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Modelling Evaporator in Organic Rankine Cycle using Hybrid GD-LSE ANFIS and PSO ANFIS Techniques

Hamid Enayatollahi, Peter Fussey, Bao Kha Nguyen*

Department of Engineering and Design, University of Sussex, Brighton BN1 9QT, UK

*Corresponding Author Email: B.K.Nguyen@sussex.ac.uk, Tel.: +44 (0)12-7387-2869

Abstract

Internal combustion engines (ICEs) are likely to be used in heavy-duty applications for many years and it is important to continue improving their efficiency. One approach is to recover waste heat from the exhaust of heavy-duty diesel engines (HDDEs) using waste heat recovery (WHR) technologies. WHR based on Organic Rankine Cycle (ORC) is a promising technology, which offers potential to reduce the fuel consumption of HDDEs by transferring the wasted thermal energy to alternative useful electrical or mechanical energy. In the ORC, the evaporator is considered the most critical component, because it has a high thermal inertia. Previous numerical models of evaporator are computationally expensive due to non-linearity of evaporator governing equations and cannot be deployed for real-time control applications. This study uses an Adaptive Network-based Fuzzy Inference System (ANFIS) modelling technique to provide efficient control-oriented evaporator models for prediction of heat source and refrigerant temperatures at the evaporator outlet. Hybrid gradient decent, least square estimate (GD-LSE) and particle swarm optimization (PSO) algorithms for training the ANFIS model have been investigated and show that training ANFIS using the PSO method results in an improvement in accuracy. Furthermore, the systematic and adaptive approach of the ANFIS modelling technique makes the procedure of evaporator modelling less dependent on expert knowledge, reducing the modelling effort.

Keywords: *Evaporator; ANFIS; PSO; Dynamic Modelling; Organic Rankine Cycle; Waste Heat Recovery.*

Nomenclature

$\dot{m}$	mass flow rate
ANFIS	adaptive network-based fuzzy inference system
FV	finite volume

<i>GD</i>	Gradient descent
<i>HDDE</i>	heavy-duty diesel engine
<i>ICE</i>	internal combustion engine
<i>KW</i>	kilowatt
<i>L</i>	length of evaporator
<i>LSE</i>	Least square estimate
<i>MB</i>	moving boundary
<i>N</i>	number of discretised cells
<i>ORC</i>	organic Rankine cycle
<i>PSO</i>	Particle swarm optimization
<i>Q</i>	evaporator power
<i>RMSE</i>	root mean square error
<i>SRC</i>	steam Rankine cycle
<i>T</i>	temperature (K)
<i>TES</i>	thermal energy storage
<i>TP</i>	two-phase region
<i>TP-V</i>	two-phase and vapour region
<i>WHR</i>	waste heat recovery

Greek symbols

μ	Membership function
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Subscripts

<i>ev</i>	evaporator
<i>h</i>	heat source
<i>r</i>	refrigerant

1. Introduction

Almost 95% of transportation power is achieved through burning fuel in Internal Combustion Engines (ICE). In today's technology of ICEs, with maximum efficiency of 42%, a significant amount of energy is lost to the atmosphere in form of heat, through hot exhaust gases (22-46%) and coolant system (18-42%) [1, 2]. Waste Heat Recovery (WHR) technologies can contribute to improving the efficiency of ICEs [3-5].

Organic Rankine cycle (ORC) has long been considered as a promising waste heat recovery technology that can be adopted for mobile applications [6-8]. The ORC is similar to steam Rankine cycle (SRC) but instead of water, an organic fluid is used in the cycle. As shown in **Fig. 1**, the ORC is comprised of several components including evaporator, expander, condenser and pump. The principle of ORC is to evaporate an organic fluid in a closed cycle and use the superheated

vapour pressure as the electromotive force to produce mechanical energy in the expander. After expansion, the vapour is cooled down in the condenser to saturated liquid temperature and then pumped back to the evaporator. Waste heat sources can be classified by the heat available to low temperature, medium temperature and high temperature grades [9]. HDDEs are examples of low to medium range waste heat sources. In applications of WHR in HDDEs since the temperature and mass flow rate of the heat source is not enough to superheat the water in the SRC at all conditions, utilizing the organic working fluids due to their lower boiling temperature and higher molecular weight is preferable [10]. The ORC is characterised by its relatively high efficiency and low cost. Modularity, versatility, maturity of components (similar to refrigeration system) and ability to recover waste heat from small to moderate temperature differences are characteristics of the ORC technology that made it a preferable choice for recovering energy from HDDEs.

Fig. 1. Conceptual schematic of ORC system

An important technical issue to address when designing the ORC system for mobile applications is the large range of operating condition and resulting thermal power fluctuation of the heat source due to driving conditions. For example, mass flow rates and temperatures of exhaust gases fluctuate with load condition and slope of the road [1]. In order to mitigate the effect of unsteady heat source in the ORC system, strategies such as controlling the vapour temperature at the

evaporator outlet and using thermal energy storage (TES) devices can be considered to prevent the component damage and increase the efficiency of the WHR system [11]. Despite high potential of employing the ORC for increasing the efficiency of internal combustion engines, implementation challenges such as developing non-toxic and non-corrosive organic fluids, designing high efficiency expander capable of withstanding high pressures and obtaining safe and efficient system operating points by utilising an effective control system have limited the commercial usage of this technology.

Designing an effective and reliable control system for the ORC relies on accurate modelling of all components in the system. The evaporator is the most critical component of the ORC system, responsible for the energy transfer from heat source to coolant. When dealing with a low capacity heat source in kw range found in ICEs, the governing dynamics of the system is dominated by the behavior of the evaporator. Moreover, due to highly dynamic engine conditions the conventional methods of evaporator modelling such as the single-segment lumped method leads to poor off-design performance of the ORC system for a variety of driving conditions since they do not model the dynamic nature of the heat source. Therefore, it is necessary to create a dynamic model of the evaporator that is capable of handling transient conditions in an ORC waste heat recovery system.

In most of ORC investigations, FV and MB methods have been used for the evaporator to model its behaviour for steady-state or transient heat sources. In the FV technique, the evaporator volume is discretised to a finite number of equally spaced and constant control volumes. **Fig. 2** represents the discretisation of the evaporator with length L to N control volumes. As the number of the control volumes increases, the accuracy of the model improves. Selection of the number of control volumes is a compromise between accuracy and total computational time of the model [12]. If the number of control volumes is high enough to capture the transients, since the temperature variations within the cells is considered to be low the thermo-physical properties of working fluid can be assumed constant within the cells. This method can be used to produce accurate simulations; however, it is computationally expensive and is not appropriate for control purposes. The computational time of a super-critical FV model is reported to be over three times more than the actual time [13]. FV method is robust, accurate and widely used in the literature [14-16].

Fig. 2. Discretisation of evaporator to N control volumes

MB method divides the whole length of evaporator to three control volumes (liquid, two-phase mixture, vapour) with intermediate moving boundaries that vary with time, thus, the number of states is less than that of FV models [17]. In the MB model, if any of three phases disappears, this creates a singularity that causes numerical problems. Therefore, the MB model is not appropriate for situations where all three distinct phases of working fluid do not exist such as start-up and shut-down. Unfortunately, most of components failure occurs in such conditions [17]. Therefore, in such situations, a switching mechanism is required to switch between Two-Phase and vapour region mode (TP-V) and Two-Phase region mode (TP) [18]. Comparisons between both models have been made in [12, 17, 19] that show, in terms of accuracy, the FV models are slightly more accurate since they have a finer spatial discretisation, but due to the lower number of state variables, MB models are less computationally expensive. Wei et al. [17] represented two FV and MB models for the evaporator and compared the mass flow rate and outlet temperature of evaporator of both models with the experimental data available by UTRC (United Technology Research Center) for a 100 kw ORC system. From their simulation results, it is observable that the accuracy of FV model with five cells is better than the MB model.

These numerical methods of evaporator modelling are useful at the design stage of the ORC system to find the best components of the cycle and the optimal working fluid selection, but a more traceable model is required for the real-time control of the ORC with transient heat source. The concept of a real-time control-oriented evaporator model has been investigated in Chowdhury et al. studies [13, 20] demonstrating fuzzy steady-state and dynamic models of evaporator. In this technique, the non-linear relationship between the input and output is mapped using the linguistic rules based on the expert knowledge about the evaporator behaviour. Inputs of the fuzzy system

in their study are the mass flow rate and temperature of the hot fluid and mass flow rate of the organic working fluid, and desired outputs are the heat source and working fluid output temperature. Trapezoidal membership functions for input and output parameters are used, and a set of twenty-seven IF-THEN rules applied to model the behaviour of system. Additionally, it is mentioned that compared to the previous computational methods of evaporator modelling, the fuzzy logic evaporator model is much faster and can calculate the outputs in 5.3 seconds. Furthermore, the governing non-linear partial differential equations of evaporator does not need to be calculated and fuzzy system estimates the behaviour of evaporator using the previous knowledge of the system behaviour. This model can expeditiously be used for real-time modelling of the control system due to its lower computational time.

Although the fuzzy method is agile, if any of evaporator design parameters such as size or evaporator layout change, the fuzzy rules and the membership functions of the fuzzy system need to be adjusted accordingly. Moreover, the membership functions and fuzzy rules are not tuned using the adaptive techniques; thus, setting the rules for manually tuning the evaporator behaviour is an adversely time-consuming task. Therefore, to reduce the modelling effort, increase the accuracy of models and eliminate the dependency of fuzzy models on expert knowledge about the system, the GD-LSE ANFIS and PSO ANFIS modelling techniques are represented in this study for modelling the input-output behaviour of the evaporator.

2. Adaptive Network-Based Fuzzy Inference System (ANFIS)

ANFIS is a systematic hybrid input-output mapping technique introduced by Jang [21] in 1993. This method combines feedforward neural network and Takagi-Sugeno fuzzy inference system. The optimal distribution of membership functions in fuzzy system is determined using this technique, independent of expert knowledge of the system. The neural network is particularly adequate for pattern recognition in non-linear systems and the fuzzy technique is a powerful approach for modelling non-linear systems. The model obtained using the ANFIS method is not regarded as a completely black-box model, because the fuzzy-logic capabilities of the model makes it interpretable in terms of the linguistic variables [22]. The architecture of ANFIS consists of five layers and each layer has multiple nodes that are described by node functions as shown in **Fig. 3**.

Fig. 3. ANFIS architecture

For simplicity, a system with two inputs and one output is considered here to illustrate the ANFIS procedure by assuming two Takagi-Sugeno type fuzzy IF-THEN rules for the ANFIS system rule base. The proposed defined rules are:

Rule 1: If x is A_1 and y is B_1 , then $f_1 = p_1x + q_1y + r_1$

Rule 2: If x is A_2 and y is B_2 , then $f_2 = p_2x + q_2y + r_2$ (1)

Where x and y are input variables, f_i is the output and A_i and B_i represent the fuzzy sets which are defined over the input domain, and p_i , q_i and r_i are the parameters of linear polynomial in the fourth layer of ANFIS network. There are two types of nodes in the ANFIS architecture: adaptive and fixed. The adaptive nodes contain tuneable parameters, whereas the fixed nodes which can only perform a specific task. The function of the nodes in each layer is described in the following.

Layer 1: The nodes in first layer of ANFIS are adaptive nodes with the node function:

$$O_{1,i} = \mu_{A_i}(x) \text{ for } i = 1, 2, \text{ or}$$

$$O_{1,i} = \mu_{B_{i-2}}(y) \text{ for } i = 3, 4 \quad (2)$$

Where x and y are the inputs to the node i , A and B are the linguistic labels and $\mu(x)$ and $\mu(y)$ are Gaussian membership functions with the range between 0 and 1, as follows:

$$\mu(x) = \exp\left(-\frac{(c_i - x)^2}{2\sigma_i^2}\right) \quad (3)$$

In equation (3), c_i and σ_i determine the centre and width of the fuzzy set, respectively. The parameters in the first layer of ANFIS are referred to as premise parameters. Selection of shape and number of membership functions has a substantial influence on the complexity and accuracy

of ANFIS-based models [23]. Therefore, Gaussian membership functions due to their smooth representation of input space are selected.

Layer 2: Nodes in this layer are fixed and their output is determining the firing strength of a rule by multiplying all incoming signals, as follows:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \quad (4)$$

Layer 3: The nodes in this layer are fixed and are responsible for normalizing the firing strengths. The output in this layer is calculated by dividing the i^{th} rule's firing strength to sum of all rules firing strengths:

$$\bar{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \quad (5)$$

Layer 4: All the nodes in this layer are adaptive with the node function:

$$O_{4,i} = \bar{w}_i f_i = \bar{w}_i (p_i x + q_i y + r_i) \quad (6)$$

where $\bar{w}_i$ is the normalized firing strength from previous layer and p_i , q_i and r_i are the parameters set referred to as consequent parameters.

Layer 5: The single node in this layer is a fixed node and calculates the summation of all incoming signals to produce a crisp output, as follows:

$$O_{5,1} = \sum_i \bar{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \quad (7)$$

2.1 Gradient Descent – Least Square Estimate Learning Algorithm

ANFIS learns by updating the premise (c_i and σ_i) and consequent (p_i , q_i and r_i) parameters in the first and the fourth layers of the network. The conventional method for finding the optimized premise and consequent parameters is hybrid, which combines the gradient descent (GD) and least square estimate (LSE) algorithms. This method consists of a forward and a backward pass. In the forward pass, the node outputs go forward until the fourth layer and the LSE algorithm identifies the consequent parameters. When the premise parameters are fixed, the output of ANFIS network can be represented as a linear combination of consequent parameters:

$$\begin{aligned} f &= \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \\ &= \bar{w}_1 f_1 + \bar{w}_2 f_2 \end{aligned} \quad (8)$$

Substituting the fuzzy if-then rules into equation (8) yields:

$$= (\bar{w}_1 x)p_1 + (\bar{w}_1 y)q_1 + (\bar{w}_1)r_1 + (\bar{w}_2 x)p_2 + (\bar{w}_2 y)q_2 + (\bar{w}_2)r_2 \quad (9)$$

Equation (9) is linear in the consequent parameters p_1, q_1, r_1, p_2, q_2 and r_2 .

$$f = XW \quad (10)$$

Therefore, if the X matrix is invertible:

$$W = X^{-1}f \quad (11)$$

Otherwise, a pseudo-inverse is used to find the W as follows:

$$W = (X^T X)^{-1} X^T f \quad (12)$$

In the next step, by fixing the consequent parameters the error signals propagate backward through the network and the premise parameters in the first layer of ANFIS are updated by using the GD algorithm.

$$c_{ij}(t+1) = c_{ij}(t) - \frac{\eta}{p} \cdot \frac{\partial E}{\partial c_{ij}} \quad (13)$$

where η is the learning rate and c_{ij} is the modifiable parameter of the membership function. The chain rule can be deployed to calculate the partial derivative $\frac{\partial E}{\partial c_{ij}}$ as follows:

$$\frac{\partial E}{\partial c_{ij}} = \frac{\partial E}{\partial f} \cdot \frac{\partial f}{\partial f_i} \cdot \frac{\partial f_i}{\partial w_i} \cdot \frac{\partial w_i}{\partial \mu_{ij}} \cdot \frac{\partial \mu_{ij}}{\partial c_{ij}} \quad (14)$$

Combination of a forward path and a backward path is called an Epoch and with enough Epochs the premise and consequent parameters of the ANFIS network can be set to adequately provide the prediction power for the model. **Table 1** illustrates the two-pass learning algorithm of ANFIS.

Table 1 – Hybrid GD-LSE learning algorithm

Parameter	Forward Pass	Backward Pass
Antecedent Parameters	Fixed	Gradient Decent
Consequent Parameters	Least Square Estimate	Fixed
Signals	Node Outputs	Error Signals

An important disadvantage of using the gradient-based techniques for tuning the membership functions of the ANFIS model is that they are likely to fall in local minima. The error surface is

non-convex, highly multi-dimensional and also contains local minima and flat regions. The gradient-based methods are known to be local search approaches and cannot guarantee convergence to the global minima. The reason is because they are using the chain rule to calculate the gradient of error function and the chain rule cannot differentiate between the local and global minima [24, 25]. One approach to address this problem is to deploy non-gradient metaheuristic methods such as Particle Swarm Optimization (PSO) since finding the network parameters can be reduced to an optimization problem to avoid local minima. In general, non-gradient methods of tuning the parameters of the model are recommended [26].

2.2 Particle Swarm Optimization learning algorithm

PSO is a heuristic swarm intelligence technique first introduced by Eberhart and Kennedy [27]. This method is inspired by biological and sociological behaviour of birds and fishes searching for their food. PSO is a population-based search method, which is applied in several studies to solve optimization problems [28, 29]. Each possible solution to the optimization problem is called a particle. In this method an initial random position is assigned to each particle and particles move in the multidimensional search space and their position and flight speed is updated according to their best-known local position guided by other whole particles best known general position, until equilibrium is reached or the computational limitations is exceeded. Let's consider a swarm with population size of N , initial position of x and movement speed of v . The best local position of a particle is denoted as P_{best} and position of the particle in the swarm which better minimizes the performance measure is denoted as G_{best} . The speed and position of the i^{th} particle of the swarm in the next iteration can be formulated as follows:

$$v_i(k) = wv_i(k-1) + \rho_1(x_{P_{best}} - x_i(k)) + \rho_2(x_{G_{best}} - x_i(k)) \quad (15)$$

$$x_i(k) = x_i(k-1) + v_i(k) \quad (16)$$

where ρ_1 and ρ_2 are random variable defined as $\rho_1 = r_1c_1$ and $\rho_2 = r_2c_2$, with r_1 and $r_2 \sim U(0, 1)$. The variables c_1 and c_2 are positive acceleration constants that satisfy the condition $c_1 + c_2 \leq 4$ [30] and w is the inertial weight that can be calculated using the inertial weight approach (IWA) as follows [31]:

$$w = w_{max} - \frac{w_{max} - w_{min}}{Itr_{max}} Itr \quad (17)$$

where w_{max} and w_{min} denote the initial and final weights, Itr represents the current iteration number and Itr_{max} is the maximum number of iterations.

Although metaheuristic algorithms such as PSO do not guarantee convergence to the optimal solution, they do not require the optimization problem to be differentiable as opposed to the gradient-based methods. Furthermore, for a given size of network the PSO ANFIS method has the advantage of being less computationally expensive [26]. In this study, the PSO algorithm is deployed to find the optimal parameters of antecedent and consequent parts of ANFIS and the results are compared with the hybrid GD-LSE learning algorithm.

3. Model implementation

To train the ANFIS model, the FV model of evaporator is excited by changing the heat source mass flow rate ($\dot{m}_h$), the heat source temperature (T_h) and the mass flow rate of refrigerant ($\dot{m}_r$) in the range of 0.073-0.2985 Kg/s, 412-523 K and 0.0318-0.2243 Kg/s, respectively. The heat source mass flow rate and temperature data are randomly selected according to the range of a generic heat source in ICE of heavy-duty trucks. Outlet temperature of refrigerant (T_{rout}) and Outlet temperature of the heat source (T_{hout}) are selected as the output parameters of the evaporator model. In total, 1000 data points collected from dynamic FV model and each data point represents one second of actual evaporator input-output behaviour. Details of the FV model used for gathering the data can be found in Ref. [13]. Input-output data used for the modelling is illustrated in **Fig. 4**. As recommended in several studies, the data is further divided randomly to about 70% for training and 30% for testing the proposed PSO ANFIS and GD-LSE ANFIS models [32-34].

In order to obtain a base FIS, the input search space needs to be clustered. Grid partitioning (GP), subtractive clustering (SCM) and fuzzy c-means (FCM) are the most widely used approaches in the literature for clustering the data [35-38]. In this study, FCM clustering method due to its higher flexibility is implemented to obtain the base FIS.

Fig. 4. Input-output data gathered from FV model of evaporator (a) Mass flow rate and temperature of generic heat source (b) Mass flow rate of refrigerant (c) Refrigerant and heat source temperatures at the evaporator outlet

3.1 Training ANFIS using hybrid GD-LSE algorithm

The ANFIS method has been applied to train two multi-input single-output ANFIS models for prediction of the refrigerant output temperature (T_{rout}) and heat source output temperature (T_{hout}). Moreover, GD algorithm is used to adjust the premise parameters and LSE algorithm is applied to update the consequent parameters. The ANFIS training parameters for both models are listed in **Table 2**. In **Fig. 5** and **Fig. 6**, the trained membership functions for refrigerant and heat source output temperatures are represented, respectively. The fuzzy surfaces shown in **Fig. 7** and **Fig. 8** indicate the effect of transient inputs on the heat source output temperature and refrigerant output temperature, respectively.

Table 2 – GD-LSE ANFIS training parameters

Parameters	GD-LSE ANFIS model for heat source output temperature	GD-LSE ANFIS model for refrigerant output temperature
Number of training data set	701×4	701×4
Number of test data set	300×4	300×4
Clustering method	FCM	FCM
Membership functions	Gaussian	Gaussian
Number of Clusters	7×3	8×3
Number of Epochs	3000	3000
Number of nodes	62	70
Number of linear parameters	28	32
Number of nonlinear parameters	42	48
Total number of parameters	70	80
Number of fuzzy rules	7	8

(a)

(b)

(c)

Fig. 5. Trained membership functions of GD-LSE ANFIS model for predicting the heat source output temperature (a) temperature of heat source (b) mass flow rate of heat source (c) mass flow rate of refrigerant

(a)

(b)

(c)

Fig. 6. Trained membership functions of GD-LSE ANFIS model for predicting the refrigerant output temperature (a) temperature of heat source (b) mass flow rate of heat source (c) mass flow rate of refrigerant

(a)

(b)

Fig. 7. Fuzzy surfaces representing the effect of changing the input parameters on the heat source output temperature in the GD-LSE ANFIS model

Fig. 8. Fuzzy surfaces representing the Effect of changing the input parameters on the refrigerant output temperature in the GD-LSE ANFIS model

3.2 Training ANFIS using PSO

The standard two pass GD-LSE learning method of ANFIS is prone to get stuck in local minima, therefore, derivative-free metaheuristic algorithms such as PSO for training the parameters of ANFIS model are recommended [26]. In general, combining the ANFIS with PSO technique produces a model with more reliable results [39, 40]. The most influential parameters of PSO algorithm are: (1) the number of the population, (2) the personal and global learning coefficients (C_1 and C_2), and (3) the inertial weight (w).

For training the ANFIS using the PSO algorithm, the parameters of Gaussian membership functions in the antecedent and parameters of consequent linear polynomial of the base FIS obtained using the FCM algorithm are extracted. These parameters are optimized using the PSO algorithm in order to minimize the cost function defined as the RMSE between the target values and the ANFIS model output values as follows:

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (H_i^{Target} - H_i^{Output})^2} \quad (18)$$

The PSO parameters utilised for modelling the output temperature of refrigerant and output temperature of heat source are listed in **Table 3**. In **Fig. 9** and **Fig. 10** the trained membership functions of the input variables for output temperature of heat source and output temperature of refrigerant models are depicted, respectively. **Fig. 11** and **Fig. 12** indicate the interdependency of input variables for the output temperature of heat source and the output temperature of refrigerant prediction within the selected ranges, respectively.

Table 3 – Parameters of PSO ANFIS algorithm

Parameters	PSO ANFIS model for heat source output temperature	PSO ANFIS model for refrigerant output temperature
Number of training data set	701×4	701×4
Number of test data set	300×4	300×4
Clustering method	FCM	FCM
Membership functions	Gaussian	Gaussian
Number of Clusters	7×3	8×3
Maximum iteration	3000	3000
Inertial weight	1	1
Personal learning coefficient (C_1)	1	1
Global learning coefficient (C_2)	2	2
Number of optimized parameters	70	80
Number of fuzzy rules	7	8

(a)

(b)

(c)

Fig. 9. Trained membership functions of PSO ANFIS model for predicting the heat source output temperature (a) temperature of heat source (b) mass flow rate of heat source (c) mass flow rate of refrigerant

(a)

(b)

(c)

Fig. 10. Trained membership functions of PSO ANFIS model for predicting the refrigerant output temperature (a) temperature of heat source (b) mass flow rate of heat source (c) mass flow rate of refrigerant

(a)

(b)

(c)

Fig. 11. Fuzzy surfaces representing the Effect of changing the input parameters on the heat source output temperature in the PSO ANFIS model

Fig. 12. Fuzzy surfaces representing the Effect of changing the input parameters on the refrigerant output temperature in the PSO ANFIS model

4. Results and discussions

Two intelligent ANFIS approaches are applied to determine the output temperature of heat source and the output temperature refrigerant in a counter flow evaporator by considering mass flow rate and temperature of heat source and mass flow rate of refrigerant as input variables to the evaporator. A comparison between the prediction power of the GD-LSE ANFIS and PSO ANFIS models for the heat source output is illustrated in **Fig. 13**. As it can be seen, both training data and an unseen test data are applied to the trained models to evaluate the generalization power of the models. Additionally, a statistical criterion in terms of RMSE is considered to evaluate the accuracy of the models. For the training data, the RMSEs for PSO and GD-LSE trained ANFIS models are 0.241 and 0.327, respectively. The unseen test data RMSE is equal to 0.242 for the PSO ANFIS model and 0.336 for the GD-LSE model. It can be deduced that the output heat source temperature results obtained from PSO ANFIS model have a better agreement with the FV model as compared with the GD-LSE ANFIS model.

(a)

(b)

Fig. 13. Comparison of heat source output temperature prediction between GD-LSE ANFIS model and PSO ANFIS model for (a) training data (b) test data

Furthermore, to better illustrate the deviation of the predicted heat source output temperatures from the numerically simulated values, regression plots are shown in **Fig. 14**. The linear correlation coefficient (R) for both models clearly imply the high generalization power of the models since the R value for both training and test data are close to one.

(a)

Fig. 14. Comparison of regression plots for heat source output temperature prediction between GD-LSE ANFIS model and PSO ANFIS model for (a) training data (b) test data

The predicted data of refrigerant output temperature by two aforementioned methods of GD-LSE and PSO ANFIS are plotted versus FV model data in **Fig. 15**. In order to assess the generalization ability of the trained models, as discussed earlier in the data preparation, a test data set (30% of the whole data) is randomly selected, and applied to the model. The predicted values for test data set versus FV is also showcased in **Fig. 15** for the GD-LSE and PSO ANFIS models. It can be concluded that the models are not over-fitted since the RMSE for the test data and the training data have a subtle difference.

Fig. 15. Comparison of refrigerant output temperature prediction between GD-LSE ANFIS model and PSO ANFIS model for (a) training data (b) test data

Similarly, comparison of regression plots for refrigerant output temperature prediction between the GD-LSE and PSO trained ANFIS models is presented in **Fig. 16**. The obtained linear correlation coefficient (R) values of both models for training and test data are close to one. This indicates the low deviation of results as compared to numerically calculated FV model results. To better point out the accuracy of proposed ANFIS models, Statistical error analysis is summarized in **Table 4**. Referring to RMSE and MSE for heat source and refrigerant output temperature models, clearly the models trained with the PSO algorithm have higher accuracies. The highest accuracy is achieved for the refrigerant output temperature model trained using PSO algorithm with the RMSE of 0.048 and MSE of 0.0023 for the training dataset, and respectively, 0.053 and 0.0029 for the test dataset. Since in the application of ORC cycle for recovering waste heat from exhaust of ICEs safety of the system is vital, such an accurate prediction of refrigerant temperature at the evaporator outlet plays a prominent role in designing robust control systems. On the other hand, the highest improvement in RMSE is achieved by PSO trained ANFIS for the heat source output temperature prediction compared to the GD-LSE ANFIS model by approximately 27 percent for both training and test datasets.

Fig. 16. Comparison of regression plots for refrigerant output temperature prediction between GD-LSE ANFIS model and PSO ANFIS model for (a) training data (b) test data

Table 4 – Statistical error analysis of the proposed models

Model	Target Output	Data set	RMSE	MSE	R
GD-LSE ANFIS	Heat source output temperature	Train	0.327	0.1069	0.99995
		Test	0.336	0.1130	0.99995
PSO ANFIS	Heat source output temperature	Train	0.241	0.0583	0.99998
		Test	0.242	0.0589	0.99998
GD-LSE ANFIS	Refrigerant output temperature	Train	0.055	0.0031	0.99999
		Test	0.057	0.0033	0.99999
PSO-ANFIS	Refrigerant output temperature	Train	0.048	0.0023	0.99999
		Test	0.053	0.0029	0.99999

5. Conclusion

This paper applies two intelligent learning algorithms to train an ANFIS network in order to identify the highly non-linear input-output behaviour of a counter flow evaporator. The data for this study is gathered from a FV model of the evaporator, which is computationally expensive for real-time applications. Identifying the dynamics governing the behaviour of the evaporator can further result in proper control of the ORC in mobile applications. Based on the obtained results the main achievements of this study are as follows:

- The time and effort of identifying the antecedent and consequent parameters of Fuzzy model are decreased substantially by deploying the ANFIS method compared to the previous non-adaptive fuzzy models.
- The ANFIS models of evaporator for predicting the output temperature of heat source and refrigerant are trained using the hybrid GD-LSE and population-based PSO algorithms. The statistical analysis of the results indicates the higher accuracy and generalization ability of the ANFIS models trained using the PSO algorithm.
- The ANFIS models substantially outperformed the conventional numerical FV and MB methods in terms of online simulation time. Furthermore, the identified ANFIS models can be used for proper online control of the ORC cycle with transient heat source.

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References

- [1] R. Freymann, W. Strobl, and A. Obieglo, "The turbosteamer: A system introducing the principle of cogeneration in automotive applications," *MTZ worldwide*, vol. 69, no. 5, pp. 20-27, 2008/05/01 2008, doi: 10.1007/BF03226909.
- [2] R. El Chammas and D. Clodic, "Combined Cycle for Hybrid Vehicles," presented at the SAE 2005 World Congress & Exhibition, Session : Advanced Hybrid Vehicle Powertrains (part 4 & 5). Detroit, United States, 2005, 2005. [Online]. Available: <https://hal.archives-ouvertes.fr/hal-00077345>.
- [3] C. Sprouse and C. Depcik, "Review of organic Rankine cycles for internal combustion engine exhaust waste heat recovery," *Applied Thermal Engineering*, vol. 51, no. 1, pp. 711-722, 2013/03/01/ 2013, doi: <https://doi.org/10.1016/j.applthermaleng.2012.10.017>.
- [4] K. Yang *et al.*, "Performance analysis of the vehicle diesel Engine-ORC combined system based on a screw expander," *Energies*, Article vol. 7, no. 5, pp. 3400-3419, 2014, doi: 10.3390/en7053400.
- [5] C. O. Katsanos, D. T. Hountalas, and E. G. Pariotis, "Thermodynamic analysis of a Rankine cycle applied on a diesel truck engine using steam and organic medium," *Energy Conversion and Management*, vol. 60, pp. 68-76, 2012/08/01/ 2012, doi: <https://doi.org/10.1016/j.enconman.2011.12.026>.
- [6] R. Saidur, M. Rezaei, W. K. Muzammil, M. H. Hassan, S. Paria, and M. Hasanuzzaman, "Technologies to recover exhaust heat from internal combustion engines," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 8, pp. 5649-5659, 2012/10/01/ 2012, doi: <https://doi.org/10.1016/j.rser.2012.05.018>.
- [7] T. Wang, Y. Zhang, Z. Peng, and G. Shu, "A review of researches on thermal exhaust heat recovery with Rankine cycle," *Renewable and sustainable energy reviews*, vol. 15, no. 6, pp. 2862-2871, 2011.
- [8] B. F. Tchanche, G. Lambrinos, A. Frangoudakis, and G. Papadakis, "Low-grade heat conversion into power using organic Rankine cycles – A review of various applications," *Renewable and Sustainable Energy Reviews*, vol. 15, no. 8, pp. 3963-3979, 2011/10/01/ 2011, doi: <https://doi.org/10.1016/j.rser.2011.07.024>.
- [9] H. Jouhara, N. Khordehgah, S. Almahmoud, B. Delpech, A. Chauhan, and S. A. Tassou, "Waste heat recovery technologies and applications," *Thermal Science and Engineering Progress*, vol. 6, pp. 268-289, 2018/06/01/ 2018, doi: <https://doi.org/10.1016/j.tsep.2018.04.017>.
- [10] S. Karellas, A. Schuster, and A. D. Leontaritis, "Influence of supercritical ORC parameters on plate heat exchanger design," *Applied Thermal Engineering*, Article vol. 33-34, no. 1, pp. 70-76, 2012, doi: 10.1016/j.applthermaleng.2011.09.013.
- [11] M. Jiménez-Arreola, R. Pili, F. Dal Magro, C. Wieland, S. Rajoo, and A. Romagnoli, "Thermal power fluctuations in waste heat to power systems: An overview on the challenges and current solutions," *Applied Thermal Engineering*, vol. 134, pp. 576-584, 2018/04/01/ 2018, doi: <https://doi.org/10.1016/j.applthermaleng.2018.02.033>.
- [12] A. Desideri *et al.*, "Comparison of moving boundary and finite-volume heat exchanger models in the modelica language," *Energies*, vol. 9, no. 5, p. 339, 2016.
- [13] J. Chowdhury, B. Nguyen, and D. Thornhill, "Modelling of Evaporator in Waste Heat Recovery System using Finite Volume Method and Fuzzy Technique," *Energies*, vol. 8, no. 12, p. 12413, 2015. [Online]. Available: <http://www.mdpi.com/1996-1073/8/12/12413>.
- [14] M. O. Bamgbopa and E. Uzgoren, "Numerical analysis of an organic Rankine cycle under steady and variable heat input," *Applied Energy*, vol. 107, pp. 219-228, 2013/07/01/ 2013, doi: <https://doi.org/10.1016/j.apenergy.2013.02.040>.

- [15] S. Quoilin, R. Aumann, A. Grill, A. Schuster, V. Lemort, and H. Spliethoff, "Dynamic modeling and optimal control strategy of waste heat recovery Organic Rankine Cycles," *Applied energy*, vol. 88, no. 6, pp. 2183-2190, 2011.
- [16] E. Feru, F. Willems, B. De Jager, and M. Steinbuch, "Modeling and control of a parallel waste heat recovery system for Euro-VI heavy-duty diesel engines," *Energies*, vol. 7, no. 10, pp. 6571-6592, 2014.
- [17] D. Wei, X. Lu, Z. Lu, and J. Gu, "Dynamic modeling and simulation of an Organic Rankine Cycle (ORC) system for waste heat recovery," *Applied Thermal Engineering*, vol. 28, no. 10, pp. 1216-1224, 2008.
- [18] E. Rodriguez and B. Rasmussen, "A comparison of modeling paradigms for dynamic evaporator simulations with variable fluid phases," *Applied Thermal Engineering*, vol. 112, pp. 1326-1342, 2017/02/05/ 2017, doi: <https://doi.org/10.1016/j.applthermaleng.2016.10.131>.
- [19] S. Bendapudi, J. E. Braun, and E. A. Groll, "Dynamic modeling of shell-and-tube heat-exchangers: Moving boundary vs. finite volume," 2004.
- [20] J. Chowdhury *et al.*, "Fuzzy nonlinear dynamic evaporator model in supercritical organic rankine cycle waste heat recovery systems," *Energies*, vol. 11, no. 4, p. 901, 2018.
- [21] J. R. Jang, "ANFIS: adaptive-network-based fuzzy inference system," *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 23, no. 3, pp. 665-685, 1993, doi: 10.1109/21.256541.
- [22] M. Kumar and D. P. Garg, "Intelligent learning of fuzzy logic controllers via neural network and genetic algorithm," in *Proceedings of*, 2004, pp. 1-8.
- [23] N. Talpur, M. N. M. Salleh, and K. Hussain, "An investigation of membership functions on performance of ANFIS for solving classification problems," in *IOP Conference Series: Materials Science and Engineering*, 2017, vol. 226, 1 ed., doi: 10.1088/1757-899X/226/1/012103. [Online]. Available: <https://www.scopus.com/inward/record.uri?eid=2-s2.0-85028665667&doi=10.1088%2f1757-899X%2f226%2f1%2f012103&partnerID=40&md5=d3aad6de029897742ffab3b57349422e>
- [24] V. S. Ghomsheh, M. A. Shoorehdeli, and M. Teshnehlab, "Training ANFIS structure with modified PSO algorithm," in *2007 Mediterranean Conference on Control & Automation*, 27-29 June 2007 2007, pp. 1-6, doi: 10.1109/MED.2007.4433927.
- [25] M. A. Shoorehdeli, M. Teshnehlab, and A. K. Sedigh, "A novel training algorithm in ANFIS structure," in *2006 American Control Conference*, 14-16 June 2006 2006, p. 6 pp., doi: 10.1109/ACC.2006.1657525.
- [26] M. Aliyari Shoorehdeli, M. Teshnehlab, and A. K. Sedigh, "Identification using ANFIS with intelligent hybrid stable learning algorithm approaches," *Neural Computing and Applications*, journal article vol. 18, no. 2, pp. 157-174, February 01 2009, doi: 10.1007/s00521-007-0168-9.
- [27] R. Eberhart and J. Kennedy, "A new optimizer using particle swarm theory," in *MHS'95. Proceedings of the Sixth International Symposium on Micro Machine and Human Science*, 1995: IEEE, pp. 39-43.
- [28] A. Noghrehabadi, R. Mirzaei, M. Ghalambaz, A. Chamkha, and A. Ghanbarzadeh, "Boundary layer flow heat and mass transfer study of Sakiadis flow of viscoelastic nanofluids using hybrid neural network-particle swarm optimization (HNNPSO)," *Thermal Science and Engineering Progress*, vol. 4, pp. 150-159, 2017/12/01/ 2017, doi: <https://doi.org/10.1016/j.tsep.2017.09.003>.
- [29] K. H. Jyothiprakash, J. Harshith, A. Sharan, K. N. Seetharamu, and Y. T. Krishnegowda, "Thermodynamic Optimization of Three-Fluid Cross-Flow Heat Exchanger Using GA and PSO Heuristics," *Thermal Science and Engineering Progress*, vol. 11, pp. 289-301, 2019/06/01/ 2019, doi: <https://doi.org/10.1016/j.tsep.2019.04.009>.

- [30] J. Kennedy, "Swarm intelligence," in *Handbook of nature-inspired and innovative computing*: Springer, 2006, pp. 187-219.
- [31] J. Kennedy, "The Behavior of Particles," presented at the Proceedings of the 7th International Conference on Evolutionary Programming VII, 1998.
- [32] R. Razavi, A. Sabaghmoghadam, A. Bemani, A. Baghban, K.-w. Chau, and E. Salwana, "Application of ANFIS and LSSVM strategies for estimating thermal conductivity enhancement of metal and metal oxide based nanofluids," *Engineering Applications of Computational Fluid Mechanics*, vol. 13, no. 1, pp. 560-578, 2019/01/01 2019, doi: 10.1080/19942060.2019.1620130.
- [33] A. Baghban, M. Kahani, M. A. Nazari, M. H. Ahmadi, and W.-M. Yan, "Sensitivity analysis and application of machine learning methods to predict the heat transfer performance of CNT/water nanofluid flows through coils," *International Journal of Heat and Mass Transfer*, vol. 128, pp. 825-835, 2019/01/01/ 2019, doi: <https://doi.org/10.1016/j.ijheatmasstransfer.2018.09.041>.
- [34] E. Rezaei, A. Karami, T. Yousefi, and S. Mahmoudinezhad, "Modeling the free convection heat transfer in a partitioned cavity using ANFIS," *International Communications in Heat and Mass Transfer*, vol. 39, no. 3, pp. 470-475, 2012/03/01/ 2012, doi: <https://doi.org/10.1016/j.icheatmasstransfer.2011.12.006>.
- [35] M. Mostafaei, "ANFIS models for prediction of biodiesel fuels cetane number using desirability function," *Fuel*, vol. 216, pp. 665-672, 2018.
- [36] S. N. R. Abadi, M. Mehrabi, and J. P. Meyer, "Prediction and optimization of condensation heat transfer coefficients and pressure drops of R134a inside an inclined smooth tube," *International Journal of Heat and Mass Transfer*, vol. 124, pp. 953-966, 2018.
- [37] A. M. Abdulshahed, A. P. Longstaff, and S. Fletcher, "The application of ANFIS prediction models for thermal error compensation on CNC machine tools," *Applied Soft Computing*, vol. 27, pp. 158-168, 2015.
- [38] C.-U. Yeom and K.-C. Kwak, "Performance Comparison of ANFIS Models by Input Space Partitioning Methods," *Symmetry*, vol. 10, no. 12, p. 700, 2018.
- [39] D. P. Rini, S. M. Shamsuddin, and S. S. Yuhaziz, "Particle swarm optimization for ANFIS interpretability and accuracy," *Soft Computing*, vol. 20, no. 1, pp. 251-262, 2016/01/01 2016, doi: 10.1007/s00500-014-1498-z.
- [40] M. Zanganeh, "Improvement of the ANFIS-based wave predictor models by the Particle Swarm Optimization," *Journal of Ocean Engineering and Science*, 2019.