Merges Multi-Objective Reinforcement Learning with Lightweight Surrogate Models to Dynamically Throttle Machine Power States Based on Real-Time Edge Analytics and Dynamic Energy Grid Tariffs

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Abstract

Manufacturing accounts for a substantial share of global electricity consumption, and dynamic tariff mechanisms create economic incentives for intelligent load regulation. However, existing machine tool power management methods struggle to respond in real time at the edge to the multi-objective trade-off between tariff fluctuations and production constraints. This study proposes a framework that merges multi-objective reinforcement learning with lightweight surrogate models to dynamically throttle machine power states within an edge analytics environment. A design science research methodology is adopted, and the framework is validated in a simulated edge computing environment. Results show that the proposed framework achieves 89.4% classification accuracy in predicting optimal power states, reduces energy costs by 23.7% compared with a static scheduling baseline, and keeps production constraint violation rates below 2.1%. The study concludes that a surrogate-assisted multi-objective reinforcement learning framework can deliver effective power state throttling decisions within millisecond-level time budgets, offering a deployable technical pathway for manufacturers to participate in dynamic tariff response.

Keywords: Multi-objective reinforcement learning, surrogate models, edge analytics, dynamic tariffs, machine power management

1. Introduction

1.1 Background

Global manufacturing electricity consumption accounts for approximately one-third of total end-use electricity, and power state management of machine tools and production equipment is a key element of industrial energy efficiency optimization [6]. At the same time, power systems are undergoing a profound transition from rigid pricing to dynamic tariff mechanisms. Real-time pricing, time-of-use pricing, and critical peak pricing have been deployed in multiple electricity markets, with the core logic of transmitting time-varying wholesale price signals to end users to incentivize demand-side response behavior [14].

Manufacturing facility electricity loads possess significant flexible regulation potential. The power difference of machine tools between standby, idle, and machining states can reach several multiples, while buffer times and batch intervals in production scheduling provide time windows for dynamic power state adjustment [15]. However, converting this potential into actual economic benefits requires the manufacturing system to complete a "sense-decide-execute" loop at second-to-minute time scales: sensing tariff signals and production states, weighing energy cost savings against production output losses, and executing power state switching commands.

Reinforcement learning has been widely explored for energy management problems due to its advantages in sequential decision-making. Multi-objective reinforcement learning further extends this paradigm to scenarios with conflicting objectives, characterizing the Pareto frontier between energy costs and production output through vector-valued reward functions [3][16]. Meanwhile, edge computing architectures enable analytics tasks to be executed near the data source, avoiding the latency overhead of cloud round-trips [4][8].

However, deploying multi-objective reinforcement learning for edge-side machine tool power control faces a fundamental tension: the decision quality required for policy optimization demands accurate surrogate models to evaluate the long-term consequences of candidate actions, while the computational resources and latency budgets of edge devices strictly limit model complexity. Surrogate models—which replace expensive simulations or physical evaluations with computationally cheap approximations—have become a core methodological tool for resolving this tension [1][7].

1.2 Problem Statement

Existing research exhibits significant gaps across three interrelated dimensions.

First, the application of multi-objective reinforcement learning in industrial energy management has primarily focused on the production scheduling level, while fine-grained dynamic regulation of machine tool power states has not been adequately explored. Existing reinforcement learning-based energy-saving scheduling studies mostly focus on task allocation and machine selection, treating power states as static constraints rather than optimizable decision variables [6][15]. Although deep reinforcement learning-based energy-efficient job shop scheduling studies define state spaces related to power states, their decision granularity remains at the scheduling level and does not address edge-side real-time power switching [12][19].

Second, research on surrogate-assisted reinforcement learning has mainly concentrated on continuous control benchmark environments (such as MuJoCo), and its effectiveness in discrete action spaces and multi-objective preference trade-off scenarios has not been validated. Studies employing random forest surrogate models to assist multi-objective evolutionary optimization demonstrate that surrogate models can effectively reduce evaluation costs in high-dimensional policy parameter spaces, but the transfer of this method to multi-objective reinforcement learning—especially for edge deployment—remains insufficiently addressed [7][17].

Third, the integration of edge analytics with dynamic tariff response in manufacturing has been examined primarily at the facility level rather than the machine level. Edge analytics frameworks for real-time process optimization in smart manufacturing have demonstrated the feasibility of hybrid machine learning approaches for latency-sensitive industrial tasks [1], but these frameworks do not incorporate tariff-aware decision-making or multi-objective power state control. Consequently, no validated framework exists that jointly optimizes machine power states under dynamic tariffs while satisfying edge latency constraints and production requirements.

1.3 Objectives of the Study

General objective:

To design and validate a framework that merges multi-objective reinforcement learning with lightweight surrogate models for dynamic machine power state throttling based on real-time edge analytics and dynamic energy grid tariffs.

Specific objectives:

1. To identify the key state variables and reward components that govern the trade-off between energy cost and production output in machine-level power state throttling.
2. To design a hybrid framework that integrates multi-objective reinforcement learning with a lightweight surrogate model suitable for edge deployment.
3. To validate the framework against static scheduling and single-objective baselines using accuracy, cost reduction, constraint violation, and latency metrics.

1.4 Research Questions

1. What combination of state variables and reward components most accurately predicts optimal machine power states under dynamic tariffs?
2. How does the proposed surrogate-assisted multi-objective reinforcement learning framework compare with traditional static and single-objective methods in terms of energy cost, production constraints, and inference latency?
3. What are the implementation barriers and design considerations for deploying such a framework on resource-constrained edge devices?

1.5 Significance of the Study

For practitioners and administrators: The framework provides an actionable pathway for manufacturing facility managers to participate in demand response programs without compromising production commitments. The surrogate model architecture enables deployment on existing edge gateways, reducing infrastructure investment.

For policymakers: The findings inform the design of dynamic tariff structures that account for machine-level flexibility, supporting more granular demand-side management policies.

For academic literature: This study extends multi-objective reinforcement learning theory by demonstrating its applicability in discrete-action, preference-constrained industrial settings, and contributes to the emerging literature on surrogate-assisted reinforcement learning.

For future researchers: The framework establishes a replicable experimental protocol for evaluating edge-deployed energy management policies, providing a foundation for extensions to other equipment types and tariff structures.

1.6 Scope and Limitations

This study focuses on machine tool power state throttling (standby, idle, and machining states) within a simulated discrete manufacturing environment. The temporal scope covers a 12-month simulation period with hourly tariff signals. The geographic context is a generic deregulated electricity market with real-time pricing. Excluded from scope are: HVAC and compressed air systems, multi-facility coordination, and real hardware deployment. Key limitations include reliance on simulated production data, assumption of stable historical production patterns, and the absence of human-in-the-loop operator behavior modeling.

2. Literature Review

2.1 Conceptual Review

Multi-Objective Reinforcement Learning (MORL). MORL extends standard reinforcement learning to problems with vector-valued rewards, where multiple conflicting objectives must be balanced. The agent learns a policy that approximates the Pareto frontier over objective trade-offs [3][16]. In manufacturing energy management, the primary objectives are energy cost minimization and production output maximization.

Lightweight Surrogate Models. Surrogate models are computationally inexpensive approximations of expensive-to-evaluate functions. In reinforcement learning, they serve as learned dynamics models or value function approximators that reduce the number of expensive environment interactions [7][17]. Lightweight variants—such as pruned decision trees, shallow neural networks, and Gaussian process approximations—are suitable for edge deployment.

Edge Analytics. Edge analytics refers to the execution of data processing and machine learning inference at or near the data source, rather than in centralized cloud infrastructure. This architecture reduces latency, bandwidth consumption, and privacy risks [4][8]. In smart manufacturing, edge analytics enables real-time process optimization [1].

Dynamic Energy Grid Tariffs. Dynamic tariffs are electricity pricing mechanisms in which the price per unit of energy varies over time in response to wholesale market conditions, grid congestion, or renewable generation availability. Common forms include real-time pricing, time-of-use pricing, and critical peak pricing [14].

Machine Power States. Machine tools typically operate in distinct power states: off, standby, idle (spindle running without cutting), and machining (active cutting). Transitions between states incur time and energy penalties, and the optimal state depends on production schedule, tariff signals, and transition costs [15].

2.2 Theoretical Framework

This study is grounded in three theoretical pillars.

Bellman's Principle of Optimality. The sequential decision problem of power state throttling is formally modeled as a Markov Decision Process (MDP), where the optimal policy satisfies the Bellman optimality equation. This provides the mathematical foundation for the reinforcement learning formulation.

Pareto Optimality Theory. Multi-objective optimization seeks solutions that are non-dominated with respect to all objectives. The Pareto frontier concept provides the theoretical basis for evaluating trade-offs between energy cost and production output, and for defining the MORL reward structure [3].

Bias-Variance Trade-off in Surrogate Modeling. The lightweight surrogate model introduces approximation bias in exchange for reduced variance in policy evaluation. This trade-off is central to the design of the proposed framework, as the surrogate must be sufficiently accurate to guide policy improvement while remaining computationally tractable on edge devices [7].

2.3 Empirical Review

Hasan et al. [1] proposed a hybrid machine learning approach for edge analytics in smart manufacturing, demonstrating that lightweight models can achieve real-time process optimization with acceptable accuracy. However, their framework did not incorporate tariff-aware decision-making or multi-objective power state control, leaving the energy-cost dimension unaddressed.

Zhang et al. [12] applied deep reinforcement learning to energy-efficient job shop scheduling, achieving significant energy savings compared with rule-based dispatching. Nevertheless, their decision granularity remained at the scheduling level, and the approach did not address edge deployment constraints or dynamic tariff signals.

Wang et al. [17] employed random forest surrogate models to assist multi-objective evolutionary optimization, showing that surrogate assistance reduced evaluation costs by up to 60%. However, their study was limited to continuous optimization benchmarks and did not extend to reinforcement learning or industrial control.

Liu et al. [7] reviewed surrogate-assisted evolutionary computation and identified key challenges in high-dimensional, discrete, and multi-objective settings. They noted that surrogate model transferability across problem instances remains an open issue, which directly motivates the present study's focus on lightweight, deployable surrogates.

Chen et al. [4] examined edge computing architectures for industrial IoT and highlighted latency and resource constraints as primary barriers to deploying complex machine learning models at the edge. Their findings inform the design requirements for the proposed framework.

2.4 Research Gap

No validated framework exists that jointly merges multi-objective reinforcement learning with lightweight surrogate models for machine-level power state throttling under dynamic tariffs in an edge analytics environment. Existing studies address either energy-efficient scheduling [12][19], surrogate-assisted optimization [7][17], or edge analytics for manufacturing [1][4] in isolation, but none integrates these three strands into a coherent, deployable decision framework. This study fills that gap by designing and validating such a framework, with explicit attention to edge latency budgets, multi-objective trade-offs, and production constraint satisfaction.

3. Methodology

3.1 Research Design

This study adopts a design science research (DSR) methodology, which is appropriate for developing and evaluating artifacts—here, the surrogate-assisted MORL framework—that address practical problems. The DSR process follows three cycles: relevance (problem identification from industrial practice), design (framework construction), and rigor (quantitative validation against baselines). This design is justified because the research objective is prescriptive (how to build a deployable system) rather than purely descriptive.

3.2 Study Area / Population

The study targets discrete manufacturing facilities with machine tools capable of operating in multiple power states and connected to edge computing gateways. The population of interest comprises production lines in deregulated electricity markets where dynamic tariffs are available. A simulated production line with 10 machine tools is used as the study unit.

3.3 Sample Size and Sampling Technique

A stratified sampling approach is used to generate 12 months of simulated production episodes, stratified by shift (day/swing/night), day type (weekday/weekend), and tariff regime (low/medium/high price). A total of 8,760 hourly decision points are generated, yielding 8,760 state-action-reward tuples for training and evaluation. This sample size is justified by the need to capture seasonal tariff variation and production pattern diversity.

3.4 Data Collection Methods

Data sources include: (1) synthetic production schedules generated from realistic job shop distributions; (2) historical tariff profiles from a deregulated market, normalized to hourly resolution; and (3) machine power specifications from manufacturer datasheets for three machine tool classes. Data types extracted include power draw (kW) per state, transition times (seconds), production throughput (units/hour), and tariff price ($/kWh). The 12-month period covers seasonal tariff variation. Simulated data are used because real machine-level tariff response data are not publicly available; the simulation is calibrated to published industrial energy datasets.

3.5 Research Instruments

The framework is implemented in Python 3.10 using PyTorch for the MORL policy network, scikit-learn for the surrogate model (gradient-boosted trees with depth pruning), and a custom edge simulation environment. Preprocessing steps include: normalization of power and tariff variables, one-hot encoding of machine states, and temporal feature engineering (hour-of-day, day-of-week, rolling tariff averages). The edge analytics pipeline follows the hybrid machine learning architecture described by Hasan et al. [1], adapted for tariff-aware decision-making.

3.6 Validity and Reliability

Content validity: State variables and reward components were reviewed against prior energy management literature [6][15] and validated by domain experts.

Predictive validity: The surrogate model's predictions were compared against ground-truth environment rollouts using held-out episodes.

Inter-rater reliability: Not applicable, as the study uses quantitative simulation rather than human coding. Reliability is instead established through repeated runs with different random seeds (n=10), reporting mean and standard deviation of all metrics.

3.7 Data Analysis Techniques

Three models are compared: (1) a static scheduling baseline (fixed power states per shift); (2) a single-objective reinforcement learning agent (energy cost only); and (3) the proposed surrogate-assisted MORL framework. Performance metrics include classification accuracy of optimal power state prediction, energy cost reduction (%), production constraint violation rate (%), and inference latency (ms). Five-fold cross-validation is used for surrogate model evaluation, and policy performance is evaluated over 1,000 held-out episodes. Statistical significance is assessed using paired t-tests at $\alpha=0.05$, following methodological guidance from [7].

3.8 Ethical Considerations

The study uses de-identified, publicly available tariff data and simulated production data. No personally identifiable information or protected health information is accessed. The research qualifies for IRB exemption under 45 CFR 46.104(d)(4) as it involves no human subjects.

4. Results

4.1 Data Presentation

Table 1. Key Indicators by Model (12-Month Simulation)

Indicator	Static Baseline	Single-Objective RL	Proposed Framework
Energy cost ($/month)	42,800 (SD 3,200)	36,100 (SD 2,800)	32,650 (SD 2,400)
Production violation rate (%)	0.8 (SD 0.3)	4.7 (SD 1.1)	2.1 (SD 0.6)
Inference latency (ms)	N/A	18.4 (SD 3.2)	6.7 (SD 1.4)
State prediction accuracy (%)	N/A	82.1 (SD 2.5)	89.4 (SD 1.8)

Table 1 presents the comparative performance across the three models. The proposed framework achieves the lowest energy cost while maintaining production violations below the 2.5% threshold.

4.2 Analysis of Results

The proposed framework achieves 89.4% classification accuracy in predicting optimal power states, outperforming the single-objective RL agent (82.1%) by 7.3 percentage points ($p < 0.01$). Energy cost reduction relative to the static baseline is 23.7%, compared with 15.7% for the single-objective agent. The production constraint violation rate is 2.1%, significantly lower than the single-objective agent's 4.7% ($p < 0.001$), demonstrating the effectiveness of the multi-objective formulation in balancing competing goals.

Feature importance analysis reveals that the top predictors of optimal power state are: current tariff price (weight 0.31), time-to-next-scheduled-job (0.24), machine transition cost (0.18), rolling tariff average (0.14), and current production buffer level (0.13). Inference latency of 6.7 ms confirms the framework's suitability for edge deployment within typical industrial control cycle budgets.

5. Discussion

5.1 Interpretation

The findings confirm that merging multi-objective reinforcement learning with lightweight surrogate models enables effective machine power state throttling under dynamic tariffs. The 89.4% accuracy answers Research Question 1 by identifying the key state variables that govern the trade-off. The cost and constraint results answer Research Question 2 by demonstrating superiority over both static and single-objective baselines. The 6.7 ms latency addresses Research Question 3 by showing that edge deployment is feasible.

These results align with prior findings on surrogate-assisted optimization [7][17] and extend them to the reinforcement learning domain. The framework also supports the theoretical framework by demonstrating that Pareto-optimal trade-offs can be approximated with lightweight models, consistent with the bias-variance trade-off principle.

5.2 Implications

Academic implications: This study extends MORL theory to discrete-action, preference-constrained industrial control, and introduces a replicable surrogate-assisted architecture that bridges reinforcement learning and edge analytics.

Practical implications: Facility managers should monitor tariff signals, production buffer levels, and machine transition costs as key decision inputs. Expected cost reductions of 20-25% are achievable with inference latencies under 10 ms, compatible with existing edge gateways. Policymakers should consider machine-level flexibility in demand response program design.

5.3 Limitations

1. The study relies on simulated production data, which may not capture all real-world variability.
2. The assumption of stable historical production patterns may not hold under disruptive conditions.
3. The framework is validated on a simulated 10-machine line, limiting generalizability to larger facilities.
4. Human operator behavior and manual override effects are not modeled.

5.4 Future Research Directions

1. Extension to other equipment types (CNC machining centers, injection molding machines).
2. Longitudinal deployment studies examining operator interaction and trust.
3. Integration with renewable generation forecasting for proactive power state planning.
4. Multi-facility coordination under distribution network constraints.

6. Conclusion

This study designed and validated a framework that merges multi-objective reinforcement learning with lightweight surrogate models for dynamic machine power state throttling under real-time edge analytics and dynamic tariffs. The framework achieved 89.4% prediction accuracy, 23.7% energy cost reduction, and sub-10 ms inference latency, demonstrating that edge-deployable multi-objective control is feasible. The main contribution is a replicable architecture that integrates surrogate modeling, MORL, and edge analytics into a coherent decision pipeline. Practitioners can adopt this framework to participate in demand response without compromising production commitments. Future work should extend the approach to broader equipment classes and real-world deployment settings.

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