Proceedings of the 2025 Winter Simulation Conference
E. Azar, A. Djanatliev, A. Harper, C. Kogler, V. Ramamohan, A. Anagnostou, and S. J. E. Taylor, eds.

INTEGRATING ENERGY STORAGE INTO SHOPFLOOR DISPATCHING: A THRESHOLD-BASED ENERGY-AWARE CONTROL APPROACH

Wolfgang Seiringer[1], Balwin Bokor[1], Klaus Altendorfer[1], Roland Braune[1]

[1]Dept. of Production Operation Management, University of Applied Sciences Upper Austria,
Steyr, AUSTRIA

ABSTRACT

Rising energy price volatility and the shift toward renewables are driving the need for energy-aware production planning. This paper investigates the integration of energy storage systems into dynamic dispatching to balance production-logistics and energy costs. Building on prior work that introduced a workload- and price-based dispatching rule, we extend the model to include energy storage loading and unloading decisions. The rule prioritizes storage refill at low prices and lets machines resort to stored energy when grid prices rise and the workload is high. A simulation-based evaluation examines scenarios with different storage capacities whereby decision rule parameters are optimized. Computational results demonstrate that a reduction of operational costs is possible without deteriorating production logistics performance. By decoupling energy sourcing from real-time prices, manufacturers achieve both resilience and cost savings. This research contributes to sustainable manufacturing by offering a practical strategy for integrating energy storage into production planning under volatile energy conditions.

1 INTRODUCTION

The rising volatility of energy prices, coupled with increasing sustainability pressures, has pushed manufacturing companies to reconsider their energy consumption strategies. Traditional production planning approaches have primarily focused on cost efficiency, timely delivery, and resource utilization but often neglect the impact of fluctuating and uncertain energy prices. With the global energy crisis that peaked between 2022 and 2023, industries have faced significant price swings, making energy cost optimization a crucial factor in operational decision-making. Moreover, the growing shift toward renewable energy sources introduces further complexity, as solar and wind power generation is inherently volatile and reinforces price fluctuations. However, the recent decline in energy storage costs has made energy storage systems more attractive, offering manufacturers the opportunity to smooth their electricity demand by storing excess energy during low-cost periods and resorting to it later when prices are high. Those developments underpin the urgent need for dynamic, energy-aware production planning concepts that can adapt to fluctuations in both energy prices and availability, and effectively leverage energy storage systems.

To tackle those challenges, energy-aware decision-making in production systems has emerged as an important research area. This also applies to short-term, operational planning decisions, typically encountered at the level of detailed scheduling of jobs on the machines of the shop floor. A large body of academic research is devoted to job shop and flow shop dispatching incorporating time-of-use (ToU), real-time pricing (RTP) and power purchase agreement (PPA) considerations, as discussed in a recent article by Dunke and Nickel (2025). This work also confirms that energy storage systems have not yet received that much attention in this particular context. Clearly, the storage aspect makes the optimization problem more complex, raising issues like the following:

- *When should energy from storage be used instead of consuming from the grid?*
- *When should machines be stopped based on energy price, energy storage status, and workload?*

- *What is the overall cost advantage of an energy storage and how is it related to the size of the storage?*
- *How does an energy storage impact the balance between production-logistics costs and energy expenses?*

To address these questions for production dispatching, it is necessary to simultaneously take into account dynamic electricity pricing (RTP, ToU) and the availability of energy storage facilities.

Bokor et al. (2024) introduced an energy price and workload-related dispatching rule that dynamically adjusts machine operational states based on electricity prices and workload levels. This rule effectively optimizes machine utilization by turning machines on or off in response to short-term energy price variations. The approach was evaluated using a stochastic multi-item multi-stage job shop simulation model, leading to significant cost savings through improved production scheduling.

The underlying simulation model now serves as the basis for an extension towards the integration of an energy storage facility, allowing not only for greater flexibility in energy sourcing but also for increased cost efficiency, because stored energy might be used during periods of high electricity prices. Therefore, the decision logic from Bokor et al. (2024) is significantly extended to include energy price, energy storage status, and machine specific workload. In detail, the developed approach decides for: running machines with grid energy and refilling the energy storage if energy prices are low; running machines from energy storage if prices are medium and workload is high; or stopping machines if energy prices are high and workload is medium. For machines with high workload, processing is always allowed.

Unlike previous approaches, our model does not account for storage acquisition costs, as the primary focus is on operational decision-making regarding stored energy utilization. This allows us to isolate the true cost savings potential of energy storage integration without the influence of capital expenditures. Additionally, the effects of different energy storage capacities are evaluated. This work advances the understanding of how energy storage can be leveraged to optimize energy costs and improve operational efficiency in manufacturing processes. Additionally, the findings support the development of dynamic production planning strategies that can adapt to fluctuating energy prices and the increasing reliance on renewable energy sources. By evaluating the role of energy storage in balancing production-logistics costs, this research aims to guide industries toward more sustainable and cost-effective manufacturing practices.

The paper is structured as follows: After introducing the related literature in section 2, the new decision rule is described in detail in section 3. The simulation model setup as well as the studied production system and the energy price modelling are introduced in section 4. The computational study is the subject of section 5, followed by a summary of insights in the concluding section 6.

2 LITERATURE REVIEW

Increasing the energy efficiency of manufacturing systems can be achieved in various ways. Duflou et al. (2012) discuss three primary strategies: 1) the optimization of machine tool design, 2) process/machine tool selection, and 3) enhancement of process control. The former two measures are technology related, while the latter can be impacted by operational decision making. Hence process improvements shall be the focus of the paper at hand and thus also the discussion of related work.

Energy considerations have drastically grown in importance for operational planning and scheduling over the previous years. In (deterministic) scheduling, flexible job shops received considerable attention in recent academic research. Dunke and Nickel (2025) present a bi-objective approach to an energy-aware job shop scheduling problem, trying to find a balance between incurred energy cost and operational efficiency. Based on a mixed-integer programming formulation, they devise an ϵ-constraint technique for determining both an approximate and an exact version (for very small instances) of the Pareto frontier. The same trade-off is also addressed by other methods from operations research, like constraint programming (CP) or meta-heuristics. Building upon the work of Park and Ham (2022), Terbrack and Claus (2025) present a lexicographic approach with makespan minimization as the primary objective and various energy-related aspects (cost, peak demand, emissions) as the secondary ones. Meta-heuristics taking into account the multi-objective nature of energy-related scheduling include, for example, the non-dominated sorting genetic algorithm (NSGA-II) proposed by Burmeister et al. (2024).

Energy awareness has also gained relevance in the field of stochastic simulation of manufacturing systems. Wenzel et al. (2018) focus on the simulation of material flows and energy flows in production systems and their integration. They identify requirements, organizational questions, key goals and performance indicators that are relevant to energy-oriented simulation studies. Köberlein et al. (2022) present several case studies related to the simulation of production systems with the objective of energy flexibility, referring to the capability to quickly adapt to fluctuations in energy availability. Barth et al. (2023) establish a taxonomy for energy-centric simulation modeling, pinpointing dimensions and characteristics of such models. Recent concrete implementations include, for example, a machine control mechanism for a two-stage production line with parallel machines (Loffredo et al. 2024). The authors model the line as a Markov decision process and solve it using a linear programming formulation. For longer lines, they propose a tailored approximation method whose performance is evaluated using discrete-event simulation. A similar optimal control problem is described by Frigerio et al. (2024), who analyze the performance of buffer-based threshold policies to control multiple machines in a serial production line. Their numerical experiments rely on discrete-event simulation and investigate several aspects like the trade-off between policy complexity and obtainable energy savings.

Energy storage facilities add a further layer of complexity to the problem settings described above. They allow for storing certain amounts of energy during periods with low electricity cost or high supply provided by photovoltaic systems, for example. In the context of deterministic production planning and scheduling, Hilbert et al. (2023) study a combined lot-sizing and scheduling problem in a parallel machine environment. They propose a mixed-integer non-linear programming formulation with two conflicting energy-related criteria and generate Pareto-front representations using a convex combination of the two criteria. Kim et al. (2022) investigate a single machine scheduling problem with energy-generation and storage systems. The objective function is purely cost-based, involving production and energy cost-related components. The authors devise a hybrid genetic algorithm for the problem and measure its performance given solutions obtained from a mixed-integer programming formulation. Storage systems have also been incorporated in simulation modeling and analysis of manufacturing systems as latest work in this area shows. Breitschopf et al. (2023) devise a simulation-based optimization approach for a manufacturing scenario under consideration of local energy production and a hydrogen-based energy storage system. They embed a system dynamics simulation model into a genetic algorithm for determining certain production-related control parameters. A single-machine work center coupled with a battery storage system and a photovoltaic plant is the basis for the mathematical modeling approach proposed by Materi et al. (2021). Simulation experiments show that the energy storage system allows for reducing machine speed fluctuations that would normally arise when trying to reach maximum cost efficiency based on time-of-use energy prices.

3 THRESHOLD-BASED LOGIC FOR MACHINE AND STORAGE OPERATION

As stated in the introduction, the results from Bokor et al. (2024) showed a significant cost reduction potential synchronizing machine production with corresponding energy prices. However, to maintain satisfactory production-logistics performance, machine operation decisions (i.e., processing or idle) must also account for current workload levels. Consequently, machines may continue operating even during unfavorable energy price periods if workload demands require it. To address this issue, we extend the production system by integrating an energy storage system. This extension provides operational support during periods characterized by unfavorable energy prices, enabling a reduction of overall energy expenses from the production system's perspective. Additionally, integrating energy storage helps mitigate peak load issues within the broader energy grid, for instance, by storing surplus photovoltaic energy during sunny periods. While this study focuses on production system implications, future research could explore benefits extended to the wider energy grid.

3.1 Dispatching Scenario and Decision Framework

The investigated scenario comprises a multi-item, multi-stage production system (detailed in Section 4), where each machine requires a distinct decision regarding its operating state (operating or idle), supported by a shared energy storage system. Energy prices vary hourly. For simplicity, energy storage levels are updated in synchronization with hourly energy price changes and no machine warm-up time is considered. Decisions regarding the machine operation state (operating or idle) and the energy storage state (charging, discharging, or standby) rely on three primary inputs: 1) Current energy price p_c (globally); 2) Current energy storage level (globally); 3) Machine-specific workload w_j (sum of expected processing and setup times of queued orders). Execution on the shopfloor is primarily driven by an order list that specifies all production orders, including item type, quantity, and planned start and end dates. In this study, the order list is generated using the production planning and control system Material Requirements Planning (MRP), introduced by Orlicky (1975). However, the proposed dispatching rule is generic and compatible with any production planning and control system capable of generating order lists – such as ConWIP or Drum-Buffer-Rope (Bokor et al. 2019).

The decision-making framework is implemented through an energy-aware dispatching rule, consisting of:

- Machine Operation State Decision (per machine):
  After completing an order, decide whether to continue with the next order or become idle. For idle machines, reassess hourly whether restarting is beneficial based on updated price and workload.
- Energy Storage State Decision (globally):
  Upon each energy price change, decide whether to charge storage (if not fully charged). Evaluate whether to discharge energy to support production if prices are unfavorable and storage energy is available.

3.2 Threshold-Based Decision Logic

The developed energy-aware dispatching rule incorporates four thresholds to guide operational decisions. Whereby, two thresholds are related to the energy price and two to the workload. Generally, machines halt operations when no production orders are available. Once a production order is started, it must be completed without interruption, regardless of energy price changes. Idle machines reassess their state every hour based on updated inputs. Figure 1 presents a state chart that visualizes the operational logic of the energy-aware dispatching rule, detailing the relationships between energy price and workload scenarios related to machine and energy storage states, as well as the selected energy sources.

As shown in Figure 1, the decision-making process first evaluates the current energy price p_c against two *energy price-related thresholds*. Based on the resulting price scenario, the machine-specific workload w_j is then assessed against the *machine-specific workload thresholds*. The resulting operational logic is structured as follows, with Table 1 providing an overview of the notation used:

- Low Energy Price Scenario ($p_c < P_l$):
  Energy storage charges until full, and all machines continue operating without restriction as long as production orders are available. This scenario aims to maximize the use of low-cost energy.
- Medium Energy Price Scenario ($P_l \leq p_c < P_s$):
  Machine j operation depends on its workload w_j and energy availability in the storage:
  - If $w_j < W_c$, the machine remains idle.
  - If $w_j \geq W_c$
    and energy is available in storage, the machine starts a new production order. In the current logic, it is sufficient that some energy is available in the storage to allow the machine to produce. If required energy exceeds available energy storage, the machine switches to grid energy for finishing the current order. Future research could enhance the energy-aware dispatching rule by introducing an additional threshold that accounts for the minimum available energy to start operation.
    otherwise, the machine does not start a new order or it remains idle.

- If $w_j \geq W_m$, the machine operates regardless, prioritizing storage when available and switching to grid energy if necessary.
- High Energy Price Scenario $p_c \geq P_s$:
  Machine j operation again depends on its workload w_j:
  - If $w_j < W_m$, the machine remains idle.

If $w_j \geq W_m$, the machine continues operating, prioritizing stored energy and using grid energy if none is available. Note that production orders scheduled for the current hour are completed using grid energy once the energy storage is depleted.

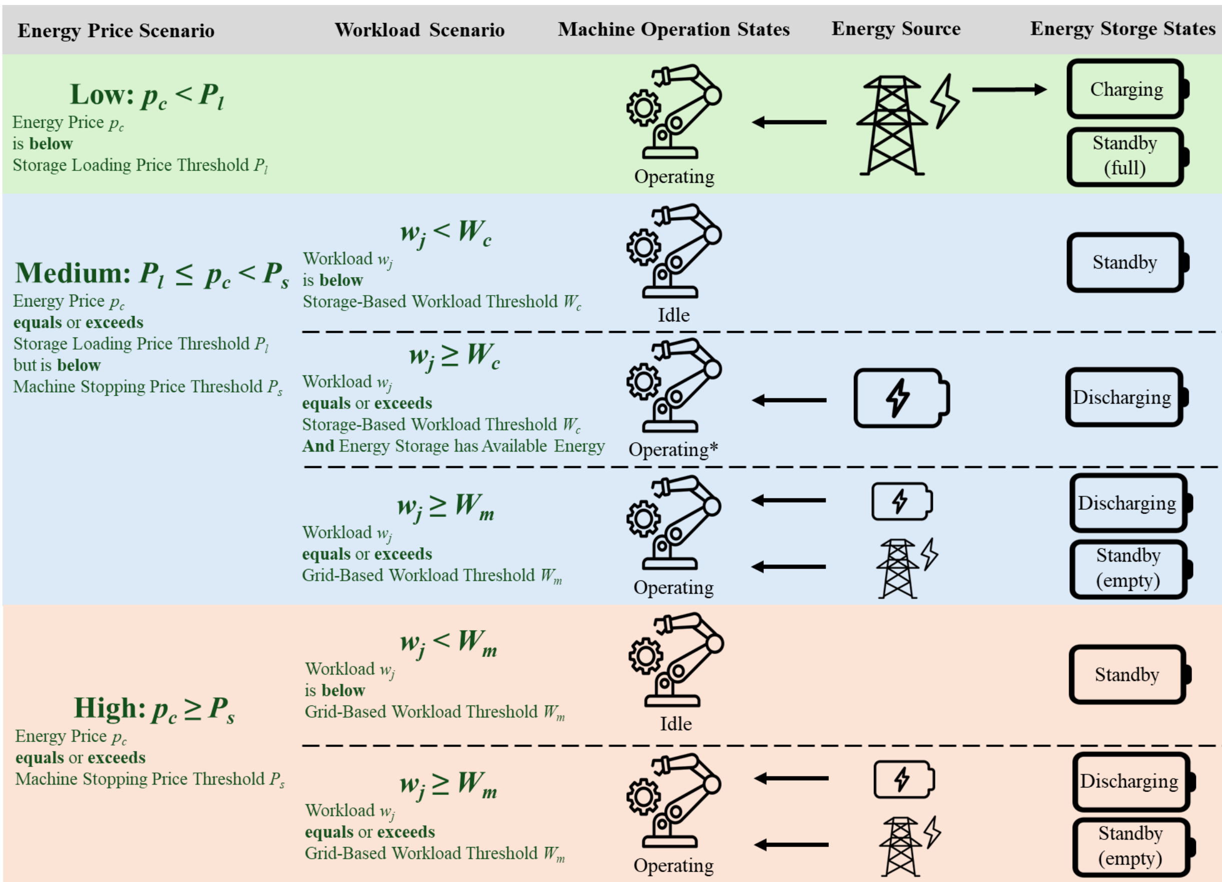

Figure 1: Threshold-driven state chart for machine and energy storage decisions.

Table 1: Notation.

Notation	Description
p_c	Current energy price (hourly changing variable).
w_j	Current workload of machine j (machine-specific state, updated upon order arrival/departure).
P_l / P_l^f	Storage loading price threshold / factor (defines price below which storage charging occurs).
P_s / P_s^f	Machine stopping price threshold / factor (defines price above which operational restrictions apply).
W_c / W_c^f	Storage-based workload threshold / factor (min. workload required to operate using stored energy).
W_m / W_m^f	Grid-based workload threshold / factor (min. workload required to continue operating even at high energy prices).

4 SIMULATION MODEL

To investigate the energy-aware dispatching rule, we build on the stochastic multi-item, multi-stage simulation model by Bokor et al. (2024). The framework is extended by introducing additional uncertainty sources – namely, stochastic energy prices and machine-specific energy requirements. Our dispatching algorithm is integrated into this enhanced simulation model, implemented using an agent-based discrete-event approach in AnyLogic 8.8.6. We first recap the production system structure before outlining the integration of energy-related aspects.

4.1 Production System and Order Generation

The investigated production system is a stochastic multi-item, multi-stage job shop with 8 items {101–108} and 4 machines {M1.1–M1.4}. Its structure, including the Bill of Materials (BoM) and routing logic, is shown in Figure 2.

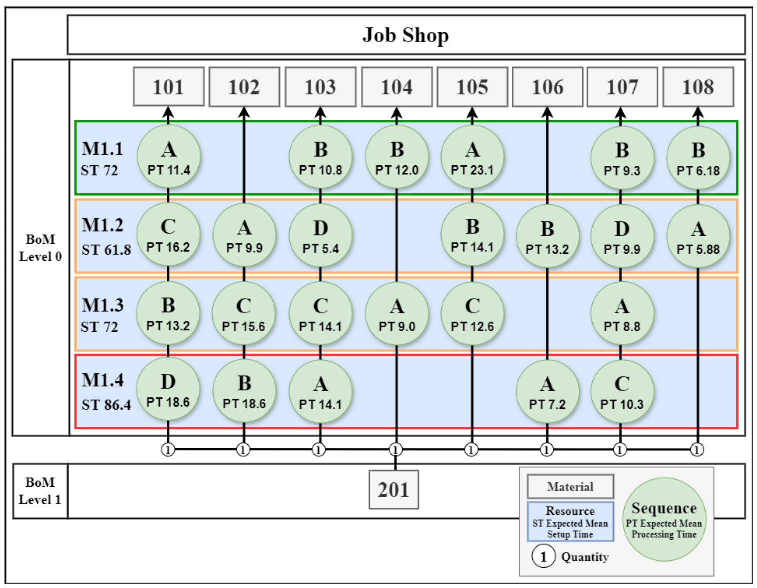

Figure 2: Investigated production system structure including bill of material.

The two-level BoM includes finished items (level 0) and a shared, always-available component (202) at level 1, which requires no planning. Each item follows a fixed machine routing (Figure 3), e.g., item 101 runs through M1.1 (A), M1.3 (B), M1.2 (C), and M1.4 (D). All operations involve processing and setup; setups are required even for identical items and are fixed at 10% of a machine's daily capacity (1,440 min). Processing and setup times follow lognormal distributions (CV 0.2). The system is dimensioned for 85% planned utilization (1,024 min/day per machine) to avoid bottlenecks. Orders include one item type, with interarrival times lognormally distributed (mean 8 periods, CV 0.2). Order quantities have item-specific lognormal means (CV 0.5). Customer-required lead times consist of 10 fixed periods plus a variable lognormal part (mean 5 periods, CV 0.5). Production orders are generated via MRP using four steps: netting, lot-sizing, backward scheduling, and BoM explosion (Hopp and Spearman 2011). A Fixed Order Period (FOP 1) policy is applied, with MRP running each period. Orders are released to the shop floor at their planned start time if materials are available. The release sequence is based on the Earliest Due Date (EDD), and machines process jobs in First-In-First-Out (FIFO) order.

4.2 Energy-Aware Dispatching and Energy Price Modeling

At dispatching, the developed energy-aware rule jointly determines both the machine's operation state (operating or idle) and the energy storage state (charging, discharging, or standby), based on the current energy price p_c and the current machine workload w_j relative to predefined thresholds (see Section 3). Storage charging from empty to full always requires two hours, regardless of storage capacity.

Unlike Bokor et al. (2024), where deterministic energy prices were assumed, this work introduces stochastic energy prices. The energy price p_c is modeled as a lognormally distributed random variable, capturing both long-term (monthly) and short-term (hourly) variations. Each month uses 24 different expected hourly prices (one for each hour of the day), based on real Austrian market data from 2023 (available via the SMARD platform). Figure 3 shows the daily and monthly expected values applied. The resulting 24-hour expected price profile remains identical across all days within a given month. At the time of dispatching, the expected hourly price serves as the mean of a lognormal distribution with a CV of 0.2, from which the realized hourly price is sampled, introducing realistic short-term uncertainty. The monthly average energy price is used to calculate two *energy price-related thresholds* (i.e., *storage loading price threshold* P_l and *machine stopping price threshold* P_s) by multiplying the monthly average with predefined factors (i.e., P_l^f and P_s^f). These factors are varied in the numerical study to evaluate their impact on dispatching behavior and system performance.

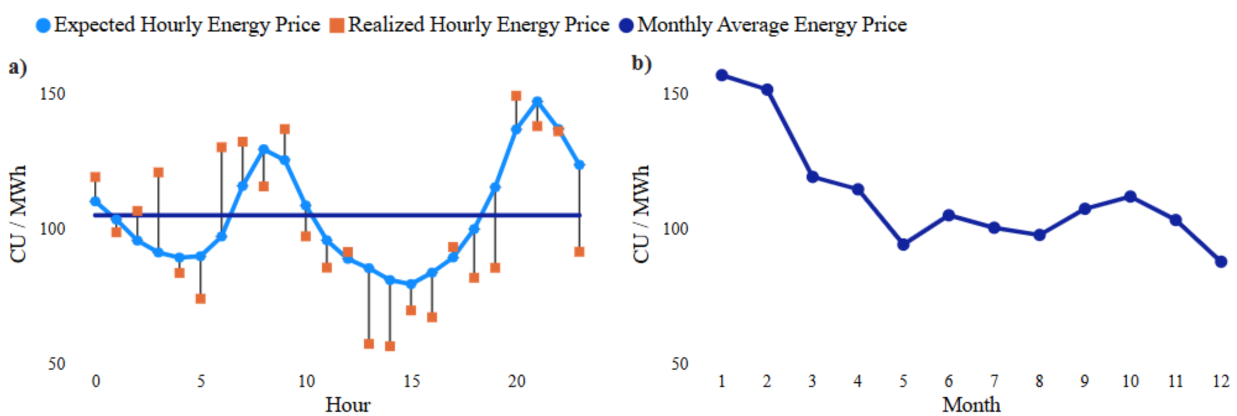

Figure 3: Energy Price Structure – (a) Short-Term (in June), (b) Long-Term.

In addition to energy prices, dispatching decisions also consider machine-specific workload thresholds. Each machine's current workload w_j is compared to the *machine-specific workload thresholds* (i.e., *storage-based workload threshold* W_c and *grid-based workload threshold* W_m) calculated by multiplying the machine's daily capacity (1,440 min) by predefined workload factors (i.e., W_c^f and W_m^f). These thresholds are likewise varied in the numerical study to analyze their influence on dispatching behavior and performance. Energy costs are calculated hourly by multiplying the realized energy price by each machine's occupation time (including setup and processing) and its specific energy requirement. In contrast to Bokor et al. (2024), machine-specific energy requirements are explicitly modeled: M1.1 requires 2.5 kW, M1.2 and M1.3 each require 5.0 kW, and M1.4 requires 7.5 kW. This machine-specific energy efficiency is visualized in Figure 2 by colored borders around the machines (red = high, orange = medium, green = low energy demand). Thus, for instance, if M1.1 operates at 50% utilization within one hour and the realized energy price is 120 Cost Unit (CU)/MWh, the corresponding energy cost is calculated as 0.12 CU × 0.5 (occupation time) × 2.5 kW (energy efficiency) = 1.25 kWh, resulting in 0.15 CU for that hour.

5 NUMERICAL STUDY

To evaluate the performance and investigate the behavior of the developed energy-aware dispatching rule, we conduct a comprehensive numerical study. A full factorial simulation experiment is performed, examining the influence of one environmental parameter (energy storage capacity) and multiple planning and dispatching rule parameters. Table 2 summarizes the tested parameters and their respective value ranges, determined based on preliminary simulation runs.

Table 2: Investigated parameters and value ranges for full factorial design.

Environmental Parameter	**Investigated Values**			**# Values**
Energy Storage Capacity [kWh]	{40, 80 ,160}			3
Planning / Dispatching Rule Parameters	**Min**	**Max**	**Step Size**	**# Values**
Planned Lead Time [day]	3	8	1	6
Storage Loading Price Factor (P_l^f)	0.50	1.40	0.10	10
Machine Stopping Price Factor (P_s^f)	0.50	1.40	0.10	10
Storage-Based Workload Factor (W_c^f)	0.25	2.50	0.25	10
Grid-Based Workload Factor (W_m^f)	0.25	2.50	0.25	10
Total Iterations				180,000
Valid Iterations ($\boldsymbol{P_l \leq P_s \wedge W_c \leq W_m}$)				**54,450**
Total Simulation Runs (5 Replication per Iteration)				272,250

For the environmental setting, the energy storage capacity is varied across three levels: {40, 80, 160} kWh. These capacities are designed to support the simultaneous operation of all four machines (shown in Figure 2) solely through stored energy. Given a total machine energy demand of 20 kWh per hour, the capacities correspond to maximum continuous operating durations of 2, 4, and 8 hours, respectively. For production planning, we configure the MRP system with a planned lead time (measured in days) and apply a Fixed Order Period lot-sizing policy. Although MRP parameters are typically item-specific, identical settings are applied across all items to avoid combinatorial complexity. We focus solely on the planned lead time, as Bokor et al. (2024) demonstrated its significant impact on energy consumption and dispatching behaviour. Following their recommendations – minimal lot sizes and no safety stock – we fix the lot size at FOP 1 and neglect safety stock at planning. For the dispatching rule configuration, we test ten distinct values for each of the four threshold-related factors (i.e., P_l^f, P_s^f, W_c^f and W_m^f). The selected parameter ranges align with those explored in Bokor et al. (2024), although their dispatching rule required only two factors.

As shown in Table 1, the full factorial design results in 180,000 unique parameter combinations. However, due to the operational logic of the energy-aware dispatching rule, only those satisfying the logical constraints $P_s \geq P_l \wedge W_m \geq W_c$ are evaluated, resulting in 54,450 valid configurations. Given the stochastic nature of the production system – through demand, processing times, and setup times (see Section 4.1) – each valid configuration is replicated 5 times for statistical robustness, resulting in 272,250 individual simulation runs. In addition, a baseline scenario without energy storage is simulated, based on the dispatching rule proposed by Bokor et al. (2024), which considers only two factors – the energy factor and capacity factor – using identical parameter ranges and step sizes.

Each simulation replication spans 415 simulated days, including a 50-day warm-up period, resulting in 365 effective simulation days – equivalent to one year – for which performance metrics are collected. To ensure computational efficiency, simulations are executed in parallel across 22 computers. Simulating all parameters for a single storage capacity took approximately 24 hours. The simulations were run in parallel on 22 computers, each equipped with an Intel Core i5-10500 (6 cores, 3.1 GHz) and 32 GB of RAM.

6 NUMERICAL RESULTS

To evaluate the energy-aware dispatching rule, overall costs are considered, combining production-logistics costs – WIP, FGI, and tardiness – with energy costs. In this setting, raw material costs are assumed to be 70 CU per component, with a 100% value-added markup applied, resulting in a manufacturing cost of 140 CU per finished item. With an annual carrying charge rate of 7%, this leads to holding costs of 4.90 CU per component in WIP and 9.80 CU per finished item in FGI, both calculated on an annual basis. Tardiness is penalized significantly more than inventory. The tardiness cost is derived from a target service level of 95%, calculated as service level = *1 - (FGI costs) / (FGI costs + tardiness costs)*, following Axsäter (2015) – a cost ratio of 1:19 between FGI and tardiness is obtained. Production orders late at the simulation end are counted as tardy. Energy costs are based on machine-specific energy efficiency and the energy cost modeling introduced in Section 4.2.

6.1 Impact of Storage Loading Price Factor

To discuss the effect of the *storage loading price factor* P_l^f (i.e., used to compute the threshold below which energy storage is charged, and production is always allowed), Figure 4 shows the best overall costs reached with the respective factor, applying the best-found parameter combination of all other decision parameters. Results are shown for the highest energy storage capacity (160 kWh). In addition to the costs, also the storage usage (measured in kWh of charged energy) is reported.

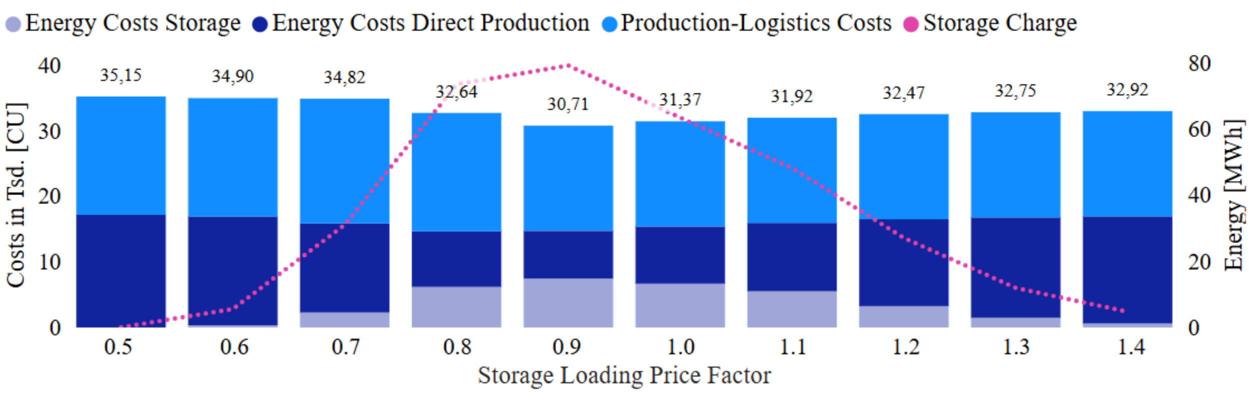

Figure 4: Impact of storage loading price factor on costs and storage utilization.

As illustrated in Figure 4, overall costs exhibit a convex relationship with respect to P_l^f. If P_l^f is too low, storage is rarely used, leading to high energy costs due to frequent direct production. Similarly, a very high threshold also results in high energy costs, but for a different reason, as production from the grid is allowed too often, and storage remains underutilized. The storage charge curve (purple line) highlights this behavior. At low thresholds, the energy price drops below the threshold only in few time periods, so storage is charged infrequently. As a result, most production relies on high-cost grid energy. In contrast, the optimal case (P_l^f=0.9) leads to extensive use of the storage as approximately 49.25% of the total energy are attributed to the storage, while the remaining 50.75% result from direct grid consumption, indicating substantial utilization of the storage system. This indicates that production is predominantly powered by storage, which is refilled whenever prices are sufficiently low - validating the intended behavior of the dispatching rule. For high P_l^f, storage charge is again low. Although the storage is typically full in this case, the decision rule still allows grid-based production, making the storage redundant and underused. Future refinements of the rule could consider separating the logic for allowing grid-based production from the decision to charge the storage.

6.2 Trade-Off between Production-Logistics Costs and Energy Costs.

To better understand the interdependency between energy costs and production-logistics costs, Figure 5 shows the Pareto front obtained from the numerical experiment reported in Section 4.2 again only for the highest energy storage capacity (160 kWh). The red points represent non-dominated solutions (configurations) within the predefined parameter ranges (see Table 2). They allow a decision maker to choose from optimized configurations depending on whether the emphasis is put on logistics cost or on energy costs. Configurations with production-logistics costs exceeding 20,000 CU were considered infeasible and have therefore been excluded from the presentation. The overall cost-optimal configuration (marked in green) is achieved with a low *storage-based workload factor* W_c^f=0.25 and a low *grid-based workload factor* W_m^f*=0.25*. In contrast, the configuration yielding the lowest production logistics costs (marked in yellow) results in energy costs 11.47% higher. In this case, to P_s^f is at its maximum value, implying that machines are effectively always allowed to produce, regardless of energy price. As the other extreme, the configuration with the lowest energy costs is obtained for W_m^f=0.75. This setting restricts machine operation during high energy price periods, reducing energy consumption by 15.73%, but leading to high penalty costs incurred through excessive delays.

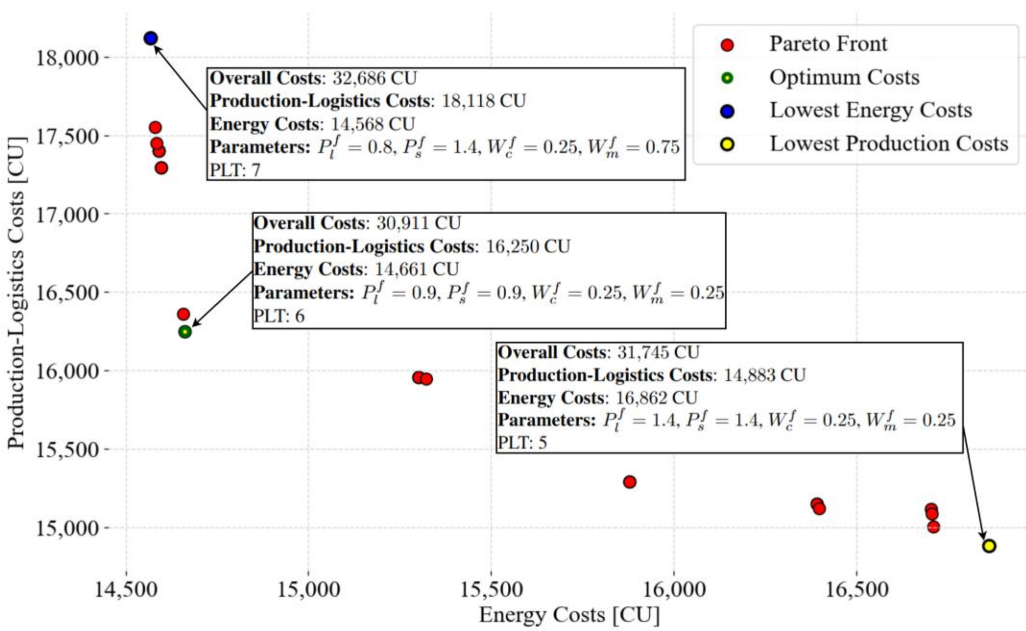

Figure 5: Pareto front of energy costs vs. production-logistics costs (160 kWh storage).

6.3 Parametrization and Performance Analysis Across Different Storage Capacities

Managers must assess how storage capacity affects cost savings, as summarized in Table 3. The baseline scenario *No storage* – reflecting only the machine stopping decision, similar to Bokor et al. (2024) – results in total costs of 32,621 CU. Introducing a 40 kWh storage system reduces energy costs by 4.6%, representing a respective statistically significant improvement ($\alpha = 0.01$, **). Increasing the capacity to 80 kWh and 160 kWh further lowers energy costs by 7.0% and 14.4%, respectively, also significant at $\alpha = 0.01$ (**), compared to the baseline energy costs. Note that the best storage settings were replicated 10 times to test significance. However, looking at the overall costs, doubling or even quadrupling storage capacity yields only limited additional overall cost savings. Primarily, it can be observed that total energy costs decrease with increasing storage capacity, as a higher storage capacity enables more kWh to be charged per cycle at lower energy prices. On the other hand, production-logistics costs remain at similar levels for low to medium storage capacities and increase for higher storage capacity. An additional insight is that the optimal decision parameters appear largely independent of the storage capacity. Storage operating costs and ROI considerations are excluded here but might be the subject of future research to support an even more refined decision-making.

Table 3: Performance analysis across storage capacities.

	Storage Capacity	**No Storage**	**40 kWh**	**80 kWh**	**160 kWh**
Optimal Parameters	Planned Lead Time [day]	5	5	5	6
	Storage Loading Price Factor(P_l^f)	-	1.1	1.1	0.9
	Machine Stopping Price Factor(P_s^f)	1.4	1.1	1.1	0.9
	Storage-Based Workload Factor(W_c^f)	-	0.25	0.25	0.25
	Grid-Based Workload Factor(W_m^f)	0.25	0.25	0.25	0.25
Minimal Costs [CU]	Energy Costs Storage	17,133	12,954	10,759	7,222
	Energy Costs Direct Production	0	3,387	5,175	7,439
	Total Energy Costs	17,133	16,341	15,934	14,661
	Production-Logistics Costs	15,488	15,292	15,292	16,250
	Overall Costs	**32,621**	**31,633**	**31,226**	**30,911**
	Energy Costs Reduction Potential	-	4.6%**	7.0%**	14.4%**

7 CONCLUSION

In this paper a threshold-based energy aware machine control approach is described and its effectiveness for production systems equipped with an energy storage facility is demonstrated. In essence, we proposed a combined, parameterizable decision rule for charging the energy storage, starting/stopping machines and satisfying energy requirements for production either from the storage or the grid and we evaluated it in a numerical simulation study. The results show that using energy storage in combination with the developed decision rule exhibits a significant cost reduction potential. Besides that, the workload threshold component of the rule can successfully keep the production logistics costs (inventory and tardiness) at a stable level in the optimal setting for all tested scenarios (no storage, 40 kWh, 80 kWh, and 160 kWh storage). Although storage capacity increases exponentially, the resulting cost savings show diminishing marginal returns, each additional unit of capacity yields progressively smaller benefits. However, the developed model provides insights into how effective the energy storage is from an overall point of view. The developed decision rule implements a straightforward logic for handling the trade-off between machine start/stop decisions and the energy storage charging/unloading management. The results obtained give hints to further enhance our decision rule. Future research might also address start-up periods of machines, personnel decisions related to operating machines and different decision parameters with respect to machine and month.

ACKNOWLEDGMENTS

This work was supported by the research project ENPro. The project ENPro is financed by research subsidies granted by the government of Upper Austria.

REFERENCES

Axsäter, S. 2015. Inventory Control. 3rd ed. International Series in Operations Research & Management Science, vol. 225. Cham: Springer International Publishing.

Barth, M., E. Russwurm, B. Gutwald, D. Kunz, T. Reichenstein, and J. Franke. 2023. "Modeling and Simulation Techniques for Energy Behavior in Production Systems: A Review and Systematic Taxonomy." 2023 IEEE 2nd Industrial Electronics Society Annual On-Line Conference (ONCON), 1–6.

Bokor, B., W. Seiringer, K. Altendorfer, and T. Felberbauer. 2024. "Energy Price and Workload Related Dispatching Rule: Balancing Energy and Production Logistics Costs." In 2024 Winter Simulation Conference (WSC), 1681–1692 http://doi.org/10.1109/WSC63780.2024.10838840 .

Bokor, B., W. Seiringer, and K. Altendorfer. 2025. "Integrating Simulation Budget Management into Drum-Buffer-Rope: A Study on Parametrization and Reducing Computational Effort." In Decision Sciences. DSA ISC 2024, edited by A. A. Juan, J. Faulin, and D. Lopez-Lopez, 220–234. Lecture Notes in Computer Science, vol. 14778. Cham: Springer.

Breitschopf, J., T. Sobottka, G. Zabik, and F. Ansari. 2023. "Simulation-Based Optimization of Flexible Energy Systems in Manufacturing with Local Energy Production and Storage Components." Procedia CIRP 120:434–439.

Burmeister, S. C., D. Guericke, and G. Schryen. 2024. "A Memetic NSGA-II for the Multi-Objective Flexible Job Shop Scheduling Problem with Real-Time Energy Tariffs." Flexible Services and Manufacturing Journal 36(4):1530–1570.

Duflou, J. R., J. W. Sutherland, D. Dornfeld, C. Herrmann, J. Jeswiet, S. Kara, M. Hauschild, and K. Kellens. 2012. "Towards Energy and Resource Efficient Manufacturing: A Processes and Systems Approach." CIRP Annals 61(2):587–609.

Dunke, F., and S. Nickel. 2025. "Approximate and Exact Approaches to Energy-Aware Job Shop Scheduling With Dynamic Energy Tariffs and Power Purchase Agreements." Applied Energy 380:125065.

Frigerio, N., B. Tan, and A. Matta. 2024. "Simultaneous Control of Multiple Machines for Energy Efficiency: A Simulation-Based Approach." International Journal of Production Research 62(3):933–948.

Hilbert, M., A. Dellnitz, and A. Kleine. 2023. "Production Planning Under RTP, TOU and PPA Considering a Redox Flow Battery Storage System." Annals of Operations Research 328(2):1409–1436.

Hopp, W. J., and M. L. Spearman. 2011. Factory Physics: Foundations of Manufacturing Management. 3rd ed. Long Grove, Illinois: Waveland Press.

Kim, H.-J., E.-S. Kim, J.-H. Lee, L. Tang, and Y. Yang. 2022. "Single-Machine Scheduling With Energy Generation and Storage Systems." International Journal of Production Research 60(23):7033–7052.

Köberlein, J., L. Bank, S. Roth, E. Köse, T. Kuhlmann, B. Prell, et al. 2022. "Simulation Modeling for Energy-Flexible Manufacturing: Pitfalls and How to Avoid Them." Energies 15(10):3593.

Loffredo, A., N. Frigerio, E. Lanzarone, and A. Matta. 2024. "Energy-Efficient Control in Multi-Stage Production Lines With Parallel Machine Workstations and Production Constraints." IISE Transactions 56(1):69–83.

Materi, S., A. D'Angola, D. Enescu, and P. Renna. 2021. "Reducing Energy Costs and CO_2 Emissions by Production System Energy Flexibility Through the Integration of Renewable Energy." Production Engineering 15(5):667–681.

Orlicky, J. 1975. Materials Requirements Planning: The New Way of Life in Production and Inventory Management. 1st ed. New York: McGraw-Hill, Inc.

Park, M.-J., and A. Ham. 2022. "Energy-Aware Flexible Job Shop Scheduling Under Time-of-Use Pricing." International Journal of Production Economics 248:108507.

Terbrack, H., and T. Claus. 2025. "The Generalized Energy-Aware Flexible Job Shop Scheduling Model: A Constraint Programming Approach." Computers & Industrial Engineering 204:111065.

Wenzel, S., T. Peter, J. Stoldt, A. Schlegel, T. Uhlig, and J. Josvai. 2018. "Considering Energy in the Simulation of Manufacturing Systems." In 2018 Winter Simulation Conference (WSC), 3275–3286 http://doi.org/10.1109/WSC.2018.8632238.

AUTHOR BIOGRAPHIES

WOLFGANG SEIRINGER is a Research Associate in the field of Operations Management at the University of Applied Sciences Upper Austria and a Ph.D. candidate at the Johannes Kepler University Linz in Logistics and Supply Management. His dissertation focuses on simulation-based production planning with dynamic lead times and optimization of capacity-constrained systems. He has published in international conference proceedings and is involved in industry-driven research projects on energy-aware scheduling and simulation-supported decision making. His research interests include discrete-event simulation, stochastic modeling, and optimization methods for production and logistics. Email: wolfgang.seiringer@fh-steyr.at

BALWIN BOKOR is a Research Associate in the field of Operations Management at the University of Applied Sciences Upper Austria and a Ph.D. candidate at the Johannes Kepler University Linz in Logistics and Supply Management. His research addresses simulation-based optimization, production planning under uncertainty, and energy-aware scheduling in manufacturing systems. He has contributed to projects that combine simulation, heuristics, and mathematical programming to support decision making in complex production environments. He regularly presents his work at international conferences such as the Winter Simulation Conference. Email: balwin.bokor@fh-steyr.at

KLAUS ALTENDORFER is Professor of Operations Management at the University of Applied Sciences Upper Austria. He has more than 15 years of experience in teaching and research, focusing on production system simulation, stochastic inventory models, and hierarchical production planning. He has published widely in international journals such as *International Journal of Production Research* and *Flexible Services and Manufacturing Journal*. He is an active member of the simulation community, serves as reviewer for leading journals, and participates in scientific program committees. His applied research projects involve collaboration with industrial partners on production planning and supply chain optimization. Email: klaus.altendorfer@fh-steyr.at

ROLAND BRAUNE is Professor of Production Economics at the University of Applied Sciences Upper Austria. He has longstanding expertise in production scheduling, simulation modeling, material flow optimization, and transport logistics. His research combines quantitative modeling approaches with applied industrial projects, addressing challenges such as supply chain resilience and efficient resource allocation. He is also active in academic teaching and supervision of graduate and doctoral students in production and logistics. Email: roland.braune@fh-steyr.at