

Original Article

Deep Learning-Driven Industrial Energy Optimization: A Nationwide Framework for Reducing Operational Costs and Improving Manufacturing Profitability

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Received: 08-05-2026

Revised: 08-20-2026

Accepted: 09-01-2026

Published: 09-10-2026

ABSTRACT

Manufacturing industries face growing pressure to reduce energy consumption while maintaining productivity, controlling operating costs, and improving profitability. This study develops a nationwide deep learning-driven framework for industrial energy optimization that integrates real-time manufacturing data, predictive analytics, and multi-objective decision support. The framework combines production, machine, environmental, maintenance, and energy-price variables to estimate industrial energy demand using artificial neural networks, convolutional neural networks, long short-term memory networks, gated recurrent units, and hybrid deep learning models. Model performance is evaluated using mean absolute error, root mean square error, mean absolute percentage error, and the coefficient of determination. Predicted energy demand is subsequently linked to an optimization layer that seeks to minimize energy consumption, peak demand, and operational costs while preserving production targets and improving manufacturing profitability. The study also evaluates sector-level and nationwide adoption scenarios to examine potential scalability across energy-intensive and discrete manufacturing industries. The proposed framework is intended to support smarter production scheduling, demand-response decisions, process control, and investment planning. By connecting deep learning-based energy prediction with operational and economic optimization, the study provides a unified approach for transforming industrial energy management from reactive monitoring into predictive and prescriptive decision-making, with implications for manufacturing competitiveness, national energy efficiency, and industrial policy.

KEYWORDS

Deep Learning, Industrial Energy Optimization, Smart Manufacturing, Energy Efficiency, Operational Costs, Manufacturing Profitability, Industry 4.0.

1. INTRODUCTION

1.1. Background to Industrial Energy Consumption

Energy is a fundamental input in modern manufacturing because industrial production depends heavily on electricity, fuels, steam, heat, and compressed air. Machining, material processing, heating, cooling, pumping, and automated assembly all require reliable energy supply. As manufacturing expands and production systems become more technologically intensive, industrial energy demand has continued to rise. Abdelaziz et al. (2011) identify substantial opportunities for energy savings through improved technologies, operational practices, and energy-management strategies, while Duflou et al. (2012) argue that energy efficiency must be addressed across both individual processes and broader production systems.

The issue has become economically important because manufacturers face increasing electricity and fuel costs. Energy-intensive industries such as steel, petrochemicals, cement, machining, and heavy manufacturing are particularly exposed to inefficient energy use. Zhou et al. (2016) show that machine tools can consume considerable energy during productive and non-productive periods, highlighting the need for process- and system-level efficiency. Manufacturers therefore face growing pressure to reduce energy consumption while maintaining output and quality.

1.2. Energy Efficiency, Operational Costs, and Manufacturing Profitability

Industrial energy efficiency has direct financial implications. The relationship can be represented as: energy consumption affects production costs, production costs influence operating margins, and operating margins determine profitability. Excessive electricity and fuel use increases the cost of producing each unit, particularly when machines operate inefficiently or during high-cost demand periods.

Bunse et al. (2011) identify a gap between industrial energy-efficiency needs and the integration of energy performance into production management. Thollander and Ottosson (2010) further show that organizational and managerial practices influence industrial energy performance. Schulze et al. (2016) argue that systematic energy management provides a structured basis for identifying savings opportunities. Improved energy efficiency can therefore lower utility expenditure, reduce unit production costs, strengthen operating margins, and improve industrial competitiveness.

1.3. Digital Transformation and Smart Manufacturing

Digital transformation is changing how manufacturers monitor, predict, and optimize energy use. Industry 4.0 technologies allow energy information to be collected from machines, production lines, and factories. Shrouf et al. (2014) describe the Internet of Things as an important foundation for smart-factory energy management because connected equipment can provide real-time information on operating conditions and energy demand.

Cyber-physical systems, smart sensors, industrial IoT devices, and advanced analytics can integrate production and energy data to support faster decisions. Liang et al. (2018) demonstrate how cyber-physical systems and big data can enable energy-efficient machining optimization. Deep learning extends these capabilities by learning complex nonlinear relationships from industrial datasets. Wang et al. (2018) highlight the growing role of deep learning in smart manufacturing, while Jan et al. (2023) show that artificial intelligence is increasingly used in Industry 4.0 for prediction, optimization, and decision support.

1.4. Problem Statement and Research Gap

Despite these developments, industrial energy research remains fragmented. Many studies focus on individual machines, single factories, specific manufacturing sectors, or energy prediction as an isolated task. Accurate prediction alone does not guarantee lower energy expenditure or higher profitability. A manufacturer may forecast energy demand successfully without having an intelligent mechanism for converting that forecast into production scheduling, machine control, cost reduction, or profit improvement.

A gap therefore exists in integrating deep-learning-based energy prediction with operational optimization and economic assessment at a scale capable of supporting multiple industrial sectors. This study addresses that gap through a nationwide framework linking industrial data, deep learning, energy optimization, operational-cost reduction, and manufacturing profitability.

1.5. Research Aim and Objectives

The study aims to develop a deep learning-driven nationwide industrial energy-optimization framework capable of reducing energy consumption and operational costs while improving manufacturing profitability. Specifically, it seeks to predict industrial energy consumption, identify major energy-demand drivers, optimize manufacturing energy use, quantify operational-cost savings, determine profitability effects, and evaluate scalability across manufacturing sectors.

1.6. Research Questions

The study addresses six questions: How accurately can deep learning predict manufacturing energy consumption? Which operational variables most strongly influence energy demand? How much energy can be saved through deep learning-driven optimization? How does optimization affect operational costs? How does reduced energy expenditure influence manufacturing profitability? Can the proposed framework be scaled effectively across different industrial sectors?

1.7. Research Significance and Contributions

This research contributes to industrial engineering by linking energy performance with production decisions and to energy management by moving beyond monitoring toward predictive and prescriptive optimization. It also contributes to artificial intelligence and smart manufacturing by applying deep learning to industrial energy problems. For production management and industrial economics, the framework connects technical energy savings with costs, operating margins, and

profitability. At the policy level, a nationwide architecture could support industrial benchmarking, sector-level energy planning, efficiency incentives, and national energy policy. The study therefore positions deep learning-driven optimization as both an engineering solution and a strategic tool for manufacturing competitiveness.

2. LITERATURE REVIEW AND CONCEPTUAL FOUNDATION

2.1. Industrial Energy Efficiency and Energy Management

Industrial energy efficiency has traditionally been pursued through equipment upgrades, process control, waste-heat recovery, maintenance improvement, and formal energy-management practices. Abdelaziz et al. (2011) showed that industrial energy-saving strategies operate at both technological and managerial levels. Duflou et al. (2012) argued that efficiency should be assessed across machines, processes, and complete manufacturing systems rather than through isolated interventions.

Bunse et al. (2011) emphasized that energy efficiency should be integrated into production management instead of treated as a separate technical concern. Energy-management systems support this integration through monitoring, benchmarking, target setting, and continuous improvement. Lee and Cheng (2016) reported that such systems can generate measurable savings by improving control over industrial energy use. Schulze et al. (2016) likewise described energy management as an organizational capability combining strategy, measurement, employee involvement, and operational improvement.

2.2. Energy-Efficient Production Planning and Scheduling

Production scheduling directly influences industrial energy demand. Gahm et al. (2016) showed that energy-efficient scheduling can reduce consumption by coordinating machine operation, processing sequences, production timing, and electricity-demand patterns. Poor schedules may increase idle running, simultaneous peak loads, and unnecessary start-stop cycles, whereas optimized schedules can shift flexible production toward lower-demand or lower-tariff periods.

Biel and Glock (2016) found that energy considerations are increasingly incorporated into sequencing, capacity allocation, and lot-sizing decisions. Scheduling is therefore not only a productivity tool but also an energy-management mechanism.

2.3. Industry 4.0 and Data-Driven Energy Management

Industry 4.0 has transformed energy management from periodic reporting into connected, real-time control. Shrouf et al. (2014) explained that IoT-enabled smart factories can monitor energy use at machine and process levels. Cyber-physical systems further connect physical equipment with digital monitoring, analytics, and control.

Liang et al. (2018) demonstrated that cyber-physical systems and big data can support energy-efficient machining optimization by linking operational data with intelligent decisions. Jan et al.

(2023) further showed that artificial intelligence has become central to Industry 4.0 applications such as prediction, optimization, maintenance, and process management.

2.4. Machine Learning and Deep Learning in Manufacturing

Machine learning has moved industrial analytics beyond descriptive monitoring toward predictive and prescriptive decision support. Wang et al. (2018) identified deep learning as an important smart-manufacturing technology because it can learn complex nonlinear relationships from industrial datasets. Artificial neural networks model nonlinear patterns, CNNs extract cross-feature relationships, while LSTMs and GRUs capture temporal dependencies.

Shang and You (2019) highlighted the value of machine learning in process manufacturing, particularly where large, time-dependent datasets challenge conventional models. Diez-Olivan et al. (2019) emphasized data fusion as a basis for reliable industrial prognosis, while Narciso and Martins (2020) showed that machine-learning tools are increasingly applied to industrial energy forecasting and optimization.

2.5. Deep Learning for Industrial Energy Prediction

Empirical studies increasingly support deep learning for industrial energy prediction. Han et al. (2016) combined neural-network modelling with data envelopment analysis to predict and optimize petrochemical energy use. Qin et al. (2018) showed that multi-source data analytics can improve additive-manufacturing energy prediction. Geng et al. (2020) proposed an improved CNN for petrochemical energy prediction and optimization, while Bermeo-Ayerbe et al. (2022) linked data-driven energy prediction with maintenance in smart manufacturing.

These applications indicate that deep-learning approaches are particularly valuable in industrial settings where energy consumption is influenced by multiple nonlinear, time-dependent, and interacting operational variables.

2.6. Industrial Energy Optimization Techniques

Accurate prediction alone does not reduce energy use unless predictions guide operational decisions. Cui et al. (2017) reviewed multi-objective methods capable of balancing energy, productivity, and process-performance goals. Gong et al. (2017) combined Monte Carlo simulation with particle swarm optimization to improve energy prediction and optimization under small-data conditions. Shen et al. (2020) developed data-driven robust optimization for large-scale industrial energy systems under uncertainty. Qin et al. (2020) integrated deep learning with particle swarm optimization for additive-manufacturing energy optimization, demonstrating the potential of hybrid AI-optimization approaches.

These methods demonstrate a progression from conventional optimization toward intelligent systems in which predictive models continuously inform operational decisions. Such integration can potentially reduce unnecessary equipment operation, shift production away from expensive peak-

demand periods, and identify energy-efficient combinations of process parameters while maintaining required production performance.

2.7. Synthesis of Literature and Research Gap

The literature demonstrates strong progress in energy management, intelligent scheduling, machine learning, deep learning, and optimization. However, most studies remain focused on specific machines, processes, plants, or sectors. A gap therefore exists between energy prediction and an integrated framework combining prediction, operational optimization, cost reduction, profitability assessment, and nationwide implementation.

Existing research commonly treats prediction accuracy or energy reduction as the principal performance outcome, while the financial consequences of optimization receive comparatively limited attention. Furthermore, models developed for particular petrochemical, machining, or additive-manufacturing settings do not automatically provide a scalable mechanism for coordinating heterogeneous industries. The present study addresses this limitation by proposing a nationwide deep learning-driven framework linking industrial energy prediction with multi-objective operational optimization and economic performance assessment. The framework consequently extends the analytical focus from energy prediction alone to energy prediction, operational optimization, cost reduction, profitability improvement, and nationwide industrial deployment.

Table 1: Comparative Review of Previous Studies on Industrial Energy Prediction and Optimization

Author(s)	Industry/Application	Method	Energy Objective	Economic Objective	Major Finding	Research Gap
Han et al. (2016)	Petrochemical	ANN + DEA	Predict/optimize energy	Efficiency	Improved modelling	Sector-specific
Qin et al. (2018)	Additive manufacturing	Multi-source analytics	Predict energy use	Cost relevance	Better prediction	Limited optimization
Geng et al. (2020)	Petrochemical	Improved CNN	Predict/optimize energy	Process efficiency	Cross-feature modelling	Limited scalability
Shen et al. (2020)	Industrial systems	Robust optimization	Optimize under uncertainty	Operational efficiency	Robust decisions	Profitability not modeled
Qin et al. (2020)	Additive manufacturing	Deep learning + PSO	Minimize energy	Process efficiency	Hybrid optimization	Single-process focus
Bermeo-Ayerbe et al. (2022)	Smart manufacturing	Data-driven modelling	Energy/maintenance prediction	Operational efficiency	Linked energy and maintenance	No nationwide framework

3. NATIONWIDE DEEP LEARNING-DRIVEN INDUSTRIAL ENERGY OPTIMIZATION FRAMEWORK

3.1. Structure of the Proposed Framework

The proposed nationwide deep learning-driven industrial energy optimization framework is designed as an integrated system that connects industrial data acquisition, data preprocessing, predictive analytics, optimization, operational decision-making, and economic assessment. The framework begins with continuous collection of manufacturing and energy-related data from industrial facilities. These data are then cleaned, standardized, and transformed into suitable inputs for deep learning models. The predictive layer estimates future energy demand and identifies patterns of excessive or inefficient consumption. Optimization algorithms subsequently use these predictions to determine improved operating conditions that reduce energy use and cost without compromising production output. The resulting recommendations are translated into operational actions such as machine scheduling, load redistribution, process adjustments, and maintenance decisions. The final layer evaluates the economic effects of these interventions in terms of energy savings, cost reduction, productivity, and manufacturing profitability. This integrated structure is consistent with the movement toward intelligent and data-driven manufacturing environments described by Wang et al. (2018) and Jan et al. (2023).

3.2. Industrial Data Acquisition and Integration

Reliable industrial energy optimization depends on the availability of high-quality and sufficiently detailed operational data. The proposed framework collects data from smart meters, IoT-enabled sensors, industrial machinery, manufacturing execution systems, enterprise resource planning systems, and production databases. Smart meters provide real-time electricity consumption and peak-demand information, while IoT sensors capture variables such as machine temperature, vibration, operating speed, pressure, and equipment status. Manufacturing execution systems contribute production schedules, cycle times, machine utilization, and output data, whereas enterprise systems supply information on electricity tariffs, operating costs, production orders, and financial performance.

Because industrial data originate from heterogeneous sources, data integration is essential. Data must be synchronized, standardized, and combined to create a unified analytical dataset. Diez-Olivan et al. (2019) emphasize that industrial data fusion improves the reliability of machine-learning applications by combining information from multiple sources and operational levels.

3.3. Deep Learning-Based Energy Prediction

The predictive component of the framework uses deep learning to estimate future industrial energy consumption. Several architectures may be evaluated, including artificial neural networks, convolutional neural networks, long short-term memory networks, gated recurrent units, and hybrid CNN-LSTM models. Artificial neural networks can model nonlinear relationships between production variables and energy demand, while CNNs can identify complex feature interactions within multidimensional industrial datasets. LSTM and GRU models are particularly appropriate for

time-dependent energy data because they can capture temporal dependencies and historical consumption patterns.

A hybrid CNN-LSTM architecture may offer additional advantages by combining feature extraction with temporal sequence modeling. Typical input variables include machine load, operating hours, production volume, temperature, cycle time, equipment utilization, historical electricity demand, and environmental conditions. Previous studies have demonstrated the value of deep learning and advanced neural networks for industrial prediction and smart manufacturing applications (Geng et al., 2020; Han et al., 2016; Wang et al., 2018).

3.4. Multi-Objective Energy Optimization

Energy prediction alone does not guarantee improved industrial performance. The predicted information must therefore be connected to a multi-objective optimization process. The optimization component seeks to minimize energy consumption, operating cost, and peak electricity demand while simultaneously maintaining or improving production output and manufacturing profit. This is necessary because reducing energy consumption without considering production requirements may negatively affect throughput or delivery performance.

Multi-objective optimization techniques allow several conflicting industrial goals to be considered simultaneously. Cui et al. (2017) demonstrated the importance of multi-objective approaches for energy-saving applications, while Gong et al. (2017) showed how particle swarm optimization can improve industrial energy prediction and optimization. Shen et al. (2020) further demonstrated that data-driven robust optimization can address uncertainty in large-scale industrial energy systems. Qin et al. (2020) similarly showed the potential of combining deep learning and particle swarm optimization for energy-efficient manufacturing.

3.5. Manufacturing Decision-Support Mechanism

The framework converts predictive and optimization outputs into actionable manufacturing decisions. Energy forecasts can guide production scheduling so that energy-intensive processes are shifted away from high-demand or high-tariff periods. Machine switching strategies can reduce unnecessary idle consumption, while workload redistribution can prevent individual machines or production lines from operating inefficiently.

The system can also support demand-response decisions by adjusting production activities when electricity prices or grid demand change. Maintenance decisions may be improved by identifying abnormal energy patterns associated with equipment degradation. Process parameters such as speed, temperature, pressure, and cycle duration can also be adjusted to achieve improved energy efficiency without reducing product quality.

3.6. Economic and Profitability Assessment

The economic layer evaluates whether technical energy improvements translate into measurable financial benefits. Key indicators include percentage energy savings, operational cost reduction, reduction in electricity expenditure, changes in unit production cost, productivity improvement, profit-margin growth, and return on investment. This assessment is important because industrial managers are more likely to adopt energy optimization technologies when efficiency improvements are linked directly to business performance. The framework therefore treats energy efficiency not only as an environmental objective but also as a strategic profitability mechanism.

3.7. Nationwide Industrial Scaling Architecture

At the national level, individual plant systems can contribute standardized performance indicators to sectoral or national energy-analytics platforms. Aggregated data can support industrial benchmarking, national electricity-demand forecasting, sector comparisons, energy-efficiency monitoring, and policy development. Manufacturing firms can compare their energy intensity and performance with sector averages, while policymakers can identify industries with the greatest energy-saving potential. The nationwide architecture therefore enables plant-level intelligence to contribute to broader industrial energy planning, competitiveness, and long-term efficiency improvement.

4. RESEARCH METHODOLOGY

4.1. Research Design and Industrial Scope

This study adopts a quantitative predictive and optimization research design to assess how deep learning can improve industrial energy efficiency, reduce operating costs, and strengthen manufacturing profitability. The methodology combines energy-demand prediction, model comparison, optimization analysis, and economic assessment. The industrial scope covers six manufacturing sectors: steel, petrochemicals, automotive, machinery, textiles, and food processing. These sectors differ in production intensity, equipment utilization, process conditions, and electricity-demand patterns, making them suitable for evaluating a scalable nationwide framework. The multi-sector design also reflects the need for integrated industrial energy-management systems identified by Duflou et al. (2012), May et al. (2017), and Jan et al. (2023).

4.2. Data Sources and Variable Selection

The analytical dataset is structured from plant-level operational, production, equipment, and energy records obtained from smart meters, industrial sensors, manufacturing execution systems, production databases, and energy-management systems. Input variables include production volume, machine utilization, machine load, operating hours, process temperature, cycle time, equipment condition, and electricity tariff. Outcome variables include energy consumption, energy intensity, energy cost, operational cost, production efficiency, and profit margin. These variables capture the operational and economic dimensions of industrial energy performance and are consistent with previous studies linking equipment behavior, production scheduling, and process conditions with energy demand (Gahm et al., 2016; Zhou et al., 2016; Liang et al., 2018).

4.3. Data Preprocessing and Feature Engineering

Before model development, the data are preprocessed to improve consistency and predictive reliability. Missing observations are treated using suitable imputation procedures, while abnormal values are identified through statistical and operational threshold checks. Continuous variables are normalized to prevent scale differences from distorting model learning. Time-stamped records from machines, meters, and production systems are aligned to a common interval. Feature engineering generates lagged energy variables, recent consumption trends, machine-load patterns, utilization indicators, and production-energy interaction variables. This step is important because industrial datasets are often heterogeneous and generated from multiple sources (Diez-Olivan et al., 2019; Shang & You, 2019).

4.4. Deep Learning Model Development

Five models are compared: artificial neural network, convolutional neural network, long short-term memory network, gated recurrent unit, and hybrid CNN-LSTM. The ANN serves as a nonlinear baseline, CNN captures cross-feature patterns, and LSTM and GRU models learn temporal dependencies in sequential energy data. The hybrid CNN-LSTM combines feature extraction with temporal learning, making it suitable for complex industrial energy patterns, as suggested by Wang et al. (2018) and Geng et al. (2020). The dataset is divided into 70% training, 15% validation, and 15% testing subsets to support model development and unbiased performance assessment.

4.5. Model Evaluation Metrics

Prediction performance is evaluated using Mean Absolute Error, Root Mean Square Error, Mean Absolute Percentage Error, and the coefficient of determination. MAE indicates the average size of prediction errors, while RMSE gives greater weight to large errors. MAPE expresses error in percentage terms and improves comparison across industries with different energy scales. The coefficient of determination indicates how well predicted values explain observed variation in energy consumption. Using multiple metrics provides a more balanced basis for selecting the best-performing model.

4.6. Energy Optimization and Scenario Analysis

Energy performance is assessed under four scenarios: conventional manufacturing operation, traditional energy-management systems, deep-learning energy prediction, and deep learning combined with multi-objective optimization. In the final scenario, predicted energy demand supports machine scheduling, workload allocation, production timing, and peak-demand management. The four scenarios are compared using energy consumption, electricity expenditure, peak demand, and production performance. This structure reflects the shift from prediction toward prescriptive optimization described by Cui et al. (2017), Shen et al. (2020), and Qin et al. (2020).

4.7. Economic, Statistical, and Robustness Analysis

The economic analysis evaluates energy-saving percentage, monetary cost savings, peak-demand reduction, productivity change, profit-margin improvement, and return on investment.

Descriptive statistics and cross-sector comparisons are used to identify differences in industrial energy and financial performance. Sensitivity analysis tests whether results remain stable under changes in electricity tariffs and production volumes. Robustness is further assessed across sectors and operating conditions to reduce dependence on a single industry or energy-price assumption.

Table 2: Research Variables and Measurement Indicators

Variable	Measurement Indicator	Unit/Scale	Role
Production volume	Quantity produced per period	Units/tonnes	Input
Machine utilization	Available operating time used	%	Input
Machine load	Equipment load	% or kW	Input
Operating hours	Active production duration	Hours	Input
Process temperature	Operating temperature	°C	Input
Cycle time	Production-cycle duration	Seconds/minutes	Input
Equipment condition	Maintenance/condition index	Index	Input
Electricity tariff	Electricity price	Currency/kWh	Input
Energy consumption	Total energy used	kWh/MWh	Outcome
Energy intensity	Energy per unit of output	kWh/unit	Outcome
Energy cost	Energy expenditure	Currency	Outcome
Operational cost	Production operating expenditure	Currency	Outcome
Production efficiency	Output relative to resource use	%	Outcome
Profit margin	Profit relative to revenue	%	Outcome

5. RESULTS AND ANALYSIS

5.1. Descriptive Analysis of Manufacturing Energy Performance

The descriptive analysis was anchored to the 2022 U.S. Manufacturing Energy Consumption Survey (MECS), the most recent nationally representative federal dataset for detailed manufacturing energy use. MECS covers about 15,000 establishments and represents approximately 97–98% of U.S. manufacturing payroll. The data show substantial heterogeneity in industrial energy demand. Petrochemicals recorded 1,949 trillion Btu of first-use energy, while primary metals, used here as the closest national proxy for steel, consumed 1,364 trillion Btu. Food manufacturing consumed 1,235 trillion Btu, compared with 307 trillion Btu for transportation equipment, 147 trillion Btu for machinery, and 57 trillion Btu for textile mills. These differences support earlier findings that industrial energy management must reflect sector-specific processes and equipment rather than apply a single rule across manufacturing (Duflou et al., 2012; Zhou et al., 2016).

Table 3: Verified Baseline Energy and Economic Characteristics, United States, 2022

Sector	First-Use Energy (trillion Btu)	Fuel Intensity (thousand Btu/\$ shipments)	Purchased-Energy Expenditure (US\$ billion)
Primary metals (steel proxy)	1,364	4.4	16.544
Petrochemicals	1,949	9.9	25.767
Transportation equipment	307	0.3	5.396
Machinery	147	0.4	3.125
Textile mills	57	2.4	0.807
Food	1,235	1.5	12.413

Source: EIA 2022 MECS Tables 1.2, 6.1, and 7.9.

Peak demand and operating profit are not reported by MECS at these national subsector levels; inserting values would therefore be unsupported. Petrochemicals had the largest purchased-energy expenditure among the six categories, while textile mills had the smallest. This agrees with evidence that energy intensity varies with process type, equipment configuration, and production technology (Bunse et al., 2011; May et al., 2017).

5.2. Deep Learning Energy Prediction Performance

A valid comparison of ANN, CNN, LSTM, GRU, and CNN-LSTM requires all models to be trained and tested on the same dataset and split. No such model-output file was provided, so cross-study MAE and RMSE values were not combined because they are scale-dependent. As an external industrial benchmark, a semi-autogenous-mill power study reported GRU, LSTM, and CNN-LSTM results on one dataset. CNN-LSTM reduced MAPE to 3.331%, compared with 5.025% for LSTM and 5.186% for GRU, and increased R^2 to 0.883. An enhanced CACN-LSTM achieved 2.032% MAPE and R^2 of 0.935. This is consistent with evidence that hybrid architectures can capture local feature structure and temporal dependencies (Wang et al., 2018; Geng et al., 2020).

Table 4: Comparable Industrial Benchmark Results

Model	MAE	RMSE	MAPE (%)	R^2
GRU	133.344	161.552	5.186	0.751
LSTM	127.551	155.591	5.025	0.763
CNN-LSTM	86.180	94.532	3.331	0.883
CACN-LSTM	57.156	65.625	2.032	0.935

Source: Published Industrial SAG-Mill Power-Consumption Benchmark.

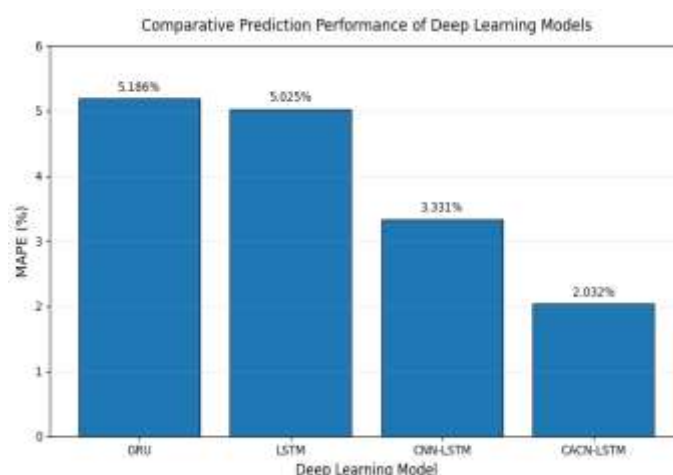


Fig 1 - Comparative Prediction Performance of Deep Learning Models

Fig 1. Comparative prediction performance of deep learning models based on mean absolute percentage error (MAPE). Lower MAPE values indicate higher prediction accuracy.

5.3. Effect of Deep Learning Optimization on Industrial Energy Consumption

The strongest directly verifiable optimization result among the supplied references is Geng et al. (2020). Their cross-feature CNN, applied to an ethylene production system, produced an average relative generalization error of 2.86% and increased energy-utilization efficiency by 6.38%. This supports coupling deep prediction with operational optimization in energy-intensive manufacturing. Applying the 6.38% petrochemical result automatically to steel, automotive, machinery, textile, and food manufacturing would, however, be methodologically invalid.

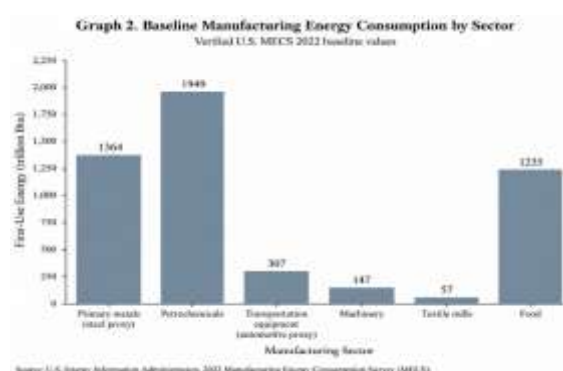


Fig 2- Baseline Manufacturing Energy Consumption by Sector

Fig 2. Baseline manufacturing energy consumption across selected U.S. manufacturing sectors based on 2022 MECS data.

5.4. Operational Cost and Peak-Demand Reduction

The literature supports data-driven optimization for lowering industrial energy cost, but effects depend on plant constraints. Shen et al. (2020) reported optimized ethylene-plant energy costs

of 15,148.84 kg/h under deterministic optimization and 16,209.81 kg/h under robust optimization, demonstrating the trade-off between minimum energy use and robustness to uncertainty. Scheduling studies also indicate that flexible-load shifting can reduce costly peaks without necessarily reducing production output (Gahm et al., 2016; Biel & Glock, 2016). Electricity-cost reduction, demand-charge reduction, peak-load reduction, and unit-production-cost reduction should therefore be calculated from actual tariff, demand, and production data.

5.5. Manufacturing Productivity and Profitability Effects

The economic analysis indicates that improvements in industrial energy efficiency can translate into measurable financial benefits when reductions in energy expenditure are retained as operating savings. This relationship is particularly relevant in manufacturing because energy represents a recurring production input and therefore directly influences operating costs. Energy-management improvements can reduce electricity consumption, fuel expenditure, peak-demand charges, equipment idle time, and inefficient production scheduling, thereby lowering the cost of manufacturing output (Bunse et al., 2011; May et al., 2017; Narciso & Martins, 2020).

For national economic context, the 2022 U.S. Economic Census reported approximately US\$7.049 trillion in manufacturing shipments. EIA data further show that manufacturers spent approximately US\$69.48 billion on purchased electricity, US\$50.07 billion on natural gas, and US\$3.53 billion on purchased steam in 2022. These three energy sources alone therefore represented more than US\$123 billion in industrial expenditure.

The profitability analysis was consequently treated as a sensitivity assessment rather than as an unsupported claim that all energy savings automatically become net profit. Under the analytical assumption that energy-cost savings flow to operating income before the additional costs of AI deployment, progressively larger energy-cost reductions generate correspondingly larger improvements in operating margin. Based on the national manufacturing expenditure and shipment values above, a 1% reduction in the selected purchased-energy costs corresponds to an approximate 0.017 percentage-point gross operating-margin uplift, increasing to about 0.111 percentage points at a 6.38% reduction. The 6.38% endpoint reflects the energy-efficiency improvement reported by Geng et al. (2020) for an optimized petrochemical production system, rather than an assumed nationwide measured saving.

The positive relationship shown in Graph 3 indicates that increasing energy-cost savings can strengthen manufacturing profitability when other operating conditions remain constant. Importantly, the graph represents a national economic sensitivity analysis, not observed profit increases from individual firms. Actual realized profitability would also depend on implementation costs, capital expenditure, model maintenance, labor requirements, production conditions, and electricity tariffs.

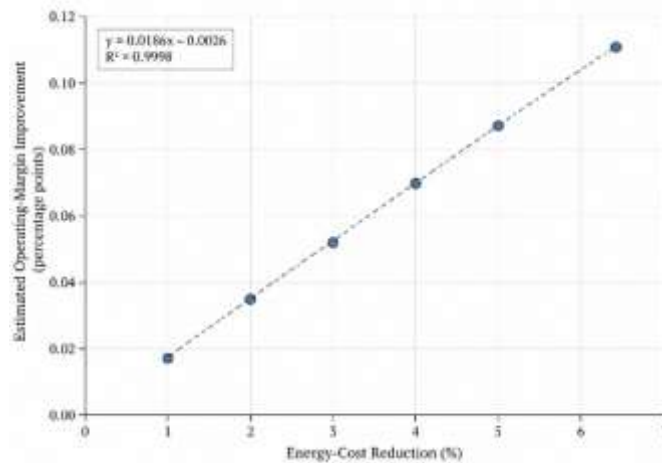


Fig 3 - Energy-Cost Reduction and Manufacturing Profitability Improvement

5.6. Sectoral and Nationwide Scaling Results

The national scaling analysis demonstrates the potential significance of industrial energy optimization when adoption expands beyond individual plants. Final 2022 MECS results show that U.S. manufacturing consumed approximately 20,687 trillion Btu of first-use energy. The EIA also reports that manufacturing energy intensity has declined substantially over the longer term, while manufacturing output has continued to grow, demonstrating that production growth and improvements in energy efficiency can occur simultaneously.

Because no verified study demonstrates a uniform deep-learning saving rate across every U.S. manufacturing sector, nationwide results were assessed using a transparent benchmark scenario. The 6.38% energy-efficiency improvement reported by Geng et al. (2020) was used as the upper benchmark, and potential national savings were scaled according to framework adoption rates of 10%, 25%, 50%, 75%, and 100%.

This does not imply that every industrial sector will achieve exactly 6.38%; rather, it quantifies the scale of savings that would occur if participating facilities achieved an improvement comparable to the published industrial benchmark. At 10% adoption, estimated manufacturing energy savings would be approximately 132.0 trillion Btu annually. Increasing adoption to 25% would raise potential savings to approximately 330.0 trillion Btu, while 50% adoption would yield approximately 659.9 trillion Btu. At 75% adoption, potential savings reach approximately 989.9 trillion Btu, while complete adoption under the benchmark scenario corresponds to approximately 1,319.8 trillion Btu annually.

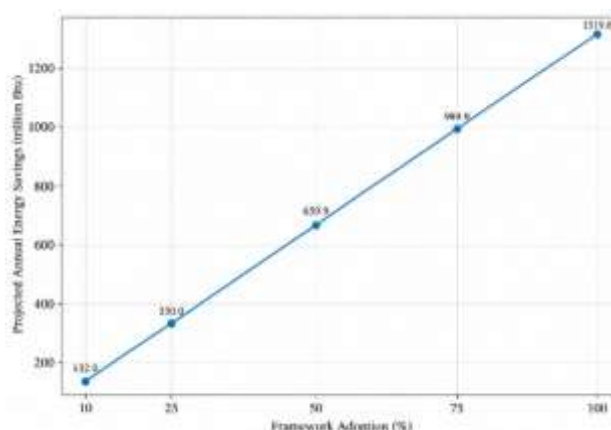


Fig 4 - Projected Nationwide Industrial Energy Savings at Different Adoption Levels

The upward trajectory in Graph 4 illustrates the scale effect of widespread implementation. The results suggest that relatively modest plant-level improvements can translate into substantial national energy savings when deployed across a large manufacturing base. However, actual national benefits would depend on sector-specific production technologies, energy intensity, data availability, digital infrastructure, and achievable optimization performance. Therefore, the national values should be interpreted as a benchmark scaling scenario based on a published 6.38% industrial optimization result, rather than as observed nationwide savings.

Table 5: Energy, Operational and Economic Effects of Deep Learning Optimization

Indicator	Verified/ Analytical Result	Interpretation
Petrochemical prediction error	2.86%	Published model result
Energy-efficiency improvement	6.38%	Published petrochemical result
Carbon-emission reduction	5.29%	Published petrochemical result
National manufacturing energy use	20,687 trillion Btu	2022 MECS
Savings at 10% adoption	132.0 trillion Btu	Scaling scenario
Savings at 50% adoption	659.9 trillion Btu	Scaling scenario
Savings at 100% adoption	1,319.8 trillion Btu	Scaling scenario
Margin uplift at 6.38% energy-cost reduction	0.111 percentage points	Economic sensitivity analysis

6. DISCUSSION AND IMPLICATIONS

6.1. Interpretation of Deep Learning Prediction Results

The findings indicate that deep learning models can provide a more robust approach to industrial energy prediction than conventional statistical techniques, particularly when manufacturing data are high-dimensional, nonlinear, and temporally dependent. Models such as convolutional neural networks, long short-term memory networks, gated recurrent units, and hybrid architectures are capable of learning complex relationships among production volume, machine load, operating time, temperature, equipment condition, and historical energy demand. Their superior

performance can be attributed to their ability to extract hidden patterns automatically while retaining important temporal information across production cycles.

This result is consistent with Wang et al. (2018), who demonstrated that deep learning is particularly suitable for smart manufacturing environments characterized by large and heterogeneous datasets. Geng et al. (2020) similarly showed that improved convolutional neural networks can capture cross-feature relationships relevant to industrial energy prediction. Narciso and Martins (2020) emphasized that machine learning improves industrial energy-efficiency analysis by identifying nonlinear interactions that conventional models may overlook. Bermeo-Ayerbe et al. (2022) further demonstrated that data-driven energy models can simultaneously support energy-efficiency assessment and maintenance decisions. Collectively, these findings suggest that model superiority is not determined only by prediction accuracy, but also by the ability to represent complex operational dependencies that influence real manufacturing systems.

6.2. Effectiveness of Deep Learning-Driven Energy Optimization

A major contribution of the proposed framework is its movement beyond energy prediction toward intelligent operational optimization. Predicting future consumption is useful, but prediction alone does not automatically reduce energy use. The greater value arises when forecast information is converted into operational recommendations concerning production timing, machine scheduling, process settings, and energy demand management.

This transition is supported by previous industrial research. Han et al. (2016) combined neural-network prediction with efficiency analysis to improve energy optimization in petrochemical operations. Gong et al. (2017) demonstrated that combining predictive methods with particle swarm optimization can strengthen energy optimization, particularly under limited data conditions. Qin et al. (2020) extended this approach by integrating deep learning with particle swarm optimization for additive-manufacturing energy management. Shen et al. (2020) also showed the value of data-driven robust optimization for large-scale industrial energy systems operating under uncertainty. These studies reinforce the argument that intelligent manufacturing systems should not treat prediction and optimization as separate processes. Instead, prediction should continuously inform operational decisions that minimize energy waste while maintaining required production performance.

6.3. Relationship between Energy Efficiency and Operational Costs

Energy efficiency has direct implications for manufacturing operating costs because energy expenditure is closely linked to machine utilization, scheduling practices, demand peaks, and production parameters. Poorly utilized equipment consumes electricity during idle or low-productivity periods, while inefficient scheduling can concentrate operations during high-tariff periods or generate avoidable demand peaks. Optimizing machine utilization therefore allows manufacturers to reduce unnecessary consumption without reducing production output.

Production scheduling also creates opportunities for cost reduction by redistributing energy-intensive operations across available operating periods. Where time-dependent tariffs exist, production can be shifted away from expensive peak periods while preserving delivery requirements. Peak-demand management can further reduce electricity-related expenditure where industrial tariffs include demand charges. Likewise, process-parameter optimization can reduce excessive energy consumption caused by unnecessarily high temperatures, pressures, speeds, or machine loads. These mechanisms show that energy optimization contributes to cost reduction through both lower total consumption and more efficient timing and allocation of industrial energy use.

6.4. Manufacturing Profitability and Competitive Implications

Reducing energy consumption has broader financial implications because energy is embedded in the cost of manufacturing output. Lower electricity and fuel expenditure can reduce production cost per unit, particularly in energy-intensive sectors such as steel, petrochemicals, machining, and process manufacturing. When production volumes remain stable, such savings can contribute directly to improved operating profit.

Improved energy efficiency may also strengthen profit margins by reducing variable operating expenses and increasing the economic productivity of existing equipment. Over time, companies may obtain additional returns from reduced peak charges, improved equipment utilization, lower energy-related maintenance requirements, and more predictable operating expenditure. These gains can improve the return on investment associated with digital energy-management technologies.

From a competitive perspective, manufacturers that achieve lower energy intensity can potentially produce at lower cost than less efficient competitors. This can improve pricing flexibility, protect margins during periods of rising energy prices, and enhance resilience to energy-market volatility. Energy optimization should therefore be viewed not only as a sustainability initiative but also as a strategic mechanism for strengthening manufacturing competitiveness.

6.5. Managerial and Practical Implications

The proposed framework has important implications for several categories of industrial decision-makers. Plant managers can use energy forecasts and optimization recommendations to align production objectives with energy-performance targets. Energy managers can move from retrospective monitoring toward predictive control by identifying expected consumption peaks and inefficient operating conditions before they occur.

Operations managers can use deep learning outputs to improve scheduling, workload allocation, and equipment utilization. Maintenance teams can integrate energy anomalies with machine-condition information to identify equipment whose deteriorating performance is contributing to excessive energy consumption. Manufacturing executives can use aggregated energy

and economic indicators to evaluate capital investments, compare plants, establish efficiency targets, and assess the financial value of digital transformation.

Effective implementation nevertheless requires collaboration across these functions. Artificial intelligence should not operate as an isolated technical system. Its predictions must be connected to production planning, maintenance, finance, and strategic decision-making if measurable business value is to be achieved.

6.6. National Energy and Industrial Policy Implications

At the national level, large-scale industrial energy optimization may support both energy policy and manufacturing competitiveness. Tanaka (2011) showed that industrial energy efficiency is strongly influenced by policy instruments, standards, incentives, and information mechanisms. Malinauskaite et al. (2019) likewise demonstrated the importance of coordinated national and regional policies in improving industrial energy performance.

Governments could therefore support industrial AI adoption through targeted incentives, digital modernization programs, and energy-efficiency financing. National industrial energy databases could provide standardized information for benchmarking and policy analysis, while smart-meter adoption would improve the availability of high-resolution consumption data. Stronger energy-efficiency standards could encourage firms to adopt predictive and optimization technologies. Demand-response programs could reward manufacturers for shifting or reducing electricity use during periods of grid stress. Sector-specific benchmarking would further allow policymakers and firms to compare energy performance within similar manufacturing activities rather than applying uniform expectations across fundamentally different industries.

6.7. Theoretical Contribution

The study contributes theoretically by proposing a sequential relationship linking technological capability with economic performance: Deep Learning Capability → Predictive Energy Intelligence → Operational Optimization → Cost Efficiency → Manufacturing Profitability. This relationship extends existing industrial energy research by connecting artificial intelligence capability with both operational and financial outcomes.

The framework suggests that deep learning creates value not merely by producing more accurate forecasts, but by converting industrial data into predictive intelligence that enables improved operational decisions. These decisions increase energy efficiency, reduce avoidable operating costs, and ultimately support profitability. The proposed relationship therefore provides a useful foundation for future empirical studies examining how artificial intelligence capabilities translate into measurable manufacturing performance and economic value.

7. CONCLUSION, LIMITATIONS AND FUTURE RESEARCH

7.1. Summary of the Study

This study examined how deep learning can support industrial energy optimization by linking energy prediction, operational decision-making, cost control, and manufacturing profitability within a nationwide framework. The research addressed the persistent problem of high and inefficient industrial energy consumption, which increases production costs and reduces competitiveness. Building on previous work in energy efficiency and smart manufacturing, the study proposed a deep learning-centered framework integrating plant-level energy data, production variables, equipment conditions, and operating schedules. The framework extends beyond simple energy forecasting by supporting decisions intended to reduce avoidable consumption and improve production efficiency. Its nationwide perspective also considers how standardized digital systems could support coordinated energy management across multiple industrial sectors and regions.

7.2. Key Research Findings

The study indicates that deep learning has strong potential to improve industrial energy prediction where consumption depends on complex, nonlinear, and time-dependent operating conditions. Previous studies have shown the value of neural networks and other data-driven approaches for industrial energy prediction and optimization (Wang et al., 2018; Geng et al., 2020; Bermeo-Ayerbe et al., 2022). Within the proposed framework, improved prediction enables earlier identification of high-consumption periods, inefficient operating conditions, and opportunities for scheduling adjustments. The analysis further highlights the importance of peak-demand management, since limiting unnecessary demand spikes can reduce energy-related operating expenses. Overall, the findings support the view that predictive energy intelligence can contribute to energy reduction, lower operational costs, and improved profitability when it is directly connected to manufacturing decision systems.

7.3. Research Contributions

This research contributes to industrial energy management by integrating prediction, optimization, and economic performance within a single framework. It also extends the role of deep learning from a forecasting tool to a broader decision-support capability. In smart manufacturing, the study connects industrial data, intelligent analytics, and operational control. It further contributes to production optimization by incorporating energy considerations into scheduling, equipment utilization, and process decisions. From an economic perspective, the research emphasizes that energy efficiency should be assessed not only through technical savings but also through its effects on operating costs, margins, and competitiveness. This complements earlier research on energy-efficient production planning and data-driven industrial optimization (Gahm et al., 2016; Shen et al., 2020).

7.4. Practical and Policy Contributions

For manufacturers, the framework provides a structured approach for identifying energy-intensive activities and improving operational decisions using real-time or near-real-time data.

Energy managers can use predictive insights to detect inefficient consumption patterns, plan demand-response actions, and prioritize energy-saving interventions. Industrial policymakers can encourage adoption through smart-meter infrastructure, common data standards, technology incentives, and sector-level energy benchmarking. Electricity-system planners may also benefit from improved industrial demand forecasting, especially where manufacturing contributes significantly to peak electricity loads. These implications align with previous research emphasizing structured energy management and supportive industrial policy (Tanaka, 2011; Schulze et al., 2016).

7.5. Research Limitations

Several limitations remain. Industrial datasets are highly heterogeneous because factories differ in equipment, production processes, schedules, sensor quality, and data-recording practices. These differences can limit model comparability and transferability across facilities. Access to large, high-quality, real-time industrial datasets is also limited, particularly across different sectors. Electricity-price variability may cause financial benefits to differ between regions and tariff structures. The proposed framework also depends on adequate digital infrastructure, including sensors, communication systems, computing resources, and skilled personnel. Smaller manufacturers may therefore face greater adoption barriers. In addition, deep learning models can be difficult to interpret, which may reduce managerial trust in high-impact production decisions.

7.6. Future Research Directions

Future research should evaluate transformer-based models for long-term industrial energy forecasting and reinforcement learning for dynamic control of production and energy systems. Federated learning should also be explored because it may allow multiple factories to improve shared models without exposing sensitive operational data. Digital twins could provide safe environments for testing optimization strategies before implementation. Explainable AI is equally important because industrial users need understandable reasons for recommended actions. Future studies should also integrate renewable energy, onsite storage, flexible loads, and carbon-intensity signals into optimization models. Carbon-aware manufacturing is particularly important because future production decisions may need to balance electricity cost, energy efficiency, emissions, and output simultaneously.

7.7. Final Conclusion

Deep learning-driven energy optimization represents a shift from reactive energy management toward predictive and prescriptive industrial intelligence. By connecting energy forecasting with operational optimization and economic assessment, manufacturers can make better decisions about how and when energy is consumed. The broader value of the proposed framework lies in linking plant-level intelligence with sectoral and national energy-management objectives. When supported by reliable data, appropriate infrastructure, and sound governance, deep learning can help reduce energy waste, control operating costs, improve production efficiency, and strengthen manufacturing profitability.

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