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A Fuzzy QoS Optimization Method with Energy Efficiency for the Internet of Vehicles

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Abstract: Energy efficiency plays an important role in the Internet of vehicles, but it is very difficult to fit the need of QoS (Quality of Service) and energy efficiency at the same time. Here a QoS order is proposed for the Internet of vehicles. First, the multi attribute decision making of QoS in the Internet of vehicles is illustrated here. Then a QoS optimization with energy efficiency is set up to seek prior choice. Second, regarding uncertain attributes to the QoS optimization, a fuzzy QoS tool is introduced to optimize its performance. Third, a comprehensive experimental analysis of fuzzy QoS results is presented to verify its effectiveness and compare with other references. Last, some interesting conclusions and future research work are indicated at the end of the paper.

Keywords: The Internet of Vehicles, Fuzzy QoS, Energy Efficiency, Decision Analysis

1. Introduction

With the development of wireless communication technology and the need of the vehicle safety, great attention has been paid to vehicle technology and the Internet of vehicles [1]. Zhang (2016) built a soft computing based on maximizing consensus and fuzzy QoS approach to fuzzy intuitionistic fuzzy group decision making [2]. There exist a great number of vehicle technology theories and applications. For example, Ibanez (2016) extended Contreras-Castillo, Juan Integration challenges of Intelligent transportation systems with connected vehicle, cloud computing, and Internet of things technologies [3]. Lin (2016) developed admission control over the Internet of Vehicles attached with medical sensors for ubiquitous healthcare applications [4]. Yi (2016) concerned deploying energy routers in an energy internet based on electric vehicles [5]. Zhang (2016) introduced the innovation and development of the Internet of Vehicles [6]. Liang (2016) gave a secure-efficient data collection algorithm based on self-adaptive sensing model in mobile Internet of Vehicles [7].

Because the uncertainty of QoS problem also involves fuzzy sets, the concept of QoS is extended to develop a solution to the multi-attribute decision-making (MADM) problems with interval value fuzzy data. Van (2016) indicated fuzzy set approach to fuzzy co-clustering for data classification [8]. Sahin (2016) illustrated fuzzy multicriteria decision making method based on the improved accuracy function for fuzzy intuitionistic fuzzy sets [9]. Pramanik (2016) described fuzzy planar graphs in machine learning and cybernetics [10], where a numerical example is used to illustrate the proposed method and discuss distance measurement. In addition, the experimental analysis is also employed to compare the different dispersion measurement to determine priorities.

However, QoS measurement of Internet of Vehicles is very complex involving many conflicted factors. Li (2015) offered an energy efficient min delay-based geocast routing protocol for the Internet of Vehicles [11]. Jin (2015) illustrated an industrial-QoS-oriented remote wireless communication protocol for the Internet of Construction Vehicles [12]. Cheng (2015) reviewed the routing in internet of vehicles [13]. Alam (2015) presented workload model based dynamic adaptation of social Internet of Vehicles [14]. Kumar (2015) studied coalition games for spatio-temporal big data in Internet of Vehicles environment with a comparative analysis [15]. Lee (2015) proposed a guidance control of vehicles based on visual feedback via internet [16]. Pin (2015) implied a SWIMMING model, namely seamless and efficient wifi-based internet access from moving vehicles [17]. Salahuddin (2015) talked about software-defined networking for RSU clouds in support of the Internet of Vehicles [18]. Alam (2015) illustrated toward social Internet of Vehicles, with concept, architecture, and applications [19]. Kumar (2014) illustrated a Bayesian coalition game as-a-service for content distribution in the Internet of Vehicles [20]. These technologies mentioned above have also proved vehicle technology widely used in our life.

But it is very difficult to fit the need of QoS (Quality of Service) and energy efficiency at the same time, for example, energy efficiency may be conflict with QoS [5], [11]. Yang (2014) described an overview of the Internet of Vehicles [21]. Fu (2014) discussed reservation based optimal parking lot recommendation model in the Internet of Vehicle Environment [22]. Harigovindan (2014) made a research on proportional fair resource allocation in vehicle-to-infrastructure networks for drive-thru Internet applications [23]. Here a QoS order is proposed for the Internet of vehicles. First, the multi attribute decision making of QoS in the Internet of vehicles is illustrated here. Then a QoS optimization with energy efficiency is set up to seek prior choice. Second, regarding uncertain attributes to the QoS optimization, a fuzzy QoS tool is introduced to optimize its performance. Third, a comprehensive experimental analysis of fuzzy QoS results is presented to verify its effectiveness and compare with other references. Last, some interesting conclusions and future research work are indicated at the end of the paper.

2. QoS Order for the Internet of Vehicles

2.1. Multiple Attribute Decision Making of QoS

The Internet of Vehicles System is an application of the concept of Internet of Things (IoT) in the traffic environment, such as a carpooling/ridesharing system, a private vehicle and the carsharing model, as shown in Figure.1. The system can provide decision-makers with the necessary data, information and background to help clarify the decision-making objectives and identify driving problems, establish or modify the decision-making model, provide various options, and evaluation and optimization of various options. Through the human-computer interaction function analysis, comparison and judgment, in order to provide the necessary support for the right decision in driving.

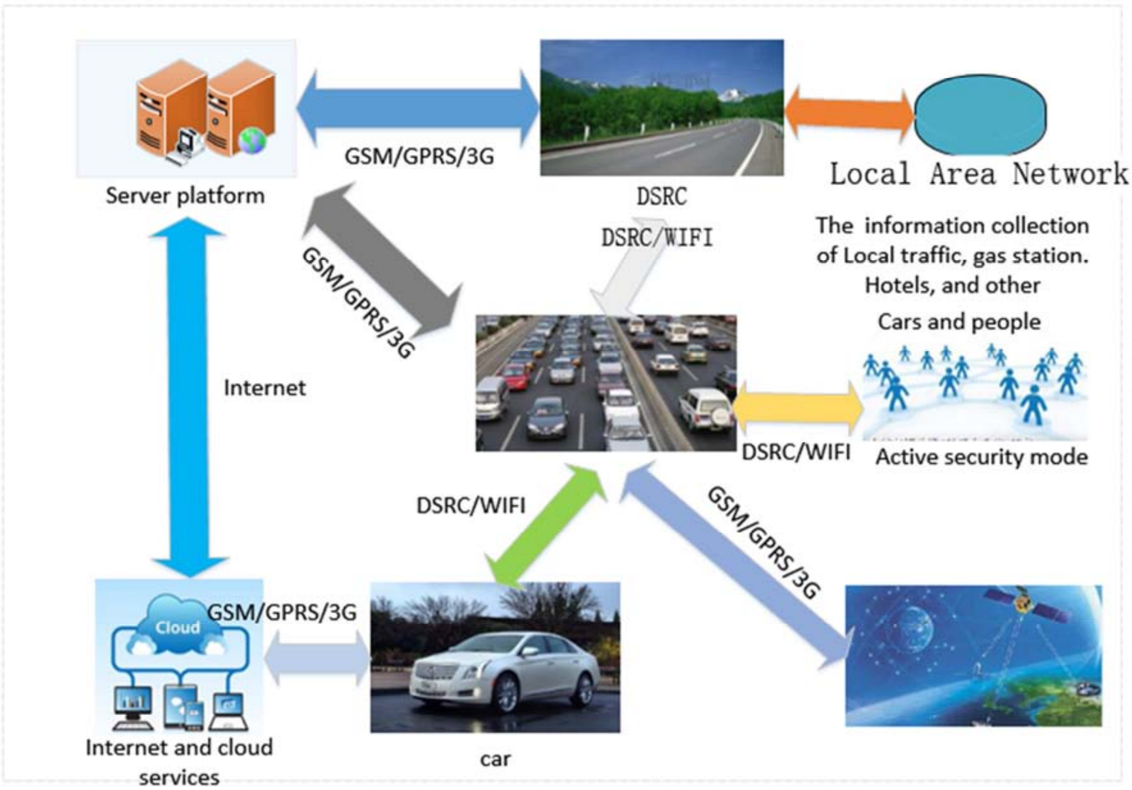


Figure 1. *The Internet of Vehicles System.*

The decision matrix can display the problem of the authoritative MADM, i and the ith attribute become the representative elements ϑ_i, regarding to the ith attribute ϕ_j. In this paper, fuzzy decision matrices P is developed by the normalized matrices. Y is generously interacted including the decision attributes in the decision problem itself. Y will always be limited and nonzero, the cardinal number of which X equals M. Let Int ([0, 1]) represent a string of all closed cells [0,1]. A fuzzy QoS ϑ_i of the ith substituted on Y is computed by

$$\vartheta_i = \left\{\left\langle \phi, N_{\vartheta_i(\phi)}\right\rangle \middle| \phi \in Y\right\} \tag{1}$$

Where

$$A_{\vartheta_i} : Y \to Int([0,1]),$$

such that

$$\phi \to A_{\vartheta_i}(\phi) = \left[A^-_{\vartheta_i}(\phi), A^+_{\vartheta_i}(\phi)\right].$$

Fuzzy QoS theory is mathematics identical to the Intuitionistic Fuzzy Sets theory, and it is distinguished by three functions to express the belongingness, the non-belongingness, and the hesitation. Now that fuzzy QoS is equally generalized fuzzy sets to express the QoS method using the fuzzy notation, a fuzzy QoS B_i of the ith substitute on Y is computed by

$$\vartheta_i = \left\{\left\langle \phi, \omega_{\vartheta_i}(\phi), \varsigma_{\vartheta_i}(\phi)\right\rangle \middle| \phi \in Y\right\} \tag{2}$$

with $\omega_{\vartheta_i}(\phi) : Y \to [0,1]$ and $\varsigma_{\vartheta_i}(\phi) : Y \to [0,1]$, such that $0 \le \omega_{\vartheta_i}(\phi) + \varsigma_{\vartheta_i}(\phi) \le 1$ for all $\phi \in Y$. $\omega_{\vartheta_i}(\phi)$ and $\varsigma_{\vartheta_i}(\phi)$ are the membership and the non-membership of the ith alternative regarding to the attribute ϕ, respectively. For each element $\phi \in Y$, the uncertainty index of ϕ in ϑ_i can be defined as follow:

$$\alpha_{\vartheta_i}(\phi) = 1 - \omega_{\vartheta_i}(\phi) - \varsigma_{\vartheta_i}(\phi) \tag{3}$$

Where $\alpha_{\vartheta_i}(\phi) \in [0,1]$, $\forall \phi \in Y$. $\alpha_{\vartheta_i}(\phi)$ reflects decision of makers to determine the membership's performance. Although the membership level of the fuzzy QoS does not have a specific set of peers as an ordinary fuzzy set, the shortage of specificity makes it more practicable for decision making. There is

$$\begin{aligned} A_{\vartheta_i}(\phi) &= \left[A^-_{\vartheta_i}(\phi), A^+_{\vartheta_i}(\phi)\right] \\ &\left[\omega_{\vartheta_i}(\phi), 1 - \varsigma_{\vartheta_i}(\phi)\right] \\ &\left[\omega_{\vartheta_i}(\phi), \omega_{\vartheta_i}(\phi) + \alpha_{\vartheta_i}(\phi)\right] \end{aligned} \tag{4}$$

Interval $\left[A^-_{\vartheta_i}(\phi), A^+_{\vartheta_i}(\phi)\right]$ displays all possibilities of membership with the hesitant to an extent $\alpha_{\vartheta_i}(\phi)$. Taking $i = 1,2,\cdots a$; $j = 1,2,\cdots b$; and $\left[A^-_{\vartheta_i}(\phi), A^+_{\vartheta_i}(\phi)\right]$, or equivalently, $\left(\omega_{\vartheta_i}(\phi), \varsigma_{\vartheta_i}(\phi), \alpha_{\vartheta_i}(\phi)\right)$ by fuzzy notation, into consideration, the *ith* alternative can be gotten according to the *y*th attribute.

There is

$$P = \begin{bmatrix} \left[A^-_{\vartheta_1}(\phi_1), A^+_{\vartheta_1}(\phi_1)\right] & \left[A^-_{\vartheta_1}(\phi_2), A^+_{\vartheta_1}(\phi_2)\right] & \cdots & \left[A^-_{\vartheta_1}(\phi_b), A^+_{\vartheta_1}(\phi_b)\right] \\ \left[A^-_{\vartheta_2}(\phi_1), A^+_{\vartheta_2}(\phi_1)\right] & \left[A^-_{\vartheta_2}(\phi_2), A^+_{\vartheta_2}(\phi_2)\right] & \cdots & \left[A^-_{\vartheta_2}(\phi_b), A^+_{\vartheta_2}(\phi_b)\right] \\ \vdots & \vdots & \ddots & ⋰ \\ \left[A^-_{\vartheta_a}(\phi_1), A^+_{\vartheta_a}(\phi_1)\right] & \left[A^-_{\vartheta_a}(\phi_2), A^+_{\vartheta_a}(\phi_2)\right] & \cdots & \left[A^-_{\vartheta_a}(\phi_b), A^+_{\vartheta_a}(\phi_b)\right] \end{bmatrix}$$
$$\begin{bmatrix} \left(\omega_{\vartheta_1}(\phi_1), \varsigma_{\vartheta_1}(\phi_1), \alpha_{\vartheta_1}(\phi_1)\right) & \left(\omega_{\vartheta_1}(\phi_2), \varsigma_{\vartheta_1}(\phi_2), \alpha_{\vartheta_1}(\phi_2)\right) & \cdots & \left(\omega_{\vartheta_1}(\phi_b), \varsigma_{\vartheta_1}(\phi_b), \alpha_{\vartheta_1}(\phi_b)\right) \\ \left(\omega_{\vartheta_2}(\phi_1), \varsigma_{\vartheta_2}(\phi_1), \alpha_{\vartheta_2}(\phi_1)\right) & \left(\omega_{\vartheta_2}(\phi_2), \varsigma_{\vartheta_2}(\phi_2), \alpha_{\vartheta_2}(\phi_2)\right) & \cdots & \left(\omega_{\vartheta_2}(\phi_b), \varsigma_{\vartheta_2}(\phi_b), \alpha_{\vartheta_2}(\phi_b)\right) \\ \vdots & \vdots & \ddots & ⋰ \\ \left(\omega_{\vartheta_a}(\phi_1), \varsigma_{\vartheta_a}(\phi_1), \alpha_{\vartheta_a}(\phi_1)\right) & \left(\omega_{\vartheta_a}(\phi_2), \varsigma_{\vartheta_a}(\phi_2), \alpha_{\vartheta_a}(\phi_2)\right) & \cdots & \left(\omega_{\vartheta_a}(\phi_b), \varsigma_{\vartheta_a}(\phi_b), \alpha_{\vartheta_a}(\phi_b)\right) \end{bmatrix} \tag{5}$$

Because all attributes cannot be considered equally important, a set of grades of significance must be accepted, expressed as T from the decision maker. It can also be expressed as a decision attribute in the decision-maker's subjective importance assessment process. Then

$$\begin{aligned} T &= \left\{\left\langle \phi, A_{T(\phi)}\right\rangle \middle| \phi \in Y\right\} \\ &= \left\{\left\langle \phi, \omega_{T(\phi)}, \varsigma_{T(\phi)}\right\rangle \middle| \phi \in Y\right\} \end{aligned} \tag{6}$$

where $A_T : Y \to Int([0,1]), \phi \to A_{T(\phi)} = \left[A^-_T(\phi), A^+_T(\phi)\right]$. What is more, $\omega_{T(\phi)} : Y \to [0,1]$ and $\varsigma_{T(\phi)} : Y \to [0,1]$ define the significance of an attribute. For each $\phi \in Y$, there is

$$\alpha_{T(\phi)} = 1 - \varsigma_{T(\phi)} - \omega_{T(\phi)} \tag{7}$$

2.2. QoS Optimization with Energy Efficiency

As energy efficiency plays an important role in the Internet of vehicles, here a QoS optimization with energy efficiency is set up to seek prior choice. According to two fuzzy QoS ϑ_i, and T, there is

$$\begin{aligned}\vartheta_i \cdot T &= \left\{\left\langle \phi, A_{\vartheta_i} \cdot T(\phi)\right\rangle \middle| \phi \in Y\right\} \\ &= \left\{\left\langle \phi, \omega_{\vartheta_i}(\phi) \cdot \omega_T(\phi), \varsigma_T(\phi) - \varsigma_{\vartheta_i}(\phi) \cdot \varsigma_T(\phi) + \varsigma_{\vartheta_i}(\phi) \cdot \right\rangle \middle| \phi \in Y\right\}\end{aligned} \tag{8}$$

And

$$\alpha_{\vartheta_i} \cdot T(\phi) = 1 + \varsigma_{\vartheta_i}(\phi) \cdot \varsigma_T(\phi) - \varsigma_{\vartheta_i}(\phi) - \omega_{\vartheta_i}(\phi) \cdot \omega_T(\phi) - \varsigma_T(\phi) \tag{9}$$

The decision matrix P' is

$$P' = \begin{bmatrix} \left[A^-_{\vartheta_1 \cdot T}(\phi_1), A^+_{\vartheta_1 \cdot T}(\phi_1)\right] & \cdots & \left[A^-_{\vartheta_1 \cdot T}(\phi_b), A^+_{\vartheta_1 \cdot T}(\phi_b)\right] \\ \vdots & \ddots & \iddots \\ \left[A^-_{\vartheta_a \cdot T}(\phi_1), A^+_{\vartheta_a \cdot T}(\phi_1)\right] & \cdots & \left[A^-_{\vartheta_a \cdot T}(\phi_{b1}), A^+_{\vartheta_a \cdot T}(\phi_b)\right] \end{bmatrix} \tag{10}$$

Suppose J_1 is a benefit attribute set, there is:

$$\begin{aligned}\vartheta^* &= \left\{\left\langle \phi_j, \left[\left[\max_i \omega_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_1\right], \left[\min_i \omega_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_2\right]\right], \left[\left[\max_i \varsigma_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_1\right], \left[\min_i \varsigma_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_2\right]\right]\right\rangle \middle| i = 1,2,\cdots a\right\} \\ &\left\{\left\langle \phi_1, \omega_{\vartheta^* \cdot T}(\phi_1), \varsigma_{\vartheta^* \cdot T}(\phi_1)\right\rangle, \left\langle \phi_2, \omega_{\vartheta^* \cdot T}(\phi_2), \varsigma_{\vartheta^* \cdot T}(\phi_2)\right\rangle, \cdots \left\langle \phi_b, \omega_{\vartheta^* \cdot T}(\phi_b), \varsigma_{\vartheta^* \cdot T}(\phi_b)\right\rangle\right\}\end{aligned} \tag{11}$$

$$\begin{aligned}\vartheta^- &= \left\{\left\langle \phi, \left[\left[\min_i \omega_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_1\right], \left[\max_i \omega_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_2\right]\right], \left[\left[\max_i \varsigma_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_1\right], \left[\min_i \varsigma_{\vartheta_i} \cdot T(\phi_j) \middle| j \in J_2\right]\right]\right\rangle \middle| i = 1,2,\cdots a\right\} \\ &\left\{\left\langle \phi_1, \omega_{\vartheta^- \cdot T}(\phi_1), \varsigma_{\vartheta^- \cdot T}(\phi_1)\right\rangle, \left\langle \phi_2, \omega_{\vartheta^- \cdot T}(\phi_2), \varsigma_{\vartheta^- \cdot T}(\phi_2)\right\rangle, \cdots \left\langle \phi_b, \omega_{\vartheta^- \cdot T}(\phi_b), \varsigma_{\vartheta^- \cdot T}(\phi_b)\right\rangle\right\}\end{aligned} \tag{12}$$

The separation between substitutes can be achieved by the Hamming distance, including inductive Hamming distance, Euclidean distance and normalization. The separation of measured values R_i* and R_i-, positive and negative ideal solutions of each alternative interval, severally, are grew out from Hamming distance.

The relative closeness of a substituted ϑ_i is with respect to the fuzzy positive-ideal solution, and ϑ^* is defined as a general formula as follows:

$$K_{i^*} = \frac{R_{i^-}}{R_{i^*} + R_{i^-}}, \tag{13}$$

where $0 \le K_{i^*} \le 1$ and $i = 1,2, \ldots,$ a. Then, the preference order of substitutions can be ranked relaying on the descending order of K_{i^*} 'r.

QoS method about the fuzzy version is summarized as following steps:

- Construct the decision matrix P.
- Construct the fuzzy weighted matrix P.
- Calculate the fuzzy positive and negative ideal solutions.
- Calculate the relative closeness.
- Rank the preference order.

3. Experimental Analysis

3.1. Problem Description

In this part, a numerical example in the Internet of vehicles linked with a decision making problem is displayed to verify the proposed fuzzy QoS method. A QoS optimization with energy efficiency is set up to seek prior choice, and the decision matrix *D* in Step 1 is presented as below:

Table 1. *The QoS decision matrix D.*

P=	ϱ_1	ϱ_2	ϱ_3	ϱ_4	ϱ_5	ϱ_6
ϕ_1	(0.34, 0.67)	(0.35,0.82)	(0.36,0.33)	(0.36,0.58)	(0.53,0.67)	(0.35, 0.51)
ϕ_2	(0.32, 0.34)	(0.66, 0.64)	(0.39, 0.64)	(0.46, 0.28)	(0.64, 0.97)	(0.89, 0.36)
ϕ_3	(0.67, 0.78)	(0.31, 0.43)	(0.21, 0.75)	(0.54, 0.32)	(0.47, 0.18)	(0.36, 0.12)
ϕ_4	(0.14, 0.53)	(0.84,0.47)	(0.29, 0.25)	(0.51,0.33)	(0.64, 0.44)	(0.35, 0.87)

Step 1, supposing fuzzy QoS is proposed to evaluate the fuzzy decision matrices referring to six choices of four attributes.

Supposing that the subjective importance of attributes T is given by the decision makers as

$$\begin{array}{ccccc} & \phi_1 & \phi_2 & \phi_3 & \phi_4 \\ \mathrm{T} = & [0.79,0.62] & [0.72,0.76] & [0.57,0.82] & [0.63,0.66] \end{array}$$

$$\begin{array}{ccccc} & \phi_1 & \phi_2 & \phi_3 & \phi_4 \\ = & [(0.79,0.06,0.04) & (0.72,0.30,0.09) & (0.57,0.08,0.05) & (0.63,0.26,0.12)] \end{array}$$

And the fuzzy decision matrix can be calculated as in Table 2.

Table 2. *Fuzzy QoS decision matrix. P.*

P=	ϱ_1	ϱ_2	ϱ_3	ϱ_4	ϱ_5	ϱ_6
ϕ_1	(0.34,0.34,0.67)	(0.25,0.35,0.82)	(0.21,0.36,0.33)	(0.39,0.36,0.58)	(0.57,0.53,0.67)	(0.35,0.64,0.51)
ϕ_2	(0.32,0.44,0.34)	(0.66,0.42,0.64)	(0.39,0.77,0.64)	(0.46,0.29,0.28)	(0.64,0.89,0.97)	(0.89,0.75,0.36)
ϕ_3	(0.67,0.39,0.78)	(0.31,0.28,0.43)	(0.21,0.47,0.75)	(0.54,0.43,0.32)	(0.47,0.85,0.18)	(0.36,0.78,0.12)
ϕ_4	(0.14,0.77,0.53)	(0.84,0.49,0.47)	(0.29,0.76,0.25)	(0.51,0.46,0.33)	(0.64,0.25,0.44)	(0.35,0.78,0.87)

Applying Step 2, the fuzzy decision matrix P and weighted decision matrix P are then computed as Table 3 and 4, respectively.

Table 3. *The weighted QoS decision matrix P.*

P=	ϱ_1	ϱ_2	ϱ_3	ϱ_4	ϱ_5	ϱ_6
ϕ_1	(0.54, 0.37)	(0.45,0.22)	(0.56,0.53)	(0.76,0.28)	(0.43,0.67)	(0.45, 0.57)
ϕ_2	(0.35, 0.35)	(0.67, 0.74)	(0.49, 0.54)	(0.26, 0.22)	(0.54, 0.87)	(0.59, 0.46)
ϕ_3	(0.65, 0.75)	(0.32, 0.53)	(0.25, 0.65)	(0.45 0.35)	(0.45, 0.17)	(0.37, 0.52)
ϕ_4	(0.13, 0.55)	(0.64,0.57)	(0.59, 0.35)	(0.51,0.53)	(0.65, 0.54)	(0.45, 0.77)

Table 4. *The fuzzy weighted QoS decision matrix P.*

P=	ϱ_1	ϱ_2	ϱ_3	ϱ_4	ϱ_5	ϱ_6
ϕ_1	(0.34,0.34,0.67)	(0.25,0.35,0.82)	(0.21,0.36,0.33)	(0.39,0.36,0.58)	(0.57,0.53,0.67)	(0.35,0.64,0.51)
ϕ_2	(0.32,0.44,0.34)	(0.66,0.42,0.64)	(0.39,0.77,0.64)	(0.46,0.29,0.28)	(0.64,0.89,0.97)	(0.89,0.75,0.36)
ϕ_3	(0.67,0.39,0.78)	(0.31,0.28,0.43)	(0.21,0.47,0.75)	(0.54,0.43,0.32)	(0.47,0.85,0.18)	(0.36,0.78,0.12)
ϕ_4	(0.14,0.77,0.53)	(0.84,0.49,0.47)	(0.29,0.76,0.25)	(0.51,0.46,0.33)	(0.64,0.25,0.44)	(0.35,0.78,0.87)

3.2. Results

In this section, assuming that ϕ_1, ϕ_2 , and ϕ_4 are facilitate attributes and ϕ_3 is an energy attribute. That is $J_1 = \{\phi 1, \phi 2, \phi 3\}$ $J1 = \{\phi 1, \phi 2, \phi 4\}$ and $J_2 = \{\phi 3\}$.

Applying to Step 3, the active-ideal settlements is gotten then

$\vartheta^* = [(0.33,0.22,0.45)\ (0.18,0.62,0.22)\ (0.38,,0.38,0.34)\ (0.60,0.68,0.02)]$

The fuzzy passive-ideal settlement is as follows:

$\vartheta^- = [(0.01,0.52,0.37)\ \ (0.18,0.62,0.22)\ \ (0.47,0.68,0.25)\ \ (0.20,0.50,0.20)]$

The departure methods are based upon the Hamming range, the Euclidean range and their formalized editions, described in Figure 2.

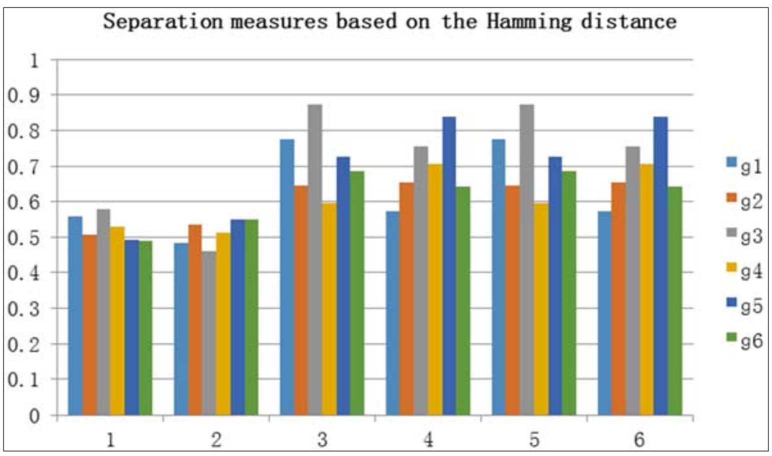


Figure 2. *Separation measures for the numerical example.*

Step 4 is used to calculate the opposite close relationship to the fuzzy ideal settlements. The K_{i^*} values and homologous rankings of the explained case with the distinct departure methods are enumerated, including $K_{i^*}^{p_1}$, $K_{i^*}^{p_2}$, $K_{i^*}^{p_3}$ are based upon the Hamming range, $K_{i^*}^{h_1}$, $K_{i^*}^{h_2}$, $K_{i^*}^{h_3}$ are based upon the formalized Hamming range, $K_{i^*}^{f_1}$,, $K_{i^*}^{f_2}$, $K_{i^*}^{f_3}$ are based upon the Euclidean range, and$K_{i^*}^{o_1}$, $K_{i^*}^{o_2}$, $K_{i^*}^{o_3}$ are based upon the formalized Euclidean range.

$$\vartheta^- = [(0.01,0.52,0.37)\ (0.18,0.90,0.22)\ (0.38,0.30,0.34)(0.20,0.98,0.12)]$$

The numerical example presents that there are various ways of the same results among distinct range measures. To be honest, 12 distance circumscription, i.e., *p1, p2, p3, h1, h2, h3, f1, f2, f3, o1, o2, o3*, always emerge only five outcomes.

Acquiring that $K_{i^*}^{p_1} \geq K_{i^*}^{p_2}, K_{i^-}^{p_2} \geq K_{i^-}^{p_3}, K_{i^*}^{h_1} \geq K_{i^*}^{h_2}$, and, however, supposing (9) and (10), one can easily check that $K_{i^*}^{p_1} = K_{i^*}^{p_2}, K_{i^-}^{p_2} = K_{i^-}^{p_3}, K_{i^*}^{h_1} = K_{i^*}^{h_2}$ and $K_{i^-}^{h_2} = K_{i^-}^{h_3}$ for each alternative are conspicuously obtained.

For benefit attributes of QoS for the Internet of Vehicles, there is

$$\frac{1}{2}\left(|\omega_{\varrho_i} \cdot T(\emptyset_j) - \omega_{\vartheta^*} \cdot T(\emptyset_j)| + |\varsigma_{\varrho_i} \cdot T(\emptyset_j) - \varsigma_{\vartheta^*} \cdot T(\emptyset_j)| + |\alpha_{\varrho_i} \cdot T(\emptyset_j) - \alpha_{\vartheta^*} \cdot T(\emptyset_j)|\right)$$

$$= \frac{1}{2}\left[\left(\omega_{\varrho_i} \cdot T(\emptyset_j) - \omega_{\vartheta^*} \cdot T(\emptyset_j) + \varsigma_{\varrho_i} \cdot T(\emptyset_j) - \varsigma_{\vartheta^*} \cdot T(\emptyset_j)\right) + \left|\left(1 - \varsigma_{\varrho_i} \cdot T(\emptyset_j)\right) - \omega_{\varrho_i} \cdot T(\emptyset_j) - \varsigma_{\vartheta^*} \cdot T(\emptyset_j) - \left(1 - \omega_{\vartheta^*} \cdot T(\emptyset_j)\right)\right|\right] \quad (14)$$

$$= \max\left\{\left|\omega_{\varrho_i} \cdot T(\emptyset_j) - \omega_{\vartheta^*} \cdot T(\emptyset_j)\right|, \left|\varsigma_{\varrho_i} \cdot T(\emptyset_j) - \varsigma_{\vartheta^*} \cdot T(\emptyset_j)\right|\right\}$$

The compared results of the numerical example based on reference [11], [17] and [20] are shown in Figure 3, 4, and 5.

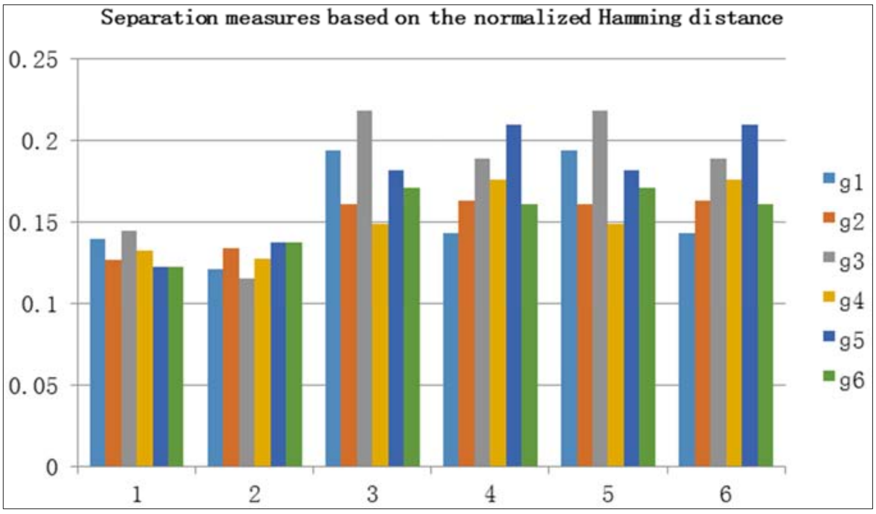


Figure 3. *Compared result of reference [11].*

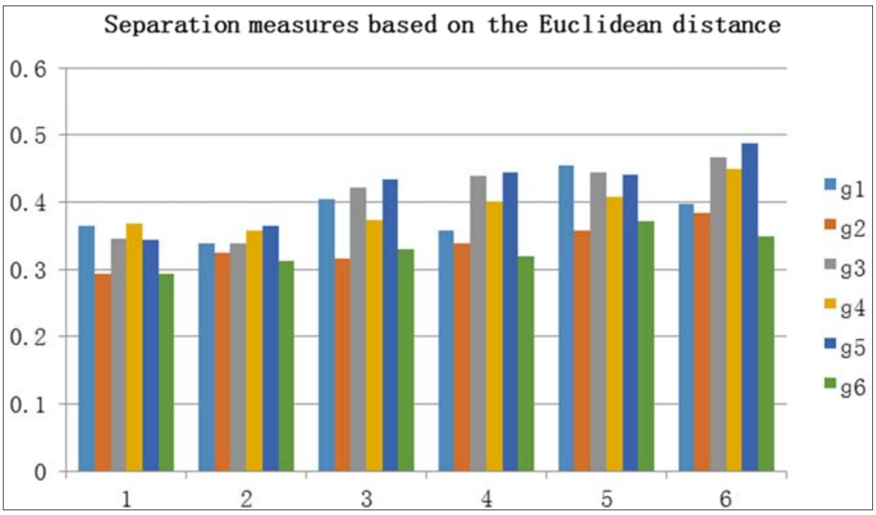


Figure 4. *Compared result of reference [17].*

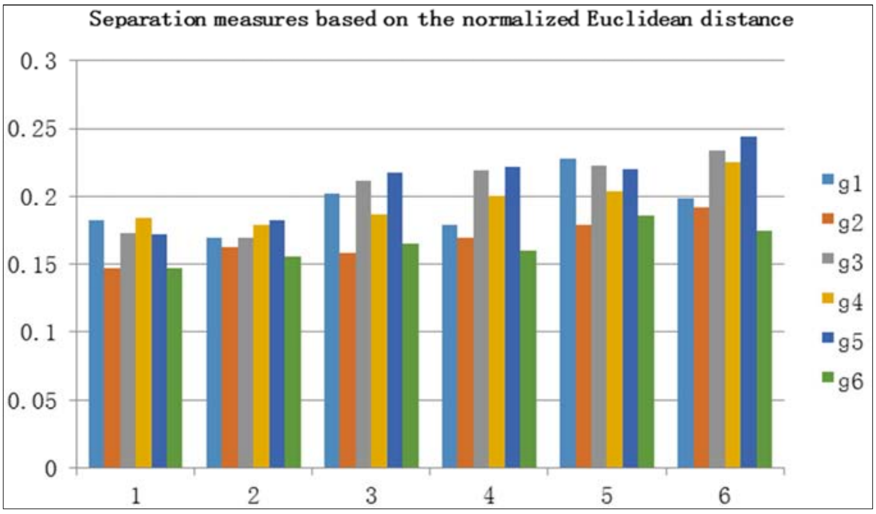


Figure 5. *Compared result of reference [20].*

Five results can be obtained from distance measures: (i) $K_{i^*}^{p_1}=K_{i^*}^{h_2}$; (ii) $K_{i^*}^{p_2}=K_{i^*}^{h_2}=K_{i^*}^{p_3}=K_{i^*}^{h_2}$; (iii) $K_{i^*}^{f_1}=K_{i^*}^{o_1}$; (iv) $K_{i^*}^{f_2}=K_{i^*}^{o_2}$; and (v) $K_{i^*}^{f_3}=K_{i^*}^{o_3}$. On condition that the fuzzy QoS results are identical whatever canonical or normalized versions, *p1, p2, f1, f2* and *f3* are considered to conduct the experimental analysis.

For energy efficiency attributes of QoS for the Internet of Vehicles, there is

$$\frac{1}{2}\left(|\omega_{g_i}\cdot T(\emptyset_j)-\omega_{\vartheta^*}\cdot T(\emptyset_j)|+|\varsigma_{g_i}\cdot T(\emptyset_j)-\varsigma_{\vartheta^*}\cdot T(\emptyset_j)|+|\alpha_{g_i}\cdot T(\emptyset_j)-\alpha_{\vartheta^*}\cdot T(\emptyset_j)|\right)$$

$$=\frac{1}{2}\left[\left(\omega_{g_i}\cdot T(\emptyset_j)-\omega_{\vartheta^*}\cdot T(\emptyset_j)+\varsigma_{g_i}\cdot T(\emptyset_j)-\varsigma_{\vartheta^*}\cdot T(\emptyset_j)\right)+\left|\left(1-\varsigma_{g_i}\cdot T(\emptyset_j)\right)-\omega_{g_i}\cdot T(\emptyset_j)-\varsigma_{\vartheta^*}\cdot T(\emptyset_j)-\left(1-\omega_{\vartheta^*}\cdot T(\emptyset_j)\right)\right|\right]$$

$$=\max\left\{\left|\omega_{g_i}\cdot T(\emptyset_j)-\omega_{\vartheta^*}\cdot T(\emptyset_j)\right|,\left|\varsigma_{g_i}\cdot T(\emptyset_j)-\varsigma_{\vartheta^*}\cdot T(\emptyset_j)\right|\right\} \tag{15}$$

It follows evidently that $R_{i^*}^{p_2}=R_{i^*}^{p_3}$. Similarly, it can be proved that $R_{i-}^{p_2}=R_{i-}^{p_3}$, $R_{i^*}^{h_2}=R_{i^*}^{h_3}$, and $R_{i-}^{h_2}=R_{i-}^{h_3}$.

Consequently, $K_{i^*}^{p_2}=K_{i^*}^{p_3}$ and $K_{i^*}^{h_2}=K_{i^*}^{h_3}$

Besides, the results show that the relative closeness and the corresponding preference are based on the Hamming distance, which are founded on the normalized counterpart. The Euclidean distance and its normalized version follow the rule. That is,

$$K_{i^*}^{hk}=\frac{R_{i-}^{hk}}{R_{i^*}^{hk}+R_{i-}^{hk}}=\frac{1/bR_{i-}^{pk}}{1/b(R_{i^*}^{pk}+R_{i-}^{pk})}=K_{i^*}^{pk}$$

$$K_{i^*}^{ok}=\frac{R_{i-}^{ok}}{R_{i^*}^{ok}+R_{i-}^{ok}}=\frac{1/bR_{i-}^{fk}}{1/b(R_{i^*}^{fk}+R_{i-}^{fk})}=K_{i^*}^{fk}$$

3.3. Further Discussion

Judging from the six steps of the fuzzy QoS method with energy efficiency, the computational experiments are conducted, as shown in figure 6.

For each instance, all available pairs of distance measures will be thought, including (p_1,p_2), (p_1,f_1), (p_1,f_2), (p_1,f_3), (p_2,f_1), (p_2,f_2), (f_1,f_2), (f_1,f_3) and (f_2,f_3). More particularly, in each combination of m and n values, the comparison analysis of each distance is performed 100 times. Next, the chief computational consequence and contrast analysis are presented. A QoS optimization with energy efficiency is set up to seek prior choice.

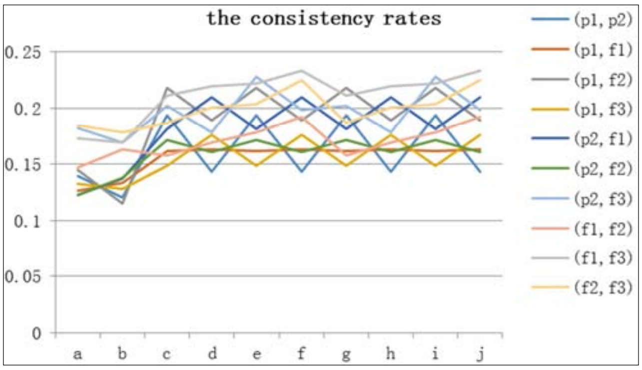


Figure 6. *Experimental results: the consistency rates of (p, f).*

The uniformity rate gauges the concordance between two complete preference orders surrendered by different distances for each a*b combination. There is no need to care about which distance definition will be applied. The reckoned results illustrate that the consistency rates are higher when the number of alternatives in a decision problem is smaller. However, if m increases, the consistency rates will drastically drop. Furthermore, in most cases, the closer the value of m approaches 13, the consistency rate approximates 0. At this part, that the optimal orders are seldom identical applying dissimilar distance gauges where fuzzy QoS measure is what should be emphasized.

From these statistics example, the fuzzy QoS with energy efficiency by five distance measures are compared by generating and computing uncertain problems in different cases. A comprehensive comparative research of superiority rank sequence numbers includes the consistency rate, the paradox rate of the best choice, and average correlation coefficients to be conducted. The fuzzy rules are shown in figure 7 a and b.

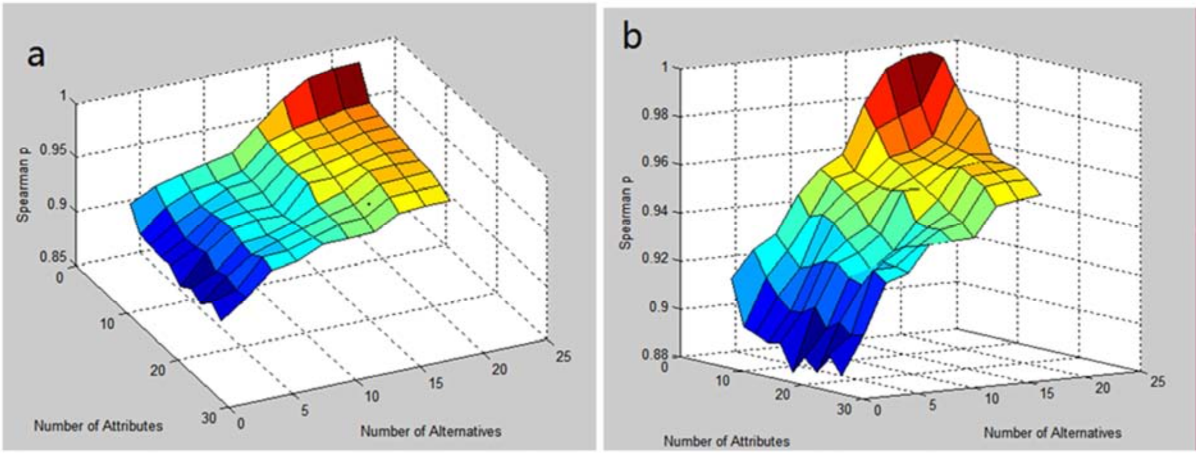


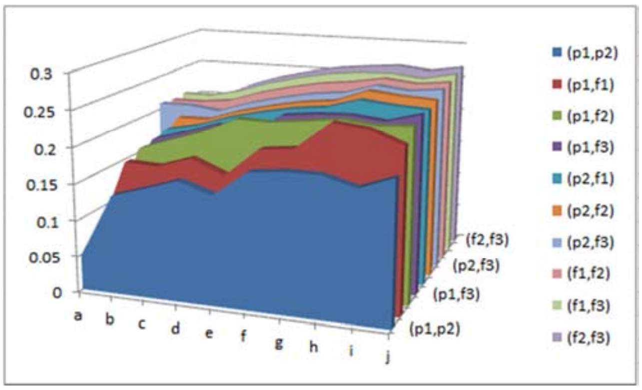
Figure 7. *Comparison of different fuzzy rules.*

First, two real numbers, η_1 and η_2 are equally distributed over the interval [0,1]. Secondly, let $\omega_{\varrho_i}(\emptyset_j) = \min\{\eta_1, \eta_2\}$ and $\varsigma_{\varrho_i}(\emptyset_j) = 1 - \max\{\eta_1, \eta_2\}$. Finally, $\alpha_{\varrho_i}(\emptyset_j) = 1 - \omega_{\varrho_i}(\emptyset_j) - \varsigma_{\varrho_i}(\emptyset_j)$. the data of $\left(\omega_T(\emptyset_j), \varsigma_T(\emptyset_j), \alpha_T(\emptyset_j)\right) r$ can be created in an analogous measure.

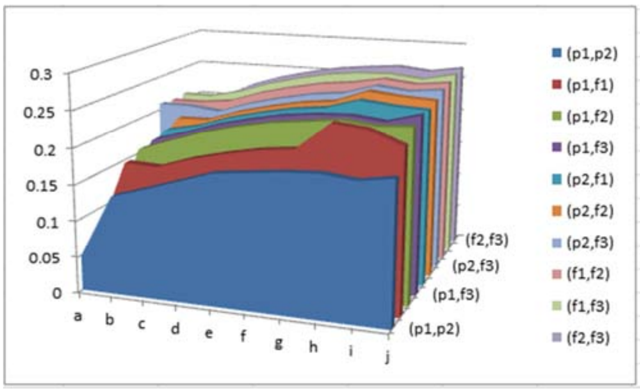
The quantity of attributes umber on consistency rates whose effect is not much significant as same as in the same data, which is reflected from the curves' closeness that is dissimilar to the quantity of attributes. Although taking many attributes into consideration, the consequences of consistency rates produce resembling models. Consequently, changes in the quantity of substitutes are more resourceful to consistency rates than in the quantity of attributes.

Figure. 8 presents the experimental comparison of energy efficiency between the proposed model and the other models in references [11], [17], [20]. The paradox rate rises in the QoS with energy efficiency. It is seemed that the contradiction rate has a soaring tendency with the quantity of properties. Nevertheless, this direction is pretty abnormal when b>7. Besides, the distinguish among the paradox graphs for b>7 is not as remarkable as in lower n values (i.e., 3 and 5). The paradox rates of the optimal available in pair (p_1, f_2) are fairly higher than the left for most of m*n combination. Conversely, the paradox rates in pair (f_2, f_3) are fairly lower than the left. Figure. 8 portrays an appearance that the high level of paradox rates depend on 0.1-0.2. It means that the presumption for the most prioritizing is available to apply individual distance steps with illogicality evaluated to be 10-20%. It indicates the distance steps of applying individual in the fuzzy QoS approach may affect the ultimate alternatives by decision-makers.

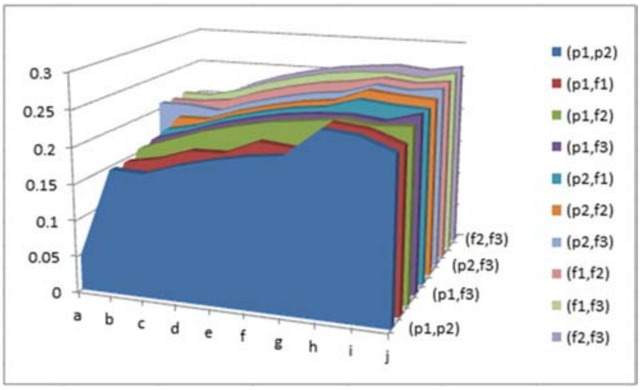
One of the ranking inconsistency advantages can be tested for the paradox rate of the optimal choice. Now that decision makers are always anxious about the best alternative, matching the first rank frequently is more significant than matching all ranks. Hence, the paradox rate of the first rank is between double consequences applying different distances. For instance, supposing that the ranking of a string of six substitutes is identical to $\varrho_2 > \varrho_6 > \varrho_3 > \varrho_1 > \varrho_4 > \varrho_5$, which is depended on p_1 and the other measures. Applying f_1, corresponding results can be yielded, then a complication of a ranking paradox of the optimal available has created.



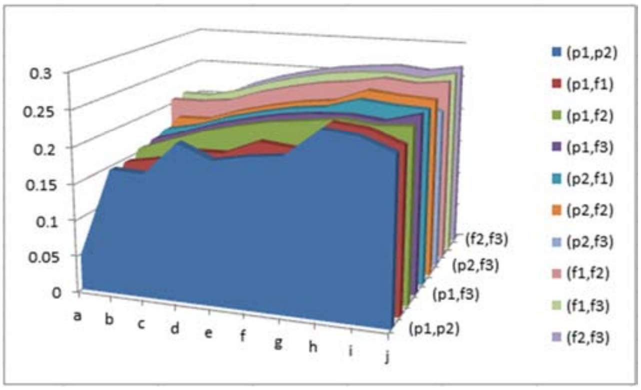
a. proposed model



b. reference [11]



c. reference [17]



d. reference [20]

Figure 8. *Experimental comparison of energy efficiency.*

As shown in the diagram figure 8, the preference profiles between pair (p_1, f_2) have lower average correlation coefficients and pair (p_1, f_3) is the second lowest. On the other sides, the preference profiles between pair (f_1, f_3) (f_2, f_3) have the highest strongest values and pair (f_1, f_3) has the second highest strongest values. Note that the biggest difference is always appeared in [11] based on hamming distance and Euclidean distance based on [17] between the interval value fuzzy QoS. Besides, the more properties are drawn, it is more likely that the ranking distinction between pair (p_1, f_2) will be enlarged [20]. Finally, the correlation of Euclidean distance is usually better than hamming distance or Euclidean distance and the correlation between the hamming distances is stronger. In order to the shape of the graphics in the data, regression analysis further. Using the second order regression model to capture the select number of members, the number of application properties needs only several steps in the correlation coefficient. From the previous analysis, found in the choice of the number and the spear, the correlation coefficient between effective subordinate relations of the proposed model takes advantages over those in references [11], [17], [20], as well as the correlation coefficient between the passive members. However, it is also found that the relative membership degree is not linear with the selection and the increase in the number, and the impact seems to be reduced. In addition, the effect is also different in step distance to nod.

Exclusion of average correlation coefficients is the third checkup measure. The conclusions are put forward in Figure 9. Aiming at each pair of range steps, there exists a coincident towards that the mean of correlation. With the increase of n, correlation coefficient of standard deviation will increase. On the contrary, the meaning of the correlation coefficient increases with the decrease in the number of attributes.

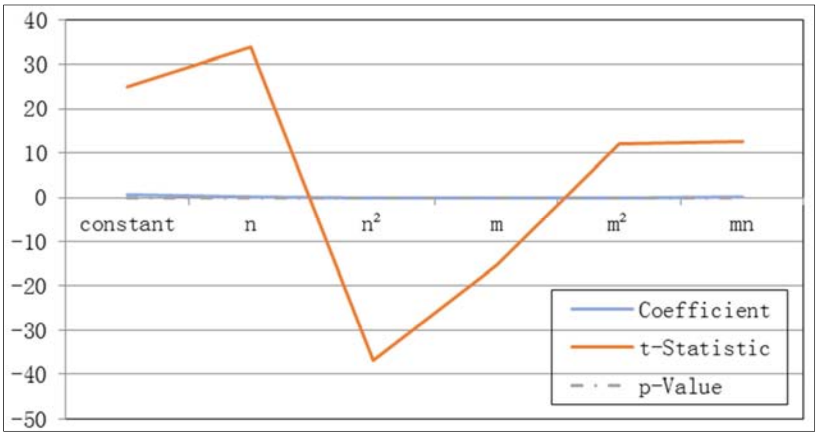


Figure 9. *Evaluated Spearmen correlation.*

In addition, along with the increase in the number of replacement, correlation coefficient of standard deviation will also increase. As a result, the average correlation coefficient of the difference is not obvious in the big m value. The number of attributes and correlation coefficient change in opposite directions.

In order to examine the influences of the number of choices (a) and the number of properties (b) on the correlation between two distance steps, the sectional derivatives of evaluated Spearmen correlation strongest $\tilde{p}$ with respect to m and n are obtained as shown in figure 9.

Where Z(a,b) is a fictitious variable which is worth to 1 if the relevant strongest is acquired from a pair (a,b) of distance steps or 0 or else. The ε is the stochastic term indicating the influences caused by other elements that are not contemplated in this pattern. Assuming that ε is an absolute fictitious variable with limited meaning and variance. The total sample size is 100. The conclusions are listed in Table 5.

From Table 3, most of the strongest QoS indexes are important under 80% important level except for the variables of $Z(f_2, f_3)b$, $Z(f_1, f_2)b$, and $Z(f_1, f_3)b$. In general, the model is important in terms of F -test and the explanatory energy is lower than ever.

Table 5. *The second-order regression model of correlation coefficients.*

Variable	Coefficient	t-Statistic	p-Value
$z(p_1,f_1)$	-0.017	-5.621	0.012
$z(p_1,f_3)$	-0.160	-17.026	0.013
$z(p_2,f_2)$	-0.051	-5.919	0.012
$z(f_2,f_2)$	0.113	3.834	0.020
$z(f_2,f_3)$	0.061	17.564	0.018

F=17.35; F (p-value)=0.1; R^2 =0.913; and adj-R^2 =0.915.

Judging from (11) and (12), the influence of number of choices is positive, whereas, the influence of number of properties is negative in general. That is more choices make higher similarity of the preference orders of choices under different distance steps, but more properties get the passive conclusion. In addition, those influences are in reverse proportion of the numbers of choices and properties. In the meantime, the influences of b and a are distinct between distinct distance steps. The influences of b and a on p are important higher in the distance pairs of $f(p_1, f_2), f(p_1, f_3)$, $f(p_2, f_1), f(p_2, f_2)$, and $f(p_2, f_3)$ opposite to the distance pair of (p_1, p_2) . The opposite influence of (f_1, f_2), (f_1, f_3), and (f_2, f_3) are mixed. From the magnitude of strongest in Table 5, the influences of the number of choices becomes greater and have more deviations.

4. Conclusions

In this thesis, a fuzzy version of the QoS technique was displayed with a relative analysis of distance steps. Stochastic problems of distinct sizes were computed and tested in order to the relative of fuzzy QoS rankings determined by distinct distance steps. The distinct circumscription of fuzzy QoS distances indeed has important effects on the final conclusions of the fuzzy QoS means, which had been demonstrated by the laboratorial analysis.

In practice, first of all, the number of properties has only a minor effective effect in view of uniformity rates. What's more, the consistency rate is between two distance steps reduces gradually as the number of decision choices in a problem increases. In a decision problem, the fuzzy QoS means using the distinct distance definitions may have different preference orders when the number of choices is greater than 5. Second, the best choices suggested by the fuzzy QoS means using distinct distance definitions might be illogical in some degree. Third, as the number of choices increases, there is greater chance that the most preferred choices based on different distances will differ basically, when properties changes will have greater impact on contradiction rates especially lower number of properties.

In future work, the relationship of the number of choices, number of properties, and different distance steps to Spearmen correlation strongest will be extended for a profound analysis in a second-order regression model. The influence of the number of choices is advantage while the influence of the number of properties is disadvantage, which should be clearly compared in the more regression analysis.

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