Using ANFIS technique in prediction of reverse flow in a solar chimney

Minh-Thu T Huynh, Thinh N Doan and Y Q Nguyen
Faculty of Engineering, Van Lang University,
45 Nguyen Khac Nhu St., Co Giang Ward, Dist. 1, Ho Chi Minh City, Viet Nam
Email: y.nq@vlu.edu.vn

Abstract. In solar chimney, in order to save resources in Computational Fluid Dynamics (CFD), this study aims to combine Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict reverse flow and investigate the ventilation performance. The inputs to the model are heat flux in the range of 200-1000W/m$^2$, gap of 0.04-0.25m and height of 1-1.4m, while outputs are penetration depth and mass flow rate. The results of $R^2$ and RMSE are reasonable for training and testing data, hence the ANFIS model is validated.

Keywords: solar chimney, CFD, machine learning, ANFIS, reverse flow

1. Introduction
Passive ventilation for buildings using solar chimney has been studied since 1993 by Bansal et al. [1]. With a well-designed solar chimney, it is said that the air changes per hour (ACH) even meet the standard recommended by ASHRAE [2]. In addition, indoor temperature can be reduced up to 3.5°C from an experimental study of Chungloo and Limmeechokchai [3]. In a study by Miyazaki et al. [4], a Tokyo’s office building can save up to 50% of the annual energy required for ventilation.

For solar chimney principle, due to higher temperature air heated by solar energy makes air flow out of the channel; hence, induces natural ventilation. However, Zamora and Kaiser [5] have detected the sudden change of the flow pattern due to the development of reverse flow regions, as they said it should be an optimal inter-plate spacing that maximizes the induced mass flow rate. Reverse flow in the solar chimney was also examined quantitatively by calculating its penetration depth by Khanal and Lei [6]. They have proposed the inclined wall design in order to enhance ventilation performance. Reverse flow in a solar chimney normally occurs at the outlet and in reality, it is quite complicated as it depends on the weather condition, height, and width or gap of the solar chimney. Since it causes a decrease in ventilation, Nguyen [7] has tried to suppress the reverse flow, which, by rearranging the heat transfer surface on the opposite side in the upper and lower halves of the solar chimney.

Machine Learning (ML) has been applied to many fields in order to solve complicated problems in Fluid Dynamics. As in the study of evaporator performance in Organic Rankine Cycle, due to its high nonlinear behavior and high thermal inertia, Enayatollahi et al [8] has utilized machine learning to solve such a complicated problem. Pourtousi et al [9] have also combined CFD and ANFIS for the bubble column hydrodynamics study. They mentioned that using both experiment and numerical methods in the field are still difficult due to cost and time. Another study of Beigzadeh [10] is to investigate the heat transfer...
performance in flat and discontinuous fins as it was complex. Computational Fluid Dynamics is utilized to provide data for Adaptive Neuro-Fuzzy to model the performance.

One of the popular Machine learning techniques is ANFIS, which stands for Adaptive Neuro-Fuzzy Inference System. It was a class of adaptive networks that incorporate both neural networks and fuzzy logic principles and first introduced by Jang [13]. ANFIS has two popular types: Mamdami [14] and Sugeno [15]. Since ANFIS combines two advantages of fuzzy logic and neural networks, it can solve many kinds of complicated nonlinear problems in acceptable time and does not require expert knowledge.

In this work, we propose to implement an adaptive neuro-fuzzy inference strategy (ANFIS) with sugeno type to predict the penetrating depth and mass flow rate of solar chimney for different scenarios. CFD models were built to provide data for training and testing the ANFIS model.

2. Modeling setup
2.1. Modeling in ANSYS
The solar chimney model in this study is in the vertical plane with channel gap G and height H, as sketched in figure 1. A uniform heat flux I is applied on one wall. The opposite wall is considered as adiabatic with no-slip conditions. Air at the inlet and outlet of the channel are set as atmospheric pressure. Flow is assumed steady and incompressible. The conservation equations of mass, momentum and energy are described by RANS (Reynolds Averaged Navier–Stokes equations) method in CFD on a staggered grid using a finite volume solver ANSYS Fluent Academic version 2020 R2. For solving the turbulence quantities, the RNG k-ε turbulence model is used.

In the numerical setups, as the momentum and mass conservation equations were solved simultaneously, the SIMPLE numerical scheme was selected for handling the coupling. In addition, as the staggered grid system was employed, the pressure at the cell center was interpolated to the cell faces with the PRESTO! Method. Other discretization schemes of the equations included the second-order upwind scheme for momentum equation and energy conservation equation, and first-order upwind scheme for the equations for k and ε are applied.

The above setups have been tested intensively and compared with experimental data. Details can be seen in our previous studies [11][12].

2.2. Modeling in ANFIS
The typical ANFIS structure is sketched in figure 2. It is assumed with two inputs and one output. This study is based on the model developed by Jang [13].

The membership function (MF) in the current study is selected as Gaussian functions:
\[ \mu_i = e^{-\frac{(x-c_i)^2}{2\sigma_i^2}} \]  

where \( \sigma_i \) and \( c_i \) with \( i = (1, 2) \) are the fuzzy set parameters.

To evaluate the accuracy of produced outputs, two statistical indices of R² and RMSE are used.

**Figure 2.** Typical ANFIS architecture.

### 3. Results and discussions

#### 3.1. Reverse flow from the CFD model

(a) \( H=1 \text{m}, L=1000 \text{W/m}^2, G=0.1 \text{m} \), reverse flow.  
(b) \( H=1 \text{m}, L=1000 \text{W/m}^2, G=0.05 \text{m} \), no reverse flow.

**Figure 3.** Examples of flow fields obtained with the CFD model: velocity vector and contour, and temperature fields.

Figure 3 shows examples of the flow field obtained with the CFD model for the solar chimney with \( H=1.0 \text{ m} \) and \( L=1000 \text{ W/m}^2 \). The gap changed from \( G=0.1 \text{ m} \) (figure 3a) to 0.05 m (figure 3b). The heat source was on the left wall of the air channel. It is seen that at the lower gap (\( G=0.05 \text{ m} \), figure 3b), the thermal layer developed along the heated surface and induced an air flow in the whole channel gap. At the larger gap (\( G=0.1 \text{ m} \), figure 3a), the thermal layer was close to the heated surface and did not expand.
to the center of the channel. At the outlet of the channel, the right side of the channel was not heated. A reverse flow appears near the right wall at the outlet. The area of the reverse flow is indicated by the green region in the middle image of figure 3a. The reverse flow in figure 3a contracted the flow area at the outlet and increase flow resistance. As a result, the induced air flow rate was influenced. Figure 4 shows the induced flow rate and the penetration depth, $D_p$ (see figure 3a), of the reverse flow for a solar chimney with $H=1.1$ m and $I=400$ W/m$^2$. A reverse flow existed for $G>0.04$ m. $D_p$ increased with the gap. As the reverse flow region was still small, at $G=0.04$ m and 0.08 m, the flow rate continued to increase with the gap. However, as the gap was above 0.08 m, the reverse flow region exceedingly increased and resulted in a reduction of the induced flow rate. At $G=0.24$ m, the flow rate was almost similar to that at $G=0.04$ m.

![graph](image)

Figure 4. Mass flow rate and penetration depth change with channel gap at $I=400$ W/m$^2$, $H=1.1$ m.

3.2. ANFIS model training

As aimed to predict $D_p$ and the mass flow rate with the ANFIS model, data were generated with the CFD model with different $G$, $H$, and $I$ to the penetration depth $D_p$, if exists, and mass flow rate $\dot{m}$. The range of parameters considered in this study are 0.04-0.25 m for gap width, 1-1.4 m for solar chimney height and up to 200-1000 W/m$^2$ for heat flux. Total number dataset is 112, in which 80% is used for training models and the rest 20% is for testing. All dataset is shuffled randomly.

In this ANFIS model, 2 Gaussian membership functions are used for $I$ and $H$; while 5 Gaussian membership functions for $G$. The fuzzy set parameters of each membership function are in table 1. After training, respectively for $D_p$ and $\dot{m}$, the results give RMSE of 5.4E-05 and 4.5E-06; and $R^2$ of 0.99998 and 0.99996. Those results are quite reasonable for the outputs in this study.

| Input | MF  | Type of MF | $\sigma$  | $c$      |
|-------|-----|------------|-----------|----------|
| $I$ (W/m$^2$) | in1mf1 | Gaussianmf | 3.82E+02  | 2.00E+02 |
|       | in1mf2 | Gaussianmf | 3.82E+02  | 1.10E+03 |
| $G$ (m) | in2mf1 | Gaussianmf | 2.23E-02  | 4.00E-02 |

Table 1. ANFIS model inputs.
3.3. ANFIS model validation
In order to validate the above ANFIS model, as mentioned above, the rest 20% of the data set is estimated using the above training model. Figure 5 shows the comparison between CFD results and those from the ANFIS model for penetration depth and mass flow rate for different solar chimney gaps.

|          |          |          |          |          |
|----------|----------|----------|----------|----------|
|          |          | 2.23E-02 | 9.25E-02 |
|          |          | 2.23E-02 | 1.45E-01 |
|          |          | 2.23E-02 | 1.98E-01 |
|          |          | 2.23E-02 | 2.50E-01 |
|          |          | 1.70E-01 | 1.00E+00 |
|          |          | 1.70E-01 | 1.40E+00 |

From the result, respectively for $Dp$ and $\dot{m}$, RMSE are 0.000455 and 0.0000427; and $R^2$ are 0.9998 and 0.9996. Those outcomes are quite tolerable, hence the above ANFIS model is validated.

It is seen in figure 5 that the predictions from ANFIS agreed very well with the CFD results for both the flow rate and the penetration depth, even for the cases without a reverse flow ($Dp=0.0$ m). It is noted that the data set in figure 5 was randomly picked from the CFD results for different heights and heat fluxes. Therefore, the good agreement between the two results in figure 5 also shows the ability to predict the mass flow rate and the penetration depth of the ANFIS model to overcome the major drawbacks of the CFD model, i.e. expensive computational cost.

4. Conclusion
This study attempted to introduce the precision of Adaptive Neuro-Fuzzy Inference System (ANFIS) model for evaluating the reverse flow in a solar chimney in order to maximize ventilation performance, which is the mass flow rate in this study. For saving resources in simulation and experiment efforts, the numerical data obtained from the CFD modeling for range of heat fluxes, channel gap, and height were used for training the ANFIS. By comparing penetration depth and mass flow rate between CFD and
The ANFIS model for both training and testing, it can be confirmed that the ANFIS model is validated with acceptable RMSE and $R^2$. Consequently, reverse flow with different scenarios can be estimated using ANFIS technique simultaneously. Therefore, the optimal design of a solar chimney can be achieved to maximize the advantage for ventilation as well as energy saving.

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