assignments, and operator allocations influence overall performance. In this regard, FIG 1 shows a schematic workflow integrating a Digital Twin with the optimization model. Orders are first processed

[1] BATTwin is a European project developing a multilevel Digital Twin platform for Zero-Defect Manufacturing in Li-ion battery production, funded by the European Climate, Infrastructure and Environment Executive Agency (grant No. 101137954).

by the optimization model, which considers constraints and objectives. The Digital Twin/Simulation layer evaluates potential schedules, providing insights about machine performance, process dynamics, and operator allocation. Real-time production feedback is then fed back into both the optimization and digital twin, creating a closed-loop system that continuously updates and refines scheduling decisions. This combination of simulation, and real-time feedback enables robust, scalable, and explainable scheduling solutions, addressing challenges of multi-objective optimization in flexible manufacturing systems.

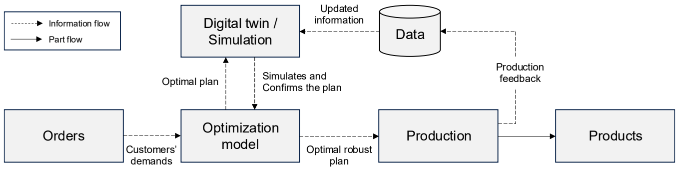

FIG. 1 – Adaptive scheduling framework.

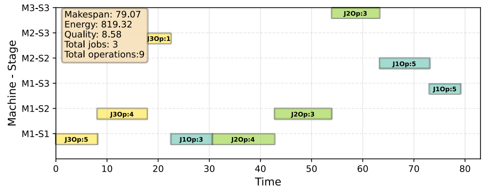

FIG. 2 – An exemplary optimal scheduling plan

For this purpose, we consider a system composed of three jobs, each decomposed into three sequential operations processed across three stages. The system is staffed by five operators, each characterized by distinct capability profiles that affect their performance on specific machines. A Monte Carlo simulation is subsequently employed to assess the reliability of the resulting schedule, which depends on the joint assignment of jobs, operators, machines, and the associated stochastic processing times. As part of limitations in this example, the simulation model is positioned outside the optimization loop and serves only to validate the reliability of the selected plans. FIG 2 presents an optimal scheduling solution obtained from the proposed Mixed-Integer Linear Model (MILM). The simulation-assisted MILM scheduling framework, implemented in Python, enables the identification of schedules that simultaneously minimize makespan, reduce energy consumption, and maximize throughput quality, while explicitly accounting for both machine capabilities and operator constraints. From the proposed plan, for example, we can deduce that the first task of job J_2 is scheduled at stage S_1, executed by machine M_1, with operator Op_4 assigned to carry it out efficiently. Based on the developed simulation model, the reliability of this schedule is estimated as $\underline{P(Makespan \leq 79.07) \approx 48.3\%}$.

3 Conclusions and perspectives

This paper studied the increasing complexity of modern manufacturing scheduling, where efficiency, quality, and sustainability must be jointly optimized under flexible machine and operator constraints. Integrating real-time feedback from digital twins into optimization frameworks has emerged as a powerful approach, enabling adaptive and data-informed decision-making. By combining exact methods and metaheuristics, such frameworks can navigate the multi-objective landscape of contemporary production systems effectively. Looking forward, the adoption of surrogate models offers a promising alternative to further enhance performance. By approximating expensive simulations or high-fidelity digital twin responses, surrogate models can significantly reduce computational costs while maintaining solution accuracy.

References

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