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A Novel Way to Select the Optimal Electrical Power Demand Management Provider for Robust Smart Grid

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Abstract— The smart grid is an integrated management of power demand and supply that cannot be achieved without efficient power demand management because it integrates information technology and shares power information in real time to maximize power efficiency. Efficient power demand management must prevent or minimize risks in advance between the customer and the demand management provider. This study proposes a method that can evaluate the risks that impede efficient power demand management and select the most robust demand management provider with respect to these risks. This paper applies the Grey system theory to obtain objectivity by calculating the quantitative value and risk ambiguity of uncertainty. Six power demand management service providers are evaluated through the opinion of four risk management experts considering eight risk factors with a view to selecting the optimum power demand management service provider for the consumer. In conclusion, this study applies the Grey system theory to the risk factors of six power demand management service providers, determines the ranking from the best power demand management service provider to the inferior power demand management service provider, and provides the most desirable provider to customers.

Keywords—Smart grid, Power demand management, Uncertainty, Power demand management provider

I. INTRODUCTION

THE power system in Korea has been designed to produce more than 10% electricity in excess than required so that an uninterrupted supply of power can be obtained when more electricity becomes necessary than the predicted maximum consumption amount. However, such a situation gives rise to certain problems, such as requirement of additional supply of fuel and various power generation facilities, wastage of electric power, decrease in energy efficiency, and increased emission of carbon dioxide.

If electricity can be produced only as much as required, or if the amount of electricity produced can be completely used, it would result in the most efficient way of using electricity, and certain environmental problems such as global warming can be solved. Negawatt is a term which stemmed from such a situation. Negawatt is a virtual unit that measures the amount of energy saved by increasing efficiency or reducing consumption; for example, when a company saves energy and sells it to electrical grids. Negawatt is used as a concept that includes efficiency policy to increase power usage efficiency or lower power usage than power generation, and has a close relationship with smart grid which emphasizes power efficiency [1]. Smart grid is a technology that maximizes efficiency while preventing energy wastage by applying information and communication technology to power network under known conditions of electricity usage, electricity supply, and power line status. Smart grid means integrating and interconnecting all users (producers, operators, marketers, and consumers) by combining electricity and IT infrastructure to efficiently balance demand and supply in increasingly complex networks [2]. The goal of a smart grid is to save energy, and the way to save energy is to produce only the necessary amount of electricity, sell the remaining electricity, store it, use it when needed. This includes the use of a distributed power scheme to improve transmission and distribution efficiency.

Power demand management is closely related to smart grid because it is recognized as an energy source (Negawatt) that uses power efficiently and saves power. A smart grid cannot achieve its purpose without efficient power demand management because it integrates management of power supply and demand with information technology and improves efficiency of power energy by sharing power information in real time [3].

Consumers who use electricity need to use electric power when their electricity rates are low and to build a system that can be sold back to electric power demand management providers when some power remains leftover. Such a system has the same goal as that of a smart grid. Therefore, it is necessary for the consumer to select an electric power demand management company which can sell electric power at the most stable and cheap price and purchase any surplus electric power at an expensive price.

On the other side, power demand management operators are affected by various risk factors. The risks faced by the power demand management providers are all different, and therefore, different operators use different strategies to address those risk factors [4] [5]. The important risk factors that impede efficient management of power demand are investment cost, security, learning cost, facility stability, skill manager, uncertainty of profit, new technology and system [6]. The power demand management company which can minimize the above-mentioned risks is selected by the consumer, whereas the one which does not have a choice to combat such risks becomes the lowest preference of the consumer. Even if it is chosen, there is a large probability that it will cause huge losses to the consumers.

The present study has proposed a method to select the most stable and reliable power demand management company as one of the smart grid's means to save energy. The selection of the most robust power demand managers is very important for consumers because power demand management operators which are connected to consumers, and at the same time, conduct multiple electricity demand management projects are exposed to various conditions and risks. In this regard, a business analysis algorithm is used to select an efficient power demand management operator, to analyze the business, and link it to the business model so that consumers can earn a lot of business revenue. To solve these problems, we have proposed an effective method to select the optimal power demand management service providers.

II. LITERATURE REVIEW

The supplier selection problem, which selects a supplier such as a service provider covered in this study, belongs to the multiple attribute decision making (MADM) problem and is a very important research area. Previous studies used the linear waiting methods (LW) [7], the analytic hierarchy process (AHP) [8], and mathematical programming (MP) [9] to select suppliers. Recently, deep learning's convolutional neural network (CNN) showed high forecasting accuracy in the demand forecasting field of smart grid [10]. Deep learning and data mining were applied to short-term electricity load forecasting in smart grid, and the proposed CNN technique showed higher accuracy than the existing support vector regression (SVR) [11]. LW is a very simple technique, but there is a problem of totally relying on human judgment and giving equal weight to properties. Since AHP assumes that we know for certain the relative importance of the attributes that affect supplier performance, we cannot effectively calculate risk and uncertainty in predicting supplier performance. MP can be expressed as a mathematical model to obtain effective results, but it is difficult to express the real problems as the mathematical models and it is difficult to consider the qualitative factors that occur in the real world.

In the MADM method of selecting a supplier such as a service provider, decision makers prefer preferences according to subjective judgment because they have characteristics of suppliers or preferences for alternatives and it is necessary to consider such subjective judgment. Existing MADM methods [12] are applied when the rankings and weightings of attributes are known precisely. However, since decision makers' judgment is uncertain and cannot be estimated by numerical values, there is a problem in applying the existing MADM methods. Fuzzy-based approaches [13] are generally applied to solve problems arising under uncertainty and ambiguity. However, since this method does not consider the condition of the fuzziness, an efficient method that can be applied in this case is the Grey system theory [14].

The advantage of the Grey system theory [14-18] used in the present study is that it considers the condition of the fuzziness not found in the fuzzy theory [13]. In other words, the Grey system theory can handle flexibility in a fuzzy situation.

III. POWER DEMAND MANAGEMENT RISKS

Power energy management can be explained in terms of supply management and demand management. Supply management is the creation and operation of a power plant to generate enough power for consumers. Demand management, on the other hand, deals with efficient use of the produced electricity and reselling (or repurchasing) any unused electricity. The power supply management aspect is no longer welcome mainly because of the cost of constructing a power plant and environmental problems. Demand management of electricity is divided into demand response and efficiency improvement. The former involves reduction of electricity use by consumers, whereas the latter deals with reduction in the electricity usage by replacing electric power equipment with high efficiency equipment, through preliminary agreement. Generally, power supply problems occur at peak time when power usage is very high [19].

The risk factors that hinder effective demand management of electricity are described in Table 1 [6]. The risk factors are presented in eight categories: investment cost, security, learning cost, facility safety, skill manager, uncertainty of profit, new technology and system. Furthermore, the risk factor is classified into a cost attribute that needs minimization and a benefit attribute that needs maximization so that a qualitative attribute is expressed. In other words, it is necessary to classify the investment cost, learning cost, and uncertainty of profit as cost attributes (needs minimization), whereas, security, facility safety, skill manager, new technology and system as benefit attributes (needs maximization) so that the attributes of risk are reflected effectively.

Although the risk factors are very diverse, the reason presented as shown in Table 1 is to provide the power demand management provider that is the most beneficial to customers by simultaneously pursuing minimization of cost and maximization of profits. In the customer's position, when cost elements are minimized and profit elements are maximized, they have an alternative to choose from its. Cost elements and profit elements select the most common elements in the power demand management field to maintain objectivity of judgment.

Table 1 risk factors that impede efficient demand side management

Risk factor	Attribute	Contents
investment cost	cost	Equipment required for efficient demand management of electric power has a high initial investment cost.
security	profit	System damage due to privacy breach and hacking due to information leakage.
learning cost	cost	New technology and system adaptation require large learning costs.
facility safety	profit	Loss due to unexpected technical problems.
skill manager	profit	Lack of expertise in power demand management systems and equipment, need for skilled period and expenses for training.
uncertainty of profit	cost	There are uncertainties on the accuracy of measurement due to energy saving and profitability.
new technology	profit	New technologies such as smart meters, smart sensors and smart home appliances are required for efficient power demand management, but it is difficult to verify sufficiently.
system	profit	Effective power demand management requires institutional support, such as tariffs, subsidies, taxation, financing, and certification system, but there is uncertainty due to insufficient systems and changes in the system depending on the political and economic situation.

Table 1 lists eight risk factors that hinder effective management of power demand, but there are a variety of risk factors that hamper efficient power demand management. The risk factors vary depending on conditions including situation of the electric power demand management company, and region relate to the various risk factors, according to conditions such as the situation and the size of the consumer who performs electric power trading with the electric power demand management company. The effect of this is also different.

The present study considered the most typical risk factors that can occur without depending on the situation and area of electric power demand management provider, and the situation and size of the consumer. That is, the risk factors presented in Table 1 that impede the management of power demand were selected to include not only the representative of the risk factors, but also the cost attributes and the profit attributes of the risks.

In section 3 the method of minimizing the risk of each risk factor has been applied while evaluating the risk factors presented in Table 1 and maximizing the profit when profit occurs. The attributes of the risk factors have qualitative characteristics, and these qualitative characteristics must be calculated in the objective and quantitative ways to reflect these characteristics because they would provide reliable evaluation results.

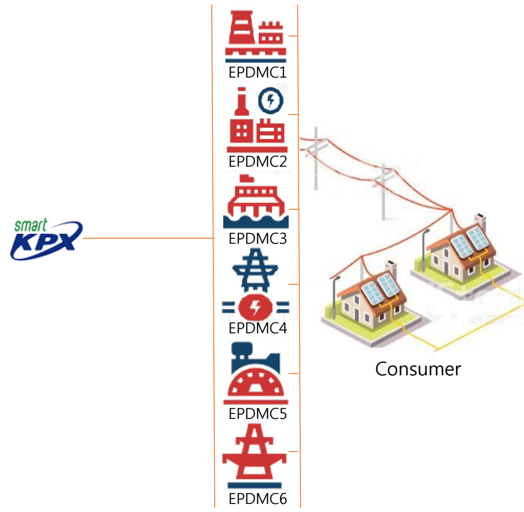

Fig. 1 electricity demand management provider selection model

IV. EXPERIMENT AND RESULTS ANALYSIS

The model considered in this study consists of six power demand management service providers ($EPDMC_1$~$EPDMC_6$) providing services and customers receiving services as shown in Fig. 1 below.

The power demand management selection model in Fig. 1 was based on the risk factors listed in Table 1 to select the optimal power demand management provider for the consumers who consider the profit attributes (security, facility safety, skill manager, new technology, system) and cost attributes (investment cost, learning cost, uncertainty of profit) at the same time. The power demand management provider must maximize the profit attributes and minimize the cost attributes.

The Grey system theory is one of the ways to solve the problem of complexity and uncertainty with discrete data and incomplete information. Grey system means a system in which some information is known and some is unknown. The quality and quantity of information in the Grey system form a continuum from the absence of information to the state of complete information (from black through Grey to white). Since uncertainty is always present, the information is somewhere in the Grey area, and the Grey system theory is a technique that utilizes this information. The Grey system theory also gives good results in mathematical analysis of systems with uncertain information. If a case in which all information is known in a specific system is expressed as white and a case in which information is not known at all is expressed as black, the case where information is known incompletely and indefinitely is

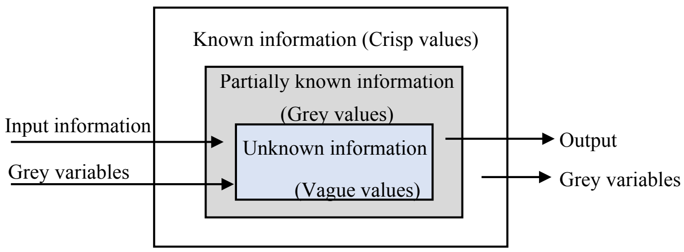

Fig. 2 the basic concept of Grey system theory

expressed as Grey and these areas are expressed as Grey area. The incomplete and uncertain relation of information is expressed as Grey relation, and the handling of such information is called Grey system theory. This technique uses the Grey number, which is represented by the boundary values between the known and unknown information and can be expressed as shown in Fig. 2 [18, 20].

Grey system theory is very effective when applied to problems that involve subjective judgment of decision makers on various attributes and are not explicitly weighted. 'The problem of selecting a service provider such as the electric power demand management operator proposed in this study is difficult because the uncertain information exists between the customers and the service providers. In this case, Grey system theory can be applied as an efficient alternative.

To apply the Grey system theory, it is necessary to define the basic definition of Grey system, Grey set, and Grey number. Therefore, this paper is based on the contents of Li et al. [14] and Park [18] as follows.

Definition 1: If X is a universal set, the Grey set of X, S is defined as the mapping value of $\underline{\mu}_S(x)$ and $\overline{\mu}_S(x)$.

$$S=\begin{cases}\overline{\mu}_S(x): x \to [0,1] \\ \underline{\mu}_S(x): x \to [0,1]\end{cases} \tag{1}$$

In (1), $\overline{\mu}_S(x)$ and $\underline{\mu}_S(x)$ mean $\overline{\mu}_S(x) \geq \underline{\mu}_S(x)$, $x \in$ X, X= R, $\underline{\mu}_S(x)$ and $\overline{\mu}_S(x)$ denote the lower membership function and upper membership function in set S, respectively. When the lower and upper bound of x are estimated, x is defined as the interval Grey number. If $\underline{\mu}_S(x)$ and $\overline{\mu}_S(x)$ are equal, the Grey set S becomes a fuzzy set, which means that the process must consider the condition of fuzziness.

Definition 2: The Grey number is defined as a number with uncertain and fuzzy information. The ratings of attributes are expressed as a numerical interval because they can be explained by linguistic variables. Since the numerical interval contains uncertain information, the Grey number is usually written as $\otimes x$, $\otimes x = x\Big|_{\underline{\mu}}^{\overline{\mu}}$.

Definition 3: If only the lower limit of x can be estimated, x is defined as the lower limit Grey number and is expressed using (2).

$$\otimes x = [\,\underline{x}, \infty] \tag{2}$$

Definition 4: If only the upper limit of x can be estimated, x is defined as the upper limit Grey number and is expressed using (3).

$$\otimes x = [-\infty, \overline{x}] \tag{3}$$

Definition 5: If the lower limit and upper limit of x can be estimated, then x is defined as the interval Grey number and is expressed using (4).

$$\otimes x = [\underline{x}, \overline{x}] \tag{4}$$

Definition 6: The basic operating rules for Grey numbers are defined as sets of intervals instead of using real numbers. The four basic Grey number operations (addition, subtraction, multiplication, and division) for Grey numbers, $\otimes x_1 = [\underline{x}_1, \overline{x}_1]$ and $\otimes x_2 = [\underline{x}_2, \overline{x}_2]$ are defined as (5)~(8).

$$\text{Addition: } \otimes x_1 + \otimes x_2 = [\underline{x}_1 + \underline{x}_2, \overline{x}_1 + \overline{x}_2] \tag{5}$$

$$\text{Subtraction: } \otimes x_1 - \otimes x_2 = [\underline{x}_1 - \underline{x}_2, \overline{x}_1 - \overline{x}_2] \tag{6}$$

$$\text{Multiplication: } \otimes x_1 \times \otimes x_2 = [\min(\underline{x}_1\underline{x}_2, \underline{x}_1\overline{x}_2, \overline{x}_1\underline{x}_2, \overline{x}_1\overline{x}_2), \max(\underline{x}_1\underline{x}_2, \underline{x}_1\overline{x}_2, \overline{x}_1\underline{x}_2, \overline{x}_1\overline{x}_2)] \tag{7}$$

$$\text{Division: } \otimes x_1 \div \otimes x_2 = [\underline{x}_1, \overline{x}_1] \times [\tfrac{1}{\underline{x}_2}, \tfrac{1}{\overline{x}_2}] \tag{8}$$

Definition 7: The length of Grey number, $\otimes x$, $L(\otimes x)$ is defined as (9).

$$L(\otimes x) = [\overline{x} - \underline{x}] \tag{9}$$

Definition 8: The possibility degree of $\otimes x_1 \leq \otimes x_2$ for two Grey numbers, $\otimes x_1 = [\underline{x}_1, \overline{x}_1]$ and $\otimes x_2 = [\underline{x}_2, \overline{x}_2]$ is defined as (10).

$$P\{\otimes x_1 \leq \otimes x_2\} = \frac{\max(0, T^* - \max(0, \overline{x}_1 - \underline{x}_2))}{T^*} \tag{10}$$

where $T^* = L(\otimes x_1) + L(\otimes x_2)$.

For positional relationship between $\otimes x_1$ and $\otimes x_2$, four possible cases exist on the real number axis. The relationship between $\otimes x_1$ and $\otimes x_2$ is defined as follows:

(1) If $\underline{x}_1 = \underline{x}_2$ and $\overline{x}_1 = \overline{x}_2$, it is defined as $\otimes x_1$ is equal to $\otimes x_2$ and symbolized as $\otimes x_1 = \otimes x_2$. Then $P\{\otimes x_1 \leq \otimes x_2\} = 0.5$.

(2) If $\underline{x}_2 > \overline{x}_1$, it is defined as $\otimes x_2$ is larger than $\otimes x_1$ and symbolized as $\otimes x_2 > \otimes x_1$. Then $P\{\otimes x_1 \leq \otimes x_2\} = 1$.

(3) If $\overline{x}_2 < \underline{x}_1$, it is defined as $\otimes x_2$ is smaller than $\otimes x_1$ and symbolized as $\otimes x_2 < \otimes x_1$. Then $P\{\otimes x_1 \leq \otimes x_2\} = 0$.

(4) If there is an intercrossing part in $\otimes x_1$ and $\otimes x_2$, when $P\{\otimes x_1 \leq \otimes x_2\} > 0.5$, it is defined as $\otimes x_2$ is larger than $\otimes x_1$ and symbolized as $\otimes x_2 > \otimes x_1$. When $P\{\otimes x_1 \leq \otimes x_2\} < 0.5$, it is defined as $\otimes x_2$ is smaller than $\otimes x_1$ and symbolized as $\otimes x_2 < \otimes x_1$.

This paper uses the Grey system theory algorithm explained in Park [18]'s study and its contents are described in Table 2. The Grey system theory algorithm of Table 2 consists of Step 0, which determines the information of risk experts to step 8, which selects the most robust power demand management company for the properties and alternatives of risk.

Table 2 Grey system theory algorithm

Steps	Contents
Step 0	This step gathers the decision makers' opinion about risk attributes and alternatives. Decision makers evaluate the absolute importance of each attribute and assess how important each attribute is in each alternative being evaluated.
Step 1	This step evaluates the Grey weight ($\otimes w$) of each attribute. If the decision makers evaluate the absolute importance of each attribute, the importance of each evaluated attribute will have an interval value. In this case, the average value is calculated for the lower and upper limit value, respectively, and this value is called Grey weight.
Step 2	This step makes criteria rating values (R_{ij}). Decision makers evaluate the importance of attributes for each alternative, and each evaluated attribute computes the mean value of the lower and upper bounds of the interval for each alternative and stores this value in R_{ij}.
Step 3	This step establishes the Grey decision matrix ($\otimes$R). The Grey decision matrix constructs a matrix with attributes × alternatives for each R_{ij} value calculated in Step 2.
Step 4	This step normalizes the Grey decision matrix (R^*). The attributes of Grey decision matrix, R^*, $\otimes R^*_{mn}$ can have either a benefit (maximization) attribute or a cost (minimization) attribute. For a benefit (maximization) attribute $\otimes R^*_{ij}$ is expressed as $\otimes R^*_{ij} = [\frac{\underline{R}_{ij}}{R^{max}_j}, \frac{\overline{R}_{ij}}{R^{max}_j}]$ and $R^{max}_j = max_{1\leq i\leq m}\{\overline{R}_{ij}\}$, whereas for a cost (minimization) attribute $\otimes R^*_{ij}$ is expressed as $\otimes R^*_{ij} = [\frac{R^{min}_j}{\overline{R}_{ij}}, \frac{R^{min}_j}{\underline{R}_{ij}}]$ and $R^{min}_j = min_{1\leq i\leq m}\{\underline{R}_{ij}\}$.
Step 5	This step calculates the weighted and normalized Grey decision matrix (D^*). This step normalizes the importance of attributes and alternatives and forms matrices at the same time. In other words, this step shows the absolute importance of each attribute and the result of calculating how this attribute affects each alternative.
Step 6	This step chooses the ideal alternative. This step determines the ideal alternative consisting of the interval between the maximum and minimum values of each alternative to compare with each alternative.
Step 7	This step calculates the Grey possibility degree between the compared alternatives of all alternatives. This step uses the alternatives and the ideal alternatives to determine the Grey possibility degree that each alternative is acceptable.
Step 8	This step ranks the order of power demand management company alternatives. This step ranks the Grey possibility degrees of the alternatives in order. That is, the most optimal alternative is selected in this step.

This study assumes the following experimental conditions and the algorithm in Table 2 is applied to evaluate the selection model of the power demand management company in Figure 1.

1) The Grey numbers of the linguistic variables for the risk factors is determined by considering the fatalness and possibility of the risks that threaten the power demand management operator.

2) The attributes of risk that threaten the electric power demand management business is eight in number, viz. C_1: investment cost, C_2: security, C_3: learning cost, C_4: facility safety, C_5: skill manager, C_6: uncertainty of profit, C_7: new technology, C_8: system.

3) Four decision makers (DM_1~DM_4) evaluate the impact of the risk on the electric power demand management provider.

4) Six power demand management operators ($EPDMC_1$ ~ $EPDMC_6$) is alternatives for consumers and transactions.

The assumptions described above and the algorithm presented in Table 2 are verified through numerical examples and the method for selecting the optimal power demand management provider is as follows.

Step 0: Grey numbers of the fatalness and the possibility of the hazards is determined using decision information from the power demand management risk experts. Also, the likelihood for each risk occurring in a power demand management operator and the vulnerability of the risk factors makes the decision information of the risk expert in the power demand management. Table 3 is the Grey numbers of the fatalness and the possibility of the risks provided by the risk experts to assess each risk, while Table 4 is individual assessment of the risk factors (C_1~C_8) by four smart city power demand management risk experts (DM_1~DM_4). Table 5 shows the results evaluated by four risk experts for six power demand management companies ($EPDMC_1$~$EPDMC_6$).

Table 3 Grey numbers for the fatalness and possibility of alternatives

For the fatalness of attribute			For the possibility of alternative		
Linguistic variables	Grey numbers		Linguistic variables	Grey numbers	
VL (Very Low)	0.0	0.1	N (None)	0	1
L (Low)	0.1	0.2	PR (Pretty Rare)	1	2
ML (Medium Low)	0.2	0.4	R (Rare)	2	4
M (Medium)	0.4	0.7	U (Usual)	4	7
MH (Medium High)	0.7	0.8	AU (Above Usual)	7	8
H (High)	0.8	0.9	S (Superior)	8	9
VH (Very High)	0.9	1.0	VS (Very Superior)	9	10

Table 4 evaluation of power demand management risk experts for attributes

Attributes	Decision makers			
	DM_1	DM_2	DM_3	DM_4
C_1	VH	H	VH	H
C_2	M	M	MH	H
C_3	L	ML	M	L
C_4	MH	H	H	MH
C_5	M	M	ML	MH
C_6	H	H	MH	VH
C_7	ML	ML	L	L
C_8	MH	H	VH	MH

Table 5 risk expert assessment of risk factors for each alternative

$EPDMC_i$	C_i / DM_i	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
$EPDMC_1$	DM_1	N	PR	AU	PR	S	PR	S	R
	DM_2	PR	R	VS	U	AU	S	N	R
	DM_3	U	R	S	AU	VS	S	PR	N
	DM_4	U	R	VS	S	AU	S	R	VS
$EPDMC_2$	DM_1	S	N	VS	AU	R	AU	AU	AU
	DM_2	VS	N	PR	VS	VS	AU	S	R
	DM_3	N	U	U	S	S	PR	AU	U
	DM_4	PR	R	U	S	S	R	AU	PR
$EPDMC_3$	DM_1	R	U	AU	AU	VS	VS	R	U
	DM_2	N	N	R	S	S	AU	N	AU
	DM_3	U	S	AU	S	S	R	U	U
	DM_4	R	R	R	VS	S	U	R	S
$EPDMC_4$	DM_1	N	R	R	S	S	PR	U	AU
	DM_2	PR	U	S	VS	AU	PR	PR	S
	DM_3	PR	AU	S	VS	S	R	N	VS
	DM_4	PR	S	AU	AU	VS	U	N	S
$EPDMC_5$	DM_1	R	AU	S	AU	S	R	R	S
	DM_2	R	AU	S	AU	VS	U	AU	S
	DM_3	R	S	VS	S	R	AU	S	AU
	DM_4	U	R	VS	S	PR	AU	PR	VS
$EPDMC_6$	DM_1	PR	AU	U	VS	AU	R	PR	VS
	DM_2	R	S	S	VS	U	PR	N	S
	DM_3	PR	VS	AU	S	S	R	R	AU
	DM_4	R	S	S	VS	S	N	U	U

Step 1: The Grey weight of each attribute is calculated ($\otimes W_j$). Table 6 shows the Grey weights for each attribute.

Table 6 Grey weight of each attribute

C_i	$\otimes W$	Lower	Upper
C_1	w_1	0.850	0.950
C_2	w_2	0.575	0.775
C_3	w_3	0.200	0.375
C_4	w_4	0.750	0.850
C_5	w_5	0.425	0.650
C_6	w_6	0.800	0.900
C_7	w_7	0.150	0.300
C_8	w_8	0.775	0.875

Step 2: This step generates criteria rating values (R_{ij}). The risk expert results (VL~VH, N~VS) for each of the risk factors in Table 5 are converted to quantitative values using the Grey numbers of Table 3. Table 7 shows the criteria ranking value of attributes considering the characteristics of attributes.

Table 7 criteria ranking value of attributes

C_i	Criteria ranking value	Characteristic of attribute
C_1	0.750	cost
C_2	9.000	benefit
C_3	4.500	cost
C_4	9.750	benefit
C_5	9.250	benefit
C_6	1.250	cost
C_7	8.250	benefit
C_8	9.000	benefit

Step 3: A Grey decision matrix is constructed ($\otimes R$). Table 8 shows the Grey decision matrix.

Table 8 Grey decision matrix

$EPDMC_j$ / R_{ij}	$EPDMC_1$		$EPDMC_2$		$EPDMC_3$		$EPDMC_4$		$EPDMC_5$		$EPDMC_6$	
R_{1j}	2.250	4.250	4.500	5.500	2.000	4.000	0.750	1.750	2.500	4.750	1.500	3.000
R_{2j}	1.750	3.500	1.500	3.250	3.500	5.250	5.250	7.000	6.000	7.250	8.000	9.000
R_{3j}	8.250	9.250	4.500	6.500	4.500	6.000	6.250	7.500	8.500	9.500	6.750	8.250
R_{4j}	5.000	6.500	8.000	9.000	8.000	9.000	8.250	9.250	7.500	8.500	8.750	9.750
R_{5j}	7.750	8.750	6.750	8.000	8.250	9.250	8.000	9.000	5.000	6.250	6.750	8.250
R_{6j}	6.250	7.250	4.250	5.500	5.500	7.250	2.000	3.750	5.000	6.750	1.250	2.750
R_{7j}	2.750	4.000	7.250	8.250	2.000	4.000	1.250	2.750	4.500	5.750	1.750	3.500
R_{8j}	3.250	4.750	3.500	5.250	5.750	7.750	8.000	9.000	8.000	9.000	7.000	8.500

Step 4: The Grey decision matrix is the normalized value of R^*. Table 9 shows the results of the normalized Grey decision matrix.

Table 9 normalization of Grey decision matrix

$EPDMC_j$ / R_{ij}^*	$EPDMC_1$		$EPDMC_2$		$EPDMC_3$		$EPDMC_4$		$EPDMC_5$		$EPDMC_6$	
R_{1j}	3.000	5.667	6.000	7.333	2.667	5.333	1.000	2.333	3.333	6.333	2.000	4.000
R_{2j}	0.194	0.389	0.167	0.361	0.389	0.583	0.583	0.778	0.667	0.806	0.889	1.000
R_{3j}	1.833	2.056	1.000	1.444	1.000	1.333	1.389	1.667	1.889	2.111	1.500	1.833
R_{4j}	0.513	0.667	0.821	0.923	0.821	0.923	0.846	0.949	0.769	0.872	0.897	1.000
R_{5j}	0.838	0.946	0.730	0.865	0.892	1.000	0.865	0.973	0.541	0.676	0.730	0.892
R_{6j}	5.000	5.800	3.400	4.400	4.400	5.800	1.600	3.000	4.000	5.400	1.000	2.200
R_{7j}	0.333	0.485	0.879	1.000	0.242	0.485	0.152	0.333	0.545	0.697	0.212	0.424
R_{8j}	0.361	0.528	0.389	0.583	0.639	0.861	0.889	1.000	0.889	1.000	0.778	0.944

Step 5: The normalized Grey decision matrix is the weighted value of D^*. Table 10 shows the Grey decision matrix with weights and normalization.

Table 10 weighted normalized Grey decision matrix

$EPDMC_j$ / D_{ij}^*	$EPDMC_1$		$EPDMC_2$		$EPDMC_3$		$EPDMC_4$		$EPDMC_5$		$EPDMC_6$	
D_{1j}^*	2.550	5.383	5.100	6.967	2.267	5.067	0.850	2.217	2.833	6.017	1.700	3.800
D_{2j}^*	0.112	0.301	0.096	0.280	0.224	0.452	0.335	0.603	0.383	0.624	0.511	0.775
D_{3j}^*	0.367	0.771	0.200	0.542	0.200	0.500	0.278	0.625	0.378	0.792	0.300	0.688
D_{4j}^*	0.385	0.567	0.615	0.785	0.615	0.785	0.635	0.806	0.577	0.741	0.673	0.850
D_{5j}^*	0.356	0.615	0.310	0.562	0.379	0.650	0.368	0.632	0.230	0.439	0.310	0.580
D_{6j}^*	4.000	5.220	2.720	3.960	3.520	5.220	1.280	2.700	3.200	4.860	0.800	1.980
D_{7j}^*	0.050	0.145	0.132	0.300	0.036	0.145	0.023	0.100	0.082	0.209	0.032	0.127
D_{8j}^*	0.280	0.462	0.301	0.510	0.495	0.753	0.689	0.875	0.689	0.875	0.603	0.826

Step 6: This step makes an ideal alternative ($EPDMC_{max}$). An ideal alternative at this stage is a virtual power demand management operator created to evaluate each power demand management operator. Table 11 presents an ideal power demand management company ($EPDMC_{max}$).

Table 11 ideal electronic power demand management company

	C_i	Upper	Lower
$EPDMC_{max}$	C_1	5.100	6.967
	C_2	0.511	0.775
	C_3	0.378	0.792
	C_4	0.673	0.850
	C_5	0.379	0.650
	C_6	4.000	5.220
	C_7	0.132	0.300
	C_8	0.689	0.875

Step 7: This step calculates the probability degree of Grey by comparing each power demand management operator with the ideal power demand management provider. Table 12 shows the likelihood of Grey.

Table 12 Grey possibility degree

$EPDMC_i$ / C_i	$EPDMC_1$	$EPDMC_2$	$EPDMC_3$	$EPDMC_4$	$EPDMC_5$	$EPDMC_6$
C_1	0.940	0.500	1.000	1.000	0.818	1.000
C_2	1.000	1.000	1.000	0.827	0.776	0.500
C_3	0.520	0.783	0.829	0.675	0.500	0.614
C_4	1.000	0.678	0.678	0.618	0.801	0.500
C_5	0.555	0.650	0.500	0.527	0.875	0.629
C_6	0.500	1.000	0.582	1.000	0.701	1.000
C_7	0.948	0.500	0.951	1.000	0.738	1.000
C_8	1.000	1.000	0.855	0.500	0.500	0.664

Step 8: In this step the ranking of the overall power demand management operators is determined. The optimal power demand management service provider is the smallest of $P\{EPDMC_i \leq EPDMC_{max}\}$ (see Table 13). In this experiment, $EPDMC_5$ is selected.

Table 13 priority order of electronic power demand management companies

$EPDMC_i$	$EPDMC_1$	$EPDMC_2$	$EPDMC_3$	$EPDMC_4$	$EPDMC_5$	$EPDMC_6$
Average	0.808	0.764	0.799	0.768	0.714	0.738
Rank	6	3	5	4	1	2

Table 13 shows the evaluation results of six power demand management companies. The optimal power demand management provider is $EPDMC_5$ with a value of 0.714, which should be selected by the consumers. The next rank of $EPDMC_5$ is $EPDMC_6$ with a value of 0.738, which is larger than the value of $EPDMC_5$, but can be considered as the second choice since there is no significant difference. The next rank is $EPDMC_2$-$EPDMC_4$ with a value of 0.764-0.768 and the last rank is $EPDMC_3$ - $EPDMC_1$ with a value of 0.799-0.808. In this experiment, the ranking of the electric power demand management companies is classified into three groups, viz. EPDMC_5 - EPDMC_6 , EPDMC_2 - EPDMC_4 , and EPDMC_3 -EPDMC_1. This further explains the existence of three groups of similar demand power management operators.

V. Conclusions and Future works

This paper proposed a method to select the optimum power demand management service provider considering the risk factors that occur in the process of implementing smart grid that efficiently manage the energy of smart city. In regard to power demand management, optimal power energy management is highly desirable because it aims to minimize power consumption by minimizing environmental destruction while efficiently using it, and reselling any unused surplus power.

On the consumer side, the cost of purchasing electricity and the profits obtained from reselling the remaining electricity will depend on the power demand management service providers (EPDMC_1~EPDMC_6) that the consumer chooses. Consumers can also benefit from favorable conditions when they use (or produce) and resell the remaining power. In the end, the selection of a power demand management service provider is an important issue that causes financial loss or gain for the consumers. The most optimal power demand management service provider is the company that guarantees the highest return to customers by minimizing the cost components and maximizing the profit components among the risk factors that may arise.

This study investigated the risk factors (C_1~C_8), such as investment cost, security, learning cost, facility stability, skill manager, uncertainty of profit, new technology, and system to select the optimal power demand management service provider. The risk factors presented here are objects that can be accepted objectively by anyone who is not biased on the electric power demand management service provider or the consumer. The attributes of the presented risk factors were reflected in the cost and profit perspectives, and the qualitative attributes of the risk factors were reflected in the selection of the power demand management service provider.

The current study used the Grey system theory to reflect the ambiguity and uncertainty of the risk factors during selection of the optimal power demand management service provider. This technique can quantify the effects of the risk by objectifying the qualitative nature of the risk factors that impede the effective achievement of smart grid in a smart city. By employing this technique, this study reflected the decision of six power demand management service providers (EPDMC_1~EPDMC_6) with eight risk factors (C_1 ~ C_8) by four risk management experts (DM_1~DM_4) and proposed a method to maximize the profit of consumers through the selection of power demand management service provider. It is very difficult to select a power demand management service provider that can guarantee the most efficiency in the consumer segment, because the electric power facilities and systems have a lot of initial installation costs and cannot be changed immediately if any problem arises in the installed electric power facilities and systems.

This paper applied the Grey system theory to the risk factors of six candidate electric power demand management providers to objectively evaluate the impact of the risk factors that impede the efficient smart grid in a smart city. The risk experts based on the Grey numbers presented the evaluation of the risk factors. This study selected the electric power demand management service provider, EPDMC_5, and presented it to consumers.

In the case of multi-attribute decision problems, the decision maker's judgment is often uncertain and cannot be expressed as an exact numerical value, so this study can be effectively applied in such cases. This study asked experts in the field of power demand management to review the results obtained through this technique, and obtained the opinion that the results were reasonable.

Finally, future research is necessary to establish a system that would consider additional risk factors because the risks that impede the effective operation of the smart grid are so diverse. In addition, the decision makers of risks cannot always specify the same Grey numbers depending on the circumstances, such as the conditions under which they were taken, or subjective opinion of the individual. Therefore, it is recommended to designate the Grey numbers as probabilistic distributions so that the ambiguity of the decision makers can be captured and how much difference is there from the results given as fixed Grey numbers can be checked. Furthermore, the proposed technique in the present study needs also to be applied to real problems to verify its practical efficiency.

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