Modeling of Thermodynamic Properties based on Neurofuzzy System for Steam Power Plant

Hataitep Wongsuwarn

Abstract— **Thermodynamic properties of substance are needed in numerical simulation and controller of industrial process. In this paper, the thermodynamic properties are modeled by usage of Neurofuzzy system (NFs) and subtractive clustering. And, these thermodynamic properties are used to calculated energy properties within the experimental steam power plant. Neurofuzzy models are constructed from each subsystem of thermodynamic properties, such as saturated water or superheat steams. Comparing experimental results of nonlinear Neurofuzzy model with several backpropagation neural networks (BNNs), our NFs modeling is close to thermodynamic properties than neural network. Moreover, the proposed NFs model can be use to suitable for the experimental steam power plant. Thus, our proposed NFs modeling should be applied to any plant based on using for thermodynamic properties.**

Index Terms— **Intelligence System, Neurofuzzy System, Fuzzy logic, Modeling, Steam power plant.**

I. Introduction

Thermodynamic properties of substance are needed in numerical simulation and controller of industrial process. Simulation is used in process and control design, safety analysis, and operator training. Controller needs thermodynamic properties for calculating energy in system. Properties that are often needed are e.g. temperature (T), pressure (P), enthalpy (h), entropy(s), specific volume (v) or internal energy (u) in difference process condition. Fast calculation of these properties is also necessary in measurement of several process variables, needed for process control in distributed system(s) [4, 5].

Conventional Algorithms for the calculation thermodynamic properties typically consist of several iterative steps including calls to complex functions and interpolations in tables based on both theory and experimental data [3,4, 15]. The iterative algorithms are too slow to be used, e.g. in dynamic process simulators that should run faster than real-time. Methods based on tables and linear interpolations are fast, but in practice limited to cases with only two or three changing inputs.

Thermodynamic property equations of water steam involve the solution of complex nonlinear equations. To simplify this complex situation, this paper proposes an alternative approach based Neurofuzzy system (NFs) to determine thermodynamic properties. Intelligence system are widely accepted as a technology offering an alternative way to tackle complex and ill-defined problems [6-9, 13, 16, 17], such as Neural Network (NN), Neurofuzzy (NFs), etc. This method is fault tolerant in the sense that it is able to handle noisy and incomplete data, and able to deal with non-linear problems, and once trained can perform prediction and generalization at high speeds [8]. According to Haykin [6] a neural network may be regarded as massively parallel distributed processor that has a natural propensity for storing knowledge and making it available for use.

The main focus of this work has been to develop empirical equations of specific volume, enthalpy and entropy of Water Steam for both saturated liquid–vapor region and superheated vapor region. This paper shows that property values predicted with NFs can be used to define the thermodynamic properties instead of approximate and complex analytic equations. So, the thermodynamic properties of power plant systems using NFs will be easier than using complex numerical iterative methods. In order to be useful, the method should be applicable to various substances, the accuracy given by the user should be achieved, and the resulting NF model should be fast in the simulation mode and practicable mode.

The paper is organized as follows: Section 2 presents the background about backpropagation neural networks (BNNs) and Neurofuzzy system (NFs). Section 3 presents the NFs model for thermodynamic properties. A section 4 is devoted to experimental investigations and the evaluation of thermodynamic property models from NNs and NFs. This section provides the basis for the selection of different variables used in the model, and the structure of model. Moreover, the results of an experimented in the mini steam power plant was includes here in. The main conclusions of the work are presented in Section 5, with remarks on future directions.

II. Neural Network and Neurofuzzy Approaches for the Time Series Stock Market Prediction

A. Neural Networks (NNs) for Modeling and Identification

The neural networks are used for two main tasks: function approximation and pattern classification. In function approximation, the neural network is trained to approximate a mapping between its inputs and outputs. Many neural network models have been proven as universal approximations, i.e. the network can approximate any continuous arbitrary function

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well. The pattern classification problem can be regarded as a specific case of the function approximation. The mapping is done from the input space to a finite number of output classes.

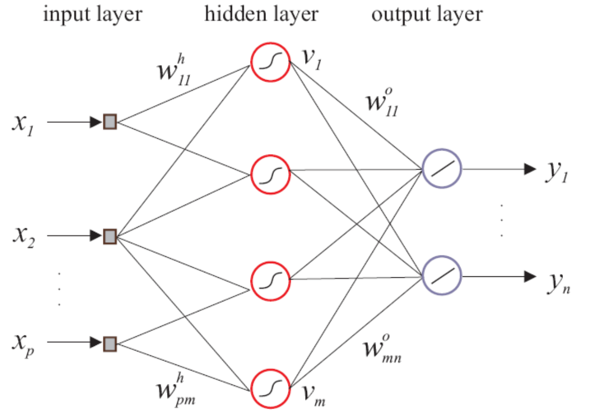

Fig 1 A feedforward neural network with one hidden layer [18]

For function approximation, a well-known model of NNs is a feed forward multi-layer neural network (MNN). It has one input layer, one output layer and a number of hidden layers between them. For illustration purposes, consider a MNN with one hidden layer (Figure 1). The input-layer neurons do not perform any computations. They merely distribute the inputs to the weights of the hidden layer. In the neurons of the hidden layer, first the weighted sum of the inputs is computed

$$z_j = \sum_{i=1}^{p} w_{ij}^h x_i = (W_j^h)^T X_i, \quad j = 1,2,\ldots,m \tag{1}$$

It is then passed through a nonlinear *activation function*, such as the tangent hyperbolic:

$$v_j = \frac{1-\exp(-2z_j)}{1+\exp(-2z_j)}, \quad j = 1,2,\ldots,m \tag{2}$$

Other typical *activation functions* are the threshold function (hard limiter), the sigmoid function, and etc. The neurons in the output layer are linear, i.e., only compute the weighted sum of their inputs's computed:

$$yl = \sum_{j=1}^{h} w_{jl}^o v_j = (W_l^o)^T X, \quad l = 1,2,\ldots,n \tag{3}$$

Training is the adaptation of weights in a multi-layer network such that the error between the desired output and the network output is minimized. A network with one hidden layer is sufficient for most approximation tasks. More layers can give a better fit, but the training time takes longer. Choosing the right number of neurons in the hidden layer is essential for a good result. Too few neurons give a poor fit, while too many neurons result in overtraining of the net (poor generalization of unseen data). A compromise is usually sought by trial and error methods.

The backpropagation algorithm [18] has emerged as one of the most widely used learning procedures for multi-layer networks. There are many variations of the backpropagation algorithm, several of which will be discussed in the next section. The simplest implementation of backpropagation learning updates the network weights and biases in the direction in which the performance function decreases most rapidly.

B. Neurofuzzy System (NFs) for Modeling and Identification

Both neural networks and the fuzzy system imitate human reasoning process. In fuzzy systems, relationships are represented explicitly in forms of if-then rules. In neural networks, the relations are not explicitly given, but are coded in designed networks and parameters. Neurofuzzy systems combine the semantic transparency of rule-based fuzzy systems with the learning capability of neural networks. Depending on the structure of if-then rules, two main types of fuzzy models are distinguished as mamdani (or linguistic) and takagi-sugeno models [17]. The mamdani model is typically used in knowledge-based (expert) systems, while the takagi-sugeno model is used in data-driven systems

In this paper, we consider only the Takagi - Sugeno-Kang (TSK) model. Takagi, Sugeno and Kang [17] formalized a systematic approach for generating fuzzy rules from an input-output data pairs. The fuzzy if-then rules, for the pure fuzzy inference system, are of the following form:

$$if\ x_1\ is\ A_1\ and\ x_2\ is\ A_2\ and\ x_N\ is\ A_N\ then\ y = f(x) \tag{4}$$

Where $x = [x_1, x_2, ..., x_N]^T, A_1, A_2, \ldots, A_N$ fuzzy sets are in the antecedent, while y is a crisp function in the consequent part. The function is a polynomial function of input variables $x_1, x_2, x_3, \ldots, x_N$. The aggregated values of the membership function for the vector are assumed either in a form of the MIN operator or in the product form. The M fuzzy rules in the form Eq. (4) are N membership functions $\mu_1, \mu_2, \mu_3, \ldots, \mu_N$. Each antecedent is followed by the consequent:

$$y_i = p_{i0} + \sum_{j=1}^{N} p_{ij} x_j \tag{5}$$

Where p_{ij} are the adjustable coefficients, for $i = 1,2,3,\ldots,M$ and $j = 1,2,3,\ldots,N$.

The first-order TSK fuzzy model could be expressed in a similar fashion. Consider an example with two rules:

$$if\ x_1\ is\ A_{11}\ and\ x_2\ is\ A_{21}\ and\ then\ y_1 = p_{11}x_1 + p_{12}x_2 + p_{10}$$

$$if\ x_1\ is\ A_{12}\ and\ x_2\ is\ A_{22}\ and\ then\ y_2 = p_{21}x_1 + p_{22}x_2 + p_{20}$$

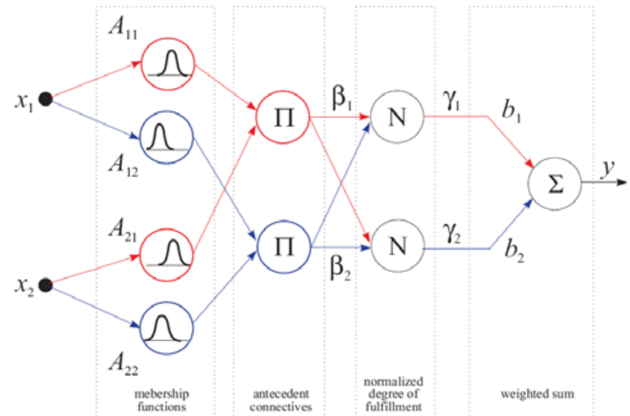

Fig.2 An example of a first-order TSK fuzzy model with two rules systems [1]

Figure 2 shows a network representation of those two rules. The node in the first layer computes the membership degree of the inputs in the antecedent fuzzy sets. The product node $\prod$ in the second layer represent the antecedent connective (here the "and" operator). The normalization node N and the summation node $\sum$ realize the fuzzy-mean operator. for which the corresponding network is given in Figure 2 Applying fuzzy singleton, a generalized bell function such as membership function and algebraic product aggregation of input variables, at the existence of M rules the neurofuzzy TSK system output signal upon excitation by the vector, are described by

$$y(x) = \frac{1}{\sum_{r=1}^{M}[\prod_{j=1}^{N} \mu_r(x_j)]} \times \sum_{k=1}^{M}\left(\left[\prod_{j=1}^{N} \mu_r(x_j)\right]\left[p_{k0} + \sum_{j=1}^{N} p_{kj} x_j\right]\right) \quad (6)$$

The adjusted parameters of the system are nonlinear parameters of bell function ($c_j^{(k)}, \sigma_j^{(k)}, b_j^{(k)}$), the fuzzifier functions and linear parameters (weight) of the TSK function for every $j = 1,2,\ldots,N$ and $k = 1,2,\ldots,M$. In contrast to the mamdani fuzzy inference system, the TSK model generates a crisp output values instead of fuzzy ones. This network is simplified. Thus, the defuzzifier is not necessary. So, the learning of Neurofuzzy network, which adapts parameters of the bell shape membership functions ($c_j^{(k)}, \sigma_j^{(k)}, b_j^{(k)}$) and consequent coefficients, p_{ij} can be done either in supervised or self-organizing modes. In this study, we apply a hybrid method which is one-shot least-squares estimation of consequent parameters with iterative gradient-based optimization of membership functions. The important problem in the TSK network is to determine the number of rules that should be used in modeling data. More rules mean better representation of data processing, but increased of complexity of the network and a high cost of data processing. Therefore, the procedure for automatically determining number of rules is required. In our solution, each rule should be associated with one cluster of data. Fuzzy c-means is a supervised algorithm, because it is necessary to indicate how many clusters C to looks for. If C is not known beforehand, it is necessary to apply an unsupervised algorithm. Subtractive clustering is based on a measure of the density of data points in the feature space [1]. The idea is to find regions in the feature space with high densities of data points. The point with the highest number of neighbors is selected as centre for a cluster. The data points within a prespecified, fuzzy radius are then removed (subtracted), and the algorithm looks for a new point having the highest number of neighbors. This process continues until all data points are examined.

In conclusion, Figure 3 summarizes the Neurofuzzy Networks System (NFs). Construction process data called "training data sets" can be used to construct Neurofuzzy systems. We do not need prior knowledge ala "knowledge-based (expert) systems". In this way, the membership functions of input variables are designed by the subtractive clustering method. Fuzzy rules (including the associated parameters) are constructed from scratch by using numerical data. And the parameters of this model (the membership functions, consequent parameters) are then fine-tuned by process data.

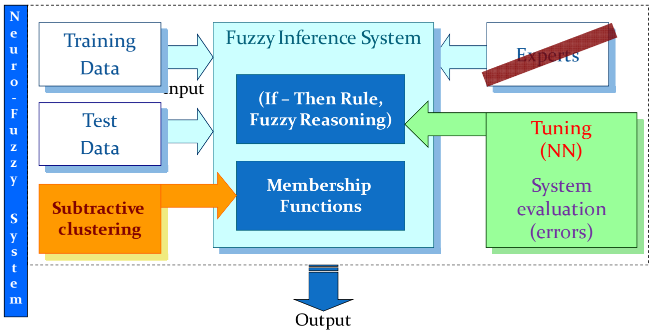

Fig. 3 Constructing Neurofuzzy Networks

The advantage of the TSK fuzzy system is to provide a compact system. Therefore, some classical system identification methods, such as parameter estimation and order determination algorithms, could be developed to get the fuzzy inference rules by using input/output data. Similar to neural networks, Neurofuzzy systems are universal approximators. Therefore, the TSK fuzzy inference systems are general for many complex nonlinear practical problems, such as time series data.

III. Methodology for the Modeling of Thermodynamic Properties

A. *Thermodynamic Properties*

The thermodynamic properties typically change drastically near the phase boundaries of the materials. Thus different model structures are optimal in different parts of the input space. Division of the input space into sub-region specific functional transformations are the initial step in the modelling. The values of thermodynamic properties may also differ considerably in different parts of input space when only a single phase is considerate. In spite of the function approximation method used, it is very difficult to achieve an accurate approximation for small output values without a proper transformation.

STEAM TABLES
Saturated Water - Temperature Table

Temp. °C T	Sat. Press. kPa p_{sat}	Specific Volume m^3/kg		Internal Energy kJ/kg			Enthalpy kJ/kg	
		Sat. liquid v_f	Sat. vapor v_g	Sat. liquid u_f	Evap. u_{fg}	Sat. vapor u_g	Sat. liquid h_f	Evap. h_{fg}
0.01	0.6113	0.001 000	206.14	0.00	2375.3	2375.3	0.01	2501.3
5	0.8721	0.001 000	147.12	20.97	2361.3	2382.3	20.98	2489.6
10	1.2276	0.001 000	106.38	42.00	2347.2	2389.2	42.01	2477.7
15	1.7051	0.001 001	77.93	62.99	2333.1	2396.1	62.99	2465.9
20	**2.339**	**0.001 002**	**57.79**	**83.95**	**2319.0**	**2402.9**	**83.96**	**2454.1**
25	3.169	0.001 003	43.36	104.88	2304.9	2409.8	104.89	2442.3
30	4.246	0.001 004	32.89	125.78	2290.8	2416.6	125.79	2430.5
35	5.628	0.001 006	25.22	146.67	2276.7	2423.4	146.68	2418.6
40	7.384	0.001 008	19.52	167.56	2262.6	2430.1	167.57	2406.7
45	**9.593**	**0.001 010**	**15.26**	**188.44**	**2248.4**	**2436.8**	**188.45**	**2394.8**
50	12.349	0.001 012	12.03	209.32	2234.2	2443.5	209.33	2382.7
55	15.758	0.001 015	9.568	230.21	2219.9	2450.1	230.23	2370.7
60	19.940	0.001 017	7.671	251.11	2205.5	2456.6	251.13	2358.5
65	25.03	0.001 020	6.197	272.02	2191.1	2463.1	272.06	2346.2
70	**31.19**	**0.001 023**	**5.042**	**292.95**	**2176.6**	**2569.6**	**292.98**	**2333.8**
75	38.58	0.001 026	4.131	313.90	2162.0	2475.9	313.93	2321.4
80	47.39	0.001 029	3.407	334.86	2147.4	2482.2	334.91	2308.8
85	57.83	0.001 033	2.828	355.84	2132.6	2488.4	355.90	2296.0

Fig. 4 thermodynamic properties of saturated steam water

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Normally, thermodynamic properties of steam water is separate in 3 category such as saturated steam water, compressed steam water and superheated steam water, respectively. Figure 4 is shown example of saturated steam water. And, Figure 5 is shown example of superheat steam water.

Superheated Water Tables					
T Temp. °C	v m³/kg	u kJ/kg	h kJ/kg	s kJ/(kg·K)	v m³/kg
	$p = 0.01$ MPa (45.81°C)				
Sat.	14.674	2437.9	2584.7	8.1502	3.240
50	14.869	2443.9	2592.6	8.1749	
100	17.196	2515.5	2687.5	8.4479	3.418
150	19.512	2587.9	2783.0	8.6882	3.889
200	**21.825**	**2661.3**	**2879.5**	**8.9038**	**4.356**
250	24.136	2736.0	2977.3	9.1002	4.820
300	26.445	2812.1	3076.5	9.2813	5.284
400	31.063	2968.9	3279.6	9.6077	6.209
500	35.679	3132.3	3489.1	9.8978	7.134
600	**40.295**	**3302.5**	**3705.4**	**10.1608**	**8.057**
700	44.911	3479.6	3928.7	10.4028	8.981
800	49.526	3663.8	4159.0	10.6281	9.904
900	54.141	3855.0	4396.4	10.8396	10.828
1000	58.757	4053.0	4640.6	11.0393	11.751
1100	**63.372**	**4257.5**	**4891.2**	**11.2287**	**12.674**
1200	67.987	4467.9	5147.8	11.4091	13.597

Fig. 5 thermodynamic properties of superheat steam water

B. The proposed NFs system for Thermodynamic Properties modeling

In this paper, a new method for the modeling of thermodynamic properties is described. The method based on NFs and it is applied to the description of temperature (T), Saturated Vapor pressure (Psat), specific volume of Saturated liquid (vf), specific volume of Saturated vapor (vg), Internal energy of Saturated liquid (uf), Internal energy of Saturated vapor (ug), Enthalpy of Saturated liquid (hf), Enthalpy of Saturated vapor (hg), Entropy of Saturated liquid (sf), Entropy of Saturated vapor (sg), see in Figure 1. Inputs for the network are Temperature (T) and Pressure (P) of the water steam; output is status and remaining quality such as v, u, h and s, see in Figure 6. Status is separate in 5 types, such as compressed fluid, saturated liquid, mixture, saturated vapor and superheat. Similarly, for the superheated vapor region, inputs are the temperature (T) and pressure (P) while outputs

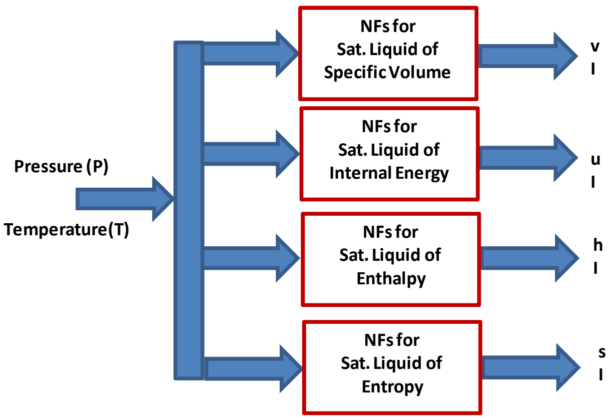

Fig. 6 The scenario of MFs model for thermodynamic properties of steam water

are the specific volume, enthalpy and entropy as same as saturated water steam. Sample patterns are shown in Figure 4 for saturated steam water cases and Figure 5 for Superheat case. Temperature (and its saturation pressure) range is between 0.01 °C (0.6113 kPa) to 374.14 °C (22.09 MPa) for saturated liquid – vapor region while the pressure range is also between 10 kPa (45.81 °C) and 2.5 MPa (223.99 °C) for superheated vapor region.

In summary, input of NFs is 2 Inputs that are temperature (T) and pressure (P). And, Output of NFs is 2 outputs. Thus, This NFs have 4 subsystems for calculating remain variable, such a specific volume and its status (V, Saturated liquid). NFs model is described in Figure 6.

C. Preprocessing of input and Evaluating Function for the proposed NFs Model

In general, the thermodynamics properties data have bias due to differences in name and spans. Normalization can be used to reduce the range of the data set to values appropriate for inputs to the activation function being used. The normalization and scaling formula is

$$y = \frac{2x - (\max + \min)}{(\max - \min)}, \qquad (7)$$

Where

x is the data before normalizing,

y is the data after normalizing.

Basically, each of thermodynamic properties are not same scale. Thus, Normalization use to individual for any thermodynamic properties, so the same maximum and minimum data are used to normalize them. The max is derived from the maximum value of the any properties, and the same applies to the minimum. The maximum and minimum values are from the training and validation data sets. The outputs of the NFs and NN will be rescaled back to the original value according to the same formula.

There are several kinds of error function used in evaluating of approximating method, namely, Mean absolute Deviation (MAD), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE). In this paper, like a neural network model, we used two error functions for our NFs system; the Percentile Variance Accounted For (VAF) [22] is selected for evaluating the NFs model. The VAF of two equal signals is 100%. If the signals differ, the VAF is lower. When y1 and y2 are matrices, VAF is calculated for each column. The VAF index is often used to assess the quality of a model by comparing the true output and the output of the model. The VAF between two signals is defined as follows:

$$\mathrm{VAF} = 100\% * [1 - \frac{\mathrm{var}(y1 - y2)}{\mathrm{var}(y1)}] \qquad (12)$$

D. Compact Steam Power Plant

From Figure 7, this is compact steam power plant. The unit is designed to simulate modern steam power plant. Main components consist of a feed water system, a boiler, a steam turbine, a generator and lamp load, a condenser with a condensate tank and a pump, and a cooling tower. Accessories such as fuel tank, fuel flow meter, feed water meter, and a stack are also included. Instruments are provided for measurement of pressures, temperatures, output voltage and currents. The capacity of boiler is Approximately 63 kW (53,900 kcal/h) and rated of evaporation is 100 kg/hr. And,

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Steam Turbine generates power within 0.5 kW for 5 kg/cm^2 saturated steam at 80 kg/hr. Figure 8 shown the front panel of a monitoring and controlling system. This front panel is shown enthalpy of subsystem of power plant, such as at boiler, turbine, condenser and cooling tower. Any enthalpy is calculated by NFs system. Input of NFs is temperature and pressure at measuring location.

Fig. 7 Typical Thermodynamic Process Diagram of the Training Boiler

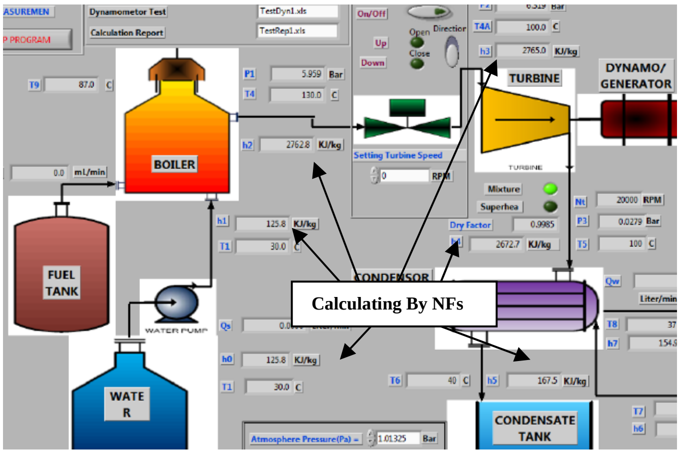

Fig. 8 Front panel of monitoring and controlling system

IV. Results and Discussions

The model realization could be run having 8 subsystems. Each subsystem has same two inputs. But, they are difference on one output such as specific volume of Saturated liquid (vf), specific volume of Saturated vapour (vg), Internal energy of Saturated liquid (uf), Internal energy of Saturated vapour (ug), Enthalpy of Saturated liquid (hf), Enthalpy of Saturated vapour (hg), Entropy of Saturated liquid (sf), Entropy of Saturated vapour (sg), respectively.

All the experimental investigations were run according to the above presented scenario and were focused on the accuracy within 99% VAF for training sets and 90% VAF for testing sets. At the beginning of each realization, the data set, including both saturated water steam, compressed liquid water and superheat water steam phase. Totally data set is 620 data sets. The training sets are 90% of totally data sets (558 data sets) and testing is 10% of totally data sets (62 data sets). Both of data sets were generating with random method.

We now compare the performance of our proposed neurofuzzy system to feedforward Neural Network Modeling including three types of learning algorithm methods. Their learning method are Batch Gradient Descent (TRAINGD), Scaled Conjugate Gradient (TRAINSCG) and Levenberg – Marquardt (TRAINLM) methods The neural network model has one hidden layer with 20 nodes. And, learning iteration is 10000 epochs. After trained their learning method, we found scaled conjugate better than other learning method. But, we can conclude that our proposed neurofuzzy demonstrated a considerably better four relation types than neural network with scaled conjugate gradient learning. The corresponding Percentile Variance Accounted For (VAF) are given in section III.C.

Table1 Input and output variables in thermodynamic properties model

Input	
T	Temperature
P	Pressure
Output	
v	Specific volume
u	Internal Energy
h	Enthalpy
s	Entropy
I	Status

Table2 Thermodynamic properties model based on NN and NFs

Model No.	Name	Training Algorithm	Input	Output	Elaph Time (s)	VAF Training Sets	VAF Test Set
1	NN_V	TRAINLM	T P	v I	500	99.43	90.01
		TRAINGD	T P	v I	235	99.01	91.12
		TRAINSCG	T P	v I	345	99.23	90.15
	NFs_V	Subtrative	T P	v I	100	99.77	95.45
2	NN_U	TRAINLM	T P	v I	445	99.78	89.91
		TRAINGD	T P	v I	254	99.55	90.11
		TRAINSCG	T P	v I	333	99.23	92.23
	NFs_U	Subtrative	T P	v I	90	99.85	98.23
3	NN_H	TRAINLM	T P	v I	345	99.23	90.01
		TRAINGD	T P	v I	123	99.31	90.01
		TRAINSCG	T P	v I	321	99.45	90.01
	NFs_H	Subtrative	T P	v I	120	99.88	99.31
4	NN_S	TRAINLM	T P	v I	235	99.11	93.22
		TRAINGD	T P	v I	355	99.56	92.32
		TRAINSCG	T P	v I	213	99.78	90.12
	NFs_S	Subtrative	T P	v I	80	99.55	95.56

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The comparisons of different models such as BPN and the TSK fuzzy rule model are listed in Table 2. As we can observe here, the modeled results from TSK fuzzy rule model are much better than those from BPN or multiple regressions which justify the TSK fuzzy rule model is the best. The all results exhibit that Backpropagation Neural Networks (BNNs) and Neurofuzzy System (NFs) can be model several thermodynamic properties satisfactory as a new method instead of approximate and complex analytic equation.

V. Conclusion

A novel method for the modeling of thermodynamics properties of material and mixture material such as water steam was developed. The method was applied to the mixture of vapor and water called water steam. The desired outputs are accuracy within 99% VAF for training sets and 90% VAF for testing sets, respectively. From experimental results, our proposed model is achieved in every testing data. Both of intelligence systems, which are BNNs and NFs, were successful in the training and testing data. But, NFs always was accuracy than BNNs. Moreover, NFs model was proved to be faster and accuracy than BNN and the conventional iterative algorithm used for generation of the training and testing data sets. An advantage in using the NFs model is applied to calculating Enthalpy of boiler, turbine, condenser and cooling tower in real compact power plant. With Real-time Enthalpy, the software was monitoring, controlling and calculating efficiency of the experimental mini steam power plant.

The developed procedure can probably adapt for the description of thermodynamic and other material properties of several substances. By using the NFs, the approximations previously requiring several iterations for solving complicated function is reduced to a single function call.

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References

[1] Babuska, A. R., (2002) 'Neuro-fuzzy methods for modeling and identification', Recent Advances in intelligent Paradigms and Application, pp. 161–186.

[2] A. Chouai, S. Laugier and D. Richon, (2002) 'Modeling of thermodynamic properties using neural networks Apllication to refrigerant', *Fluid Phase Equillibria*, Vol. 199, pp. 53-62.

[3] A. Lapedes and R. Farber, (1987) 'Nonlinear signal processing using neural networks', *IEEE Conference on Neural Information Processing System -- Natural and Synthetic*, pp. 101 – 107.

[4] R. Liija and K. Juslin, (1987) 'Fast calculation of material properties applied to water and steam", *Technical Research Center of Finland*, VTT Research Note 807.

[5] K. C. Lin and B. Zhang, (1997) 'Function generation in real-time simulation', *Simulation*, Vol. 68:3, pp. 157-163.

[6] S. Haykin, (1994) '*Neural Networks: A Comprehensive Foundation'*, Macmillan,New York.

[7] J.-S.R. Jang, C.T. Sun, E. Mizutani, (1997) *'Neuro-fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence',* Spring.

[8] S.A. Kalogirou, S. Panteliou, A. Dentsoras, (1999) 'Modeling of solar domestic water heating systems using artificial neural networks', *Solar Energy*, Vol. 65, pp. 335–342.

[9] S.A. Kalogirou, (2003) 'Artificial intelligence for the modeling and control of combustion processes: a review', *Progress in Energy and Combustion Science*, Vol. 29, pp. 515–566.

[10] R. Lilja and J. Hamalainen,(1999) 'Modeling of Thermodynamic Properties of Substances by Neural Network, Int. Joint Conf. on Neural Networks (IJCNN'99), pp. 3927-3932.

[11] A. Moghadassi, F. Parvizian and S. Hosseini,(2009) 'A New Approach Based on Artificial Neural Networks for Prediction of High Pressure Vapor-liquid Equilibrium', *Australian Journal of Basic and Applied Sciences*, Vol. 3(3), pp. 1851 – 1862.

[12] M. Mohammadzaher, A. Mirsepahi, O. Asef-afshar and H. Koohi, (2007) 'Neuro-Fuzzy Modeling od Superheating System of a Steam Power Plant', *Applied Mathematical Sciences*, Vol. 1., no. 42, pp. 2091-2099.

[13] A. Palau, E. Velo, L. Puigjaner, (1999) 'Use of neural networks and expert systems to control a gas/solid sorption chilling machine', *International Journal of Refrigeration*, Vol. 22, pp. 59–66.

[14] D. E. Rumelhart and J. L. McClelland, (1986) 'Parallel distributed processing', *Explorations in the micro-structure of cognition*, Vol. 1, The MIT Press, pp. 318-362.

[15] E. Schmidt, (1982) 'Properties of water and steam in SI-Units', 3th edition, Springer-Verlag, Berlin.

[16] R. Sharma, D. Singhal, R. Ghosh, A. Dwivedi, (1999) 'Potential applications of artificial neural networks to thermodynamics: vapor–liquid equilibrium predictions', *Computers and Chemical Engineering*, Vol. 23, pp. 385–390.

[17] T. Takagi, and M. Sugeno, (1985) 'Fuzzy identification of systems and its application to modeling and control', *IEEE Transactions on. SMC*, Vol. 5, pp. 116-132.

[18] Trippi, R. and Lee, K. (1996) 'Artificial Intelligence in Finance & Investing', Chicago, IL,Irwin.