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Mating-Based Manta Ray Foraging Optimization for Fuzzy-Hammerstein Model of an Electric Water Heater

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ABSTRACT

This paper presents an improved variant of the Manta Ray Foraging Optimization (MRFO) algorithm. The optimization method of the original MRFO is a combination of random and spiral strategies. Like other optimization algorithms, MRFO still has a limitation when applied to a complex real-world problem. In this work, mating strategy of a barnacle species is incorporated into the MRFO algorithm. It allows good features of the parent manta ray to be inherited by its offspring thus creating a high-quality population. The proposed algorithm is applied to acquire a dynamic model of an electric water heater. A fuzzy-Hammerstein model is chosen as the candidate model for the water heater considering electrical voltage and water temperature as the input and output responses respectively. The result of the modelling has shown MRFO and the proposed MRFO variant have satisfactorily acquired the dynamic model of the water heater. The improved MRFO variant has tracked the output temperature response more accurately than the original MRFO at costs 425 and 508 respectively.

1. Introduction

Water heater is an important equipment in our daily lives. Gas, electricity and solar are the examples of the commonly found energy sources available. Solar water heater is more environmentally friendly and cost-saving depending on climate while gas water heater has a faster response but has a lower Energy Factor. Electric water heater has higher efficiency or an Energy Factor greater than 0.9 as reported in the study of Energysage [1]. The amount of electricity needed to heat the water and the loss of thermal energy are minimal. An electric water heater converts electricity into heat through a heating element such as a coil. Iron, nickel, chromium and copper are the types of materials used to make the heating element. A resistance from the materials produces a thermal energy known as heat when an electric current is applied. The temperature of water is increased if the heating element is properly immersed in the water. An electric water heater is widely used for commercial and industrial use as well as for residential purposes. Typical usage for

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residential includes cleaning, bathing, cooking and heating spaces such as rooms and kitchens. Examples of commercial usage include heating large spaces such as restaurants, hotels, aircraft and public buildings. An electric water heater has a wider application in industries including chemical and food processing industries, plantation, paper and metal manufacturing and wastewater treatment. Global Market Insights [2] has reported that the demand for electric water heaters keeps on growing worldwide with the forecasted cumulative annual growth rate of about 4.9%. With the increasing demand for electric water heaters in various sectors, good control of its working mechanism should be considered. It affects the electric water heater's performance in maintaining a quick response to achieve the desired water temperature and the equipment's stability to maintain the temperature. As in manufacturing applications, slow response and unstable temperature might affect the quality of a final product, extend production time, increase cost and low profitability. The aforementioned issues indicate that modelling and control of an electric heater is an important area to study as shown in the literature [3].

Nowadays, various potential control mechanisms are available to maintain the performance of a water heater ranging from conventional, modern state-space, artificial intelligence and adaptive controllers. In literature of LaMeres *et al.,* [4], a fuzzy logic controller was used to control the average power of an electric water heater in a residential area during high-demand electricity and off-peak periods. The power is determined based on minimum and maximum range of desired temperature as well as the distribution level of power demand. The strategy successfully controlled the daily usage of electric power in the residential area. Kamran *et al.,* [5] used Proportional-Integral-Derivative (PID) control mechanism to accurately control temperature level at a desired 450 ℃. The heated water was broken into hydrogen and oxygen elements from the water which were then used to generate power.

On the other hand, modelling of an electric water heater is an equally important subject as control. A dynamic model of an electric water heater should be developed before its control design. An accurate model is crucial as it represents the actual water heater and is used in the control design process as well as to study the dynamic behaviour of the water heater system. Low-accurate dynamic model causes the designed controller unable to perform satisfactorily when it is applied to the actual water heater. Dolan *et al.,* [6] developed a dynamic model of an electric water heater for residential usage using a Monte carlo rejection method. The developed model was used to optimize power demand for various load profiles. Paull *et al.,* [7] developed a water heater model to predict household water usage patterns. It then was used to generate a power load profile based on usage behaviour. Thermal losses and water usage data were included as inputs for the model while the output was the water temperature flowing out from the heater. The model was derived based on the energy flow analysis method and represented in differential equation form. In another work of Khurram *et al.,* [8], the dynamic model was derived based on the Markov model associated with energy measurement and demand response from the load.

A more recent dynamic modelling approach is conducted through data-driven. Given an input-output data pair from actual hardware is available, a dynamic model of the physical system can be satisfactorily acquired. Candidate models can be adopted from linear models such as Autoregressive with Exogeneous input (ARX) [9], Autoregressive moving average with exogenous input (ARMAX) [10], box-jenkin [11]. Nonlinear candidate models such as Nonlinear ARX [12], Nonlinear ARMAX [13], Hammerstein [14], Hammerstein-Wiener [15], fuzzy [16], neural network (NN) [17], convolution NN [18] and long-short term NN [19], are more promising than the linear ones in capturing the dynamic behaviour of the physical system. As the nonlinear model is more complex and highly challenging, a metaheuristic algorithm is commonly adopted as an optimization tool. This is evidenced from the works presented in spiral-fuzzy model [20], Bacterial Foraging Algorithm (BFA)-NN model [21], Levy flight-fuzzy model [22], Spiral-ARX model [23], Sooty Tern-ARX model [24] and Particle Swarm Optimization (PSO)-NN model [25].

The aforementioned literatures show that a nonlinear model such as fuzzy-Hammerstein has better captured dynamic features of a real-world physical system. However, determining parameters of the nonlinear is challenging while MRFO algorithm has not yet been used to solve the problem. This work significantly contributes to the method of acquiring parameters of the nonlinear water heater model with better accuracy through an improved metaheuristic algorithm. This paper presents a data-driven dynamic modelling for an electric water heater. A pair of input-output data captured from the electric water heater is used to optimize the pre-defined fuzzy-Hammerstein model. A Mating-based Manta Ray Foraging Optimization (MMRFO) algorithm is proposed and used to optimize the parameters of the fuzzy-Hammerstein in comparison to the original MRFO algorithm as reported in the literature [26]. The paper is organized as follows. Section 2 presents the proposed MMRFO algorithm, its corresponding concept, equations and pseudocode in detail. Section 3 presents the electric heater system used in the work and its principle of operation. Section 4 elaborates optimization of the fuzzy-Hammerstein model and modelling result. Section 5 concludes the work presented within the scope of the paper.

2. Mating-Based Manta Ray Foraging Optimization Algorithm

Mating-based Mata Ray Foraging Optimization (MMRFO) algorithm is a synergy between MRFO and a mating technique adopted from barnacle species as reported by Sulaiman *et al.,* [27]. The algorithm comprises of three main phases known as Chain, Cyclone and Mating strategies. Chain and Cyclone are foraging strategies adopted from manta ray species while mating is a strategy adopted from barnacle species. In the Chain foraging, a group of manta rays form a line heading towards a position rich of plankton. Plankton is viewed as a type of food for the manta rays. Mathematical representation of the Chain foraging is shown as Eq. (1a) and Eq. (1b).

$$x_i^d(k+1) = x_i^d(k) + r.(x_{best}^d(k) - x_i^d(k)) + \alpha.(x_{best}^d(k) - x_i^d(k)) \quad i = 1 \tag{1a}$$

$$x_i^d(k+1) = x_i^d(k) + r.(x_{i-1}^d(k) - x_i^d(k)) + \alpha.(x_{best}^d(k) - x_i^d(k)) \quad i = 2,...,N \tag{1b}$$

where $x_i^d(k+1)$ is the location of the i^{th} manta ray. k is the iteration and d is a dimension of a problem that is intended to solve. $x_{best}^d(k)$ is the location of the current best manta ray. r is a random vector between [0,1] and N is the maximum number of searching agent. α is a log function and defined with respect to random value shown as Eq. (1c).

$$\alpha = 2.r.\sqrt{|\log(r)|} \tag{1c}$$

In the second foraging strategy or the Cyclonic foraging, the group of manta rays swim in a spiral form towards the plankton food. A spiral trajectory is developed in reference to the plankton position and relative position of a searching agent to its front agent. Mathematical representations of Cyclonic foraging are shown as Eq. (2a) and Eq. (2b).

$$x_i^d(k+1) = x_{best}^d + r.(x_{best}^d(k) - x_i^d(k)) + \beta.(x_{best}^d(k) - x_i^d(k)) \quad i = 1 \tag{2a}$$

$$x_i^d(k+1) = x_{best}^d(k) + r.(x_{i-1}^d(k) - x_i^d(k)) + \beta.(x_{best}^d(k) - x_i^d(k)) \quad i = 2,...,N \tag{2b}$$

where α is similar to Eq. (1c), β is a sine function defined with respect to the maximum as well as current iterations. β is represented as Eq. (2c).

$$\beta = 2e^{r_1 \frac{T-t+1}{T}} \sin(2\pi r_1) \tag{2c}$$

where r_1 is a random number between [0,1] while T and t are maximum and current iterations respectively. As an alternatively to the Eq. (2a) and Eq. (2b), the Cyclonic foraging can be represented by Eq. (2d) and Eq. (2e). Those equations are used interchangeably depending on a generated random value. Here, the spiral trajectory is developed in reference to the generated random value rather than the best agent position.

$$x_i^d(k+1) = x_{rand}^d + r.(x_{rand}^d(k) - x_i^d(k)) + \beta.(x_{rand}^d(k) - x_i^d(k)) \quad i = 1 \tag{2d}$$

$$x_i^d(k+1) = x_{rand}^d(k) + r.(x_{i-1}^d(k) - x_i^d(k)) + \beta.(x_{rand}^d(k) - x_i^d(k)) \quad i = 2,...,N \tag{2e}$$

where x_{rand}^d is a random position defined within the searching area. The x_{rand}^d is defined as Eq. (2f).

$$x_{rand}^d = x_{\min} + r \times (x_{\max} - x_{\min}) \tag{2f}$$

where $x_{\min}$ and $x_{\max}$ are the lower and upper boundaries of the searching area respectively while the r is a random value between [0,1].

In the third or the final phase of the MRFO operation, every searching agent rolls around the food source location repeatedly. The operation is known as Somersault foraging where it can be mathematically defined as Eq. (3).

$$x_i^d(k+1) = x_i^d(k) + S.(r_2.x_{best}^d - r_3.x_i^d(k)) \quad i = 1...N \tag{3}$$

where *S* is a constant defined as 2, r_1 and r_2 are random numbers in the range [0,1]. Unless a stopping condition is met, all these three phases are continuously repeated.

In general, the MMRFO algorithm consists of eight steps. The step-by-step description of the proposed MMRFO is presented as follows.

Step 1: Initialize manta ray populations, x_N^d
Step 2: Compute searching agent's fitness, f_i and determine the best agent x_{best}^d.
Step 3: For *i* = 1 to *N*
 If $rand < 0.5$
  Conduct Cyclone foraging phase and execute Eq. (2a) to Eq. (2f).
 Else
  Conduct chain foraging phase and execute Eq. (1a) to Eq. (1c).
 End
End
Step 4: Execute Mating operation.

Apply a random operator for the whole manta ray population to produce male and female parent as *ray_m* and *ray_f* respectively.

$x_{ray\_m}^{N}$ = random permutation (1, *N*). Apply a random value between the range [1, *N*] to the male.

$x_{ray\_f}^{N}$ = random permutation (1, *N*). Apply a random value between the range [1, *N*] to the female.

Step 5: Generate manta ray offspring, $x_{i,OS}^{d}(k+1)$ as in Eq. (4). $p = rand$, $q = 1-p$. $rand$ is a random value to generate random number between the range [0, 1].

$$x_{i,OS}^{d}(k+1) = p.x_{ray\_m}^{d} + q.x_{ray\_f}^{d} \quad (4)$$

Step 6: Calculate fitness cost of the newly generated manta ray $x_{i}^{d}(k+1)$ and offspring, $x_{i,OS}^{d}(k+1)$

Step 7: Sort the manta ray off-springs $x_{i,OS}^{d}(k+1)$ and the newly updated manta ray $x_{i}^{d}(k+1)$ based on their fitness value. The first *N* manta ray with the lowest fitness cost $f_{i,new}^{N}(k+1)$ are considered as the new manta ray $x_{i,new}^{N}(k+1)$. Determine the best manta ray, $x_{best}^{d}(k+1)$.

Step 8: Repeat Step 3 to Step 7 until stopping criteria are met.

3. Mating-Based Manta Ray Foraging Optimization Algorithm

Figure 1 shows a schematic diagram of the electric water heater system used in the experiment as reported by Abonyi *et al.,* [28]. Main elements of the system include heating unit, control valve, CV flow rate meter, F_w temperature sensor, T_{in}, T_{out} , water chamber and a computer. A data acquisition card, PCL-812 is inserted to transfer data between the system and computer. It is a two-way communication system where the data is transmitted to or received from the system or the computer. Data processing, manipulation and analysis are done inside the computer unit. The operation of the system starts with a water source is supplied to the water chamber through an automatic control valve. Heating elements are placed in the chamber to heat the water inside the chamber. A temperature sensor is placed at the outlet and inlet pipes of the water chamber for measuring temperature of the outgoing and incoming water respectively. Both temperature readings are transmitted to the computer via the data acquisition card. A flow rate meter is placed at the inlet pipe of the control valve for measuring the flow rate of the incoming water source. The flow rate reading is also transmitted to the computer via the data acquisition card. A designed controller inside the computer controls the system which controls the valve opening and valve closing to regulate the water flow into the chamber. It also controls electrical power to the heating element based on the reading of the temperature sensors.

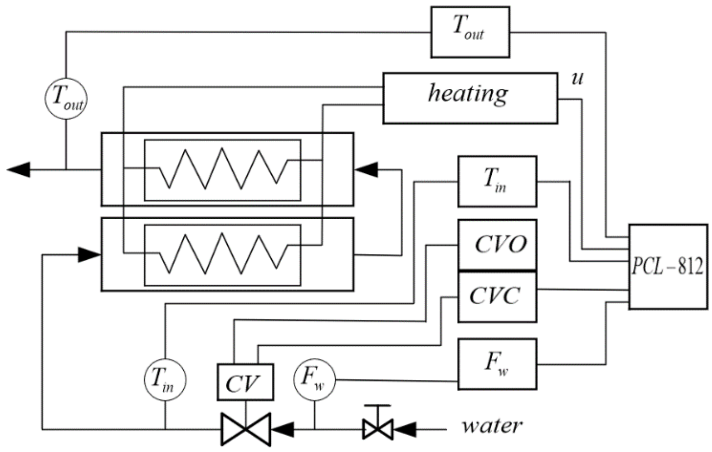

Fig. 1. Schematic diagram of electric water heater

In the experiment, a series of input-output data was recorded from the system for developing a dynamic equation for the system. The input-data considered in the experiment was the control signal from the control unit which has the reading in the range [0-1]. A random signal was applied to the heating element such that it could capture the whole dynamic of the system. The output-data was the temperature of the outgoing water flowing through the outlet pipe of the water chamber measured in the range between [15,33] ^{o}C. This was the reaction of the outgoing water temperature in response to the applied signal into the heating unit. The visual responses of both recorded input-output data pair are shown in Figure 2 and Figure 3 respectively. The figures show 450 input-output data pair were acquired with a sampling time of 2 seconds. These data were taken from the previous experiment as reported by Abonyi *et al.,* [28].

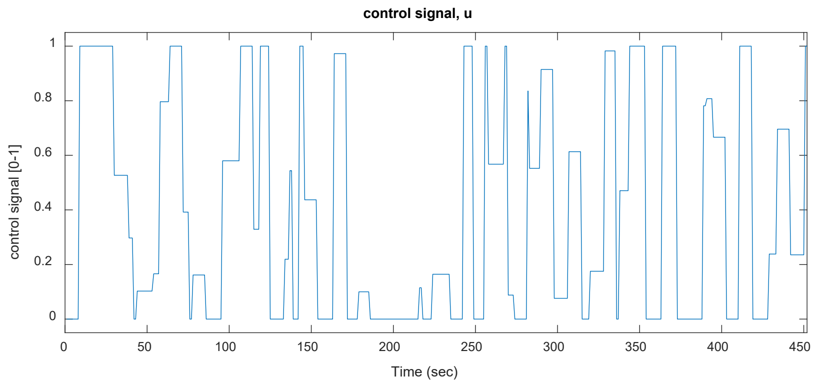

Fig. 2. Response of the control signal

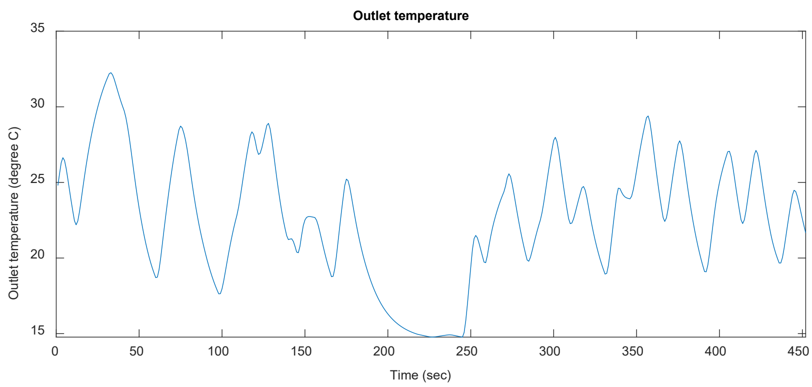

Fig. 3. Response of the outlet temperature

4. Fuzzy-Hammerstein Dynamic Modelling

The concept of nonlinear Fuzzy-Hammerstein model is presented in this section. The nonlinear part comes from the fuzzy-logic model. As the name implies, fuzzy-Hammerstein model comprises of a combination of a nonlinear fuzzy-logic model and a linear dynamic model. The nonlinear behaviour of the fuzzy-logic model is used to capture the presence of uncertainty in the system. Explanation about the fuzzy membership function, linguistic rules, transfer function of the linear model and a complete dynamic equation of the fuzzy-Hammerstein are presented in detail.

4.1. Fuzzy-Hammerstein Model

The structure of Fuzzy-Hammerstein is adopted Abonyi *et al.,* [29] and is shown in Figure 4. In the first part, it consists of a static nonlinear function, $v = f(u)$ while in the second part, it consists of a linear function, G. The nonlinear model is defined with respect to input signal, u that is the input data recorded from the experiment. Both nonlinear and linear are cascaded together such that the output signal of the nonlinear function is injected into the linear model. The output signal of the linear model is considered as temperature of the outgoing water, Y.

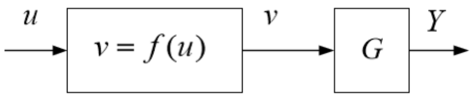

Fig. 4. Hammerstein structure

As the nonlinear model is represented by a fuzzy-logic structure, it should consist of fuzzy linguistic rules and membership function. In the work, 6 fuzzy logic rules as presented in the form of expression shown in Eq. (5).

$$R_j := \quad If\ \ u\ is\ A_j,\ \ then\ \ v\ is\ d_j \tag{5}$$

where A_j, d_j and R_j are j^{th} antecedent and j^{th} consequent of the j^{th} fuzzy rule respectively. u and v are the fuzzy input and output respectively. Triangular membership function is applied at the fuzzy input and they are evenly distributed along the universe of discourse of the input signal on the horizontal axis. The membership function is defined in the range between [0, 1] on the vertical axis.

On the other hand, the dynamic equation for the linear model is shown as Eq. (6).

$$y(k+1) = a_1 y(k) + a_2 y(k-1) + a_3 y(k-2) + a_4 y(k-3) + b_1 v(k-3) + b_2 v(k-4) \tag{6}$$

where a_1, a_2, a_3, a_4 are coefficients of the output while b_1, b_2 are coefficients of the input of the linear model. Rearranging Eq. (6) and considering discrete sample time as q^{-2}, the overall linear part of the fuzzy-Hammerstein model is represented as Eq. (7).

$$C(q) = \frac{b_1 q^{-1} + b_2 q^{-2}}{1 - a_1 q^{-1} - a_2 q^{-2} - a_3 q^{-3} - a_4 q^{-4}} (q^{-2}) \tag{7}$$

The general expression of the complete fuzzy-Hammerstein dynamic model is then shown as Eq. (8).

$$y(k+1) = \sum_{i=1}^{n_y} a_i y(k-i+1) + \sum_{j=1}^{N_R} \sum_{i=1}^{n_u} b_i^j \beta_j (u(k-i-n_d+1)) \tag{8}$$

where N_R is the number of fuzzy rules, n_u is the number of inputs and n_d is the discrete time delay. Figure 5 represents the complete structure of the fuzzy-Hammerstein dynamic model.

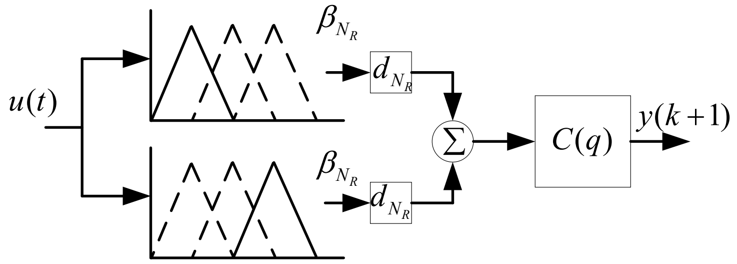

Fig. 5. Fuzzy-Hammerstein structure

4.2 Optimization of Fuzzy-Hammerstein Model

The proposed MMRFO and MRFO algorithms were applied to optimally obtain coefficients of the consequent part of the fuzzy rules as in Eq. (5) and coefficients of the linear model as in Eq. (6). In the work, 6 coefficients for the fuzzy rules and 6 coefficients for the linear model that were optimized simultaneously. Experimental setup for MMRFO and MRFO algorithms was defined as 100 iterations, 10 search agents, search range between [0, 5] and 12-dimensional problem. β and α coefficients for MMRFO were defined as 0.5 while for MRFO the value was defined as 2. Eq. (9) and Eq. (10) show the optimized linear and nonlinear results of the MMRFO-based fuzzy Hammerstein model respectively. Eq. (11) and Eq. (12) present the optimized linear and nonlinear results of the MRFO-based fuzzy Hammerstein model respectively.

$$C_{MMRFO}(q) = \frac{0.180z^{-1}+0.988z^{-2}}{1-0.522z^{-1}-0.169z^{-2}-0.086z^{-3}-0.111z^{-4}} z^{-2} \tag{9}$$

$$d_{MMRFO} = [1.526 \;\; 1.467 \;\; 2.278 \;\; 2.945 \;\; 2.491 \;\; 3.261] \tag{10}$$

$$C_{MRFO}(q) = \frac{0.608z^{-1}+3.135z^{-2}}{1-0.353z^{-1}-0.151z^{-2}-0.381z^{-3}-0.040z^{-4}} z^{-2} \tag{11}$$

$$d_{MRFO} = [0.183 \;\; 0.260 \;\; 0.359 \;\; 0.585 \;\; 0.800 \;\; 0.877] \tag{12}$$

Figure 6 shows a comparison of convergence curve for both MRFO and MMRFO in optimizing electric water heater model during the modelling phase. The vertical axis shows the fitness cost in log-based scale. It shows that MRFO has found a good location at the beginning of operation but has slowly converged to a local optima solution. It has settled down at fitness cost 508 at iteration 100. The proposed MMRFO has found a little bit far location at the beginning but has converged relatively faster than the MRFO until iteration 30. From iteration 31 onwards, it has slowly converged and finally reached fitness cost 425. MMRFO has intercepted MRFO at iteration 26 and has converged to a lower cost function result indicating a higher accuracy.

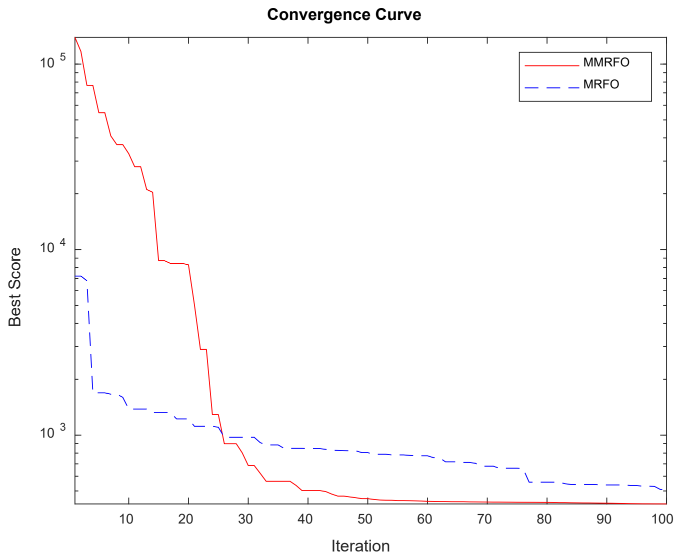

Fig. 6. Convergence curve of the fitness cost

Figure 7 shows a comparison of temperature responses at the water heater outlet in the modelling phase between MMRFO and MRFO algorithms and the actual data. The smoothed-black is the temperature response of heater output from actual system, dashed-blue and dotted-dashed-red lines represent temperature response of heater output optimized by MMRFO and MRFO respectively. It shows the MMRFO has tracked the temperature response of heater output better than MRFO. The worst temperature response of MRFO-based model is at the 15 ℃ between the period of [200, 250] seconds. Here, the output temperature response of MRFO-optimized model has deviated a bit more than the output temperature response of MMRFO-optimized model from the actual response. In general, both MMRFO and MRFO has successfully imitated the actual response in modelling phase.

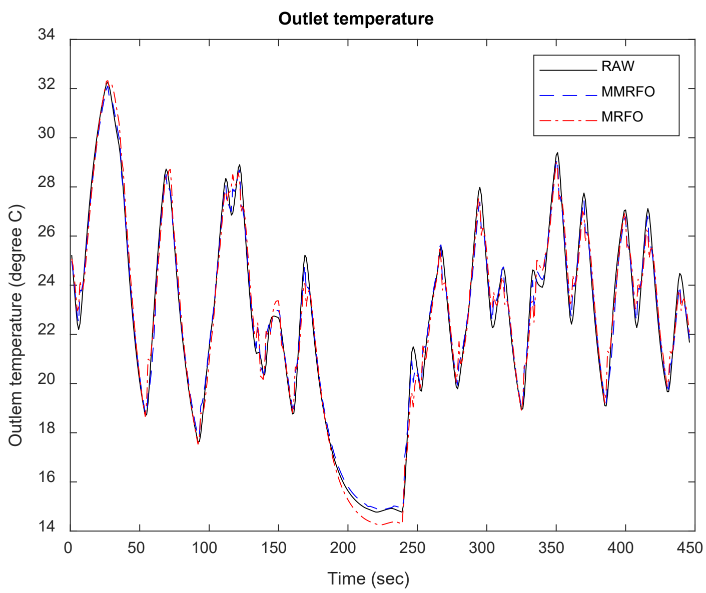

Fig. 7. Temperature response in modelling part

Figure 8 shows a comparison of temperature responses of heater output in validation phase between MMRFO and MRFO algorithms and actual data. It shows the MMRFO-based model has validated a better response than the MRFO-based model for the whole temperature. However, at the highest temperature between the period [1600, 2700] seconds, the response of MMRFO-based model has significantly deviated from the actual response compared to other time instants. On the other hand, the temperature response of the MRFO-based model has shown much more deviation than the MMRFO-based model. The MRFO-based model has shown a larger error between the periods of [0, 1000] and [3300, 3800] seconds. It able to portray the overall pattern of temperature response but has shown a larger gap than the MMRFO-based model if compared to the actual data in smoothed-black line. Overall, the plot shows that the temperature response of MMRFO-optimized model has a better performance than the temperature response of MRFO-optimized model.

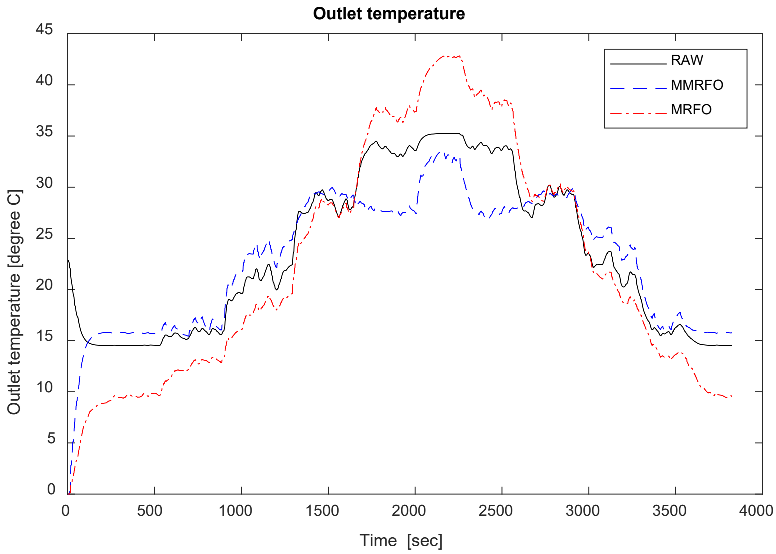

Fig. 8. Temperature response in validation part

5. Conclusion

Mating-based Manta Ray Foraging Optimization (MMRFO) has been proposed in the paper. It is an improved version of the original MRFO algorithm. Mating strategy of a barnacle species has been incorporated into the MRFO algorithm and complementing the existing Cyclone, Chain and Somersault foraging strategies. Through the mating, some good features of the parents Manta Ray are inherited into new offspring of the species. It also has retained communication between the best-so-far manta ray agent and all other manta ray agents. The algorithm has been adopted to optimize the parameters of nonlinear fuzzy-Hammerstein model for an electric water heater. Both numerical value and graphical plot of the results have been included comparing the performance of both MMRFO and MRFO algorithms. The result of the experiment conducted on the fuzzy-Hammerstein model optimization has shown that both algorithms have satisfactorily tracked the output temperature from the actual electric heater system. However, the output temperature of the heater optimized by MMRFO has acquired a better dynamic model than the MRFO in both modelling and validation phases. The proposed algorithm will be applied to optimize parameters of a fuzzy logic controller for the developed electric water heater in the future. In a more complex problem, it will be further tested in solving a constraint and multi-objective economic dispatch problem.

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