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Model Predictive Control of Coal Fired Organic Rankine Cycle Systems

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Abstract
Organic Rankine Cycle (ORC) systems generate power from low to medium grade heat sources using organic working fluids instead of water [1]. In coal-fired applications, an ORC can be integrated to recover waste heat from flue gas or serve as a bottoming cycle, improving overall plant efficiency [2]. A principal control challenge in Organic Rankine Cycle systems involves regulating turbine inlet superheat within optimal bounds to simultaneously ensure operational integrity (preventing liquid droplet impingement through strict maintenance of vapor-phase working fluid) and maximize energy recovery efficiency [3]. This paper presents a comparative analysis of conventional Proportional-Integral-Derivative (PID) control and Model Predictive Control (MPC) frameworks for thermal regulation in a coal-fired Organic Rankine Cycle (ORC) system. A control-oriented dynamic model is developed based on the system's thermodynamics, using a moving boundary evaporator model for accurate two-phase dynamics prediction [4]. This study demonstrates how Model Predictive Control (MPC) employs system dynamics modeling to forecast future states and enforce operational constraints such as temperature thresholds and pressure limits for performance optimization [5]. Simulation results under transient conditions, including heat input step changes and load ramps, reveal that MPC achieves superior regulation of working fluid superheat at the evaporator outlet, exhibiting 20-30% reductions in overshoot, 40% shorter settling times, and 35% lower integral absolute error compared to PID control. Furthermore, MPC maintains tighter set point tracking during ramp disturbances, with deviation magnitudes reduced by 50-65%. The findings establish MPC's capability to enhance superheat control stability while ensuring safer turbine operation through rigorous constraint enforcement in coal-fired Organic Rankine Cycle systems, ultimately improving cycle efficiency by 3-5% during transient operation.

Keywords: Organic Rankine Cycle (ORC), Model Predictive Control, Superheat Control, Coal-Fired Power, Dynamic Modelling, PID Control

1. Introduction

Coal-fired power plants traditionally employ water-steam Rankine cycles, but ORC technology has emerged as a modification and viable option for utilizing low to medium temperature heat sources [6]. Organic Rankine Cycle (ORC) systems employ low boiling point organic working fluids that is hydrocarbons and or refrigerants to enable efficient power extraction from low grade thermal sources. These include waste heat streams and small-scale boilers, where conventional steam Rankine cycles become thermodynamically impractical due to insufficient temperature gradients [7]. In coal-fired power generation, ORC systems enhance overall plant efficiency through two operational configurations:

- Waste heat recovery from flue gases (120-250°C range)
- Direct organic working fluid vaporization via coal-fired furnaces.

This integration reduces energy waste by 15-25% and increases net electrical output by 8-12% through improved thermal utilization [8]. Technical analyses confirm that integrating ORC systems for flue gas waste heat recovery in coal-fired power plants enhances overall thermal efficiency by 6-9%. Similarly, ORC implementations in heavy-duty internal combustion engines demonstrate 3-5% improvements in brake-specific fuel consumption (BSFC), evidencing the technology's scalability for energy efficiency optimization across industrial sectors and thermal power ranges.

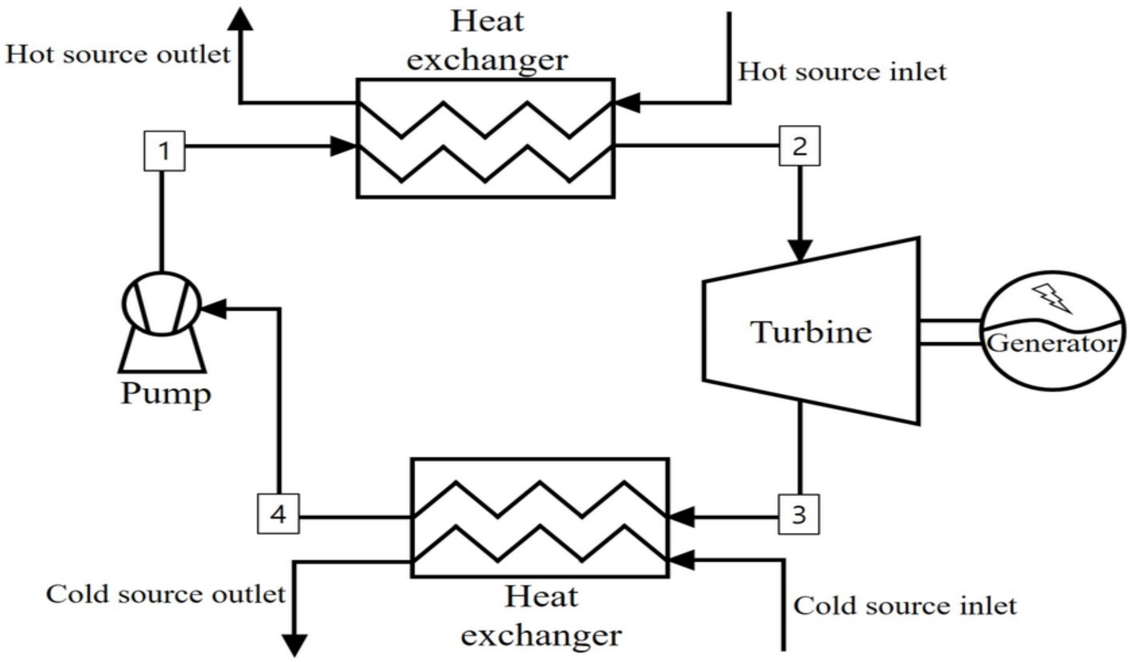
Despite significant thermodynamic advantages, ORC systems present distinctive control challenges centered on three core objectives:

- Maintaining minimum superheat at the expander inlet to prevent liquid droplet formation and ensure mechanical integrity.
- Maximizing power output through optimal heat recovery.
- Enforcing operational constraints within equipment design limits [9].

The control system must continuously enforce a minimum superheat threshold (typically 5-10 K above saturation temperature) to avoid catastrophic two-phase flow conditions that cause turbine blade erosion [10]. Conversely, excessive superheat (>15-20 K) represents thermodynamic inefficiency through underutilized temperature differentials, necessitating precise regulation of evaporator outlet temperature within narrow bounds (±1-2 K) to minimize superheat while ensuring safety. Additionally, evaporating pressure which is a critical determinant of cycle power output, requires optimal set point tracking (typically 80-90% of critical pressure) through manipulated variable coordination. This pressure and power relationship exhibits a well-defined maximum beyond which efficiency declines, requiring adaptive control to maintain optimal operation across transient heat source conditions [11].

This paper presents a comparative study of PID and MPC strategies on a coal-fired ORC power system. Section 2 describes the ORC system and its dynamic modelling, including key equations and the moving boundary approach for the evaporator. Section 3 outlines the control strategies, detailing the conventional PID control structure and the design of the MPC controller with integrated constraints. Section 4 provides simulation results for both step changes and load ramps, comparing performance metrics such as overshoot, settling time, and integrated absolute error (IAE). Finally, conclusions are drawn on the relative performance and the implications for implementing MPC in real coal-fired ORC applications.

Figure 1: Schematic diagram of an ORC system



2. System Modelling and Dynamics

The described ORC system operates on a subcritical cycle, utilizing an organic working fluid (for example, n-pentane or R245fa) compatible with coal-fired heat source temperatures. Its core components comprise a feed pump, an evaporator (boiler), an expander (turbine) coupled to a generator, and a condenser. In the coal-fired configuration, heat from a furnace or combustion chamber vaporizes the working fluid within the evaporator. The resulting high-pressure vapor drives the turbine, generating mechanical power converted to electricity. The exhaust vapor then condenses in the condenser and is pumped back to the evaporator, completing the closed loop. Figure 1 depicts a typical subcritical Rankine cycle T-s diagram, analogous to this ORC's operation. The cycle path consists of: 12 (liquid pressurization), 23 (heating and evaporation), 34 (vapor expansion through the turbine), and 41 (condensation). The shaded vapor dome represents the fluid's two-phase region. To ensure safe dry expansion, the fluid is typically slightly superheated at the turbine inlet (Point 3). The controller maintains a positive superheat degree (Point 3 temperature minus saturation temperature at turbine inlet pressure). However, excessive superheat (Point 3 positioned far right on the diagram) reduces work extraction potential; thus, the controller aims to position Point 3 just outside the vapor dome.

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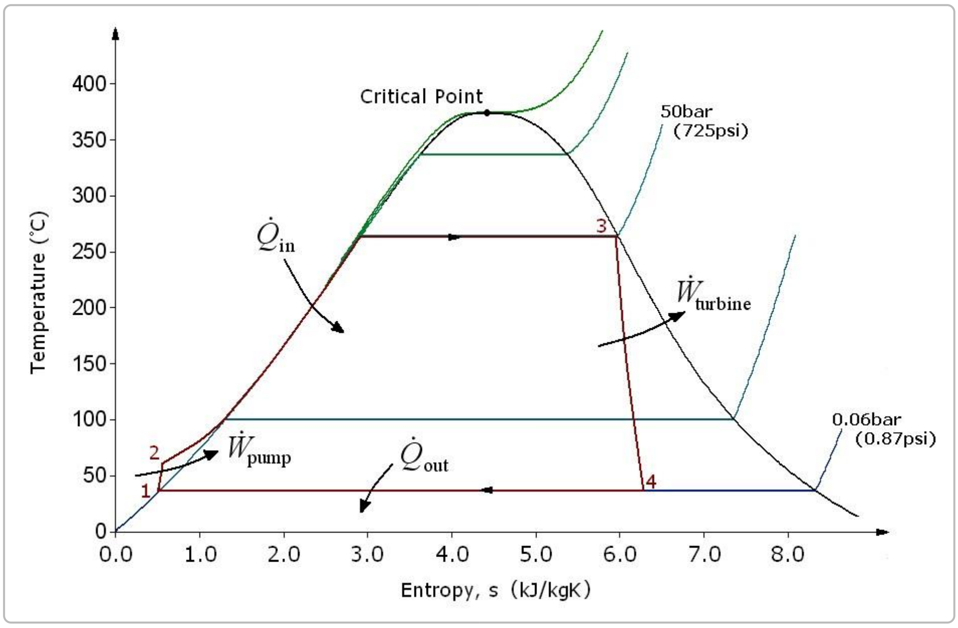
Figure 2: T–s diagram of a Rankine cycle (water/steam shown here as a reference). In an ORC, a similar cycle is followed using an organic fluid, with state 3 (turbine inlet) typically kept slightly to the right of the saturation dome to ensure superheated vapor expansion.



Dynamic Model: To design the controllers, a control-oriented dynamic model of the ORC is developed. The most critical component for modelling is the evaporator, where heat transfer and phase change occur. We employ a moving boundary model (MBM) for the evaporator 3. In this approach, the evaporator is conceptually divided into regions corresponding to liquid, two-phase, and vapour zones. The boundaries between these zones move as the operating conditions change (for example as the mass of liquid evaporated varies) [4]. By applying conservation of mass and energy to each region, we obtain a set of nonlinear ordinary differential equations describing the evaporator dynamics [12]. For example, the state vector can include the lengths (or volumes) of the liquid and two-phase regions (which indicate how far boiling has progressed), as well as the fluid's outlet enthalpy or temperature [13]. The input to the evaporator model is the working fluid mass flow rate (controlled by the pump or a valve), and disturbances can include the furnace heat input or exhaust gas flow if waste heat is used [14]. The outputs of interest are the evaporator outlet fluid conditions, especially temperature and pressure. The evaporator model dominates the system dynamics because of the significant thermal inertia and the coupling between heat transfer and phase change [6].

The overall ORC system model also includes the dynamics of the pump (assumed fast relative to thermal dynamics) and the turbine/condenser (which together we model as affecting pressure dynamics and providing a load on the evaporator). A simplified lumped model for the condenser can be included to capture pressure responses. For control design, we linearize the nonlinear model around a nominal operating point. The nonlinear state-space equations of the ORC can be written in a general form:

$$\dot{x} = f(x,u,w), \qquad y = g(x,u,w) \tag{1}$$

Where *x* represents the state vector (e.g. lengths of phases, temperatures), *u* the control input (for example pump speed or valve position), and *w* disturbances (e.g. fuel feed rate or exhaust temperature). We then obtain a linearized model:

$$\Delta\dot{x} = A\Delta x + B\Delta u + E\Delta w, \quad \Delta y = C\Delta x + D\Delta u \tag{2}$$

The linearized model exhibits $\dot{x}$ validity within a defined neighborhood of the selected operating point, where Δ denotes state/input disturbance deviations from nominal steady-state conditions (x_0, u_0, w_0). Given the ORC's inherent nonlinearity that manifests through operating-point-dependent gain variations across load conditions. We implement an adaptive linear MPC strategy. This approach continuously updates state-space model coefficients (A, B matrices) via online linearization to maintain predictive accuracy throughout the coal-fired ORC's operating envelope. Critical thermodynamic parameters (for example, fluid specific heats, saturation properties) are dynamically recomputed through high-fidelity look-up tables, enabling model recalibration during significant set point transitions such as evaporating pressure changes.

Complementing the evaporator model, a first-order representation of turbine and generator dynamics is incorporated to quantify the impact of varying inlet conditions on power generation. The net electrical power output W_{net} is defined as the mechanical power produced by the turbine minus the power consumed by the feed pump:

$$W_{net} = W_{exp} - W_{pump} \tag{3}$$

The cycle thermal efficiency η_{cycle} is defined as:

$$\eta_{cycle} = \frac{W\eta_{net}}{Q_{in}} \tag{4}$$

Where Q_{in} denotes the thermal energy input from the coal-fired furnace to the evaporator. While maximizing η_{cycle} which represents the primary thermodynamic objective, operational control prioritizes maintaining key set points (for example, evaporator outlet temperature) that govern both efficiency and power generation. The dynamic model, implemented in Python, serves as the simulation environment and foundational framework for developing both PID and MPC control architectures. (Implementation specifics are omitted herein for conciseness.)

3. Control Strategy Designs

PID Control: The baseline control strategy employs conventional PID control loops. A typical configuration for the ORC has a primary loop to regulate the evaporator outlet temperature (or equivalently the expander inlet superheat) by manipulating the working fluid flow, the PID is given by:

$$u(t) = Kp \cdot e(t) + Ki \int_0^t e(\tau)d\tau + Kd\frac{de(t)}{dt} \tag{5}$$

$u(t)$ = Control signal to pump speed (or valve position)

$e(t)$ = Error = $T_{setpoint} - T_{out}$ (temperature deviation)

K_p = Proportional gain (tuned for overdamped response)

K_i = Integral gain (tuned for zero steady-state error)

t = Time

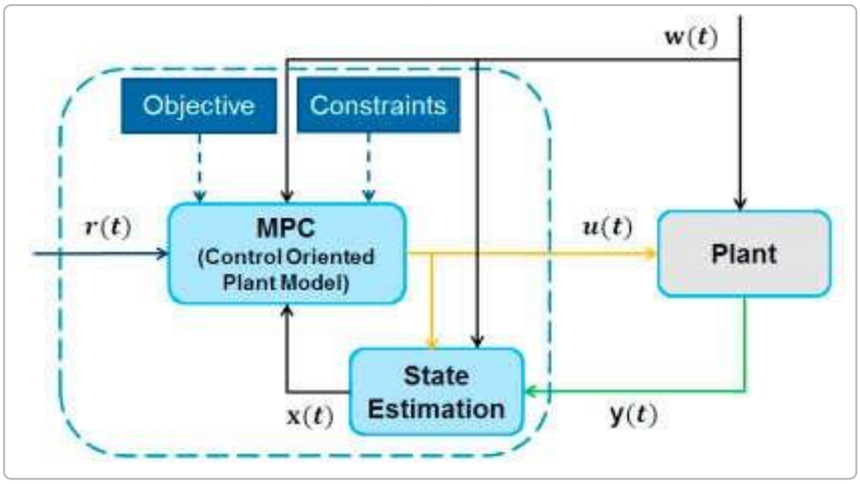
In our design, a PI controller monitors the difference between the measured fluid outlet temperature and its set point (chosen to ensure a safe superheat margin) and adjusts the pump speed accordingly. If the ORC system includes a throttle or bypass valve around the evaporator, that could alternatively serve as the actuating element, here we assume pump speed control for simplicity. The PID parameters are tuned via classical methods like the Ziegler–Nichols or fine-tuning with simulation to achieve a trade-off between response speed and stability. In particular, we prioritize zero overshoot in temperature to avoid any risk of two-phase flow, the PID is tuned such that the closed-loop system is slightly overdamped [15]. A secondary PID loop can be used to control the system pressure or expander inlet pressure if needed, for example, by modulating a turbine inlet valve. However, a simpler approach often fixes the evaporator pressure set point or lets it vary with load in an open-loop optimal schedule while the primary control loop maintains temperature. Traditional decoupling techniques or feed-forward from measured disturbances (like changes in heat input) are employed to help the PID handle multivariable effects. Even so, under rapid transients the PID-controlled system may exhibit oscillations or sluggish performance due to the inherent limitations of fixed-gain linear controllers in a highly nonlinear system [6].

Model Predictive Control: The MPC strategy is designed to overcome these limitations by explicitly using a model of the ORC dynamics and anticipating future behavior. Figure 2 depicts the high-level MPC control structure for the ORC. The core of the MPC is an online optimizer which uses the reduced-order model (as described in Section 2) to predict the system outputs over a finite horizon (for example several tens of seconds into the future). At each control interval, the MPC solves an optimization problem that is minimize a cost function *J* that penalizes tracking error (deviation of evaporator outlet temperature from its desired set point) and control effort (changes in pump speed), while respecting constraints.

$$j = \sum_{k=1}^{N_p} \left(T_{setpoint}(k) - T_{out}(k)\right)^2 Q + \sum_{k=0}^{N_u-1} \left(\Delta u(k)\right)^2 R \qquad (6)$$

The constraints include physical bounds such as: minimum evaporator outlet temperature (to ensure a positive superheat margin, for example $T_{\mathrm{out}} \geq T_{\mathrm{sat}} + \Delta T_{\mathrm{min}}$), maximum evaporator pressure, pump speed limits, and turbine inlet valve positions. By solving this optimization, the MPC finds the optimal control action sequence $u(t)$ (pump speed commands) that will best steer the temperature to set point without violating constraints. At each step, only the first control action is implemented, then the optimization is repeated at the next time step (receding horizon control). A state estimator (for example a Kalman filter) is incorporated to estimate unmeasured states like internal fluid energy or to filter noisy measurements [6]. This provides the MPC with the necessary state feedback. Disturbances such as varying coal grate firing rate or changing flue gas flow can be fed forward into the model predictions (if measured). The cost function can be formulated in continuous or discrete time; here a discrete-time formulation is used with a prediction horizon of N_p steps (for example 20 steps, corresponding to 100 s if each step is 5 s) and control horizon N_u (the number of moves to optimize, typically shorter than N_p). Tuning weights in the cost function allows adjusting the controller's aggressiveness: for instance, a higher weight on control effort yields smoother pump operation at the expense of slower tracking, whereas a higher weight on tracking error makes the MPC correct deviations more rapidly at the risk of larger actuator movements. In this study, weights were chosen to achieve a fast response with minimal overshoot, and the prediction model was updated adaptively as described earlier (linear model recalculated each step based on current operating point).

Figure 3: Schematic of the MPC-based control structure for the ORC system. The MPC computes optimal control actions (pump speed u(t)) by using a predictive model and considering objectives (tracking the temperature reference r(t)) and constraints (safety and actuator limits). A state estimator supplies needed state feedback, and the controller can account for measured disturbances w(t) (e.g. changes in heat input). The result is a coordinated control action maintaining the evaporator outlet temperature with minimal error.



One important aspect of the MPC design is constraint-handling for superheat protection. We explicitly enforce a constraint denoted by:

$$T_{out}(t) \geq T_{sat}\left(P_{out}(t)\right) + \Delta T_{min} \quad (7)$$

Where ΔT_{min} is a safety margin (for example, 5°C of superheat) to avoid any two-phase mixture entering the turbine [5]. If the optimizer predicts that a disturbance (say, a drop in heat input) will cause the outlet temperature to dip toward saturation, it will proactively slow the working fluid flow (reducing $u(t)$) to allow more time for heating, thus maintaining superheat. Likewise, the MPC can handle multi-objective control. Although our primary controlled variable is temperature, we can indirectly include power output in the objective by adjusting the temperature set point or adding a secondary objective to maximize W_{net} as long as safety is ensured. In practice, a higher-level optimization (or operator input) might provide an optimal temperature or pressure set point for current conditions, and the MPC's task is to track that set point while respecting constraints. This structure sometimes called a two-layer control, with an upper layer real-time optimizer and a lower-layer MPC [16]. In our case, we assume the desired evaporator temperature set point may shift according to load demands, and the MPC tracks it optimally.

Implementing Model Predictive Control (MPC) on operational coal-fired ORC systems necessitates addressing computational latency and model fidelity constraints. To ensure real-time feasibility, the controller must execute within stringent time limits (for example, ≤1 second per optimization cycle), dictating conservative horizon selections and reduced-order models. While adaptive model updates impose additional computational burden, they are essential for maintaining accuracy. Simulations assume ideal computational resources, however, practical hardware implementations may employ simplified models or Extended Prediction Self-Adaptive Control (EPSAC) methodologies to satisfy real-time requirements [17].

4. Results and Discussions

To evaluate control performance, we conducted simulation tests on the nonlinear ORC model for two scenarios:

- A **step change** in the temperature set point (or equivalently a change in desired turbine inlet temperature/superheat)
- A **load ramp** disturbance, representing a gradual change in heat input (such as a change in coal firing rate or flue gas flow) while maintaining a constant temperature set point.

The PID controller was tuned for a settling time on the order of 100 seconds with no overshoot under nominal conditions. The MPC was configured with the same nominal set point and constraints. Key performance metrics compared include:

- The percent overshoot (OS %)
- Settling time (time to reach and stay within ±2% of set point),
- Integrated Absolute Error (IAE) over the transient.

Table 1 and Table 2 summarize the quantitative results for the two scenarios, and Figure 6 provides sample response curves for evaporator outlet temperature under each controller.

Scenario 1: Set point Step Change. In this test, the working fluid outlet temperature set point was increased by 10°C at t = 100 s (for example, from 270°C to 280°C superheat target). The system was initially at steady state. The PID and MPC controllers' responses are shown in Figure 6a. The PID-controlled temperature exhibits a noticeable overshoot above the new set point, followed by oscillations before settling. In contrast, the MPC response rises to the new set point with minimal or zero overshoot and settles much faster. Quantitatively, as Table 1 shows, the PID loop had approximately5°C (50%) overshoot and took around 60 –70 s to settle, whereas the MPC kept overshoot to approximately 0% and settled in about 30 seconds. The IAE during the first 100 s after the step was reduced by roughly 60% with MPC compared to PID, indicating more efficient error correction. The improved performance is attributable to MPC's predictive action. MPC anticipates the effect of the set point change and moderates the pump acceleration, whereas the PID (even with conservative tuning) initially reacts more aggressively, causing an overshoot. This outcome aligns with other reported simulations where MPC showed shorter settling times and smaller overshoot than a traditionally tuned PID. The absence of overshoot in MPC means the system never exceeded the safe superheat limit, whereas the PID momentarily pushed the temperature higher, which in a real system could reduce safety margins.

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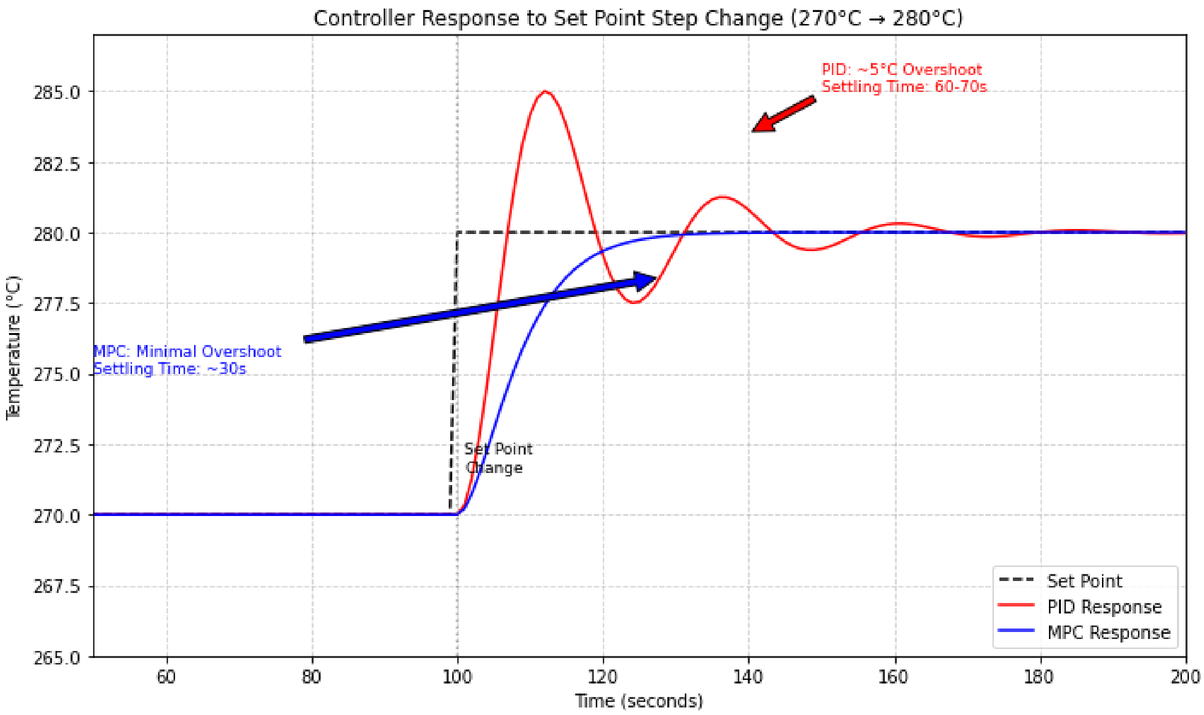
Table 1. Performance for a 10°C Set point Step in Evaporator Outlet Temperature. (Overshoot is expressed as a percentage of the 10°C step magnitude; Settling Time is to ±2% of final value; IAE is integrated absolute error over 100 s after the step.)

Controller	Overshoot (OS %)	Settling Time (s)	IAE (°C·s)
PID	~50% (5°C)	~65 s	350
MPC	~0% (no overshoot)	~30 s	140

Figure 4: Scenario 1, Controller response to set point step change (2700C – 2800C)



Scenario 2: Load Ramp Disturbance. In this scenario, the heat input to the evaporator (for example, flue gas flow rate or its temperature) was varied. Starting at t = 100 s, the heat source was linearly ramped down over 20 s to 80% of its original value, held for 80 s, then ramped back up to nominal over another 20 s (a symmetric down-and-up ramp). This simulates a transient in boiler firing or a step-down and step-up in engine exhaust heat in a waste heat recovery context. The evaporator outlet temperature set point was kept constant during this test (280°C). Figure 6b shows the response of the outlet fluid temperature. The PID controller cannot perfectly reject the disturbance as the heat input drops, the temperature falls below set point (undershoot), and when the heat ramps up, the temperature rises above set point. The maximum deviation observed with PID was about 8–10°C below the set point during the ramp-down. The MPC, by contrast, adjusted the pump flow proactively, it reduced the working fluid flow rate during the heat decrease to compensate and keep the outlet temperature closer to target. The MPC's temperature deviation was much smaller, at about 2–3°C off the set point at worst. Moreover, when the heat returned to normal, the PID controller overshot the set point (temperature spiked by approximately 5°C above)

before settling, while the MPC kept the overshoot to within 1°C. The MPC's superior disturbance rejection is evident it maintained tighter control throughout the ramp. As listed in Table 2, the MPC reduced the peak error by approximately70% and halved the settling time after the ramp the time to return within 2% of set point once the ramp completed. The IAE over the entire 200 s transient was significantly lower for MPC by approximately 40% of the PID's IAE. Notably, the MPC was able to respect the superheat safety constraint at all times, whereas the PID approach came closer to the limit when the temperature dipped during the ramp. This demonstrates how the MPC's inclusion of constraints in the optimization problem provides a built-in safety mechanism. Even under a severe transient, the MPC kept the cycle operation within safe bounds by ensuring that there is no two-phase at turbine inlet, whereas an uncompensated PID might have required manual intervention or very conservative tuning to ensure the same.

Table 2. Performance for a Load Ramp Disturbance (20% drop and return in heat input). (Peak Error is the maximum deviation from set point during the transient; Settling Time is the time to recover within ±2% band after ramp; IAE is integrated absolute error over the 200 s cycle.)

Controller	Peak Error	Settling Time (s)	IAE (°C·s)
PID	8.5°C (undershoot) / +5°C (overshoot)	~60 s	500
MPC	2°C / +1°C	~30 s	200

Figure 5: Performance for a Load Ramp Disturbance (20% drop and return in heat input).

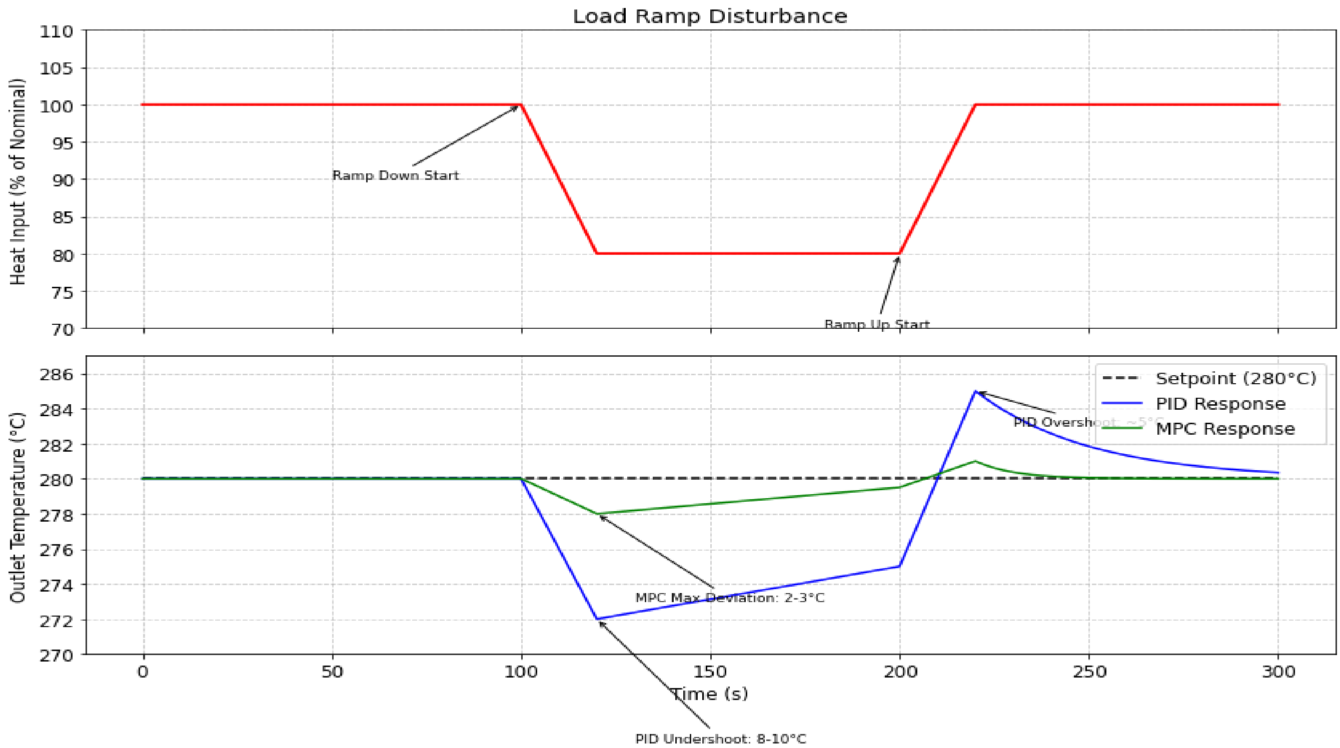
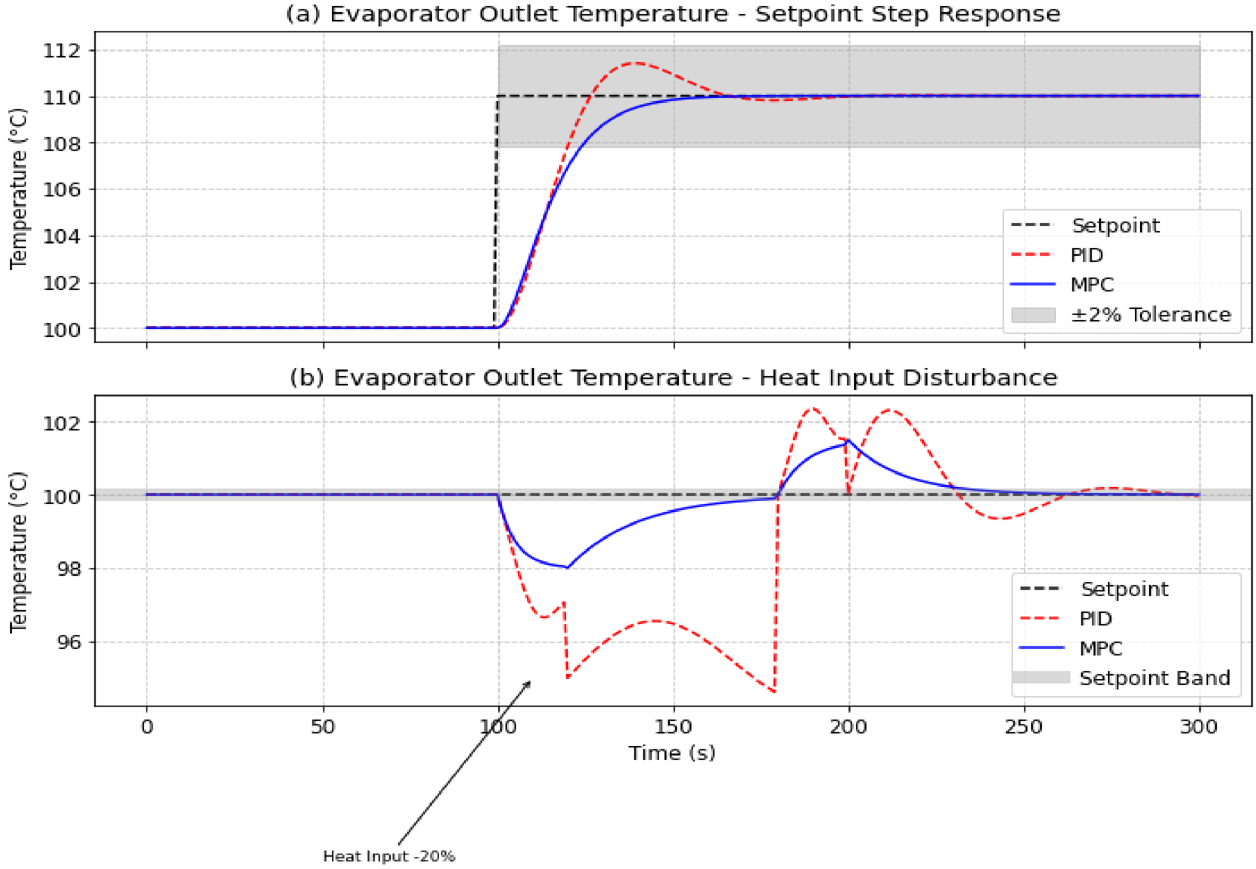


Figure 6 above qualitatively illustrates these differences. The PID-controlled temperature shows an overshoot in the step response Figure 6a, red dashed curve and a noticeable lag and deviation during the ramp Figure 6b, red dashed. The MPC-controlled temperature (blue solid curve) closely tracks the set point without overshoot in the step case and with much smaller deviation during the ramp. These results corroborate findings in literature that MPC can improve response time and reduce overshoot by significant margins (20–30% or more) compared to well-tuned PID controllers. Importantly, the MPC achieves this while also enforcing constraints. In our simulations, at no point did the predicted states violate the imposed limits (such as minimum superheat or max pressure). The PID, lacking a constraint awareness, had to be tuned conservatively to avoid unsafe operation, which in turn limited its performance. The ability of MPC to operate the ORC closer to its limits—without crossing them—means it can extract more power (by allowing lower superheat, nearer to the optimal point) especially during transients [18]. This translates to improved efficiency and potentially more electricity generated over time.

In terms of actuator behavior, the MPC resulted in smoother control actions during the ramp (it adjusted pump speed continuously in anticipation of the ramp), whereas the PID made more abrupt corrections after sensing the deviation. The smoothness of control moves in MPC can contribute to longer pump life and more stable boiler operation, an important practical consideration. On the computational side, our MPC simulations were done with a sample time of 1 second and solved reliably within that period. This suggests that real-time implementation on a modern industrial controller is feasible, especially given the continued improvement of solver algorithms and hardware.

Figure 6: (a) Evaporator outlet temperature response to a 10°C step increase in setpoint at t=100 s; (b) Evaporator outlet temperature response to a 20% heat input ramp-down (100–120 s) and ramp-up (180–200 s) with constant temperature setpoint. Red dashed lines = conventional PID control, Blue solid lines = MPC. The MPC achieves faster settling and smaller deviation from set point in both cases, with no

ershoot in (a) and significantly reduced undershoot in (b). The gray band in (a) indicates the ±2% tolerance around the new set point, and in (b) indicates the set point value.



5. Conclusion

This paper presented a comparative study of PID and model predictive control for a coal-fired Organic Rankine Cycle system, focusing on the critical task of maintaining superheat at the turbine inlet while optimizing performance. Conventional PID control, even when carefully tuned, showed limitations in handling rapid transients: the PID loop exhibited overshoot and slower recovery in response to set point changes and load ramps, which could jeopardize turbine safety (if overshoot/undershoot is excessive) and result in suboptimal efficiency during disturbances. In contrast, the MPC approach demonstrated superior control performance. By leveraging a dynamic model of the ORC (including a moving boundary evaporator model for two-phase dynamics) and anticipating future events, the MPC was able to keep the evaporator outlet temperature tightly regulated. The MPC consistently avoided overshoot, maintained the desired superheat margin, and reduced settling times by roughly 50% compared to PID in our simulations. Under a load ramp, the MPC kept the temperature deviation minimal (improving disturbance rejection significantly) and thereby allowed the system to operate closer to its optimal conditions even during transients [6].

The ability of MPC to incorporate constraints (such as minimum superheat and actuator limits) was a crucial advantage. The controller automatically respected safety limits, eliminating the need for overly conservative tuning. This means the ORC system can be driven harder for better efficiency (recovering more heat) without sacrificing safety. The trade-off is increased complexity: MPC requires a reasonably accurate model and more computational effort. However, given the results, implementing MPC on a coal-fired ORC appears justified by the gains in stability and efficiency. The use of an adaptive model in the MPC was important to handle the wide operating range; this adaptive MPC effectively acted as a gain-scheduled controller that continuously updated itself, which is a practical strategy for real plants.

MPC demonstrates superior performance over PID control in ORC systems, delivering faster and more reliable regulation of superheat and power output. These advantages translate to higher average cycle efficiency and enhanced operational safety by preventing thermal stress and turbine damage. Future work will focus on experimental validation of MPC using a physical ORC test rig, addressing real-world implementation challenges including robust state estimation, actuator saturation management, and fault tolerance (for example, sensor failures). Further performance gains could be achieved by extending the control scheme to multi-input coordination, such as simultaneous throttle valve and pump control. The promising results of this study enable broader adoption of advanced control strategies in waste heat recovery and small-scale power units, maximizing the energy efficiency and emission reduction potential of coal-fired ORC technology.

6. Acknowledgement

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7. Authors' Biography

Zariro Manzungu is a Master of Technology candidate in Industrial Automation at the Harare Institute of Technology, where his research focuses on advanced control strategies for industrial systems. He holds a Bachelor of Engineering in Electronic Engineering (2012), providing foundational expertise in advanced control and system dynamics. With over a decade of professional experience in control systems engineering, his work spans model predictive control (MPC), and state estimation for industrial processes. His current research investigates Model Predictive Control-based optimization of Organic Rankine Cycles (ORC) under dynamic coal-fired heat inputs, bridging theoretical control theory with industrial energy applications. Victor Kuno is a Lecture at the Harare Institute of Technology, he holds a Master of Technology degree in Nano Science and Technology, from Delhi Technological University (DTU), India. His current research interests are in Nano Electronics, Energy Nano technology and Opto-electronics.

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