Modeling of Organic Rankine Cycle for Waste Heat Recovery Using RBF Neural Networks

Kailong Liu [1], Kang Li [2], Jianhua Zhang [3], Mingming Lin [4]

School of Electronics, Electrical Engineering and Computer Science,
Queen's University Belfast, Belfast, BT9 5AH, UK
State Key Laboratory of Alternate Electrical Power System with Renewable Energy Sources,
North China Electric Power University, Beijing, 102206, China
[1] kliu02@qub.ac.uk [2] k.li@qub.ac.uk [3] zjh@ncepu.edu.cn [4] linmm1232008@126.com

Abstract—**The Organic Rankine Cycle (ORC) process is promised to significantly recycle the medium and low temperature heat source, achieve better performance to recover low grade waste heat than traditional waste heat recovery processes in the industrial applications. An accurate ORC model is indispensable for the optimization and control of ORC systems. A new Radial Basis Function (RBF) modelling approach, which combines the node selection based on Fast Recursive algorithm (FRA) and non-linear parameters optimization using the PSO algorithm is proposed to model the ORC system. The experimental results verify that the resultant models have achieved high training accuracy and desirable generalization performance.**

I. Introduction

It has been widely acknowledged that new renewable energy resources as well as effective energy-saving have become the core hotspot of the global energy research in the area of industrial applications;. In Europe, the total amount of fuel consumption for vehicles would be 150 billion litres every year. Almost 60-70 % energies of fossil fuels get burned in internal combustion engines and go into atmosphere through the exhaust gas and cooling medium. This would cause a huge waste of energy as well as pollute the environment [1].

Interest in low-grade heat recovery for industrial applications has increased dramatically in the past decades [2, 3]. The Organic Rankine cycle (ORC) which uses organic medium as the cycle fluid can effectively recycle the medium and low temperature heat source [4]. It has high efficiency, low requirement of working pressure containment, gas area expansion process of expander, and environmental friendly with novel working fluid, etc [3].

The majority of current researches on ORC waste heat recovery are to enhance the efficiency of the ORC circulatory system [5]. They focused on the fliter of organic substance [6, 7], analysis of the thermodynamics and thermal economics of ORC systems [3, 8], experiments and optimization design for ORC systems [3, 9, 10]. Since the ORC system operation involves complex thermal dynamics, research on dynamic modeling and optimal control of ORC systems are very limited.

Although abundant results are available on the working fluid selection for ORCs [11], few papers propose a detailed modelling of the cycle: static models have been proposed by Quoilin [12, 13] and Mathias [14]. And dynamic model of a WHR ORC using a turbine was proposed by Wei [15]. Dynamic mechanism modelling and control of ORC has been proposed by Zhang [16, 17, 18] and Hou [19]. However, the dynamic modelling of ORC system using advanced identification method has not been properly addressed. It is clear that waste heat recovery based on the ORC system is a complex process characterized by nonlinearity, uncertainty, multivariable coupling and load disturbance. Such processes cannot be described fully and accurately with mechanism modelling methods due to ideal assumption used in mechanism equations. Black-box models can describe ORC system behaviour using advanced identification methods without resorting to the knowledge of the underlying thermodynamic processes occurring in each component of ORC system. Among all black-box modelling methods, the RBF neural network has been widely adopted due to its simple structure and powerful approximation ability in modelling non-linear systems. One of the main issues involved in RBF neural modeling is the determination of the network structure. In this paper, in order to remove less significant and redundant RBF hidden nodes and increase the accuracy and generalization capacity of the neural network models, a fast non-linear model identification method (Fast Recursive algorithm) is used to pre-select the suitable nodes for the RBF neural network. On the other side, the Particle Swarm Optimization (PSO) algorithm is used to optimize the basis function parameters instead of using gradient-based searches.

The rest of the paper is organized as follows. Orangic rankine cycle for waste heat process are reviewed in Section II. A brief introduction of RBF neural networks as well as PSO optimization algotithm is presented in Section III and a fast forward node selection method is discussed in Section IV. After presenting the proposed method in Section V, experimental results of the proposed modeling approach are given in Section VI. Section VII concludes the paper and points out the future work.

II. Organic Rankine Cycle System

The schematic diagram of ORC system which is used for waste heat recovery is shown in Fig.1. It consists of

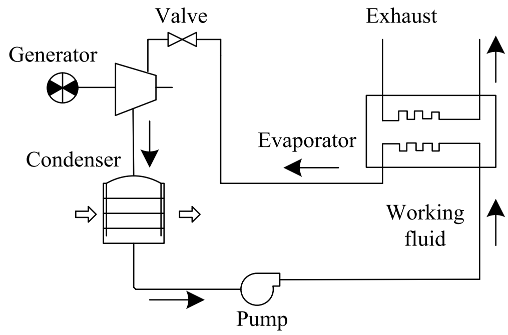

Fig. 1. Schematic diagram of ORC system

an evaporator which changes working fluid from sub-cooled liquid phase to superheated vapor as well as a condenser which changes working fluid from superheated phase to liquid, a pump which can force working fluid into evaporator and a generator (turbine expander) for power generation.

ORC (Organic Rankine cycle) is utilized to generate electric power from waste heat in this diagram. The selected working fluid is R123. It should be noted that fluid selection is an important and preliminary issue in ORC design [11, 20, 21]. The flue gas waste heat is transferred to the evaporator where working fluid R123 is heated before it enters into a turbine expander (generator), the vaporized R123 drives the expander for power generation. The vapor from the expander is then condensed into liquid state in an air-cooled condenser. The liquid working fluid R123 is pressurized by the pump and sent back to the evaporator again. Considering that the evaporator and expander are key components in the ORC system in power generation using waste heat, the condenser mass flow rate has only a minor effect on the cycle and it is not necessary to control the condenser during ORC operation, this paper mainly focuses on the modeling of the evaporator and expander. The big impact and easy measurable variables for evaporator and expander are then chosen for ORC system identification.

III. Preliminaries

A. *RBF neural networks model*

Among various model types, Radial Basis Function (RBF) neural network (NN) has been widely adopted due to its simple structure and powerful approximation ability to model non-linear systems.

The RBF network is a feed forward neural network with one hidden layer as shown in Fig.2.

Consider a general multi-inputs and single-output (MISO) RBF network, the mathematical model with m inputs and n hidden nodes can be formulated as

$$y(t) = \sum_{k=1}^{n} \theta_k \phi_k(\mathbf{x}(t); \mathbf{w}_k) + \varepsilon(t) \tag{1}$$

where $y(t)$ is the system output at sample time t, $\mathbf{x}(t) \in \Re^m$ is the input vector, $\phi_k(\mathbf{x}(t); \mathbf{w}_k)$ denotes the radial basis function, and $\mathbf{w}_k = [\sigma_k, \mathbf{c}_k^T] \in \Re^{m+1}$ is the hidden layer parameter vector which includes the width $\sigma_k \in \Re^1$ and centres $\mathbf{c}_k \in \Re^m$. θ_k represents the output layer weight for each RBF node, and $\varepsilon(t)$ is the modelling error at sample time t. The radial basis function ϕ_k of input vector $\mathbf{x}(t)$ is chosen as Gaussian function defined as follows:

$$\phi_k(X) = exp(-\frac{1}{2\sigma_k^2}\|X - c_k\|^2), k = 1, 2, ..., n \tag{2}$$

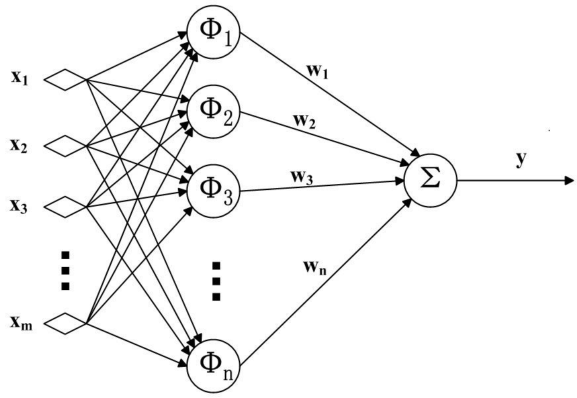

Fig. 2. RBF network structure

B. *PSO Optimization*

Particle Swarm Optimization (PSO) is a popular swarm intelligence method that was originally proposed in [22].It has been widely applied to optimization problems scheduling, neural network training and task assignment. In ORC identification models, PSO is used to optimize the nonlinear parameters (center and width of nodes).

In PSO each particle in the swarm represents a possible solution which moves through the problem search space seeking an optimal or satisfactory solution . The position of each particle is adjusted according to its velocity and the difference among its current position, the best position it has found so far, and the best position to date found by its neighbours [23].

Suppose $\mathbf{x}_i$ denotes the ith particle in the swarm, $\mathbf{v}_i$ represents its velocity, $\mathbf{p}_i$ is the best position it has found so far, while $\mathbf{p}_g$ denotes the best position from the entire swarm. In inertia-weighted PSO [24, 25], $\mathbf{v}_i$ and $\mathbf{x}_i$ are updated as:

$$\mathbf{v}_i \leftarrow w\mathbf{v}_i + c_1\mathbf{r}_1(\mathbf{p}_i - \mathbf{x}_i) + c_2\mathbf{r}_2(\mathbf{p}_g - \mathbf{x}_i) \tag{3}$$

$$\mathbf{x}_i \leftarrow \mathbf{x}_i + \mathbf{v}_i \tag{4}$$

where w is the inertia weight used to scale the previous velocity term, c_1 and c_2 are acceleration coefficients, and $\mathbf{r}_1$ and $\mathbf{r}_2$ are two vectors comprising random values uniformly generated between 0 and 1.

IV. Fast forward RBF node selection

To model a system using an RBF network, the structure should firstly be determined, including the selection of neural input X and the number of hidden layer nodes. The main issues involved in constructing RBF network are selecting the suitable nodes and optimizing non-linear parameters in the basis function. Some studies optimize the basis function parameters using gradient-based approaches, but they are often trapped within a local optimum. If lots of nodes are used in the RBF network, the number of the model parameters will be too large and the computational cost can be extremely high. Furthermore, it would cause over-fitting problem. To pre-select the suitable nodes and optimize the RBF neural network structure, a fast nonlinear model identification method (Fast Recursive algorithm) is used.

The Fast Recursive algorithm (FRA) is a fast forward method to select both model structure and estimate model parameters [26]. In ORC identification models the FRA is proposed to pre-select the RBF neural network nodes. The relationship between the RBF hidden nodes and RBF output can be formulated as a linear-in-the-parameters model shown as (1); The radial basis function ϕ_k which has most net contribution to the cost function can be selected based on the FRA methods.

The FRA is introduced by defining a recursive matrix $\mathbf{M}_k$ and a residual matrix $\mathbf{R}_k$. Thus

$$\mathbf{M}_k \triangleq \mathbf{\Phi}_k^T \mathbf{\Phi}_k \quad k = 1, \cdots, n \tag{5}$$

$$\mathbf{R}_k \triangleq I - \mathbf{\Phi}_k \mathbf{M}_k^{-1} \mathbf{\Phi}_k^T \qquad \mathbf{R}_0 \triangleq I \tag{6}$$

where $\mathbf{\Phi}_k^T \in \Re^{N \times k}$ contains the first k columns of the regression matrix $\mathbf{\Phi}$. According to [26] and [27], the matrix terms $\mathbf{R}_k, k = 0, \cdots, n$ have the following attractive properties:

$$\mathbf{R}_{k+1} = \mathbf{R}_k - \frac{\mathbf{R}_k \mathbf{p}_{k+1} \mathbf{p}_{k+1}^T \mathbf{R}_k^T}{\mathbf{p}_{k+1}^T \mathbf{R}_k \mathbf{p}_{k+1}}, \ k = 0, 1, \cdots, n-1 \tag{7}$$

$$\mathbf{R}_k^T = \mathbf{R}_k; \quad (\mathbf{R}_k)^2 = \mathbf{R}_k, \quad k = 0, 1, \cdots, n \tag{8}$$

$$\mathbf{R}_i \mathbf{R}_j = \mathbf{R}_j \mathbf{R}_i = \mathbf{R}_i, \quad i \geq j; \ i, j = 0, 1, \cdots, n \tag{9}$$

$$\mathbf{R}_k \boldsymbol{\phi} = \begin{cases} \mathbf{0}, & rank([\mathbf{P}_k, \boldsymbol{\phi}_j]) = k \\ \boldsymbol{\phi}_j^{(k)} \neq \mathbf{0}, & rank([\mathbf{P}_k, \boldsymbol{\phi}_j]) = k+1 \end{cases}, \tag{10}$$

j = 0,1,$\cdots$,n

The cost function can now be rewritten as:

$$E(\mathbf{P}_k) = \mathbf{y}^T \mathbf{R}_k \mathbf{y} \tag{11}$$

In forward stepwise construction, the RBF nodes are optimized once at a time. Suppose at the k-th step, one more RBF node $\mathbf{p}_{k+1}$ is to be added. The net contribution of $\mathbf{p}_{k+1}$ to the cost function can then be calculated as:

$$\begin{aligned} \Delta E_{k+1}(\mathbf{P}_k, \mathbf{p}_{k+1}) &= \mathbf{y}^T(\mathbf{R}_k - \mathbf{R}_{k+1})\mathbf{y} \\ &= \frac{\mathbf{y}^T \mathbf{R}_k \mathbf{p}_{k+1} \mathbf{p}_{k+1}^T \mathbf{R}_k \mathbf{y}}{\mathbf{p}_{k+1}^T \mathbf{R}_k \mathbf{p}_{k+1}} \\ &= \frac{(\mathbf{y}^T \mathbf{p}_{k+1}^{(k)})^2}{\mathbf{p}_{k+1}^T \mathbf{p}_{k+1}^{(k)}} \end{aligned} \tag{12}$$

where $\mathbf{p}_{k+1}^{(k)} \triangleq \mathbf{R}_k \mathbf{p}_{k+1}$. In this way, the candidate hidden node will be selected continuously based on the cost function for which each selected hidden node should make the maximum contributions.

V. FRA based RBF construction algorithm

With regards to RBF neural modelling, there are three key steps, i.e. determination of the network size, optimization of the basis function parameters and estimation of the output weights.

In this modelling experiment, Root Mean-Squared Error (RMSE) based cost function is formulated as the criterion for PSO optimization. The RMSE is defined as follows:

$$RMSE = \sqrt{\frac{SSE}{N}} = \sqrt{\frac{(\hat{\mathbf{y}} - \mathbf{y})^T(\hat{\mathbf{y}} - \mathbf{y})}{N}} \tag{13}$$

where SSE is the sum-squared error, $\hat{\mathbf{y}}$ is the prediction value of the RBF neural model and y is the measured data set, and N is the number of samples. The implementation of the RBF modelling procedure has three major steps illustrated as follows.

A. determination of the network structure

The inputs and the number of hidden nodes are two keys for RBF neural network construction. In this paper, considering a MISO RBF network is used to model the ORC system, a number of approaches could be used to determine the input vectors [27, 28]. However in this paper, the trial and error method is adopted to empirically select input vectors and some input vectors will be chosen as the centres of the initial RBF nodes. The application of the above methods to determine the network construction will be further introduced.

B. node selection and parameters optimization

The number of hidden nodes will be selected using the FRA method. To further improve the network performance, the non-linear parameters σ_k, $\mathbf{c}_k$ in (1) are then optimized using the PSO algorithm. The cost function (RMSE) is chosen as the fitness function for the optimization process.

C. output weights estimation

The output weights $\mathbf{w}_k$ in (1) is given as

$$\theta = \left(\phi^T \phi\right)^{-1} \phi^T y \tag{14}$$

The detailed neural model construction procedure can be summarized as follows.

1) Initialization:

Randomly chose 100 data samples as initial centers of RBF hidden nodes;

2) Node selection:

a) Use FRA to select RBF nodes that contribute mostly to the cost function reduction;

b) Repeat selection step until SSE criteria is achieved.

3) Parameter optimization for the RBF neural model using PSO algorithm.

VI. Experimental Rerult

ORC system data obtained from North China Electric Power University(NCEPU) is used for modeling the ORC system. NCEPU has a 100 kW waste heat utilization power system and has built mechanism models for the system. Experimental results have demonstrated that the mechanism models can produce satisfactory performance and the main operating parameters for this ORC system are listed in Table I. The generated power in ORC system is a complex function of all parameters in the cycle. For system identification we want easy measurable variables. It should be known that increasing the expander torque means increasing the expander inlet pressure, the pressure ratio over the evaporator is changed and this way the output power is increased. So the expander torque has a big effect on the evaporator pressure. In order to use the easy measurable and big impact variables for ORC system identification, the expander torque (N.m) is chosen as the system input and the evaporator pressure (kPa) is chosen as the system output in this experiment. During nominal operating conditions, Pseudo-Random Binary Sequence (PRBS) was adopted as the input signals to satisfy the persistent excitation conditions. The expander torque data as well as evaporate pressure data have 2000 samples respectively,as shown in Fig. 3. The sampling time has been set as 200s and data samples are normalized so the range is between -1 and 1.

TABLE I
ORC system Operating Parameters

Operating Parameters	Value
heat source temperature,°C	150
expander torque,$N.m$	12
heat source mass flow,kg/h	2020
pump rotate speed,rmp	115
working fluid	R123
evaporator pressure, kPa	833
cooling water temperature,°C	16-20
superheat,°C	39.2
cooling water mass flow,kg/h	2620

The model inputs are selected as $N_{exp}(t-1)$, $N_{exp}(t-2)$,$N_{exp}(t-3)$, $P_e(t-1)$,$P_e(t-2)$. $P_e(t)$ is the ORC system output. $N_{exp}(t)$ and $P_e(t)$ are the expander torque and evaporate pressure at current time respectively. l_u, l_y in $N_{exp}(t-l_u)$, $P_e(t-l_y)$ are the delays of the expander torque and evaporate pressure respectively. 600 continuous data samples selected randomly from ORC test data were used for RBF neural modeling and the other continuous 600 data samples were used for RBF modeling validation. In this experiment, the final numbers of RBF nodes after FRA selection is 7. The total number of generations for PSO is set as 50 and the population size is set to 20. Besides the proposed FRA-PSO-RBF approach, random nodes selection which generates the nodes parameters randomly is implemented respectively for comparison purpose.

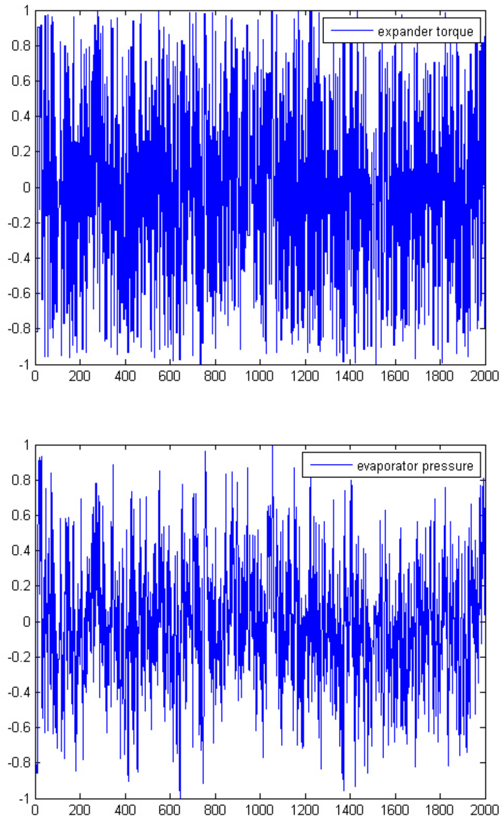

Fig. 3. ORC test data

The simulation results are shown in Figures 5-8. It can be seen that both the training and validation errors for the two methods are small enough, indicating that the resultant models are accurate enough to satisfy the ORC system operation,and it also confirmed the good performance of the proposed parameters optimization method. The model optimization procedure revealed that the two approaches reduced the training error within less than 10 generations and after 30 generations, the FRA-PSO-RBF approach began to outperform the PSO-RBF approach without nodes selection. The training error along generation with nodes selection for PSO optimization process is illustrated in Figures 4.It can be observed that the training error decreased rapidly within less than 5 generations and finally reached nearly 4.5×10^{-5} after 48 generations.

ORC model validation results are illustrated in Figures 7-8. Here another 600 samples comprising data of the expander torque as well as evaporate pressure are used as the validation data set. It can be seen clearly that both these two approaches

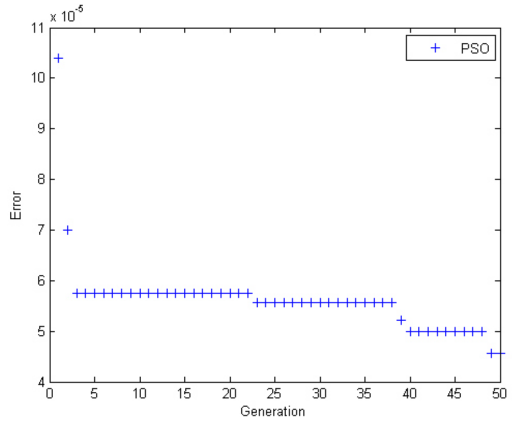

Fig. 4. Training error alone different generation

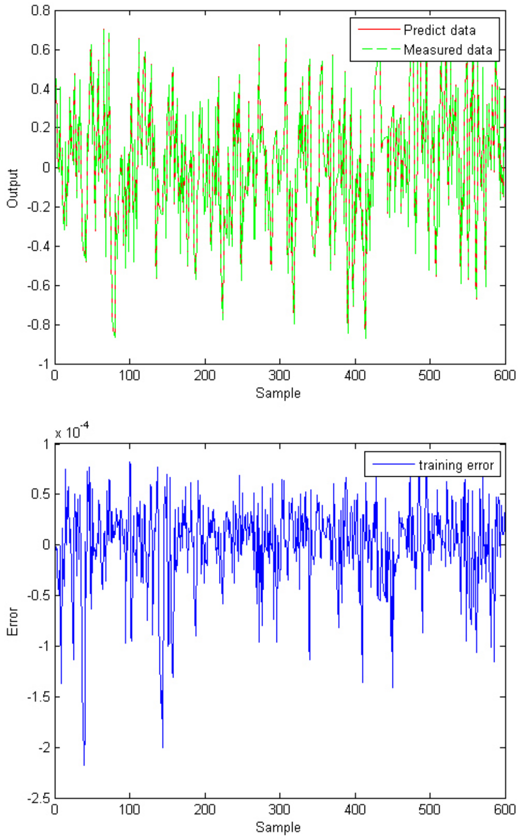

Fig. 5. training results and errors without nodes selection (Solid line:PSO-RBF prediction; Dashed line: actual system output)

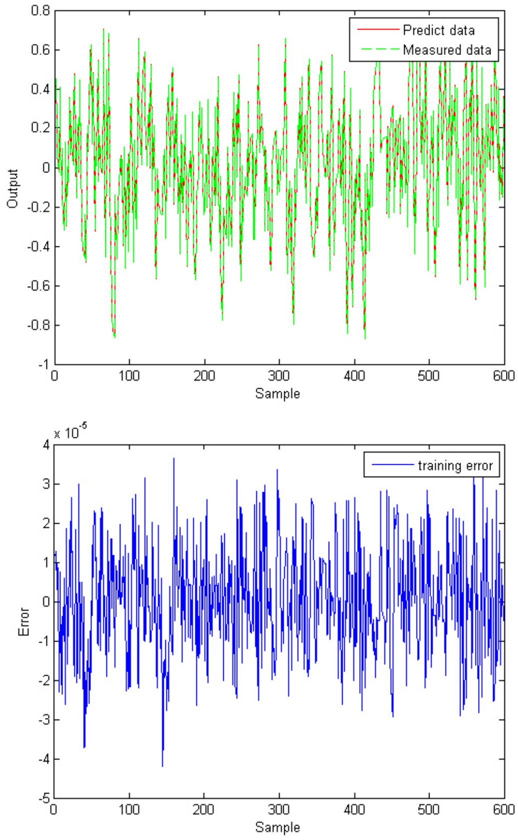

Fig. 6. training results and errors with nodes selection (Solid line:FRA-PSO-RBF prediction; Dashed line: actual system output)

approximate the ORC Nexp-Pe curve well (Nexp is the ORC model input and Pe stands for the ORC model output). Validation errors for these two models are also given. With nodes selection, the maximum spike in the overall error profile is 1.5×10^{-4}, which is better than the validation error without nodes selection(the maximum error is nearly up to 7×10^{-4}).The improvement is significant and this is largely due to the introduction of the RBF nodes pre-selection rather than randomly identifying hidden nodes. The average deviations of model predictions from actual measurements are compared in Table II.It is clear that the two approaches have again achieved satisfactory prediction accuracy as expected. The model average deviation is as low as $1.7E^{-}5$ for the PSO-RBF approach and $6E^{-}6$ for the FRA-PSO-RBF approach respectively on the validation dataset. It is clear that the FRA-PSO-RBF model with nodes selection preformed better as well on the validation data which shows its better generalization capability.

TABLE II
AVERAGE DEVIATION OF MODEL PREDICTIONS

Model method	PSO-RBF without nodes selection	FRA-PSO-RBF with nodes selection
Average Deviation Value	0.000017	**0.000006**

VII. CONCLUDING SUMMARY

In this paper, a novel RBF neural modelling approach is proposed to model an ORC system in the waste heat process.

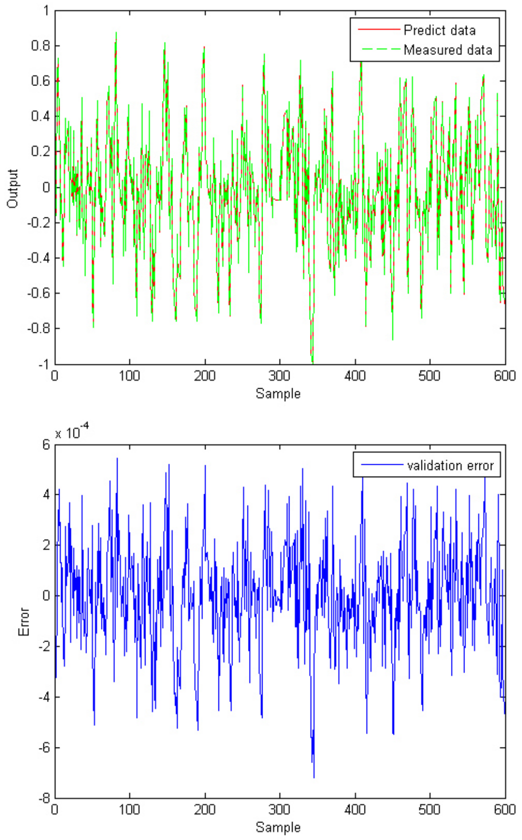

Fig. 7. validation results and errors without nodes selection (Solid line:PSO-RBF prediction; Dashed line: actual system output)

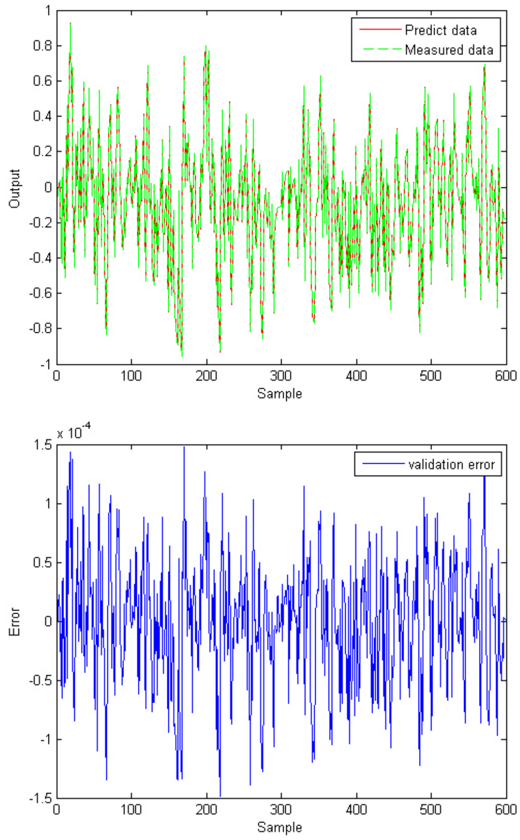

Fig. 8. validation results and errors with nodes selection (Solid line:FRA-PSO-RBF prediction; Dashed line: actual system output)

To simplify the RBF model structure and improve model accuracy, the Fast Recursive algorithm (FRA) is used to pre-select the centers of RBF neural network nodes. The contribution of each selected RBF centre is reviewed, and insignificant centres are replaced. Moreover, to further optimize the ORC model, Particle Swarm Optimization (PSO) is used to optimize the non-linear parameters in the RBF model. Compared with the RBF model with randomly selected centre, the FRA-PSO-RBF model with nodes selection performs better both on the training and validation data sets, shows better model accuracy and generalization capability.

The model, trained by data set obtained through a standard test procedure, is applied to an ORC system for predicting the evaporator pressure outputs. Although the model shows acceptable approximation performance, some problems still remain to be solved. Firstly, input selection is a key in compact RBF configuration, but it is determined by trial and error in this paper. Secondly, other optimization algorithms such as Vortex Search optimization (VSO) [29], Teaching-learning based optimization (TLBO) [30], and Imperialist Competitive Algorithm (ICA) [31] can be used to improve the model accuracy and generalization capability. Thirdly, the heuristically optimized RBF model is more suitable for off-line modelling due to its expensive computation efforts as well as long training procedure. Some on-line identification methods such as Kalman filters [32] can be used for building ORC models for online real-time applications. Finally, when load demand changes or the waste heat sources vary, some advanced control strategies need to be applied to control the ORC process in order to keep vital operating parameters within allowable ranges.

ACKNOWLEDGMENT

The author would also like to thank UK Engineering and Physical Sciences Research Council (EPSRC) International Doctoral Scholarship for sponsoring his research. This work is partially supported by the Royal Society and NSFC jointly funded International Exchange and Newton Fund project under grants IE141469 and 6141101209, and UK EPSRC under grant EP/L001063/1.

REFERENCES

[1] B. F. Tchanche, G. Lambrinos, A. Frangoudakis, and G. Papadakis, "Low-grade heat conversion into power using organic rankine cycles–a review of various ap-

plications," *Renewable and Sustainable Energy Reviews*, vol. 15, no. 8, pp. 3963–3979, 2011.

[2] 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.

[3] Y. Dai, J. Wang, and L. Gao, "Parametric optimization and comparative study of organic rankine cycle (orc) for low grade waste heat recovery," *Energy Conversion and Management*, vol. 50, no. 3, pp. 576–582, 2009.

[4] T.-C. Hung, T. Shai, and S. Wang, "A review of organic rankine cycles (orcs) for the recovery of low-grade waste heat," *Energy*, vol. 22, no. 7, pp. 661–667, 1997.

[5] 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.

[6] B.-T. Liu, K.-H. Chien, and C.-C. Wang, "Effect of working fluids on organic rankine cycle for waste heat recovery," *Energy*, vol. 29, no. 8, pp. 1207–1217, 2004.

[7] J. Bao and L. Zhao, "A review of working fluid and expander selections for organic rankine cycle," *Renewable and Sustainable Energy Reviews*, vol. 24, pp. 325–342, 2013.

[8] D. Wei, X. Lu, Z. Lu, and J. Gu, "Performance analysis and optimization of organic rankine cycle (orc) for waste heat recovery," *Energy conversion and Management*, vol. 48, no. 4, pp. 1113–1119, 2007.

[9] Z. Shengjun, W. Huaixin, and G. Tao, "Performance comparison and parametric optimization of subcritical organic rankine cycle (orc) and transcritical power cycle system for low-temperature geothermal power generation," *Applied energy*, vol. 88, no. 8, pp. 2740–2754, 2011.

[10] S. Quoilin, S. Declaye, B. F. Tchanche, and V. Lemort, "Thermo-economic optimization of waste heat recovery organic rankine cycles," *Applied Thermal Engineering*, vol. 31, no. 14, pp. 2885–2893, 2011.

[11] H. Gao, C. Liu, C. He, X. Xu, S. Wu, and Y. Li, "Performance analysis and working fluid selection of a supercritical organic rankine cycle for low grade waste heat recovery," *Energies*, vol. 5, no. 9, pp. 3233–3247, 2012.

[12] S. Quoilin, V. Lemort, and J. Lebrun, "Experimental study and modeling of an organic rankine cycle using scroll expander," *Applied energy*, vol. 87, no. 4, pp. 1260–1268, 2010.

[13] V. Lemort, S. Quoilin, C. Cuevas, and J. Lebrun, "Testing and modeling a scroll expander integrated into an organic rankine cycle," *Applied Thermal Engineering*, vol. 29, no. 14, pp. 3094–3102, 2009.

[14] J. A. Mathias, J. R. Johnston, J. Cao, D. K. Priedeman, and R. N. Christensen, "Experimental testing of gerotor and scroll expanders used in, and energetic and exergetic modeling of, an organic rankine cycle," *Journal of Energy Resources Technology*, vol. 131, no. 1, p. 012201, 2009.

[15] 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.

[16] J. Zhang, W. Zhang, G. Hou, and F. Fang, "Dynamic modeling and multivariable control of organic rankine cycles in waste heat utilizing processes," *Computers & Mathematics with Applications*, vol. 64, no. 5, pp. 908–921, 2012.

[17] J. Zhang, Y. Zhou, Y. Li, G. Hou, and F. Fang, "Generalized predictive control applied in waste heat recovery power plants," *Applied energy*, vol. 102, pp. 320–326, 2013.

[18] J. Zhang, J. Feng, Y. Zhou, F. Fang, and H. Yue, "Linear active disturbance rejection control of waste heat recovery systems with organic rankine cycles," *Energies*, vol. 5, no. 12, pp. 5111–5125, 2012.

[19] G. Hou, S. Bi, M. Lin, J. Zhang, and J. Xu, "Minimum variance control of organic rankine cycle based waste heat recovery," *Energy Conversion and Management*, vol. 86, pp. 576–586, 2014.

[20] E. Wang, H. Zhang, B. Fan, M. Ouyang, Y. Zhao, and Q. Mu, "Study of working fluid selection of organic rankine cycle (orc) for engine waste heat recovery," *Energy*, vol. 36, no. 5, pp. 3406–3418, 2011.

[21] S. Masheiti, B. Agnew, and S. Walker, "An evaluation of r 134 a and r 245 fa as the working fluid in an organic rankine cycle energized from a low temperature geothermal energy source," *Journal of Energy and Power Engineering*, vol. 5, no. 5, pp. 392–402, 2011.

[22] R. Poli, J. Kennedy, and T. Blackwell, "Particle swarm optimization," *Swarm intelligence*, vol. 1, no. 1, pp. 33–57, 2007.

[23] J. Kennedy, "Particle swarm optimization," in *Encyclopedia of Machine Learning*. Springer, 2010, pp. 760–766.

[24] S. Chen, X. Hong, B. L. Luk, and C. J. Harris, "Nonlinear system identification using particle swarm optimisation tuned radial basis function models," *International Journal of Bio-Inspired Computation*, vol. 1, no. 4, pp. 246–258, 2009.

[25] M. Clerc and J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *Evolutionary Computation, IEEE Transactions on*, vol. 6, no. 1, pp. 58–73, 2002.

[26] K. Li, J.-X. Peng, and G. W. Irwin, "A fast nonlinear model identification method," *Automatic Control, IEEE Transactions on*, vol. 50, no. 8, pp. 1211–1216, 2005.

[27] K. Li, J.-X. Peng, and E.-W. Bai, "A two-stage algorithm for identification of nonlinear dynamic systems," *Automatica*, vol. 42, no. 7, pp. 1189–1197, 2006.

[28] J.-X. Peng, K. Li, and G. W. Irwin, "A new jacobian matrix for optimal learning of single-layer neural networks," *Neural Networks, IEEE Transactions on*, vol. 19, no. 1, pp. 119–129, 2008.

[29] B. Doğan and T. Ölmez, "A new metaheuristic for nu-

merical function optimization: Vortex search algorithm," *Information Sciences*, vol. 293, pp. 125–145, 2015.

[30] R. V. Rao, V. J. Savsani, and D. Vakharia, "Teaching–learning-based optimization: a novel method for constrained mechanical design optimization problems," *Computer-Aided Design*, vol. 43, no. 3, pp. 303–315, 2011.

[31] E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: an algorithm for optimization inspired by imperialistic competition," in *Evolutionary computation, 2007. CEC 2007. IEEE Congress on*. IEEE, 2007, pp. 4661–4667.

[32] E. Wan, R. Van Der Merwe *et al.*, "The unscented kalman filter for nonlinear estimation," in *Adaptive Systems for Signal Processing, Communications, and Control Symposium 2000. AS-SPCC. The IEEE 2000*. IEEE, 2000, pp. 153–158.