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Process regulation control using Echo State Networks: an ESN-based deep neural network approach for PID control

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Abstract

In automation systems, Proportional-Integral-Derivative (PID) controllers are extensively used for their simplicity, reliability, and ability to maintain desired process levels by continuously adjusting control inputs to minimize the error between the set-point and the actual process variable. Despite the advantages, they have to face challenges such as handling non-linearities, sensitivity to parameter tuning, limited adaptability to changing process dynamics, and susceptibility to disturbances. For these reasons, various advanced control strategies and adaptive algorithms based on deep neural network are being developed and implemented. The aim of the proposed study is to introduce an innovative method for the regulation of processes, using an ESN-based deep neural network model. As preliminary results a case study on a heating system is considered. The model was trained using data generated under the control of a PID controller and tested on a using a TCLab module. The results indicate that the trained model effectively predicts the outputs of the heating system and the corresponding temperature values in alignment with the target temperatures. This study would be a starting point for a future deep methodological exploration of the mathematical aspects of ESN models to ensure the long-term stability of the system and its limitations.

Keywords: PID; ESN; Control System; Deep Learning; Temperature control.

1. Introduction

In the context of automation systems, PID controllers are extensively employed due to their simplicity, reliability, and effectiveness in maintaining desired levels of the process variables [1]. They play a critical role in temperature, pressure, and flow control in industries such as chemical, pharmaceutical, and food processing or to ensure precise regulation in HVAC systems, industrial ovens, furnaces, and refrigeration units, etc [2, 3]. Another field in which PID is

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widely used is automotive, such as in the area of autonomous or semi-autonomous driver assistance systems [4], even in the face of complex vehicle models [5, 6, 7] model-free approaches such as PIDs can be adopted under appropriate assumptions and simplifications. Despite their widespread use, they often encounter significant challenges including difficulties in handling non-linearities, sensitivity to parameter tuning, limited adaptability to changing process dynamics, and susceptibility to disturbance signals, including high frequency measurement noises and low frequency signal drift due to load disturbances [8]. In order to reduce the these issues, various advanced control strategies and adaptive algorithms are being developed and implemented. For instance, adaptive PID controllers that dynamically adjust their parameters in response to changing process conditions have shown improved performance in non-linear and time-varying systems and in the context of wireless sensor network application [9, 10]. Additionally, the integration of machine learning techniques, such as neural networks and fuzzy logic, has enhanced the robustness and adaptability of PID controllers to disturbances and noise [11]. Moreover, model predictive control (MPC) is increasingly being adopted as an alternative to traditional PID controllers due to its superior handling of multi-variable interactions and constraints [12]. In recent years, with the rise of artificial intelligence, numerous studies have been conducted on how to apply machine learning algorithms to enhance the performance and adaptability of these controllers [13, 14, 15]. Among all type of neural networks the Recurrent Neural Networks (RNNs) are widely used for their ability to handle sequential and time-series data, making them suitable for modeling the dynamic behavior of control systems. In fact, they can learn from historical data to predict future behavior and adjust control actions accordingly [16]. For example, the Long Short-Term Memory (LSTM) algorithm has been used in an innovative method for the control of interior space heating system in accordance with the created test recipe [17, 18, 19]. While Ahmadi [20] introduced a deep dynamic neural network to tune online the parameters of the traditional PID controller in order to overcome the effects of uncertainties in the closed-loop control system. Following the same trend, [21] proposed a LSTM network and Multi-layer Perceptron (MLP) for self-tuning proportional–integral–derivative (PID) controller to reduce the number of tuning attempts with a practically achievable small amount of data acquisition. Instead, with the aim to replace the PID controller to control a cart position and handlebar angle of the Segway, [22] introduced a new method based on Multi Layer Perception (MLP) model. In another context, the optimization of the indoor temperature control for energy-saving using LSTM has been proposed in building energy [23] while the application of Virtual Reference Feedback Tuning (VRFT) for control of nonlinear systems with regulators defined by RNN networks has been investigated in [24, 25]. Although the proposed algorithms based on RNNs are very promising, their practical applicability in real-world contexts is limited due to their computational complexity. This significant drawback hinders their deployment in environments where computational resources are constrained or where real-time processing is essential. Consequently, this study presents an innovative method for the control of a heating system based on Echo State Network (ESN), a viable alternative that offers a simpler and more efficient computational framework, making them more suitable for practical applications while still maintaining robust performance in handling complex and nonlinear dynamics. Indeed, LSTM networks usually require more RAM due to the numerous internal states and backpropagation through time calculation. In contrast, ESNs has only the reservoir states (randomly inizialized) and simple linear readout weights (using the Ridge Regression) [26]. In this contex, the main advantages of using ESN can be summarized as simpler training process, faster convergence and training time, lower computational cost and resources, flexibility in reservoir design and energy efficiency. Therefore, this study presents an innovative method for the control of a heating system operated with a test recipe inputted by the user, using an ESN-based deep neural network model. The model was trained using data generated under the control of a PID controller and subsequently tested on a randomly generated test recipe within a TCLab module. The graphical results indicate that the trained model effectively predicts the heating system's outputs and the corresponding temperature values in alignment with the target temperatures. Obviously, there is the need for a deeper methodological exploration of the mathematical aspects of ESN models to ensure the long-term stability of the system and its limitations.

The remainder of the paper is as follows. Section 2 introduces methodology, including the bench test for real testing, the ESN description and the model performance metrics. Section 3 deals with its application on a specific case study showing the results. Finally, the last Section 4 concludes the work that highlights forthcoming developments.

2. Materials and Methods

The goal of the proposed solution was to achieve parameter-independent temperature control by employing an ESN-based model trained with data from a PID controller, rather than relying on PID control itself. The workflow consisted of several steps, including the bench test, the reference set-points, creating the dataset and subsequently designing and training the ESN model, and subsequently evaluating the model's performance (See Figure 1).

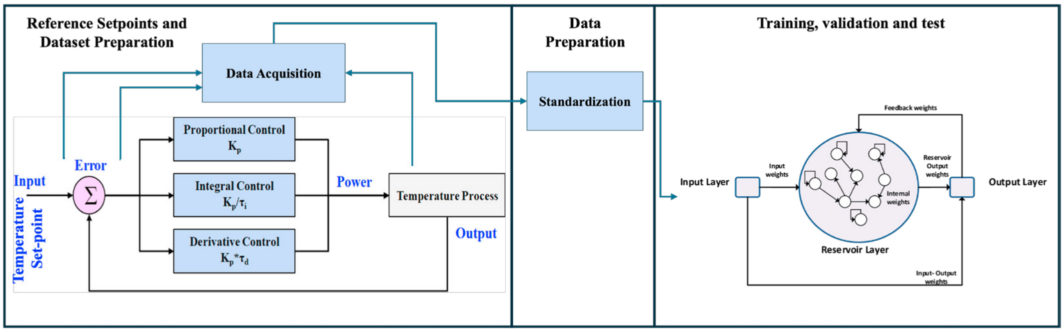

Fig. 1: System Architecture for ESN training.

2.1. Bench Test

The Temperature control lab device, the *TCLab*, has been used as a micro-controller temperature control device [28]. It is composed by two transistors as heaters, two temperature sensors and a USB Serial Connection to transfer data to a computer. About the software implementation, the Python programming language has been used, including libraries such as NumPy and Pandas for data manipulation and tclab for interfacing with the hardware board. The ESN model has been developed using a custom class, allowing the control over the architecture.

2.2. Reference set-points and dataset

The data set used for the proposed solution is made up by using input-output data from the designed PID controller. To prevent the introduction of training errors and to ensure high accuracy of the ESN network, it is crucial for the temperature control system, managed by the existing PID controller, to successfully achieve the target temperature values. To this end, a target temperature profile with many set-points, was developed for testing the PID controller, utilizing random values within a specific range. The set-points temperature have been generated in a temperature range between $0-100$ °C. The recipe was created for an approximately 60.000 seconds with many set-points and then tested on the PID controller (See Table 1). The Ziegler-Nichols oscillation method has been used to find the optimal PID

Table 1: Sample data showing the control variable Q_1, the actual temperature T_1, and the temperature set-point profile $T_{\text{SET-POINT}}$.

Q_1	26.556	26.552	26.549	26.546	26.542	26.539	26.535	26.532	100	100
T_1	37.064	37.064	37.064	37.064	37.064	37.064	37.064	37.064	37.064	37.064
$T_{SET-POINT}$	37	37	37	37	37	37	37	37	55	55

parameters [29] which was $K_p = 5.0$, $\tau_I = 95.0$ and $\tau_D = 0.0$. As shown in Figure 2 the output of the PID controller successfully captured the target temperatures.

In the Figure, Q_1 represents the percentage representation of the control output. T_1 represents the temperature value (in °C) of the system controlled by the PID while $T_{SET-POINT}$ indicates the set-points temperature (in °C).

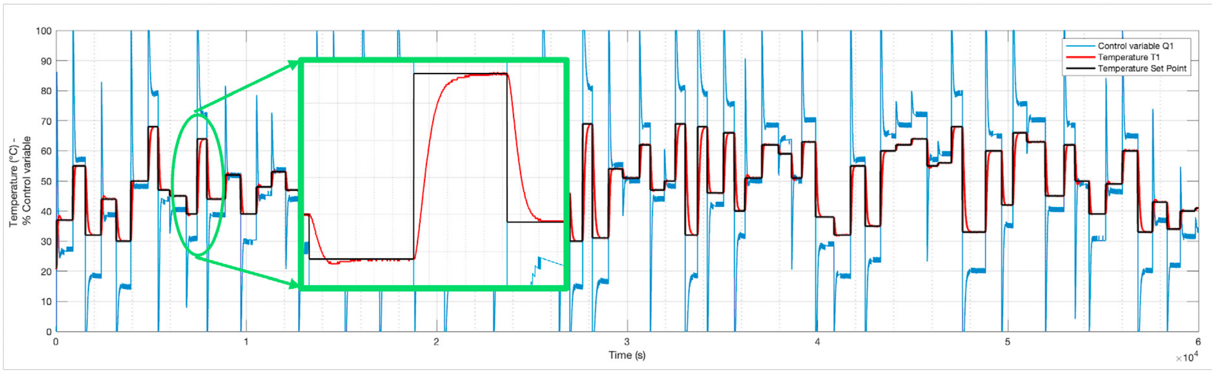

Fig. 2: Test for generating training data for the ESN model.

2.3. Echo State Network

The ESN [27] is a specific type of Recurrent Neural Network (RNN) characterized by its ability to retain historical information and use it to influence future predictions. This characteristic is referred to as "echo," which describes how the hidden state transmits past information to the future, adding this information to the current time step input. The reservoir equation in the ESN is formalized as follows:

$$\mathbf{h}(t) = \tanh(\mathbf{W}_x\mathbf{x}(t) + \mathbf{W}_h\mathbf{h}(t-1) + \mathbf{b}_h) \tag{1}$$

where t represents the current time step, $\mathbf{x} \in \mathbb{R}^{N_x}$ is the input time series, $\mathbf{h} \in \mathbb{R}^{N_h}$ is the hidden state vector, $\mathbf{W}_x \in \mathbb{R}^{N_h \times N_x}$ is the input weight matrix, $\mathbf{W}_h \in \mathbb{R}^{N_h \times N_h}$ is the recurrent weight matrix, $\mathbf{b}_h \in \mathbb{R}^{N_h}$ is the reservoir bias vector and tanh is the non-linearity function. The readout equation in the ESN is formalized as follows:

$$\mathbf{o}(t) = \mathbf{W}_o\mathbf{h}(t) + \mathbf{b}_o \tag{2}$$

where $\mathbf{o} \in \mathbb{R}^{N_o}$ is the predicted output vector, $\mathbf{W}_o \in \mathbb{R}^{N_o \times N_h}$ is the readout weight matrix and $\mathbf{b}_o \in \mathbb{R}^{N_h}$ is the readout bias vector. The only trained parameters in the ESN model are $\mathbf{W}_o$ and $\mathbf{b}_o$, making the training process particularly efficient. An effective technique for training the readout is Ridge Regression, formalized as follows:

$$\mathbf{W}_o = \mathbf{Y}^T\mathbf{H}(\mathbf{H}^T\mathbf{H} + \lambda\mathbf{I})^{-1} \quad \mathbf{b}_o = \mathbf{Y}^T\mathbf{s}(\mathbf{s}^T\mathbf{s} + \lambda\mathbf{I})^{-1} \tag{3}$$

where $\mathbf{Y} \in \mathbb{R}^{N_n \times N_o}$ is the output matrix of the training set, $\mathbf{H} \in \mathbb{R}^{N_n \times N_h}$ is the matrix of hidden states, $\mathbf{s} \in \mathbb{R}^{N_n}$ is a vector of ones, λ is the Tikhonov regularization hyperparameter and N_n represents the number of examples in the training set.

2.4. Model Evaluation Metrics

In order to evaluate the goodness of the different ESN-networks (using different hyperparameters) a *FIT* index has been used [30]:

$$\mathbf{FIT}(\%) = 100 * (1 - \frac{||U|| - ||U_{ESN}||}{||U|| - ||\overline{U}||}) \tag{4}$$

where $\mathbf{U}$ is the acquired control variable, $\mathbf{U}_{ESN}$ is the control variable simulated by the network and $\overline{\mathbf{U}}$ is the mean value of the acquired control variable $\mathbf{U}$. Instead, for the predictions accuracy, two metrics have been used, the Root Mean Square Error (RMSE), and the Mean Absolute Percentage Error (MAPE).

3. Results and Discussions

The dataset was recorded at a rate of one data point per second. Accordingly, the dataset consisting of 60.000 data points is partitioned into three distinct subsets: the D-train (60%), the validation set D-valid (20%), and the test set D-test (20%). This partitioning is guided by the principle of representativeness and the sequential nature of time series data, ensuring that the temporal integrity of the dataset is maintained. For prediction in the ESN algorithm, the data of the last 1.200 seconds were used. The model is configured with i) an input size of 2, meaning it processes two-dimensional input data (the Temperature T_1 and the Temperature Set-point $T_{SET-POINT}$), ii) a reservoir, which forms the core of the ESN, composed by 50 neurons and structured into four layers, enhancing its ability to model intricate dynamics by leveraging multiple processing stages, iii) the leakage rate of 0.5, indicating that the internal states of the reservoir are updated at a moderate pace, balancing the trade-off between memory retention and adaptability to new inputs, iv) the spectral radius, a crucial parameter for ensuring the echo state property, is set to 0.5 to maintain the stability and dynamic behavior of the reservoir and v) regularization is applied with a value of 1, which can aid in preventing overfitting during training. Finally, for the learning function a one-shot Ridge Regression learning rule has been applied. The selection of the best hyper-parameters has been based on the FIT index value which was 91%. Lastly, *RMSE* and *MAPE* were evaluated as efficacy indexes of the prediction. The *RMSE* values are 2.22 for training and 2.82 for testing, indicating low average squared differences between predicted and actual values while suggesting that the model's predictions are closely aligned with the actual values. Instead, the *MAPE* values are 2.73 for training and 2.10 for testing, reflecting low average prediction errors. The ESN model, trained using the dataset composed by the outputs from the PID controller, was first evaluated using the test dataset. How highlighted in Figure 3 the PID controller and ESN network outputs produce very similar results. Specifically, the figure shows T_1 as the real system

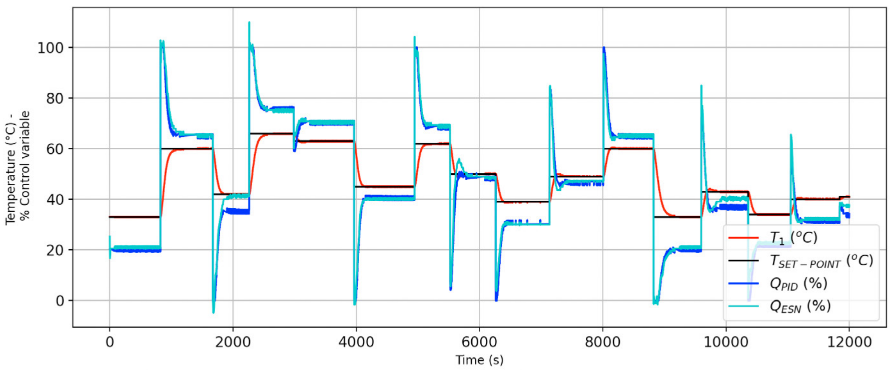

Fig. 3: ESN Training results.

temperature, Q_{PID} as the resistance output percentage controlled by the PID, Q_{ESN} as the resistance output percentage controlled by the ESN model, and $T_{SET-POINT}$ as the target temperature. For more complete analysis, a new test was used to independently visualize the temperature output and evaluate the trained model without the influence of the PID controller. The test comprised a 9.000 seconds sequence featuring varying set-points and rapid ramps, as depicted in Figure 4. In the final stage of the testing phase, to verify the effectiveness of the proposed solution, the ESN network model was evaluated independently of the PID controller using four different types of temperature set-points which are i) rapid ramp and rapid soak, ii) three set-point and one ramp, iii) sinusoidal wave at 1 Hz frequency and iv) four set-point and one ramp (see Figure 5). The resulting graph from the test output shown in Figure 6 illustrates that the ESN network effectively achieved the temperature set-points and controlled the outputs. The Figure comprises four subplots (a, b, c, and d), each illustrating the performance of an Echo State Network (ESN) in controlling temperature

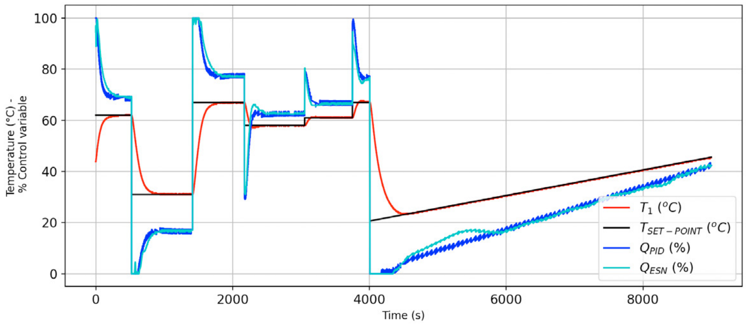

Fig. 4: Comparison of temperature control using PID and ESN-based models.

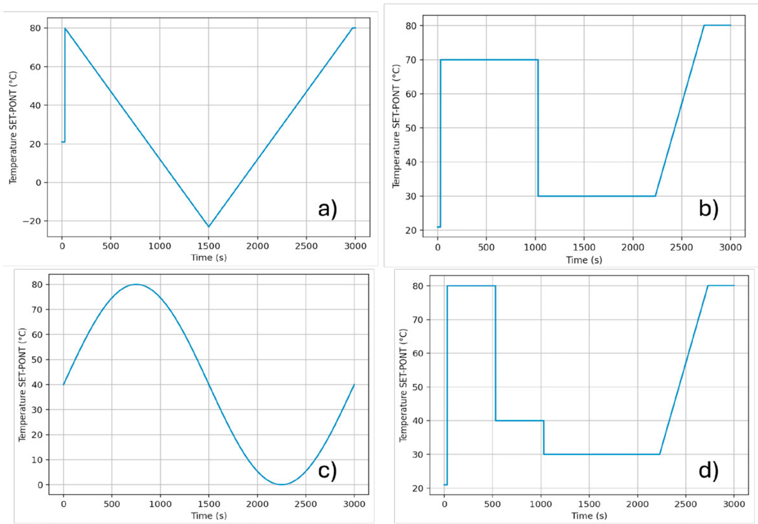

Fig. 5: Temperature set-point profiles.

set-points compared to a traditional PID control system. The key parameters represented are the temperature set-point ($T_{\text{SET-POINT}}$), the actual temperature (T_1), and the control variable output of the ESN (Q_{ESN}).

In subplot (a), the set-point trajectory is characterized by gradual increases (ramp) and decreases (soak). The ESN model demonstrates effective control, closely following the set-point curve. The actual temperature (T_1) shows a delayed response initially but aligns well with the set-point over time. The control effort (Q_{ESN}) starts high to rapidly bring the temperature up and then decreases as the set-point levels off, indicating effective management of control dynamics. Subplot (b) and (d) depicts sharp set-point changes. The ESN model exhibits a quick and precise response, maintaining the temperature close to the desired set-point. The control variable output (Q_{ESN}) spikes in response to the set-point changes and then stabilizes, showcasing the ESN capability to handle rapid transitions effectively. Finally, in subplot (c), the set-point follows a sinusoidal pattern. The ESN model closely tracks the set-point, though with slight lag during rapid changes. The control effort (Q_{ESN}) modulates smoothly, demonstrating proficiency in handling continuous and smooth variations in temperature. Overall, the ESN-based control system performs admirably compared to traditional PID systems. The ESN exhibits rapid response, adaptive control effort, and maintains stability and accuracy across various set-point profiles. The analysis suggests that the ESN-based deep neural network model is a viable and potentially alternative to the traditional PID control algorithm for temperature regulation, capable of handling different set-point profiles with rapid, adaptive, and stable control responses. In summary, the ESN model should demonstrate enhanced accuracy and adaptability to handle nonlinear dynamics compared to the PID controller, which is limited to simpler linear control scenarios. However, these advantages lead to increased computational requirements and complexity in model tuning, requiring a trade-off between performance and implementation simplicity.

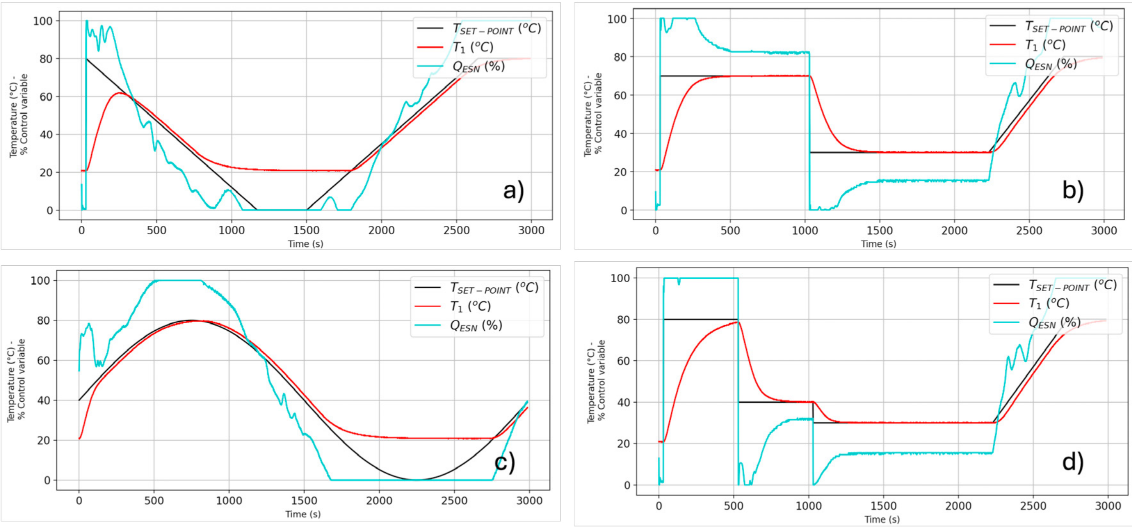

Fig. 6: Performance of the ESN-based control system across four different temperature set-point profiles (a, b, c, d).

4. Conclusion and future works

The results of this study show the significant potential of the ESN-based deep neural network model as a robust alternative to traditional PID control algorithms in the context of temperature regulation. The ESN model exhibits superior performance across various set-point profiles, effectively managing both gradual and fast changes with minimal lag and overshoot. Furthermore, the ESN model's compatibility with embedded systems makes it a highly attractive option for integration into various control devices and in various applications such as position and speed control of electric motors, torque control of motion-distributing joints, regulation of chemical processes, and so on.. Its ability to process and respond to dynamic inputs in real-time, combined with its lightweight computational requirements, positions the ESN as a viable solution for modern control systems seeking enhanced performance and adaptability. However, while the initial findings are promising, there is a need for a deeper methodological exploration of the mathematical aspects of ESN models to ensure the long-term stability of the system, performance and computational costs to provide a deeper understanding of their respective advantages and limitations. In the future works, rigorous mathematical analysis will be crucial in validating the robustness of the ESN model under various operational conditions and in identifying potential areas for improvement. To fully realize this potential, future work must also focus on the mathematical underpinnings of ESN stability and performance, ensuring a comprehensive understanding and reliable implementation of this advanced control strategy.

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