



Digital Twin-Based Optimization of Energy Efficiency in Industrial Production Systems: A Simulation and Machine Learning Framework

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ABSTRACT

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Factories draw heavily on energy supplies, leaving manufacturers with the difficult task of cutting power use without hurting output. We built a simulation-based digital twin of an industrial production system to forecast power usage and production efficiency, as well as test different operational scenarios. A full year of synthetic hourly operating figures was generated, capturing equipment load, machine utilization, run time, ambient temperature, output rates, and energy use. To forecast efficiency and energy demand, we trained Random Forest, XGBoost, and Artificial Neural Network models, then judged their accuracy using Mean Absolute Error, Root Mean Square Error, and the coefficient of determination. Across both targets, XGBoost yielded the lowest error rates alongside the highest coefficient of determination. We then integrated this top model into the digital twin, optimizing operating scenarios against a set floor for production efficiency. Pairing batch consolidation with balanced equipment loads trimmed simulated power draw by 17.1% and cut energy per finished item by 19.1% with a minor boost to efficiency; by contrast, an aggressive load-slashing plan saved more power but missed the efficiency floor. These results demonstrate that combining digital twins with machine learning helps operators make better, energy-conscious choices on the shop floor. We outline what these findings mean for plant managers, energy engineers, and Industry 4.0 specialists, while pointing to future research using data collected from operating plants.

Introduction

A substantial portion of industrial energy goes straight into manufacturing, making process- and system-level efficiency a pressing operational priority as power prices climb and environmental standards tighten (Duflou et al., 2012). Scholars in sustainable manufacturing have pointed out for years that cutting power use must happen across broad production lines as well as individual machines, requiring rigorous engineering approaches to lower consumption without denting output (Haapala et al., 2013). Striking such a balance hinges on having dependable projections of plant power requirements under shifting operating states, which requires precise energy forecasting (Walther & Weigold, 2021).

Digital twins provide a viable path toward solving that problem. Defined as a virtual model tied to an actual asset via data streams, a digital twin lets engineers track, evaluate, and test the physical equipment entirely in software (Tao et al., 2019). For manufacturing environments, researchers have proposed digital twins that blend physical and cyber data across product design, production, and service (Tao et al., 2018), with work also exploring how they pair with big data analytics to underpin smart manufacturing and Industry 4.0 (Qi & Tao, 2018). Review papers have grouped digital twin research by how deeply physical and digital objects share data (Kritzinger et al., 2018) and have detailed foundational concepts, enabling technologies, and real-world industrial uses (Liu et al., 2021; Leng et al., 2021).

More recently, digital twins have also seen initial use in manufacturing energy management. Ma et al., (2022) paired digital twins with big data to outline a sustainable smart manufacturing framework for energy-intensive sectors, showing lower energy use and reduced costs across two industrial cases. Bermeo-Ayerbe et al., (2022) used a digital twin approach to construct an adaptive, real-time data-driven energy model for industrial equipment, whereas Zou et al., (2017) created a data-driven system model alongside real-time control rules meant to lift both energy efficiency and profits. Machine learning has become widely viewed as a primary analytical engine behind digital twins, a point underscored by Chen et al., (2023) in their review of machine learning within predictive-maintenance digital twins.

Even with these advancements, notable gaps persist. Most published studies rely on just one predictive model or a single control scheme, and side-by-side comparisons of different machine learning algorithms inside an energy-predicting digital twin are less frequent. Predictive models are also often introduced without running them through operational scenarios, missing much of the point of a digital twin, which is to trial what-if choices before applying them to physical assets. Lastly, energy cuts are seldom analyzed alongside factory throughput, even though cutting power simply by throttling output does manufacturers little good (Duflou et al., 2012; Zou et al., 2017).

This study tackled those gaps by building a simulation-based digital twin for an industrial plant, centering the framework on machine utilization, production rate, temperature, energy consumption, operating time, and equipment load. Random Forest, XGBoost, and Artificial Neural Network models were benchmarked against each other for estimating energy use and production efficiency, evaluated by Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). The top-ranking model was embedded in the digital twin to run scenario-based optimizations, keeping production steady while driving energy consumption down.

Literature Review

Manufacturing Energy Efficiency

The earliest work on industrial energy consumption tended to look at machines and operations in isolation. By analyzing the environmental footprint of machining through its operational energy demands, Dahmus and Gutowski (2004) helped position energy use as a primary metric of manufacturing performance. Avram and Xirouchakis (2011) assessed the energy a machine tool system draws during its use phase, showing why it matters to track power consumption through each operational state. Duflou et al., (2012) later surveyed methods for boosting energy and resource efficiency in discrete part manufacturing, framing improvements through a process and systems perspective that spanned machine, line, and plant tiers. Haapala et al., (2013) surveyed sustainable manufacturing research and pointed to modeling and decision-support tools as key drivers of progress; more recently, Sihag and Sangwan (2020) confirmed machine tool energy use remains an active field in their systematic review.

Architectures and Concepts of the Digital Twin

Manufacturing scholars have written extensively about the digital twin concept. Negri et al., (2017) examined how cyber-physical production systems employ digital twins, drawing particular attention to simulation, monitoring, and control. Schleich et al., (2017) designed a reference model to structure digital twins across design and production engineering, stressing how critical it is that virtual models mirror physical products and processes consistently. Kritzinger et al., (2018) classified published studies according to how much data flows automatically between physical systems and their virtual counterparts, drawing boundaries that help separate true digital twins from digital models and shadows. Qi and Tao (2018) weighed digital twins against big data as drivers of smart manufacturing and Industry 4.0, while Tao et al., (2018) detailed a data-heavy, digital twin

framework spanning design, fabrication, and product service. Tao et al., (2019) delivered an assessment of industrial digital twins, whereas Liu et al., (2021) and Leng et al., (2021) each surveyed foundational concepts, technologies, and applications, specifically considering how they inform smart manufacturing system design.

Applying Digital Twins to Energy Management in Production Systems

Energy considerations are drawing attention from an expanding corner of the digital twin literature. Ma et al., (2022) combined digital twins with big data analytics inside an energy-intensive industrial setting and proved out lower energy use and expenses over two separate cases. Bermeo-Ayerbe et al., (2022) built an online, adaptive data-driven energy model under a digital twin architecture, showing it more than doubled estimation fit relative to a static version while picking up shifts in energy use that point to necessary maintenance. Zou et al., (2017) built a data-driven stochastic model of a manufacturing plant to pinpoint potential energy savings and gauge their effect on throughput, integrating it with real-time distributed feedback control. Taken together, these papers demonstrate how digital twins can bridge the gap between predicting energy use and controlling operations, though most rely on a single model rather than testing alternatives against each other.

Machine Learning in Data-Driven Energy Prediction

Before any efficiency gains can be measured, one first has to be able to predict energy consumption. In a systematic review of 72 articles on forecasting electrical energy use in manufacturing, Walther and Weigold (2021) grouped the literature by system boundary, modeling technique, modeling focus, modeling horizon, modeling perspective, modeling purpose, and model output, using those patterns to map out future research. What their review makes clear is both the wide variety of methods being used and the need to align the chosen technique with what the model is meant to do and where its boundaries lie. Chen et al., (2023) surveyed progress in digital twins for predictive maintenance and looked at how machine learning functions within them, emphasizing that machine learning models serve as the analytical core across many implementations. Bermeo-Ayerbe et al., (2022) and Zou et al., (2017) took a similar line, turning to data-driven formulations instead of purely phenomenological ones. These earlier studies point to the need for a head-to-head comparison of tree ensembles and neural networks inside a digital twin, especially when a single dataset has to feed predictions for several targets like energy consumption and production efficiency.

Scenario Optimization and the Unaddressed Gap

The real strength of a digital twin is that operators can test out scenarios virtually before committing changes to the actual equipment. Both the systems view from Duflou et al., (2012) and the control strategy in Zou et al., (2017) recognize that energy cuts cannot be evaluated in isolation from output, since saving power at the expense of production volume rarely makes sense. Ma et al., (2022) took a matching stance, treating sustainability as a target that must be met in tandem with productivity and cost. Yet almost none of the papers surveyed bring together a comparison of several machine learning algorithms with scenario optimization bounded by production constraints inside a single digital twin framework. This investigation was designed to close that specific gap.

Methodology

Research Design

The work relied on a quantitative research design centered on simulation. A discrete production line was modeled as the physical layer of a digital twin framework, which linked directly to a virtual side made up of a data repository, predictive models, and an engine for scenario evaluation. This setup worked in a closed loop: the simulated line sent operating data to the repository, those records trained and validated predictive models, and those models tested different operating scenarios so the recommended settings could be returned to the line.

Simulation of the Production System and Data Generation

A Python-based discrete-event simulation of a multi-station line served as the physical layer. Running the simulation at hourly increments for a full year produced 8,760 observations. Every observation tracked six metrics: machine utilization (productive time as a percentage of available time), hourly production rate in units, enclosure temperature in degrees Celsius, daily operating time in hours, equipment load as a percentage of rated capacity, and hourly energy consumption in kilowatt-hours. Production efficiency was calculated as

actual output divided by rated output, given as a percentage. Stochastic order arrivals supplied demand shifts across work shifts, days of the week, and seasons, while random noise and sporadic missing values were introduced to mimic industrial sensor conditions. Because these were simulated data, the relationships between variables came entirely from the simulation rules, meaning the results show how the framework performs rather than describing any actual manufacturing plant.

Data Preprocessing

Gaps from missing readings were filled by linear interpolation between surrounding time steps, while the interquartile range rule was used to filter out extreme values. Predictors were scaled to zero mean and unit variance for the Artificial Neural Network, but left on their raw scales for the tree models. Divided strictly by chronological order, the data went into a 70% training set, a 15% validation set, and a 15% test set, which kept evaluation confined to later periods untouched during training or tuning.

Predictive Model Development

Two outcomes were targeted for prediction: hourly energy consumption and production efficiency. Energy consumption was modeled using machine utilization, production rate, temperature, operating time, and equipment load; production efficiency used the same predictors minus production rate. Three models were constructed for each prediction target. A Random Forest regressor was trained as an ensemble of decision trees, with tree count, maximum depth, and minimum leaf samples optimized through grid search against the validation set. The XGBoost regressor was configured as a gradient-boosted ensemble of shallow trees, with early stopping enabled and the learning rate, boost rounds, maximum depth, and regularization tuned on the validation set. The Artificial Neural Network used a feedforward design with two hidden layers, rectified linear unit activation, and the Adam optimizer; early stopping was applied, and validation data served to tune neuron counts, batch size, and epoch limits.

Model Evaluation

Three metrics were used to gauge how well the models performed on the test subset. MAE was taken as the average absolute difference between what was predicted and what actually occurred. Because it weights large errors more heavily, RMSE was included and calculated by taking the square root of the mean squared differences. The coefficient of determination (R^2) measured what share of the variance in the actual values the model managed to explain. Better predictive performance was seen in higher R^2 values alongside lower MAE and RMSE results. To further check the digital twin's fidelity, energy consumption forecasts from the top-performing model were set against simulated actual usage across representative hours.

Scenario-Based Optimization

Operating scenarios were assessed by embedding the top energy and efficiency models directly into the digital twin. Two controllable operating levers were established: equipment load balancing, which spread work across machines to bring down peak equipment load, and consolidated batching, which pooled production into fewer, larger batches to increase machine utilization and curb idle time. A grid search across targets for utilization and equipment load was used to assess different combinations of lever settings. The optimization sought to lower both hourly energy consumption and energy per unit produced, provided that predicted production efficiency stayed at 85% or higher. A baseline scenario based on typical observed operations was evaluated alongside four representative scenarios from the search, comparing their utilization, equipment load, energy consumption, percentage shift in energy use, production efficiency, and energy per unit.

Analysis

This section presents the descriptive features of the simulated operational data, how operating variables relate to energy use, the relative performance of all three machine learning models, the digital twin's fidelity, and what the scenario-based optimization produced.

Table 1

Descriptive Statistics of Simulated Operational Variables (N = 8,760)

Variable	Mean	SD	Minimum	Maximum
Machine Utilization (%)	68.4	14.2	21.0	97.5
Production Rate (units/h)	112.6	26.8	18.0	176.0
Temperature (°C)	41.7	6.3	24.5	63.9
Operating Time (h/day)	15.8	3.6	6.0	22.5
Equipment Load (%)	72.9	15.7	25.0	100.0
Energy Consumption (kWh)	384.5	92.6	118.2	671.4

Note. SD = standard deviation. Values were derived from one year of simulated hourly data.

Table 2

Pearson Correlations between Operating Variables and Energy Consumption

Variable	r	p
Machine Utilization	.78	< .001
Equipment Load	.72	< .001
Production Rate	.69	< .001
Operating Time	.41	< .001
Temperature	.33	< .001

Note. N = 8,760. All correlations were statistically significant at the .001 level.

As shown in Table 2, energy consumption correlated most strongly and positively with machine utilization, equipment load, and production rate, whereas operating time and temperature demonstrated moderate relationships. Test-subset predictive metrics for each of the three models across both targets are reported in Table 3.

Table 3

Predictive Performance of the Machine Learning Models on the Test Subset

Target	Model	MAE	RMSE	R ²
Energy Consumption (kWh)	Random Forest	14.8	19.7	.953
	XGBoost	12.3	16.4	.968
	Artificial Neural Network	16.9	22.1	.941
Production Efficiency (%)	Random Forest	1.84	2.43	.917

Target	Model	MAE	RMSE	R ²
	XGBoost	1.52	2.01	.944
	Artificial Neural Network	1.97	2.61	.903

Note. MAE = Mean Absolute Error; RMSE = Root Mean Square Error; R² = coefficient of determination. MAE and RMSE are expressed in the units of each target. Lower MAE and RMSE and higher R² indicate better performance.

Across both energy consumption and production efficiency, XGBoost yielded the lowest MAE and RMSE alongside the highest R², with Random Forest taking second place and the Artificial Neural Network ranking last. We integrated XGBoost into the digital twin since it delivered the strongest results across both targets. The fidelity of these energy forecasts is broken down across typical weekday hours in Table 4.

Table 4

Digital Twin Fidelity: Actual Versus XGBoost-Predicted Energy Consumption for a Representative Weekday

Hour	Actual (kWh)	Predicted (kWh)	Absolute Error (kWh)	Error (%)
06:00	212.4	219.1	6.7	3.2
09:00	398.7	388.9	9.8	2.5
12:00	512.3	526.0	13.7	2.7
15:00	487.6	474.2	13.4	2.7
18:00	341.9	350.8	8.9	2.6
21:00	226.8	221.5	5.3	2.3

Note. Error (%) = absolute error divided by actual energy consumption. Values were rounded to one decimal place.

Across the hours examined, the digital twin tracked simulated energy use closely, showing percentage errors between 2.3% and 3.2%. The results of the scenario-based optimization appear in Table 5.

Table 5

Scenario-Based Optimization Results under a Minimum Production-Efficiency Constraint of 85%

Scenario	Utilization (%)	Load (%)	Energy (kWh/h)	Change (%)	Efficiency (%)	kWh/unit
So: Baseline	68	73	384.5	0.0	86.2	3.41
S1: Load balancing	72	68	351.8	-8.5	87.1	3.11
S2: Consolidated batching	78	70	337.4	-12.2	88.4	2.94
S3: Combined S1 + S2	80	66	318.9	-17.1	88.9	2.76

Scenario	Utilization (%)	Load (%)	Energy (kWh/h)	Change (%)	Efficiency (%)	kWh/unit
S4: Aggressive load reduction	64	58	301.2	-21.7	79.5	3.10

Note. Energy values were predicted by the XGBoost model and efficiency values by the XGBoost efficiency model. Change (%) is relative to the baseline. Scenario S4 did not satisfy the 85% production-efficiency constraint.

Scenario S3, which combined load balancing and consolidated batching, produced the lowest energy consumption among the scenarios that satisfied the production-efficiency constraint, reducing energy by 17.1% relative to the baseline and lowering energy per unit from 3.41 to 2.76 kWh, a reduction of 19.1%, while production efficiency rose from 86.2% to 88.9%. Scenario S4 cut the most absolute energy of all, but it dropped production efficiency to 79.5%—violating the 85% rule—and left unit energy above that of S3, demonstrating that lowering load without keeping output up is an inefficient path to saving energy.

Discussion

These results show that combining a simulation-based digital twin with a solid machine learning model can guide energy-conscious choices on a production line. Across both targets, XGBoost beat out Random Forest and the Artificial Neural Network; because its errors were low, the digital twin's hourly energy estimates stayed within roughly 2% to 3% of the simulated numbers. Since simulated data generated these outcomes, the performance order reflects only the modeled environment and cannot be taken as proof that XGBoost will come out ahead in every facility. Walther and Weigold (2021) showed that forecasting energy use in manufacturing involves varied methods depending on model purpose and system boundaries, a reality that justifies testing multiple algorithms against facility-specific data before settling on one for a digital twin.

How hard and how evenly machines ran largely governed energy demand in this simulated line, as shown by how tightly energy use tracked machine utilization, equipment load, and production rate. That relationship explains why the scenario testing targeted those two specific operational levers. By pairing higher utilization from consolidated batching with lower peak equipment load from balancing, the scenario runs lowered total energy and energy per unit without hurting production efficiency. That matches the systems approach outlined by Duflou et al. (2012), where line-wide coordination across equipment yields savings that single-machine adjustments cannot, and it aligns directionally with findings by Ma et al. (2022) and Zou et al. (2017) showing that data-driven or twin-based control cuts factory energy use and spending.

Stacking scenario S3 against S4 shows why setting a strict production constraint is necessary. Though S4 cut gross energy the furthest, it did so by throttling back load and throughput, pulling production efficiency under the limit and pushing energy per unit above the level achieved in S3. Testing these scenarios against production metrics alongside energy metrics reflects Zou et al.'s (2017) point that energy-reduction options must always be weighed against their consequences for output. A broader takeaway is that the digital twin exposed this balance virtually before anyone touched the actual equipment, fulfilling one of the chief promises of digital twin systems described by Tao et al. (2019). Several limitations should be noted: the study relied on simulated records, tested only two scenario levers, and ran the digital twin offline against historical simulated batches instead of continuous, online deployment like the adaptive framework in Bermeo-Ayerbe et al. (2022).

Conclusion and Recommendations

In this study, a simulation-driven digital twin framework was built for a manufacturing system to benchmark Random Forest, XGBoost, and Artificial Neural Network models for forecasting energy and production efficiency, as well as to optimize operational setups across scenarios. Across both target metrics, XGBoost secured the lowest MAE and RMSE alongside the highest R^2 , allowing the twin to follow hourly energy use within an error band of roughly 2% to 3%. Using the twin, balancing equipment loads alongside consolidated batching cut simulated energy use by 17.1% and unit energy by 19.1% while respecting the 85% production-efficiency threshold, whereas an aggressive load-slashing alternative broke that rule. Manufacturers setting up digital twins to manage energy ought to benchmark several machine learning algorithms on their actual plant data prior to selection; likewise, every prospective operating scenario should be weighed against both production performance and energy consumption, not energy figures alone. Plant managers should focus on

measures that raise machine utilization while cutting peak equipment loads—the two variables tied most closely to energy consumption in this study—and run a small pilot on one section of the line before applying digital twin recommendations across the entire facility. Subsequent work needs to swap simulated inputs for genuine data across multiple plants, incorporate online learning to help models adjust as demand and machinery shift, bring in extra levers like setpoint control, scheduling, and energy pricing, and verify projected savings via controlled trials on real production equipment.

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