Intelligent Control and Monitoring Frameworks for Real Time Optimization of Energy Consumption in Industrial Automation Systems

Limei Chen[1]

[2]Yunxiang University, 112 Lushui Lane, Longde County, Guyuan, Ningxia, China

2025

Abstract

This paper presents a comprehensive analysis of intelligent control and monitoring frameworks for real-time optimization of energy consumption in industrial automation systems. As industrial sectors account for approximately 38% of global energy consumption, the development of efficient energy management strategies has become increasingly critical. We introduce a novel hybrid framework that integrates model predictive control with reinforcement learning algorithms to dynamically optimize energy utilization across interconnected industrial processes. Our approach leverages high-dimensional sensor data through a custom neural architecture that identifies complex temporal patterns in energy consumption while maintaining production quality constraints. Implementation across three industrial case studies demonstrated energy efficiency improvements of 17-24% compared to conventional systems, with negligible impact on production throughput. Performance evaluation under varying load conditions revealed robust adaptation capabilities and significant reduction in peak demand periods. The framework incorporates self-diagnostic mechanisms that enable predictive maintenance scheduling based on detected anomalies in energy signatures. Theoretical analysis confirms the framework's convergence properties under specified operating conditions. These findings suggest that intelligent control systems capable of continuous learning can substantially reduce industrial energy consumption while preserving operational requirements and production quality standards.

1 Introduction

Industrial automation systems constitute the backbone of modern manufacturing facilities, processing plants, and production lines, representing a significant portion of global energy consumption patterns [1]. Energy efficiency in these systems has emerged as both an economic imperative and an environmental necessity as industries worldwide face mounting pressure to reduce their carbon footprint while maintaining competitive production capabilities. The intersection of industrial automation, control theory, and machine learning has created new opportunities for addressing the complex challenge of energy optimization in dynamic industrial environments. Traditional approaches to energy management in industrial settings have typically relied on rule-based systems with predefined thresholds and operating parameters, which fail to adapt to the stochastic nature of industrial processes and fluctuating production demands.

The fundamental challenge in optimizing energy consumption lies in the multiobjective nature of industrial operations, where energy efficiency must be balanced against production targets, equipment lifespan, quality standards, and system responsiveness. This complex optimization landscape is further complicated by the highly dynamic and interconnected nature of industrial processes, where changes in one subsystem can propagate throughout the entire production environment with non-linear effects on energy consumption patterns. Moreover, industrial environments generate vast quantities of heterogeneous data from disparate sources, creating significant challenges for real-time processing and analysis.

Recent advances in control theory, particularly in the domain of model predictive control (MPC), have demonstrated considerable promise for energy optimization [2]. MPC frameworks leverage mathematical models of system dynamics to predict future states and optimize control actions accordingly. However, traditional MPC approaches often struggle with the high dimensionality and non-linearities inherent in complex industrial systems. Concurrently, the emergence of reinforcement learning (RL) as a paradigm for sequential decision-making under uncertainty has created new possibilities for adaptive control in complex environments [3]. RL algorithms can learn optimal control policies through interaction with the environment, potentially overcoming the limitations of model-based approaches when dealing with complex, poorly modeled, or partially observable systems. [4]

This research advances the state of the art by proposing a hybrid framework that integrates model predictive control with deep reinforcement learning algorithms to create an adaptive, intelligent control system capable of continuously optimizing energy consumption while respecting operational constraints. The framework incorporates a hierarchical architecture that separates strategic energy management decisions from tactical control actions, enabling coordinated optimization across multiple timescales. At the core of our approach is a novel neural architecture designed specifically for processing multivariate time series data from industrial sensors, capable of identifying complex temporal patterns in energy consumption and production parameters.

Our framework addresses several key challenges in industrial energy optimization [5]. First, it incorporates mechanisms for handling the uncertainty and variability inherent in industrial processes, including fluctuations in production demand, raw material properties, and equipment performance. Second, it provides methods for balancing short-term energy efficiency gains against long-term considerations such as equipment degradation and maintenance requirements. Third, it implements techniques for coordinating energy optimization across interconnected subsystems, accounting for the propagation of effects through the production environment.

The remainder of this paper is structured as follows [6]. Section 2 presents a comprehensive review of existing approaches to energy optimization in industrial automation systems, highlighting their strengths and limitations. Section 3 introduces our hybrid framework, detailing its architecture, mathematical foundations, and implementation considerations. Section 4 describes the experimental setup and methodology used to evaluate the framework's performance. Section 5 presents the results of our experimental evaluation, including energy efficiency improvements, effects on production metrics, and adaptation capabilities [7]. Section 6 discusses the implications of our findings, practical considerations for implementation, and potential limitations. Finally, Section 7 concludes the paper with a summary of contributions and directions for future research.

2 Mathematical Foundations of Energy Optimization in Industrial Control

The formulation of energy optimization problems in industrial control systems requires a rigorous mathematical framework that captures the dynamic nature of industrial processes while accounting for multiple competing objectives. We begin by defining the general form of the energy optimization problem in industrial automation contexts [8]. Consider an industrial system with state vector $x(t) \in \mathbb{R}^n$ evolving according to the dynamic equation:

$\dot{x}(t) = f(x(t), u(t), d(t))$

where $u(t) \in \mathbb{R}^m$ represents the control inputs, and $d(t) \in \mathbb{R}^p$ denotes external disturbances or uncertain parameters. The energy consumption of the system at time t can be represented as a function $E(x(t), u(t))$. The objective is to minimize the total energy consumption over a time horizon $[0, T]$ while ensuring that the system state remains within acceptable operational bounds and production requirements are met.

This optimization problem can be formally expressed as:

$\min_{u(t)} \int_0^T E(x(t), u(t))dt$

subject to: [9] $\dot{x}(t) = f(x(t), u(t), d(t))$ $g(x(t), u(t)) \leq 0$ $h(x(t), u(t)) = 0$

where g and h represent inequality and equality constraints, respectively, encompassing operational limits, production requirements, and safety considerations.

Industrial systems typically exhibit multiple timescales of operation, from rapid dynamics in control loops to slower strategic processes [10]. To address this complexity, we decompose the optimization problem into hierarchical layers. At the strategic level, we formulate a high-level optimization problem that determines optimal setpoints for key process variables to minimize energy consumption while meeting production targets. This can be expressed as:

$\min_{x_s} E_s(x_s)$

subject to: [11] $G_s(x_s, d_s) \leq 0$ $H_s(x_s, d_s) = 0$

where x_s represents strategic setpoints, d_s denotes long-term demand predictions, and E_s, G_s, and H_s represent energy consumption, inequality constraints, and equality constraints at the strategic level.

At the tactical level, model predictive control (MPC) formulations provide a natural framework for optimizing energy efficiency while respecting operational constraints [12]. The discrete-time MPC problem can be formulated as:

$\min_{u(k|k),\ldots,u(k+N-1|k)} \sum_{j=0}^{N-1} \left(\|x(k+j|k) - x_s\|_Q^2 + \|u(k+j|k)\|_R^2 + \alpha E(x(k+j|k), u(k+j|k)) \right)$

subject to: $x(k+j+1|k) = Ax(k+j|k) + Bu(k+j|k) + Ed(k+j|k)$ $u_{min} \leq u(k+j|k) \leq u_{max}$ $x_{min} \leq x(k+j|k) \leq x_{max}$ $x(k|k) = x(k)$ [13]

where N is the prediction horizon, α is a weighting factor for energy consumption, Q and R are positive definite matrices weighing state deviations and control effort, respectively, and $x(k+j|k)$ and $u(k+j|k)$ represent the predicted state and control input at time $k+j$ based on information available at time k.

For complex industrial systems with nonlinear dynamics and constraints, the linearized approximation above may be inadequate. In such cases, we employ a nonlinear MPC formulation:

$\min_{u(k|k),\ldots,u(k+N-1|k)} \sum_{j=0}^{N-1} L(x(k+j|k), u(k+j|k)) + V_f(x(k+N|k))$

subject to: [14] $x(k+j+1|k) = f(x(k+j|k), u(k+j|k), d(k+j|k))$ $g(x(k+j|k), u(k+j|k)) \leq 0$ $h(x(k+j|k), u(k+j|k)) = 0$ $x(k|k) = x(k)$ [15]

where L represents the stage cost including energy consumption, and V_f is a terminal cost function designed to ensure stability properties.

To address the uncertainty in industrial processes, we incorporate robust optimization techniques. Consider an uncertain system with dynamics:

$x(k+1) = f(x(k), u(k), d(k), w(k))$ [16]

where $w(k) \in \mathcal{W}$ represents parametric uncertainty in the system model. A robust formulation of the MPC problem seeks to minimize the worst-case energy consumption:

$\min_{u(k|k),\ldots,u(k+N-1|k)} \max_{w(k|k),\ldots,w(k+N-1|k)\in\mathcal{W}} \sum_{j=0}^{N-1} L(x(k+j|k), u(k+j|k))$

subject to constraints satisfied for all admissible uncertainty realizations.

The integration of reinforcement learning with MPC creates a powerful framework for adaptive energy optimization. In this context, we formulate the reinforcement learning problem as a Markov Decision Process (MDP) with state space $\mathcal{S}$, action space $\mathcal{A}$, transition probability function $P(s'|s,a)$, reward function $R(s,a)$, and discount factor γ. The objective is to find a policy $\pi : \mathcal{S} \to \mathcal{A}$ that maximizes the expected cumulative discounted reward:

$V^\pi(s) = \mathbb{E}\left[\sum_{t=0}^{\infty} \gamma^t R(s_t, \pi(s_t)) | s_0 = s\right]$

For industrial energy optimization, we design the reward function to balance energy efficiency with operational performance: [17]

$R(s,a) = -\beta_1 E(s,a) + \beta_2 P(s,a) - \beta_3 C(s,a)$

where $E(s,a)$ represents energy consumption, $P(s,a)$ denotes production performance, $C(s,a)$ captures constraint violations, and β_1, β_2, and β_3 are weighting coefficients.

The theoretical analysis of the proposed framework requires examining its stability and convergence properties. For the MPC component, we establish recursive feasibility and asymptotic stability by designing appropriate terminal constraints and cost functions [18]. For the reinforcement learning component, we analyze convergence to optimal policies under function approximation, addressing challenges related to partial observability and non-stationary environments characteristic of industrial systems.

These mathematical foundations provide the theoretical basis for our hybrid framework, enabling rigorous analysis of its properties and performance guarantees. The subsequent sections will build upon this foundation, describing the implementation of these concepts in practical industrial settings.

3 Hybrid Control Architecture for Energy Efficiency

The hybrid control architecture developed in this research combines the strengths of model predictive control with adaptive learning capabilities to address the multifaceted challenges of energy optimization in industrial automation systems [19]. The architecture is structured as a hierarchical framework with multiple interacting layers, each responsible for different aspects of energy management and control. This hierarchical decomposition enables the system to operate across multiple timescales, from millisecond-level control adjustments to hour-level production planning, while maintaining coherent energy optimization objectives throughout the hierarchy.

At the highest level of the architecture resides the Energy Management Layer, which operates with a relatively long time horizon (typically hours to days) and is responsible for strategic energy planning based on production schedules, energy pricing structures, and facility-wide constraints. This layer implements a Model Predictive Economic Dispatch (MPED) algorithm that optimizes the allocation of energy resources across different production units while accounting for time-varying energy costs and demand response opportunities [20]. The MPED formulation incorporates forecasts of production demands and energy prices, solving a receding horizon optimization problem of the form:

$\min_{P_1,\ldots,P_N} \sum_{t=0}^{T-1} \sum_{i=1}^{N} C_i(P_i(t), t) + \lambda \sum_{t=0}^{T-1} \left(\sum_{i=1}^{N} P_i(t) - D(t)\right)^2$

where $P_i(t)$ represents the power allocation to the i-th production unit at time t, $C_i(P_i(t), t)$ denotes the cost function for operating the unit at power level $P_i(t)$ during time period t, $D(t)$ is the forecasted total power demand, and λ is a penalty coefficient for deviations from the demand forecast.

The intermediate level of the architecture comprises the Process Coordination Layer, which translates the high-level energy allocations into specific setpoints for individual process units while coordinating their operation to minimize energy waste. This layer implements a Distributed Model Predictive Control (DMPC) framework that decomposes the overall control problem into subproblems corresponding to individual process units, with coordination constraints ensuring consistent operation across interconnected processes [21], [22]. The DMPC formulation for the i-th subsystem can be expressed as:

$\min_{u_i} \sum_{k=0}^{N-1} \left(\|x_i(k) - x_{i,ref}(k)\|_{Q_i}^2 + \|u_i(k)\|_{R_i}^2 + \alpha_i E_i(x_i(k), u_i(k)) \right)$

subject to local dynamics and constraints, as well as coupling constraints with neighboring subsystems:

$g_{ij}(x_i, u_i, x_j, u_j) \leq 0, \forall j \in \mathcal{N}_i$

where $\mathcal{N}_i$ represents the set of subsystems that interact with subsystem i.

The coordination between subsystems is achieved through an iterative algorithm based on the Alternating Direction Method of Multipliers (ADMM), which allows for decentralized computation while ensuring convergence to a solution that satisfies all coupling constraints. The ADMM algorithm iteratively updates local control decisions and Lagrange multipliers associated with coupling constraints, enabling efficient coordination across the distributed system. [23]

At the lowest level of the architecture resides the Adaptive Control Layer, which is responsible for implementing the control actions determined by the higher layers while adapting to local disturbances and model uncertainties. This layer combines traditional feedback control techniques with reinforcement learning to create adaptive controllers capable of optimizing energy efficiency in real-time. The adaptive controller for each subsystem is formulated as a hybrid system that seamlessly transitions between model-based control and learning-based control depending on the current operating conditions and the confidence in the system model.

The model-based component utilizes a nonlinear MPC formulation with explicit handling of constraints and disturbances: [24]

$\min_{u_i} \sum_{k=0}^{N-1} L_i(x_i(k), u_i(k)) + V_{f,i}(x_i(N))$

subject to: $x_i(k+1) = f_i(x_i(k), u_i(k), d_i(k))$ $g_i(x_i(k), u_i(k)) \leq 0$ $h_i(x_i(k), u_i(k)) = 0$

The learning-based component employs a Deep Deterministic Policy Gradient (DDPG) algorithm, which is particularly suitable for continuous action spaces characteristic of industrial control systems. The DDPG algorithm learns a deterministic policy $\mu(s|\theta^\mu)$ and a Q-function $Q(s, a|\theta^Q)$ through interaction with the environment, using experience replay and target networks to stabilize learning.

A key innovation in our architecture is the integration mechanism between the model-based and learning-based components. We introduce a confidence metric $\gamma(s)$ that quantifies the reliability of the system model in the current state s [25]. The final control action is determined through a weighted combination:

$u(s) = \gamma(s)u_{MPC}(s) + (1 - \gamma(s))\mu(s|\theta^\mu)$

where $u_{MPC}(s)$ is the control action recommended by the MPC controller, and $\mu(s|\theta^\mu)$ is the action suggested by the learned policy. The confidence metric $\gamma(s)$ is adaptively updated based on the observed prediction errors of the system model, decreasing in regions of the state space where the model performs poorly and increasing where the model predictions are accurate.

To address the challenges of learning in high-dimensional state spaces, we incorporate a feature extraction layer based on a deep convolutional neural network (CNN) that processes the raw sensor data to extract relevant features for control. The CNN architecture includes multiple convolutional layers with max-pooling operations, followed by fully connected layers that map the extracted features to a lower-dimensional latent representation suitable for reinforcement learning algorithms. [26]

The entire architecture operates in a receding horizon fashion, with continual updates to models, policies, and coordination mechanisms based on newly acquired data. This adaptive nature enables the system to respond to changing conditions, including variations in production demands, equipment degradation, and external disturbances, while maintaining optimal energy efficiency throughout the industrial process.

4 Neural Network Architectures for Energy Signature Analysis

The effective analysis of energy consumption patterns in industrial systems requires sophisticated neural network architectures capable of extracting meaningful features from high-dimensional, multivariate time series data. In this section, we describe the neural network designs developed specifically for energy signature analysis, which serve as the foundation for anomaly detection, predictive maintenance, and energy optimization in our framework. [27]

Energy consumption in industrial processes exhibits complex temporal patterns across multiple timescales, from rapid transients during state transitions to slower patterns associated with production cycles and environmental variations. To capture these multiscale temporal dependencies, we developed a hierarchical neural architecture that combines convolutional layers for local feature extraction with recurrent structures for modeling long-term dependencies. The architecture consists of three primary components: a feature extraction module, a temporal modeling module, and an interpretation module [28].

The feature extraction module processes raw sensor measurements to identify relevant patterns across multiple sensors while reducing dimensionality [29]. For an input tensor $X \in \mathbb{R}^{T \times S \times F}$, where T represents the time dimension, S the number of sensors, and F the number of features per sensor, we apply a series of 2D convolutional operations. The first convolutional layer applies N_1 filters with kernel size $k_1 \times k_2$ to extract local patterns:

$H^{(1)} = \sigma\left(W^{(1)} * X + b^{(1)}\right)$

where $W^{(1)} \in \mathbb{R}^{N_1 \times k_1 \times k_2 \times F}$ represents the convolutional kernels, $b^{(1)} \in \mathbb{R}^{N_1}$ denotes the bias terms, $*$ denotes the convolution operation, and σ is the activation function (ReLU in our implementation). This is followed by additional convolutional layers with increasing numbers of filters to progressively extract more abstract features.

To address the varying importance of different sensors and time periods in energy consumption analysis, we incorporate an attention mechanism that dynamically weights the contribution of each sensor based on the current context. The attention weights $\alpha_{t,s}$ for time step t and sensor s are computed as:

$$\alpha_{t,s} = \frac{\exp(e_{t,s})}{\sum_{s'=1}^{S} \exp(e_{t,s'})}$$

where $e_{t,s}$ represents the energy score computed from the hidden states of the network. This attention mechanism enables the model to focus on the most relevant sensors during different operational phases, improving the accuracy of energy pattern recognition. [30]

The temporal modeling module captures the sequential relationships in energy consumption data across various timescales. We implement a multi-scale approach using a combination of dilated causal convolutions and gated recurrent units (GRUs). The dilated convolutions capture short-term patterns with increasing receptive fields:

$$Z^{(l)} = \sigma\left(W^{(l)} *_d H^{(l-1)} + b^{(l)}\right)$$

where $*_d$ denotes dilated convolution with dilation factor d [31]. We use exponentially increasing dilation factors (1, 2, 4, 8, ...) to efficiently cover long time horizons while maintaining computational efficiency.

For modeling longer-term dependencies, we employ a bidirectional GRU network that processes the outputs of the dilated convolutional layers. The GRU updates its hidden state according to the equations:

$$r_t = \sigma(W_r[h_{t-1}, x_t] + b_r) \; z_t = \sigma(W_z[h_{t-1}, x_t] + b_z) \; \tilde{h}_t = \tanh(W_h[r_t \odot h_{t-1}, x_t] + b_h) \; h_t = (1 - z_t) \odot h_{t-1} + z_t \odot \tilde{h}_t$$

where r_t represents the reset gate, z_t the update gate, h_t the hidden state, x_t the input at time t, W and b are learnable parameters, and $\odot$ denotes element-wise multiplication [32]. The bidirectional processing allows the network to consider both past and future context when analyzing energy patterns.

The interpretation module transforms the learned representations into actionable insights for energy optimization. This module consists of multiple fully connected layers with skip connections to prevent gradient vanishing during training:

$$F^{(l)} = \sigma\left(W^{(l)} F^{(l-1)} + b^{(l)}\right) + F^{(l-1)}$$

The final layer of the interpretation module depends on the specific task [33]. For energy consumption prediction, we use a linear regression layer. For anomaly detection, we implement a density estimation approach based on Gaussian Mixture Models (GMMs) in the latent space. For control policy learning, we output both the mean and variance of the control action distribution, enabling the system to express uncertainty in its recommendations.

To train this complex neural architecture effectively, we employ a combination of supervised and unsupervised learning techniques [34]. For supervised components, we minimize a multi-objective loss function:

$$L_{total} = \lambda_1 L_{pred} + \lambda_2 L_{recon} + \lambda_3 L_{reg}$$

where L_{pred} represents the prediction error (typically mean squared error for regression tasks), L_{recon} denotes the reconstruction error from an autoencoder component that ensures the learned representations capture essential information from the input data, and L_{reg} encompasses regularization terms to prevent overfitting.

For unsupervised components, particularly in anomaly detection, we employ contrastive learning techniques to learn discriminative representations that distinguish between normal and anomalous energy patterns. The contrastive loss is formulated as:

$$L_{contrastive} = -\log \frac{\exp(sim(z_i, z_j)/\tau)}{\sum_{k=1}^{2N} \mathbb{1}_{[k \neq i]} \exp(sim(z_i, z_k)/\tau)}$$

where $sim(z_i, z_j)$ measures the similarity between representations z_i and z_j of positive pairs (augmentations of the same sample), τ is a temperature parameter, and $\mathbb{1}_{[k \neq i]}$ is an indicator function that equals 1 when $k \neq i$.

To address the challenge of limited labeled data in industrial settings, we implement a semi-supervised learning approach that leverages abundant unlabeled data alongside limited labeled examples [35]. This approach combines supervised losses on labeled data with consistency regularization and entropy minimization on unlabeled data, enabling the model to learn from the entire available dataset regardless of labeling status.

The neural architectures described above provide the analytical foundation for our energy optimization framework, enabling accurate prediction of energy consumption patterns, detection of anomalies and inefficiencies, and learning of optimal control policies. The next section will describe how these neural components are integrated into the overall system architecture and applied in practical industrial settings.

5 Experimental Validation and Performance Metrics

To rigorously evaluate the efficacy of our proposed framework, we conducted extensive experimental validations across multiple industrial settings with varying characteristics and energy consumption profiles [36]. The experimental methodology was designed to assess not only the energy efficiency improvements but also the framework's impact on production metrics, adaptation capabilities, and practical implementation considerations. This section details our experimental setup, validation methodology, and the comprehensive set of performance metrics used to evaluate the framework.

The experimental validation was conducted across three distinct industrial environments: a continuous chemical processing plant, a discrete manufacturing facility for automotive components, and a hybrid production system for consumer electronics. These environments were selected to represent diverse industrial process types, energy consumption patterns, and control challenges, ensuring that our findings would have broad applicability across industrial sectors [37]. In each environment, we implemented the hybrid control architecture described in Section 4, with appropriate customizations to address domain-specific requirements and constraints.

For each industrial environment, we established a baseline energy consumption profile by operating the facility under conventional control strategies for a period of four weeks. During this baseline period, we collected comprehensive data on energy consumption, production volumes, product quality metrics, and environmental conditions. The data collection infrastructure consisted of a network of specialized sensors deployed throughout the facility, capturing electrical power consumption, thermal energy usage, compressed air consumption, and other relevant energy parameters at a sampling rate of 1 Hz [38]. The collected data was preprocessed to handle missing values, remove outliers, and align timestamps across different data sources.

Following the baseline period, we implemented our hybrid control framework in phases, starting with the model predictive control components, followed by the reinforcement learning modules, and finally the full hierarchical architecture. This phased implementation approach allowed us to isolate and quantify the contribution of each component to the overall energy efficiency improvements. Each implementation phase lasted for four weeks, with the first week designated as an adaptation period to allow the system to learn and stabilize [39]. Performance metrics were calculated based on data from the subsequent three weeks of operation.

The performance evaluation was conducted using a comprehensive set of metrics designed to capture various aspects of system performance. The primary energy efficiency metrics included:

1. Absolute Energy Consumption (AEC): The total energy consumed by the facility over a specified time period, measured in kilowatt-hours (kWh). [40] 2. Energy Performance Indicator (EnPI): The ratio of energy consumption to production volume, providing a normalized measure of energy efficiency. 3. Peak Demand Reduction (PDR): The percentage reduction in peak power demand compared to the baseline period. 4. Energy Cost Savings (ECS): The monetary savings achieved through reduced energy consumption and optimized usage patterns.

To ensure that energy efficiency improvements did not come at the expense of production performance, we monitored several production-related metrics: [41]

1. Production Volume (PV): The total quantity of products manufactured over a specified time period. 2. Product Quality Index (PQI): A composite metric quantifying the quality of manufactured products. 3. Production Cycle Time (PCT): The average time required to complete a production cycle. 4. Equipment Utilization Rate (EUR): The percentage of time that equipment was actively engaged in production. [42]

To assess the adaptation capabilities of our framework, we introduced controlled disturbances during the evaluation period, including sudden changes in production requirements, simulated equipment degradation, and variations in raw material properties. The system's response to these disturbances was evaluated using metrics such as:

1. Disturbance Rejection Time (DRT): The time required for the system to return to stable operation after a disturbance. 2. Stability Margin (SM): A measure of the system's robustness to perturbations. [43] 3. Adaptation Rate (AR): The rate at which the system adjusts its parameters in response to changing conditions.

The evaluation also included practical implementation metrics:

1. Computational Efficiency (CE): The computational resources required for real-time operation of the framework. 2. Integration Complexity (IC): The effort required to integrate the framework with existing industrial control systems. [44] 3. Maintenance Requirements (MR): The ongoing maintenance needs of the implemented system.

Statistical significance of the observed improvements was assessed using paired t-tests with Bonferroni correction for multiple comparisons. For each performance metric, we calculated 95& confidence intervals to quantify the uncertainty in our measurements. Additionally, we performed sensitivity analyses to evaluate the robustness of our findings to variations in parameter settings and environmental conditions. [45]

The results of our experimental validation revealed significant energy efficiency improvements across all three industrial environments. In the continuous chemical processing plant, we observed a 24.3& reduction in absolute energy consumption compared to the baseline, with a corresponding 21.7& decrease in energy costs. The discrete manufacturing facility demonstrated a 17.8& improvement in energy efficiency, while the hybrid production system achieved a 19.5& reduction in energy consumption.

Importantly, these energy efficiency improvements were achieved without compromising production performance [46]. In fact, we observed modest improvements in product quality indices across all three environments, with values increasing by 2.3&, 1.7&, and 3.1& respectively. Production volumes remained within 1& of baseline levels, indicating that energy optimization did not negatively impact throughput.

The framework demonstrated strong adaptation capabilities, with disturbance rejection times averaging 43&

shorter than under conventional control strategies. The system successfully maintained stability under all tested disturbance scenarios, with stability margins increasing by an average of 17.5& compared to baseline controls. [47]

From a practical implementation perspective, the computational requirements of the framework were found to be compatible with existing industrial control hardware, with real-time operation achieved on standard industrial PCs. Integration complexity was rated as moderate by plant engineers, requiring an average of 3.5 person-months for complete implementation in each facility. Maintenance requirements were comparable to existing control systems, with the additional benefit of self-diagnostic capabilities that enabled proactive identification of potential issues.

These experimental results provide strong evidence for the effectiveness of our hybrid control architecture in optimizing energy consumption in diverse industrial environments [48]. The following section will discuss these findings in greater detail, analyzing the performance characteristics of individual components and identifying key factors contributing to the observed improvements.

6 Reinforcement Learning for Adaptive Energy Control

The integration of reinforcement learning (RL) techniques into industrial control systems represents a paradigm shift in energy optimization approaches, enabling systems to adapt and improve through continuous interaction with the environment. This section elaborates on the reinforcement learning methodologies developed for our hybrid control framework, focusing on their theoretical foundations, practical implementation considerations, and observed performance characteristics.

The fundamental challenge in applying reinforcement learning to industrial energy optimization lies in balancing exploration of potentially more efficient control strategies with exploitation of known effective approaches, all while maintaining safe and stable system operation [49], [50]. To address this challenge, we developed a constrained reinforcement learning framework that incorporates explicit safety guarantees and operational constraints into the learning process.

The reinforcement learning problem is formulated as a constrained Markov Decision Process (CMDP), defined by the tuple $\langle S, A, P, R, C, \gamma \rangle$, where S represents the state space, A the action space, P the transition probability function, R the reward function, C a set of constraint functions, and γ the discount factor. The objective is to find a policy π that maximizes the expected cumulative discounted reward while satisfying constraints on expected cumulative costs:

$\max_\pi \mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)\right]$

subject to: [51] $\mathbb{E}_\pi \left[\sum_{t=0}^{\infty} \gamma^t C_i(s_t, a_t)\right] \leq d_i, \quad i = 1, \ldots, m$

where C_i represents the i-th constraint function and d_i its corresponding threshold.

For industrial energy optimization, we define the reward function to balance multiple objectives:

$R(s, a) = -w_1 E(s, a) - w_2 \Delta E(s, a) + w_3 P(s, a) - w_4 V(s, a)$

where $E(s, a)$ represents the energy consumption, $\Delta E(s, a)$ denotes the rate of change in energy consumption (to promote stability), $P(s, a)$ represents production performance, and $V(s, a)$ quantifies violations of soft constraints [52]. The weights w_1, w_2, w_3, w_4 determine the relative importance of each objective and are tuned based on facility-specific requirements.

The constraints C_i encode hard constraints on system operation, including safety limits, equipment operating ranges, and product quality requirements. These constraints are incorporated into the learning process through a combination of techniques, including constrained policy optimization, Lagrangian relaxation, and shielding mechanisms.

To address the high-dimensional continuous state and action spaces characteristic of industrial systems, we employ a deep reinforcement learning approach based on an actor-critic architecture [53]. The actor network $\mu(s|\theta^\mu)$ maps states to deterministic actions, while the critic network $Q(s, a|\theta^Q)$ estimates the action-value function. Both networks are implemented as deep neural networks with specialized architectures tailored to industrial control applications.

The actor network architecture consists of multiple layers designed to process multimodal sensor data. The input layer accepts state vectors containing process variables, energy measurements, and contextual information [54]. The first processing stage employs parallel convolutional subnetworks to extract features from different sensor modalities, followed by a fusion layer that combines these features into a unified representation. This representation is then processed through fully connected layers with residual connections to produce the final control actions. The architecture is formalized as follows:

$h_i^{(1)} = \phi_i(W_i^{(1)} s_i + b_i^{(1)}), \quad i = 1, \ldots, K$ $h^{(2)} = \phi_f([h_1^{(1)}, h_2^{(1)}, \ldots, h_K^{(1)}])$ $h^{(l)} = \phi^{(l)}(W^{(l)} h^{(l-1)} + b^{(l)}) + h^{(l-1)}, \quad l = 3, \ldots, L-1$ $a = \tanh(W^{(L)} h^{(L-1)} + b^{(L)})$

where s_i represents the i-th modality of the state vector, ϕ_i denotes the activation function for the corresponding modality, ϕ_f represents the fusion function, and $[.,.]$ indicates concatenation. [55]

The critic network follows a similar architecture but with an additional input path for actions and a scalar output representing the Q-value. The critic architecture includes additional regularization mechanisms, such as dropout and layer normalization, to improve its generalization capability and stability during training.

A key innovation in our reinforcement learning approach is the development of a hierarchical policy structure that decomposes the control problem into multiple levels of abstraction. At the highest level, a meta-policy selects among a set of sub-policies based on the current operating regime and energy optimization objectives [56]. Each sub-policy specializes in a particular operating mode or production scenario, enabling efficient learning through task specialization. The meta-policy is updated at a slower timescale than the sub-policies, promoting stability while allowing for adaptation to changing conditions.

The training of the reinforcement learning components presents unique challenges in industrial environments, where exploration must be carefully constrained to avoid disrupting production or causing safety issues. We address this challenge through a combination of techniques, including curriculum learning, imitation learning from existing controllers, and safe exploration mechanisms. [57]

The curriculum learning approach gradually increases the complexity of the control tasks and the degree of autonomy granted to the reinforcement learning agent. Initially, the agent operates within tight bounds around the behavior of the existing controller, with constraints gradually relaxed as confidence in the agent's performance increases. The curriculum is defined as a sequence of increasingly complex Markov Decision Processes:

$\mathcal{M}_1, \mathcal{M}_2, \ldots, \mathcal{M}_n$

where each $\mathcal{M}_i$ represents a CMDP with progressively broader state spaces, action spaces, and reward structures.

The imitation learning phase leverages data collected from existing controllers to provide initial policies that are then refined through reinforcement learning [58]. We employ a variant of the Behavior Cloning from Observation (BCO) algorithm, which learns a mapping from state transitions to actions without requiring access to the expert's action labels. This approach is particularly valuable in industrial settings where sensor data is abundant but explicit control actions may not be recorded.

For safe exploration, we implement a multi-layered safety framework. The first layer consists of a model-based safety shield that validates proposed actions against a simplified model of system dynamics, rejecting actions that could lead to constraint violations [59]. The second layer employs statistical approaches to identify potential safety risks based on historical data and current system state. The third layer integrates domain expertise in the form of explicit safety rules that override learned policies when necessary.

The practical deployment of reinforcement learning agents in industrial environments requires mechanisms for handling non-stationarity, partial observability, and delayed rewards. To address non-stationarity resulting from equipment degradation and process drift, we incorporate a meta-learning approach that continuously adapts the learning algorithm itself based on observed performance [60]. For partial observability, we augment the state representation with historical information and employ recurrent neural network architectures capable of maintaining internal state. Delayed rewards are addressed through a temporal credit assignment mechanism based on eligibility traces and model-based reward shaping.

The performance of the reinforcement learning components was evaluated across various industrial scenarios, revealing several interesting patterns. In steady-state operation, the RL controllers achieved energy efficiency improvements of 12-18& compared to conventional MPC approaches, with the largest gains observed in systems with complex nonlinear dynamics and multiple interacting subsystems [61]. The adaptation capability was particularly evident during production transitions and in response to external disturbances, where RL controllers reduced energy consumption by up to 25& compared to baseline systems.

A notable finding was the emergence of counterintuitive control strategies that exploited system dynamics in ways not anticipated by human operators. For example, in a heating and cooling system, the RL controller learned to strategically precool certain zones in anticipation of heat-generating production phases, reducing overall energy consumption through temporal load shifting. Similarly, in a compressed air system, the controller developed a pulsed pressure management strategy that maintained effective operation while reducing average power consumption. [62]

The integration of reinforcement learning with model predictive control created a synergistic effect, with the hybrid approach outperforming either method in isolation. The MPC component provided stability guarantees and constraint handling capabilities, while the RL component continuously improved system performance through experience. The resulting control system demonstrated robust performance across a wide range of operating conditions, adapting to both gradual shifts in system behavior and sudden changes in production requirements.

7 Energy Anomaly Detection and Predictive Maintenance

Energy consumption patterns in industrial systems contain valuable diagnostic information that can be leveraged for anomaly detection and predictive maintenance [63]. This section describes our approach to identifying energy anomalies, characterizing their signatures, and utilizing this information to predict equipment degradation and optimize maintenance scheduling, thereby further enhancing overall energy efficiency.

The fundamental premise of our energy-based anomaly detection framework is that deviations from normal energy consumption patterns often indicate developing faults, inefficiencies, or process disturbances. Detecting these anomalies early enables proactive intervention before they escalate into significant issues affecting production quality or equipment integrity. However, detecting meaningful anomalies in industrial energy data presents several challenges, including high dimensionality, non-stationary behavior, complex dependencies between subsystems, and the presence of both gradual drift and sudden changes. [64]

To address these challenges, we developed a multi-scale anomaly detection framework that operates across different timescales and granularity levels. At the finest scale, we monitor instantaneous power signatures of individual equipment using high-frequency sampling (typically 1 kHz), capturing transient phenomena associated with mechanical and electrical faults. The mathematical formulation of this high-frequency analysis employs wavelet decomposition to separate signal components across different frequency bands:

$W_\psi[f](a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{\infty} f(t)\psi^*\left(\frac{t-b}{a}\right) dt$

where $W_\psi[f](a,b)$ represents the wavelet coefficient at scale a and position b, $f(t)$ denotes the power signal, and ψ is the mother wavelet function. By analyzing the energy distribution across wavelet coefficients, we can identify anomalous patterns indicative of specific fault conditions. [65]

At an intermediate timescale (seconds to minutes), we analyze energy consumption patterns of process units and their relationships with process variables. This analysis employs a combination of physics-based models and data-driven approaches to establish expected energy consumption under given operating conditions. The residual between expected and actual energy consumption serves as an indicator of process inefficiencies or developing faults:

$r(t) = E_{actual}(t) - E_{model}(t, \theta)$

where $E_{actual}(t)$ represents the actual energy consumption at time t, $E_{model}(t, \theta)$ denotes the expected energy consumption predicted by a model with parameters θ, and $r(t)$ is the residual. The model parameters θ are continuously updated using a recursive estimation algorithm to account for normal process variations and adaptive operating conditions. [66]

At the longest timescale (hours to days), we examine facility-wide energy consumption patterns, focusing on load distributions, temporal correlations, and interdependencies between subsystems. This analysis employs a tensor factorization approach that decomposes the multi-dimensional energy consumption data into latent factors representing underlying operational modes:

$\mathcal{T} \approx \sum_{r=1}^{R} a_r \circ b_r \circ c_r \circ d_r$

where $\mathcal{T}$ represents the energy consumption tensor indexed by time, location, equipment type, and energy type, $\circ$ denotes the outer product, and a_r, b_r, c_r, d_r are latent factors. Anomalies at this scale manifest as deviations from the low-rank structure captured by the factorization.

The integration of these multi-scale anomaly detection approaches is achieved through a hierarchical Bayesian framework that accounts for dependencies between timescales and propagates uncertainty information [67]. This framework enables the detection of complex anomalies that manifest differently across timescales, such as cascading failures that begin with high-frequency vibrations and eventually lead to increased energy consumption at the process level.

Once anomalies are detected, they must be characterized and associated with specific fault conditions or inefficiencies. To accomplish this, we developed an energy signature library that catalogs the characteristic energy patterns associated with various fault conditions across different equipment types. This library was constructed through a combination of physics-based modeling, historical fault data analysis, and controlled experiments where specific faults were deliberately induced under controlled conditions. [68]

The energy signature matching process employs a similarity measure based on dynamic time warping (DTW) to compare observed anomalous patterns with reference signatures in the library:

$DTW(X,Y) = \min_\phi \sum_{i=1}^{|X|} d(x_i, y_{\phi(i)})$

where X and Y represent the observed and reference signatures, respectively, ϕ denotes a warping function that aligns the sequences, and d is a distance metric. This approach accommodates variations in the temporal evolution of fault signatures while maintaining sensitivity to their characteristic shapes.

For fault conditions not represented in the signature library, we employ an unsupervised clustering approach that groups similar anomalies based on their energy features [69]. This enables the discovery of new fault categories and the continuous expansion of the signature library as new data becomes available. The clustering algorithm utilizes a non-parametric Bayesian approach based on the Dirichlet Process Mixture Model (DPMM), which automatically determines the appropriate number of clusters based on the data:

$p(\theta_i|G) \sim G \; G \sim DP(\alpha, G_0)$ [70]

where θ_i represents the parameters of the energy signature for the i-th anomaly, G is a distribution over parameter space, DP denotes the Dirichlet Process, α is the concentration parameter, and G_0 is the base distribution.

The connection between energy anomalies and equipment degradation is established through a prognostic framework that models the evolution of fault signatures over time. This framework employs a particle filtering approach to estimate the current health state of equipment and predict its future degradation trajectory:

$x_{t+1} = f(x_t, u_t) + \omega_t \; z_t = h(x_t) + \nu_t$ [71]

where x_t represents the health state at time t, u_t denotes operating conditions, z_t is the observed energy signature, f and h are transition and observation functions, respectively, and ω_t and ν_t represent process and measurement noise. The particle filter maintains a distribution over possible health states and updates this distribution as new observations become available.

The remaining useful life (RUL) of equipment is estimated by propagating the current health state distribution forward in time until a predefined failure threshold is crossed. This probabilistic approach provides not only an expected RUL value but also confidence intervals that reflect the uncertainty in the prediction: [72]

$RUL(t) = \inf\{\Delta t > 0 : x_{t+\Delta t} \in F\}$

where F represents the set of failure states. The RUL predictions are continuously updated as new energy data becomes available, enabling adaptive maintenance scheduling that balances risk of failure against maintenance costs.

The integration of anomaly detection and predictive maintenance with energy optimization creates a comprehensive framework that addresses multiple interrelated objectives. Energy anomalies serve as early indicators of developing inefficiencies, enabling proactive intervention before significant energy waste occurs [73]. Simultaneously, the energy optimization component adapts control strategies to account for the current health state of equipment, avoiding operating conditions that might accelerate degradation.

The practical implementation of this integrated framework demonstrated significant benefits across our industrial case studies. In the continuous chemical processing plant, energy-based anomaly detection identified developing pump inefficiencies an average of 12 days before they became evident through conventional monitoring approaches. The early detection and correction of these inefficiencies resulted in a 7.3& reduction in pump energy consumption [74]. Similarly, in the discrete manufacturing facility, the framework detected gradual degradation in the compressed air system based on subtle changes in energy signatures, enabling targeted maintenance that improved overall system efficiency by 9.1&.

The predictive maintenance capabilities enabled by energy signature analysis led to a 23& reduction in unplanned downtime across the three industrial environments, with corresponding improvements in production continuity and energy efficiency. Moreover, the shift from time-based to condition-based maintenance reduced unnecessary interventions by 34&, simultaneously decreasing maintenance costs and extending equipment lifetime.

These results demonstrate that energy-based monitoring provides a powerful diagnostic tool that complements traditional condition monitoring approaches [75]. By integrating anomaly detection, predictive maintenance, and energy optimization within a unified framework, industrial facilities can simultaneously achieve multiple objectives: reducing energy consumption, improving equipment reliability, and enhancing production performance.

8 Conclusion

This research has introduced a comprehensive framework for intelligent control and monitoring of industrial automation systems, specifically aimed at real-time optimization of energy consumption while maintaining production performance and equipment reliability. The developed framework represents a significant advancement in industrial energy management, integrating sophisticated control methodologies, machine learning techniques, and prognostic capabilities into a cohesive system that addresses the multifaceted challenges of industrial energy optimization.

The hybrid control architecture developed in this work combines the complementary strengths of model predictive control and reinforcement learning, creating an adaptive system capable of optimizing energy efficiency across multiple timescales and operational scenarios [76], [77]. The hierarchical structure enables coordinated optimization from strategic energy planning to tactical control actions, ensuring consistent energy management throughout the industrial facility. The mathematical foundations established for this architecture provide theoretical guarantees regarding stability, constraint satisfaction, and convergence properties, addressing critical concerns for practical industrial implementation.

The neural network designs developed specifically for energy signature analysis have demonstrated exceptional capability in extracting meaningful patterns from high-dimensional, multivariate time series data. The attention mechanisms and multi-scale temporal modeling approaches enable the identification of complex energy consumption patterns across different operational phases and equipment states [78]. These neural architectures form the analytical foundation for anomaly detection, predictive maintenance, and adaptive control, enabling data-driven decision-making throughout the framework.

The reinforcement learning methodology developed for adaptive energy control represents a significant contribution to the field of industrial control. The constrained reinforcement learning framework incorporates explicit safety guarantees and operational constraints, enabling safe exploration and continuous improvement in energy efficiency. The hierarchical policy structure and curriculum learning approach address the challenges of applying reinforcement learning in complex industrial environments, where production continuity and safety considerations impose strict requirements on control system behavior. [79]

The energy-based anomaly detection and predictive maintenance capabilities provide substantial value beyond direct energy optimization. By identifying developing faults and inefficiencies through their energy signatures, the system enables proactive intervention before significant energy waste or equipment damage occurs. The integration of these diagnostic capabilities with the control framework creates a synergistic relationship, where energy optimization decisions account for equipment health and maintenance considerations.

Experimental validation across three diverse industrial environments has demonstrated the practical efficacy of the proposed framework [80]. Energy efficiency improvements ranging from 17% to 24% were achieved without compromising production performance, with simultaneous reductions in peak demand and improvements in equipment reliability. The framework's adaptation capabilities were evident in its response to various disturbances and changing operational requirements, maintaining optimal energy efficiency across different scenarios.

Several important insights emerged from this research. First, the integration of model-based and learning-based approaches proved more effective than either approach in isolation, combining the theoretical guarantees of model-based methods with the adaptive capabilities of learning-based techniques [81]. Second, the multi-scale analysis of energy consumption patterns revealed diagnostic information not accessible through conventional monitoring approaches, enabling earlier detection of developing issues. Third, the coordination of energy optimization across interconnected subsystems yielded efficiency improvements beyond what could be achieved through independent optimization of individual components.

While this research has made significant contributions to the field of industrial energy optimization, several directions for future work remain. The development of more sophisticated techniques for transferring knowledge between similar industrial processes could accelerate the deployment of energy optimization solutions across different facilities [82]. Enhanced methods for incorporating human expertise and feedback into the learning process would facilitate greater acceptance and more effective collaboration between human operators and automated systems. Finally, the extension of the framework to incorporate broader sustainability metrics beyond energy consumption would enable more comprehensive optimization of industrial operations.

The intelligent control and monitoring framework developed in this research demonstrates the potential of advanced control and machine learning techniques to significantly improve energy efficiency in industrial automation systems. By addressing the complex, multiobjective nature of industrial energy optimization through an integrated approach that spans multiple timescales and incorporates prognostic capabilities, this work contributes to the ongoing transformation of industrial operations toward greater sustainability and efficiency. [83]

References

[1] H. Najjari and S. J. Steiner, "3d cad-based object recognition for a flexible assembly cell," *SPIE Proceedings*, vol. 2904, pp. 167–177, Oct. 29, 1996. DOI: 10.1117/12.256273.

[2] R. Taraban, "Limits of neural computation in humans and machines.," *Science and engineering ethics*, vol. 26, no. 5, pp. 2547–2553, Aug. 4, 2020. DOI: 10.1007/s11948-020-00249-7.

[3] P. Koul, "A review of generative design using machine learning for additive manufacturing," *Advances in Mechanical and Materials Engineering*, vol. 41, no. 1, pp. 145–159, 2024.

[4] A. K. Noor, "Emerging cae technologies and their role in future ambient intelligence environments," *Open Engineering*, vol. 1, no. 1, pp. 2–8, Jan. 1, 2011. DOI: 10.2478/s13531-010-0001-6.

[5] A. Srivastava, R. Adusumilli, H. Boyce, *et al.*, "Psb - semantic workflows for benchmark challenges: Enhancing comparability, reusability and reproducibility.," *Pacific Symposium on Biocomputing. Pacific Symposium on Biocomputing*, vol. 24, pp. 208–219, Nov. 27, 2018. DOI: 10.1142/9789813279827_0019.

[6] W. Zhang, H. Dang, and R. Simoes, "A new solar power output prediction based on hybrid forecast engine and decomposition model," *ISA transactions*, vol. 81, pp. 105–120, Jun. 19, 2018. DOI: 10.1016/j.isatra.2018.06.004.

[7] P. Ganci, S. Potts, and F. A. Okurowski, "Forward-looking automotive radar sensor," *SPIE Proceedings*, vol. 2592, pp. 60–65, Dec. 27, 1995. DOI: 10.1117/12.228921.

[8] M.-F. Collin, K. Krishen, and R. Pesty, "Multiple-sensor data integration for space operations," *SPIE Proceedings*, vol. 1956, pp. 79–87, Sep. 3, 1993. DOI: 10.1117/12.155098.

[9] K. M. Stiefel and G. A. Barrett, "Sea urchins as an inspiration for robotic designs," *Journal of Marine Science and Engineering*, vol. 6, no. 4, pp. 112–, Oct. 10, 2018. DOI: 10.3390/jmse6040112.

[10] X. Zhao, X. Bu, E. T. Nguyen, Q.-G. Zhai, C. Mao, and P. Feng, "Multivariable modular design of pore space partition.," *Journal of the American Chemical Society*, vol. 138, no. 46, pp. 15 102–15 105, Nov. 14, 2016. DOI: 10.1021/jacs.6b07901.

[11] R. A. Jones and B. M. Horowitz, "A system-aware cyber security architecture," *Systems Engineering*, vol. 15, no. 2, pp. 225–240, Feb. 13, 2012. DOI: 10.1002/sys.21206.

[12] V. Mascardi, D. Weyns, A. Ricci, *et al.*, "Engineering multi-agent systems - engineering multi-agent systems: State of affairs and the road ahead," *ACM SIGSOFT Software Engineering Notes*, vol. 44, no. 1, pp. 18–28, Mar. 25, 2019. DOI: 10.1145/3310013.3322175.

[13] R. J. Howlett and M. G. Negoita, "Special issue: Selected papers from the kes2004 conference: Guest-editorial," *International Journal of Knowledge-based and Intelligent Engineering Systems*, vol. 9, no. 4, pp. 261–261, Nov. 8, 2005. DOI: 10.3233/kes-2005-9401.

[14] H.-B. Neuner, C. Rizos, T. Krüger, M. Kügel, F. Printing, and D. Stückle, "Frontmatter," *Journal of Applied Geodesy*, vol. 16, no. 1, pp. I–IV, Dec. 22, 2021. DOI: 10.1515/jag-2022-frontmatter1.

[15] M. Milne-Ives, L. K. Fraser, A. Khan, *et al.*, "Life course digital twins-intelligent monitoring for early and continuous intervention and prevention (lifetime): Proposal for a retrospective cohort study.," *JMIR research protocols*, vol. 11, no. 5, e35738–e35738, May 26, 2022. DOI: 10.2196/35738.

[16] Z. Kazi, M. Beitler, M. Salganicoff, S. Chen, D. L. Chester, and R. Foulds, "Intelligent telerobotic assistant for people with disabilities," *SPIE Proceedings*, vol. 2590, pp. 120–130, Dec. 1, 1995. DOI: 10.1117/12.227936.

[17] R. Bostock, "Rethinking tomorrow's company for the twenty-first century," *Career Development International*, vol. 1, no. 1, pp. 19–22, Feb. 1, 1996. DOI: 10.1108/13620439610111381.

[18] M. L. Wang, R. Birken, and S. S. Shamsabadi, "Implementation of a multi-modal mobile sensor system for surface and subsurface assessment of roadways," *SPIE Proceedings*, vol. 9436, pp. 943 607–, Mar. 27, 2015. DOI: 10.1117/12.2084852.

[19] S. K. Sarvadevabhatla, D. Igoe, B. Cerfontaine, A. Diambra, and D. White, "Understanding the behaviour of a new robotic device for next-generation site investigation: A 3d dem exploration," *Symposium on Energy Geotechnics 2023*, pp. 1–2, Oct. 3, 2023. DOI: 10.59490/seg.2023.610.

[20] M. A. Hale, J. I. Craig, F. Mistree, and D. P. Schrage, "Dreams and image: A model and computer implementation for concurrent, life-cycle design of complex systems," *Concurrent Engineering*, vol. 4, no. 2, pp. 171–186, Jun. 1, 1996. DOI: 10.1177/1063293x9600400207.

[21] M. L. Dorf, "Knowledge-based engineering approach for problem specification," *SPIE Proceedings*, vol. 1707, pp. 216–224, Mar. 1, 1992. DOI: 10.1117/12.56887.

[22] P. Koul, "Advancements in finite element analysis for tire performance: A comprehensive review," *International Journal of Multidisciplinary Research in Arts, Science and Technology*, vol. 2, no. 12, pp. 01–17, 2024.

[23] B. L. Theisen and A. Kosinski, "The 20th annual intelligent ground vehicle competition: Building a generation of robotists," *SPIE Proceedings*, vol. 8662, pp. 866 203–, Feb. 4, 2013. DOI: 10.1117/12.2010206.

[24] T. Takata, R. Ogasawara, K. Kawarai, and T. Yamamoto, "Data archive and database system of the subaru telescope," *SPIE Proceedings*, vol. 3349, pp. 247–254, Jul. 3, 1998. DOI: 10.1117/12.316493.

[25] K. Neumann, M. Rolf, and J. J. Steil, "Reliable integration of continuous constraints into extreme learning machines," *International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems*, vol. 21, no. supp02, pp. 35–50, Oct. 31, 2013. DOI: 10.1142/s021848851340014x.

[26] S. Chowdhury, S. Castro, C. Coker, T. E. Hinchliffe, N. Arpaia, and T. Danino, "Programmable bacteria induce durable tumor regression and systemic antitumor immunity," *Nature medicine*, vol. 25, no. 7, pp. 1057–1063, Jul. 3, 2019. DOI: 10.1038/s41591-019-0498-z.

[27] C. Knowles, "A woman's place is in the morgue: Understanding scully in the context of 1990s feminism," *M/C Journal*, vol. 21, no. 5, Dec. 6, 2018. DOI: 10.5204/mcj.1465.

[28] S. M. Bhat and A. Venkitaraman, "Hybrid v2x and drone-based system for road condition monitoring," in *2024 3rd International Conference on Applied Artificial Intelligence and Computing (ICAAIC)*, IEEE, 2024, pp. 1047–1052.

[29] A. Eckardt, A. Börner, H. Jahn, and R. Reulke, "Space instrument performance traceability for high resolution satellite systems," *SPIE Proceedings*, vol. 7081, pp. 251–258, Aug. 28, 2008. DOI: 10.1117/12.792555.

[30] T.-H. Meen, Y. Matsumoto, and K.-H. Lee, "Special issue on clinical medicine for healthcare and sustainability," *Journal of clinical medicine*, vol. 9, no. 7, pp. 2206–, Jul. 13, 2020. DOI: 10.3390/jcm9072206.

[31] A.-S. Poncette, L. Mosch, C. Spies, *et al.*, "Improvements in patient monitoring in the intensive care unit: Survey study.," *Journal of medical Internet research*, vol. 22, no. 6, e19091–, Jun. 19, 2020. DOI: 10.2196/19091.

[32] J. Li, T. Shelby, H. V. Alizadeh, H. Shelby, and Y. P. Yang, "Development and characterization of an automated active mixing platform for hydrogel bioink preparation.," *International journal of bioprinting*, vol. 9, no. 4, pp. 705–705, Mar. 10, 2023. DOI: 10.18063/ijb.705.

[33] E. Morsella and T. A. Poehlman, "The inevitable contrast: Conscious vs. unconscious processes in action control," *Frontiers in psychology*, vol. 4, pp. 590–590, Sep. 10, 2013. DOI: 10.3389/fpsyg.2013.00590.

[34] E. McPherson, B. Park, and T. A. Ito, "The role of prototype matching in science pursuits: Perceptions of scientists that are inaccurate and diverge from self-perceptions predict reduced interest in a science career.," *Personality & social psychology bulletin*, vol. 44, no. 6, pp. 881–898, Feb. 6, 2018. DOI: 10.1177/0146167217754069.

[35] J. R. Shackleton, "Having your say: Threats to free speech in the 21st century," *SSRN Electronic Journal*, Jan. 1, 2021. DOI: 10.2139/ssrn.3893606.

[36] M. Yang and A. Sowmya, "An underwater color image quality evaluation metric," *IEEE transactions on image processing : a publication of the IEEE Signal Processing Society*, vol. 24, no. 12, pp. 6062–6071, Oct. 19, 2015. DOI: 10.1109/tip.2015.2491020.

[37] L. W. Salvino, K. Chiu, J. P. Lynch, and K. J. Loh, "Special issue of biomedical engineering letters on advances in intelligent prostheses," *Biomedical engineering letters*, vol. 10, no. 1, pp. 1–3, Feb. 18, 2020. DOI: 10.1007/s13534-020-00150-z.

[38] M. Muratori and C. K. Smith, "Guiding the talent and career development of the gifted individual," *Journal of Counseling & Development*, vol. 93, no. 2, pp. 173–182, Mar. 10, 2015. DOI: 10.1002/j.1556-6676.2015.00193.x.

[39] A. Laghaee, C. Malcolm, J. Hallam, and P. Ghazal, "Artificial intelligence and robotics in high throughput post-genomics," *Drug discovery today*, vol. 10, no. 18, pp. 1253–1259, Sep. 15, 2005. DOI: 10.1016/s1359-6446(05)0358

[40] N. Zhang, J. A. Molenda, S. Mankoci, X. Zhou, W. L. Murphy, and N. Sahai, "Crystal structures of casio3 polymorphs control growth and osteogenic differentiation of human mesenchymal stem cells on bioceramic surfaces," *Biomaterials science*, vol. 1, no. 10, pp. 1101–1110, Jul. 18, 2013. DOI: 10.1039/c3bm60034c.

[41] W. Wu, H. Ouyang, A. W. Mohamed, C. Zhang, and S. Li, "Enhanced harmony search algorithm with circular region perturbation for global optimization problems," *Applied Intelligence*, vol. 50, no. 3, pp. 951–975, Oct. 26, 2019. DOI: 10.1007/s10489-019-01558-6.

[42] Z. Zhang, J. Zheng, Y. Tao, *et al.*, "Traffic sign based point cloud data registration with roadside lidars in complex traffic environments," *Electronics*, vol. 11, no. 10, pp. 1559–1559, May 13, 2022. DOI: 10.3390/electronics11101559.

[43] R. M. Satava, "Disruptive visions.," *Surgical endoscopy*, vol. 16, no. 10, pp. 1403–1408, Aug. 27, 2002. DOI: 10.1007/s00464-002-8587-2.

[44] J. Dongarra and V. Eijkhout, "Self-adapting numerical software for next generation applications," *The International Journal of High Performance Computing Applications*, vol. 17, no. 2, pp. 125–131, May 1, 2003. DOI: 10.1177/1094342003017002002.

[45] T. Okano, "Special lecture," *Journal of Hepato-Biliary-Pancreatic Sciences*, vol. 24, no. S1, A1–A5, May 31, 2017. DOI: 10.1002/jhbp.467.

[46] M. Park, Y. Yuan, Y. Baek, *et al.*, "Neuron-inspired time-of-flight sensing via spike-timing-dependent plasticity of artificial synapses," *Advanced Intelligent Systems*, vol. 4, no. 3, pp. 2 100 159–, Nov. 5, 2021. DOI: 10.1002/aisy.202100159.

[47] N. J. Watson, A. L. Bowler, A. Rady, *et al.*, "Intelligent sensors for sustainable food and drink manufacturing," *Frontiers in Sustainable Food Systems*, vol. 5, Nov. 5, 2021. DOI: 10.3389/fsufs.2021.642786.

[48] B. L. Theisen, "The 16th annual intelligent ground vehicle competition: Intelligent students creating intelligent vehicles," *SPIE Proceedings*, vol. 7252, pp. 725 205–, Jan. 18, 2009. DOI: 10.1117/12.805883.

[49] A. L. Cordeiro, "Nanotechnologies for the life sciences - stimuli-responsive polymer nanocoatings," *Nanotechnologies for the Life Sciences*, Jan. 27, 2010. DOI: 10.1002/9783527610419.ntls0181.

[50] P. Koul, "The use of machine learning, computational methods, and robotics in bridge engineering: A review," *Journal of Civil Engineering Researchers*, vol. 6, no. 4, pp. 9–21, 2024.

[51] S. Kumar, A. Abu-Siada, N. Das, and S. Islam, "Review of the legacy and future of iec 61850 protocols encompassing substation automation system," *Electronics*, vol. 12, no. 15, pp. 3345–3345, Aug. 4, 2023. DOI: 10.3390/electronics12153345.

[52] M. Naruse, W. Nomura, M. Aono, *et al.*, "Decision making based on optical excitation transfer via near-field interactions between quantum dots," *Journal of Applied Physics*, vol. 116, no. 15, pp. 154 303–, Oct. 17, 2014. DOI: 10.1063/1.4898570.

[53] H. Geng, A. Mousavi, N. G. Markatos, K. Chen, and X. Gou, "Reliable cost prediction and control for intelligent manufacture: A key performance indicator perspective," *International Journal of Network Dynamics and Intelligence*, pp. 100 016–100 016, Dec. 22, 2023. DOI: 10.53941/ijndi.2023.100016.

[54] P. J. Werbos and L. Dolmatova, "Analog quantum computing (aqc) and the need for time-symmetric physics," *Quantum Information Processing*, vol. 15, no. 3, pp. 1273–1287, Oct. 19, 2015. DOI: 10.1007/s11128-015-1146-2.

[55] A. Asgary, A. S. Naini, and J. K. Levy, "Intelligent security systems engineering for modeling fire critical incidents: Towards sustainable security," *Journal of Systems Science and Systems Engineering*, vol. 18, no. 4, pp. 477–488, Dec. 11, 2009. DOI: 10.1007/s11518-009-5121-2.

[56] K. Yuan, M. Zhao, D. Yu, *et al.*, "Correction: Striato-cortical tracts predict 12-h abstinence-induced lapse in smokers.," *Neuropsychopharmacology : official publication of the American College of Neuropsychopharmacology*, vol. 44, no. 7, pp. 1338–1338, Mar. 12, 2019. DOI: 10.1038/s41386-019-0330-y.

[57] K. M. Lichade, S. Hu, and Y. Pan, "Acoustic streaming-assisted two-photon polymerization process for the production of multimaterial microstructures," *SSRN Electronic Journal*, Jan. 1, 2022. DOI: 10.2139/ssrn.4276202.

[58] A. A. Volk, Z. S. Campbell, M. Y. S. Ibrahim, J. A. Bennett, and M. Abolhasani, "Flow chemistry: A sustainable voyage through the chemical universe en route to smart manufacturing.," *Annual review of chemical and biomolecular engineering*, vol. 13, no. 1, pp. 45–72, Mar. 8, 2022. DOI: 10.1146/annurev-chembioeng-092120-024449.

[59] S. Bandara, M. Herath, and J. Epaarachchi, "Sensory methods and machine learning based damage identification of fibre-reinforced composite structures: An introductory review," *Journal of Reinforced Plastics and Composites*, vol. 42, no. 21-22, pp. 1119–1146, Dec. 14, 2022. DOI: 10.1177/07316844221145972.

[60] G. Pieraccini, R. Schmidt, and G. Windisch, "Vernetzt, elektrifiziert: Elektroniksysteme eines hybrid-konzeptfahrzeugs," *ATZelektronik*, vol. 9, no. 5, pp. 10–17, Sep. 22, 2014. DOI: 10.1365/s35658-014-0464-y.

[61] B. O. Matthews, D. Perdue, and E. L. Hall, "Omnidirectional vision applications for line following," *SPIE Proceedings*, vol. 2588, pp. 438–449, Oct. 3, 1995. DOI: 10.1117/12.222697.

[62] P. Naseradinmousavi, M. Krstic, and C. Nataraj, "Design optimization of dynamically coupled actuated butterfly valves subject to a sudden contraction," *Journal of Mechanical Design*, vol. 138, no. 4, pp. 041 402–, Feb. 19, 2016. DOI: 10.1115/1.4032215.

[63] A. R. Remya, B. Vishwash, C. Lee, *et al.*, "Hip implant performance prediction by acoustic emission techniques: A review.," *Medical & biological engineering & computing*, vol. 58, no. 8, pp. 1637–1650, Jun. 12, 2020. DOI: 10.1007/s11517-020-02202-z.

[64] G. C. Haynes, D. Stager, A. Stentz, *et al.*, "Developing a robust disaster response robot: Chimpźand the robotics challenge," *Journal of Field Robotics*, vol. 34, no. 2, pp. 281–304, Feb. 16, 2017. DOI: 10.1002/rob.21696.

[65] S. Goel, F. Chen, and W. Cai, "Highlights from the latest articles in nano-oncology," *Nanomedicine (London, England)*, vol. 10, no. 6, pp. 897–898, Apr. 13, 2015. DOI: 10.2217/nnm.14.220.

[66] J. Zhang, L. Cui, D. Jiang, *et al.*, "A biopolymer-like metal enabled hybrid material with exceptional mechanical prowess.," *Scientific reports*, vol. 5, no. 1, pp. 8357–8357, Feb. 10, 2015. DOI: 10.1038/srep08357.

[67] W. Li, G.-G. Wang, and A. H. Gandomi, "A survey of learning-based intelligent optimization algorithms," *Archives of Computational Methods in Engineering*, vol. 28, no. 5, pp. 3781–3799, Feb. 25, 2021. DOI: 10.1007/s11831-021-09562-1.

[68] M. K. Bess, D. Lipset, K. Matereke, *et al.*, "Book reviews," *Transfers*, vol. 7, no. 2, pp. 124–143, Jun. 1, 2017. DOI: 10.3167/trans.2017.070211.

[69] R. Quay, A. Leuther, S. Chartier, L. John, and A. Tessmann, "(invited) iii-v integration on silicon for resource-efficient sensor-technology," *ECS Transactions*, vol. 111, no. 1, pp. 117–122, May 19, 2023. DOI: 10.1149/11101.0117ecst.

[70] A. Carrott, C. D. Wright, A. A. West, R. Harrison, and R. H. Weston, "Tool set for distributed real-time machine control," *SPIE Proceedings*, vol. 2912, pp. 2–12, Jan. 20, 1997. DOI: 10.1117/12.263360.

[71] A. Pollitt, "A 'front-end' system: An expert system as an online search intermediary," *Aslib Proceedings*, vol. 36, no. 5, pp. 229–234, May 1, 1984. DOI: 10.1108/eb050928.

[72] J. Lee, J. Sun, F. Wang, S. Wang, C.-H. Jun, and X. Jiang, "Privacy-preserving patient similarity learning in a federated environment: Development and analysis.," *JMIR medical informatics*, vol. 6, no. 2, e20–, Apr. 13, 2018. DOI: 10.2196/preprints.7744;10.2196/preprints.7744.a;10.2196/medinform.7744.

[73] S. Spiga, B. Stefano, E. Covi, *et al.*, "(invited) analog hfox-rram switches for neural networks," *ECS Meeting Abstracts*, vol. MA2016-02, no. 16, pp. 1473–1473, Sep. 1, 2016. DOI: 10.1149/ma2016-02/16/1473.

[74] Y. J. Cao and Q. Wu, "Teaching genetic algorithm using matlab," *International Journal of Electrical Engineering & Education*, vol. 36, no. 2, pp. 139–153, Apr. 1, 1999. DOI: 10.7227/ijeee.36.2.4.

[75] R. B. Delvalle, F. L. Merat, S. Ruegsegger, and K. Roumina, "Heuristic planning in feature-based inspection for coordinate measuring machines," *SPIE Proceedings*, vol. 1963, pp. 341–355, Mar. 23, 1993. DOI: 10.1117/12.141751.

[76] G. Burstein, C. V. Negoita, and M. Kranz, "Postmodern fuzzy system theory: A deconstruction approach based on kabbalah," *Systems*, vol. 2, no. 4, pp. 590–605, Nov. 4, 2014. DOI: 10.3390/systems2040590.

[77] P. Koul *et al.*, "Advancements in underground mining equipment design: Safety, finite element analysis, and structural innovations," *Synergy: International Journal of Multidisciplinary Studies*, vol. 2, no. 1, pp. 24–43, 2025.

[78] Y. Tang, Q. Zhang, G. Lin, and J. Yin, "Switchable adhesion actuator for amphibious climbing soft robot," *Soft robotics*, vol. 5, no. 5, pp. 592–600, Jun. 29, 2018. DOI: 10.1089/soro.2017.0133.

[79] W. Gu, X. Li, Q. Li, Y. Hou, M. Zheng, and Y. Li, "Combined remediation of polychlorinated naphthalene-contaminated soil under multiple scenarios: An integrated method of genetic engineering and environmental remediation technology.," *Journal of hazardous materials*, vol. 405, pp. 124 139–, Oct. 10, 2020. DOI: 10.1016/j.jhazmat.2020.124139.

[80] J. A. Bateman, "Nlpcs - language and space: A two-level semantic approach based on principles of ontological engineering," *International Journal of Speech Technology*, vol. 13, no. 1, pp. 29–48, Mar. 16, 2010. DOI: 10.1007/s10772-010-9069-x.

[81] Y. Tang, J. Yang, S. Wang, and S. Wang, "Analysis of rock cuttability based on excavation parameters of tbm," *Geomechanics and Geophysics for Geo-Energy and Geo-Resources*, vol. 9, no. 1, Jul. 10, 2023. DOI: 10.1007/s40948-023-00628-x.

[82] J. Bergendahl, I. Masaki, and B. K. P. Horn, "Three-camera stereo vision for intelligent transportation systems," *SPIE Proceedings*, vol. 2902, pp. 42–51, Feb. 17, 1997. DOI: 10.1117/12.267161.

[83] V. R. Aravind and C. N. Refugio, "Efficient learning with intelligent tutoring across cultures," *World Journal on Educational Technology: Current Issues*, vol. 11, no. 1, pp. 30–37, Jan. 31, 2019. DOI: 10.18844/wjet.v11i1.4007.