PV/T solar collector performance evaluation: generation of fuzzy rules by using weighted subsethood-based algorithm

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Abstract. A photovoltaic/thermal solar collector operates efficiently if the surrounding conditions are in a favorable state; where the factors or parameters such as solar radiation, ambient temperature, photovoltaic collector temperature and air mass flow rates are taken into consideration to ensure the performance of the collector achieves optimum level. Dependency on surrounding conditions limited the width of analysis that could be done on the factors affecting the performance of the solar collector. This study aims to generate fuzzy rules for solar collector performance evaluation. Experiments on the performance of a single passage air photovoltaic/thermal solar collector have been carried out, and a set of membership functions representing all significant factors has been generated. Then fuzzy rules of forecasting were developed using a weighted subsethood-based algorithm to predict the efficiency of the photovoltaic/thermal solar collector. In this fuzzy time series application, the concept of fuzzy rule-based systems was embedded to generate fuzzy if-then rules. The results showed that the PV/T solar collector performance with changes in parameters could be predicted based on the fuzzy rules that have been generated, and thus further could be used to determine the optimum factors conditions required to achieve optimum collector performance without having to carry out experiments.

1. Introduction

In fulfilling the global demand for energy, solar energy is considered one of the high potential renewable energy which has significant importance and uses since it is environmentally friendly, clean, and reliable. As early as the mid 1970s, the interest of researchers in photovoltaic/thermal (PV/T) solar collector study has started [1]. The focus and development of the study have increased since then. There are many parts of the collector study that have been in the researchers’ interest, including the design and the theoretical and experimental studies of the solar collector performances.

The operation of PV/T solar collector with air as a working fluid is much depending on the parameters affecting its efficiency. Factors such as solar radiation, PV temperature, air mass flowrate affect the collector’s performance in a significant way. Previously, the velocity of air that is forced into the collector is done manually by the researcher [1]. However, it does not necessarily for the fan to be operated at full speed every time to remove the heat. There must be a balance between the input and
output energy used in the collector system. From the data collected through the experiment conducted in this study, fuzzy rule-based system is used to generate fuzzy rules that represent the effect of the parameters on the collector’s efficiency.

The successful use of solar energy systems depends on the efficiency of the collector. The collector harnesses most energy at its optimum surrounding condition. Hence, there is a need to determine the effect of parameters affecting its operation to help improve the performance of the solar collector to its optimum level. Therefore, to ease the decision making in improving the performance of PV/T solar collectors, a set of rules is necessary for the researcher to observe the effect of any change in any parameter on the efficiencies of the collector.

There were numerous applications of fuzzy rule-based systems in real world problem classifications in the area of fuzzy systems. More and more studies over the past few years have demonstrated that fuzzy rule-based system is ready to be used and reliable since it produces higher precision results, as supported by [2].

A weighted subsethood-based algorithm (WSBA) is used in this study as it is suitable for fuzzy rules generation. WSBA is relatively an easier method, and there is the possibility of the generation of highly accurate results in the presence of fewer rules to be compared to other models [3].

The objectives of this paper are to analyze and develop membership functions for each parameter that affects the PV/T solar collector performance. Secondly is to generate fuzzy rules for a PV/T solar collector performance evaluation using a weighted subsethood-based algorithm.

2. Methods

2.1. Data collection and pre-processing
The data is collected from the operation of the PV/T solar collector comprises parameters affecting the efficiency of the collector, which are the PV temperature, ambient temperature, output temperature, solar radiation, voltage and current output, and air mass flow rate. The data were collected from the experiment carried out in Universiti Teknologi PETRONAS. The PV performance dataset was divided into two subsets, PV-1(a) and PV-1(b), which were used for training and testing, respectively. PV-1 consists of 25 cases. The PV performance data is analyzed by one the electrical efficiency and thermal efficiency. Thermal efficiency comprised of radiation, air mass flowrate, PV temperature, and the temperature difference between output temperature and ambient temperature. Meanwhile, the electrical efficiency comprised of 4 attributes, which are radiation, current, voltage and output temperature. The classification outcomes of the PV performance were categorized as Low, Medium, and High. However, this paper was written with a focus on the development of fuzzy rules for thermal efficiency.

2.1.1. Fuzzy membership functions of attributes. From the data collected, fuzzy membership functions for each attribute have been developed. As an example, Figure 1 shows the fuzzy membership function of solar radiation. In order to transform solar radiation data into fuzzy values, this function is used in the calculation. Figure 2 – 4 shows the fuzzy membership functions that have been developed for other attributes. The membership function for the outcome; thermal efficiency, is shown in Figure 5.
### Figure 1. Membership Function for Solar Radiation

### Figure 2. Membership Function for Air Mass Flowrate

### Figure 3. Membership Function for PV Temperature

### Figure 4. Membership Function for Temperature Difference

### Figure 5. Membership Function for Thermal Efficiency

#### 2.1.2 Fuzzy rule generation

In this phase, the fuzzy model that is based on the weighted subsethood-based algorithm is produced. In this method, rules are generated according to the general Mamdani fuzzy laws [4]. There are four steps that have been taken into the process, as referred to in work done by previous researches [5,6].

Step 1: Based on the classification outcomes, the training dataset PV-1(a) in Table 1 was separated into three subgroups. The measure of location $Q_k$ is used to calculate the classification outcomes as follows [7]:

\[
Q_k = \frac{\sum_{i=1}^{n} x_i}{n}
\]
\[ Q_k = L_k + \left( \frac{k N - F_k}{f_k} \right) C_k \]  

where \( k = 1,2,3 \).

- \( L_k \) = the class lower boundary where \( Q_k \) lies,
- \( N \) = total observations number,
- \( F_k \) = cumulative frequency before the \( Q_k \) class,
- \( f_k \) = the class frequency where \( Q_k \) lies;
- \( C_k \) = class size where \( Q_k \) lies.

Step 2: The fuzzy subsethood values for each linguistic term are set in every subgroup. These rules have been made to address the classification issued. The fuzzy subsethood value \( A \), which was a subset of \( B \) is denoted by \( S(B, A) \), where \( S(B, A) \in [0.1]^{[26][27]} \):

\[ S(B, A) = \frac{M(B, A)}{M(B)} = \frac{\sum_{x \in B} \nabla(\mu_B(x), \mu_A(x))}{\sum_{x \in B} \mu_B(x)} \]  

where \( S(B, A) \) refers to fuzzy subsethood value of fuzzy set \( A \) to fuzzy set \( B \), \( \mu_A(x) \) and \( \mu_B(x) \) refer to membership value in \( x \) in set \( A \) and \( B \) respectively.

Step 3: Based on the subsethood values in Step 2, we weighted each linguistic term between 0 and 1. The maximum weightage represents the most important, while the minimum weightage represents the least importance. The fuzzy sets are now associated with various linguistic variables through an expansion of the subsethood explication. With the assumption that the value of the subsethood for a particular linguistic term, \( A_j \) of the linguistic variable \( A \) with respect to classification \( X \) was \( S(X, A) \) and that \( A_1, A_2, \ldots, A_l \) was within the set of possible linguistic terms for \( A \), then \( A_i \)'s relative weight, \( W \) with respect to \( X \) was:

\[ W(X, A_i) = \frac{S(X, A_i)}{\max_{j=1\ldots l} S(X, A_j)} \]  

Where \( W(X, A_i) \in [0,1] \) and \( i = 1,2,\ldots,l \). Now, each conditional attribute has a specific weightage for each linguistic term. The largest and smallest subsethood values portray the most and least important ones. The weights assigned to every antecedent through fuzzy rules were non-negative numbers, which with change to the learning datasets, the weightage could be modified. In addition, these weights were incorporated into linguistic terms, which in turn were associated with the conditional attributes. Thus, the compound weightage \( T(A) \) of the weighted conjunction of linguistic terms for each \( A \) is calculated as follows:

\[ T(A) = \left( \frac{W_1}{W_2}(A_j) \nabla \ldots \nabla \frac{W_m}{W}(A_m) \right) \]  

where \( A \) were the conditional attributes, \( \nabla \) the t-norm operator \( A_i \), \( i = 1,2,\ldots,m \) the linguistic terms of \( A \) which have been conjunctively combined, and \( W \) the largest one of \( m \) associated weights, \( W(X, A_i) \). A t-norm (also called triangular norm) is a type of binary operation that is used in the
framework of possibilistic metric spaces and in multi-values logic, specifically in fuzzy logic. A t-norm generalizes intersection in a lattice and conjunction in logic.

Similarly, the formula below can be used to determine the compound weight, \( T(B) \), of the weighted disjunction of the linguistic terms related to a variable \( B \):

\[
T(B) = \left( \sum_{i=1}^{n} \frac{w_i}{w_2} \left( B_i \right) \right)
\]

(5)

Where \( \lor \) is the t-conorm operator and \( B_i, i = 1,2,...,n \) is the linguistic terms of variable \( B \) which have been combined disjunctively. T-conorms (or S-norms) are dual to t-norms under the operation of reversing the order that assigns \( 1-x \) to \( x \) on \([0,1]\).

Step 4: The rules set are generated in this step. To create the fuzzy if-then rules, the weighted conjunction and weighted disjunction that gave rise to the weightage in the subsethood-based algorithm were used. With reference to the subsethood-based algorithm, “OR” and “AND” were deduced based on the t-conorm and t-norm operators, respectively. In the process, the linguistic rules generated by the weighted subsethood-based algorithm can be exposed in terms of an amalgamation of fuzzy general rules and fuzzy quantifiers. Quantifiers such as “some” or “all” can be used to describe the weights of each linguistic term. “All” is assigned with a weightage of 1, while “some” otherwise. The way we interpret the degree of the “some” depends on the weightage of each linguistic term. These learned rules are utilized in the implementation of fuzzy rule based-system, where the rule with the largest overall weightage determined the conclusion classification.

2.2. Final classification output

The classification of the PV/T solar collector performance evaluation can be performed after the ruleset is obtained. Then, using the ruleset generated and the transformed fuzzy values, the fuzzy rules were calculated. The min-max operator is used in this phase, and the classification result is decided based on the highest truth-value.

2.3. Testing the rule set for classification task

The rule set which was trained using PV-1(a) dataset for classification of the PV/T solar collector performance evaluation was tested using PV-1(b) dataset. The forecasting rules were created and used in the current phase to determine the forecasting trend for individual performance evaluation.

3. Numerical example

The data collected from the experiment carried out was divided into two subsets of data, PV-1(a) and PV-1(b). PV-1 (a) is the training dataset of the thermal performance of the PV/T solar collector shown in Table 1 while PV-1 (b) shown in Table 6 is the testing dataset.

Table 2 shows the terms used to represent the linguistic terms in the entire PV/T solar collector performance evaluation. Meanwhile, Table 3 shows the subgroups with respect to the classification outcomes calculated based on equation (1). According to classification outcomes, the training dataset was divided into three subgroups; Low, Medium, and High.

The subsethood values were calculated for each linguistic term in each subgroup and the subsethood values calculated according to each classification results are shown in Table 4. Table 5 shows the weights for each linguistic term.

| Table 1. Training Dataset PV-1(a) |
|-----------------------------------|
| Case | Radiation | Mass Flowrate | PV Temperature | Temperature Difference | Thermal Efficiency | Outcome |
| 1    | 66        | 0.00123       | 307.72         | 4.27                   | 0.37146           | High    |
| 2    | 116       | 0.00061       | 309.97         | 7.85                   | 0.19336           | High    |
| Label | Linguistic Term                  |
|-------|----------------------------------|
| A1    | Radiation is low                |
| A2    | Radiation is medium              |
| A3    | Radiation is high                |
| B1    | Mass flowrate is low             |
| B2    | Mass flowrate is medium          |
| B3    | Mass flowrate is high            |
| C1    | PV Temperature is low            |

Table 2. Labels Used for Each Linguistic Term in Pv-1(A) Dataset
C2  PV Temperature is medium
C3  PV Temperature is high
D1  Temperature difference is low
D2  Temperature difference is medium
D3  Temperature difference is high
X1  Thermal Efficiency is low
X2  Thermal Efficiency is medium
X3  Thermal Efficiency is high

Table 3. Subgroups of PV-1(A) with Respect to Classification Outcomes

| Subgroup | Cases | Outcome |
|----------|-------|---------|
| Subgroup 1 | 4, 25, 32, 34, 36 | Low |
| Subgroup 2 | 5, 9, 13, 16, 19, 20, 21, 24, 26, 28, 29, 33, 37 | Medium |
| Subgroup 3 | 1, 11, 27, 31, 35 | High |

Table 4. Subsethood Values Calculated from PV-1(A) Dataset

| Linguistic Term | A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | C3 | D1 | D2 | D3 |
|----------------|----|----|----|----|----|----|----|----|----|----|----|----|
| Thermal efficiency | Low (X1) | 0.13 | 0.24 | 0.62 | 0.79 | 0.21 | 0 | 0.20 | 0.14 | 0.66 | 0.16 | 0.40 | 0.44 |
|                 | Medium (X2) | 0.40 | 0.53 | 0.28 | 0.42 | 0.64 | 0.24 | 0.51 | 0.32 | 0.43 | 0.38 | 0.41 | 0.43 |
|                 | High (X3) | 0.52 | 0.17 | 0.31 | 0 | 0 | 0.91 | 0.75 | 0.23 | 0.02 | 0.47 | 0.28 | 0.25 |

Table 5. Weight for Each Linguistic Term for PV-1(A) Dataset

| Linguistic Term | A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | C3 | D1 | D2 | D3 |
|----------------|----|----|----|----|----|----|----|----|----|----|----|----|
| Thermal efficiency | Low (X1) | 0.21 | 0.39 | 1 | 1 | 0.26 | 0 | 0.30 | 0.21 | 1 | 0.36 | 0.90 | 1 |
|                 | Medium (X2) | 0.76 | 1 | 0.52 | 0.65 | 1 | 0.37 | 1.00 | 0.63 | 0.85 | 0.89 | 0.96 | 1 |
|                 | High (X3) | 1 | 0.34 | 0.59 | 0 | 0.1 | 1 | 1 | 0.31 | 0.03 | 1 | 0.60 | 0.53 |

Based on the process stated above, the results of the rule set that have been generated are shown in Figure 6 as follows:

IF Radiation is (0.21A1 OR 0.39A2 OR A3) AND Mass Flowrate is (B1 OR 0.26B2) AND PV Temperature (0.3C1 OR 0.21C2 OR C3) AND Temperature Difference is (0.36D1 OR 0.9D2 OR D3), THEN Thermal Efficiency is Low.

IF Radiation is (0.76A1 OR A2 OR 0.52A3) AND Mass Flowrate is (0.65B1 OR B2 OR 0.37B3) AND PV Temperature (C1 OR 0.63C2 OR 0.85C3) AND Temperature Difference is (0.89D1 OR 0.96D2 OR D3), THEN Thermal Efficiency is Medium.

IF Radiation is (A1 OR 0.34A2 OR 0.59A3) AND Mass Flowrate is (0.1B2 OR B3) AND PV Temperature (C1 OR 0.31C2 OR 0.03C3) AND Temperature Difference is (D1 OR 0.6D2 OR 0.53D3), THEN Thermal Efficiency is High.

Figure 6. Rule set generated for PV-1(a) dataset

Referring to the values in Table 1, given that the value of radiation, \( A_i \), is 66W/m², air mass flowrate, \( B_i \), is 0.00123 kg/s, PV temperature, \( C_i \), is 307.72 K, temperature difference, \( D_i \), is 4.27 K, where \( A_i \), \( B_i \), \( C_i \) and \( D_i \), \( i = 1,2,3 \) refer to the linguistic terms depicted in Table 3. These values need to be transformed into fuzzy values, using fuzzy membership function shown in the calculation.
The fuzzy membership function in Figure 1 is used to transform the solar radiation data into fuzzy values. The calculations are as follows:

1. If the solar radiation, \( A \) falls in the low region (\( A < 460 \)), the fuzzy value is equal to 1.

2. If the solar radiation, \( A \) falls in the low region (\( 460 < A \leq 673 \)), the fuzzy value is

\[
\mu(A) = \frac{673 - A}{673 - 460}
\]

3. If the solar radiation, \( A \) falls in the medium region (\( 460 < A \leq 673 \)), the fuzzy value is

\[
\mu(A) = \frac{A - 460}{673 - 460}
\]

4. If the solar radiation, \( A \) falls in the medium region (\( 673 < A < 807.5 \)), the fuzzy value is

\[
\mu(A) = \frac{807.5 - A}{807.5 - 673}
\]

5. If the solar radiation, \( A \) falls in the high region (\( 673 \leq G \leq 807.5 \)), the fuzzy value is

\[
\mu(A) = \frac{A - 807.5}{807.5 - 673}
\]

6. If the solar radiation, \( G \) falls in the high region (\( A > 807.5 \)), the fuzzy value is 1.

7. Elsewhere, the fuzzy value is equal to 0.

For the other attributes, B, C and D, the calculation will follow the respective membership functions shown in Figure 2-4. Therefore, from the above calculations, the transformed fuzzy values are as follows:

\[
\begin{align*}
\mu_{A_1}(66) &= 1, \quad \mu_{A_2}(66) = 0, \quad \mu_{A_3}(66) = 0, \quad \mu_{B_1}(0.00123) = 0, \quad \mu_{B_2}(0.00123) = 0, \quad \mu_{B_3}(0.00123) = 1, \\
\mu_{C_1}(307.72) &= 1, \quad \mu_{C_2}(307.72) = 0, \quad \mu_{C_3}(307.72) = 0, \quad \mu_{D_1}(4.27) = 1, \quad \mu_{D_2}(4.27) = 0, \\
\mu_{D_3}(4.27) &= 0
\end{align*}
\]

Then, the following rules were calculated using the ruleset generated as shown in Figure 6 and the above transformed values. In this process, the Min-Max Operator is used.

Rule 1: \( X = \min[\max(0.21,0.0),\max(0.0,0),\max(0.3,0),\max(0.36,0.0)] = 0 \)

Rule 2: \( X = \min[\max(0.76,0.0),\max(0.0,0.37),\max(1.0,0),\max(1.0,0)] = 0.37 \)

Rule 3: \( X = \min[\max(1.0,0),\max(0,0),\max(1.0,0),\max(1.0,0)] = 1 \)

Based on the rules calculated above, the classification result is \( X_3 \), which is the thermal efficiency is High because the highest truth-values is associated with Rule 3.

4. Results and discussion

In this part, the fuzzy rules that have been generated were tested on the testing set PV-1(b) to verify the algorithm. Table 6 below shows the results obtained for every dataset when calculated using the fuzzy rules to be compared to the actual categorization.

**Table 6. Testing Dataset PV-1(b)**

| Case | Radiation | Mass Flowrate | PV Temperature | Temperature Difference | Thermal Efficiency | Actual Outcome | Predicted Outcome |
|------|-----------|---------------|----------------|-----------------------|-------------------|---------------|------------------|
| 1    | 68        | 0.00130       | 306.70         | 2.73                  | 0.24219           | High          | High             |
Based on the results obtained, it has been shown that the predicted results are 79%, similar to the actual data. This shows the predictions are good enough to be validated with the testing dataset [8]. However, the results could be further improved with a wider dataset and tested with a variety of parameters.

As conclusion, the set of rules generated could be useful in conducting analysis on the performance of solar collector on the changes of parameters affecting its efficiency. This method could save time and cost to conduct more set of experiments, and could further improve the collector’s efficiency up to its optimum point.
References

[1] Chow T T, Pei G, Fong K F, Lin Z, Chan A L S and Ji J 2009 *Appl. Energy* **86** 310-16

[2] Ruspini E H, Bonissone P P and Pedrycz W 1998 *Handbook of fuzzy computation*

[3] Chen S M and Tsai F M 2008 *Expert Syst. Appl.* **35** 611-21

[4] Izquierdo S and Izquierdo L R 2017 *Mamdani fuzzy systems for modelling and simulation: A critical assessment*

[5] Rasmani K A and Shen Q 2004 *Proc. of 2004 UK Workshop Comp. Intel. Citeseer* p 181-8

[6] Rahim N F, Othman M, Sokkalingam R and Kadir E A 2018 *IEEE Access* **6** 32216-24

[7] Dodd E L 1938 *The American Mathematical Monthly* **45** 302-6

[8] Voyant C, Nottion G, Kalogirou S, Nivet M L, Paoli C, Mott, F and Fouilloy A 2017 *Machine learning methods for solar radiation forecasting: A review* *Renew. Energy* **105** p 569-82