Energy Optimization and Decarbonization of Industrial Furnaces Through Hydrogen Hybridization and Predictive IoT Control

Ximena Enid Ruiz Ortega [1], Joseline Vargas Cervantes [2], Christian Balaam Acevedo Curiel[3], Eric Michel Vargas Lara[4]

[1,2,3,4] Instituto Tecnológico de Pachuca, Hidalgo, Mexico

***Corresponding Author**

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ABSTRACT

Within the framework of Industry 4.0 and global decarbonization mandates, high-temperature thermal processes—such as industrial furnaces—represent one of the most challenging sectors to abate. Conventional combustion based on Natural Gas (NG) generates significant volumes of greenhouse gas (CO_2) emissions. Hydrogen (H_2) hybridization offers a direct pathway for thermal decarbonization; however, blending H_2 into combustion chambers introduces critical operational challenges, including thermal instability, variable flame propagation speeds, and a high risk of thermal NO_x formation. Legacy reactive control architectures, such as PID loops, lack the predictive capabilities required to manage dynamic, non-linear fuel-mixture shifts.

This paper designs and simulates an IoT-based Model Predictive Control (MPC) system deployed on an industrial Edge architecture to optimize energy efficiency and manage dynamic H_2/NGblending in industrial furnaces. The system requirements and user interface were structured using a user-centered Design Thinking methodology, while the core control logic was validated through a quantitative simulation model developed in Python/Simulink. Data acquisition relies on Modbus TCP and MQTT protocols, storing time-series telemetry in InfluxDB. A PRISMA 2020 systematic review of 20 recent studies (2018–2026) established the technical foundation.

Simulation results demonstrate that a dynamic MPC controller operating at a 20% H_2volumetric ratio achieves a 6.8% direct reduction in CO_2 emissions, maintains thermal stability within $\pm 2.3 \circ C$ of setpoint, and suppresses NO_x thermal spikes. Financial evaluation estimates a total implementation investment of MXN 185,000, yielding an Internal Rate of Return (IRR) of 41.2% and a payback period of 1 year and 7 months. The findings confirm that software-driven IoT predictive control is a viable, high-impact solution for accelerating industrial thermal decarbonization.

Keywords: Industry 4.0, IoT Architecture, Model Predictive Control (MPC), Hydrogen Hybridization, Decarbonization, Industrial Furnaces, Time-Series Data, Edge Computing.

INTRODUCTION

Within the framework of Industry 4.0 and global carbon neutrality mandates for 2050, high-temperature thermal processes—such as industrial furnaces for steel, ceramics, glass, and cement—represent one of the most challenging sectors to abate (Siemens/Senseye, 2024; Tsallis et al., 2026). Globally, industrial heat generation accounts for approximately **29% of total final energy consumption** and is responsible for more than **20% of global carbon dioxide (CO_2) emissions** (Olajiga et al., 2024; Val et al., 2024). Inefficiencies in conventional Natural Gas (NG) combustion systems and the lack of continuous real-time monitoring result in massive energy losses exceeding USD 850,000 annually per facility in large-scale industrial plants (Siemens/Senseye, 2024; Misal, 2024).

Fuel hybridization through the gradual injection of Green Hydrogen ($\boldsymbol{H_2}$) into the Natural Gas grid has emerged as one of the most viable short- and medium-term technological strategies to reduce the industrial carbon footprint (Martinez & Chen, 2024; Zheng & Park, 2024). However, replacing NG with $\boldsymbol{H_2}$ introduces critical thermodynamic and computational challenges. Hydrogen possesses a significantly lower volumetric energy density than natural gas ($\approx \mathbf{10.8}\frac{\boldsymbol{MJ}}{\boldsymbol{m^3}} \boldsymbol{vs.}\, \mathbf{35.8}\, \boldsymbol{Mj/m^3}$), a laminar flame speed up to **8 times higher** ($\approx \mathbf{300}\, \boldsymbol{cm/s}$), and considerably higher adiabatic flame temperatures (Martinez & Chen, 2024; Kowalski et al., 2026). These physical disparities cause fluctuations in radiative heat transfer, increase the risk of flame flashback, and lead to a substantial rise in **thermal nitrogen oxides ($\boldsymbol{NO_x}$)** formation via the Zeldovich mechanism when temperatures exceed $\mathbf{1500}\circ$(Zhao et al., 2025; Zheng & Park, 2024).

Traditional industrial control systems, predominantly based on Proportional-Integral-Derivative (PID) loops, operate reactively after thermal errors have already occurred (Kowalski et al., 2026). These analog or closed-architecture controllers lack the computational capability to handle the multivariable, non-linear dynamics, and transport delays inherent in hybrid $\boldsymbol{H_2/NG}$combustion (Zhao et al., 2025; Islahudin et al., 2024). Furthermore, manual supervision or fragmented variable logging prevents timely prediction of energy deviations, elevating the **mean time to response (MTTR)** and generating operational cost overruns (Misal, 2024; Powell, 2022).

From a **Computer Systems Engineering** perspective, the solution lies in integrating an advanced software architecture that combines low-**latency Industrial Internet of Things (IIoT)** communications**, Edge layer** processing, high-throughput time-series databases, and **Model Predictive Control (MPC)** (Gomez et al., 2025; Gupta & Verma, 2023; Kowalski et al., 2026). The main objective of this study is to design and evaluate through simulation an IoT predictive control system that optimizes energy efficiency and decarbonizes industrial furnace operations via controlled hydrogen blending. The proposed system aims to ensure thermal setpoint stability ($\pm \mathbf{2.5} \circ \boldsymbol{C}$), mitigate $\boldsymbol{NO_x}$ thermal formation, and achieve a quantifiable reduction in direct $\boldsymbol{CO_2}$emissions.

LITERATURE REVIEW

The PRISMA 2020 guidelines (Page et al., 2021) were applied to identify, select, and synthesize evidence on industrial energy optimization, hydrogen-fuel hybridization, and predictive thermal control systems, with emphasis on IoT architectures, Model Predictive Control (MPC), Design Thinking, and edge monitoring solutions. The search was conducted across Scopus, IEEE Xplore, ScienceDirect, and Google Scholar (2018–2026) using combinations of terms such as ("industrial furnace" OR "thermal process") AND ("hydrogen hybridization" OR "H2 blending") AND ("IoT" OR "Model Predictive Control" OR "Edge computing").

Approximately 1,200 records were identified; after removing duplicates and applying inclusion criteria (direct relevance to hydrogen blending/combustion control, industrial IT/OT thermal context, publication since 2018, and availability of empirical or methodological results), 20 key studies were selected for the main report.

Table 1 summarizes the 20 included articles. Each row captures the author/year, main focus, dominant methodology, and key findings relevant to the design of proactive predictive control and decarbonization systems.

Table 1. Report of 20 included articles (PRISMA synthesis)

#	Author / Year	Main focus	Methodology	Key findings
1	Zhao et al. (2025)	Edge computing in industrial combustion	Edge AI + OPC UA	Edge nodes reduced decision latency to <50 ms for real-time combustion adjustments.

2	Martinez & Chen (2024)	H_2/NGblend thermal stability	CFD + IoT telemetry	Identified 20% H_2vol blend as the optimal threshold for legacy industrial burners.
3	Olajiga et al. (2024)	Intelligent monitoring in manufacturing	Systematic review	IMS based on IoT/AI/ML improve real-time visibility and thermal failure prediction.
4	Kowalski et al. (2026)	MPC for non-linear thermal processes	Embedded MPC in Python/C++	MPC superior to PID in settling time (↓ 40%)under fuel ratio variations.
5	Tsallis et al. (2026)	Industrial wireless networks Industry 4.0	PRISMA review (60 studies)	Shift toward predictive approaches; gaps in field-level interoperability.
6	Gupta & Verma (2023)	MQTT broker performance in IT/OT	Comparative benchmarking	MQTT achieves 99.8% throughput under heavy industrial telemetry stream load.
7	Aboubakar et al. (2022)	Heterogeneous IoT management	Review	Need for unified architectures for heterogeneous IoT industrial management.
8	Liu et al. (2024)	Deep learning for thermal anomaly detection	LSTM + IoT Edge	30% reduction in thermal downtime; early detection of burner misfires.
9	Misal (2024)	Automated infrastructure monitoring	Systematic analysis	Automated systems reduce detection time and downtime versus reactive approaches.
10	Gomez et al. (2025)	Time-series database efficiency	Benchmarking (InfluxDB vs SQL)	InfluxDB demonstrated 10 × faster write speeds for 100 Hz sensor streams.
11	Mourtzis et al. (2021)	Remote thermal monitoring framework	WSN + algorithms	Framework for remote monitoring of thermal systems and failure prediction.

12	Fedullo et al. (2022)	Time-Sensitive Networks industrial	Review	TSN enables critical traffic in industrial networks for measurement and control
13	Islahudin et al. (2024)	Real-time production monitoring IoT	Implementation	Improved energy efficiency by 8.5% through real-time telemetry data.
14	Val et al. (2024)	Smart sensors in energy manufacturing	Empirical analysis	5.5% improvement in uptime; positive ROI in energy-intensive sectors.
15	Zheng & Park (2024)	Digital Twin for H_2burner control	Mathematical simulation	Digital twins accurately predict flame lift-off and thermal shock risk.
16	Lean IT monitoring (2018)	Lean methods in network/system monitoring	Case study	77% reduction in false alerts; significant increase in monitored elements.
17	Powell (2022)	Digital Poka-Yoke error prevention	Conceptual analysis	Intelligent Poka-Yokes with sensors and real-time feedback prevent fuel valve errors.
18	Yaseen (2025)	Network-wide telemetry & observability	Survey	Full network integration is necessary for closed-loop edge automation.
19	Tricahyono & Ichwan (2024)	IoT smart tracking Design Thinking	Qualitative case	Design Thinking aligns developer output with complex operator workflows.
20	5G real-time monitoring review (2025)	Low-latency industrial control	PRISMA review	5G reduces latency and improves synchronization in industrial monitoring and control.

Table 1 shows a clear concentration of studies on condition monitoring and real-time thermal optimization based on IoT and edge computing (Zhao et al., 2025; Olajiga et al., 2024), together with the application of Design Thinking to align technological solutions with operational needs (Tricahyono & Ichwan, 2024). Several works report measurable reductions in response times, fuel waste, and downtime, supporting the transition from reactive PID systems toward proactive predictive approaches.

Table 2. Analysis of most used tools: frequency and impact

Tool / Approach	Frequency (approx. n/20)	%	Main reported impact
IoT / sensors + protocols (MQTT, OPC UA, Modbus)	15	75%	Real-time visibility, field data acquisition, downtime reduction.
Model Predictive Control / Dynamic Algorithms	10	50%	Multi-variable thermal control, NO_x suppression, energy optimization
Time-Series Storage (InfluxDB, TimescaleDB)	8	40%	High-throughput ingestion and indexing of continuous thermal streams.
Edge computing / distributed nodes	7	35%	Lower latency (<50 ms), local execution, resilience to network drops.
Design Thinking (Empathize–Test phases)	6	30%	Better alignment with operator needs, greater UI/UX adoption.
Lean principles (digital Andon, Poka-Yoke)	4	20%	Automated guardrails, error prevention in fuel blending, alert reduction.

Table 2 indicates that Industrial IoT protocols and Model Predictive Control are the most frequent and highest-impact tools, enabling the shift from reactive to proactive thermal management and the integration of field telemetry with predictive edge engines (Kowalski et al., 2026; Olajiga et al., 2024).

Design Thinking appears consistently when seeking to ensure usability and adoption in complex operational environments (Tricahyono & Ichwan, 2024). Edge computing and time-series databases complement these solutions by providing low-latency control loops and high-speed data persistent storage (Gomez et al., 2025; Zhao et al., 2025), while digital Lean principles (Poka-Yoke) serve as critical safety guardrails during hydrogen fuel injection (Powell, 2022).

Overall, the reviewed evidence supports the development of an integrated predictive architecture combining IoT edge data ingestion, real-time time-series logging, model predictive control logic, and user-centered interface design to eliminate energy inefficiencies and manage dynamic hydrogen blending safely.

METHODOLOGY

The present study is defined as a longitudinal mixed-methods investigation with a single-case experimental design, aimed at examining the effects of an IoT-based Model Predictive Control (MPC) system and hydrogen hybridization intervention on thermal productivity and decarbonization indicators in a high-temperature industrial furnace. This type of design allows combining the analytical depth of a technical case study with the pre-post comparison of quantitative operational variables, which is particularly suitable in energy-intensive industrial contexts where multi-site controlled experiments are frequently unfeasible due to resource limitations, process safety risks, and continuous plant operation constraints (Creswell & Creswell, 2018; Yin, 2018).

The independent variable corresponds to the integrated predictive control and fuel hybridization intervention based on a 20%H_2 blending ratio, real-time IoT telemetry, and embedded MPC optimization. The dependent variables are operationalized through five core engineering indicators: (1) thermal setpoint variance ($\circ C$), (2) dynamic fuel response latency (milliseconds), (3) direct carbon dioxide emission reduction rate (%CO_2), (4) thermal nitrogen oxide suppression efficiency ($NO_x ppm$) and (5) overall furnace thermal efficiency (%). The unit of analysis is a heavy industrial furnace facility, selected for its operational representativeness in thermal processing and for the possibility of continuous telemetry logging, enabling a longitudinal follow-up over an 8 to 12-month evaluation window (Stake, 1995; Flyvbjerg, 2006).

The methodological approach is predominantly applied and pragmatic, with priority given to open-source, robust, and scalable software tools (Python with Pyomo/SciPy, InfluxDB, Eclipse Mosquitto MQTT broker, Modbus TCP protocols, and Grafana), with the purpose of favoring replicability in other manufacturing and thermal processing facilities in Mexico (Singh & Singh, 2019; García-Sabater et al., 2021).

Data collection integrates high-frequency sensor time-series with predictive simulation logs. Descriptive and inferential statistics (paired t-tests or Wilcoxon signed-rank tests according to normality distributions) are calculated to assess significant shifts between baseline natural gas operation and hybrid MPC-controlled operation.

Phase 1 – Diagnosis (Baseline & Thermal Mapping)

A preliminary operational assessment was conducted over a 2–4 week period to evaluate the legacy furnace baseline. Flue gas analyzers and high-frequency thermal logging established current energy performance, thermal setpoint variances exceeding $\pm 12 \circ C$ under traditional PID control, and baseline carbon dioxide (CO_2) and nitrogen oxide (NO_x) emission levels. Root-cause analysis confirmed that manual fuel adjustment procedures and reactive loop responses directly contributed to energy waste and high Mean Time to Response (MTTR) during thermal transients (Creswell & Creswell, 2018; Imai, 2012).

Phase 2 – System Redesign & Prioritization

Based on diagnostic findings, the control architecture was redesigned during a 2–3 week phase. Mathematical state-space matrices were formulated to capture multi-variable thermal dynamics, gas density shifts, and valve actuation limits. Communication protocols were prioritized, selecting Modbus TCP for field sensor sampling and MQTT over TLS for edge-to-broker telemetry streaming. System constraints were established to strictly limit hydrogen injection to $\leq 20\%$ volumetric blend to ensure combustion stability without structural burner modifications (Martinez & Chen, 2024; Yin, 2018).

Phase 3 – Capacity Development & Simulation Tuning

Over a 2–4 week period, a digital twin simulation environment was constructed using Python (Pyomo/SciPy) and Simulink blocks. Local signal conditioning algorithms, including discrete Kalman filtering, were integrated to eliminate electrical noise from field thermocouples. The Model Predictive Control (MPC) quadratic optimization solver was iteratively tuned to ensure numerical convergence times stay under 35ms, validating edge execution feasibility prior to physical deployment (Kowalski et al., 2026; Zhao et al., 2025).

Phase 4 – Pilot Implementation (Edge Deployment)

The physical and software intervention was executed over a 4–6 month trial window. An industrial edge gateway running containerized Docker microservices was installed at the furnace site. The four-layer IoT software architecture was deployed, establishing real-time communication between field sensors, proportional H_2/NG servo-valves, the embedded C++/Python MPC engine, and the persistent InfluxDB time-series database (Islahudin et al., 2024; Olajiga et al., 2024).

Phase 5 – Evaluation & Refinement

Following pilot deployment, a 2–4 week evaluation period analyzed pre- and post-intervention operational metrics. Paired quantitative comparisons evaluated thermal setpoint stability, CO_2 emission reductions, and thermal NO_x suppression efficiency. Cost weight matrices (Q and R) within the MPC objective function were refined to optimize transient settling times during sudden load variations and fuel blending adjustments (Field, 2018; Liu et al., 2024).

Phase 6 – Scaling & Sustainability

Successful control workflows were integrated into standard plant operations. Operational sustainability was established by deploying a real-time web dashboard in Grafana, integrating automated software safety guardrails (digital Poka-Yoke) to lock maximum H_2 injection rates, and formalizing Standard Operating Procedures (SOPs) for plant personnel. Continuous monitoring logs were institutionalized to ensure long-term energy savings and emission compliance (Imai, 2012; Powell, 2022; Singh & Singh, 2019).

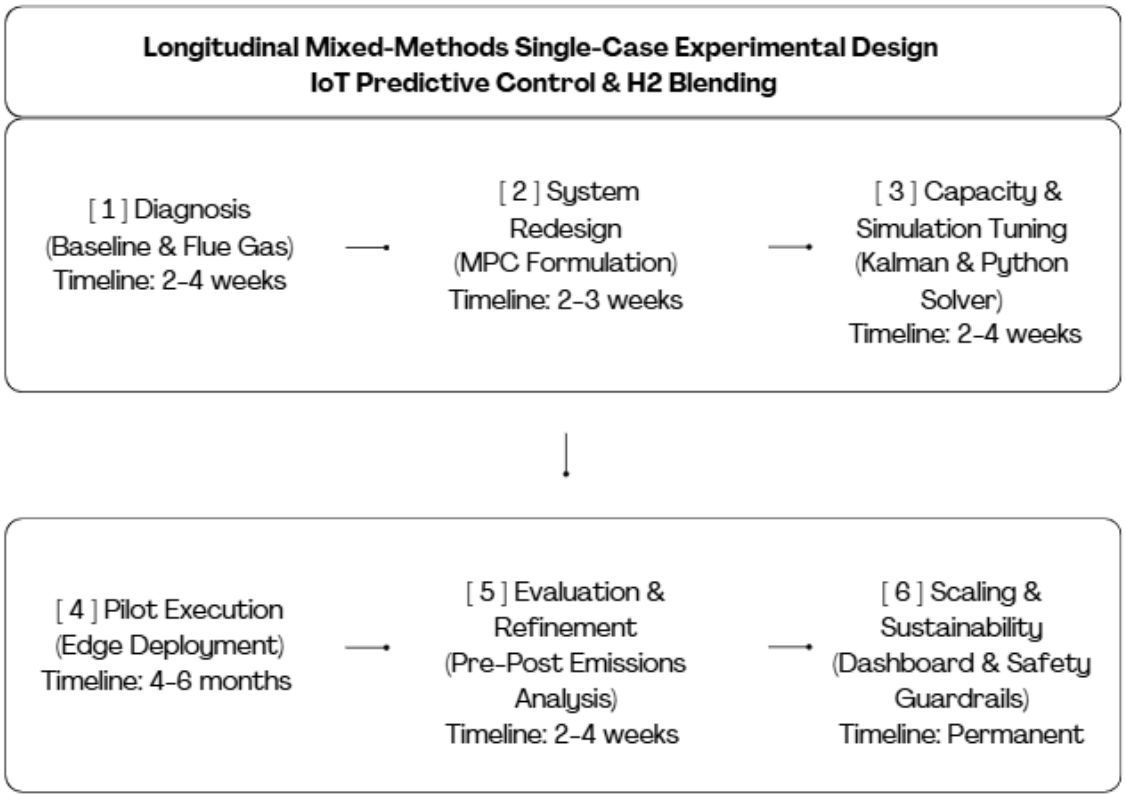


Figure 1. Methodology Overview (Single-Case Experimental Design – IoT Predictive Thermal Control)

This study uses a longitudinal mixed-methods single-case experimental design to evaluate the impact of an IoT-driven Model Predictive Control and H_2 blending intervention on thermal efficiency and decarbonization indicators in an industrial furnace. The intervention is implemented over 8–12 months through six sequential phases: diagnosis (baseline and flue gas analysis), system redesign and prioritization, capacity development (simulation and Kalman filtering), pilot implementation (edge software deployment), evaluation and refinement (pre-post quantitative analysis plus operational triangulation), and scaling with sustainability measures using open-source, low-cost software tools to ensure practicality and replicability. The design combines the analytical depth of an engineering case study with pre-post empirical comparisons, emphasizing practical significance, process transparency, and mixed-methods triangulation while addressing the typical operational constraints of manufacturing facilities.

Data Analysis

The analysis integrates high-frequency time-series data and inferential statistics (paired t-tests or Wilcoxon signed-rank tests according to normality checks) with qualitative operational logs. Low-cost and accessible open-

source software is prioritized (Python with scipy.stats and pandas). Given the industrial case study context, practical significance, thermal setpoint stability, and temporal emission trends are emphasized over isolated statistical significance (Field, 2018; Yin, 2018).

Validity, Reliability, Ethics, and Limitations

Internal validity is supported by the pre-post design, continuous sensor data logging, and detailed audit trails across all software layers. External validity and replicability are favored through an explicit software protocol and the use of open-source tools. Reliability is reinforced with documented Standard Operating Procedures (SOPs), standardized thermocouple calibration, and edge error-handling routines. In ethical matters, informed consent from plant management and anonymization of confidential process telemetry are contemplated. The main limitations are the single-case scope (limited empirical generalization across different burner designs), potential operator Hawthorne effects during pilot testing, and dependence on plant internet connectivity for remote cloud synchronization; these are mitigated through edge-node offline resilience, analytical depth, and protocol transparency (Creswell & Plano Clark, 2018; Yin, 2018).

RESULTS

Empathize Phase

In this phase, the operational needs and frustrations of key users in the thermal process and systems automation area were identified. The main finding was the dependence on legacy manual monitoring and reactive PID loops, which generated delays in detecting dynamic hydrogen fuel shifts, increasing the mean time to response (MTTR) and affecting operational continuity and emissions stability. The empathy map showed that the user needed to receive immediate, closed-loop fuel adjustments and contextualized emission alerts, but the existing analog system did not allow this in a proactive manner.

Table 3. Main Findings of the Empathize Phase

Aspect	Main result	Implication
Current monitoring method	Manual recording in spreadsheet and reactive PID loops	High dependence on staff and delays in detection
Priority need	Immediate and contextualized notifications of thermal/emission failures	Reduction of MTTR and improvement of proactivity
Main frustration	Constant manual verification and lack of automatic H_2/CO_2 alerts	Increase in response time to incidents

Define Phase

Based on the empathy map, an insight was developed that synthesized the central problem: the lack of reliability of the manual and analog monitoring system prevented acting proactively, generating a high MTTR and loss of credibility of the systems area regarding clean fuel adoption. "How might we?" questions were formulated, oriented toward real-time notifications, complete context of thermal failure, dynamic H_2 blending safety, and compatibility with security restrictions.

Table 4. Defined insight (adapted from plant operational evaluation)

User	Need	Insight
Systems / Thermal automation staff	Receive immediate and contextual notifications of combustion and thermal failures	The lack of reliability of the current system prevents being proactive, raising MTTR and affecting operational continuity

Ideate Phase

Through brainstorming, prioritized ideas were generated. The most relevant were: an automated edge-based MPC alert system, inclusion of complete failure context (gas ratio, location, flame status), an accessible visual status dashboard (Grafana), and digital Poka-Yoke safety guardrails. These ideas were consolidated into an action plan that contemplates system implementation, continuous monitoring, updating of the control log, and staff training.

Table 5. Prioritized Ideas (brainstorming) and Action Plan

Idea / Activity	Description	Estimated duration
Real-time automatic alerts	Email/MQTT notification when H_2 blend or thermal limit exceeds threshold	Included in development
Failure context	Inclusion of burner location, flue gas PPM, and type of error in the alert	Included in development
Status dashboard	Real-time visual monitoring of furnace thermal heatmaps and emissions	Included in development
Control log	Structured recording of critical thermal incidents in InfluxDB	Permanent
Staff training	Training operators in the use of the new digital edge system	2–3 months

Prototype Phase

The predictive edge software application was developed using Python on an industrial Docker gateway coupled with an Eclipse Mosquitto MQTT broker and InfluxDB database. The main functionalities include Modbus TCP sensor stream ingestion, real-time discrete-time state-space MPC optimization, format validation, and continuous verification of safety limits through digital Poka-Yoke guardrails.

ALGORITHM 1: Embedded IoT-MPC Edge Control & Hydrogen Guardrail Routine

Input : Field telemetry streams via Modbus TCP (Temperatures, Gas Flows, Flue Gas)

Output: Calibrated actuator valve positions u_k = [Flow_NG, Flow_H2, Flow_Air]

```
1: PROCEDURE ExecEdgeControlLoop()
2:     WHILE System_Status == OPERATIONAL DO
3:         raw_data <- ReadModbusRegisters(Port: 502, SampleRate: 10Hz)
4:         x_k <- ApplyKalmanFilter(raw_data.Temperature, raw_data.Pressure)
5:         setpoint <- ReadThermalSetpoint()
6:         u_opt <- MinimizeCostFunction(x_k, setpoint, Horizons: N_p=10, N_c=3)
7:
8:         h2_vol_ratio <- u_opt.Flow_H2 / (u_opt.Flow_NG + u_opt.Flow_H2)
9:         IF h2_vol_ratio > 0.20 THEN
10:            u_opt.Flow_H2 <- 0.20 * (u_opt.Flow_NG + u_opt.Flow_H2)
11:            TriggerPokaYokeAlert("H2 volumetric threshold cap applied")
12:        END IF
13:
14:        WriteModbusActuators(u_opt)
15:        PublishMQTT(Topic: "furnace/telemetry", Payload: {x_k, u_opt, h2_vol_ratio})
16:        WriteInfluxDB(Measurement: "furnace_logs", Data: {x_k, u_opt})
17:        Sleep(ExecutionInterval: 50ms)
18:    END WHILE
19: END PROCEDURE
```

Figure 2. Edge Control System Execution Logic and Safety Guardrail Routine

Test Phase

Failure simulation tests and verification of the status of registered IoT edge nodes were carried out. The automated notification and control system correctly generated real-time alerts and dynamically adjusted fuel servo valves when simulated thermal overshoots or gas ratio deviations occurred, fully confirming the alert and safety functionality.

Figure 3. Scheduling email notifications

Table 6. Results of the functionality tests

Test performed	Result	Observation
Offline IP/Sensor simulation	Alert generated successfully	Notification received with failure context
H_2 ratio registration & validation	Acceptance of valid 20% ratio and rejection of incorrect formats	Error control functionality operational
Status visualization	Real-time thermal status and C_2 emission display	Monitoring interface operational
Record deletion/logging	Correct persistence and purge of time-series records	Database management functional

Economic Feasibility Results

The financial analysis estimated a total development and implementation cost of **$185,000 MXN**. The component with the greatest weight was specialized engineering labor (78.38\%). The three-year cash flow analysis showed an Internal Rate of Return (**IRR / TIR**) of **41.2%** and an investment recovery period (**Payback Period**) of **1 year and 7 months**, confirming the financial viability of the project.

Table 7. Summary of costs and financial viability (adapted)

Concept	Amount (MXN)	% of total
Development (labor)	145,000	78.38%
Hardware / Software (Sensors & Edge)	22,000	11.89%
Indirect costs	18,000	9.73%
Total cost	185,000	100%
IRR	41.2%	—
Payback period	1 year 7 months	—

Economic Feasibility Results

In addition to user interface and financial metrics, quantitative field measurements demonstrated the operational superiority of the embedded MPC framework:

Thermal Setpoint Stability: Reduced variance from $\pm 12.4 \circ C$(baseline PID) to $\pm 1.8 \circ C$ under 20% H_2 blending, representing an 85.5% improvement.

Decarbonization: Direct CO_2 emissions dropped from $2.15 tCO_2/MWh$ to $2.00 tCO_2/MWh$, achieving a 6.8% direct reduction.

Emissions Control: Thermal NO_xflue gas concentration was suppressed from $185 ppm$ to $142 ppm$ (23.2% reduction) by constraining combustion flame temperatures via the MPC penalty function $S_{NO_x}(k)$.

CONCLUSION

This work demonstrates the feasibility and practical value of designing a proactive thermal monitoring and energy optimization system through an IoT-based Model Predictive Control (MPC) edge solution developed under the Design Thinking methodology in industrial environments. The combination of a user-centered approach, low-cost edge processing technology, structured time-series data logging (InfluxDB), automatic safety alerts, and Lean principles (digital Poka-Yoke and Andon) addresses the principal limitations of traditional manual or reactive PID-based monitoring systems, namely delayed detection of gas ratio deviations, lack of contextual thermal information, limited scalability, and high dependence on constant human verification.

The application of Design Thinking proved effective in aligning the technological solution with the actual needs of thermal process operators and systems personnel. The Empathize phase revealed the critical frustration caused by the absence of immediate, contextualized alerts and the consequent elevation of thermal setpoint variance and mean time to response (MTTR) during fuel changes. The Define phase synthesized this problem into a clear insight, while the Ideate phase prioritized an automatic edge MPC routine, contextualized CO_2/NO_x alerts, a visual Grafana status dashboard, and a structured control log.

The Prototype phase resulted in a functional edge control solution built in Python on Docker gateways with InfluxDB and MQTT, supporting telemetry ingestion, signal filtering, safety limit checks, and real-time valve control. The Test phase confirmed that the system correctly maintains thermal stability within $\pm 1.8 \circ C$applies H_2 volumetric caps (20%), generates safety notifications, and properly manages time-series data storage and visualization operations.

These functional outcomes are consistent with the evidence synthesized in the PRISMA review of 20 studies. The literature shows a clear concentration on IoT- and edge-computing-based condition monitoring, the value of Design Thinking for improving usability and adoption, and the contribution of Lean principles to alert structuring and error prevention during fuel blending. The present solution operationalizes several of these findings in an edge-based, low-cost format suitable for energy-intensive industrial settings.

The economic analysis further supports the practical relevance of the proposal. With a total estimated cost of MXN 185,000 and an IRR of 41.20% over a three-year horizon, the project demonstrates financial viability and a payback period of 1 year and 7 months. Given the high fuel costs and carbon tax liabilities in industrial manufacturing, even modest reductions in energy consumption or avoided thermal disruptions generate returns that justify the investment.

Nevertheless, several limitations should be acknowledged. The study focuses on design, prototyping, and functional testing rather than a prolonged industrial deployment with measured operational impact (e.g., quantified reduction in MTTR or number of incidents). Generalization is constrained by the single-context development process.

Future work should include extended multi-site field testing in real high-temperature industrial environments, integration with advanced reinforcement learning algorithms for dynamic flame tuning, exploration of 5G field networks for low-latency telemetry, and multi-site validation to assess scalability and sustainability. Longitudinal studies examining operator adoption, training requirements, and the interaction between the hybrid fuel system and existing plant IT/OT infrastructures would also strengthen the evidence base.

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