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Data-Analytic Assessment for Flexumers Under Demand Diversification in a Power System

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ABSTRACT Under the carbon-neutral environment, the number of renewable power sources needs to be drastically increased. To respond to the large variability derived from renewable power sources, potential flexible resources have been established and researched. Among these, securing flexibility by using demand is achieved through demand response. For this purpose, it is helpful to identify flexumers—consumers with flexibility—for each player involved in the demand response. To identify the characteristics of flexumers among the demand consumers, we propose a method to classify the characteristics of flexumers into four groups based on power consumption data: price responsivity score, consistency score, flexible amount, and response time score. To verify the effectiveness of the proposed classification, the test system was evaluated with the power-consumption data from 19 companies in 11 industries. One company in the steel industry scored remarkably high in terms of a flexible amount. Overall, companies in the energy, chemical, material, filter and cement industries relatively showed characteristics suitable to flexumers. The suitability for flexumer application was quantitatively compared between industries, and other implications included the scope of criteria application and the direction of formula improvement. With the electrification of other industries, sector coupling, and the digitization of the power industry, the identification of flexumers in demand will significantly alter the plans for securing power-system flexibility. Therefore, the proposed flexumer characteristic formulas can contribute to the advancement of empirical data-based power-industry modeling by classifying resources with flexumer characteristics among the demand agents in the power system model.

INDEX TERMS Analysis of power industry players, consumer classification, data analysis flexumer, industrial power demand, power consumption data.

NOMENCLATURE

A. INDICES

- i Index of industrial demand resources.
- t Index of time slots.
- d Index of date slots.
- x Index of time zone.
- y Index of date zone.

B. SETS

- T Set of all time slots t.
- T_x Set of specific x (cf. same rate time) time slots t.
- T_{max} Set of t satisfying (13).
- T_{min} Set of t satisfying (14).
- D Set of all date slots d.
- D_y Set of specific y (cf. seasonal) date slots d.

C. PARAMETERS AND VARIABLES

- PRS_i Price responsivity score of industrial demand resource i.
- $UR_{i,x}$ Utilization rate of industrial demand resource i in specific timezone x.
- CS_i Consistency score of industrial demand resource i.
- FA_i Flexible amount of industrial demand resource i.
- RTS_i Response time score of industrial demand resource i.

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PR_i Price responsivity of industrial demand resource i.
N_i Whether the price of industrial demand resource i changes.
$RMSP_i$ Root-mean-squared percentage of industrial demand resource i.
RT_i Response time of industrial demand resource i.
N_D Total number of date slots d.
N_T Total number of time slots t.
$p_i(d,t)$ Power consumption of industrial demand resource i at date d and time t.
$m_i(d,t)$ Electricity price of industrial demand resource i at date d and time t.
$p_i^n(d,t)$ Day-normalized power consumption of industrial demand resource i at date d and time t.
$p_i^{avg}(t)$ Average power consumption of industrial demand resource i at time t over the span of D.

I. INTRODUCTION

Since the Paris Climate Agreement, reductions have been made in the use of carbon worldwide, to limit the average temperature rise of the Earth to 2°C since industrialization. Further attempts are being made to lower it from 2°C to 1.5°C and achieve carbon neutrality by 2050 [1]. To achieve this goal, energy-related organizations have suggested methods to reduce carbon usage. They have argued that the proportion of renewable energy sources in the total primary energy supply should be increased to more than 60% by 2050 and that the electrification rate must exceed 50% by 2050. Considering only the electric-power-generation field, renewable energy is expected to account for more than 88% of the energy used for power generation by 2050. Moreover, variable renewable energy (VRE), which accounted for 7% of the power-generation energy in 2018, is expected to account for 43% of electric power generation by 2030 and 63% by 2050 [2]–[4]. However, VREs, such as photovoltaic power generation and wind power generation, are much more variable than existing resources, among which the ones that can respond to variability are carbon-based (such as natural gas and coal) and must therefore be replaced. Hence, to respond to the variability of VREs, new measures, such as energy-storage systems, sector coupling, and resource aggregation, have been established and many studies are being conducted [4]–[6]. This study focuses on the demand side management of the various potential flexible resources.

Previously, demand in the power industry was a passive quantity that had to be forecasted and could not be controlled. However, with the development of advanced metering infrastructure(AMI) and the development of information and communication technology, demand can now be used as a flexible resource to balance demand and supply of electricity [7], [8]. For example, if there is an oversupply during the day due to the increase in the supply of photovoltaic power that cannot control the energy production, it can be solved by increasing the demand. After sunset, as the supply decreases, demand can be reduced to balance supply and demand. The increase or decrease in demand is carried out through a demand response program.

Demand response programs can be divided into two main categories. One is to change electricity rates with price-based demand response. Price-based demand response is mainly implemented by utilities and has been applied to reduce peak load and peak average ratio. Another method is incentive-based demand response; when system operator carries out a demand response program to balance supply and demand, it is a method of providing incentives to consumers according to the amount of increase or decrease in demand [9], [10]. The provision of flexibility through demand control is progressing in parallel with price-based demand response, and incentive-based demand response is effective in terms of providing flexibility [11]. Providing flexibility through demand can be cost-effective because it has lesser physical basis than energy storage system or sector coupling.

In an environment where demand is used as flexibility, it is important to determine whether a consumer provides flexibility. This can be confirmed from the perspective of utilities, system operator, and aggregators, which are major players in terms of demand.

1) Utility: It is necessary to design a rating system that induces demand according to the net load by subtracting the amount of renewable generation from the total demand or based on the amount of electricity supplied by adding the amount of renewable generation. If the ratio of power generation sources varies greatly, it is necessary to understand consumers and design a suitable rating plan accordingly.
2) System Operator: To solve the supply–demand imbalance through demand response, it is important to identify consumers who will provide flexibility.
3) Aggregator: There is a need for a method to easily classify consumers with flexibility in a situation where demand resources are accumulated, such as a demand response or a virtual power plant.

It is necessary for each player in the power industry to identify consumers who provide or are likely to provide such flexibility. Thus, a consumer classification method based on power consumption data is presented in section 2. The proposed method is evaluated in section 3, and industrial power data are used as evaluation data. Nine types of industrial resources are identified in the previous paper on industrial demand response [12]. Further, industrial power data contain company information, making it difficult to conduct research as such information is considered confidential. In this study, the electricity consumption data of 11 industries that obtained consent from customers for participation in the demand response are use.

II. IDENTIFYING FLEXUMERS

A. DEFINITION OF FLEXUMERS

"Flexumer" is a combination of "flexibility" and "consumer" and refers to consumers who provide flexibility to the

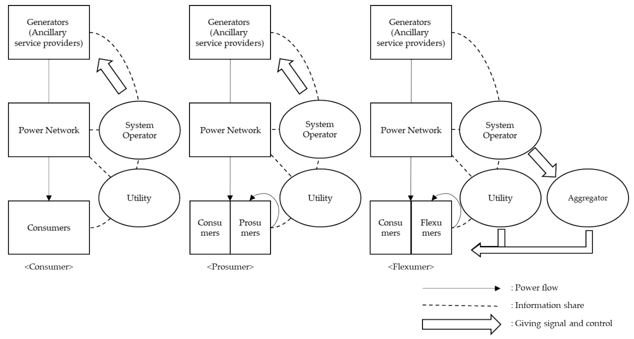

FIGURE 1. **Interactions within the power system for different types of consumers.**

power system. As shown in Figure 1, a flexumer is a consumer who, apart from being a self-supply prosumer, reduces or increases their consumption by receiving a signal from the system operator according to the system supply and demand situation.

Therefore, to distinguish themselves from consumers, flexumers must respond to signals from the system operator and identify the factors that affect the system. Since the power industry transformed into a market, prices have been the main indicators of increasing or decreasing electricity demand. Therefore, to identify flexumers among consumers, it must be determined whether the price of electricity causes a change in power consumption. Second, the consistency in the pattern of power usage must be verified; providing flexibility becomes challenging if power usage is highly inconsistent. Finally, there should be an assessment of the impact of the consumer on the power system in terms of quantity and time. Consumers can be identified as flexumers based on the quantity of demand that they can change and the time required for the change. Thus, price responsiveness, consistency, flexible amount, and response time are determined to be the defining characteristics of flexumers.

B. FORMULATION OF FLEXUMER CHARACTERISTICS

Power consumption data are used to establish the formulas for the four flexumer characteristics defined earlier, that is, price responsivity score, consistency score, flexible amount, and response time score.

1) Price responsivity score: This metric represents the change in power consumption at every instant when the price changes. Specifically, it is used to ensure that power consumption decreases when the price increases and vice versa. The price responsivity score (***PRS$_i$***) is the value obtained by dividing the number of times that the power consumption ($\boldsymbol{p_i}$) changes with a price change ($\boldsymbol{PR_i}$) by the number of price changes ($\boldsymbol{N_i}$) over a certain period (t) on a given date (d).

$$PRS_i = \frac{\sum_{d\in D}\sum_{t\in T} PR_i\,(d,t)}{\sum_{d\in D}\sum_{t\in T} N_i\,(d,t)} \tag{1}$$

$$PR_i = \begin{cases} 1 \; (p_i\,(d,t+1) - p_i\,(d,t)) \\ \qquad\qquad \cdot\,(m_i\,(d,t+1) - m_i\,(d,t)) < 0 \\ 0 \quad \text{otherwise} \end{cases} \tag{2}$$

$$N_i\,(d,t) = \begin{cases} 1 \; |m_i\,(d,t+1) - m_i\,(d,t)| > 0 \\ 0 \quad \text{otherwise} \end{cases} \tag{3}$$

From another perspective, information about the effect of electricity rates on power consumption can be extracted through a comparative analysis of daily demand patterns and changes in electricity prices. The usage ratio ($UR_{i,x}$) is the average proportion of consumption for each time period ($N_D \cdot N_{T_x}$), obtained after day min–max normalization of electricity usage. The daily demand data are expressed as values between 0 and 1 due to the aforementioned normalization, which is equivalent to the level of response to daily price variations.

$$UR_{i,x} = \frac{\sum_{d\in D}\sum_{t\in T} p_i^n(d,t)}{N_D \cdot N_{T_x}} \tag{4}$$

$$p_i^n\,(d,t) = \frac{p_i\,(d,t) - \min_{t\in T}(p_i(d,t))}{\max_{t\in T}(p_i(d,t)) - \min_{t\in T}(p_i(d,t))} \tag{5}$$

Thus, PRS_i, an indicator of when prices change, and $UR_{i,x}$, a metric for comparing usage according to prices, reflect the responsiveness to price variations.

2) Consistency score: The consistency score (CS_i) is the root-mean-squared percentage error ($RMSP_i$) between the instantaneous power value (p_i) and the average power value ($p_{i,y}^{avg}$) at a specific time [13]. For comparison with other values (i), the minimum power value ($\min p_i$) is subtracted from the mean value of $p_{i,y}^{avg}$, which is equivalent to normalization. To account for the inconsistency of seasonal variation, the date (D_y) is considered when calculating CS_i.

$$CS_i = 1 - RMSP_i \tag{6}$$

$$RMSP_i = \sqrt{\frac{\sum_{d\in D}\sum_{t\in T}\left(\frac{p_{i,y}^{avg}(t) - p_i(d,t)}{p_{i,y}^{avg}(t) - \min_{d\in D_y, t\in T}(p_i(d,t))}\right)^2}{N_{D_y} \cdot N_T}} \tag{7}$$

$$p_{i,y}^{avg}\,(\mathrm{t}) = \frac{\sum_{d\in D_y} p_i\,(d,t)}{N_{D_y}} \quad PRS_i = \frac{\sum_{d\in D}\sum_{t\in T} PR_i\,(d,t)}{\sum_{d\in D}\sum_{t\in T} N_i\,(d,t)} \tag{8}$$

3) Flexible amount: The flexible amount ($\mathrm{FA_i}$) is the difference between the maximum and minimum of the average value of resources ($\mathrm{p_i^{avg}}$) over a span of days (D).

$$FA_i = \max_{t\in T}(p_i^{avg}(t)) - \min_{t\in T}(p_i^{avg}\,(t)) \tag{9}$$

$$p_i^{avg}\,(t) = \frac{\sum_{d\in D} p_i(d,t)}{N_D} \tag{10}$$

4) Response time score: The response time (RT_i) is the smallest difference between the maximum value of the average value and the minimum value of the average value. The response time score (RTS_i) is a score that can be compared with other values. Response time score (RTS_i) is a value that increases as the response time (RT_i) is shorter.

$$RTS_i = 1 - \frac{2RT_i}{N_T} \tag{11}$$

TABLE 1. De-identified industrial data.

Type	COMPANY
Metal	A, D, K
Energy	B
Forging	C, E
Chemical	F, L
Paper	G
Steel	Q, H
Cement	I, J
Car	M, R
Material	N, O
Filter	P
Casting	S

$$RT_i = \min_{t_{max} \in T_{MAX}, t_{min} \in T_{MIN}} |t_{max} - t_{min}| \tag{12}$$

$$T_{MAX} = \left\{ t \mid t = arg \max_{t'} (p_i^{avg}(t')) \right\} \tag{13}$$

$$T_{MIN} = \left\{ t \mid t = arg \max_{t'} (p_i^{avg}(t')) \right\} \tag{14}$$

In totality, equations (1)–(14) can be applied to any dataset by changing the time slot (t), date slot (d), time zone (x), and date zone (y) accordingly.

III. TEST SYSTEM

In this study, we used industrial power-consumption data to evaluate the proposed formulations of the flexumer characteristics. In 2016, industrial demand constituted 31.9% of the power demand of the Organisation for Economic Co-operation and Development countries, which is higher than the shares of household and commercial demand. Additionally, the base resource capacity for industrial demand is large [14]. Therefore, it is the most representative demand, and can be an easy way to check the degree of reaction according to the price change. Accordingly, power-consumption data were obtained from 19 companies in 11 industries in South Korea. The industrial demand (kWh/min) was measured as the amount of power consumption in 1-minute periods from January 1 to December 31, 2019. Each industrial dataset was designated a letter from "A" to "S" to protect the information. The de-identified industrial data are shown in Table 1. The rate information employed was based on the industrial power rate announced by the Korea Electric Power Corporation, shown in Table 2.

Pre-processing was performed to eliminate and impute missing data. For cases with more than 30 missing values, the date values were removed. In the remaining cases, the missing values were linearly interpolated. Working day data were extracted by removing the weekend values.

IV. RESULTS

A. PRICE RESPONSIVITY SCORE

Price responsiveness can be measured when the price changes over time. The rate schedule (Table 2) shows that in spring, summer, and fall, six price changes occurred at 09:00, 10:00, 12:00, 13:00, 17:00, and 23:00. In winter, seven price changes occurred at 09:00, 10:00, 12:00, 17:00, 20:00, 22:00, and 23:00. Since the price changes were set based on periods of 1 h, t was set in units of 1 h. Because three time zones were established based on the price, $UR_{i,x}$ was determined by setting x as 3.

TABLE 2. Key parameters for optimization model.

Classification	MARCH–OCTOBER	NOVEMBER–FEBRUARY
Off-peak load	23:00–09:00	23:00–09:00
Mid-load	09:00–10:00 12:00–13:00 17:00–23:00	09:00–10:00 12:00–17:00 20:00–22:00
Peak load	10:00–12:00 13:00–17:00	10:00–12:00 17:00–20:00

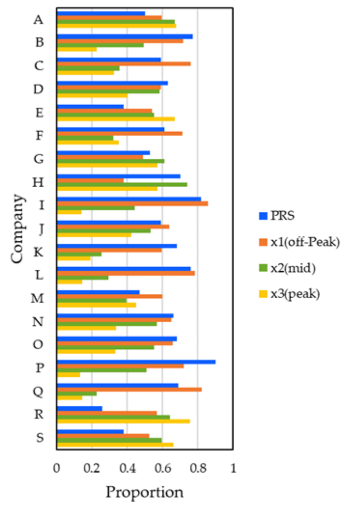

FIGURE 2. Price responsivity scores and power-usage proportion of 19 industrial companies.

Figure 2 shows the values applied to Equations (1)–(5).

The highest PRS_i was 0.9, and the lowest was 0.26. R and S achieved the lowest PRS_i values. The industries whose PRS_i values exceeded the average score of P and S (0.58) are the energy, chemical, steel, filter, cement, and material industries. Thus, PRS_i clearly distinguishes R and S as companies that do not respond to price changes. Considering PRS_i and $UR_{i,x}$ simultaneously, H exhibits a unique characteristic. Although the power-usage proportion of H is low during the off-peak, the high PRS_i of H shows that it responds well to price changes during the daytime.

B. CONSISTENCY SCORE

To measure the consistency score, D was divided into five groups by season: D_{y1} (January 1–February 28), D_{y2} (March 1–May 31), D_{y3} (June 1–August 31), D_{y4} (September 1–October 31), and D_{y5} (November 1–December 31). Figure 3 shows the values applied to Equations (6)–(8).

N achieved the highest CS_i (0.8961), whereas K achieved the lowest (0.4). A relative root-mean-squared

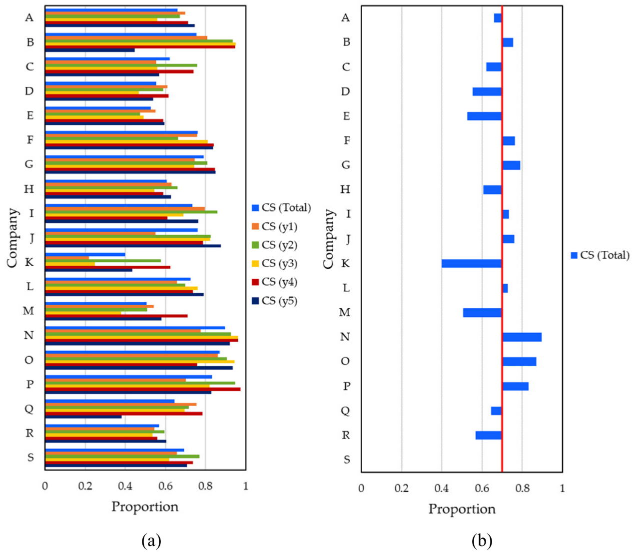

FIGURE 3. (a) Seasonal and total consistency scores; (b) Classification of total CS based on a threshold of 0.7.

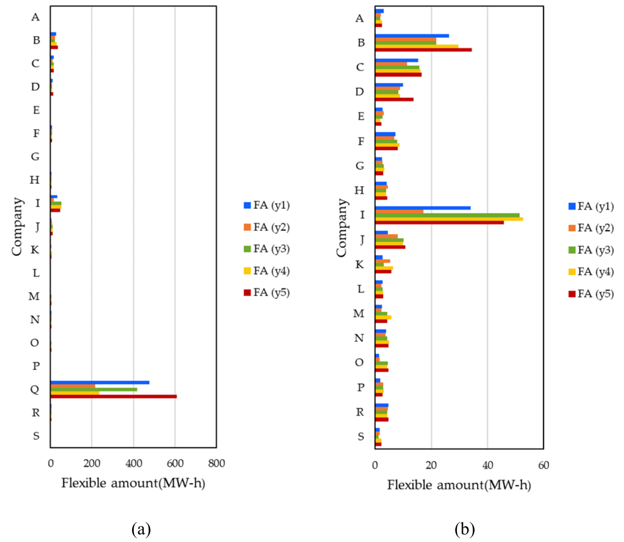

FIGURE 4. (a) Flexible amount by season (b) Flexible amount by season, with Q excluded.

error (RRMSE) was used to evaluate the customer base line (CBL), which is the expected pattern of customer consumption in the absence of the demand response that utilizes demand in the power market [15]. The RRMSE value was verified according to each situation based on 30% for Korea and 20% for Pennsylvania, New Jersey, and Maryland Interconnection (PJM), which is a regional transmission organization in the United States [16]. Because the data are from Korea companies, the values of CS_i were classified based on a threshold of 0.7; the companies whose CS_i exceeded this value—B, F, G, I, J, L, N, O, and P—were considered to exhibit a consistent demand pattern. Depending on the situation, the threshold can be freely set. In terms of industry, the energy, chemical, paper, cement, and material industries achieved satisfactory scores.

C. FLEXIBLE AMOUNT

To measure the flexibility, D was divided into the same five groups as in the case of CS_i. Figures 4 and 5 show the values applied to Equations (9) and (10).

Q's FA_i was remarkably high (216.09–609.85 MW–h). All companies had a FA_i value of 1 MW–h or more, reflecting the characteristics of industrial demand with a large base capacity.

D. RESPONSE TIME SCORE

To measure the response time score, D was again divided into the same five groups as in the case of CS_i and FA_i. Figure 6 shows the values applied to Equations (11)–(14).

D had the highest RTS_i (0.9778), and I had the lowest (0.0028). For D, G, I, and K, the scores differed significantly between seasons.

Overall, the energy, chemical, material, filter, and cement industries were classified as suitable flexumers. However, the

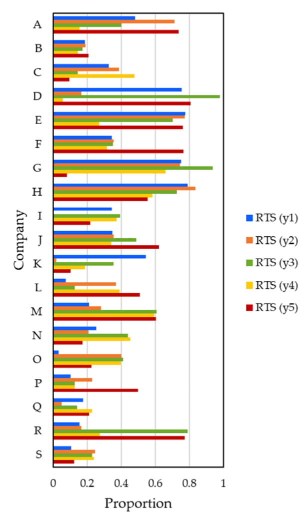

FIGURE 5. Response time scores by season.

substantial seasonal variation in RTS_i makes classification difficult.

V. DISCUSSION

A. APPLICATION OF INDICATORS

1) UTILITY

When flexumers are classified, it is possible to obtain a standard value of the flexibility amount that can be obtained through an electricity plan design by identifying flexumers who provide flexibility in response to price and consumers, and those who do not respond to price. By setting a threshold for the flexibility amount, it is possible to prevent excessive price setting by preventing vague expectations (e.g., the amount of demand will continue to decrease as the price increases). Specifically, by using the PRS_i, consumers who respond to a specific rate value and consumers who do not respond can be classified, and this value can be used to design the time of use rate. Furthermore, if the PRS_i, discussed in the next subsection, is expanded to the concept of elasticity of demand according to price changes, it is possible to set the desired quantity of demand according to the quantity supplied in the design of the real time pricing rate plan and use it to set the price to meet the demand.

2) SYSTEM OPERATOR

By identifying flexumers, it is possible to recognize consumers who can be utilized for incentive-based demand response, which can be used for information on flexibility planning to balance supply and demand. For example Q, whose FA_i was exceedingly high (216.09–609.85 MW–h), can be analyzed to secure high-quality resources in advance to balance supply and demand. Moreover, when demand response is used in the auxiliary service market, it is divided into various types according to reaction speed and duration; to classify or utilize it accordingly, the improved RTS_i suggested below can be used.

3) AGGREGATOR

Classifying consumers based on the amount of power consumption data to the aggregator can be used as a standard for primary classification, thereby saving classification time and securing greater potential at a low cost. Additionally, if the consumer converts the electricity consumption data into the corresponding indicator and provides this information to the aggregator, it would be possible to protect personal information and provide an aggregation consultation without burden before participating in aggregation.

Additionally, in terms of research, the design of power system models based on the proposed flexumer-identification metrics will lead to several changes in the evaluation of power-system operation, and is essential considering the progressing digitalization of the power industry.

B. DIVERSE IMPROVEMENT IMPLICATIONS OF FORMULAS

PRS_i indicates whether demand changes with price. Therefore, if PRS_i is modified to reflect the extent of change in demand with a given change in price, it can analyze the elasticity of demand with price changes as an additional experiment.

The seasonal variation of RTS_i is adequate to ensure system robustness. In some cases, to apply the relaxed RTS_i, this metric can be corrected in three respects. First, it is necessary to check whether RTS_i is affected noticeably by outliers. Second, it is an alternative to determine the minimum change time by clustering periods with high demand and low demand, rather than the change times between the maximum and minimum values. Finally, RTS_i can be calculated as the minimum time between the maximum and minimum demand on a daily basis.

Since we obtained the results using only 19 datasets, verification using more data is required, and the results need to be modified accordingly. Additionally, the flexumer characteristics were identified using only one company's total power-consumption data. Hence, a more accurate and effective evaluation method should be developed using power-consumption data for multiple consumer load devices or by collecting comprehensive consumer information through surveys

VI. CONCLUSION

In this study, we identified the characteristics of flexumers and presented a method for identifying flexumers among general consumers according to the characteristics of price responsivity, consistency, flexible amount, and response time. A power consumption data-based formula was used as the measurement method for each characteristic. The four formulas were tested using the power-consumption data of 19 companies in 11 industries. The results confirmed that the energy, chemical, material, filter and cement industries are suitable candidates for flexumers. Thus, the proposed flexumer-classification method is highly beneficial in terms of power system flexibility planning and facilitates power-industry modeling based on empirical data. However, the formulas need improvement, and using more data would ensure verification and could enable more effective consumer modeling.

In future studies, we will extend the versatility and universality of the flexumer characteristic formulas by utilizing potential residential and commercial power consumption data and other industrial power consumption data. Based on this, we will design a power system model to determine the ripple effect of flexumer on the power system.

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