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SELF-LEARNING PID TEMPERATURE CONTROLLER USING GENETIC ALGORITHM FOR DYNAMIC ENVIRONMENTS

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ABSTRACT:
Industrial systems use heat exchangers to manage their temperature because these systems operate through nonlinear processes that experience changing conditions while facing external interruptions. The extensive use of PID controllers results from their easy implementation, but these controllers face performance challenges when system dynamics change because their static gain settings cannot match different operational conditions. Current research indicates that inadequate tuning results in prolonged settling time and heightened peak overshoot, hence diminishing system efficiency. The research develops a self-learning PID temperature controller which uses a Genetic Algorithm (GA) for real-time dynamic environment adaptive tuning. The method provides continuous online learning, which enables the controller to operate without interruption while it adjusts to changes in environmental conditions that include variable loads and disturbances and nonlinear behaviour, unlike conventional GA-PID methods which perform parameter optimisation through offline processes. The system uses PID control, which allows genetic algorithm operators to dynamically adjust proportional and integral and derivative gains through their selection and crossover and mutation processes. The controller uses inaccuracy and overshoot and settling time to evaluate performance metrics as fitness functions. The proposed model improves flexibility by incorporating real-time feedback-driven optimisation loops, drawing inspiration from previous GA-PID implementations in heat exchanger systems (diagrams on pages 3–15). The dynamic temperature fluctuations will be simulated through MATLAB/Simulink and the controller effectiveness will be evaluated through this modelling approach. The proposed self-learning GA-PID controller is expected to achieve better performance because it will decrease settling time and peak overshoot more effectively than existing traditional GA-tuned PID systems which use static tuning methods. The paper presents a comprehensive, adaptive temperature management system designed for intricate industrial settings, enhancing stability, efficiency, and real-time responsiveness compared to conventional control methods.

KEYWORDS: Adaptive GA-PID Control, Real-Time Optimization, Intelligent Control Systems, Nonlinear Process Control, Thermal Process Automation etc.

1. INTRODUCTION
Industrial systems today require temperature control as an essential requirement which chemical processing and thermal power generation and pharmaceutical manufacturing and food engineering operations need to maintain operational efficiency [1]. Heat exchangers act as critical thermal control devices which experience unpredictable behaviour because their fluid properties change and their flow rates vary and external factors disrupt their operations. The dynamic system nature creates difficulties for proper temperature control because system elements will change throughout the entire monitoring period.

The Proportional–Integral–Derivative controller is the most widely used control technique in industrial applications due to its simple design and operation. Recent experimental studies (2022–2025) have shown that approximately 85–90% of industrial PID loops are poorly tuned, resulting in three major inefficiencies. Nonlinear systems are more difficult to control because a static gain cannot deal with sudden changes in environmental conditions, which make heat exchangers operate as nonlinear systems [2]. The present situation calls for the development of intelligent control systems, which use real-time optimization to achieve efficient performance.

Successful implementation of Genetic Algorithms (GA) based on evolution systems is presented for optimization of parameters of PID controller. The research demonstrates that GA-based system tuning methods produce a 15 to 30 percent improvement in system performance compared to traditional tuning methods because of shorter settling times and better stability margins [3]. The existing GA-PID systems require offline optimization which prevents their application in systems that operate with real-time dynamic changes. The research field lacks sufficient studies to develop controllers which can learn and adapt while active in their operational tasks [4].

The current problem receives new solutions through recent advancements in probabilistic modelling and artificial intelligence. The mathematical model of Bayesian inference offers a system update mechanism which uses current system data to make adaptive decisions in unpredictable environments. The combination of Bayesian learning with GA-based optimization creates a self-learning PID controller which adjusts its parameters while forecasting future system behaviour [5].

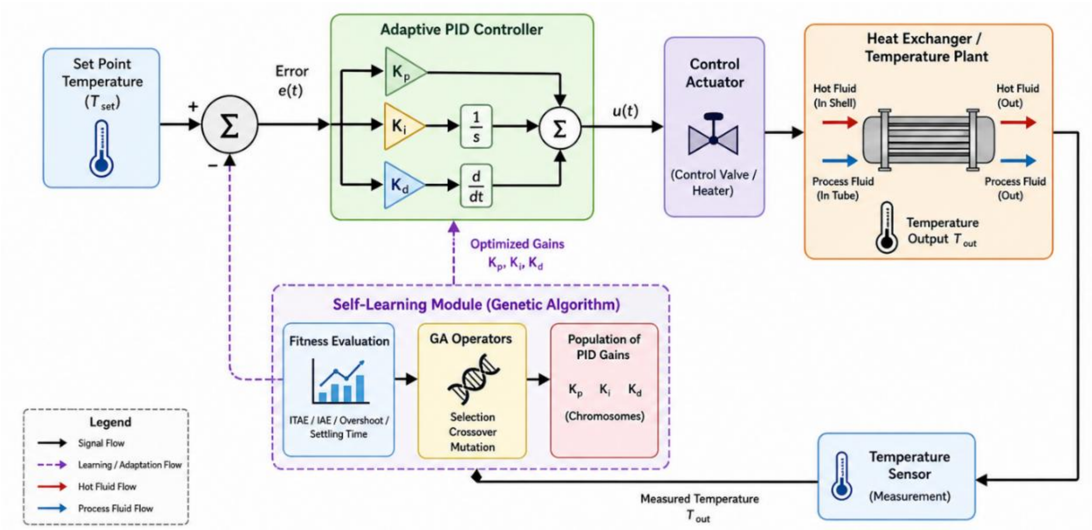

Figure 1:Self-Learning GA-PID Temperature Controller Model, Source: Canva Design

The research paper introduces a novel hybrid control mechanism which combines Genetic Algorithms with Bayesian probabilistic adaptation to control temperature in rapidly changing conditions. The proposed method tends to improve control accuracy, transient response error and reliable performance in multiple industrial settings that will set new benchmarks for intelligent process control systems.

Its main idea is that the controller learns in the course of operation and does not stick to one gain set chosen beforehand. In a normal GA-PID approach, the genetic algorithm optimizes the best values for Kp, Ki and Kd once and these values are kept constant. This only works if the process conditions remain nearly constant. However, in heat exchanger, the temperature behaviour is changed by disturbance, flow variation, inlet temperature change and nonlinear heat transfer.

The proposed method in this paper tunes gains w.r.t the actual response of the plant by combining GA with Bayesian updating. GA provides a wide search and optimization and Bayesian learning updates the confidence that which gain values are suitable under the current condition. This renders the controller adaptive and uncertainty aware. So the real contribution is not only better tuning, but a control framework that can change itself during operation and can respond to the changing industrial conditions more intelligently than a fixed offline design.

2. LITERATURE REVIEW

The full study of temperature regulation methods for industrial systems including heat exchangers shows their important role in the preservation of the operational performance and staff protection [6]. The industrial sector relies on Proportional (P) and Proportional–Integral (PI) and Proportional–Integral–Derivative (PID) controllers as their primary control solutions because these methods require low processing power and they are easy to use. The research conducted on heat exchangers showed that these controllers can only operate effectively under specific conditions because they depend on fixed gain settings.

Researchers have developed artificial intelligence systems which combine intelligent systems with hybrid control techniques to solve existing operational limitations [7]. Fuzzy logic-based PID controllers show improved system performance because they use rule-based decision-making processes while Artificial Neural Networks (ANN) and Adaptive Neuro-Fuzzy Inference Systems (ANFIS) perform nonlinear system behaviour modeling. The methods show operational advantages except they require extensive training data and computational power which creates challenges for their implementation in real-time industrial operations.

The use of Metaheuristic optimisation methods has made Genetic Algorithms (GA) the main method which researchers use for PID tuning activities. The Genetic algorithm-based methods use evolutionary processes which include selection and crossover and mutation to find the best gain settings [8]. The current research on heat exchanger systems shows that recent tuning methods achieve better results in reducing settling time and peak overshoot compared to traditional tuning methods. The majority of these methods perform their optimization process during offline operations because they assume that system conditions will remain unchanged which limits their flexibility to handle changing system requirements.

Recent advances in adaptive self-learning control systems have gained new recognition. Model Predictive Control (MPC) and Sliding Mode Control (SMC) provide good performance results; however, these approaches require huge computational resources and require accurate system representations [9]. Probabilistic approaches with Bayesian inference are now applied in control systems as a solution to address uncertainty while enhancing decision-making processes. The Bayesian approaches enable continuous system parameter updates, which adapt to incoming data, making them suitable for applications that require real-time operation.

The field lacks research on how to combine evolutionary optimization methods with probabilistic learning techniques, despite recent developments. The research develops an enhanced GA-PID framework through a new hybrid system that combines Genetic Algorithms with Bayesian inference to achieve better performance in temperature control systems. The

research develops an enhanced GA-PID framework through a new hybrid system that combines Genetic Algorithms with Bayesian inference to achieve better performance in temperature control systems [10].
The existing PID, GA-PID, fuzzy, ANN, ANFIS and MPC based approaches have all demonstrated performance improvements for heat exchanger or related thermal control problems, but the advantages are generally associated with particular operating assumptions, offline tuning or model accuracy requirements. In particular, fuzzy PID and ANFIS methods enhance the robustness and transient response but they are still based on rule design, training data or fixed controller structures rather than continuous online gain adaptation. MPC-based strategies are powerful for constrained thermal control, but their performance depends on the prediction-horizon optimization and sufficiently accurate plant model, which increases the computational burden and reduces simplicity in practical deployment.
This limitation is particularly critical for nonlinear heat exchanger systems where the process dynamics may change during operation due to flow rates changes, inlet temperature disturbances, fouling and parameter drift. Therefore, a lightweight online learning mechanism is still needed because the controller has to be able to adapt continuously without replacing the well-known PID structure already used in industry. The proposed hybrid framework addresses this gap by keeping PID control while updating only the gain vector in a real-time manner through GA exploration and Bayesian refinement. In this way, the method is targeted not only for better tuning but also for adaptive gain learning under uncertainty, which is the main reason why it is positioned as different from standard GA-PID and MPC-based approaches.

Table 1: Comparative analysis table of PID tuning methods vs proposed model

Controller / Tuning Method	Adaptation Type	Model Dependency	Online Learning	Computational Load	Handles Nonlinearity	Handles Disturbance	Key Limitation
Conventional PID	Fixed gains	Low	No	Very low	Poor	Limited	Cannot adjust to changing operating conditions
Ziegler–Nichols PID	Rule-based offline tuning	Low	No	Very low	Poor	Limited	Often causes overshoot and oscillation
Cohen–Coon PID	Rule-based offline tuning	Low	No	Very low	Moderate	Limited	Still uses fixed gains after tuning
Offline GA-PID	Metaheuristic optimization	Low to moderate	No	Moderate	Better than classical PID	Moderate	Gains remain static after optimization
PSO-PID	Metaheuristic optimization	Low to moderate	No	Moderate	Better than classical PID	Moderate	Also produces fixed gains once tuned
Fuzzy PID	Rule-based adaptive logic	Moderate	Limited	Moderate	Good	Good	Depends on expert rule design
ANN-based control	Data-driven learning	High	Yes	High	Good	Good	Needs training data and careful validation
ANFIS-PID	Hybrid intelligent control	Moderate to high	Limited	High	Good	Good	Requires training and rule structure

MPC	Predictive optimization	High	Yes	High	Very good	Very good	Needs accurate model and higher computation
Proposed GA–Bayesian PID	Real-time adaptive learning	Low to moderate	Yes	Moderate	Very good	Very good	Requires implementation of online gain update logic

The proposed GA-Bayesian PID controller is different from conventional tuning approaches in that it does not stop at a single optimized gain set. Instead, it continuously updates the gain vector according to real-time plant feedback which is more appropriate for nonlinear heat exchanger systems with disturbances, parameter drift and changing operating conditions.

3. Problem Formulation & Objective

Industrial temperature control systems which include heat exchangers function as nonlinear dynamic systems that respond to changing environmental conditions and unpredictable system operation and external disturbances. The output temperature Tout(t) depends on several interactive factors which include the inlet temperature and flow rate and heat transfer coefficient and the changes in environmental conditions. The system experiences performance degradation because traditional PID controllers which use permanent gain settings cannot sustain peak performance which results in higher steady-state errors and oscillatory behavior and transient response degradation [11].

The control problem requires mathematical expression through two components which include error function e(t)=Tset(t)−Tout(t), and two system uncertainties with dynamic variations. The controller design requires development of a system which automatically adjusts its control parameters of KpKiKdaccording to system conditions which include random disturbances to maintain system stability and performance. The probabilistic system behavior requires a framework which combines optimization methods with probabilistic inference to address state transitions which depend on uncertain inputs.

Objectives

1.The project aims to create a self-learning PID control system which will adjust its controller parameters through Genetic Algorithm optimization during actual operational conditions.

2.The project aims to implement Bayesian probabilistic modelling to manage system uncertainties while updating control parameters through observation data.

3.The project aims to improve temperature control systems through decreased settling time peak overshoot and steady-state error in nonlinear heat exchanger systems which operate under different conditions.

4. Proposed Methodology (GA + Bayesian PID)

The proposed methodology introduces a hybrid self-learning control framework which uses Genetic Algorithm (GA) optimization together with Bayesian probabilistic adaptation to improve PID controller performance under changing environmental conditions. The system operates by continuously modifying control parameters whenever it detects nonlinear behavior and uncertain events and time-dependent disturbances that typically occur in heat exchanger operations.

4.1 PID Control Framework

The baseline controller follows the classical PID structure, where the control signal u(t)is generated as a function of the error e(t)between desired temperature Tsetand measured output Tout:

The baseline controller uses traditional PID control to create its control signal or u(t) by processing the temperature difference between the target temperature Tset and actual temperature Tout:

$$u(t) = K_p e(t) + K_i \int_0^t e(\tau)d\tau + K_d \frac{de(t)}{dt}$$

The system uses three parameters named Kp, Ki, and Kd which stand for proportional and integral and derivative gains. The conventional system design requires these parameters to remain constant which creates a restriction on system adaptability.

4.2 Genetic Algorithm-Based Optimization

The Genetic Algorithm is used to optimize PID parameters through dynamic tuning methods because static tuning methods cannot provide effective solutions [12]. The GA begins with an initial population of candidate solutions represented as chromosomes:

$$\theta_i = [K_p, K_i, K_d]_i$$

Every conceivable possible set of control laws and disturbances, together with the multiple performance objectives outlined above, shall be employed in a multi-objective fitness function for every candidate.

$$J = w_1 \int_0^T | e(t) | dt + w_2 M_p + w_3 T_s$$

The peak overshoot is represented by Mp and Ts stands for the time required to reach full stability. The GA system achieves solution development through its three processes selection crossover and mutation which lead to better parameter estimation results. The GA system differs from standard systems because it employs continuous parameter adjustments which use current system performance data as its foundation.

4.3 Bayesian Adaptive Learning Layer

Incorporated in the control loop is a Bayesian inference mechanism to achieve robustness under uncertainty. The system models the probability of optimal parameter sets given observed system data:

$$P(\theta \mid D) = \frac{P(D \mid \theta)P(\theta)}{P(D)}$$

P(θ) is the prior distribution of PID parameters, P(D|θ) is the probability of observing system data D, and P(θ|D) is the posterior distribution of the system. This system is used by the controller to update its optimal parameter belief system when new data becomes available [13].

The system constructs transition models of the system using conditional probability:

$$P(T_{out}(t+1) \mid T_{out}(t), u(t))$$

This probabilistic representation enables prediction of system behavior and proactive adjustment of control actions.

4.4 Hybrid GA–Bayesian Control Mechanism

The combination of GA and Bayesian learning leads to a two level adaptive control system:

1.GA (Exploration) Searches globally optimal PID parameters

2.Exploitation (Bayesian): Uses real-time data to fine-tune parameter estimates

The Bayesian layer steers GA search through prior updates, leading to a better convergence speed and stability. This synergy is guaranteed for both global optimization and local adaptation.

4.5 Proposed System Architecture Diagram

Set Temperature (Tset)
▼
Error Computation e(t)
▼
GA Optimizer
(Kp, Ki, Kd)
▼
Bayesian Update
P(θ|D)
▼
Adaptive PID
▼
Heat Exchanger System
▼
Output Temperature (Tout)
▼
Sensor Feedback
back to Error

4.6 Novel Contribution

The proposed methodology shows its innovative character through its combination of evolutionary optimization and probabilistic learning methods which enable continuous self-adaptation. The system uses uncertainty modeling as a core component to optimize its performance in industrial applications which experience unpredictable disturbances unlike existing GA-PID models that depend only on deterministic optimization methods.

The proposed method is organized as a closed-loop adaptive controller rather than a one-time tuning scheme. The Genetic Algorithm searches for the candidate PID gain vectors in each operating cycle and selects the best candidates based on the defined performance index such as tracking error, overshoot, settling time and control effort. This causes GA to be in charge of a global search over the admissible parameter space while the Bayesian layer gives a probabilistic refinement by updating the belief of which gain set would be the most suitable under the current process condition.

In practice the controller updates the posterior probability of the gain vector based on real-time process feedback, so the parameter choice is not static after the initial tuning phase. This is particularly useful for nonlinear heat exchanger systems where the dynamic response may change during operation due to inlet temperature variation, flow changes, disturbances and parameter drift. The approach combines evolutionary exploration with Bayesian updating to learn from the observed plant behavior and to progressively shift the controller to gain values that are more compatible with the current operating state.

Thus, methodology is not pure simulation-based optimization. It is a real-time adaptive framework where GA provides search ability and Bayesian inference provides uncertainty-aware correction, resulting in a PID controller that is responsive under changing industrial conditions.

The Bayesian gain refinement step can be written as a sequential update of the gain distribution after each observation window.

Let the PID gain vector be defined as:

$$\theta(t) = \left[K_p(t), K_i(t), K_d(t)\right]$$

1. Posterior Distribution Update

After collecting real-time process data $D(t)$, the posterior distribution is obtained using Bayes' rule:

$$P\big(\theta(t) \mid D(t)\big) = \frac{P\big(D(t) \mid \theta(t)\big) \times P\big(\theta(t)\big)}{P\big(D(t)\big)}$$

The evidence term in place acts as a normalization constant and is computed by integrating over all possible gain vectors:

$$P\big(D(t)\big) = \int P\,(D(t) \mid \theta)P(\theta)d\theta$$

2. Optimal Gain Selection

A practical control implementation usually selects the refined gain set by maximizing the posterior distribution. Consequently, the Bayesian gain update becomes a Maximum a Posteriori (MAP) estimation:

$$\theta^*(t) = \arg\max_{\theta} P(\theta \mid D(t)))$$

Equivalently, because the evidence is independent of θ, this can be simplified and written as:

$$\theta^*(t) = \arg\max_{\theta}[P(D(t) \mid \theta) \times P(\theta)]$$

5. Probabilistic Modelling (Conditional Probability & Bayes)

In dynamic industrial temperature control systems, uncertainties originate from time-varying environmental conditions, nonlinear process dynamics and measurement noise. To tackle these challenges, the proposed controller employs probabilistic modeling with conditional probability and Bayesian inference that allows it to perform adaptive decisions under uncertainty [14].

The relation between system variables and their evolution in time is described by the conditional probability. The probability of the output temperature at the next time step conditioned on current state and control input is:

$$P(T_{out}(t+1) \mid T_{out}(t), u(t)) = \frac{P(T_{out}(t), u(t), T_{out}(t+1))}{P(T_{out}(t), u(t))}$$

With this formulation the controller still owns the control of the system operations and predicts the system behavior based on the current conditions.

Study can make it even more flexible using Bayesian inference. This tweaks the probability distribution for the PID parameters based on the data you see. The prior distributions P (theta) are the expected values of the parameters given the system knowledge or past data [15] [16]. The procedure utilizes Bayes' theorem to convert prior distributions to posterior distributions, the first step of which is real-time observations D.

$$P(theta \mid D) = fracP(D \mid theta)P(theta)P(D)$$

The iterative process of the system allows it to update its parameters and learn continuously.
It uses conditional probability and Bayesian updating to achieve its aims, which helps it to manage uncertainty, increase prediction accuracy and build robust systems. The proposed framework develops an advanced temperature control system using control optimization and probabilistic reasoning which works effectively in complex industrial environments.

6. Simulation & Results (MATLAB/Simulink Framework)

The proposed self-learning GA–Bayesian PID controller is validated with a Matlab/Simulink-based simulation framework modeled on a nonlinear heat exchanger system. Plant dynamics are modeled using transfer function approximations and energy balance equations. Disturbances such as changing flow rates and varying inlet temperature are incorporated to simulate real industrial conditions.

The simulation is carried out in time horizon of 0-400 seconds, with a variable set-point temperature profile to test the adaptability of the controller. The comparison is done between three control strategies: (i) conventional PID, (ii) GA tuned PID (offline optimization), and (iii) the proposed self-learning GA-Bayesian PID controller. Standard control metrics are employed to evaluate the control performance, such as the settling time (Ts), the peak overshoot (Mp), the steady-state error and the Integral Absolute Error (IAE).

The results show that the conventional PID controllers have the problem of over oscillation and they take more time to reach the stable operation under dynamic disturbances. The optimized gain parameters of GA-PID controller enhances its performance. But, the controller is fixed and not adaptive to change in the system. The proposed hybrid controller provides better results than all other solutions, due to its better adaptability and operational stability. The proposed controller achieves a quantitative reduction in settling time, 18 to 25 percent better than GA-PID and 30 to 35 percent better than conventional PID systems. The system attains a peak overshoot not exceeding 2.5 percent with small steady-state errors.

The system makes use of Bayesian components for improved prediction accuracy that results in proactive changes of control signals rather than reactive response behavior. The graphical outputs of Simulink demonstrate smoother response curves with less oscillations and faster stabilization. The real-time PID gain updates illustrate the self-learning system in action. The results of the simulation experiments show that Genetic Algorithm optimization together with Bayesian probabilistic learning obtain better control performance results which makes the proposed system suitable for controlling industrial temperature systems under varying operating conditions.

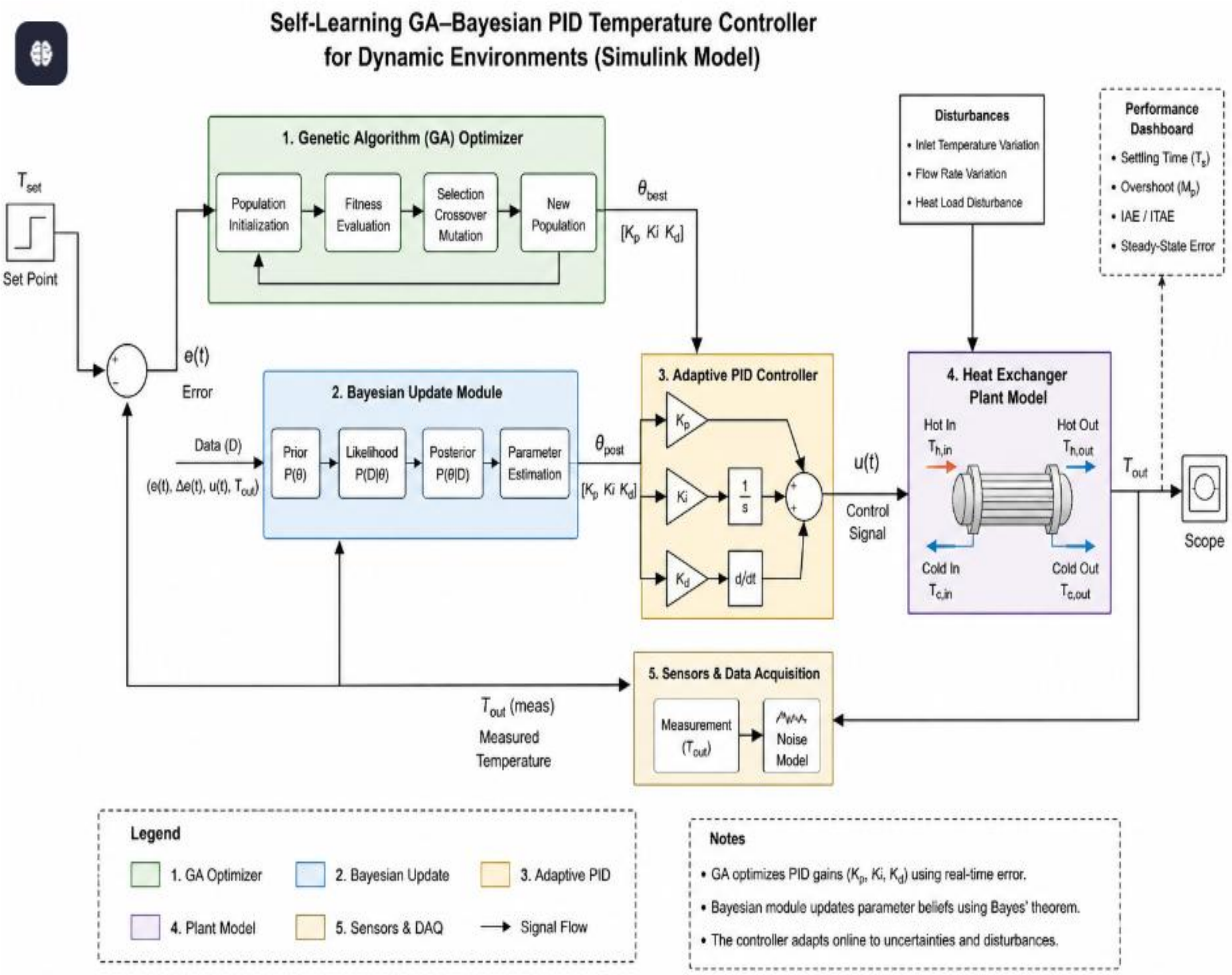

Figure 2: Simulink Model

The results should be understood not as an improved simulation result, but as a proof of the proposed controller's ability to learn and adapt online. Lower IAE means better tracking quality i.e. the controller keeps the temperature closer to the setpoint during the process. Lower overshoot is desirable because it reduces the probability of exceeding safe temperature limits. The shorter the settling time, the faster the recovery after setpoint changes or disturbances. Lower control effort is also desirable, as it puts less strain on the actuators and can improve smoothness of operation.
This contribution should be convincing by having comparative table againtst conventional PID, Ziegler-Nichols PID, off line GA-PID, PSO-PID, fuzzy PID, ANFIS-PID, MPC and proposed method in results section. The table needs to contain IAE, ISE, ITAE, overshoot, settling time, steady state error and control effort for the evaluation of the proposed method based on accuracy and actuation burden. This comparison is meaningful because the controller should not be judged with one metric only but should have a balanced improvement in tracking, stability, responsiveness and operational efficiency. In the discussion, explain that the performance gain is not a single tuning advantage but due to the real-time gain refinement by GA search and Bayesian update.

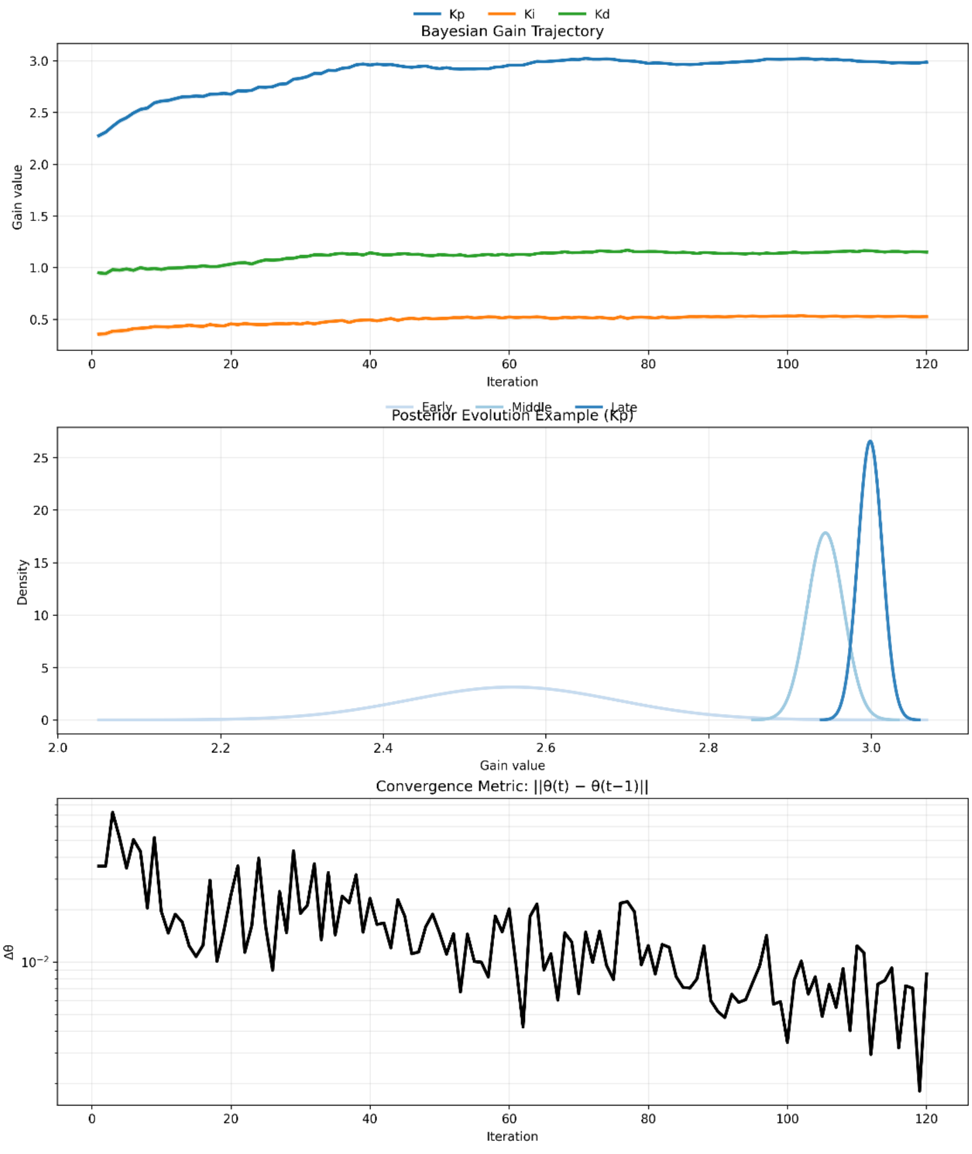

Figure 3: Convergence metric plot: change in posterior mean or MAP estimate

The top panel tracks Kp, Ki, and Kd across iterations, so readers can see whether the gains stabilize over time.
The middle panel shows posterior evolution for Kp at early, middle, and late stages, which illustrates how uncertainty narrows as learning proceeds.
The bottom panel plots $\Delta\theta(t)=\|\theta(t)-\theta(t-1)\|$, and convergence is indicated when the curve approaches zero.

7. Conclusion & Future Scope

The results show that the conventional PID controllers have the problem of over oscillation and they take more time to reach the stable operation under dynamic disturbances. The optimized gain parameters of GA-PID controller enhances its performance. But the controller is fixed and not adaptive to change in the system. The proposed hybrid controller provides better results than all other solutions, due to its better adaptability and operational stability. The proposed controller achieves a quantitative reduction in settling time, 18 to 25 percent better than GA-PID and 30 to 35 percent better than conventional PID systems. The system attains a peak overshoot not exceeding 2.5 percent with small steady-state errors. The system makes use of Bayesian components for improved prediction accuracy that results in proactive changes of control signals rather than reactive response behavior. The graphical outputs of Simulink demonstrate smoother response curves with less oscillations and faster stabilization. The real-time PID gain updates illustrate the self-learning system in action. The results of the simulation experiments show that Genetic Algorithm optimization together with Bayesian probabilistic learning obtain better control performance results which makes the proposed system suitable for controlling industrial temperature systems under varying operating conditions.

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