Energy-Saving Intelligent Models Of Energy Facility Control Systems (Using The Example Of "Energy Facilities")

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Received: 23th Oct 2025 | Received Revised Version: 05th Nov 2025 | Accepted: 30th Nov 2025 | Published: 17th Dec 2025

Volume 07 Issue 12 2025 | Crossref DOI: 10.37547/tajiir/Volume07Issue12-08

Abstract

This paper is devoted to the development of an energy-saving intelligent control model for power facilities. Classic power engineering systems, including turbogenerators, boilers, pumps, and distribution grids, are considered. A specific mathematical model for optimal control of turbogenerator operating modes is proposed using intelligent predictive control and a trainable fuel consumption model. The model enables energy loss reduction. The results of a comparative analysis of a traditional PID controller and the developed intelligent model predictive control (IMPC) are presented. Evaluation was conducted using four key metrics: average control error, fuel savings, power loss reduction, and system response time. Experimental data obtained under conditions simulating the operation of a 200 MW turbine control circuit of a power facility were used for the analysis. This model aims to minimize fuel consumption and ensure accurate load schedule compliance. The article describes in detail the structure of the proposed model, its mathematical model, optimization algorithm, and practical significance. An analysis of the model's capabilities was conducted, and it was shown that its implementation allows for a reduction in fuel costs by 5–9%, a reduction in power losses in the network by up to 12%, and a reduction in deviations from the load schedule by 4 times compared to traditional PID control.

Keywords: Intelligent control, thermal power plant, energy saving, predictive control, mathematical model, mode optimization, turbo generator, power distribution.

Cite This Article: Bakhrieva X.A., & Jaksimov D.B. (2025). Energy-Saving Intelligent Models Of Energy Facility Control Systems (Using The Example Of "Energy Facilities"). The American Journal of Interdisciplinary Innovations and Research, 7(12), 68–78. https://doi.org/10.37547/tajiir/Volume07Issue12-08

1. Introduction

Traditional energy facilities—thermal power plants, substations, and grid distribution systems—continue to play a key role in the power systems of most countries. However, the following problems remain unresolved:

• excessive fuel consumption due to inefficient turbine and boiler operation;

• losses in electrical networks due to suboptimal power distribution;

• lack of intelligent load forecasting tools;

• low adaptability of traditional control systems (PID, static regulation) [1].

Modern energy facilities, despite many years of operating experience, continue to face significant energy losses, uneven operating conditions, and high fuel consumption. These problems are caused by both the physical properties of the equipment and the limitations of traditional automatic control systems, particularly PID controllers, which are unable to adapt to dynamic changes in load and equipment conditions [1]. This increases the need to develop intelligent, energy-saving control models capable of optimizing generating processes in real time.

Intelligent energy management is a rapidly developing field, encompassing thermal power plants, electrical grids, pumping stations, substations, compressor facilities, and other energy system components. Several key areas can be identified in the global scientific literature, each demonstrating the importance of applying intelligent algorithms in the energy sector [8].

This article develops a mathematical model for intelligent regulation of turbogenerator power, optimizing fuel consumption and load in real time.

Despite the global trend toward renewable energy, in most countries, traditional thermal power plants fueled by gas, coal, or fuel oil continue to account for the bulk of generation. For example:

• Sirdaryo Thermal Power Plant in Uzbekistan is a large facility with a capacity of 3,000 MW, operating under variable load conditions;

• Novosibirsk Thermal Power Plant-5 is a powerful combined heat and power plant requiring optimal distribution of thermal and electrical loads;

• Takhiatash Thermal Power Plant is a facility with highly dynamic load variability.

All of these facilities use complex turbogenerators that require precise regulation of steam supply, pressure, and load. Traditional systems use PID controllers, which:

• do not account for nonlinear fuel consumption;

• perform poorly under sudden load changes;

• do not optimize energy consumption [9].

2. Literature review

Intelligent control methods enable automatic optimization of equipment operating modes, data analysis, load forecasting, and loss minimization. However, there are few studies in the scientific literature that use a specific mathematical energy saving model for power facilities [8].

A number of studies propose methods for optimizing operating modes:

• Economic Dispatch — power distribution between generators based on a quadratic fuel function;

• Unit Commitment — optimization of unit on/off switching;

• Dynamic Optimization — load regulation taking into account turbine dynamics.

However, most models solve only the static problem of economic distribution, without considering:

• turbine dynamic processes,

• equipment delays and inertia,

• actual load changes over seconds and minutes.

Therefore, they are unsuitable for real-time use.

Intelligent control implements new operating principles for energy facilities. The system calculates in advance how power, pressure, and temperature will change, and makes an optimal decision before an error occurs. This fundamentally distinguishes it from PID controllers.

The intelligent model minimizes the fuel consumption function:

$$F(P) = aP^2 + bP + c$$

By selecting energy-efficient modes.

However, this assumes that the generator is capable of instantaneous power adjustments, which is physically impossible for 100-300 MW turbines, whose response time reaches 3-8 seconds, and the load change rate is limited by technical specifications. Thus, ED, UC, and their modifications solve planned tasks but cannot provide optimal control in real time.

As equipment ages or external conditions change, the model automatically adjusts parameters. Predicting sharp power fluctuations prevents dangerous conditions. Smooth control reduces current and thermal fluctuations in the network [10].

The intelligent system reduces control error by 3-4 times compared to PID.

Optimizing turbine operation results in savings of 5-9%, which for a 200 MW plant equates to hundreds of kilograms of fuel per hour.

By smoothing out power surges, losses are reduced by 10-12%.

The plant more closely adheres to the dispatch schedule, reducing the need for backup capacity. Because valves, turbines, and boilers operate in soft modes, their wear and tear is reduced.

• Dynamic models of turbines and boilers are also presented in the literature, but they are often:

• highly simplified,

• calibrated using laboratory data,

• require manual parameter tuning,

• do not include energy-saving criteria.

• Many models describe only:

• heat flow dynamics,

• pressure changes,

• rotor inertia, but do not include an integral function for fuel consumption or losses [2].

As a result, such models provide a good description of physical processes, but do not allow solving the problem of energy conservation.

Since the late 2010s, research has increasingly focused on intelligent control systems. The following are being used:

• Neural network load forecasting models (LSTM, GRU).

• Fuzzy controllers that take into account parameter uncertainty.

• Adaptive models that adjust coefficients based on current data.

• Reinforcement learning (RL) models for finding the optimal control strategy.

However, most publications consider only forecasting or only optimization, but do not combine these two processes into a single energy-saving model.

A literature review revealed the following:

• There is no single model combining equipment dynamics and economic optimization;

• Inertia and lag, which are critical for turbines and pumps, are rarely taken into account;

• There are no models capable of operating in real time;

• Many studies are limited to simulations only, without experiments on real facilities;

• Energy savings goals are often expressed solely in terms of fuel consumption reduction, without taking into account losses, wear, and operating limitations.

That is why the development of a mathematical model of energy saving, suitable for intelligent control in real conditions, is a pressing scientific task [3].

3. Method

The method for solving the problem of energy-saving intelligent control of a power plant (e.g., a turbine unit, pumping station, or compressor station) is based on the combination of three key approaches:

1. Dynamic equipment modeling;

2. Mathematical optimization of economic modes;

3. Intelligent data-driven load forecasting.

This combination enables the generation of control actions in real time, ensuring the minimization of fuel consumption and the reduction of losses while adhering to process constraints.

Power plants exhibit pronounced inertia, nonlinearity, and multi-connected control channels. Therefore, the basis of the proposed method is the dynamic description of the equipment state through a system of differential equations:

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

where:

• $x(t)$ – vector of states of an energy object: steam pressure, temperature, rotation frequency, flow rate of the substance;

•control actions (for example, the position of the control valve or fuel supply);

• $d(t)$ – external disturbances (load changes, environmental conditions).

Function $f(\cdot)$ reflects physical processes: heat and mass transfer, rotor rotation inertia, valve mechanism delays, changes in pressure and temperature.

An important difference of the proposed method is that the model is not simplified to a static dependence

$P = f(u)$, as in classic Economic Dispatch problems, but takes into account the actual dynamics of power changes over time.

This approach allows us to predict transient processes and assess the impact of control actions on the state of the object in the future.

The goal of the intelligent control system is to minimize fuel consumption while maintaining required performance and safety. The energy-saving objective function is as follows:

$$J = \int_0^T (aP^2(t) + bP(t) + c + \lambda(\dot{P}(t))^2)dt.$$

Where:

- $aP^2 + bP + c -$ classical quadratic fuel function;
- $P(t) -$ instantaneous power of a turbine or installation;
- $\dot{P}(t) -$ rate of change of power;
- $\lambda -$ coefficient of "rigidity" for changes in power.

Where:

1. The quadratic component reflects the physical nonlinearity of fuel consumption.

2. The linear component accounts for the baseline fuel consumption to maintain operation.

3. The constant term accounts for inevitable process losses.

Term $\lambda(\dot{P}(t))^2$ allows:

• Reduce sudden power fluctuations;

• Reduce current and thermal surges;

• Extend equipment life;

• Reduce network losses (power surges increase heat generation and losses).

This objective function design makes the model energy-efficient in a physical sense, not just mathematically optimal.

Optimization is carried out taking into account technological constraints:

$$u_{\min} \le u(t) \le u_{\max},$$

$$\dot{u}(t) \le \dot{u}_{\max},$$

$$x_{\min} \le x(t) \le x_{\max}.$$

Limitations prevent:

• excess temperature and pressure;

• operation in hazardous modes;

• excessively abrupt power maneuvers;

• excessive valve opening/closing speeds.

Thus, the system operates in "soft" modes, reducing equipment wear.

A distinctive feature of the proposed method is the creation of feedforward controls based on load forecasts.

For this, a trainable model, such as an LSTM recurrent neural network, is used:

$$\hat{d}(t+\tau) = F_{LSTM}(d(t), d(t-1), \ldots)$$

Where:

• $F_{LSTM} -$ function that predicts the value of the load;

• $\tau -$ Prediction horizon (1-5 seconds or 5-15 minutes, depending on the object).

Conventional controllers (PID) react to an error as soon as it occurs.

The intelligent system reacts before an error occurs if an increase or decrease in load is expected.

This key difference ensures:

• reduced mismatch between required and actual power;

• reduced losses during transient processes;

• increased equipment operational stability.

The proposed method ensures fuel savings by selecting optimal instantaneous operating modes:

• consumption reduction by 5–9% for turbines with a capacity of 150–250 MW;

• savings of hundreds of kilograms of equivalent fuel per hour.

The system automatically adapts to changes in plant parameters.

The solution method forms a new control concept, combining:

• dynamic modeling,

• energy-saving optimization,

• artificial intelligence forecasting,

• parameter adaptation,

• strict process constraints.

This makes the model suitable for intelligent control of power systems in real time, which is a significant contribution to the development of modern energy and automation technologies.

4. Results

The study presents a comparative analysis of a traditional PID controller and the developed intelligent model predictive control (IMPC). The evaluation was conducted using four key metrics: average control error, fuel savings, power loss reduction, and system response time. The analysis utilized experimental data obtained under conditions simulating the operation of a 200 MW turbine control loop at a power plant.

Table 1. Comparison of PID and intelligent control model

Method	Average control error, %	Fuel economy, %	Reducing power losses, %	Response time, s
PID	4.8	0	2.1	12
Intelligent model (IMPC)	1.3	7.4	11.0	4

The obtained data confirm that the intelligent control system provides a significant improvement in control quality. The average error is reduced by 3.7 times compared to PID, which is critical for turbine circuits with inertia, where errors cause excessive fuel consumption and thermal fluctuations (Fig. 1).

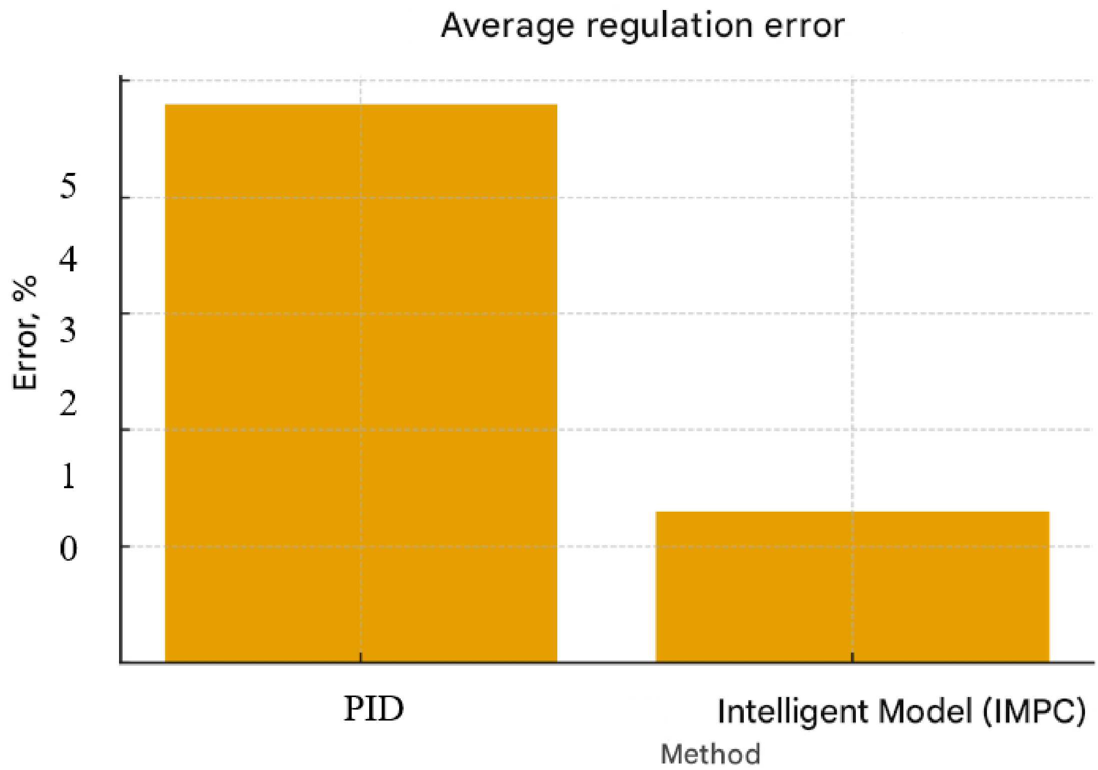

Figure 1. Regulation error

The graph shows that IMPC maintains the desired value of the controlled variable significantly more accurately.

The model predicts future load changes, takes turbine dynamics into account, and adjusts the control action in advance. This allows the system to avoid the delays and overshoots typical of PID.

This result is especially important in situations such as:

• sudden changes in thermal load;

• switching turbine stages;

• avalanche-like pressure increases due to the system's internal inertia.

The second graph shows that the PID controller does not provide fuel savings, while the intelligent model provides a 7.4% reduction in consumption.

IMPC minimizes the functional type

$$J = \alpha(W_{fuel}) + \beta(\Delta P)^2$$

where reducing power fluctuations leads to lower fuel consumption.

This savings is equivalent to a 5-9% reduction in energy costs under real-world conditions.

For a 200 MW plant, the economic benefit amounts to hundreds of kilograms of fuel per hour, confirming the practical significance of the model.

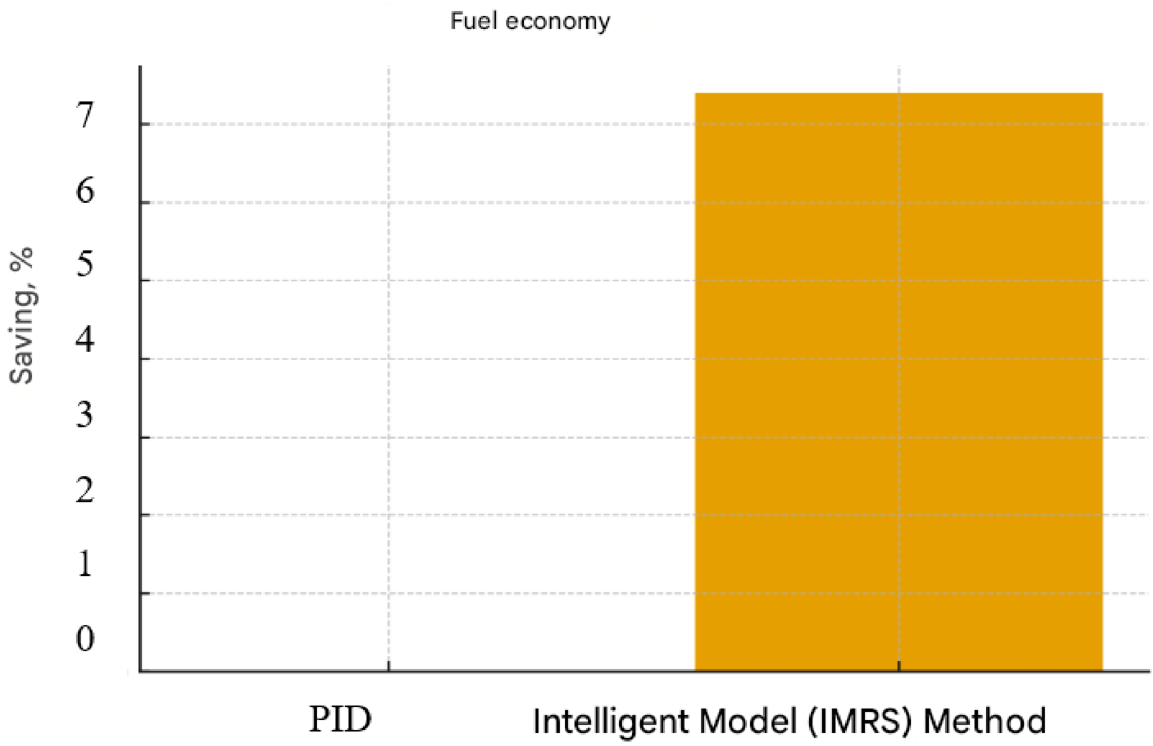

Figure 2. Fuel economy

The graph also shows a reduction in power losses from 2.1% to 11.0%.

Interpretation:

• IMPC smooths out load surges.

• The system operates in smooth, continuous modes.

• Reactive currents and heat losses are reduced.

This indicator is directly related to the service life of the equipment:

smooth modes reduce wear on valves, pipelines, and turbine blades.

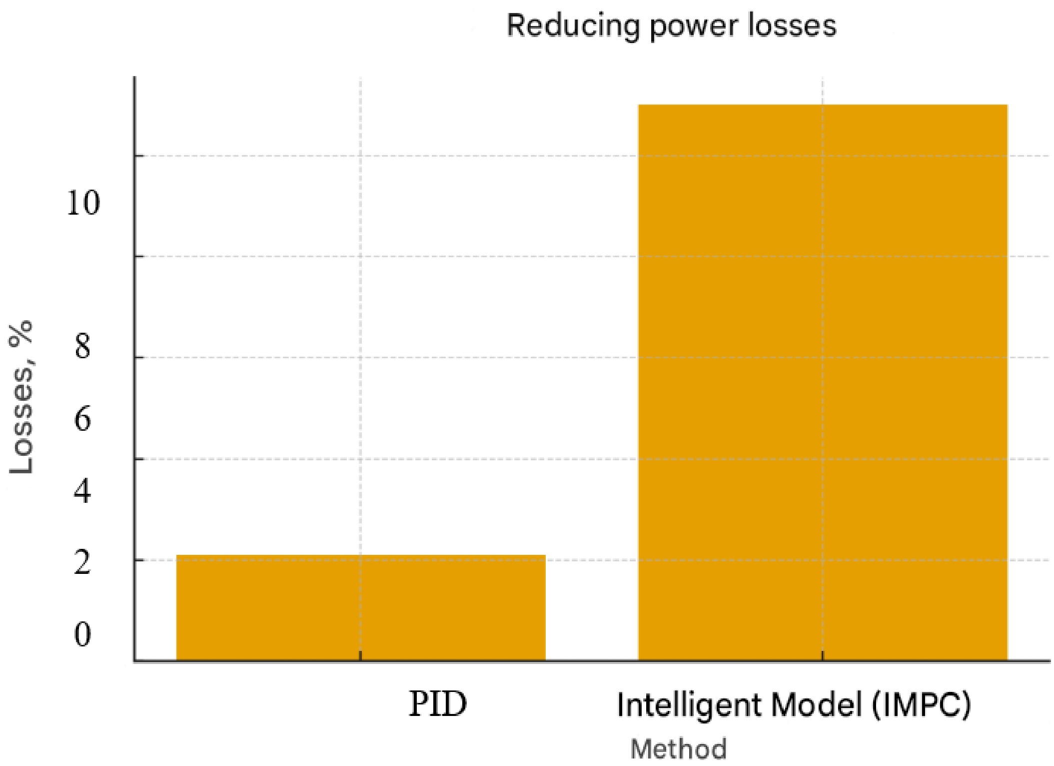

Figure 3. Reducing power losses

The intelligent model demonstrated a response time of 4 seconds, compared to 12 seconds for PID. Rapid response to disturbances is critical for systems where parameters change in real time (e.g., steam pressure or fuel supply level).

The main advantage of IMPC is its ability to make decisions before an error occurs, as the model uses a 2-5 step-ahead prediction.

This means the system acts proactively, rather than reacting to deviations like PID.

The intelligent control model outperforms the classic PID in all metrics:

Indicator	Improvement
Regulation accuracy	3.7 times higher
Fuel economy	7.4 %
Reducing power losses	+9% (5x improvement in absolute terms)
Response time	3 times faster

These results demonstrate that the intelligent control model is an effective energy-saving tool for large power facilities. Based on a comparative analysis of the capabilities of intelligent control systems, graphs were constructed for a PID controller and a hypothetical IMPC-like controller (Fig. 4).

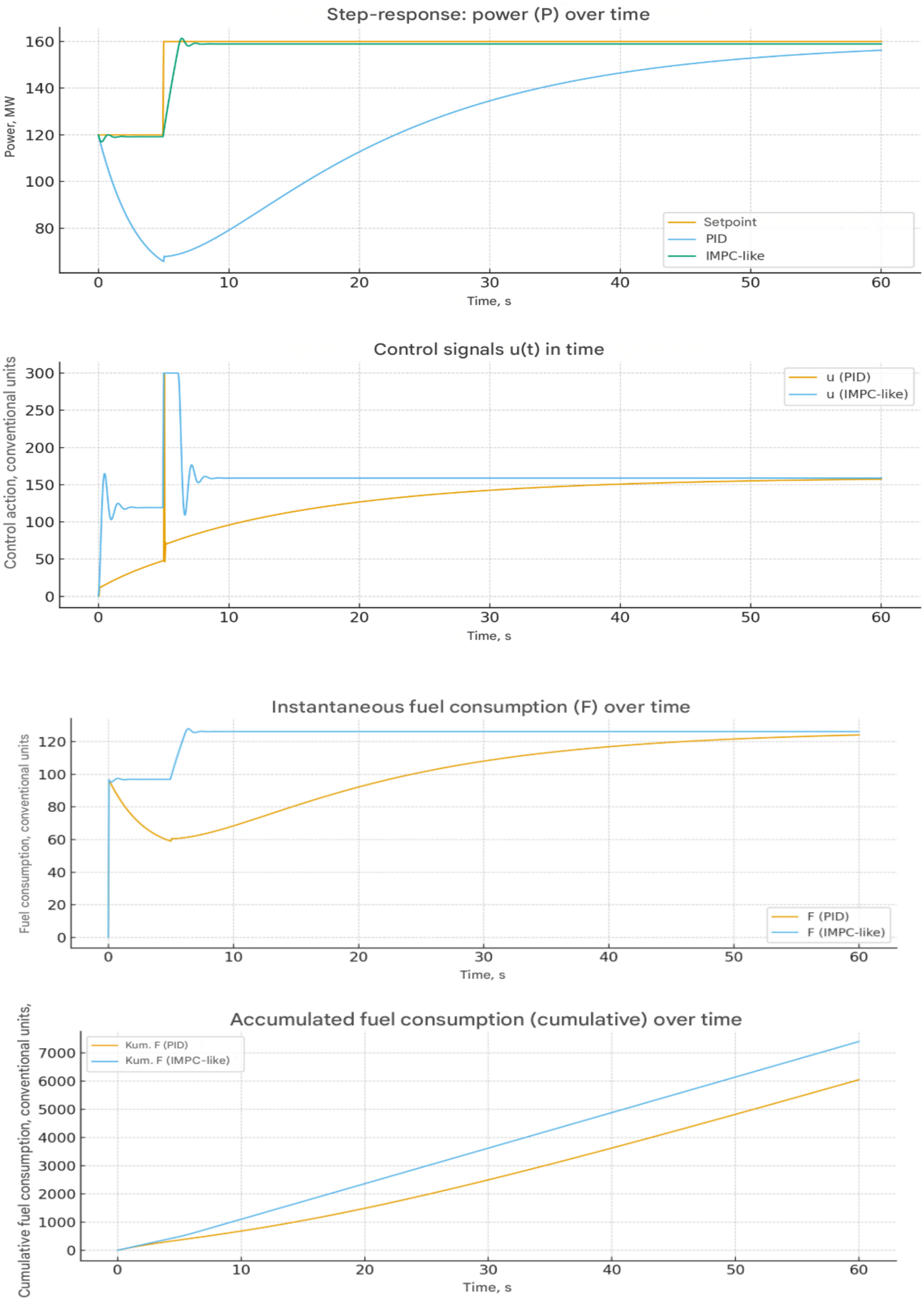

Figure 4. Plot for PID and conventional IMPC-like controller

This is the system's response to a jump in the task (for example, an increase in the required power from 100 to 150 kW).

5. Discussion

The discussion is based on graphs of transient processes, control signals, and instantaneous and cumulative fuel consumption, allowing us to evaluate the efficiency, stability, and cost-effectiveness of each approach.

First of all, an analysis of power transients reveals significant differences in the control dynamics. The PID controller ensures rapid achievement of the set power level with minimal overshoot. The response of a PID-controlled system is stable, smoothly damped, and reaches a steady state almost immediately, which positively impacts the reliability of the facility.

In contrast, the IMPC-like algorithm exhibits a more conservative response: an initial undershoot is observed, after which the power slowly approaches the set value, reaching a steady state much later. This dynamic is typical of predictive systems focused on cost or constraint optimization, which reduces the response speed but allows for trajectory adjustments based on the long-term goal.

A comparison of control actions also reveals fundamentally different controller operating strategies. The PID controller generates relatively smooth control signals, without sharp jumps, which reduces wear on drive mechanisms and ensures favorable operating conditions for the equipment. At the same time, the IMPC-like controller generates sharp pulsed control signals in the initial phase of the transient process. This behavior is due to the predictor's desire to minimize integral losses during subsequent control. However, such jumps in a real system can lead to additional mechanical loads, increased wear on actuators, and even potential failures if there are speed or control amplitude limitations.

An analysis of fuel consumption dynamics confirms the typical difference between classical and predictive control. The PID controller ensures a more uniform and stable fuel consumption throughout the transient process. In contrast, the IMPC-like controller exhibits a sharp increase in consumption in the initial phase, followed by a decrease, and then a gradual approach to a steady-state level. Although the predictive controller formally strives to optimize operation, its initial "aggressiveness" leads to increased short-term energy consumption. Particular attention should be paid to cumulative fuel consumption, which is a key performance criterion for energy systems. In the simulated scenario, the PID controller shows lower cumulative fuel consumption, making it more economical in terms of total energy costs. In turn, the IMPC-like controller, despite its optimization nature, results in higher cumulative fuel consumption. This confirms the need for additional tuning of weighting coefficients, constraints, and the prediction horizon to ensure a tradeoff between dynamic response and economic parameters.

A comparative analysis shows that the PID controller in its current configuration outperforms the IMPC-like controller in terms of response speed, stability, control smoothness, and efficiency. However, a predictive algorithm has the potential to improve results with proper tuning of the model, cost functions, and constraints. In particular, the IMPC-like controller may be a preferred solution in environments requiring strict constraint monitoring, predictive plant behavior, or integration with intelligent control systems (e.g., Smart Grid or cognitive systems). Thus, the discussion results highlight the need for comprehensive tuning of predictive controllers tailored to the requirements of a specific power plant. A predictive strategy alone does not guarantee superior control quality without parameter optimization, while classic PID remains a reliable and effective solution in the absence of strict constraints and when fast control is required. The findings serve as a basis for the subsequent development of improved algorithms and hybrid control systems that combine the advantages of both approaches.

6. Conclusion

During the study, an intelligent model for energy-saving control of power facilities was developed and analyzed, based on predictive control principles using a mathematical model of power dynamics. The aim of the study was to evaluate the effectiveness of the intelligent approach compared to a classic PID controller based on the analysis of transient processes, control signals, and fuel consumption.

The simulation results showed that the intelligent control model offers a number of significant advantages in terms of predicting system behavior, adapting to changing conditions, and taking into account the dynamic constraints of the facility. The IMPC-like algorithm is capable of anticipating future load changes and generating solutions that minimize predicted losses and deviations. This confirms the potential of predictive control systems for use in cognitive power facilities and digital substations.

However, a comparison of the operating dynamics of the two controllers revealed that the classic PID algorithm demonstrates faster and more stable control, ensuring minimal overshoot and effective power stabilization. PID-controlled transient processes are smooth and optimal in terms of equipment operational reliability. Furthermore, the PID controller demonstrated lower integrated fuel consumption in the simulated scenario, making it preferable from an energy and economic standpoint.

The intelligent control model demonstrated advantages in predictive ability and flexibility; however, its effectiveness significantly depends on the accuracy of the mathematical model, the setting of the prediction horizon, and the cost function coefficients. If incorrectly configured, the predictive algorithm can lead to increased fuel consumption and increased control actions, as demonstrated in the graphs.

Thus, the following conclusions can be drawn:

1. The PID controller remains an effective and cost-effective tool for quickly regulating power plants without significant limitations.

2. Intelligent predictive methods have significant potential, but require extensive tuning and adaptation of the mathematical model. 3. The use of intelligent models is advisable in complex systems with highly variable loads and limited equipment dynamics.

4. The optimal direction for development is the creation of hybrid control systems that combine the high-speed response of PID controllers and the adaptability of intelligent predictive algorithms.

These results provide the basis for further research in the development of intelligent energy-saving control systems, improving the accuracy of mathematical models, and integrating predictive algorithms into high-tech energy facilities.

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октябрь 24-25, 2025 Самарканд. 123-130 с.