Choosing of Telecommunications Equipment Suppliers Based on the Choquet Integral and Fuzzy Measure Variance Minimization

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Abstract

Telecommunications equipment suppliers play an important role in the functioning of corporations with large-scale distributed computer networks such as system integrators, Internet service providers and others. An important condition of sustainable development for these companies is effective and reasonable decision making concerning the choice of suppliers. At the same time, the amount of information to be considered in many industries for making decisions has grown several times. In accordance with the above, decision making support systems for the reliable choice of suppliers started to be developed. At the same time, the approaches to designing such systems possess some disadvantages. In order to overcome these disadvantages this article suggests an approach to decision making support for choosing telecommunication equipment suppliers based on the Choquet Integral and minimization of fuzzy measure variance. It deals with the task of criteria normalization, fuzzy measure identification, gives examples of expert estimations for criteria and also the results of supplier assessments based on which the decision is made.

Keywords: Approach to decision making, aggregation operator, fuzzy measure, Choquet Integral, telecommunications equipment.

1. Introduction

One of the most frequently solved daily tasks in organizations is decision making in a particular area. In modern conditions of information overload, decision support systems occupy an important place, thanks to which it is possible to reduce the cognitive load on the Decision Maker (DM), as well as increase the efficiency of decisions made through automated analysis of a larger volume of information. In particular, such systems are relevant in the field of assessing suppliers of telecommunications equipment.

This assessment is carried out in geographically distributed enterprises with extensive computer networks. In the absence of a decision support system already implemented at the enterprise, highly specialized decision support systems in the field of procurement are relevant. As noted in [1], instead of implementing a large-scale decision support system, it is better to first implement a small-scale system and then scale it at the desired pace.

Currently, solving problems of supplier evaluation and selection attract the attention of many researchers. In particular, the review [2] noted that in recent years, an increasing number of publications have considered the problem of reconciling preferences within a group of decision makers.

One possible solution to this problem is to interpret decision making models. Many of the existing decision making models are either uninterpretable or difficult to interpret, which is why they cannot be used to reconcile the preferences of several decision makers. In addition, the criteria for evaluating suppliers are interdependent [3], which requires taking into account these interdependencies when constructing appropriate models. Interpreting and at the same time allowing to take into account interdependencies, decision making models for assessing and selecting suppliers are built, in particular, on the basis of aggregation operators [4]. One of the most developed aggregation operators is the Choquet integral with respect to a fuzzy measure. It allows you to fully reflect in the model the details of the decision making process of the decision maker due to the ability to take into account the interdependencies of the aggregated criteria. At the same time, the decision maker is not required to have complete information about all aggregated criteria. Thanks to the use of the variance minimization method to identify a fuzzy measure [5], when determining the parameters of the Choquet integral, only the information available to the decision maker is taken into account and no additional subjectivity is introduced that is not due to expert knowledge [6].

This article proposes an approach to building decision support systems for choosing a supplier of telecommunications equipment. This approach includes the use of a set of supplier attributes to assess its suitability for supplying equipment, a procedure for normalizing these attributes, a procedure for identifying a fuzzy measure based on minimizing its variance, and an interpretable aggregation operator based on the Choquet integral to take into account the interdependencies between the aggregated criteria. The remainder of this article is organized as follows. Section 2 reviews work related to decision support systems used to evaluate and select suppliers, as well as work related to aggregation operators, and selects components to build our approach; Section 3 describes the proposed decision support approach, which includes: attributes of the telecommunications equipment supplier; aggregation criteria, which are obtained by normalizing the corresponding attributes; aggregation operator based on the 2-nd order Choquet integral; Section 4 describes an experiment to implement the proposed approach using the example of evaluating five telecommunications equipment suppliers, including the identification of a fuzzy measure and the results obtained. In Conclusion, results from the study are presented.

2. Related Works

Decision support systems (DSS) have recently become widespread in various fields, in particular, in the transport industry [7-9], in medicine [10-12], in nuclear energy [13], in welding [14], in economic security management [15]. In these and many others areas, DSS is used for the choice of suppliers [16]. These systems are based on different approaches to decision support. It is important for users of these systems to know exactly why and how the system made the decision and what factors play a decisive role. Otherwise, users will be wary of using decision support systems and their underlying approaches. From this point of view, the most appropriate approaches are under the general name "Explainable AI", which have recently become increasingly widespread [17,18].

Some of these approaches are based on the interpretation of machine learning as a black box [19], the others use aggregation operators.

In recent years, the field of research related to aggregation operators has developed rapidly. This is evidenced by the large number of publications devoted to these operators [20]. Such operators in general represent a way of combining different pieces of information about the same object or phenomenon. These pieces of information are collected from different sources and serve to reach a conclusion or decision [21]. Aggregation operators are very diverse and include some as simple as weighted arithmetic average [22] and the most complex ones, such as Choquet and Sugeno fuzzy discrete integrals [23] and their modifications [24, 25]. Additionally, aggregation operators can be combined in hierarchies [26].

The simplest operators either do not distinguish criteria by significance as an arithmetic mean, or assume weighting of criteria. As a rule, to solve practical problems it is necessary to distinguish the relative weights of criteria, and for even finer tuning, the aggregation operator should allow modeling the interdependencies between criteria. To build an aggregation operator, it is necessary to obtain its parameters either based on machine learning using a sufficient number of training examples, or based on the knowledge of an expert. The parameters of the aggregation operator are, in particular, the relative weights of the criteria and the degree of their interaction.

As a rule, there is not enough data to implement machine learning in the field of supplier evaluation. Based on this, various aggregation operators, such as the Schweitzer-Sklar operator [27], picture cubic fuzzy aggregation operator [28], weighted ordered average [29], Choquet integral [30, 31] and others [32] are used in the field of supplier evaluation and selection.

Such operators are built based on the preferences of the decision maker. Various methods are used to obtain and formalize these preferences [33, 34]. At the same time, many DSS for assessing and selecting a supplier are complex, which is why their creation, as well as the work of experts, takes a lot of time. On the other hand, the Choquet Integral does not require a large training set and is interpreted by means of Shapley indices, interaction indices [35], as well as visualization [36], and the ordered weighted average operator (OWA) is a special case of the Choquet Integral.

To use the Choquet Integral, it is necessary to identify a fuzzy measure. This task is difficult due to exponentially increasing complexity, so in practice fuzzy measures of k-th order are used, where k is less than the number of criteria and is usually equal to 2 [37]. Initial data for identification are obtained using various methods, such as the Analytical Hierarchy Process (AHP) [38], comparisons with the ideal alternative TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [39], the collective expert method, the Delphi method [40], trapezoidal fuzzy decision making on multiple attribute groups (GDM) [41] and others.

The main disadvantages of the listed methods for obtaining initial data for identifying a fuzzy measure are the complexity of implementation, as well as the complexity of interpreting the results obtained. At the same time, to identify a fuzzy measure based on variance minimization, the expert is required to provide only the information in which he is confident. This information is expressed in the form of expert preferences on a set of criteria, on a set of available alternatives, as well as on a set of criteria interaction indices [35]. The decision maker is not required to directly specify the weights of the importance of criteria and the values of interaction indices; it is sufficient to provide partial information about which criterion is more important, that is, preferences on sets of criteria and interaction indices can be partial. After identification, the resulting Choquet Integral can be interpreted and, if necessary, adjusted by making changes to the initial expert preferences. The criteria for evaluating telecommunications equipment suppliers are their various characteristics, such as price, quality, flexibility, efficiency, delivery quality, staff attitude, sustainability and readiness for digital technologies [42, 43]. These criteria are normalized attributes. There is currently no generally accepted procedure for normalizing attributes; there are more than 20 options for its implementation [44].

Thus, to implement our approach, we select the 2-nd order Choquet Integral together with the identification of a fuzzy measure using the variance minimization method, as well as the criteria that will be selected by the decision maker based on practical experience in working with suppliers.

3. Material and method

3.1. Attributes of the telecommunications equipment supplier

These attributes can be formulated in different ways, depending on the objectives of the assessment and on the specific expert. Let's consider a set of such attributes for the most typical case of choosing equipment suppliers for a corporate network of a geographically distributed large enterprise.

The a_1 "equipment efficiency" attribute is a set of properties of the supplied equipment. This attribute is evaluated on the basis of documents provided by the supplier describing the equipment's compliance with accepted quality standards, as well as on the basis of the equipment's operating experience obtained from this supplier [45, 46].

The a_2 "business reputation" attribute is an objectively established and practically confirmed set of customer opinions about the advantages and disadvantages of the supplier [46, 47]. This attribute is evaluated qualitatively based on expert assessments.

The a_3 "price" attribute is less important than the first two attributes, but essential when choosing a supplier. It indicates the amount for which the supplier wants to sell the equipment, and the customer is ready to buy it [46]. The price is determined either from open sources or directly as a result of communication with the supplier. Since each supplier sets the price for the manufactured equipment, this attribute allows you to find a supplier with the most favorable offer.

The a_4 "reliability of supply" attribute is related to the business reputation of the supplier. Its evaluation focuses on the following supply chain parameters: adaptability, safety, reliability, recoverability, operability and sustainability [16].

The a_5 "terms of delivery and payment" attribute reflects the customer's satisfaction with the terms offered by the supplier, which may contain the number of items, delivery dates, responsibility for transportation, payment terms [16, 46].

The a_6 "location" attribute is the least important of all the attributes listed. It evaluates the territorial remoteness of the supplier from the company and the complexity of its logistics chain. However, this attribute may be key if the supplier is very far away and if the customer incurs material costs for the delivery. In addition to those listed, it is possible to add other attributes at the discretion of the decision maker. The total number of attributes is denoted by N.

3.2. Aggregation Criteria

These criteria are obtained by normalizing the corresponding attributes. As noted above, there is no generally accepted normalization procedure. The choice of the procedure is based on the fact that its use in solving practical problems allows to get a positive result. Based on this, in the proposed approach a normalization procedure based on the linear Max-Min method was chosen [44]. According to this method, the attribute normalization procedure will consist of the following steps.

Step 1. Get the areas of definition of supplier attributes $a_1, \dots, a_N$, which are intervals and the boundaries are their minimum and maximum values $\min(a_1), \max(a_1), \dots, \min(a_N), \max(a_N)$.

Step 2. Create dependencies $g_n = \frac{1}{\max(a_n)}(a_n - \min(a_n))$, with $1 \le n \le N$ for those aggregation criteria that should grow as their corresponding attributes increase.

Step 3. Create dependencies $g_n = 1 - \frac{1}{\max(a_n)}(a_n - \min(a_n))$, with $1 \le n \le N$ for those aggregation criteria that should decrease as their corresponding attributes increase.

At the first step of this procedure, the areas of definition of qualitative and quantitative attributes are clarified such as "equipment quality", "reputation", "price", etc. For qualitative criteria a single interval is selected, and for quantitative criteria an interval the boundaries of which are the minimum and maximum values of the corresponding attribute. At the second step, aggregation criteria are formed for which the value of the criterion should also grow with the growth of the attribute. These attributes include "equipment quality" and "reputation". Figure 1 shows the result of the described procedure in relation to the attribute a_1 "equipment quality".

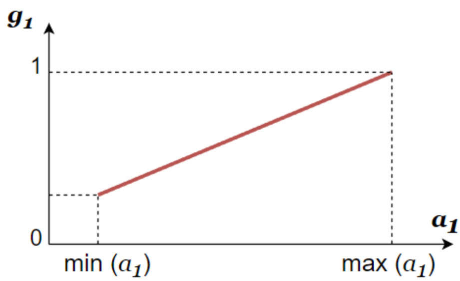

Figure 1. Normalization of attribute a_1 "equipment quality"

At the third step, criteria are formed for which the value of the criterion should decrease with the growth of the attribute. Figure 2 shows the result of the normalization procedure in relation to the attribute a_3 "price".

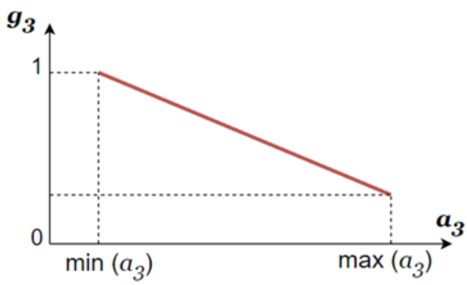

Figure 2. Normalization of attribute a_3 "price"

According to the qualitative reasoning of the decision maker, criteria g_1 and g_2, as well as criteria g_3 and g_5 are positively correlated. Indeed, the quality of the equipment is most likely higher from a supplier with a reliable reputation, and the price of equipment delivery is higher from a supplier located at a greater distance. This means that their relationship is redundant, that is, a high score of one of the criteria in each of these groups can be interpreted as a high score of both criteria in the group. Such arguments of the decision maker are formalized using the appropriate signs of the interaction indices:

$$I(1,2) < 0 \qquad (1)$$

$$I(3,5) < 0 \qquad (2)$$

According to the decision maker, the most important of the criteria is g_1, the next most important is g_3, then g_2. Criteria g_4 and g_5 are equally important and less valuable than criterion g_2. The least important of the criteria is g_6. These judgments of the decision maker are formalized using a partial weak order on the set of indices of criteria J:

$$6 \prec_J 4 \sim 5 \prec_J 2 \prec_J 3 \prec_J 1 \qquad (3)$$

By the implementations available to the decision maker we mean the values of criteria for specific suppliers, which the decision maker can judge based on experience. In the example under consideration, there are 5 such implementations corresponding to different hardware vendors:

$g^1 = (0{,}24;\ 0{,}111;\ 0{,}048;\ 0{,}055;\ 0{,}143;\ 0{,}166);$

$g^2 = (0{,}2;\ 0{,}277;\ 0{,}429;\ 0{,}222;\ 0{,}333;\ 0{,}25);$

$$g^3 = (0{,}16;\ 0{,}055;\ 0{,}19;\ 0{,}166;\ 0{,}143;\ 0{,}222);$$

$$g^4 = (0{,}08;\ 0{,}5;\ 0{,}19;\ 0{,}444;\ 0{,}286;\ 0{,}166);$$

$$g^5 = (0{,}32;\ 0{,}055;\ 0{,}143;\ 0{,}111;\ 0{,}095;\ 0{,}194).$$

Ranking these implementations by preference leads to the following partial weak order:

$$g^2 \succ g^4 \succ g^3 \sim g^5 \succ g^1 \qquad (4)$$

The non-strict order (4) reflects the preferences of the decision maker on the implementations of g^1,…, g^6 corresponding to different suppliers.

3.3. Criteria Aggregation Operator

This operator is based on the 2-nd order Choquet integral, since it allows us to formalize the above arguments of the decision maker. In addition, as already noted, its construction does not require the decision maker to explicitly specify all interactions between criteria. The integral evaluation of the supplier according to the above criteria is expressed by the formula:

$$\Omega = C_\mu(g_1,\ldots,\ g_6) = \sum_{h=1}^{H} \mu(n)\, g_n + \sum_{\{i,j\}\subseteq J} I(i,j) min(g_i, g_j) \qquad (5)$$

Here $J = \overline{1,N}$, $C_\mu(g_1,\ldots,\ g_6)$ – Choquet Integral for criteria $g_1,\ldots,\ g_6$, N – number of criteria (attributes), $\mu(n)$ is a fuzzy measure of the n-th criterion, g_n is the value of the n-th criterion, $I(i,j)$ is the interaction index for a pair of criteria i and j.

Figure 3 shows the proposed model, which includes attributes normalization, the 2-nd order Choquet integral, as well as identification of the fuzzy measure.

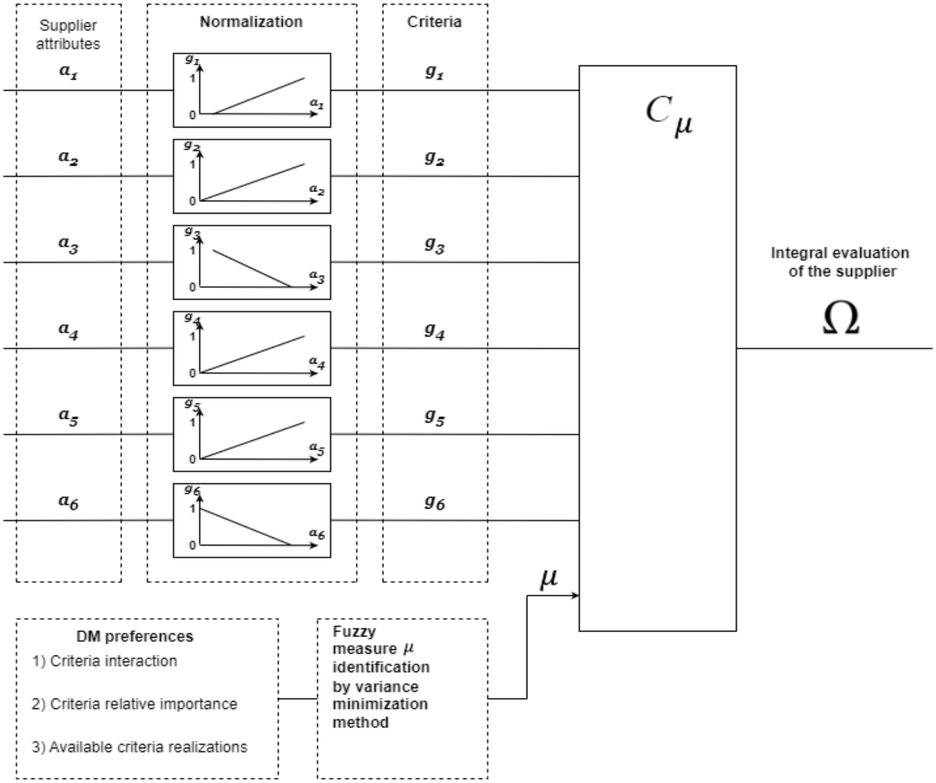

Figure 3. The decision support model

The supplier attributes are normalized, then the normalized attributes are used as aggregation criteria for the aggregation operator in the form of a Choquet integral. The parameters of the Choquet integral are a fuzzy measure, which is identified using available expert preferences in the form of interactions of criteria, the relative importance of criteria and reasoning about available implementations of criteria.

4. Experiment and Results

4.1. Fuzzy measure identification

Identification of the fuzzy measure is implemented on the basis of the method of minimizing variance, or, equivalently, maximizing entropy [48]. The input information for this method is the preferences of the decision maker formalized in the form of restrictions (1-4). To account for this information, it is necessary to translate expressions (1-3) into inequalities with established indifference thresholds.

Restrictions (1, 2) are transformed, respectively, into inequalities:

$-\delta_I \geq I(1,2) \geq -1$ (6)

$-\delta_I \geq I(3,5) \geq -1$ (7)

The non-strict order (3) is transformed into inequalities:

$\Phi(1) - \Phi(3) \geq \delta_\Phi$ (8)

$\Phi(3) - \Phi(2) \geq \delta_\Phi$ (9)

$\Phi(2) - \Phi(5) \geq \delta_\Phi$ (10)

$\Phi(2) - \Phi(4) \geq \delta_\Phi$ (11)

$\delta_\Phi \geq \Phi(4) - \Phi(5) \geq -\delta_\Phi$ (12)

$\Phi(4) - \Phi(6) \geq \delta_\Phi$ (13)

The non-strict order (4) is transformed into inequalities:

$C_\mu(g^5) - C_\mu(g^1) \geq \delta_C$ (14)

$-\delta_C \leq C_\mu(g^3) - C_\mu(g^5) \leq \delta_C$ (15)

$C_\mu(g^4) - C_\mu(g^3) \geq \delta_C$ (16)

$-\delta_C \leq C_\mu(g^2) - C_\mu(g^4) \leq \delta_C$ (17)

Here δ_I, δ_Φ, δ_C are the indifference thresholds set by the expert in accordance with the identification procedure. Taking into account the restrictions applied to prevent the selection of threshold values at which the problem of identifying a fuzzy measure is obviously not solved [49], the following values of these thresholds were selected: $\delta_I = 0{,}005$, $\delta_\Phi = 0{,}02$, $\delta_C = 0{,}055$.

The task of identifying a fuzzy measure is reduced to the task of maximizing its entropy [48]:

$$H(\mu) = \sum_{i=1}^{|J|} \sum_{G \subseteq J-i} \frac{(|J| - |G| - 1)!\,|G|!}{|J|!} h(\mu(G \cup i) - \mu(G))$$

with restrictions (6-17). Here $h(x) = \begin{cases} -x\ln x, & \text{if } x > 0 \\ 0, & \text{if } x = 0 \end{cases}$.

The result of such identification is a unique fuzzy measure μ, which can be considered as a set of parameters of the Choquet integral, at which it will reflect the preferences of the decision maker. This fuzzy measure is presented in the form of index values of criteria interaction $(1,2) = -0{,}127$, $I(3,5) = -0{,}005$, Shapley indices $\Phi(1) = 0{,}268$, $\Phi(2) = 0{,}149$, $\Phi(3) = 0{,}232$, $\Phi(4) = 0{,}134$, $\Phi(5) = 0{,}134$, $\Phi(6) = 0{,}084$.

4.2. Results and discussion

Aggregation results using operator (5) for available implementations of criteria: $C_\mu(g^1) = 0{,}132$, $C_\mu(g^2) = 0{,}284$, $C_\mu(g^3) = 0{,}157$, $C_\mu(g^4) = 0{,}259$, $C_\mu(g^5) = 0{,}182$. As expected, operator (5) in relation to the resulting fuzzy measure reflects the preferences of the decision maker, expressed in the form of constraints (1-4). This is confirmed, firstly, by the fact that the aggregation results for the available implementations correspond to the order (4), namely $C_\mu(g^1) < C_\mu(g^5) \approx C_\mu(g^3) < C_\mu(g^4) \approx C_\mu(g^2)$. Secondly, the restriction imposed on the relative importance of criteria (3) corresponds to the set of Shapley indices, namely $\Phi(1) > \Phi(3) > \Phi(2) > \Phi(5) = \Phi(4) > \Phi(6)$. Thirdly, the types of interactions between the criteria correspond to the preferences of the decision maker expressed by inequalities (1,2), which is confirmed by the signs of the corresponding interaction indices.

The input information of the configured system is the attributes of the supplier, which are normalized, resulting in the values of the corresponding criteria. The result of criteria aggregation by means of the 2-nd order Choquet integral is an integral assessment of the supplier. This assessment is used for decision-making, namely, among several alternative suppliers, the one for which the highest score obtained is selected. Within the framework of the proposed approach, it is possible to use visualization of aggregation in virtual reality [36]. This allows to reflect the properties of the aggregation operator into the properties of a virtual object that can be observed by several decision makers, which makes it possible to collectively build a decision support system.

5. Conclusion

The article proposes an approach to building a decision support system based on aggregation. The application of the approach is illustrated at the top level of decision making on the choice of a telecommunications equipment supplier. Identifying the key attributes of the supplier, as well as building a decision making model based on them by the company's managers, will allow formalizing and automating decision making about choosing a supplier. Models often work better than human decision making because they base their judgments on a well-defined logic of analyzing all criteria. Such automation will reduce the number of errors in decision-making in conditions of limited cognitive abilities, the influence of emotions, as well as the huge amount of information that the decision maker processes in modern conditions.

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CONFLICTS OF INTEREST

The authors declare no conflict of interests.

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