Fuzzy rule-based modeling of thermal heat exchanger dynamics through swarm bee colony optimization

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***Abstract*—**This paper addresses the problem of modeling the distributed dynamics of heat exchanger process. The process of heat exchange in thermal systems is generally described by partial differential equations where the dynamics of different thermal variables evolve over time and space. Approximations through lumping are often manipulated to simplify the distributed-parameter models. Simplifying assumptions may obviously induce non-negligible effects on the model performance. This study presents an alternative swarm based data-driven modeling methodology applied to heat exchanger measurement data. More precisely, fuzzy rule bases for hot and cold fluid temperatures prediction are self-generated from measurements using artificial bee colony optimization. Experimental data collected from a parallel-type heat exchanger is used to test and validate the design approach.

***Keywords*—**Modeling, self-generation, fuzzy systems, swarm optimization, distributed dynamics, heat exchanger.

I. Introduction

Heat exchange systems are important parts of many industrial processes. Basically, they are used to achieve heat transfer from one fluid to another through specific network configurations. From physical modeling viewpoint, heat exchangers belong to the class of distributed parameter systems that can be derived from conservation laws [5]. Lumped parameter models are frequently used to approximate the distributed dynamics of thermal heat exchangers. They have been involved in various engineering applications such as control design [2], [22] fault detection and diagnosis [7], [11], process monitoring and supervision [6], [12]. The lumping procedure consists in dividing the whole exchanger in a finite number of cells so that it becomes possible to derive a set of ordinary differential equations that describes its key dynamical properties. However, this gives rise to high order models when accurate modeling is required. On the other hand, some studies proposed a special type of low-order models that have been considered as a reliable representation of the heat exchanger dynamics [5]. Nevertheless, such models could not ensure good prediction capability over wide-range operation or under varying dynamics. In attempt to build convenient exchanger models with simple and transparent structure, many modeling efforts have been made in recent literature. Here, we find it interesting to recall our previously published work [10] which addressed the issue of fuzzy logic based modeling of a parallel-type heat exchanger. More precisely, we developed a data-driven Takagi-Sugeno (TS) fuzzy model [3], [4] based on the well-established Gustafson-Kessel (GK) fuzzy clustering method [1], [9], [24]. Although the constructed moderately complex model showed interesting features when it was validated over a wide operating range, the unique drawback of the approach was the number of rules which needs to be set a priori.

In the present contribution, we emphasize to resort to swarm intelligent systems [8], [21], [25] for data-driven heat exchange process modeling. In other words, we deal with the problem of extracting fuzzy rule bases for the exchanger process from measurement data using a swarm optimization technique, namely the artificial bee colony (ABC) algorithm [15]. The main aim is to construct fuzzy rules, fuzzy sets and associated parameters of the data-driven fuzzy model so that complete structure and parameters are entirely specified. The modeling procedure is achieved through a swarm based optimization strategy which determines the structure and the associated parameter simultaneously. It is formulated as a search problem in multidimensional space where each point corresponds to a potential fuzzy model. Obviously, the objective is to find an optimal or near optimal location on the search space according to specific performance criteria and predefined constraints.

Briefly, the paper is organized as follows. Section II introduces the concept of artificial bee colony optimization. Section III describes the pilot parallel heat exchanger process. The artificial bee colony based fuzzy modeling methodology applied to the exchanger process is presented in Section IV. The experimental modeling results are given in Section V. Concluding remarks are given in Section VI.

II. General ABC Optimization Strategy

Artificial bee colony (ABC) optimization is a swarm intelligence based technique which was originally proposed by Karaboga [17], [18] to solve numerical function optimization. ABC algorithm simulates the foraging behavior of honey bees that are categorized into three main groups: employed bees, onlooker bees and scout bees. Based on two essential leading modes of honey bee colony which are recruitment to a food source and abandonment of a source, the process of bees seeking for sources with high amount of nectar is the one applied to find the optimal solution for a given optimization problem.

In ABC model, three main phases are considered: employed bee phase, onlooker phase and scout phase. Employed bees investigate their food sources and share the nectar and the position information of these sources with onlooker bees. Based on a greedy selection, onlooker bees will have to choose food sources with high profitability. The employed bee whose food source has been abandoned by the bees becomes a scout bee. The algorithmic structure of ABC concept defines the position of a food source as a possible solution to the optimization problem. The nectar amount of that source represents the fitness of the associated solution. Food source positions are generated using the following equation [16]:

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$$x_{ij} = x_j^{\min} + rand(0,1).(x_j^{\max} - x_j^{\min}) \quad (1)$$

Each solution x_i ($i = 1,2,\ldots,SN$) is a D-dimensional vector of optimization parameters. In the employed phase, an employed bee produces a modification on the position of the food source in her memory and finds a neighboring food source according to the following expression:

$$v_{ij} = x_{ij} + \phi_{ij}.(x_{ij} - x_{kj}) \quad (2)$$

where ϕ_{ij} is a random number in the interval [-1, 1] and $k \in \{1,2,\ldots,SN\}$ with $k \neq i$ and $j \in \{1,2,\ldots,D\}$ are randomly chosen indexes. Greedy selection between the old and the updated food source position is performed by the employed bee based on fitness value evaluation. This valuable information about the position and the quality of the food sources are shared with the onlooker bees.

In the onlooker phase, an onlooker bee evaluates the information provided by the employed bees and selects a food source depending on its probability value p_i which depends on the evaluated fitness values [14]. The probability of a food source being selected by the onlooker bees increases as the fitness value of a food source increases. After selecting the food source, an onlooker bee produces a modification on the position of that site using the same mechanism as in (2). Greedy selection is also applied by onlooker bees so that new food sources with high nectar are memorized. During scout phase, any solution that cannot be improved through a predefined number of generations will be abandoned and replaced by a new position that is randomly determined by a scout bee according to (1).

To improve the exploitation capability of ABC algorithm, Zhu and Kwong [26] introduced a modified updating expression of the food source positions. The solution search equation described by (1) is modified so that information on the global best (gbest) solution is used to guide the search of candidate solutions. Feasible solutions are then updated using the following expression:

$$v_{ij} = x_{ij} + \phi_{ij}.(x_{ij} - x_{kj}) + \psi_{ij}(y_j - x_{ij}) \quad (3)$$

where y_j denotes the jth element of the global best solution and ψ_{ij} is a uniform random number in the interval [0, λ], where λ is a positive constant which has a non-negligible effect on the exploration and exploitation of the algorithm. This modified version is referred to as gbest-guided ABC (g-ABC).

III. HEAT EXCHANGE PILOT PLANT DESCRIPTION

The process under investigation is a co-current heat exchanger which is the main part of the pilot plant depicted in Figure 1. It consists of three subsystems: the heater, the air circuit and the water circuit. In more detail, the system is composed of an electric heater of the air (E) which supplies a heating power P, pipes for air and water circulation, a co-current gas-liquid exchanger (HE), two valves, V_r and V_e, to control the portion of the air flow which is recycled and the portion which is evacuated, respectively, and a variable speed pump (SP) to control the water flow Q_w. The water entering the heat exchanger with the temperature T_{33} is heated up to the temperature T_{34} with hot air. The amount of air coming from the electric heater with temperature T_{14} enters the heat exchanger with the temperature T_{16} after flowing through the air circulation pipe. Total or partial recycling of air can be considered depending on the position of the two motor-driven valves V_r and V_e . This allows emphasizing different operation modes of the heat exchanger in the experimental study. A bypass valve situated in the water circulation pipe can be used to simulate varying dynamics by changing the water flow rate in the range [0, 80] lit/h.

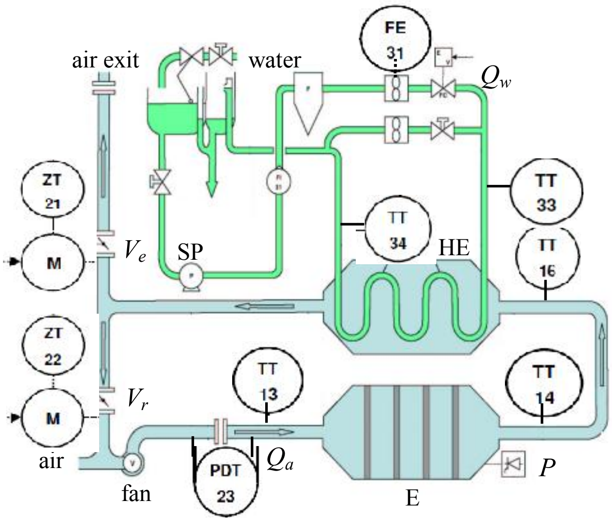

Fig. 1. The pilot parallel heat exchanger.

IV. ABC-BASED HEAT EXCHANGER FUZZY MODELING

The fuzzy modeling problem consists in finding a suitable model representation that can describe accurately the essential dynamics of the nonlinear heat exchanger process. The model is to be extracted from measurement data by using ABC optimization based methodology for automatic rule generation. The main task is to find a suitable and transparent fuzzy model structure for the co-current heat exchanger that can predict accurately its nonlinear behavior over a wide operating range. For this purpose, both water and air circuits of the thermal plant are considered. Due to physical considerations, it is clear that the normal input-output behavior of each circuit depends mainly on the heating power P, the air recycling valve position V_r , the air evacuation valve position V_e , the air temperature before the heat exchanger T_{16}, the air temperature at the outlet of the heater T_{14} , and the water temperature after the heat exchanger T_{34} . The structure of the global MIMO fuzzy model to be identified will then involve all of these physical variables. Therefore, we need to find a supervision scheme for the five measurements of T_{16} , T_{34} , T_{14} , P, V_r , based on the following NARX model structure:

$$\begin{cases} T_{34}(k+1) = \mathcal{F}_1(T_{34}(k), T_{16}(k), P(k), V_r(k)) \\ T_{16}(k+1) = \mathcal{F}_2(T_{16}(k), T_{14}(k), P(k), V_r(k)) \end{cases} \quad (4)$$

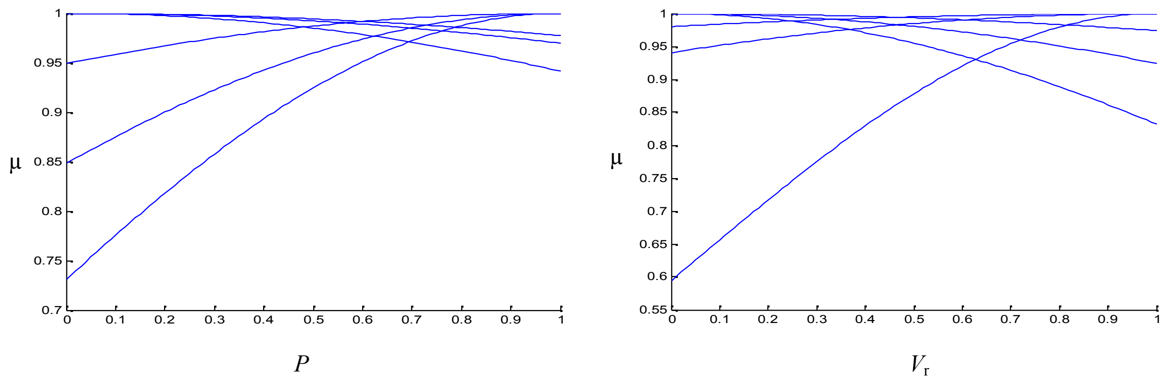

Fig. 2. Fuzzy partitions of the heat exchanger input variables for water temperature prediction.

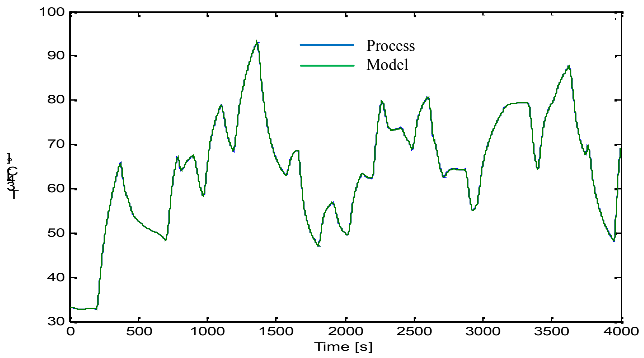

Fig. 3. Process and fuzzy model outputs on T_{34} training data

where $\mathcal{F}_1(\cdot)$ and $\mathcal{F}_2(\cdot)$ are unknown nonlinear functions.

To identify this multivariable fuzzy model, the nonlinear functions in Equation (4) are to be approximated by a set of IF-THEN fuzzy logical rules with functional consequent parts. More precisely, a TS-type fuzzy model is to be identified for each circuit in normal operation mode. To this end, real data from the pilot heat exchanger is generated in fault-free situation where the air flow rate Q_a supplied by a fan, and the water flow rate Q_w, are both kept constant. The heating power is manipulated over its whole operating domain from 0 to 10 kW. The air recycling valve position, V_r, and the air evacuation valve position V_e are controlled simultaneously in the range [0–100%].

Also, since we need to consider large variations of the process operating point, we used dynamic excitations in the heating power P, and in the valve positions, V_r and V_e, by employing an amplitude-modulated pseudo-random binary signals. The system was sampled every 2s. The fuzzy model structure used for the simultaneous prediction of the water temperature T_{34} and the air temperature T_{16} is described by a set of IF-THEN fuzzy rules of the form:

$$
\begin{aligned}
&If\ P(k)\, is\ A^i_{11}\ and\ V_r(k)\, is\ A^i_{12}\ and\ T_{16}(k)\, is\ A^i_{13}\ and\ T_{34}(k)\, is\ A^i_{14} \\
&Then\ \ T_{34}(k+1) = a^i_{10} + a^i_{11}P(k) + a^i_{12}V_r(k) + a^i_{13}T_{16}(k) + a^i_{14}T_{34}(k) \\
&If\ P(k)\, is\ A^i_{21}\ and\ V_r(k)\, is\ A^i_{22}\ and\ T_{14}(k)\, is\ A^i_{23}\ and\ T_{16}(k)\, is\ A^i_{24} \\
&Then\, T_{16}(k+1) = a^i_{20} + a^i_{21}P(k) + a^i_{22}V_r(k) + a^i_{23}T_{14}(k) + a^i_{24}T_{16}(k)
\end{aligned}
\tag{5}
$$

where A^i_{lj}, $l = 1,2,\ j = 1,\ldots,4$ is a premise fuzzy set in the *ith* rule and a^i_{lj} are rule-consequent constant parameters.

Designing the fuzzy model (5) from measurement data can be formulated as a nonlinear optimization problem. Two independent factors can be considered in the modeling process: modeling accuracy and model interpretability. The issue of accuracy is of course fundamental and critical because the main objective of fuzzy modeling is to approximate the nonlinear input-output functions by finding the optimal structure and parameters (rules number, and premise and consequent parameters) of the fuzzy model so that an acceptable matching between the model output and the process output can be reached. The accuracy of the identified model needs to be evaluated on both training and testing data, and in the most of cases the performance index to be optimized is expressed in terms of modeling accuracy. The interpretability issue is as important as modeling accuracy [19], [23]. The designer will have to formulate the modeling problem with respect to these key factors.

The construction of the TS fuzzy model (5) is achieved in two consecutive steps: structure identification and parameter estimation. The rule-premise parameters are encoded in a population of individuals and evolve together through a stochastic strategy that simulates the foraging behavior of honey bee swarms so that optimal solutions are achieved. The rule-consequents are estimated iteratively using weighted least squares. The encoding scheme is defined with respect to food source positions that correspond to candidate fuzzy models with appropriate string representation.

The steps of the ABC-based fuzzy modeling algorithm for automatic generation of the heat exchanger fuzzy rules from numerical data are briefly described as follows.

Step1. Encode all the parameters into food source.
Step2. Generate randomly an initial population of TS fuzzy models.
Step3. Evaluate the model accuracy of each individual {
Perform rule selection mechanism
Calculate rule consequents using weighted least squares estimates method.
Calculate model output using fuzzy inference engine
Calculate the fitness value (MSE)}
Step4. Perform the three-step procedure of ABC optimization as described in [14].

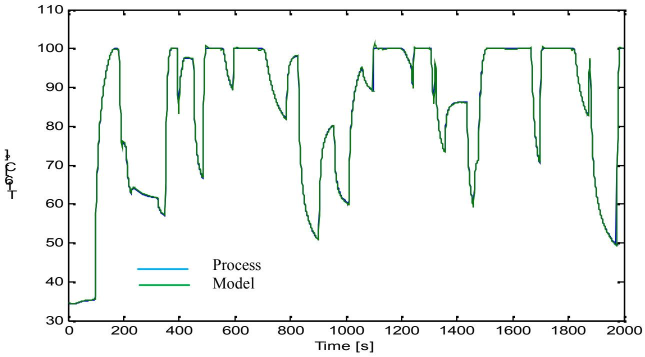

Fig. 4. Process and fuzzy model outputs on T_{16} training data

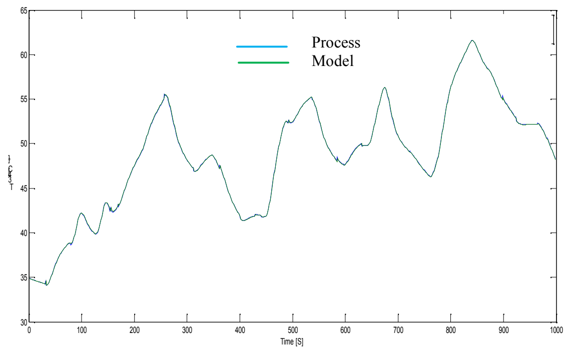

Fig. 5. Process and fuzzy model outputs on T_{34} testing data

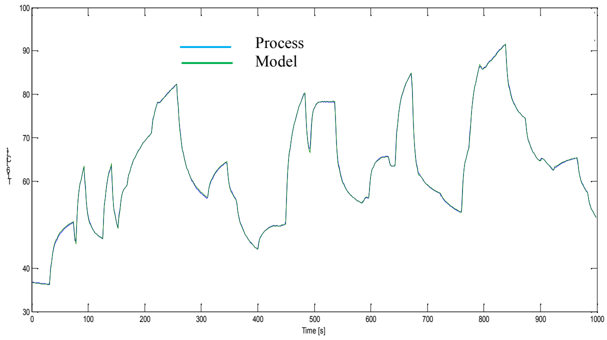

Fig. 6. Process and fuzzy model outputs on T_{16} testing data

V. Experiments and Results

The ABC based fuzzy rule generation methodology described in Section 3 is applied to a set of fault-free input-output observations which contains 2000 samples. Based on this fuzzy modeling approach, the rule number, the premise fuzzy sets and the rule-consequent parameters of the multivariable fuzzy model are generated simultaneously.

The resulting input space partitioning of the heating power and the air recycling valve position for T_{34} prediction corresponds to the membership functions depicted in Figure 2. As a result, a six-rule TS fuzzy model is developed for each output temperature. Note that the obtained fuzzy partitions cannot provide a transparent partitioning of the process operating range. Improving the model transparency with maintaining together high accuracy level results from a compromise between these two important features.

To assess the modeling performance, the identified fuzzy model is run in series-parallel configuration to the process using the real training data. The results are shown in Figures 3 and 4. One can notice easily the good matching between the process outputs and the fuzzy model outputs. This performance is maintained even during the saturation of the air temperature T_{16}, which represents an important feature of the developed fuzzy model. This demonstrates the good approximation capability of the identified fuzzy model. For validation, a second input data set different from the measurement data used in the identification experiment is applied to the heat exchanger process. The performance of the fuzzy model on validation data is depicted in Figures 5 and 6. For evaluating the overall model performance, the mean-square error (MSE) index is used:

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left[y_l(k) - \hat{y}_l(k)\right]^2 \qquad (6)$$

where N is the number of data samples, and y_l is the real process output (T_{34} or T_{16}), $\hat{y}_l$ the fuzzy model output (prediction of T_{34} or T_{16}). Table 1 shows the model performance obtained in parallel and series-parallel configurations using both identification (training) and validation (testing) signals.

TABLE I
PERFORMANCE OF THE HEAT EXCHANGER FUZZY MODEL

Method	Output	MSE (training)		MSE (testing)	
		p	s	p	s
GK [10]	T_{34}	0.0421	0.0001	0.0292	0.00008
	T_{16}	0.0097	0.0013	0.0087	0.00094
ABC	T_{34}	0.0420	9.10e-5	0.0278	4.54e-5
	T_{16}	0.0090	9.53e-4	0.0079	4.89e-4
g-ABC	T_{34}	0.0404	8.10e-5	0.0262	4.54e-5
	T_{16}	0.0087	9.51e-4	0.0071	4.65e-4

$p \rightarrow$ parallel model, $s \rightarrow$ series-parallel model

The Table also compares the modeling results with those obtained through Gustafson-Kessel (GK) fuzzy clustering approach reported in our previous work [12]. It is clear that the performance of ABC-based data-driven fuzzy model outperforms the compared results for both training and testing cases. Note that parallel model configuration is usually used in model-based fault detection and diagnosis (FDI) schemes for residual generation. The parallel training and testing mean squared errors of Table 1 let us conclude that the proposed fuzzy model may represent a very promising tool for FDI systems design.

VI. Conclusion

This paper addresses the problem of automatic fuzzy rule generation for modeling the complex dynamics of a parallel-type heat exchanger process. The modeling strategy is based on a well-established swarm optimization method, namely the artificial bee colony algorithm. The proposed approach ensures a simultaneous determination of the whole parameters of the fuzzy model that evolve together through an optimization procedure derived from the foraging behavior of honey bees. Simulations conducted on experimental measurements show clearly the performance of the identified model and demonstrate its ability to provide good approximation and prediction of the water and air temperatures. Compared to existing results, the proposed approach allows self-generation of the exchanger fuzzy model from measurements. Enhanced fuzzy model is thus identified with superior approximation and generalization capabilities. Future works might investigate other aspects related to model transparency improvement as well as its use for fault detection and diagnosis system design.

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