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Integration of statistical methods and neural networks for temperature regulation parameter optimization

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ABSTRACT

Temperature control plays a crucial role in various industrial processes, ensuring optimal performance and product quality. The conventional approach to optimizing temperature controller parameters involves manual tuning, which can be time-consuming, labor-intensive, and often lacks precision. This paper introduces an innovative methodology for optimizing the parameters of a temperature controller by integrating statistical methods in the preparation of the experimental plan utilized by neural networks. The integration of statistical techniques in designing the experimental framework enhances the efficiency of data collection, providing a robust foundation for subsequent analysis. The neural network leverages this well-structured dataset to model and optimize the temperature controller parameters, resulting in improved precision and performance. The synergistic integration of statistical methods and neural networks not only streamlines the optimization process but also enhances the reliability of the temperature control system. The effectiveness of the proposed approach is demonstrated through case studies on the Procon level/flow and temperature 38-003 process. The results show significant improvements in temperature control performance, with reduced process variability and faster response times.

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1. INTRODUCTION

In the realm of temperature regulation, achieving optimal parameter settings is crucial for efficient operation across diverse domains, spanning industrial processes to environmental control systems. The pursuit of precision and efficiency has driven researchers to explore innovative methodologies that blend the strengths of statistical techniques with the adaptability of neural networks. This paper delves into the integration of statistical methods and neural networks, presenting a synergistic approach aimed at optimizing temperature regulation parameters.

Temperature regulation is a complex and dynamic process influenced by numerous factors, necessitating sophisticated optimization strategies to enhance performance and energy efficiency. Historically, the optimization of temperature controller parameters has relied heavily on manual tuning methods. Researchers and practitioners have dedicated efforts to refining heuristics and empirical approaches to strike a balance between performance and efficiency [1], [2]. Traditional statistical methods have long been employed to analyze and model temperature dynamics, providing valuable insights into system behavior and variability. However, their effectiveness may be limited by the intricate interdependencies inherent in temperature control systems, especially in non-linear and multi-dimensional environments. Recent advancements in statistical approaches have seen an increased reliance on methods such as design of experiments (DoE) and response surface methodology (RSM) to systematically explore parameter spaces. These approaches offer structured methodologies for experimentation [3]-[5]. Concurrently, the integration of neural networks in process control has gained traction due to their ability to model complex relationships within datasets. Previous studies have showcased their efficacy in optimizing control parameters across various domains, demonstrating the potential for enhanced precision and adaptability [6]-[8]. By integrating neural networks with optimization algorithms such as particle swarm optimization (PSO) and backpropagation (BP), researchers can achieve improved control and parameter optimization outcomes [9]. Neural networks have been demonstrated to be effective in identifying and controlling nonlinear dynamical systems, showcasing their potential in enhancing temperature control system optimization [10]. Moreover, the integration of neural network-based model predictive control and inverse neural network control strategies with optimization based on neural network models has been successfully applied to controlling temperatures in various systems, such as batch crystallizers [11]. Gao and Chai [12] allow for the optimization of control strategies through neural networks, leading to enhanced temperature regulation. Additionally, the use of neural network optimization frameworks has been proposed to determine optimal weighting parameters for control systems under diverse working conditions, thereby improving the overall performance of the system. Aleksendrić *et al.* [13] optimized temperature-time curves for curing processes by utilizing dynamic artificial neural networks, highlighting the potential of neural networks in correlating temperature variables in composite materials.

Hybrid optimization methodologies that integrate statistical methods and neural networks have gained attention in recent research endeavors. By combining the strengths of different optimization techniques, such as genetic algorithms (GA), second-order cone programming (SOCP), and artificial neural networks (ANN), researchers aim to enhance the efficiency of experimental design and the modeling capabilities of neural networks for improved performance in control optimization [10], [14], [15]. These hybrid approaches have shown promise in various fields, including the optimization of machining processes, material science, and power systems. Studies have reported the effectiveness and robustness of hybrid optimization methods in achieving global optimal solutions compared to traditional optimization approaches [16]-[18]. Furthermore, the integration of artificial neural networks with optimization algorithms has demonstrated success in multi-objective optimization tasks, leading to improved outcomes in complex processes like magnetic abrasive finishing and power system design [19]. Moreover, the application of hybrid optimization techniques extends to diverse domains such as transportation systems, vehicle architectures, and energy systems. Researchers have explored hybrid design methodologies for automated generation and optimization of vehicle architectures, powertrains, and renewable energy systems, showcasing the potential for enhanced performance and efficiency through integrated optimization strategies [20]-[25]. Overall, the emerging trend of hybrid optimization methodologies represents a significant advancement in the field of optimization, offering a synergistic approach that leverages the strengths of different techniques to address complex optimization challenges effectively.

In light of the existing literature, our research proposes a new hybrid approach that integrates statistical knowledge with neural network capabilities. This comprehensive framework is developed for adaptively adjusting control parameters, considering dynamic environmental conditions and system constraints. By addressing the limitations of singular methodologies, this integration promises more efficient and precise optimization of temperature controller parameters, contributing significantly to the evolving landscape of temperature control optimization.

The proposed approach offers several advantages over conventional methods, including improved accuracy, robustness to variations, and adaptability to diverse operating conditions. Moreover, by leveraging the vast amounts of data generated in modern temperature control systems, the integrated methodology facilitates continuous learning and refinement, enabling real-time adaptation to evolving environments. Through a series of case studies and simulations, the efficacy of the integrated approach is demonstrated across various applications, showcasing its potential to revolutionize temperature regulation optimization in practical settings. By bridging the gap between statistical methodologies and neural network paradigms, this paper paves the way for enhanced efficiency, sustainability, and performance in temperature control systems, ushering in a new era of intelligent regulation technology.

2. METHOD

We explore the hybridization of Modde 6 with neural networks, a widely used statistical modeling software, for the optimization of temperature controller parameters. This combined approach offers increased modeling power and the ability to capture complex relationships between control system variables. Subsequent sections of this paper delve into a comprehensive analysis of the fundamental 38-600 process, employing a structured analysis and design technique (SADT) diagram. This analysis is followed by the different operations of Modde 6.0 and the implementation of our ANN-proportional integral derivative (PID). Experimental tests were conducted on the Feedback 38-003 Procon level and flow with temperature process [26] to validate the system's effectiveness.

2.1. SADT diagram of process 38-600

The main function of our level (A0) is the temperature control and regulation of the secondary flow by PID control. The input variables include the temperature process servovalve signal (Sr), the secondary water flow (QMVv), a fixed signal, and the water quantity. The system control data represents power and water supply, manual control (MV2, MV) and the basic process servo valve (SVB). Our output variables consist of the set secondary water flow (Qr), temperature (T5), temperature display (T5), and the current signal, represented either as 4-20 mA on degrees as shown in Figure 1.

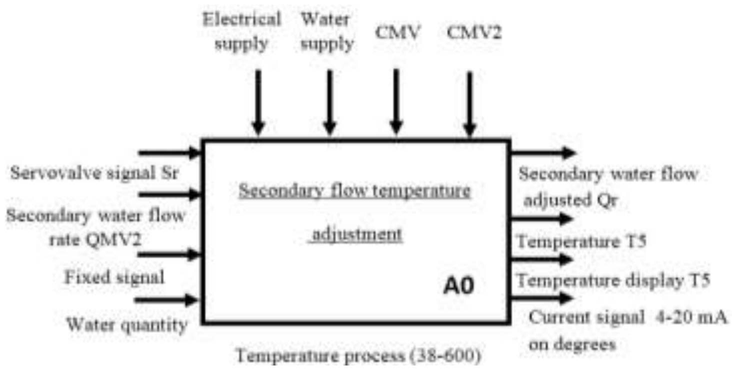

Figure 1. SADT diagram of the A0 system

2.2. Operation of modde 6.0

2.2.1. Design of experiments

Modde 6.0 provides advanced functionalities for planning DoE, helping you design effective experiments for process optimization, identifying influential factors, and optimizing results. Here are the steps involved in using Modde 6.0 for experimental design planning:

i. Selection of the experimental design type: Modde 6.0 offers various types of experimental designs. We employed fractional factorial designs (full fac (2 levels)). This design type reduces the number of required trials by evaluating only a fraction of the possible combinations of each factor's levels.
ii. Factor definition: the next step involves identifying the factors that influence the system being studied. In this case, the factors Ti, Td, and BP have been identified as inputs affecting the system. These factors are crucial for understanding the system's behavior and optimizing the experimental outcomes.
iii. Generation of the experimental plan: Modde 6.0 automates the generation of the experimental plan based on the input parameters provided. The experimental plan specifies the combinations of factor levels to be tested and any potential repetitions. By systematically laying out the experimental design, Modde 6.0 ensures that all relevant factors are considered, and the experimental process is structured for efficient data collection and analysis. The experimental plan will specify the combinations of factor levels to be tested and any potential repetitions as shown in Table 1.
iv. Experiment execution: in this step, we carried out the experiments according to the plan generated by the process.

2.2.2. The mathematical model

The mathematical model obtained by Modde 6.0 from data analysis is a mathematical equation that predicts the value of the dependent variable Y as a function of the values of the independent variables Ti, Td, BP, and the regression coefficients b0, b1, b2, ... bn. The mathematical model is a linear equation of the form:

$$Y = b0 + b1X1 + b2X2 + \ldots + bn * Xn \tag{1}$$

for our system, after entering all the results into Modde 6.0 as shown in Table 2 through direct measurements in the process, we obtained the (2).

$$Y = 8,71325 + 1,3025 * Td - 3,2925 * Ti - 0,54925 * Pb + 0,12 * Td * Ti + 1,015 * Td * Pb + 0,5 * Ti * Pb \quad (2)$$

Table 1. Analyzing data using fit

Generation of the experimental plan			Experiment execution	
Temp derivation	Temp *d'integration*	*bande passante*	temps *d'execusion*	*erreur*
10	20	3	13,57	0,1
20	20	3	12,54	0
10	30	3	4,38	0
20	30	3	6,56	0
10	30	4	4,04	0
20	30	4	7,55	0
10	30	5	4,36	0,1
20	30	5	6,19	0,1
15	25	4	6,47	0,1
10	20	4	8,5	0,1
20	20	4	14,26	0

Table 2. The list of coefficients obtained for our system

Temps *d'execusion*	Coeff. SC	Std. Err.	P	Conf. int ()
Constant	8,7132	0,64139	0,0053749	2,7596
Td	1,3025	0,67608	0,19388	2,9089
Ti	-3,2925	0,67608	0,0396728	2,9089
Pb	-0,549	0,64139	0,482034	2,7596
Td*Ti	0,12	0,67608	0,875472	2,9089
Td*Pb	1,015	0,67608	0,2721	2,9089
Ti*Pb	0,5	0,67608	0,536597	2,9089

N=9; Q2 =-0,724; Cond. no.=1,118; DF=2; R2=0,939; Y-miss=0; R2 Adj.=0,758; RSD=1,9123; Conf. lev.=0,95

2.2.3. Prediction

Prediction is accomplished using statistical models or machine learning algorithms that have been previously built from training data. Here is a summary of the prediction process:

i. Model construction: the input variables Ti, Td, and BP are selected, and the model parameters are adjusted using the training data.
ii. Data feeding to the model: the prepared data is provided to the model as input.
iii. Prediction calculation: the model utilizes the information provided by the input data to perform internal calculations and generate predictions on the target variable or desired outcome. This can be a continuous numerical value, a discrete category, or a probability.
iv. Prediction evaluation: the predictions generated by the model are evaluated by comparing the predicted results with the actual or expected results. This allows for measuring the accuracy of the model and identifying any potential errors or inconsistencies.

2.3. The ANN-PID intelligent control approach

The intelligent ANN-PID system presented here is grounded in an MLP neural network. It harnesses the gradient backpropagation algorithm to assimilate process characteristics. ANN-PID adeptly replicates the decision-making process of a human operator when configuring controller settings. After evaluating the predicted data, it is then employed by our ANN-PID by separating them into two tables: the first table contains inputs, which include the inputs (Ti, Td, and BP), and outputs, which contain the outputs (execution time and error). In our work, we wanted to test the NNStart tool, one of the tools available in MATLAB to facilitate the creation and training of neural networks. NNStart is a function in MATLAB that launches the neural network toolbox GUI. This graphical interface provides an interactive way to design, train, and simulate neural networks. It simplifies the process of creating and working with neural networks by offering a visual environment.

This network imitates the pattern of an expert operator when he is adjusting the parameters of a control regulation for an industrial process. Therefore, this is a pattern recognition problem. To solve this problem, we use the database obtained previously by Modde 6.0. Algorithm 1 represents the algorithm used to learn this pattern. We chose the back-propagation training method.

Algorithm 1. The backpropagation training method

```
Execute the training process using the backpropagation method
Training process
Initialize all elements of wi and also rand (-0.01, 0.01);
Repeat
Begin
For all i
Begin
δwi = 0;
end;
For all instances (x,c) in S;
Begin
Calculate output: Pb%, td, ti for inputs: reference, error, time reset;
12-For all i
13-Begin
δwi = δwi +ϵ×(c −O)×xi × ˙σx.w ;
end ;
end ;
For all i
Begin
wi = wi +δwi ;
end;
end
```

3. TEMPERATURE REGULATION EXPERIMENTS

In this study, we first conducted the tests outlined in the Modde 6.0 experimental design to acquaint ourselves with the process and establish the database as shown in Table 3 for parameter tuning. Subsequently, we executed more than 50 additional tests to validate the values predicted, all while continuing to utilize Modde 6.0 for this purpose. Figure 2 illustrates the optimum value obtained by the PID of the ABB-CM30 controller on the Procon level/flow and temperature 38-003 process [26] for inputs x equal to [Ti, Td, BP%]. In which, we have obtained outputs y equal to [reference value; error; response time value] without disturbance.

For x=[4; 30; 4], PID gave y=[35; 0.1; 4.35]. The curve depicted in Figure 3 illustrates the optimal PID values attained for the ABB-CM30 controller in the presence of a disturbance. This disturbance involves activating the chiller for a duration of 30 seconds after achieving stabilization. Figure 4 illustrates the optimum value obtained by the PID of the ABB-CM30 controller with two disturbances by switching on the cooler several times, each time for 30 seconds after stabilization.

Table 3. A subset of the database for testing temperature regulation

Reference	Start	Bp (%)	Ti	Td	Error	Response time
35	25	4	5	10	0	6,53
35	25	4	20	10	0	8,11
35	25	3	40	10	0,1	4,35
35	25	5	30	10	0,1	4,36
35	25	3	30	10	0	4,38

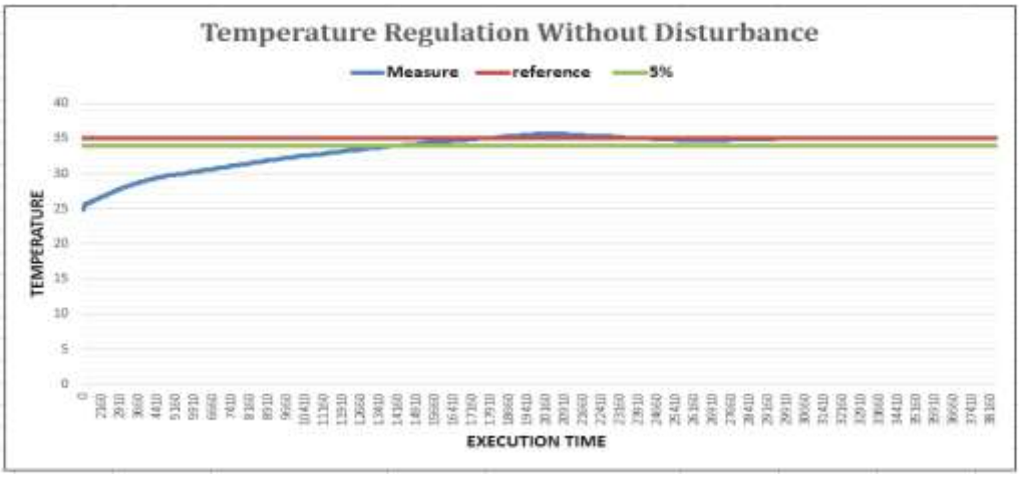

Figure 2. Temperature regulation curve for a reference of 35°

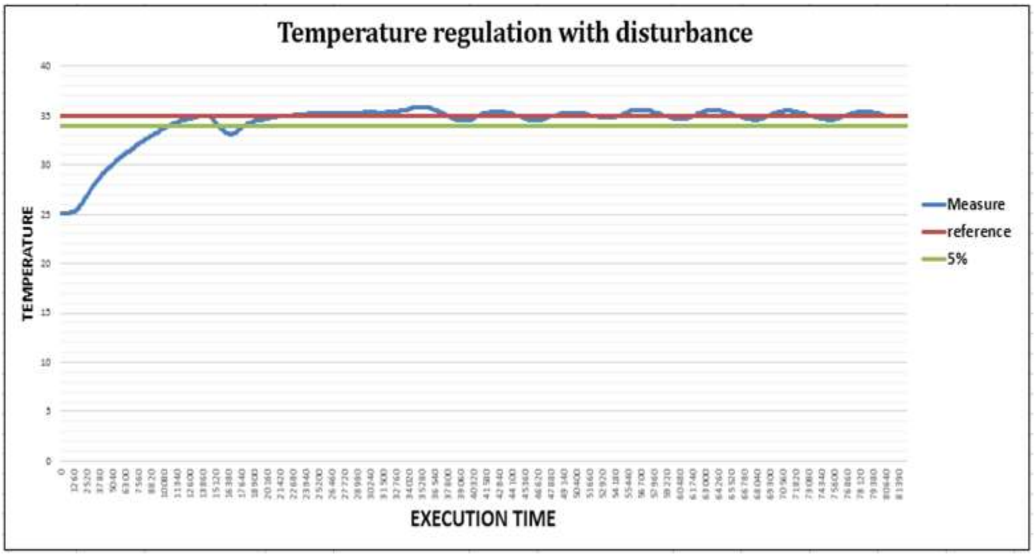

Figure 3. Temperature regulation curve for a reference of 35° with a disturbance

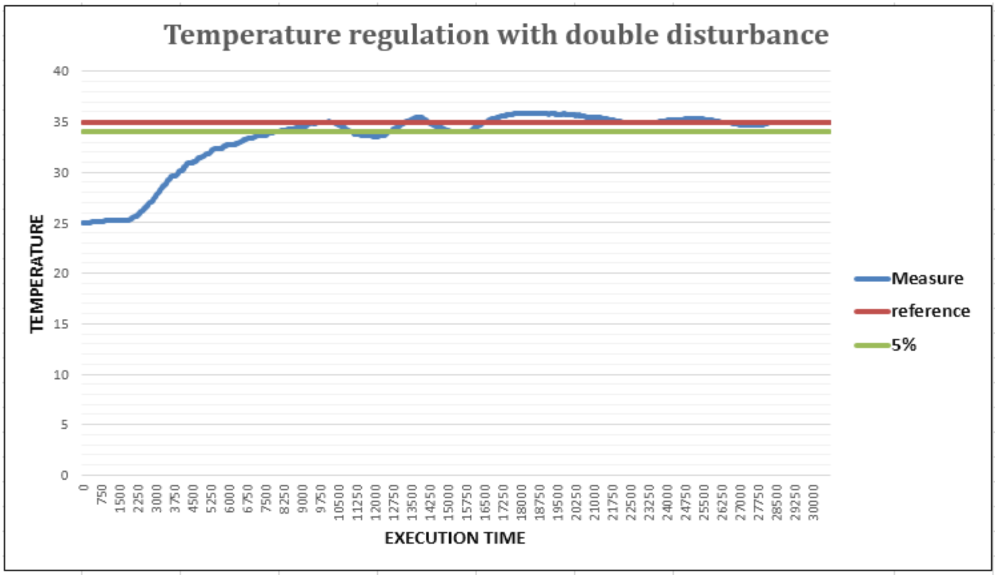

Figure 4. Temperature regulation curve for a reference of 35° with several disturbances

4. IMPLEMENTATION AND VALIDATION OF THE ANN-PID SYSTEM

The configuration that we choose to train our network with nnstart has a big influence on the aim or intended result. In order to determine the best results, we experimented with several setups. The training results curves as shown in Figures 5 and 6 illustrate our experimentation and the corresponding results.

We simulated ANN-PID reasoning for inputs x equal to [reference value; error; response time value] in order to validate our network using nnstar. wherein we were able to acquire outputs y=[Ti, Td, BP%]. The curves x=[35, 0.1, 1.42] and y=[26, 12.5] produced using ANN-PID without disruption are shown as shown in Figure 7. The value achieved by ANN-PID with two disturbances is shown in the following curve as shown in Figure 8 by turning on the cooler once for 30 seconds after stabilization. The value achieved by ANN-PID with two disturbances is shown in the following curve as shown in Figure 9, which is the result of turning on the cooler many times, each for 30 seconds after stabilization.

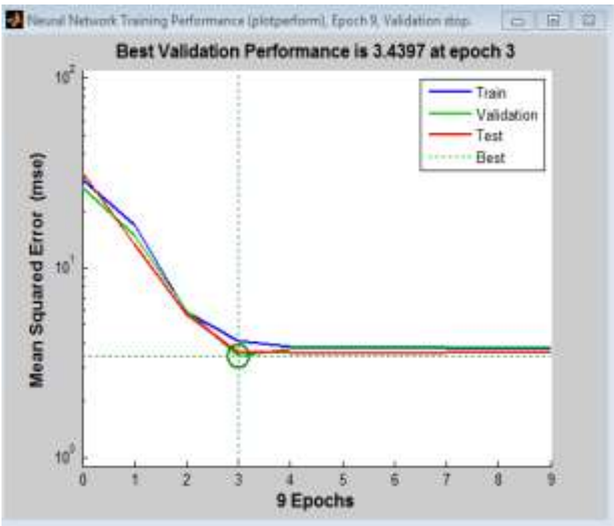

Figure 5. Network performance curve

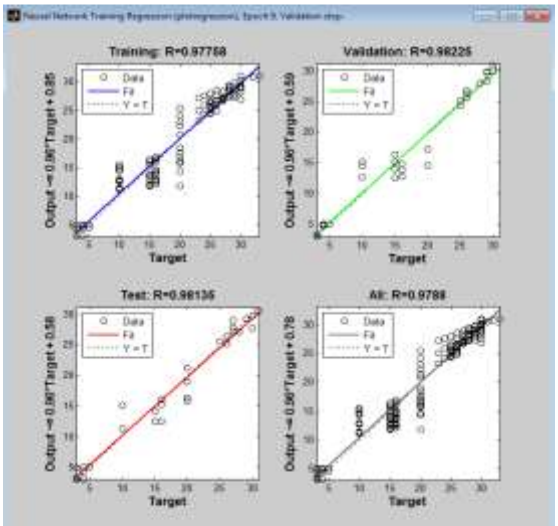

Figure 6. Network regression curve

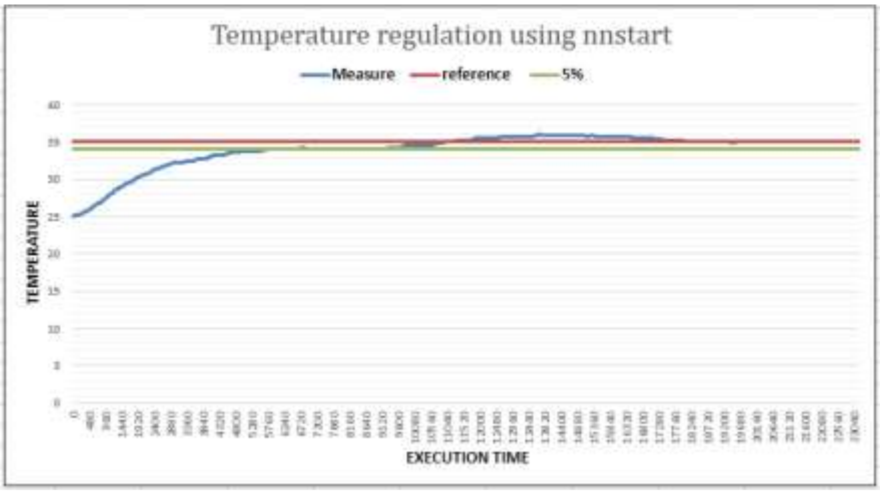

Figure 7. Temperature regulation curve for a reference of 35° using NNStart

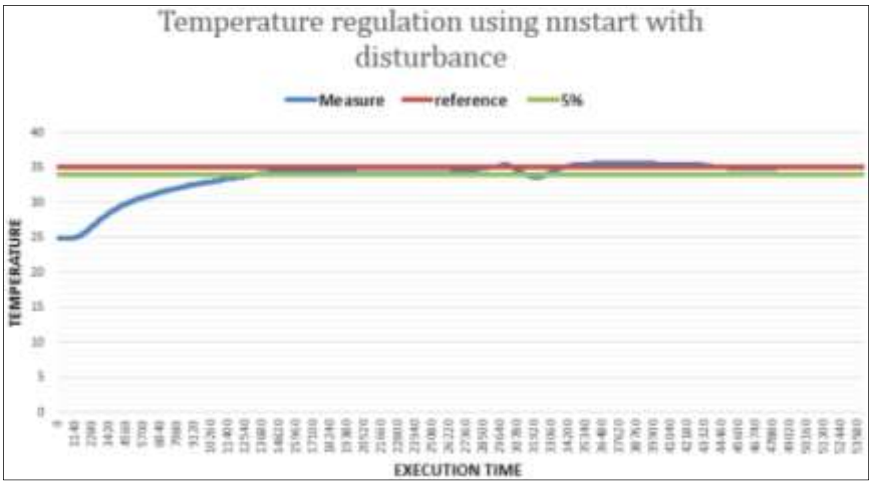

Figure 8. Temperature control curve for a 35° reference using NNStart with a single disturbance

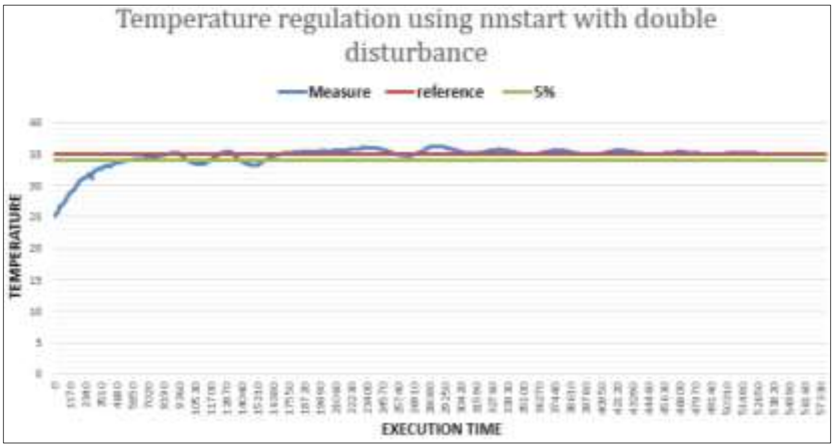

Figure 9. Temperature control curve for a 35° reference using NNStart with several disturbances

5. CONCLUSION

The hybrid approach presented in this paper offers a compelling solution through the amalgamation of the strengths inherent in both Modde 6.0 and neural networks. Modde 6.0 provides an efficient methodology for exploring the parameter space and identifying optimal combinations, while minimizing the number of experiments required. The neural network, on the other hand, models and predicts system performance as a function of controller parameters, reducing the need for extensive testing on the real system. This makes the approach innovative and powerful. The method combines the modeling capabilities of neural networks with the structured and efficient methodology of Modde 6.0, delivering optimal results while saving time and resources. This hybrid approach has the potential to be applied in various fields where the optimization of temperature control parameters is essential, opening up new perspectives for the improvement of thermal systems and industrial systems.

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