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RESEARCH ARTICLE

Designing a Data-Driven Energy Management Service: A Case Study of South Korea's National Industrial Complex

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ABSTRACT Big data plays a crucial role in energy management services by providing valuable insights to customers. However, data analytics alone cannot create value, and it is essential to effectively transform and integrate these data into energy-management services. Although numerous studies have focused on developing data-driven architectures or platforms to manage energy efficiency, few have addressed the design process of data-driven energy management services. To fill this research gap, we conducted a case study to design a novel service concept aimed at improving the energy efficiency of companies within a national industrial complex based on an analysis of electricity consumption data. Finally, our findings, supported by interviews with a small company within the complex, suggest that the proposed information and service concept can be both effective and beneficial for businesses. This study contributes to the integration of data analytics with service design, thereby improving the effectiveness and adoption of such services.

INDEX TERMS Energy management, service concept, information design, case study, data-driven, national industrial complex.

I. INTRODUCTION

Advancements in information and communication technologies (e.g., cloud computing, big data analytics, and artificial intelligence) have driven the transformation of traditional power systems, fostering their integration, digitization, automation, and personalization [1], [2], [3]. Among these advancements, big data analytics hold particular promise for significantly enhancing the efficiency of energy management [4], [5], [6]. Consequently, the incorporation of big data analytics into energy management services is rapidly accelerating their adoption and is poised to substantially boost their growth in the coming years [7], [8], [9]. This study refers to this service as a data-driven energy management service (DEMS).

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This advancement in technology has sparked significant interest in DEMS in the academic sector (e.g., [10]). Several scientific studies have proposed platforms and architectures for DEMS across various domains. For example, Marinakis et al. [10] proposed an architecture that integrates information from multiple sources to provide actionable recommendations and meaningful operational insights to various customers. Al Faruque and Vatanparvar [11] introduced a fog-computing platform that enables users to implement energy management through customized control services while minimizing implementation costs and time to market. Bayindir et al. [12] designed hardware and software architectures for an energy management system capable of real-time data monitoring. These studies have primarily focused on proposing architectures or platforms for applying data analytics to enhance energy efficiency.

However, it is crucial to recognize that data analytics alone do not generate value for DEMS users [10]. Instead, transforming data into the most current and relevant information is essential because the value and appeal of a DEMS are directly related to this information [13], [14]. This focus is vital because DEMS can be seen as a smart service that generates valuable insights to help users achieve their goals while also collecting the necessary data to produce these insights [15]. Although these studies are important, research on the information design for DEMS is required to enhance user acceptance [10], [16], [17]. Few empirical studies have examined the information design process for DEMS; however, such research is crucial for improving their acceptance and effectiveness.

The objective of this study was to address this research gap. To achieve this, a case study was conducted focusing on the concept design for energy efficiency within a new DEMS using electricity consumption data as the primary input. Specifically, this study utilizes data collected by the Korea Electric Power Corporation (KEPCO) from the National Industrial Complex in Gumi City, South Korea, to design a new DEMS. The data were used to categorize groups with similar electricity consumption patterns and develop representative electricity consumption prediction models for each group. These prediction models have the potential to enhance the targeting and customization of demand response and energy efficiency programs, improve energy reduction recommendations [18], and increase prediction accuracy and computing speed [19]. Various types of information on DEMS were derived based on these groups and prediction models. Additionally, a new DEMS was proposed to improve the energy efficiency of each group within an industrial complex.

The rest of the paper is organized as follows: Section II reviews related studies that form the foundation for the case study discussed in Section III. Section IV presents the findings of the case study, including the applicability of the designed information and service concept and the associated challenges. Finally, Section V. outlines the conclusions and limitations of the study and suggests directions for future research.

II. RELATED WORKS

A. DATA-DRIVEN ENERGY MANAGEMENT SERVICES

Most studies on DEMSs have been conducted under the term "energy management systems." Therefore, this study comprehensively reviews various studies that include both services and systems. Many studies have emphasized the importance of utilizing big data for effective and efficient energy management (e.g., [5], [20]). For example, a smart grid-enabled energy management system can significantly minimize energy consumption by monitoring energy usage and intelligently controlling all energy-consuming equipment [21]. By obtaining real-time energy measurement information, companies can make informed investment decisions, promote investments in energy-efficient technologies, and achieve positive environmental outcomes and financial savings [3], [22]. Building on advanced metering infrastructure, data have become a crucial component of energy management systems [5]. Big data analysis plays a critical role in all aspects of smart grid management, including generation, transmission, distribution, substation operations, and demand-side management [23]. By leveraging advanced tools and technologies for data collection, processing, analysis, and visualization, industries can uncover new trends and patterns. These insights allow businesses to optimize existing processes, enhance productivity and operational efficiency, and reveal hidden value.

In addition, several previous studies proposed data-driven architectures and platforms for effective energy management systems and services. Wei et al. [24] introduced an IoT-based communication architecture that utilizes a common information model to advance the development of demand response energy management systems for industrial customers. Marinakis et al. [10] proposed a service platform designed to streamline the collection of information from various sources, providing actionable recommendations and valuable operational insights for city authorities, local governments, energy managers and consultants, energy service companies, utilities, and energy suppliers. Al Faruque and Vatanparvar [11] presented a fog-computing platform that enables users to implement energy management through customized control services while minimizing implementation costs and reducing time to market. Bayindir et al. [12] designed hardware and software architectures for an energy management system capable of real-time data monitoring, which was subsequently installed at a university in Turkey. Gan et al. [25] designed and developed an interactive system based on point-energy technology for industrial energy monitoring. They created a web-based dashboard to provide energy usage information and implemented it in a local bakery.

While these studies focused on developing DEMS architectures or platforms that integrate hardware, software, data collection, and storage, there is a notable gap in research regarding the service design process, which is crucial for creating value for DEMS. Specifically, there is a lack of research on how to design and deliver information derived from data, which poses challenges in realizing the full value of DEMS. Therefore, this study aims to address this gap by designing a novel DEMS based on an analysis of the data and information derived from it.

B. PREDICTION MODEL FOR ELECTRICITY CONSUMPTION

Accurate electricity consumption prediction is crucial for effective energy management and is a key success factor for DEMS [19], [26]. Such prediction models enable precise forecasting of energy demand and supply for companies, making them highly effective for streamlining management processes [27]. This study employed machine learning models to develop prediction models that could be useful for designing a novel DEMS for companies aiming to enhance their energy efficiency.

Based on the development of a prediction model, Taylor [28] emphasized that in short-term electricity consumption predictions, future power consumption can be accurately estimated using only historical data. Factors such as temperature, economic conditions, and land use tend to remain relatively stable over short periods [29]. Hu et al. [30] highlighted that short-term prediction models enable optimal decision-making and ensure that the power grid operates safely, reliably, and economically. To develop a short-term prediction model for energy consumption, Long Short-Term Memory (LSTM) networks [31] are highly recommended, as they have consistently been effective in various time-series prediction tasks compared to other models [26], [32], [33]. LSTM is widely used for tasks involving sequential data owing to its effectiveness in capturing temporal dependencies. An LSTM unit consists of integrated input, output, and forget gates that manage information flow. Each LSTM unit also includes a cell state (c_t) that functions as a memory component, thereby enabling the network to retain and update information over time. The memory cell comprises four main components: an input gate, a self-recurrent connection neuron, a forget gate, and an output gate.

At each time step, an LSTM unit receives the current state (x_t) and the hidden state from the previous time step (h_{t-1}) through three gates. Each gate receives internal information input and the state of the memory cell (c_{t-1}). These gates process the input information from each source (e.g., h_{t-1}, c_{t-1}) and the logical function of the gate determines their activation. When the input information is processed by the nonlinear function of the input gate, the state of the memory cell associated with the forget gate overlaps to form the new memory cell state c_t. Finally, the memory cell state c_t forms the output h_t of the LSTM unit, based on the nonlinear function and the dynamic control of the output gate. The aforementioned variables interact according to the following model:

$$\begin{cases} f_t = \sigma_g(W_f x_t + U_f h_{t-1} + b_f) \\ i_t = \sigma_g(W_i x_t + U_i h_{t-1} + b_i) \\ o_t = \sigma_g(W_o x_t + U_o h_{t-1} + b_o) \\ c_t = f_t \cdot c_{t-1} + i_t \cdot \sigma_c(\partial_g(W_c x_t + U_c h_{t-1} + b_c) \\ h_t = o_t \cdot \sigma_c(c_t) \end{cases} \tag{1}$$

Guo et al. [32] conducted a comparative analysis of three commonly used machine learning models for short-term electricity consumption prediction: LSTM, support vector machine (SVM), and random forest (RF). Their results revealed that LSTM exhibited superior prediction accuracy, slightly outperforming RF, and significantly surpassing SVM. Kong et al. [33] introduced an LSTM-based electricity consumption prediction framework, demonstrating that it significantly exceeds established benchmarks in the field and provides excellent accuracy. Bouktif et al. [26] developed a prediction model for short- to medium-term aggregated electricity consumption using LSTM-based neural networks with various machine learning configurations. They utilized electricity consumption data from a major French city and demonstrated that the LSTM-based model achieved higher accuracy compared with other machine learning models. Therefore, this study chose to use the LSTM model for the prediction model development because of its proven effectiveness in various tasks, including electricity consumption prediction.

Additionally, understanding customers' daily energy consumption and the stability of their usage patterns over time is crucial for offering valuable insights into their consumption habits [18]. Similarly, incorporating customer lifestyle information could enhance the targeting and customization of demand response and energy efficiency programs and improve energy reduction recommendations [19]. Such clustering enables companies to provide valuable and customized insights to customers and deliver reliable and readily accessible information for managing energy efficiency. Therefore, we developed prediction models for each cluster of companies with similar electricity consumption patterns (e.g., if there were three clusters of all companies, three prediction models were developed). Each prediction model is used to develop a customized DEMS because each model reflects the specific patterns of its respective cluster.

C. SERVICE DESIGN FOR SMART SERVICE AND INFORMATION-INTENSIVE SERVICE

Extracting meaningful insights from energy big data is crucial for generating valuable and innovative ideas [23]. True value is realized only when customers actively use the information they receive for specific purposes [17]. The creation of information from data is directly related to the value and attractiveness of a service system [15]. Smart and information-intensive services should focus on creating information using data that help people achieve their goals and collect the data necessary to generate such useful information [13], [34]. Therefore, understanding customer needs is critical for designing new services [35]. By leveraging customer behavior data, useful insights about customers can be obtained for service design, as these data help understand customer preferences and create relevant information content [16]. This study used electricity consumption data to develop insights and create an effective DEMS tailored to energy management requirements.

Kim and Trimi [13] proposed a methodology for transforming data into actionable information to support smart services. Specifically, they introduced a morphological matrix for designing information and employed the 4W1H framework (i.e., why, what, when, and how) to describe the specific context of service usage. This study adopted this matrix to develop a new DEMS from an information design perspective. In addition, gamification enhances user engagement with services. Gamification elements such as points, leaderboards, achievements, feedback, clear goals, and narratives [36] can be integrated into service design. Hamari and Koivisto [37] found that the perceived usefulness of gamified services significantly influenced attitudes toward them, with factors such as ease of use, enjoyment, and overall attitude positively affecting continued use. Therefore, services that are both useful and engaging can be created by combining practical functions with enjoyable elements. Given the proven benefits of gamification in various services, this study hypothesizes that gamification could be a valuable tool for enhancing engagement and delivering useful information for the development of a new DEMS.

III. CASE STUDY ON THE NATIONAL INDUSTRIAL COMPLEX IN SOUTH KOREA

The Gumi National Industrial Complex has served as a key hub for machinery and electronics manufacturing companies in South Korea for more than 50 years. As a prime example of an aging industrial complex, it currently faces significant challenges related to energy inefficiency and escalating costs. According to Kim et al. [38], companies within the Gumi National Industrial Complex have shown a strong interest in effective energy management over the replacement of old machines. They recognized that implementing a new service or system was more cost-effective than upgrading outdated equipment. Consequently, many companies in this complex are actively collecting energy-related data and developing DEMSs that leverage data analysis. Based on the analysis of energy-related data, companies can identify electricity consumption patterns and develop prediction models for electricity consumption, which can help derive valuable insights for developing DEMS. However, the results from the patterns and models alone are insufficient to enhance the real value of the DEMS. It is crucial to carefully consider what type of information needs to be generated and how to effectively deliver it to customers to ensure that the data lead to practical and beneficial outcomes. Despite this potential, there is a noticeable lack of research on transforming electricity consumption predictions and clustering results into valuable information for DEMS.

Therefore, a case study was conducted, and a new DEMS was designed using electricity consumption data from companies in the Gumi National Industrial Complex. The design process involved five steps (Fig. 1): (1) data collection and preparation; (2) clustering based on electricity consumption patterns; (3) development of prediction models for each cluster; (4) design of information for the DEMS; and (5) definition of the DEMS concept. Sections III-A– III-E describe how the authors implemented the aforementioned steps in the design of a new DEMS.

A. STEP 1: DATA-DRIVEN ENERGY MANAGEMENT SERVICES

Step 1 describes the preparation of data from the Gumi National Industrial Complex, which includes detecting outliers and transforming the data into a format suitable for clustering and prediction model development in Steps 2 and 3.

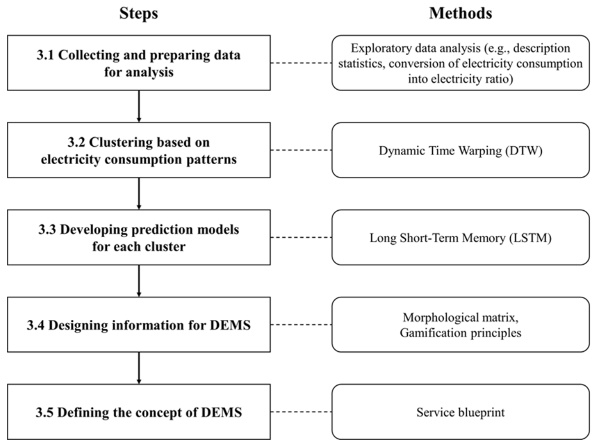
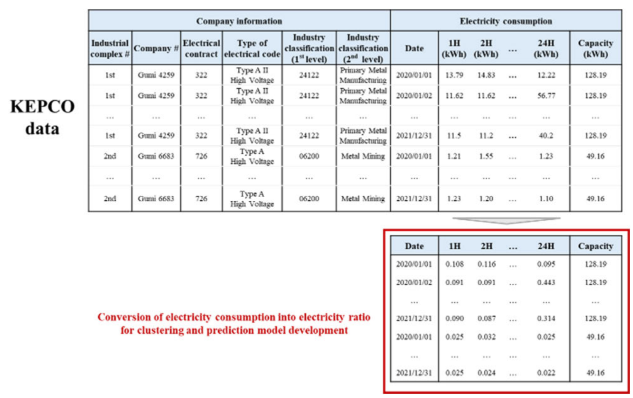


FIGURE 1. Research framework.

KEPCO collected hourly electricity consumption data from 1,143 companies in the Gumi National Industrial Complex over two years from January 1, 2020, to December 31, 2021. The data encompass a range of facilities, from small to large-scale operations, and include industry classifications such as metal manufacturing, food processing, and electrical equipment manufacturing. The KEPCO data for each company can be divided into two parts: company information and electricity consumption (upper side of Fig. 2). Company information includes details such as the company's location (i.e., industrial complex number), type and code of the electrical contract, and industry classification (e.g., metal and food processing). Electricity consumption information was collected daily and hourly for each company, with measurements recorded in kilowatt-hours (kWh).



KEPCO data

Company information						Electricity consumption					
Industrial complex #	Company #	Electrical contract	Type of electrical code	Industry classification (1st level)	Industry classification (2nd level)	Date	1H (kWh)	2H (kWh)	…	24H (kWh)	Capacity (kWh)
1st	Gumi 4259	322	Type A II High Voltage	24122	Primary Metal Manufacturing	2020/01/01	13.79	14.83	…	12.22	128.19
1st	Gumi 4259	322	Type A II High Voltage	24122	Primary Metal Manufacturing	2020/01/02	11.62	11.62	…	56.77	128.19
…	…	…	…	…	…	…	…	…	…	…	…
1st	Gumi 4259	322	Type A II High Voltage	24122	Primary Metal Manufacturing	2021/12/31	11.5	11.2	…	40.2	128.19
2nd	Gumi 6683	726	Type A High Voltage	06200	Metal Mining	2020/01/01	1.21	1.55	…	1.23	49.16
…	…	…	…	…	…	…	…	…	…	…	…
2nd	Gumi 6683	726	Type A High Voltage	06200	Metal Mining	2021/12/31	1.23	1.20	…	1.10	49.16

Conversion of electricity consumption into electricity ratio for clustering and prediction model development

Date	1H	2H	…	24H	Capacity
2020/01/01	0.108	0.116	…	0.095	128.19
2020/01/02	0.091	0.091	…	0.443	128.19
…	…	…	…	…	…
2021/12/31	0.090	0.087	…	0.314	128.19
2020/01/01	0.025	0.032	…	0.025	49.16
…	…	…	…	…	…
2021/12/31	0.025	0.024	…	0.022	49.16

FIGURE 2. Overview of collected data: Company information and electricity consumption.

The KEPCO data are categorized into various industrial sectors, each with distinct electricity consumption patterns owing to differences in production processes, equipment, technology, and energy requirements. Given these variations and the large volume of data, developing a prediction model for an entire industrial complex may be less practical. Instead, the focus was on specific industry classifications with more homogeneous energy consumption patterns. For this study, the sectors ''electronics components/computers/video/audio'' and ''communication equipment manufacturing'' were selected, as they represent 33.0% of all companies in the Gumi National Industrial Complex. In addition, this study considered the size of the companies because electricity consumption varies with company size. The company sizes within the complex were distributed as follows: 3.4% large, 25.1% medium, and 71.5% small enterprises. This distribution indicates that small enterprises constitute the majority of the complex. Consequently, the primary focus of this study was directed toward small enterprises. To identify small enterprises, the companies were filtered based on their electricity consumption values. Specifically, the maximum daily electricity consumption (i.e., capacity) was calculated for each company, and those with lower consumption were classified as small enterprises. This resulted in an analysis focusing on 335 small enterprises.

Once the target companies were selected, outliers in the electricity data were removed using the interquartile range (IQR), which is defined as the interval between the lower quartile (Q1; 25th percentile) and upper quartile (Q3; 75th percentile). First, the maximum electricity consumption values for each hour from 0:00 to 23:59 daily were identified for each company (e.g., Gumi 4259). The IQR of these maximum electricity values was then calculated, and any values exceeding Q3+1.5*IQR or falling below Q1-1.5*IQR were removed as outliers. After removing outliers, all electricity consumption data were converted into ratios relative to the capacity of each company for clustering and prediction model development. This conversion is important because the ratio values are generally more indicative than the absolute numerical values when forecasting future data. Although the numerical values reflect the absolute electricity consumption, the ratios provide a perspective on consumption levels in relation to capacity. This conversion is particularly beneficial for energy management because it facilitates immediate identification and response to high energy consumption levels. The formula for converting the electricity consumption data of each company into ratios is as follows:

$$Electricity\ ratio_{ij} = Electricity_{ij}/Capacity_j \tag{2}$$

Here, $Electricity_{ij}$ represents the electricity consumption of company j at time i, and $Capacity_j$ denotes the capacity of company j (i.e., the maximum value of electricity consumption for company j). An example of data conversion is shown in the lower part of Fig. 2

B. STEP 2: CLUSTERING BASED ON ELECTRICITY CONSUMPTION PATTERNS

Step 2 focuses on clustering companies with similar electricity consumption patterns owing to the variability in patterns among different companies. As discussed previously, the clustering results provide valuable insights into consumption patterns, which can significantly improve the targeting and customization of demand response and energy efficiency programs. It also helps to refine energy-saving recommendations [18] and may enhance both prediction accuracy and computational speed [19].

To analyze companies with similar electricity consumption patterns, we aggregated two years of data and calculated the daily averages. This approach allowed us to define the representative consumption patterns for each company and classify them using time-series clustering. For this purpose, we employed the Dynamic Time Warping (DTW) algorithm [39]. DTW is a nonlinear pattern-matching algorithm that allows pattern recognition without the need for preprocessing steps, such as data conversion or compression. Notably, it can identify similar shapes, even when there are transformations in the signal, distinguishing it from other algorithms. In short, DTW is particularly effective in recognizing similar patterns despite significant variations in time-series data, making it a valuable method for clustering electricity consumption data [8]. The calculation method for DTW is as follows: The task of pattern detection involves searching for instances of a template T in a time series S. $S = \{s_{1,}, s_2, \ldots, s_i, \ldots, s_n\}, T = \{t_{1,}, t_2, \ldots, t_j, \ldots, t_m\}$. A warping path W maps or aligns the elements of S and T to minimize the distance between them. $W = \{w_{1,}, w_2, \ldots, w_k$ is a sequence of grid points, with each w_k corresponding to the point $(i, j)_k$ (where s_i is aligned with a specific t_j). To formulate the dynamic programming problem, it is necessary to measure the distance between the two elements (3). The DTW problem is defined as finding the optimal warping paths that minimize the cumulative distance of each path, based on the distance measurements between the elements of the two time series (4).

$$\delta(i, j) = |s_i - t_j| \tag{3}$$

$$DTW(i, j) = min_w[\sum_{k=1}^{p} \delta(w_k)] \tag{4}$$

The elbow method was used to determine the optimal number of clusters, which resulted in the segmentation of companies into three different clusters (left side of Fig. 3). The lines on the right side of Fig. 3 represent the electricity consumption patterns of each cluster.

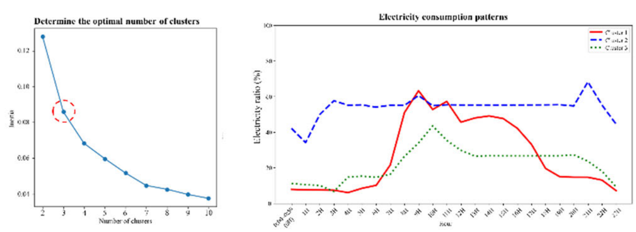


FIGURE 3. Results of DTW clustering.

The characteristics of each cluster are as follows: The first group, comprising 87 companies, exhibits electricity consumption patterns characterized by a sharp increase from 7:00 to 10:00 in the morning. Following this peak, consumption remained relatively stable, with only a slight variation from

10:00 to 15:00. After 15:00, consumption decreased sharply. This pattern suggests that these companies experience peak energy use early in the day and see a significant drop in the evening, likely reflecting operational hours that are heavily concentrated in the morning, with reduced activity later in the day. The second group, consisting of 80 companies, showed a pattern in which electricity consumption increased significantly from 1:00 to 4:00 early in the morning. Consumption remained relatively stable from 4:00 to 21:00. After 21:00, there was a notable increase in consumption, followed by a gradual decrease from 22:00 to 2:00 the next day. This pattern may indicate that these companies have high energy needs throughout the day, except during late night or early morning hours. Specifically, it can be observed that companies in this cluster undertake additional short-term work during the night, typically between 21:00 and 22:00. This could be due to large or urgent orders from partners or customers requiring rapid processing. The third group, comprising 168 companies, exhibited a notable gradual increase in electricity consumption from 4:00 to 11:00. There was a slight decrease in consumption between 11:00 and 14:00. Similar to the second group, the consumption remained steady from 14:00 to 21:00, after which it gradually decreased until midnight. This pattern suggests consistent and predictable energy use throughout the day, with a gradual increase in the morning and a decrease at night, likely corresponding to a traditional business schedule with stable daytime operations. Understanding these patterns can be beneficial for optimizing energy use and planning peak demand periods. Each group's pattern reflects different operational schedules and energy requirements, providing insights into how businesses can better manage their energy consumption.

C. STEP 3: DEVELOPING PREDICTION MODELS FOR EACH CLUSTER

Step 3 focuses on developing predictive models tailored for each cluster, enabling the provision of a customized DEMS that addresses the specific electricity consumption patterns identified in each cluster. To develop prediction models, data adjustments are necessary because there are multiple data points for electricity consumption on the same date and time, given that multiple companies belong to the same cluster. For example, on January 1, 2020, at 1:00, there were 87 data points in the first cluster, comprising 87 companies. As companies within the same cluster exhibited similar patterns, the data from these companies were aggregated into a single value to develop the prediction model.

To develop prediction models with time-series characteristics, this study employed LSTM networks, as described in Section II-B. Using LSTM, the prediction models for each cluster were trained for 200 epochs. During hyperparameter selection, we conducted experiments with time steps of 4, 8, 12, 16, 20, 24, and 48 hours, and varied the number of neurons, testing configurations with 25, 50, 100, and 200 neurons. The optimal selected hyperparameters were as follows: activation function, ReLU; number of neurons, 50; optimizer, Adam; loss function, mean absolute error (MAE); time step, 24 hours; and batch size, 32. All experiments were conducted using the Google Colab service.

For performance evaluation, the models were tested using data from individual companies, not aggregated by cluster, to ensure that each model was evaluated based on the specific data for which it was designed. The performance evaluation method used the MAE, defined as follows:

$$MAE = \frac{1}{\mathrm{n}} \sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{5}$$

where n is the total number of observations, y_i is the actual value, and $\hat{y}_i$ is the predicted value of observation i. The performance evaluation results revealed that the average MAE values for the prediction models were 0.068, 0.054, and 0.050 for the first, second, and third groups, respectively. Additionally, understanding customers' daily energy consumption and the stability of their usage patterns over time is crucial for offering valuable insights into their consumption habits [18]. Similarly, incorporating customer lifestyle information could enhance the targeting and customization of demand response and energy efficiency programs and improve energy reduction recommendations [19]. Such clustering enables companies to provide valuable and customized insights to customers and deliver reliable and readily accessible information for managing energy efficiency. Therefore, we developed prediction models for each cluster of companies with similar electricity consumption patterns (e.g., if there were three clusters of all companies, three prediction models were developed). Each prediction model is used to develop a customized DEMS because each model reflects the specific patterns of its respective cluster.

D. STEP 4: DESIGNING INFORMATION FOR DEMS

Step 4 aims to generate different types of information for the companies within each cluster to promote energy efficiency. This process requires an understanding of the distinction between data and information. Data serve as raw materials for information design, whereas information is the result of data analyses used for specific purposes [17]. Such information can take several forms, including descriptive statistics on customer behavior, comparisons of purchasing patterns among different customer groups, predictions of future process statuses, and recommendations for process improvements [13]. Previous studies on information on smart services and information-intensive services (e.g., [40]) have emphasized that the purpose of information should align with the objectives of service providers. This alignment is crucial, as it determines why and how information should be delivered to the target customers of the DEMS. The purpose of this information is to guide design and presentation, ensuring that it supports energy management goals and provides actionable insights. Based on insights from these studies, this study defines the following purposes for a new DEMS: monitoring and tracking, diagnostics, command and control, and training and education.

Monitoring and tracking are essential to continuously provide descriptive information on electricity consumption patterns. This information can be presented visually; however, auditory signals must be considered in emergencies. Diagnostics encompasses tasks ranging from reporting the system status to predicting short-term energy consumption. Thus, it includes both predictive and descriptive information. Most diagnostic information can be delivered continuously at regular intervals; however, on-demand reports and long-term forecasts can also be periodically provided. Generally, a visual presentation is sufficient for diagnostics with unnecessary auditory signals. Control and command are the most extensive and crucial components of a DEMS aimed at optimizing electrical consumption efficiency. This requires on-demand and continuous information, including descriptive and predictive data. Owing to their broad scope, information delivery methods can be either visual or auditory depending on the specific task. Training and education, although not required by all clients, are vital. It provides an in-depth understanding of DEMS, insights into energy usage in the customer's factory, and comparative reports with other customers, thereby enhancing the overall DEMS effectiveness. As training and education do not involve continuous processes, valuable descriptive and predictive information should be provided visually, either on demand or periodically.

This study assumes that the target customers for the DEMS are the employees in charge of energy management within each company and that the information will be delivered via a web-based platform. Based on these assumptions, various types of information were designed to address the four purposes of the DEMS. Fig. 4 illustrates some examples and descriptions of the design information for the DEMS. Fig. 4a shows the information designed to achieve monitoring and tracking, diagnostics, and command and control. It manages historical records of the electricity consumption ratio, provides hourly predictions, and visually presents all data. As it reflects the electricity consumption ratio relative to each company's maximum daily electricity consumption rather than just the absolute consumption value, it is particularly valuable for identifying potentially dangerous or high consumption levels. Although this information is provided to all enterprises, it is especially important for Cluster 1. Given that Cluster 1 companies experienced peak energy use early in the day and saw a significant drop at night, it is crucial for them to quickly and effectively understand the sudden changes in energy usage. This information can be useful for efficiently managing energy consumption and promptly addressing potential issues.

Fig. 4b presents the comparative results of the electricity ratio across three different criteria for each consumption period, as defined by KEPCO: off-peak, mid-peak, and on-peak periods. The graph compares the average values and the top 10% average values of companies within the same cluster (i.e., the results from Step 2), enabling the company to make easy and effective comparisons. Fig. 4c shows a ranking system that visualizes the energy-saving rate compared with the previous day, to encourage energy-saving behavior. Figs. 4b and 4c represent the statistical indicators designed to assist with the comparison and analysis by providing metrics relative to other companies. This content can be used for various purposes, including monitoring and tracking, diagnostics, commands, and controls. Additionally, the ability to compare these metrics with those of other companies enhances their value for training and educational purposes. In the context of our case study, we consider information that is particularly valuable to Cluster 3. This group included a large number of companies, allowing for a more comprehensive analysis and comparison. By providing detailed metrics, the companies in these groups can better understand their electricity consumption patterns and identify opportunities for improvement. Finally, Fig. 4d shows the information that applies gamification techniques, such as points, rankings, daily tasks, missions, and training, to encourage customer engagement and behavioral change. The points earned through these activities can be used to access the advanced features of the service. This information is valuable for command and control, training, and educational purposes.

E. STEP 5: DEFINING THE CONCEPT OF DEMS

Step 5 involves defining a service concept that outlines what to offer to customers and how to do so [41]. This step defines the primary components of information delivery—namely, when, where, and how to present the information—to electricity managers within each company. "When" represents the timing of the provision of information, indicating whether machines are operational or nonoperational. Managers responsible for electricity efficiency in each company should log into a web system for the DEMS and review electricity consumption from the previous day to check for anomalies in machines during non-operational hours. When machines are operational, the energy usage should be monitored in real-time using the information shown in Fig. 4a. Additionally, by comparing the energy consumption of the company with the patterns of other companies within the same cluster, as shown in Figs. 4b and 4c, the efficiency of the company's energy usage can be assessed. If necessary, managers can conduct interviews with employees who do not manage energy consumption and check the status of machines that show signs of anomalies. Finally, they check the educational schedule for training opportunities related to energy management provided by the government or other organizations, as illustrated in Fig. 4d. "Where" indicates the delivery channels of the information, such as machines and human sources. Examples include web systems that use smart devices as machine channels and managers as human channels. "How" indicates the delivery types of the information, such as push and pull. In the push type, a request for information is initiated by service providers. This type of information is used for critical updates that must be confirmed and addressed promptly. The pull type means that the initial request for information originates from managers.

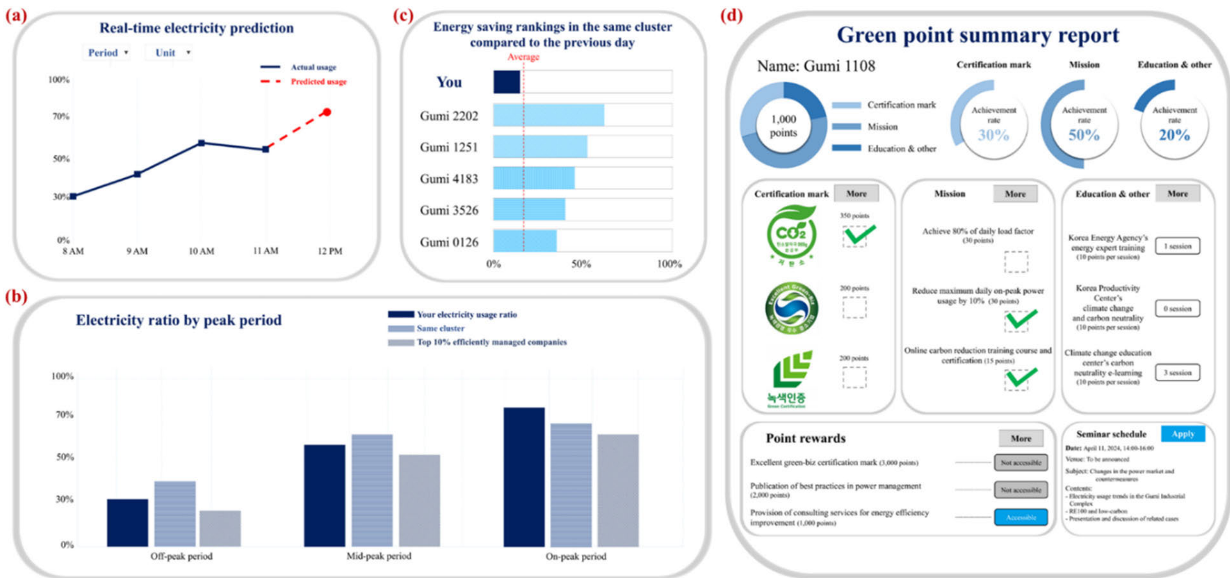


FIGURE 4. Examples of the designed information for a DEMS.

To define the service concept, we conducted a brainstorming session to design a DEMS concept based on the identified target customers (Steps 2 and 3), the designed information (Step 4), and the information delivery process (Step 5). Fig. 5 provides a detailed description of the DEMS concept.

IV. DISCUSSION

A. APPLICABILITY OF THE PROPOSED DEMS CONCEPT DATA-DRIVEN ENERGY MANAGEMENT SERVICES

To validate the effectiveness of the proposed service concept, an interview was conducted with the manager responsible for controlling electricity consumption at a small company located in the Gumi National Industrial Complex. The company specializes in the development and manufacture of plastic films, including window, PPF, electronic, electrical, and optical films. The objective of this interview was to evaluate whether the designed DEMS concept was effective for small enterprises within the Gumi National Industrial Complex. The interview questions were categorized into three types: (1) overall evaluation of the DEMS concept; (2) feedback and suggestions for improving the DEMS concept; and (3) willingness to use the DEMS concept. Before conducting the interview, we explained its objective and the proposed DEMS concept using Figs. 4 and 5 as references.

The key findings of the interviews related to the overall evaluation of the DEMS concept were as follows: One interviewee noted that the DEMS concept stands out because it provides data-driven information that helps employees focus on energy efficiency. In addition, the interviewee highlighted that when high electricity costs occur, the concept is beneficial, as it enables the identification and inference of causes through various types of data-driven information. From the perspective of data-driven information design, the interviewee highlighted the value of predictive model-based information (e.g., Fig. 4a), noting that receiving predictions before issues arise is particularly beneficial. This is especially important for small and medium-sized enterprises, where responding to problems can be challenging. Predictive information can assist proactive management. However, the interviewee suggested that in addition to showing the electricity ratio, it would be more helpful to include cost-related information. This is because electricity costs are often one of the largest expenditures for small enterprises. Finally, the interviewees found comparative information with other companies in the same cluster (Figs. 4b and 4c) to be valuable because this information could drive improvement efforts and encourage greater participation from companies by highlighting areas in which they could optimize their electricity consumption.

The main findings from the interviews in terms of feedback and suggestions for improving the DEMS concept are as follows. If the DEMS concept could provide information that includes the economic value of electricity savings, it would meet the critical needs of small enterprises within the Gumi industrial complex. As previously mentioned, the cost of electricity is a significant concern for small enterprises. In addition, the interviewees emphasized the need to provide additional information beyond electricity consumption patterns. Specifically, the interviewee suggested including guidelines on what actions to take and details on potential rewards for following the recommended actions. This would help employees understand not only the patterns of energy use but also the steps they should take and the benefits of following those steps. There was also feedback regarding rewards, indicating that it would be difficult to engage small enterprises if the rewards were not substantial. If the time taken to receive a reward is too long, there is a high likelihood that the reward will be forgotten in a noncompulsory

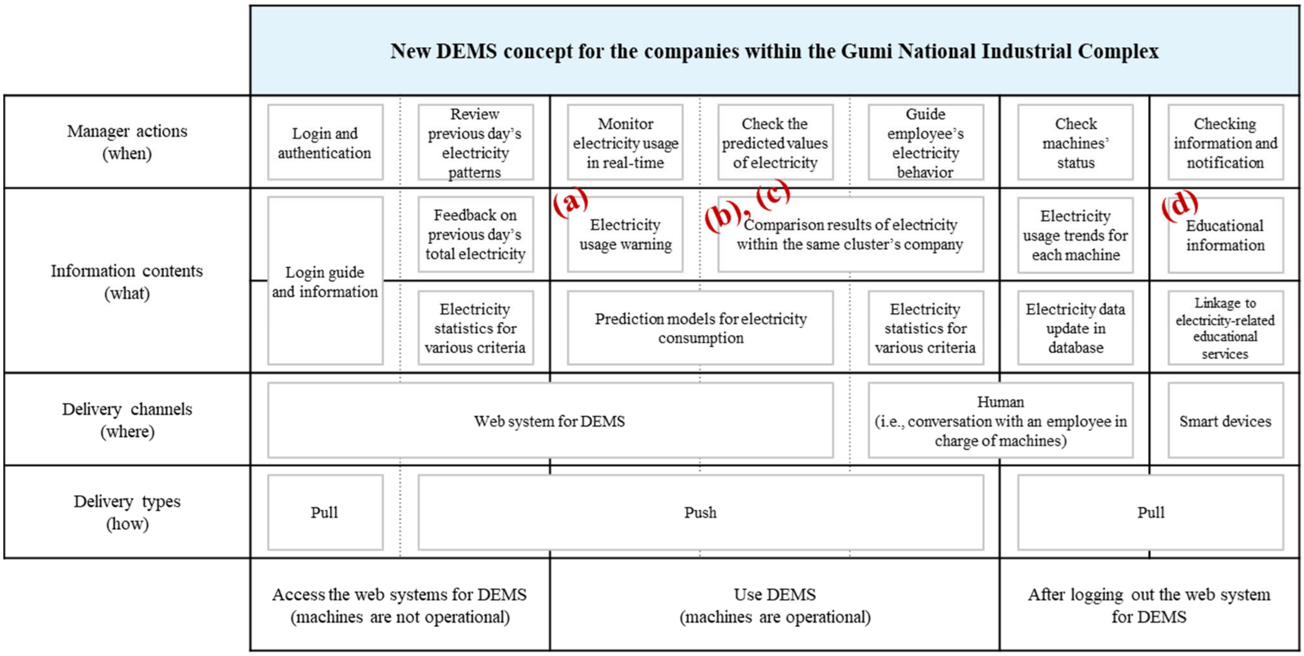


FIGURE 5. Description of a novel DEMS concept.

situation, making it difficult to maintain engagement. The current DEMS provides information through a web-based platform, but it should be extended so that service information can also be accessed via mobile devices. This was mentioned as a way of making it easier to check and manage information. The interviewees realized that extending the service to mobile devices would be effective in managing and responding to electricity-related emergencies and unexpected situations. Therefore, they believe that extending the service to mobile devices is necessary.

Finally, the results of the interview regarding the willingness to use the DEMS concept were as follows: Interviewees believed that the value of the DEMS concept was achieved by providing different types of information and enabling the management of electricity consumption during periods of relatively high electricity costs. This is expected to help achieve the goal of saving electricity costs and avoiding unnecessary expenditure. The interviewees expressed a willingness to use the DEMS concept if the service was offered at a subscription price of $20 to $30 per month. The interviewee's statement, "It is sufficient to expect that this will encourage efforts to make improvements related to energy use," confirms the potential of the DEMS concept to achieve its goals, including reducing electricity costs and avoiding unnecessary expenditures for small enterprises.

B. CHALLENGES IN DESIGNING DEMS

The design of DEMSs using data presents several challenges. This section highlights the key challenges identified in this case study: (1) data quality, (2) data security and privacy, and (3) processing speed. The first two challenges relate to data requirements, whereas the third focuses on infrastructure requirements.

The first challenge is to gather high-quality data, which directly affects the accuracy of the clustering and prediction models, and consequently, the overall quality of the service. If data are riddled with errors, they become useless because poor sensor data quality can lead to incorrect decision-making outcomes [42]. Common errors in sensor data include missing values, uncertainty, and faults, such as outliers, bias, constant values, stuck-at-zeros, and noise [43]. In our case study, data preprocessing techniques such as IQR for outlier detection were used to identify missing data and outliers that could significantly affect the overall results. Given that the data were collected from hundreds of companies, it is essential to consider and discuss standardized data collection methods and reliable data preprocessing pipelines to ensure a more reliable and high-quality DEMS.

The second challenge is data security and privacy, as the collected data must not only be of high quality but also securely protected. Implementing robust security mechanisms is crucial for safeguarding the data and information shared among stakeholders [44]. In our case study, we assumed that data-driven information, which provides information about other companies, could be sensitive and, therefore, requires stringent security measures. To address this issue, the names of the companies were pseudonymized into a simple format of "city-random number of company" (Fig. 4c). Because all companies are located in the same city, this method ensures that no specific information about any company is disclosed. Additionally, certain company-specific information can be hidden by grouping the data into clusters (Fig. 4b). In addition to the aforementioned methods, numerous approaches can be employed to ensure the security and privacy of energy data, such as encryption [45], blockchain [46], and federated learning [47]. Incorporating these technologies to address data security issues could lead to a more reliable and secure service compared to the current DEMS concept.

The third challenge is processing speed, which is essential for optimizing real-time energy management and ensuring efficient information delivery within a DEMS. In our case study, we analyzed data from hundreds of companies. We anticipate that energy consumption patterns may evolve over time for individual companies, making it necessary to retrain the predictive models to maintain accuracy. This highlights the importance of solutions that enable fast and efficient computations. To address this issue, we employed a clustering approach that significantly improved both the computation speed and prediction accuracy [19]. In addition, we used aggregated data to develop the prediction models, further reducing the computation time. Other approaches suggested by researchers can also be utilized, such as federated learning [47] or combining OLAP with in-memory processing [48].

V. CONCLUSION

This study targeted small enterprises within the Gumi National Industrial Complex to deliver valuable information using a specially designed DEMS. By leveraging electricity consumption data provided by KEPCO, we employ time-series clustering to identify distinct groups with similar consumption patterns. Furthermore, we developed representative prediction models for each group using the LSTM method to ensure tailored and accurate energy management solutions for enterprises within the same group. We designed various types of information to enhance the energy efficiency of companies in the Gumi National Industrial Complex and defined the DEMS concept by integrating the results (i.e., clustering, prediction models, and information).

The proposed DEMS concept, with various types of information, aims to lay the foundation for establishing a DEMS within the Gumi National Industrial Complex. Because DEMS employs various methods such as time-series clustering, electricity consumption prediction (i.e., LSTM), and gamification concepts, it can significantly enhance energy efficiency by offering diverse solutions to enterprises. These solutions include comparing electricity consumption, segmenting customers (time-series clustering method), monitoring and predicting energy consumption (prediction model), and increasing user engagement (gamification approach). In addition, this study believes that by identifying the key purposes of information, a DEMS can deliver information that is genuinely valuable and practical for customers and real-world applications. Finally, an interview with a small business within the complex to evaluate the proposed DEMS suggests that the concept and service approach could be effective and beneficial for businesses in the Gumi National Industrial Complex.

The methodologies and insights gained in this study can be applied to the design and implementation of DEMSs in other contexts. The combination of time-series clustering, LSTM-based prediction models, and valuable information design offers a versatile framework that can be adapted to different industrial settings. This approach not only helps optimize energy usage but also enhances operational efficiency and sustainability across various sectors, providing a robust foundation for future energy management initiatives. The proposed framework is expected to be applicable to other industries where time series data can be collected, such as renewable energy, semiconductor, smart farm, supply chain management or even polymeric sciences.

Nevertheless, our study has several limitations that should be addressed in future research. First, the availability of supplementary data such as production volumes, schedules, and sales figures for companies could significantly enhance the accuracy of our prediction models. The proposed DEMS is suggested at the conceptual level, and long-term observation and review following the service implementation are necessary for conducting such economic analyses. It would also have allowed for a more nuanced clustering of companies by considering various aspects of their operations. This, in turn, enables the design of more customized and valuable information for customers. Such data would allow for a more detailed understanding of each company's system and enable the development of more tailored services. However, incorporating data beyond electricity consumption can be challenging and involves numerous complex processes. This necessitates the establishment of a reliable framework to integrate data from various sources. Secondly, real-time processing needs must be addressed. Online transaction-processing (OLTP) systems are essential for effective real-time processing. This system should include a data module for handling customer electricity consumption, a mechanism for managing customer profiles and ensuring information security, and a real-time pricing engine for calculating electricity charges based on usage [49]. Implementing a smart grid with an OLTP-based system equipped with these components ensures operational reliability and enhances the accuracy of demand prediction through real-time bidirectional information sharing. Additionally, this approach would allow the service provider to achieve significant reliability in power distribution while reducing maintenance costs and capital expenditures associated with conductors, insulators, and transformers. Lastly, the metrics for evaluating the effectiveness of our proposed DEMS are extremely important. In developing these metrics, it is critical to incorporate the opinions of the CEOs or employees who have implemented the service. Therefore, assuming future surveys or interviews with these stakeholders, it will be necessary to develop evaluation metrics for the proposed DEMS.

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