Understanding crowd energy consumption behaviors

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ABSTRACT

Understanding crowd behavior is crucial for energy demand-side management. In this paper, we employ the fluid dynamics concept *potential flow* to model the energy demand shift patterns of the crowd in both temporal and spatial dimensions. To facilitate the use of the proposed method, we implement a visual analysis platform that allows users to interactively explore and interpret the shift patterns. During the demonstration, we will invite conference attendees to evaluate the proposed method through a hands-on experience with a real case study.

1 INTRODUCTION

Due to the current energy crisis, effective urban energy management has become more urgent than ever. Improving energy efficiency and reducing carbon emissions is a global topic that has attracted widespread attention from governments or organizations around the world. Buildings are currently the main contributor to energy consumption, accounting for 40-60% of total energy consumption [2, 11]. Urban energy management to balance demand and supply is crucial for energy efficiency. Energy balance refers to a match between supply and demand at a specific time and location. It is related not only to the operational stability of the grid, but also to the efficient use of energy, such as avoiding energy waste due to overproduction. However, energy balancing is a challenging task because most controls take place only on the production side, while much less on the demand side. In demand-side management, the dynamics of energy demand reflects demography, mobility, and urban spatial characteristics. As such, it is closely related to a variety of factors, such as climate, crowd consumption behaviors, and living habits. For example, according to the study [5], consumer behavior can affect energy consumption by up to 4.2% in the Netherlands. To better maintain the balance between supply and demand, it is critical to explore crowd consumption behaviors. However, exploration of energy demand and crowd behavior remains in its infancy [12], which requires more research efforts. Therefore, this research aims to answer the following two questions: *How does crowd behavior affect urban energy demand, and how can the effects be visualized to aid energy dispatch decisions?*

We first model the dynamics of urban energy demand in spatial and temporal dimensions, and then present a visual analysis system for user interaction. In fluid mechanics, potential flow [3] has been used to model flow dynamics, e.g., for water waves, electro-osmotic flows, and groundwater flows. Changes in energy demand have a continuum characteristic similar to that of fluid dynamics. Inspired by this, we introduce the potential flow to model the spatiotemporal dynamics of the crowd energy demand. That is, the patterns of energy demand shifts are represented as potential flows and visualized on a geographic map. With the proposed system, utilities can provision energy supply and optimize energy distribution based on demand.

2 RELATED WORK

In recent years, energy data management, including energy data analysis and visualization, has attracted increasing interest in the database community. Among others, Cerquitelli et al. [4] propose a data visualization framework, INDICE, to explore building energy efficiency by querying analytic tasks and implement a dashboard that allows different stakeholders to discover and interpret knowledge at different spatial granularities. Acquavivay et al. [1] collect and analyze the thermal energy consumption of heating systems in residential and public buildings and create an analysis platform, EDEN, to present building energy performance indicators, with the aim of raising awareness of energy savings. Karatzoglidi et al. [7] propose an automated energy prediction system, Enfore, for residential buildings. The system supports automation of data preprocessing and prediction for univariate or multivariate time series data of energy consumption. In our previous research, we propose a smart meter data analysis system, SMAS [9], for energy demand management; and propose an interactive visual analysis system, VAP [10], which allows users to explore energy consumption patterns and segment customer groups according to the patterns. In addition, we benchmark smart meter data analysis technologies [8], including in-database, in-memory, column-store and distributed data analysis. We hope that these research efforts will increase awareness of this emerging application in energy data management within the database community and stimulate further research on this topic.

3 DEMAND DYNAMICS ANALYSIS SYSTEM

Figure 1 presents an overview of the proposed visual analysis system for exploring energy demand dynamics. The system consists of three main building blocks, including (i) data and data processing, (ii) energy demand dynamics modeling, and (iii) interactive

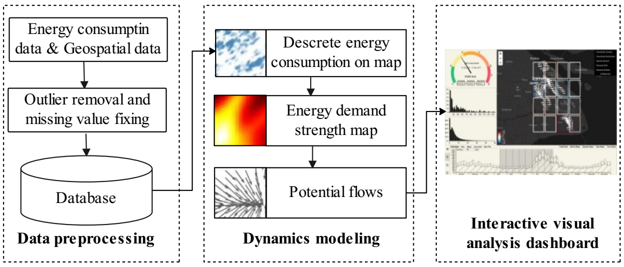

Figure 1: System overview

visual analysis dashboard. The system combines various techniques to effectively model energy demand shift patterns over spatiotemporal dimensions and visualizes the patterns in a user-friendly manner. Visual analysis is an interactive process that allows users to first make assumptions based on their own knowledge or judgment, then explore the results on the dashboard, and finally validate the assumptions and obtain new knowledge. The visual analysis system uses PostgreSQL as the underlying data management system, with an extension of PostGIS to support spatial data operations.

3.1 Data and preprocessing

The energy consumption data are electricity data collected from Pudong District, Shanghai, with a resolution of 12 hours and a duration of 2 years. Spatial information including the longitude and latitude of customers was also provided. The raw data contains noise, irregularities, and missing values. We first smooth the time series using window-based convolutional smoothing, which involves creating an approximation function to smooth the noisy data and fixing the missing values by interpolating over a curve that follows the trend of the consumption time series. Then, we use a weighted sampling method [6] to reduce bias in the data. This method adds weights to the original data points to measure their importance: The higher the weight, the more important they are in the data set. The weighted sampled data will be used in the kernel density estimation function in the next subsection to model the energy demand dynamics.

3.2 Energy demand dynamics modeling

We model the dynamics of crowd energy demand using potential flows, and show the schematic modeling process in Figure 2. According to potential flow theory [14], external flows around bodies are invicid (i.e., frictionless) and irrotational (i.e., the fluid particles are not rotating) because the viscous effects are limited to a thin layer next to the body called the boundary layer. A potential flow can be described by means of a velocity potential function, $\varphi(x, y, z, t)$, where x, y, z represents the dimensions in a 3-D spatial space at the time at t. The flow velocity is the gradient of the velocity potential, i.e., $\vec{V} = \nabla\varphi$. From vector calculus, for any scalar, φ, there is $\nabla\times\nabla\varphi = 0$. Consequently, there is $\nabla\times\vec{V} = 0$, which implies that a potential flow is an irrotational flow.

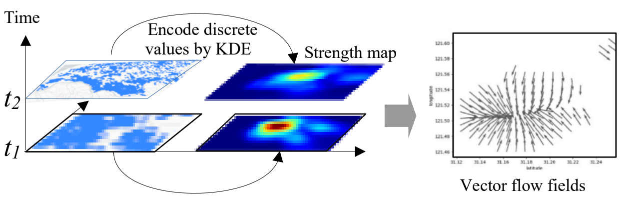

Figure 2: Schematic illustration of the modeling process

As we consider households that are spatially discrete and distributed on a 2D map (see Figure 2), the modeling process is based on the potential function, $\varphi(x, y, t)$. Here, we employ kernel density estimation (KDE) as a potential function to encode energy consumption into a continuous representation of strength map, defined as follows:

$$\hat{f}_t(\mathbf{x})\Big|_t = \frac{1}{n}\sum_{i=1}^{n} c_i K_h(\mathbf{x} - \mathbf{x}_i) = \frac{1}{nh}\sum_{i=1}^{n} c_i K\left(\frac{\mathbf{x} - \mathbf{x}_i}{h}\right) \quad (1)$$

where h is the bandwidth; $\mathbf{x}_i = (lon_i, lat_i)^T$, is the coordinate of a household i; K is the kernel function, which is a symmetric multivariate density; and c_i is a normalized value of average energy consumption used to reweight demand strength with respect to geographic distribution, which is defined as follows:

$$c_i = \lfloor \gamma E \rfloor \quad (2)$$

where E represents the energy consumption of x_i and γ is the filter coefficient defined by the users. We select the Gaussian kernel to estimate the demand strength because it can provide a reasonable estimate even for a small data set, which is defined as follows:

$$K_h(\mathbf{x} - \mathbf{x}_i) = e^{-\frac{\|\mathbf{x}-\mathbf{x}_i\|^2}{2h^2}} \quad (3)$$

With the kernel density matrix (strength map), the temporal dynamics of the energy demand over time from t_1 to t_2 can be obtained by Equation 4, which calculates the gradient of the strength difference in demand.

$$Shift|_{t_1,t_2} = \nabla(\hat{f}_{t_2} - \hat{f}_{t_1}) \quad (4)$$

The vector flow fields (arrows) in Figure 2 represent shifts in energy demand, where the arrow represents the direction of the shift and the length represents the strength of the demand; the longer the arrow, the greater the demand shift.

4 VISUAL ANALYSIS DASHBOARD

This section will first introduce the user interface, then describe the principles of visual analysis design, the used components and process, and finally give some examples of exploring spatio-temporal demand shift patterns.

4.1 User interface

Figure 3 shows the interface that allows users to interactively explore potential flows to understand spatiotemporal demand shift patterns. In the dashboard, view **A** is the control panel and the only entry point for users to interactively explore the dynamics of energy demand. Here, users can select any two discrete time periods, i.e., first click the buttons on **a1** and then select the time periods of interest through drag and drop on **a3**. The backend engine of the system will calculate the energy demand shifts for the selected time periods in real time based on the fluid dynamics model, and the results will be displayed as the potential flows in view **C**, which represents the energy-demand shift across different regions. To facilitate the use, we have predefined several commonly-used demand shift analyses, including daytime and nighttime, regular split periods, and the flexible multiple time periods, which can be selected or entered using the control components in **a2**. If the multiple time periods are selected, view **D** will display the minimized views of the shift patterns, also called the index view. For example, there are four index views shown in **D**, including 1) 2017-01-14 to 2017-05-14; 2) 2017-04-29 to 2017-05-29; 3) 2017-05-14 to 2017-06-13; and 4) 2017-05-29 to 2017- 06-28. When an index view is selected, it will be displayed in the main view **C**. The associated quantitative profile will be shown in view **B**, including total, daytime, nighttime

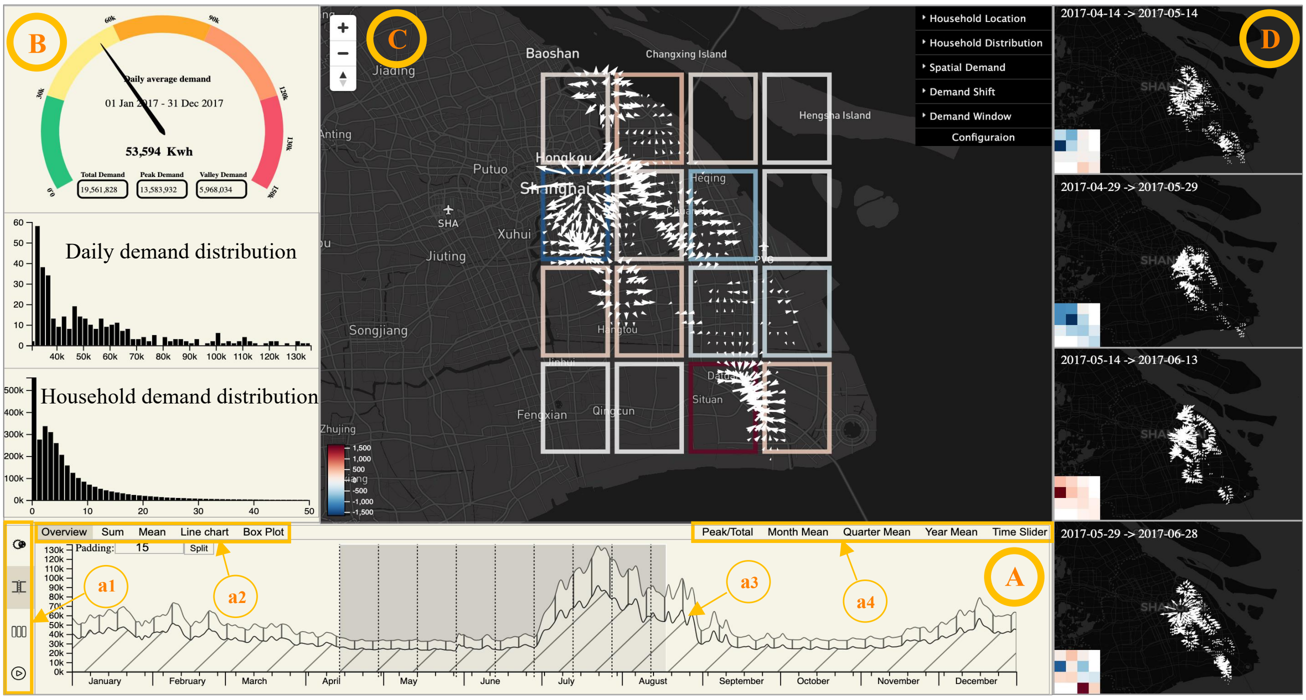

Figure 3: Interactive visual analysis dashboard

(a) Daytime → Nighttime (b) Q1/2017 → Q2/2017 (c) Q2/2017 → Q3/2017 (d) Q3/2017 → Q4/2017

Figure 4: An example of exploring spatiotemporal shift patterns of energy demand

energy demand, the statistical distribution of daily consumption and the consumption of households within the area.

4.2 Visual analysis and examples

As a visual analysis system, we introduce four visual elements to represent the demand shift:

- *Demand shift:* It is represented by a flow map where the length of the arrow encodes the strength of the demand shift;
- *Demand-shift window:* It gives the coverage of the analysis, and its border color encodes the spatial demand shift. The window-shape design will not obscure the map, but give the necessary quantitative information for the demand shift;
- *Demand-shift color legend:* It gives the corresponding absolute value for the spatial energy-demand shift in the grid area. Quantitative results for the demand shift can be calculated over spatial locations and time horizons;
- *Demand-shift badge:* It also encodes the spatial energy-demand shift φ, which has the same meaning as the demand-shift window but gives a summary of demand shift in the grid area in the index view. We use a solid grid, instead of a frame, because it is much smaller on the visual index and more prominent.

This visual analysis design follows the Schniederman Mantra: first the overview, zoom, and filter, then the details on demand [13]. With such a visual design, users can easily find the area of interest and explore more information through interactions. For example, the view **D** presents a thumbnail of the demand shift within different periods, which is represented by a small demand shift badge. If a user wants more detail, (s)he can simply click a thumbnail to show the demand shift in the main view **C**. The vector arrows visualize the energy flow directions, while the color of demand-shift windows represents an increase or a decrease of energy demand.

We now show four examples of typical energy demand shift patterns in Figure 4. Figure 4(a) represents the spatial patterns from daytime to nighttime during a workday. The heads of the potential arrows point to the red-colored area, which is the residential area in Pudong district, while the tails of the potential arrows are the commercial areas on both sides of the residential area. This indicates that the high energy demand area will shift from the commercial area to the residential area when people go home after work. Figure 4(b)-(d) are the energy demand shift patterns between any two continuous quarters in 2017, and Figure 5 shows the corresponding quantitative results of demand shift amount. It is worth noting that from Q2 to Q3 has the highest amount of demand shift, and the heads of the potential arrows are pointing to the red-colored area (see Figure 4(c)). This place is the location of Shanghai Disneyland where there are also many hotels nearby. During the summer holidays, there is often a huge tourist flow to this area, which may cause more energy consumption. The other two demand shift patterns on spatial space can

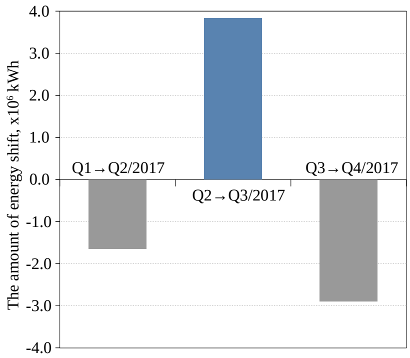

Figure 5: Demand shift amount between two quarters

be seen in Figures 4(b) and (d), and the difference in amount are both negative. The amount difference can be explained by the weather temperature. Typically, the weather in Shanghai is mild in Q2 and there is no need for heating or cooling, while winter is cold and some households use electricity for heating. Q3 is hot summer time when a significant amount of electricity is used for cooling. Therefore, Q3 is the season with the highest consumption, followed by Q1 and Q4, while Q2 is the least.

As a result, utilities can schedule their power production and plan supply for different time periods and areas based on demand shift patterns and amount differences.

5 DEMONSTRATION

During the demonstration, we will present the proposed visual analysis system in exploring crowd energy demand shift patterns using the real-world electricity data set from the Pudong district. We will first present the architecture of the entire system, including the design of the backend and frontend and the modeling approach to energy demand dynamics, and then show how to use the system, especially the visual analysis process involved, to ask questions, find answers through exploration, and gain knowledge. Finally, conference attendees will experience the system based on the following two scenarios:

S1: Exploration for district-wide demand shift patterns. In this scenario, a user can examine demand shift patterns throughout the Pudong district. This scenario will give the user hands-on experience of using the proposed visual analysis and will help the user interpret the result properly. The user will use the temporal energy demand controls in the dashboard (View **A** in Figure 3). The user first toggles the auxiliary analysis line (daily, yearly, quarterly, monthly average demand button) and selects the period of interest for analysis, then (s)he defines the exploration task in one of the following temporal types: daytime-nighttime period, regularly split period, or multiple periods. The user can toggle the corresponding button, select the period(s) of interest by brush operation, and then toggle the compute button to generate the results listed as the demand shift visual index in view **D**, finally select an index view to visualize the greater detailed demand shift pattern in view **C**. The exploratory analysis results will include the examples that were presented in Section 4.2. The user will be asked to interpret each result obtained, with the necessary assistance from us.

S2: Customized exploration for demand shift patterns and recommendation. This scenario allows the user to further explore the spatiotemporal demand shift patterns. Based on the experience from *S1*, the user can customize the analysis areas and time periods, i.e., select two or more areas on the map and two or more time periods. The user can select different areas with any shape simply by clicking and draging the mouse on the map, and then click the time split button and select different discrete time periods. The system will automatically select the corresponding households within the selected areas, supported by PostGIS geometry operations in PostgreSQL. The system will then compute the potential flow model result, and generate the index views as shown in view **D** and the statistical information in view **B**. The user will interpret the results and make the recommendation about energy distribution across different areas over time, for example, the amount of electricity to be dispatched and the dispatch time in order to achieve the supply and demand balance. The user can also provide information on the implications of the system, such as investments in energy infrastructure, energy policies, and changes in consumer behavior that lead to better energy efficiency.

6 CONCLUSION

Crowd consumption behaviors can have a significant impact on energy demand side management, e.g., balancing energy supply and demand. In this paper, we presented a novel visual analysis system for analyzing energy demand shift patterns from spatial and temporal dimensions. We have introduced the fluid dynamics concept, potential flows, to model the energy demand dynamics, and visualized it on a user-friendly dashboard. The proposed visual analysis system supports the exploration of energy demand shift patterns with different geographic areas and time periods. We presented two demo scenarios to help users gain hands-on experience using our system and gain insight into visual analysis on energy data.

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