Adaptive Neuro-Fuzzy Inference System with Dragonfly Optimization: An Advanced Control Solution for Shell and Tube Heat Exchangers

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Abstract. This study introduces a sophisticated control method for Shell and Tube Heat Exchangers (STHEs) by combining an Internal Model Control (IMC) with Adaptive Neuro-Fuzzy Inference System (ANFIS) models enhanced by the Dragonfly Algorithm. This innovative technique utilizes ANFIS for both the forward and inverse modeling of the heat exchanger, effectively capturing the intricate, nonlinear dynamics of the system. The Dragonfly Algorithm is utilized to optimize the ANFIS parameters and enhance the accuracy and adaptability of the model. In the IMC framework, the forward ANFIS model predicts the process output based on the control inputs, whereas the inverse ANFIS model determines the necessary control actions to achieve the desired temperature. This integration allows for precise and real-time adjustment of control actions, thereby improving the temperature regulation and overall system performance. The combined use of the IMC and optimized ANFIS models offers a robust solution for effective temperature control in STHE applications.

Keywords: Heat Exchanger, Control, Neuro, Fuzzy and Dragonfly.

1 Introduction

Maintaining the temperature of the hot water outlet in a Shell and Tube Heat Exchanger is a vital component of thermal management in industrial operations. These heat exchangers are favored for their effectiveness and durability in facilitating heat exchange between two fluids. In numerous applications, it is crucial to maintain the exact temperature of the outlet water to ensure optimal process efficiency and energy conservation [1]. The shell and tube heat exchanger comprises a collection of tubes housed within a cylindrical shell. One fluid travels through the tubes, while the other moves over the tubes inside the shell. Heat is transferred through the tube walls from the warmer fluid to the cooler one. Proper

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regulation of the hot water outlet temperature is essential for several reasons: it ensures product quality, optimizes energy use, and safeguards equipment [3].

Temperature control in these systems typically involves a combination of sensors, controllers, and valves. Temperature sensors are placed at strategic points to monitor the temperature of the hot water as it exits the heat exchanger. These sensors feed real-time data to a control system, which compares the actual temperature with the desired setpoint. Based on this comparison, the control system adjusts the flow rates of the fluids or modulates control valves to maintain the desired outlet temperature. For example, if the outlet temperature is too high, the system might reduce the flow of the hot fluid or increase the flow of the cooling fluid. Conversely, if the temperature is too low, the system may increase the hot fluid flow or decrease the cooling fluid flow [6].

Numerous advanced control techniques are highlighted in the literature for enhancing system performance. Proportional-Integral-Derivative (PID) controllers are favored due to their simplicity and effectiveness, yet tuning them can be challenging [1]. Model Predictive Control (MPC) has gained attention for its ability to manage multi-variable systems and constraints effectively, offering a predictive approach to control actions [2]. Adaptive control techniques are beneficial for handling parameter variations and system disturbances in real-time, making them suitable for dynamic STHE conditions [3]. Fuzzy Logic Controllers (FLCs) are employed to address non-linearities and uncertainties, providing robustness under varying operating conditions by mimicking human decision-making processes [4]. Additionally, Neural Network Controllers leverage machine learning to adapt and predict system behavior based on historical data, offering high flexibility and accuracy in temperature management [5]. Each control strategy presents unique advantages and challenges, and the choice of method often depends on the specific requirements of the STHE application and the desired level of control precision.

The Dragonfly Algorithm (DA) has emerged as a promising optimization tool, especially in the realm of clustering and Adaptive Neuro-Fuzzy Inference Systems (ANFIS). Inspired by the foraging behavior of dragonflies, this algorithm offers a balance of exploration and exploitation, making it effective for complex optimization tasks. The use of DA in clustering problems has been explored by several studies, demonstrating its efficacy in improving clustering performance. For instance, Hu, J et al. illustrated the Dragonfly Algorithm's potential in continuous function optimization, establishing a foundation for its application in clustering [6]. Bao, X et al. extended this by applying DA to optimize the number of clusters in k-means clustering, highlighting significant improvements in clustering accuracy compared to traditional methods [7] . Similarly, Cui, X et al. compared DA with other metaheuristic algorithms, finding that DA often delivered superior results in terms of both convergence speed and clustering quality [8]. The primary goal of a swarm in the natural world is survival, which means that individuals must focus on finding food and driving away threats. As illustrated in Fig. 1.the lifecycle of a dragonfly includes two key stages: the adult and the nymph.

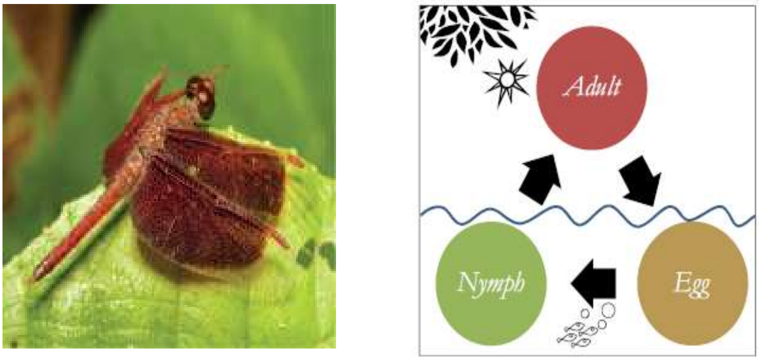

Fig. 1. Illustrates basic transformative patterns among individuals influenced by five primary factors within a swarm

ANFIS, which integrates neural networks with fuzzy logic, is another area where optimization plays a critical role. Introduced by Ja Karunakaran, P, ANFIS combines adaptive learning with fuzzy inference, allowing for complex modeling of nonlinear systems [9]. Optimizing clustering within ANFIS can substantially enhance its performance. Zhu, X., & Wang, N utilized genetic algorithms to optimize clustering parameters in ANFIS, resulting in notable improvements in predictive accuracy[10]. Similarly, Dirik, M., & Gül, M. demonstrated the effectiveness of particle swarm optimization (PSO) for tuning ANFIS parameters, showing better results on benchmark datasets [11]. These studies underscore the importance of optimization in refining ANFIS models for various applications. Ezugwu, A. E conducted a comparative analysis, showing that DA often outperformed genetic algorithms and PSO in terms of solution quality and computational efficiency [12]. This finding aligns with recent advancements in optimization methods. Gálvez, J et al. explored hybrid approaches that combine DA with other optimization strategies, achieving enhanced results in clustering tasks [13].

Karaboga, D., & Kaya, E reviewed various optimization strategies for ANFIS, noting the emerging role of DA and its potential for further research and application [14].

The practical application of DA in real-world scenarios further underscores its utility. Meraihi, Y et al. applied DA to optimize clustering for large-scale financial datasets, demonstrating its effectiveness in handling high dimensional data [15]. Parmaksiz, H et al. utilized DA-optimized ANFIS for environmental data prediction, showcasing improvements over traditional methods [16]. These applications highlight DA's versatility and effectiveness in diverse domains. Despite its advantages, challenges remain in optimizing clustering and ANFIS. Computational complexity and parameter tuning are ongoing research areas. Wu et al. addressed these challenges by proposing a modified DA variant for high-dimensional clustering problems, providing insights into future research directions. In this work, Dragonfly Algorithm based ANFIS forward and inverse models are designed and plugged into the Internal Model Controller (IMC) structure [17].

2 Mathematical Modeling of STHE

Fig. 2. provides a schematic representation of the STHE, where both hot and cold-water flow concurrently in the same direction. The hot fluid transfers its heat before exiting through its outlet, while the cold fluid absorbs this heat before it departs. Temperature sensors and controllers are employed to maintain the desired temperatures at the outlets.

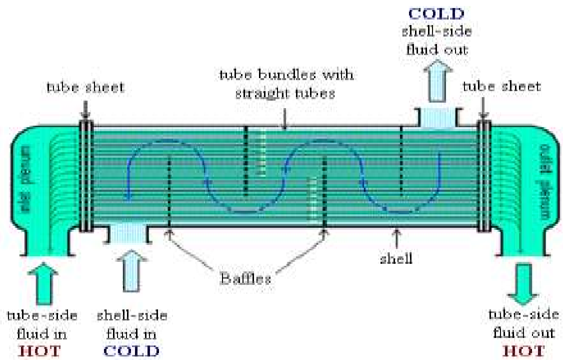

Fig. 2. Schematic diagram of a one-pass STHE.

Energy balance equation for the shell control volume is presented in eqn.(1)

$$\frac{\rho_s c_s v_s}{N} * \frac{dT_{co}}{dt} = \overset{o}{m}s\ c_s (T_{ci} - T_{co}) + \frac{h_s A_s}{N} (T_{ho} - T_{co}) \tag{1}$$

Energy balance equation for the tube control volume is presented in eqn. (2)

$$\frac{\rho_t c_t v_t}{N} * \frac{dT_{ho}}{dt} = \overset{o}{m}t\ c_t (T_{hi} - T_{ho}) + \frac{h_t A_t}{N} (T_{co} - T_{ho}) \tag{2}$$

The eqns. (1) and (2) are solved to get T_{ho} by applying $\overset{o}{m}_s(C_{in})$. C_{in} is the volumetric flow rate in LPS. The parameters used in STHE is given below.

Hot water inlet temperature	(T_{hi})	60 ^oC
Cold water inlet temperature	(T_{ci})	33 ^oC
Cold water mass flow rate	($\dot{m}_s$)	0 – 0.1222 Kg/s
Hot water mass flow rate	($\dot{m}_t$)	0.0282 Kg/s

3 Dragonfly Algorithm based ANFIS forward and Inverse Models

The Dragonfly Algorithm (DA), inspired by the foraging behavior of dragonflies, serves as a robust optimization tool for determining the optimal number of clusters in Adaptive Neuro-Fuzzy Inference Systems (ANFIS). ANFIS, a hybrid model integrating neural networks and fuzzy logic principles, is employed to model complex systems, with the number of clusters being a critical parameter influencing its performance. The objective is to identify the optimal number of clusters that either minimizes error or maximizes accuracy within the ANFIS model, achievable through a systematic application of DA.

Parameters such as the population size of candidate solutions, the range for the number of clusters, and the maximum iterations for the optimization process are determined. The algorithm begins by creating an initial set of potential solutions, each representing a different number of clusters for the ANFIS model. The effectiveness of each candidate solution is assessed by training an ANFIS model with the specified cluster count and evaluating its performance using the Integral Square Error (ISE) objective function. The

Dragonfly Algorithm then adjusts the positions of these candidate solutions based on their fitness and a series of movement rules inspired by dragonfly behavior. These rules typically encompass both exploration (searching new areas) and exploitation (enhancing current solutions).

Algorithm iterates through these steps, continuously improving the solutions and converging towards the optimal number of clusters. As the algorithm progresses, it refines its search based on the quality of solutions found and their proximity to one another, balancing the need for exploration and exploitation. Once the optimization process is complete, it is crucial to validate the results by testing the ANFIS model with the selected number of clusters on a separate validation dataset. This ensures that the model generalizes well and that the chosen number of clusters is indeed optimal for the problem at hand.

The forward DA-ANFIS model for a STHE process is trained using delayed outputs and delayed inputs. The following dataset is used for developing DA based ANFIS forward model. The SIMULINK diagram of developed DA-ANFIS forward model is shown in Fig. 3. The comparison of DA-ANFIS forward model output with that of actual STHE output is shown in Fig. 4.

Input vectors	:	$[T_{ho}(k-1) \quad T_{ho}(k-2) \quad C_{in}(k-1)]$
Output vector	:	$\widehat{T}_{ho}(k)$
Sampling interval	:	15 sec

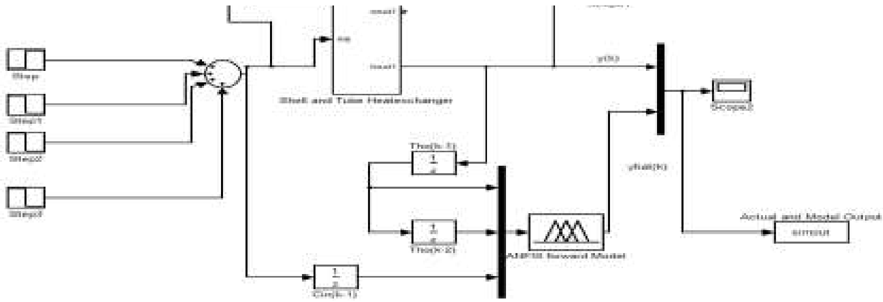

Fig. 3. SIMULINK diagram of DA-ANFIS Forward Model.

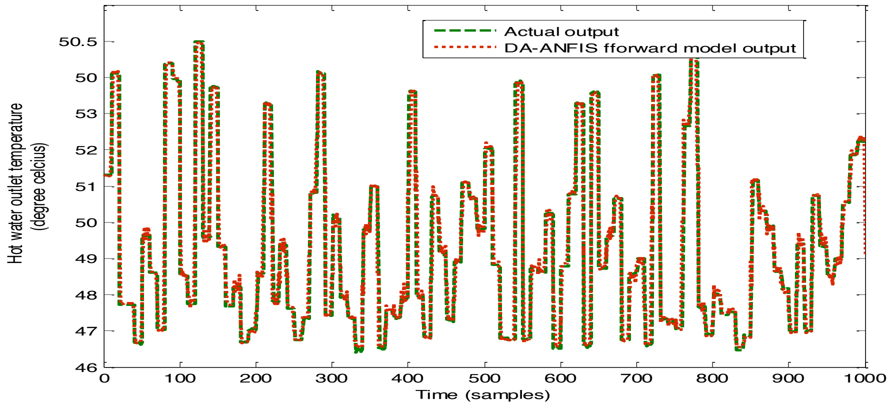

Fig. 4. Comparison of DA-ANFIS forward model output and actual STHE output.

The inverse DA-ANFIS model for a STHE process is trained using present output, delayed outputs, and delayed inputs. This approach captures the dynamic relationship between input and output variables, enhancing predictive accuracy and control in the heat exchange process. The SIMULINK diagram of developed DA-ANFIS inverse model is shown in Fig. 5. The comparison of DA-ANFIS inverse model output with that of actual STHE input is shown in Fig. 6.

Input vectors : $[T_{ho}(k) \quad T_{ho}(k-1) \quad C_{in}(k-1)]$

Output vector : $\widehat{C}_{in}(k)$

Sampling interval : 15 sec

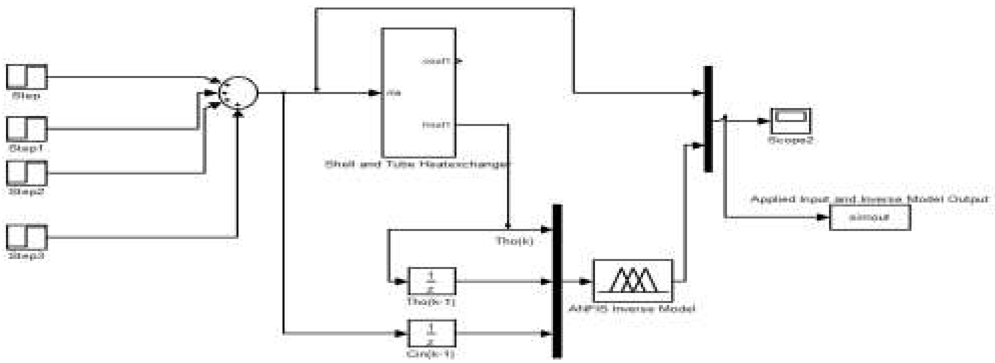

Fig. 5. SIMULINK diagram of DA-ANFIS Inverse Model.

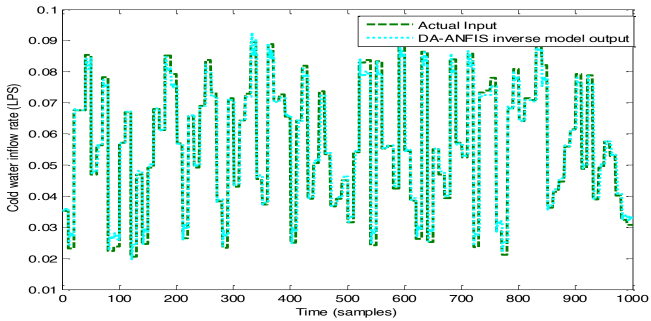

Fig. 6. Comparison of DA-ANFIS forward model output and actual STHE output.

4 Internal Model Controller for STHE

The Internal Model Controller (IMC) configuration, when integrated with Dragonfly Algorithm-based Adaptive Neuro-Fuzzy Inference System (ANFIS) forward and inverse models, provides an advanced strategy for achieving precise control in STHE. This IMC setup is designed to enhance control system performance by embedding a process model within the control loop. ANFIS effectively combines neural networks with fuzzy logic principles to model intricate systems. It adapts its fuzzy inference rules based on the input-output data, providing a flexible and accurate representation of the process dynamics. ANFIS can be used to create both forward and inverse models of the process. Forward Model predicts the output of the process given a set of inputs. It helps in understanding how the process will respond to different control actions. Inverse Model predicts the required control input to achieve a desired output. It is crucial for designing control actions that will drive the process to the desired state.

Inspired by the flight dynamics of dragonflies, the Dragonfly Algorithm serves as an optimization method. It is utilized to refine the parameters of ANFIS models, thereby optimizing their performance. The Dragan fly Algorithm optimizes the parameters of the ANFIS models, creating accurate forward and inverse models of the process. This ensures that the IMC structure has a precise representation of the process dynamics. Within the IMC framework, the forward ANFIS model is utilized to anticipate the process output by leveraging control inputs, while the inverse ANFIS model determines the necessary control actions to achieve the desired outcome. Together, these models are integrated to fine-tune the control actions effectively. The IMC structure uses feedback from the actual process output to compare with the predicted output. The Dragonfly Algorithm-based

ANFIS models help adjust the controller settings dynamically, improving the control accuracy and adaptability. The SIMULINK diagram of developed DA-ANFIS based Internal Model Controller is shown in Fig. 7.

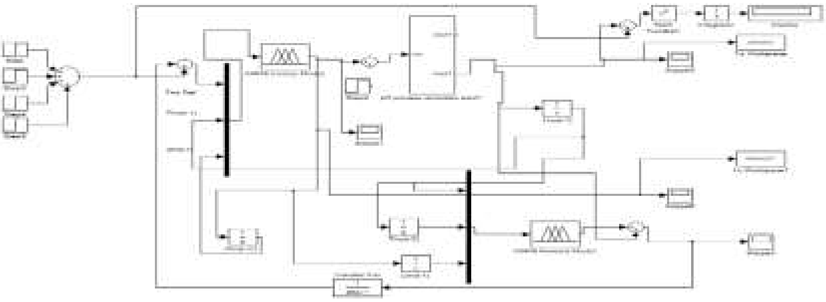

Fig. 7. DA-ANFIS based Internal Model Controller for a STHE.

5 Results and Discussion

The combination of IMC with Dragonfly Algorithm-based ANFIS models enhances overall performance by providing precise control. The IMC structure benefits from the adaptive and predictive capabilities of ANFIS, while the Dragon fly Algorithm ensures optimal parameter tuning for improved model accuracy. Fig. 8 illustrates the servo response of the STHE as the setpoint shifts from 47 to 48, 48 to 49, 49 to 50, and 50 to 51. The corresponding changes in the controller output are shown in Fig. 9. The response clearly indicates that the DA-ANFIS Internal Model Controller delivers superior performance, characterized by the absence of overshoots and undershoots, along with a rapid settling time.

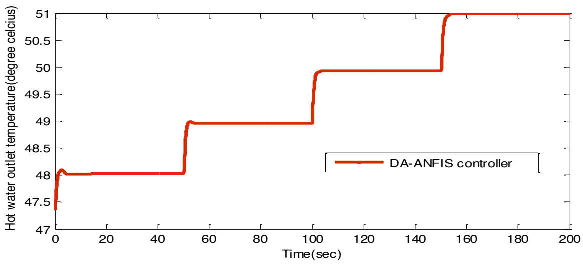

Fig. 8. Servo response of STHE with DA-ANFIS IMC.

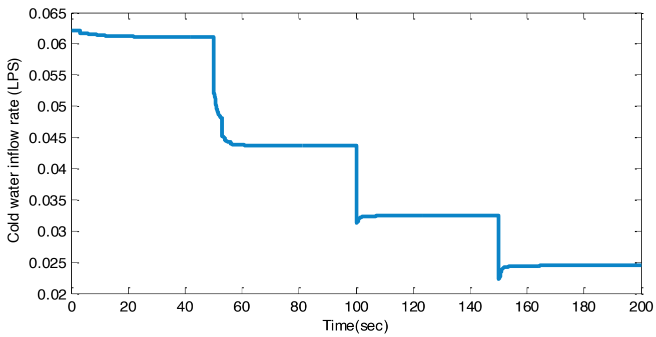

Fig. 9. Controller output of STHE with DA-ANFIS IMC.

6 Conclusion

In this research, a mathematical model was created for a shell and tube heat exchanger (STHE). The model utilized a uniformly distributed random flow of cold water as input, and the resulting changes in the hot water outlet temperature were observed. From these input-output data, forward and inverse models were developed using the Dragonfly Algorithm-Adaptive Neuro-Fuzzy Inference System (DA-ANFIS). These DA-ANFIS models were then evaluated against the actual hot water outlet temperatures and cold-water inflow data, showcasing the superior performance of the DA-ANFIS models. The forward and inverse DA-ANFIS models were incorporated into an Internal Model Control (IMC) framework. The findings indicate that the DA-ANFIS-based IMC significantly improves setpoint tracking performance, effectively eliminating overshoot and undershoot, and enhancing control accuracy.

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