2018

A Review of Electronic Expansion Valve Correlations for Air-conditioning and Heat Pump Systems

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Review of Electronic Expansion Valve Correlations for Heat Pump and Air Conditioning Systems

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ABSTRACT

Split-type air-conditioning systems with multiple indoor units and variable capacity feature, also known as variable refrigerant flow systems (VRF), are growing in both residential and commercial buildings for its flexibility in configurations and high energy efficiency through zoning control and variable capacity control. The VRF system controls its capacity by the combination of drive frequency of variable speed compressor and opening of electronic expansion valves (EEV). According to fluid dynamics analysis, the mass flow rate is a function of the EEV opening. Therefore, the accurate correlation of mass flow rate through an EEV is important in accurate prediction of the mass flow rate in the VRF systems and design the control system. The simulation and experiment studies are reviewed in this paper. Literature study shows that the most commonly used approach is power-law correlation which is recommended by ASHRAE. The relative deviation of the predicted mass flow of this method is around 5% to 40% depending on the refrigerants used. Different refrigerants including R22, R245a, R134a, R410A, R407C and R744 have been studied since 2005. Second type is polynomial fit correlation developed in 2013, which is a simplified model and has a relative deviation of 5% for 98% of the data. Third type is using Artificial Neural Network (ANN) algorithm, which has a relative deviation from 1% to 4% and has been used since 2015. In addition, a dynamic model of EEV has been developed since 2016. In conclusion, power-law correlation is the most popular method with a relatively high precision. Polynomial fit correlation is convenient to use but has a lower precision. ANN curve fitting which has a very high precision is a novel approach to be utilized in EEV correlation. However, only a few researches concentrate on this method. Therefore, more research about ANN is needed.

Keyword: EEV, air conditioning, correlation

1. INTRODUCTION

Split-type air-conditioning systems with multiple indoor units and variable capacity feature, also known as variable refrigerant flow systems (VRF), are growing in both residential and commercial buildings for its flexibility in configurations and high energy efficiency through zoning control and variable capacity control. A variable flow rate is used in the VRF system, which is able to control the refrigerant supplied to the IU (Indoor Unit) depending on the demand of the heating or cooling capacity of each individual area (Park et al., 2017). This function is commonly achieved by controlling the drive frequency of variable speed compressor and opening of electronic expansion valves (EEV). EEV is a device that controls the flow rate of refrigerant entering a direct expansion evaporator. One advantage of the EEV is that it responses faster than TEV (Thermostatic Expansion Valve) and capillary tube (Aprea and Mastrullo, 2002).

Figure 1 shows the normal structure of the EEV (Zhifang et al., 2008). The position of the needle valve is controlled by a stepping monitor. The step, also called opening degree or pulse number, can be read from the monitor directly. The function of the EEV to control the refrigerant flow is realized by changing the position of the needle valve. Eq. (1) which is derived from Bernoulli Equation has been widely used to describe the characteristics of the EEV (Wile, 1935) for single-phase flow model.

$$q = CA\sqrt{2\rho_i\left(p_i - p_o\right)} \tag{1}$$

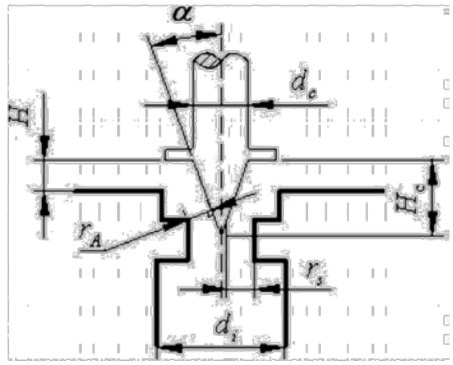

Figure 1: Geometrical structure of EEV (Zhifang et al., 2008)

The parameters (ρ_i, p_i and p_o) are the inlet density of the refrigerant, the inlet pressure and outlet pressure, respectively. The flow coefficient C can be affected by many factors, such as the pressure, geometry of the EEV and the physical properties of the refrigerant. The flow area A can be shown by Eq. (2).

$$A = \frac{\pi d_c^2}{4} - \pi\left(H_c - H\right)^2 \tan^2 \alpha = \frac{\pi D^2}{4} \tag{2}$$

The parameters d_c, H_c, H and α are the geometric parameters shown in Figure 1. D is called as orifice diameter in some literature (Zhifang et al., 2008), which is used to describe the flow area. According to fluid dynamics analysis, the mass flow rate is a function of the EEV opening. Therefore, an accurate correlation of mass flow rate through an EEV is important in predicting of the mass flow rate in the VRF systems and designing the control logic.

From 1990 to 2017 the topic of EEV has come into the focus of study. For this period, totally 236 publications were listed on Reuters Web of Science shown in Figure 2. Total 25 papers concentrated on studying the characteristics of the flow through the EEV and the correlation of the model. Three methods, which are power-law correlation method, polynomial fit correlation method and Artificial Neural Network (ANN) correlation method, were utilized to build empirical model based on simulation, experiment or both.

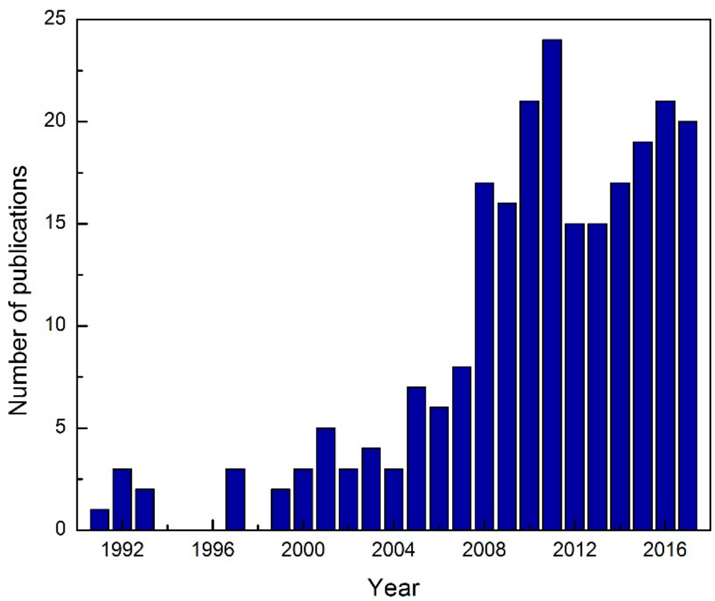

Figure 2: Number of publications appearing on Reuters Web of Science querying for "electronic expansion valve" (12/6/2017)

2. POWER-LAW CORRELATION

The power-law correlation method is the most popular way for the EEV correlation (Chen et al., 2009; Chen et al., 2017; Hou et al., 2014; Kim et al., 2010; Liang et al., 2009; Liu et al., 2016; C. Park et al., 2007; Shanwei et al., 2005; Ye et al., 2007; Zhang et al., 2006; Zhifang et al., 2008). This method is also recommended by ASHRAE (Kavanaugh and Simplified, 2006). The core of this method is to develop a power-law correlation formula of the mass flow coefficient C by several dimensionless π groups as shown in Eq. (3).

$$C = a_0 \prod_{i=1}^{n} \pi_i^{a_i} \tag{3}$$

where a_i $(i=0, 1, \ldots, n)$ are constants. The Table 1 shows some commonly used dimensionless π groups from existing literature.

Table 1: Dimensionless pi groups used from publications

Authors	Chen et al. (2009, 2017)	Tian et al. (2015)	Park et al. (2007)	Ye et al. (2007)	Zhifang et al. (2007)	Zhang et al. (2006)
π_1	$\frac{p_i}{p_c}$	$\frac{p_i - p_o}{p_c}$	$\frac{p_i - p_{sat}}{p_c}$	$\frac{p_i - p_{sat}}{p_c}$	$\frac{(p_i - p_o)\sqrt{A}}{\sigma}$	$\frac{p_i}{p_c}$
π_2	$\frac{T_{sub}}{T_c}$	$\frac{T_{sub}}{T_c}$	$\frac{T_{sub}}{T_c}$	$\frac{T_{sub}}{T_c}$	$\frac{\mu_f}{D_e\sqrt{\rho_i p_i}}$	$\frac{T_{sub}}{T_c}$
π_3	$\frac{C_{p_i} T_c \rho_i}{p_i}$	$\frac{\rho_i}{\rho_o}$	$\frac{\rho_i}{\rho_o}$	$\frac{C_{p_i} T_c \rho_i}{p_c}$		$\frac{p_o}{p_c}$
π_4	$\frac{\mu_f}{D_{eq}\sqrt{\rho_i p_c}}$	$\frac{D_e\sqrt{p_c \rho_i}}{\mu_i}$	$\frac{H}{D}$	$\frac{\mu_f}{\sqrt{\rho_i p_c A}}$		$\frac{\mu_f}{\rho_i p_c D_e^2}$
π_5	$\frac{D_{eq}}{D}$	$\frac{D_{eq}}{D}$	$\frac{D_{eq}}{D}$	$\frac{\alpha}{\pi}$		$\frac{p_{sat}}{p_c}$
π_6	$\frac{p_{th}}{p_c}$	$\frac{D_e p_i}{\sigma}$	$\frac{D_e p_i}{\sigma}$	$\frac{\sigma}{p_c\sqrt{A}}$		$\frac{D_e p_i}{\sigma}$
π_7		$\frac{c_{p_i} T_c}{h_i}$				$\frac{p_i - p_o}{p_c}$
π_8		x				x

The performance of this method varies depending on the authors and the refrigerants. The correlations were usually assessed by RD (Relative Deviation) as defined in Eq. (4). Table 2 shows the RD of the authors' models.

$$RD = \frac{q_{pre} - q_{\exp}}{q_{\exp}} \tag{4}$$

One drawback of this method is that all the dimensionless correlations for the model is based on Buckingham π theorem (Sonin, 2001), but no study shows that the relationship should obey power-law. Some research (Chen et al., 2017) also stated that the result was from Choi's work (Choi et al., 2004). Nevertheless, Choi's paper is for short tube orifices and no study proves that this work can be used in the EEV correlation case.

Table 2: Relative Deviation of mass flow rate predicted

Authors	Chen et al. (2009, 2017)	Tian et al. (2015)	Park et al. (2007)	Ye et al. (2007)	Zhifang et al. (2007)	Zhang et al. (2006)
R22	[-5.8%, 6.2%]		[-14.5%, 14.2%]			[-10.7%, 9.3%]
R407C	[-6.8%, 9.8%]			[-9.7%, 8.7%]		[-14.2%, 22.1%]
R410A	[-6.1%, 8.5%]		[-4.2%, 11.4%]			
R134a		[-17.2%, 40.3%]			[-6.8%, 6.8%]	
R245fa	[-15%, 15%]					

3. POLYNOMIAL FIT CORRELATION

This method was developed by Li (2013) as a simplified model based on the power-law correlation of EEV. According to his study, the coefficient *C* was mainly affected by the degree of subcooling and valve opening. Therefore, he gave out a simplified correlation for the mass flow correlation:

$$C = a_0 + a_1 x + a_2 x^2 + a_3 x\left(\frac{T_{sub}}{T_c}\right) + a_4\left(\frac{T_{sub}}{T_c}\right) + a_5\left(\frac{T_{sub}}{T_c}\right)^2 \quad (5)$$

The criteria he used to evaluate the result are RE (Relative Error) and RMS (Root Mean Square):

$$RE = \frac{C_{pre} - C_{\exp}}{C_{\exp}} \quad (6)$$

$$RMS = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(RE\right)^2} \quad (7)$$

This model is able to yield prediction with RE of 5% for 98% data and RMS of 2% to 3% depending on the conditions.

4. ARTIFICIAL NEURAL NETWORK CORRELATION

The Artificial Neural Network (ANN) is a method which is commonly utilized to develop unknown relations between several input and output parameters (Warren and Walter, 1943). The ANN structure is consist of an input layer, several hidden layers (always one or two in practice), and an output layer. The input neurons can include as many parameters as possible. Nevertheless, in order to reduce the time of training, only limited number of inputs are used. The input values (X_i) and output values (Y_k) are always normalized (x_i and y_k) by Eq. (8) and Eq. (9) to ensure the equivalence between the variables (Tian et al., 2015).

$$x_i = 2\left(\frac{X_i - X_{i.\min}}{X_{i,\max} - X_{i.\min}}\right) - 1 \quad (8)$$

$$y_k = 2\left(\frac{Y_k - Y_{k.\min}}{Y_{k,\max} - Y_{k.\min}}\right) - 1 \quad (9)$$

If there's only one hidden layer, the process of the ANN can be given by Eq. (10).

$$y_k = g_{output}\left\{\sum_{j=1}^{n} w'_{jk} \times \left[g_{hidden}\left(\sum_{i=1}^{m} w_{ij} x_i + b_j\right)\right] + b'_k\right\} \quad (10)$$

The normalized input parameter x_i is multiplied by the weight factor w_{ij} and added by the bias b_j to get a new value x'. The value x' can be used to get the value $g_{hidden}(x')$ for each hidden neuron by the hidden layer transfer function g_{hidden}, which is called transfer function. Similarly, the value of the hidden layer can also be multiplied by another group of weight factor w'_{jk}, summed up with another group of bias b'_k and transferred by the output transfer function g_{output} to get the kth output parameter. Researchers always use the linear function as the output transfer function. The next step of the ANN is training process, which is repeated to obtain the optimized groups of the weight factor w_{ij}, w'_{jk} and bias b_j, b'_k for each neuron with minimized deviation between the predicted data and the original data (e.g. measured data). BP (Back Propagation) is a popular method for training process.

The ANN has been used in various engineering fields due to its ability to solve physical problem in engineering applications without explicit mathematical equations (Tian et al., 2015). In the field of VRF system design, the ANN also works. For example, the ANN was used to determine the energy-efficient operation set-points of the VRF cooling system (Chung et al., 2017). As for EEV correlation, the ANN is a reasonable method due to the complexity of the fluid dynamic process and a large number of factors involved. Two research paper about using the ANN for EEV correlation have been published since 2015 (Cao et al., 2016; Tian et al., 2015).

Cao's group used Levenberg-Marquardt BP algorithm (trainlm) in MATLAB 2011b as the tool for the ANN training. There was one hidden layer. They used four input parameters which are the input pressure of the EEV, the output pressure of the EEV, the inlet subcooling temperature of the EEV and the opening degree of the EEV. They chose the most popular Tan-sigmoid function (Eq. (11)) and the n^{th}-order polynomial function (Eq. (12)) which had been found quite accurate by some researchers as the hidden layer transfer functions.

$$g_{hidden}(x) = \frac{2}{1+e^{-2x}} - 1 \tag{11}$$

$$g_{hidden}(x) = x^n \tag{12}$$

Tian's group also used Levenberg Marquardt BP algorithm (trainlm) as the gradient-based training algorithms. The transfer function of the hidden layer they chose was the Tan-sigmoid function and Log-sigmoid function (Eq. (13)).

$$g_{hidden}(x) = \frac{1}{1+e^{-x}} \tag{13}$$

Based on literature review work, they used eight non-dimensional parameters as the input parameters, as shown in Table 3.

Table 3: Dimensionless input parameters (Tian et al., 2015)

π_2	$(p_{in} - p_{out}) / p_c$
π_3	t_{sub} / t_c
π_4	ρ_{in} / ρ_{out}
π_5	$d_e \sqrt{p_c \rho_{in}} / \mu_{in}$
π_6	$d_e p_{in} / \sigma$
π_7	$c_{pin} t_c / h_{in}$
π_8	d_e / d
π_9	x

The dimensionless output is given by Eq. (14).

$$y = \pi_1 = \frac{q}{\left(d_c^2 \sqrt{\rho_i (p_i - p_o)}\right)} \tag{14}$$

Tian also did the parameter study work, in which 1 parameter was removed each time and the ANN model was training with the remaining 7 parameters. As the result they found that π_6 was the most significant factor for the ANN sensitivity and accuracy because of the surface tension, which represented metastable flow.

The ANN performance could be evaluated by several statistical coefficients. Though the two groups of authors used different name, but they used the similar standard for assessment. MRE (mean relative error by Tian, also called A.D. the average deviation by Cao) was given by Eq. (15). The correlation of Tian's group gave MRE of 4% and that of Cao's group gave 1%.

$$MRE = A.D. = \frac{1}{n}\sum_{i=1}^{n}\frac{y_{pre} - y_{\exp}}{y_{\exp}} \tag{15}$$

Furthermore, Tian also used RMSE (Root Mean Square Error) which was given by Eq. (16) for evaluation. According to their study, the ANN model showed the RMSE of 7.59 $kg \cdot h^{-1}$. In addition, Cao used another parameter, S.D. (Standard Deviation, Eq. (17)) which was 2.7% from their work to assess the performance.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_{pre} - y_{\exp}\right)^2} \tag{16}$$

$$S.D. = \sqrt{\frac{1}{N-1}\sum_{i=1}^{n}\left(\frac{y_{pre} - y_{\exp}}{y_{\exp}} - A.D.\right)^2} \tag{17}$$

Only limited study concentrated on the utilization work of the ANN for EEV correlation. Thus, various problems exist and more work needs to be done in this filed. First of all, the criteria and the procedure varied, so a clear conclusion can't be made based on the current publications. Specifically, though parameter and transfer function study are mentioned, the question which combination of the transfer function and the inputs had the best performance has not been answered yet. Secondly, these scholars all used BP algorithm for data training, while other algorithm was not either mentioned or compared. Thirdly, the compressor of their system only worked at constant speed. Nowadays, the compressor with variable frequency has been used widely. Thus, the frequency of the compressor should also be considered at the input layer.

5. DISSCUSIONS

According to the literature review work above, the three type correlations have advantages and disadvantages, which are shown in Table 4. The polynomial correlation is convenient to use due to the simplified formula. Nevertheless, its accuracy is the lowest one among the three methods, which has a relative deviation of 5% for 98% of the data. ANN correlation is complicated to use because a training process is necessary. However, it has a relative deviation from 1% to 4%, which is rather accurate. Power-law correlation is the most popular method and has been studied by a great number of researchers. Its performance (complexity and accuracy) intermediates between the polynomial correlation and ANN correlation.

Table 4: Comparison of three type correlations

	Complexity	Accuracy	Usage Frequency
Power-law Correlation	Medium	Medium	Widely Used
Polynomial Correlation	Low	Low	Seldom Used
ANN Correlation	High	High	Seldom Used

6. CONCLUSIONS

The simulation and experiment studies of EEV models are reviewed in this paper. Literature study shows that the most commonly used approach is power-law correlation which is recommended by ASHRAE. The relative deviation of the predicted mass flow of this method is around 5% to 40% depending on the refrigerants and the π groups. Different refrigerants including R22, R245a, R134a, R410A, R407C and R744 have been studied since 2005. Second type is polynomial fit correlation which is a simplified model and has a relative deviation of 5% for 98% of the data and developed in 2013. Third type is using ANN algorithm, which has a relative deviation from 1% to 4% and has been used since 2015. In addition, a dynamic model of EEV has been developed since 2016. Power-law correlation is the most popular method with a relatively high precision. Polynomial fit correlation is convenient to use but has a lower precision. ANN curve fitting which has a very high precision is a novel approach to be utilized in EEV correlation. However, only a few researches concentrate on this method. Therefore, more research about ANN is needed.

NOMENCLATURE

A	flow area [m^2]
a	constant
A.D.	average deviation
ANN	artificial neural network
C	mass flow coefficient
D	orifice diameter [m]
d_c	needle diameter [m]
EEV	electronic expansion valve
H	position of needle [m]
IU	indoor unit
MRE	mean relative error
p	pressure [kPa]
q	mass flow rate [kg/s]
RD	relative deviation
RE	relative error
RMS	root mean square
RMSE	root mean square error
S.D.	standard deviation
T	temperature [°C]
TEV	thermostatic expansion valve
VRF	variable refrigerant flow
x	refrigerant quality
Greek symbols	
α	needle angle
π	dimensionless parameter group
σ	surface tension [n/m]
μ	dynamic viscosity [kg/(m·s)]
Subscripts	
c	critical
e	experiment
eq	equivalent
f	saturated liquid
g	saturated vapor
i	inlet of EEV
o	outlet of EEV
pre	prediction
sub	subcooling
th	throat

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ACKNOWLEDGEMENT

We gratefully acknowledge the support of the Center for Environmental Energy Engineering (CEEE) at the University of Maryland, and System Air Conditioning Laboratory at LG Electronics Inc.