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# Weighted Mamdani-type Fuzzy Inference System Based on Relative Ideal Preference System

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**Abstract**

This paper presents a new method of determining weight of the fuzzy IF-THEN rules in a Fuzzy Inference System based on human intuition or expert judgment, known as the Relative Ideal Preference Scheme (RIPS). In the proposed scheme, an ideal preference rule is chosen from the given set of available fuzzy IF-THEN rules in the system which will be set with weight 1. The threshold weight and the interval between rule's weight are calculated prior to the computation of the weight of other rules. Rules are rearranged based on their level differences with respect to the ideal preferred rule. Finally, the weight of each rule is determined using the calculated threshold and interval between weights. An illustration of its implementation in a fuzzy inference system is presented with a numerical example. The proposed scheme has an advantage where the weights of the rules are determined systematically and simple.

Keywords: Fuzzy inference system, Fuzzy logic, Weighted IF-THEN rules, Relative ideal preference system

## 1. Introduction

The introduction of fuzzy set theory by Zadeh (1965) has triggered immense interests of researchers and practitioners in various fields. It has been used and applied mostly to cater mathematically the vagueness, impreciseness and subjectivity of information and data (Zimmermann, 2004) . Instead of having just bi-values of 0 and 1 in logic concept, a fuzzy set is represented by a membership value in the real unit interval [0,1] that indicates the degree of belonging of an element in a particular set (Dubois, 1980). Due to their similarity in conceptual structure, fuzzy set has been used to generalize the definition of fuzzy logic and becomes one of important disciplines in soft computing. Fuzzy set has been extended theoretically and in applications due to its usefulness in imitating human thinking and perceptions.

Fuzzy Inference System (FIS) is one of the many applications of fuzzy set with fuzzy logic. It is a system that involves a process of formulating the mapping from a given input to an output (both in crisp form) using fuzzy logic (Stoffel et al., 2010). The main components of the fuzzy inference system are

i. Input fuzzification (rule antecedent);
ii. Fuzzy rules operator application (AND and OR) to antecedent;
iii. Antecedent to consequent implication (in Inference Engine);
iv. Aggregation process of consequents (in Inference Engine);
v. Defuzzification process to obtain the output.

FIS has already been successfully applied in many technology domains such as engineering, manufacturing and expert systems (He, 1980; Stoffel et al., 2010).

## 2. Related Works on Weighted Fuzzy Inference System

The concept of weighted fuzzy inference system is not new. In many situations, the rules in a fuzzy inference system cannot be treated as equal simply because human usually has preference on one setting or situation compared to others (He, 1980). This allows the weight to represent in many forms such as degree of belief, certainty or important factor. According to the argument given by Wong and Dong (2009), imposing weight on the rules will improve the decision obtained as it imitates human intuition and believe.

The weight of the rules in the FIS can be determined in many ways, but essentially it can be categorized into two types which are soft computing methods and human intuition or expert judgment.

Several methods have been suggested to generate weighted rules using soft computing approaches (Ramakrishnan and Rao, 1992; Lu and Chan, 1997; Zolghadri and Mansoori, 2007). A method to generate weighted using fuzzy subsethood values between the term of attributes and alternatives was proposed by Chen and Lin (2005). Meanwhile, a Genetic Algorithm is used to generate and determine the weight of the fuzzy rules was introduced by Chen and Huang (2003). The human intuitive approaches (López et al., 2008; López and Macias, 2012) are no less important where the experts play their roles in the weight determination. The Hierarchy Process (AHP) method was used by López et al. (2008) to determine the weights of the rules. The weights are then applied to the system to judge prefered technologies in home and building electronic system. The same AHP method has also been used by López and Macias (2012) to select a domotic system. In both cases, expert judgment is engaged to do the pairwise comparison process in determining the weight of rules and conditions in the FIS. Nevertheless, the AHP method has a setback. When the system is large, the calculation and its complexity will increase tremendously.

The significance of using weighted rules in FIS has been demonstrated in several system applications. The weighted fuzzy rules have been implemented by Anooj (2012) in developing a clinical decision support system to predict risk level of heart disease. Here the weight of rules is determined by observing its frequencies in the database. Recently, Paul et al. (2017) improvised the method by introducing the adaptive weighted fuzzy rules to assess the risk level of heart disease. Here, the weighted fuzzy rules are constructed using Genetic Algorithm with respect to selected attributes. Fuzzy Inference system with weighted IF-THEN rules have also been applied in the developing a fuzzy classification system (Chen et al., 2006) to deal with the Iris data classification problem. Olvera-Garcia et al. (2016) have applied the weighted fuzzy rules in the assessment of air quality meanwhile a fuzzy navigation system for a mobile robot had been proposed by Meléndez et al. (2013) using an algorithm incorporating the weighted fuzzy rules.

## 3. Relative Ideal Preference Scheme for Weighted IF-THEN Rules.

The common set up in the Mamdani-type FIS is that the weights of fuzzy rules in are assumed and set to be equal (usually 1). However, in some circumstances, this setup is not appropriate to be used since some rules may have higher/lower weighted values depending on their importance or preference. For instance, suppose that a buyer would like to own a car and there are four criteria under consideration: price, safety, fuel consumption and accessories. It is natural that the buyer would prefer a LOW price, HIGH safety, LEAST fuel consumption and PLENTY accessories. The desirable preference can be written in the fuzzy IF-THEN rules as

> **IF** <price is LOW> and <safety is HIGH> and <fuel consumption is LEAST> and <accessories is PLENTY> **THEN** <choice of this car is HIGHLY PREFFERED>.

In the FIS set up, this shows that the above rule is desirable to other sets of condition in the rules for choosing an alternative in the system. Thus, it is appropriate to give a higher weight to the rule as compared to others as it is the preferred choice by the buyers. We call this rule as the "ideal preference rule (IPR)".

We propose a systematic way of determining the rule weight in the Mamdani-type FIS which we called it as the Relative Ideal Preference Scheme (RIPS). The scheme is based on human intuition or expert judgment. The procedural steps are described as follows:

*Step 1.* Let $R_i$ , $i$ = 1,...,$n$ be the set of rules and $C_j$ , $j$ = 1,...,$m$ be the set of criteria where each $C_j$ has the list of linguistic terms as in Table 1.

**Table 1**
List of linguistic terms for each criterion

| Criteria | Linguistic terms |
|---|---|
| $C_1$ | $L_{11}, L_{12}, \dots, L_{1A}$ |
| $C_2$ | $L_{21}, L_{22}, \dots, L_{2B}$ |
| … | … |
| $C_m$ | $L_{m1}, L_{m2}, \dots, L_{mN}$ |

The set of linguistic terms for the output $O$ is given as $O = \{O_1, O_2, \dots, O_S\}$. Note that some of the criteria and the output may have equal number of linguistic terms. An example of a rule ($R_k$) can be represented as:

$R_k$: **IF** <$C_1$ is $L_{12}$> and <$C_2$ is $L_{24}$> and … and <$C_m$ is $L_{m3}$> **THEN** <$O$ is $O_4$>.

*Step 2.* Determine the ideal preference rule (IPR) denoted as $R^*$ from the set of rules constructed in the FIS and assumed to be unique, that is only one rule is set as the IPR from the set of given rules. Label the preferred linguistic terms of each criterion as $L_{1\alpha}$, $L_{2\beta}$ ,…, $L_{2\eta}$ of each condition. Thus we have the IPR as

Rule $R^*$: **IF** <$C_1$ is $L_{1\alpha}$> and <$C_2$ is $L_{2\beta}$> and … and <$C_m$ is $L_{m\eta}$ > **THEN** <$O$ is $O_s$>

where $L_{1\alpha} \in \{ L_{11}, L_{12}, \dots, L_{1A} \}$, $L_{2\beta} \in \{ L_{11}, L_{12}, \dots, L_{1B}\}$, … , $L_{m\eta} \in \{ L_{11}, L_{12}, \dots, L_{1N} \}$. Put the weight for this rule as $w^*=1$ denoted as the ideal weight of the rule.

*Step 3.* Rearrange the linguistic terms of each criteria in ascending and descending order with respect to the linguistic term of IPR as in Table 2. This arrangement is made to simplify the determination of the weight of each rule in the FIS.



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**Table 2**
Rearrangement of linguistic terms with respect to the ideal preference rule

| Criteria | Linguistic terms of IPR ($w$*=1) | Other linguistic terms | | | | |
|---|---|---|---|---|---|---|
| $C_1$ | $\mathbf{L_{1\alpha}}$ | $L_{1(\alpha+1)}$ [-1] | $L_{1(\alpha+2)}$ [-2] | … | $L_{1A}$ [-(A-α)] | (ascending) |
| | | $L_{1(\alpha-1)}$ [-1] | $L_{1(\alpha-2)}$ [-2] | … | $L_{11}$ [-(α-1)] | (descending) |
| $C_2$ | $\mathbf{L_{2\beta}}$ | $L_{2(\beta+1)}$ [-1] | $L_{2(\beta+2)}$ [-2] | … | $L_{2B}$ [-(B-β)]] | (ascending) |
| | | $L_{2(\beta-1)}$ [-1] | $L_{2(\beta-2)}$ [-2] | … | $L_{21}$ [-(β-1)] | (descending) |
| … | … | … | … | … | … | |
| $C_m$ | $\mathbf{L_{m\eta}}$ | $L_{m(\eta+1)}$ [-1] | $L_{m(\eta+2)}$ [-2] | … | $L_{mN}$ [-(N-η)]] | (ascending) |
| | | $L_{m(\eta-1)}$ [-1] | $L_{m(\eta-2)}$ [-2] | … | $L_{m1}$ [-(η-1)] | (descending) |

We include the brackets [-x] in each element in Table 2 to represent the difference of level in the linguistic terms as compared to the ideal preference linguistic term. The value in brackets will indicate the level of weight difference from the weight of IPR ($w$*=1) that will be assigned to the rule. For instance, the set of linguistic terms of $C_1$ is listed as:

| | | | | | | |
|---|---|---|---|---|---|---|
| … | $L_{1(\alpha-2)}$ [-2] | $L_{1(\alpha-1)}$ [-1] | $\mathbf{L_{1\alpha}}$ (linguistic in IPR) | $L_{1(\alpha+1)}$ [-1] | $L_{1(\alpha+2)}$ [-2] | … |

and it is observed that $L_{1(\alpha-1)}$ has one lower level of weight difference from $L_{1\alpha}$ (the linguistic term used in the IPR) meanwhile $L_{1(\alpha+2)}$ has two higher level of weight difference from $L_{1\alpha}$.

*Step 4.* Using the similar approach as in Olvera-Garcia et al. (2016), determine the minimum threshold value $T$ where $T \in [0,1]$. The threshold value acts as the minimum value of priority that the user is satisfied. The value of $T$ will also ensure that no rule is neglected in the decision process using the FIS by having too low of the weight. This is to say that if the threshold is $T$ then all the fuzzy IF-THEN rules will have weights of at least $T$.

*Step 5.* Calculate the interval size value of weight denoted by $I_w$ and is given by the equation

$$I_w = (1-T)/k \tag{1}$$

where

$I_w$ = Interval size value of weight
$T$ = Threshold value of weight
$k$ = The sum of the maximum difference of level of linguistic terms for each criterion to the left or to the right to the ideal preference linguistic term.

Note that in order to obtain the value of $k$, it is sufficient to find the sum of max{n($L_{jk}$(left)), n($L_{jk}$(right))} for all criteria under consideration where n($L_{jk}$(left)) and n($L_{jk}$(right)) indicate the number of different levels of linguistic terms to the left and right to the ideal preference linguistic term respectively. As an example, suppose that "Low" is the ideal preference linguistic term from the set {Very Low, Low, Average, High, Very High}. Here the maximum difference of level is 3 as "Very High" is referred to 3 levels higher as compared to "Very Low" which is only 1 level lower from "Low".

*Step 5.* The weight of each rule is determined. The weight of the IPR is $w$*=1. The assigned weight $w_{-i}$ , $i$ = 0, 1, ... , $k$ is given as

$$w^* = 1,\ w_{-1} = 1- I_w,\ w_{-2} = 1- 2I_w,\ \ldots,\ w_{-k} = 1- kI_w = T. \tag{2}$$

*Example 1.* Let $C_1$, $C_2$ and $C_3$ be the three criteria in the FIS such that

$C_1$ has 4 linguistic terms $L_{11}$, $L_{12}$, $L_{13}$, $L_{14}$
$C_2$ has 2 linguistic terms $L_{21}$, $L_{22}$,
$C_3$ has 4 linguistic terms $L_{31}$, $L_{32}$, $L_{33}$, $L_{34}$

Let the ideal preference rule (IPR) of the system be

**IF** <$C_1$ is $L_{11}$> **and** <$C_2$ is $L_{22}$> **and** <$C_3$ is $L_{32}$ >
**THEN** <$O$ is $O_6$> . (3)

We have $k$ = 6 as the maximum distance of linguistic terms in $C_1$ is 3 (from $L_{11}$ to $L_{14}$), in $C_1$ is 1 and for $C_3$ is 2 (from $L_{32}$ to $L_{34}$). The value of $k$ = 6 is obtained by summing up 3, 1 and 2.

Suppose that the minimum threshold is fixed at $T$ = 0.7. Then we have

$I_w$ = (1-0.7)/6 = 0.05.

Hence, the weights to be used in the rules of FIS is given as

$w$* = 1 (the weight of the IPR).
$w_{-1}$ = 1- 0.05 = 0.95,
$w_{-2}$ = 1- 2(0.05) = 0.9,
$w_{-3}$ = 1- 3(0.05) = 0.85,
$w_{-4}$ = 1- 4(0.05) = 0.8,
$w_{-5}$ = 1- 5(0.05) = 0.75,



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$w_{-6}$ = 1- 6(0.05) = 0.7 = $T$.

## 4. Implementation of the Weighted Mamdani-type Fuzzy Inference System with RIPS

The implementation of the RIPS in the development of the weighted Mamdani-type FIS is illustrated as follows:

Using Example 1 in Section 3, and the set of output as $O = \{O_1, O_2, O_3, O_4, O_5, O_6\}$, let the set of rules for an FIS be given as in the fuzzy associative memory of FIS in Table 3.

**Table 3**
Fuzzy Associative Memory for FIS

| | | IF <$C_2$ is $L_{22}$> and | | |
|---|---|---|---|---|
| $C_1 \setminus C_3$ | $L_{31}$ | $L_{32}$ | $L_{33}$ | $L_{34}$ |
| $L_{11}$ | $O_6[-1]$ | $O_6*[0]$ | $O_5[-1]$ | $O_4[-2]$ |
| $L_{12}$ | $O_6[-2]$ | $O_5[-1]$ | $O_4[-2]$ | $O_4[-3]$ |
| $L_{13}$ | $O_5[-3]$ | $O_5[-2]$ | $O_3[-3]$ | $O_3[-4]$ |
| $L_{14}$ | $O_4[-4]$ | $O_4[-3]$ | $O_3[-4]$ | $O_3[-5]$ |
| | | IF <$C_2$ is $L_{21}$> and | | |
| $C_1 \setminus C_3$ | $L_{31}$ | $L_{32}$ | $L_{33}$ | $L_{34}$ |
| $L_{11}$ | $O_4[-2]$ | $O_4[-1]$ | $O_4[-2]$ | $O_3[-3]$ |
| $L_{12}$ | $O_4[-3]$ | $O_3[-2]$ | $O_3[-3]$ | $O_2[-4]$ |
| $L_{13}$ | $O_3[-4]$ | $O_3[-3]$ | $O_2[-4]$ | $O_1[-5]$ |
| $L_{14}$ | $O_2[-5]$ | $O_2[-4]$ | $O_1[-5]$ | $O_1[-6]$ |

The total number of the IF-THEN rules of the FIS is 32 and the entry with "*" is the suggested IPR denoted as in (3). Furthermore, from Table 3, the maximum difference of linguistic level from the IPR is -6 as in the rule

**IF** <$C_1$ is $L_{14}$> **and** <$C_2$ is $L_{21}$> **and** <$C_3$ is $L_{34}$ > **THEN** <$O$ is $O_1$>

and is consistent with the computation of Example 1.

Since the threshold value in Example 1 is chosen to be $T = 0.7$, the weighted rules of the FIS in the form of Fuzzy Associative Memory are calculated based on this $T$ and are as shown in Table 4.

**Table 4**
Fuzzy Associative Memory with Weighted Rules

| | | IF <$C_2$ is $L_{22}$> and | | |
|---|---|---|---|---|
| $C_1 \setminus C_3$ | $L_{31}$ | $L_{32}$ | $L_{33}$ | $L_{34}$ |
| $L_{11}$ | $O_6[0.95]$ | $O_6*[1]$ | $O_5[0.95]$ | $O_4[0.9]$ |
| $L_{12}$ | $O_6[0.9]$ | $O_5[0.95]$ | $O_4[0.9]$ | $O_4[0.85]$ |
| $L_{13}$ | $O_5[0.85]$ | $O_5[0.9]$ | $O_3[0.85]$ | $O_3[0.8]$ |
| $L_{14}$ | $O_4[0.8]$ | $O_4[0.85]$ | $O_3[0.8]$ | $O_3[0.75]$ |
| | | IF <$C_2$ is $L_{21}$> and | | |
| $C_1 \setminus C_3$ | $L_{31}$ | $L_{32}$ | $L_{33}$ | $L_{34}$ |
| $L_{11}$ | $O_4[0.9]$ | $O_4[0.95]$ | $O_4[0.9]$ | $O_3[0.85]$ |
| $L_{12}$ | $O_4[0.85]$ | $O_3[0.9]$ | $O_3[0.85]$ | $O_2[0.8]$ |
| $L_{13}$ | $O_3[0.8]$ | $O_3[0.85]$ | $O_2[0.8]$ | $O_1[0.75]$ |
| $L_{14}$ | $O_2[0.75]$ | $O_2[0.8]$ | $O_1[0.75]$ | $O_1[0.7]$ |

The weight of each rule is indicated in the square bracket [.]. Examples of some of the weighted rules extracted from Table 4 are given below.

**IF** <$C_1$ is $L_{11}$> **and** <$C_2$ is $L_{22}$> **and** <$C_3$ is $L_{32}$ > **THEN** <$O$ is $O_6$> (weight = 1)
**IF** <$C_1$ is $L_{13}$> **and** <$C_2$ is $L_{22}$> **and** <$C_3$ is $L_{33}$ > **THEN** <$O$ is $O_3$> (weight = 0.85)
**IF** <$C_1$ is $L_{14}$> **and** <$C_2$ is $L_{21}$> **and** <$C_3$ is $L_{31}$ > **THEN** <$O$ is $O_2$> (weight = 0.75)
**IF** <$C_1$ is $L_{12}$> **and** <$C_2$ is $L_{21}$> **and** <$C_3$ is $L_{34}$ > **THEN** <$O$ is $O_2$> (weight = 0.8).

We now further illustrate using numerical values in the above FIS with weighted fuzzy rules. The fuzzy logic toolbox of MATLAB is used to set up the system.

Suppose a system is developed to determine the level of risk for a loan application based on three factors namely *monthly commitment* ($C_1$), *job stability* ($C_2$) and *loan history* ($C_3$). The output is the *level of risk* denoted by $O$.

Let the criterion *monthly commitment* $C_1$ be represented by linguistic values *very low* ($L_{11}$), *low* ($L_{12}$), *average* ($L_{13}$) and *high* ($L_{14}$) with the following fuzzy numbers:

$$L_{11} = (0, 0, 4),\ L_{12} = (1, 4, 6),\ L_{13} = (4, 6, 9),\ L_{14} = (6, 10, 10) \quad (3)$$

which are in thousand Malaysian Ringgit. The criterion *job stability* $C_2$ is represented by linguistic values *unstable* ($L_{21}$) and *stable* ($L_{22}$) with the following fuzzy numbers:

$$L_{21} = (0, 0, 1, 9),\ L_{22} = (1, 9, 10, 10) \quad (4)$$



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and the criterion *loan history* $C_3$ is represented by linguistic values *low* ($L_{31}$), *average* ($L_{32}$) and *high* ($L_{33}$) with the following fuzzy numbers:

$L_{31}$= (0, 0, 4), $L_{32}$ = (1, 3, 8), $L_{33}$ = (2, 7, 9),
$L_{34}$ = (6, 10, 10). (5)

Finally, let the output $O$ be represented by linguistic values *very high* ($O_1$), *high* ($O_2$), *marginally high* ($O_3$), *medium* ($O_4$), *low* ($O_5$), *very low* ($O_6$) with the following fuzzy numbers:

$O_1$= (0, 0, 2), $O_2$ = (0, 2, 4), $O_3$ = (2, 4, 6), $O_4$ = (4, 6, 8),
$O_5$ = (6, 8, 10), $O_6$ = (8, 10, 10).

The 3-tuple and the 4-tuple representation denote triangular and trapezoidal fuzzy numbers respectively. The membership functions are illustrated in Figs. 1-4.

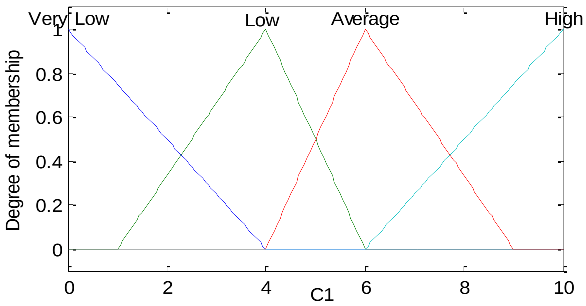


**Fig. 1.** Membership function of criteria $C_1$.

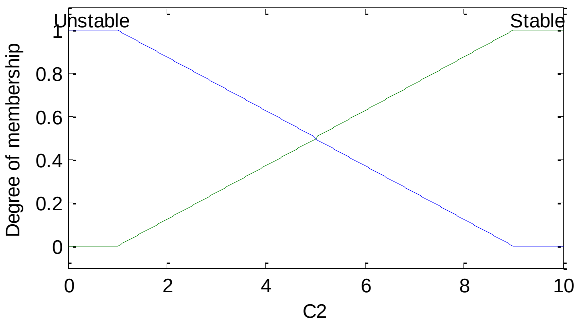


**Fig. 2.** Membership function of criteria $C_2$.

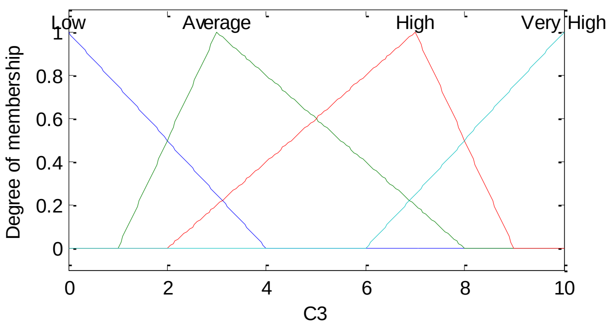


**Fig. 3.** Membership function of criteria $C_3$.

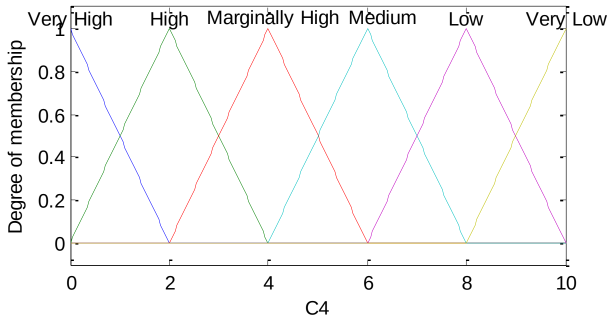


**Fig. 4.** Membership functions of output $O$.

Some of the rules extracted from the fuzzy logic toolbox are given in the following where the values in the brackets are the weights for the designated rules which are calculated using the RIPS.

1. If <monthly commitment is very low> and <job stability is unstable> and <loan history is low> then <level of risk is very high> (0.95)
2. If <monthly commitment is low> and <job stability is stable> and <loan history is low> then <level of risk is very low> (0.9)
3. If <monthly commitment is average> and <job stability is stable> and <loan history is low> then <level of risk is low> (0.85)
4. If <monthly commitment is high> and <job stability is stable> and <loan history is low> then <level of risk is medium> (0.8)
5. If <monthly commitment is very low> and <job stability is stable> and <loan history is low> then <level of risk is very low> (1)
6. If <monthly commitment is high> and <job stability is stable> and <loan history is very high> then <level of risk is medium> (0.75)

As an illustration, some values are given to $C_1$, $C_2$ and $C_3$ and the outputs are observed for the FIS with the weighted fuzzy rules. A comparison is also made with the FIS with equal weight. The observation is depicted in Table 5.

The first output is resulted from the inputs of $C_1$, $C_2$ and $C_3$ that are in the range of the IPR (refer to equation (2) – (5)). Hence it shows a high value of output, This output value is predictably the same for the equal weight and variable weight fuzzy rules since the weight given to both are $w^*$ = 1. There is a variation of the outputs when the variable weighted fuzzy rules are implemented. Depending on the weight of the rules, the output of the variable weight fuzzy rules can be lower or higher and also with smaller or larger difference than the output of the equal weight fuzzy rules of the FIS. In the numerical example, it can be seen that the outputs for applicants 8 and 10 differ when the weighted rules system is imposed as the discrepancies from the equal weight system is significantly large. Other outputs have the same category of risk, however, with different degree of output values. Hence, it can be concluded that the weighted fuzzy rules do affect some of


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the outputs of the FIS system. As mentioned earlier, the variation of weight sometimes is inevitable when there exists prioritization of some rules over the others. Thus, this situation has to be catered accordingly and the relative preference scheme in determining the weight of the criteria will be useful.

**Table 5**
A comparison of outputs between FIS with equal weighte and variable weight of fuzzy IF-THEN rules

| Input | $C_1$ | $C_2$ | $C_3$ | Risk level (with equal weighted fuzzy rules) | Risk level (with variable weighted fuzzy rules) | Percentage difference between equal and variable weight |
|---|---|---|---|---|---|---|
| 1 | 1 | 10 | 2 | 9.25 (Low) | 9.25 (Low) | 0 |
| 2 | 5 | 5 | 5 | 5 (Med) | 5.12 (Med) | +2.4% |
| 3 | 2 | 4 | 9 | 4.07 (Marg.) | 4.13 (Marg.) | +1.5% |
| 4 | 8 | 3 | 9 | 2.47 (High) | 2.56 (High) | +3.64% |
| 5 | 9 | 8 | 4 | 4.84 (Marg.) | 4.93 (Marg.) | +1.86% |
| 6 | 7 | 4 | 5 | 4.46 (Marg.) | 4.56 (Marg.) | +2.24% |
| 7 | 3 | 5 | 2 | 6.27 (Med.) | 5.67 (Med.) | -9,57% |
| 8 | 1 | 5 | 2 | 7.11 **(Low)** | 5.53 **(Med)** | -22.22% |
| 9 | 2 | 6 | 2 | 6.41 (Med.) | 5.45 (Med) | -14.98% |
| 10 | 3 | 7 | 1 | 7.7 **(Low)** | 6.31 **(Med)** | -18.05% |

## 5. Conclusion

In this paper, we have presented a new method of determining the weight of rules in FIS using a Relative Ideal Preference Scheme based on human judgment. This method is useful in developing a more effective FIS, as in many situations, rules in the FIS may not be suitable to be of equal weight due to different preference of conditions. Some rules may have a higher relative degree of importance. In the proposed method, an ideal preference rule is set with weight 1. Furthermore the threshold weight and the interval between rule's weight are calculated. The weight of each rule is determined using the computed threshold and interval between weights. The effectiveness of the method is illustrated with an example of determining the risk level of loan applicants. This Relative Ideal Preference Scheme of determining the weights of rules in the fuzzy inference system is useful when human judgment or preference has to take into consideration in the development of the FIS. The proposed scheme has the advantage over the existing approaches since the weights of rules are determined systematically and simple. However a large number of linguistic variables and linguistic values may affect the performance as it will increase the calculation time. For future study, an efficient system will be developed to overcome this problem.

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