MOBILE APPLICATION FOR ACTIVE CONSUMER PARTICIPATION IN BUILDING ENERGY SYSTEMS

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ABSTRACT

Scientific literature predicts a significant rise in energy demand over the next decades. Optimizing energy systems is a key step toward reducing energy-related greenhouse gas emissions. Recent studies show that active consumer participation and the integration of modern information and communications technologies are key techniques for successfully streamlining energy systems. The main objective in the GameOpSys research project is to develop a means to accurately predict the energy consumption of buildings based on patterns in smart meter data and user-generated input. To do so we propose a user-centered software system for communication between building occupants and energy system operators.

INTRODUCTION

Scientific literature predicts a significant rise in energy demand in the next decades (Abas et al., 2015; Allouhi et al., 2015, Clarke et al., 2009). Over the last decades, socioeconomic development has driven a demand for larger homes, a wide variety of energy-consuming entertainment services and a significant growth in commercial building stock. This has led the building sector to become the largest contributor to global energy demand and greenhouse gas emissions (Allouhi et al., 2015) accounting for 32% of the world's total energy consumption and for 19% of all energy-related greenhouse gas emissions (Lucon et al., 2014).

In the European Union (EU) buildings account for 40% of the total energy demand (European Commission, 2019). Energy consumption in residential buildings, with a share of 27% of the total demand in the EU, is the second largest contributor after transportation (Uihlein and Eder, 2009; Allouhi et al., 2015). Besides socioeconomic changes, inefficient energy systems, especially inefficient energy services are major contributors to the surge in energy consumption (van Vuuren et al., 2012). The EMF-22 study (Clarke et al., 2009) on long-time climate stabilization policies highlights energy efficiency improvement as a crucial means towards reducing greenhouse gas emissions.

It becomes apparent that research and development should improve efficiency in future energy systems and help include clean sources of energy, such as renewables. Building simulation provides the necessary framework to optimize energy efficiency within the constraints imposed by the volatile nature of renewable energy sources. It is a key research interest to accurately simulate and predict occupancy and energy demand patterns in buildings. Recent studies show that active consumer participation and the integration of modern information and communications technologies (ICTs) support the development of data-driven occupancy and demand models (Vazquez-Canteli et al., 2019; Verbong et al., 2013).

We propose a user-centered software system that facilitates bidirectional communication between building occupants and energy system operators. The system comprises data persistence, standardized interfaces for data retrieval (e.g. for data analysis services) and an intuitive user interface (UI), in the form of an Android application. The application connects occupants with the energy system and allows them to access usage statistics and visualizations.

User-Centered Data Analysis

The main objective in the GameOpSys (Gamification for optimizing the energy consumption of buildings and higher-level systems) research project is to develop a means to accurately predict the energy consumption of buildings based on patterns in smart meter data and user-generated input. Accurate forecasts provide the basis for numerous energy services such as flexibility identification, demand response, model predictive control or peer-to-peer trading. Broad availability of these services, social changes, such as increased awareness of climate change, and shifts in energy production stimulate active consumer involvement. It is an open research question as to find the level of user engagement, i.e. frequency, intensity and means of interaction to harness these societal developments in data-driven simulation approaches.

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SIMULATION AND EXPERIMENT

Residential load profiles vary substantially depending on consumer usage of appliances. Gobmaier showed that data-driven, bottom-up load modeling, based on the use of appliances, can explain up to 96.9% of variance in load profiles (Grobmainer, 2014) and Gram-Hanssen found that electricity consumption in households correlates strongly with the use of appliances (Gram-Hanssen, 2011). According to Hayn et al., knowing consumer demographics, lifestyle and behavior is likely to help predict household electricity load (Hayn et al., 2014). It is an open research question, however, whether including socio-demographic characteristics and behavioral data can increase prediction accuracy beyond the accuracy of predictions based on historic smart meter data.

In 2018, smart meter deployment rate reached 21% in Austria (Energie-Control Austria, 2019) and 44% in Europe (Kochanski et al., 2020). If consumers consent to provide their smart meter data to energy management systems, past energy consumption can be a valuable input for electricity forecasts. However, energy consumption in individual households is a dynamic, highly volatile process, which is why the accuracy of predictions based on smart meter data alone is limited (Gajowniczek and Ząbkowski, 2014). Besides, consumer empowerment through active participation goes beyond merely accepting smart meter technology.

User-Centered Monitoring Software

The user-centered energy monitoring software developed in the GameOpSys project encourages active consumer participation. It acts as a communication channel where researchers can collect behavior data and simultaneously deliver system status reports or behavior change interventions to users. Integrating user feedback into data analysis allows researchers to improve consumption models and prediction accuracy. At the same time, the software system supports various intervention mechanisms to successfully induce changes in the consumer's knowledge, attitudes and beliefs about the energy system and changes in consumption behavior.

Through the UI, consumers are asked to provide two types of information: i) household characteristics and ii) dynamic information about planned behavior for the next day. Household characteristics include number, age and gender of household members, number and type of appliances, heating system and psychological characteristics such as personal norms and ascripton of responsibility.The selection of these characteristics was guided by studies identifying determinants of household energy consumption (e.g. Hayn et al., 2014, Jones, Fuertes, and Loomas, 2015) and were extended by psychological variables that are predictive for energy saving behavior (e.g., Wang et al., 2018) and for changes in energy consumption (Abrahamse & Steg, 2009). This information is used to improve prediction models for overall energy consumption and, in case the household employs electrical heating or cooling systems, adjust for seasonal changes. However, due to the stable nature of these variables, it is likely that their influence is already captured within smart meter data. The dynamic information consists of consumption schedules, predicting occupancy and indicating when the washing machine or other appliances will be used. This data helps to improve the accuracy of the projected load profile for the next day. Conversely, asking consumers to predict their own behavior increases the likelihood that they indeed act out this behavior in order to remain self-consistent (Spangenberg and Greenwald, 1999). It is a key objective to develop a more thorough understanding of the consumption patterns, to identify the best predictors for these consumption patterns, and to examine the potential user interaction and user engagement have in building simulation and modelling.

Communication is designed to be bidirectional. While collecting data, the system simultaneously supplies users with detailed information about their energy consumption, highlighting the consequences of their behavior. Providing feedback is a prominent and common behavior change technique in sustainable consumption interventions (Lehner et al., 2016; Fischer, 2008). Awareness of behavioral consequences can motivate people to act according to their values (Stern, 2000) and increase behavioral intention by incrementing perceived self-efficacy (Ajzen, 1985). Besides, feedback highlights differences between current and ideal outcomes, thereby motivating goal directed behavior (Carver and Scheier, 1998). Because the GameOpSys project plans to optimize energy prediction, it does not only inform users about energy consumption, but about prediction accuracy as well. Consumers can observe the extent to which accuracy depends on their active participation.

Given the opportunity, active consumer participation is only possible, if people are motivated to do so (Michie et al., 2014). To encourage regular interaction with the energy system, gamification elements are integrated. Gamification uses principles and elements of game-design, like achieving, exploring, competing, or connecting with other people. Implementing such elements in an intervention-tool stimulates users and increases engagement and motivation (Bartle, 1996). In the UI, consumers learn about their achievements through

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feedback, points and badges depending on the prediction accuracy. This includes information about achievements of other users, which encourages social comparison and competition. Finally, we plan to provide an option to explore the relationship between behavior, energy consumption and energy prediction even further. Specifically, the UI will indicate time-frames where the prediction significantly diverges from the actual consumption and prompt users to re-check their behaviour during this time.

In the subsequent sections we describe the technological aspects of the system, outline the architecture and describe its components.

System Architecture

The system is designed as a data hub, routing communication between the users and data analysis services. Figure 1 shows the traversal of data through the system. It is collected in the Android application, forwarded to the server where it is processed by the data analysis services and then returned to the user as visualizations and forecasts.

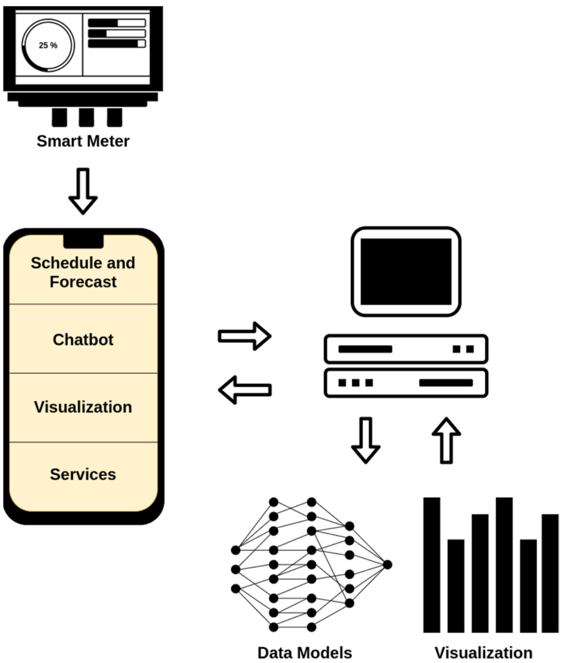

Figure 1. Schematic view of the system.

Subsequently, we describe the Android application (UI), its connection to the data storage (server) and the interfaces for the analysis and visualization services.

Front-End: Mobile Application

A substantial number of users as well as advances in mobile hardware, both in terms of computational power and sensing technology, confirm the smartphone as a suitable platform for data-collection, research and interventions (Lathia et al., 2013). Consequently, we chose to develop the UI as a mobile application. Prototypic development was confined to the Android framework. However, single components such as the server infrastructure, the API-definitions and the database are framework-agnostic. Thus, they can be reused if development is extended to iOS and/or a HTML5-based cross-platform version. The Android application was built from scratch in an agile software development process (Beck et al. 2001). The minimum API level requirement was set to 21 (Android 5.0 Lollipop), which allows us to target more than 89% of all active Android devices worldwide (Google, 2020). To ensure backward compatibility, uniform look and consistent behavior on different devices and API levels the app was built with components from the Jetpack suite in the AndroidX-namespace.

Data-visualizations are based around two groups of metrics: i) overall energy consumption in the household, and ii) projected usage of appliances. Actual consumption values, based on smart meter readings, are supplied by the grid operators. Consumers collect smart meter data from their grid operator's web portal and upload it through the app. The consumption data is selected, preprocessed and transformed on the server. It serves as a basis for visual usage statistics and future energy consumption estimates. Projected usage of appliances and occupancy is supplied by the users. Analysis services build data models based on historic smart meter data and user-generated schedules.

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Figure 2 shows a bar-chart visualization where users can see their actual energy consumption compared to the energy consumption predicted by the data models. The prediction matrix shown in Figure 3 allows users to schedule their energy consumption. The screen displays various consumers (occupants and appliances) and users can mark the timeframes where they expect these consumers to be active.

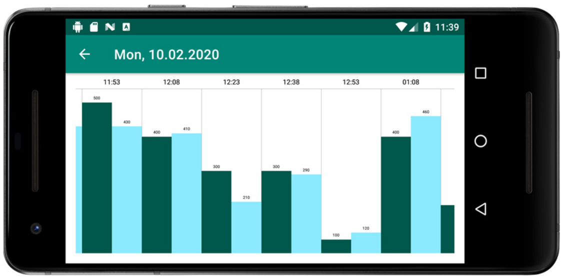

Figure 2. A window visualizing predicted and actual energy consumption.

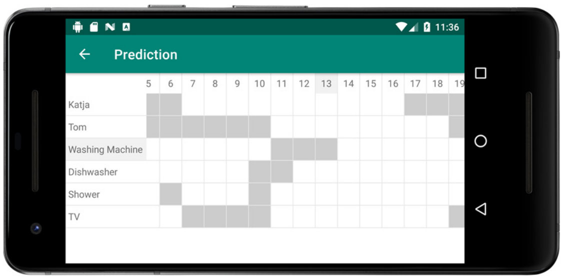

Figure 3. A prediction matrix, where users can schedule energy consumers in their households.

The graphical UI (GUI) is separated from the data access layer using the model–view–viewmodel (MVVM) pattern (Gossman, 2015). This prevents changes in the way data is retrieved from causing the need for changes in the GUI and vice-versa. Even when synchronization with the server is necessary the GUI has to be responsive and the data consistent. Thus, data-supply to the viewmodel is realized through observable, Android-lifecycle-aware, LiveData objects. This allows communication to be asynchronous and keeps the GUI up-to-date during Android-lifecycle events such as configuration changes (e.g. switching from portrait mode to landscape mode) or when the app is put into the background.

Data exchange between the app and the server is specified in an OpenAPI/2.0 document. The RESTful API definition provides a language-agnostic description and clearly defines the available endpoints (paths) on the server. The client SDK is auto-generated using Swagger's open-source code generator Codegen and integrated into the Android application as a module. Requests to the server are generated with Retrofit. Retrofit wraps the paths from the OpenAPI definition and ensures type safety for all API calls and responses. The need to synchronize data with the server, inverts control flow (Bainomugisha et al., 2013). Thus, it is necessary to apply a programming paradigm that allows the application to react to external events. The RxJava and RxAndroid extensions from the ReactiveX-library provide the necessary operators for the asynchronous, event-based calls between the Android application and the server.

Back-End: Server

To support independent deployment of components, the server is running an array of microservices (Fowler and Lewis, 2014). The software services bundle their own dependencies and configurations in virtual packages called containers. These containers are deployed, managed and updated through the Docker container engine.

Database

The core component is a document-based, distributed mongoDB database. It stores all data in JSON-like objects, which allows for flexible, dynamic schemas with nested structures.

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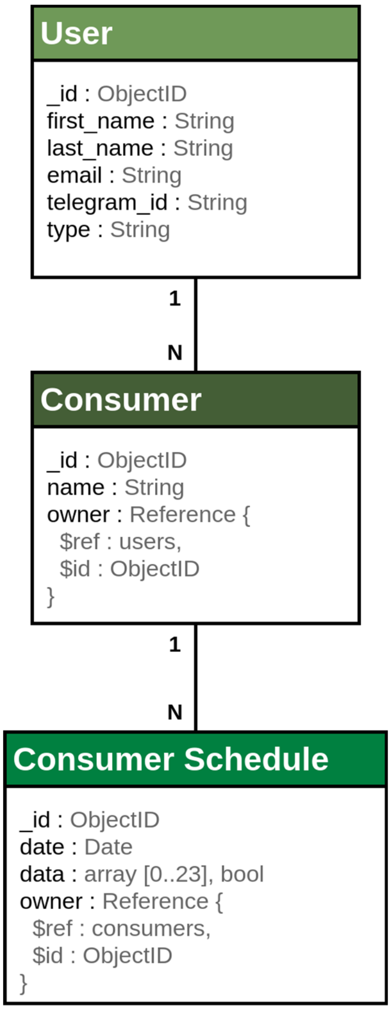

Figure 4. Data schema for consumers (appliances and occupants)

The data structure for the consumer schedules, i.e. the predictions about the expected consumption, and their relationship to user and consumer data can be seen in Figure 4.

A user designates a household, thus users can have any number of consumers, including occupants and appliances. Predictions about when each consumer is going to be active on a given day are modelled as consumer schedule objects which contain their date, a reference to the consumer they are a schedule for and a boolean array containing a 24-hour-grid. The overall household consumption is modelled through two objects: the predicted consumption, generated by the data models and the actual consumption based on the smart meter readings. Both objects contain a date and a 24-hour-grid with float values, representing the energy consumption for each hour of the day. Opposed to the consumption schedules, overall consumption is directly associated with a user.

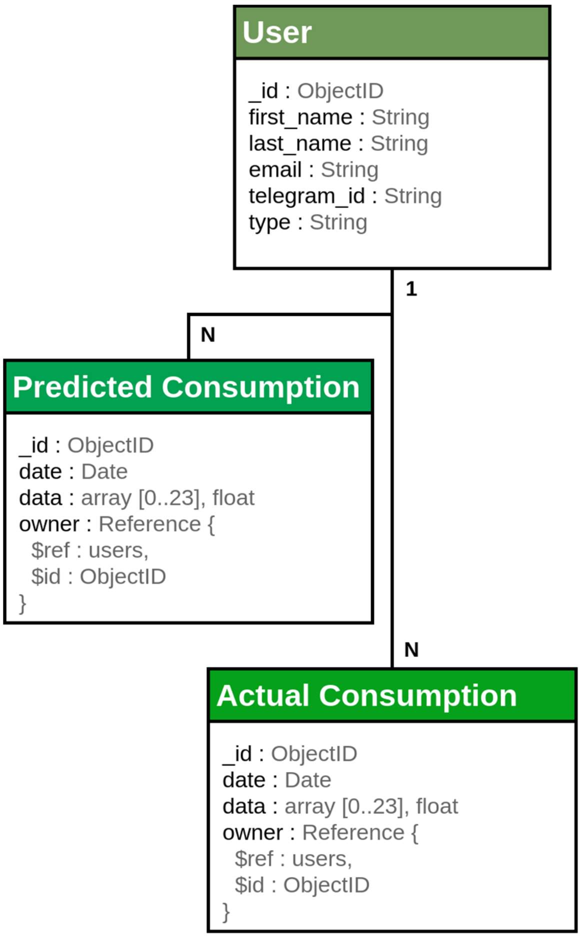

Figure 5. Data schema for overall household consumption.

Authentication

Because of the sensitive nature of the prediction and consumption data, it is a key objective to protect it from unauthorized access. To do so, the system supports two-factor authentication (2FA) which binds each user to a Telegram account. The mapping between Telegram id and user object is added manually whenever a new user is created. When users want to access their data through the app for the first time the app initiates the authentication process by sending the user's Telegram id to the server. If the id exists in the database, i.e. there is a valid mapping between this id and a user object, the server sends a one-time password to the user's Telegram account. The user is then given five minutes to access their account, obtain the one-time password and enter it into the app. The code is sent to the server and if it is valid, the server responds with a JSON-based web token (JSON web token) that the client can use for authentication during future communication. This authentication approach has two advantages over username-password authentication: i) users cannot forget their passwords, thus it is not necessary to implement a workflow to reset passwords and ii) users cannot choose weak passwords.

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Web-Connection

The server runs a flask microservice that provides the endpoints specified through the API. The flask service is a compact web framework implemented in Python. It consists of a highly customizable, lightweight core and supports the integration of extensions. Flask does not have a built-in database abstraction layer, which separates the database implementation from the API. To keep the binding between the flask service and the database loose, i.e. to allow the database to be changed without having to change the flask service, we implemented a database abstraction layer. This class wraps data operations and provides a facade for the create, read, update and delete (CRUD) calls used by API-endpoints. The connexion framework validates requests and endpoint parameters and maps the API-endpoints to their respective Python implementations. Figure 6 contains a diagram visualizing the interaction.

Data Analysis

Developing data models and tools is an ongoing process. However, first analysis scripts and data models were implemented in Python using the visualization library seaborn and the statsmodels package for statistical computations. Data analysis components can be integrated into the server infrastructure as separate services in the form of docker containers. The docker engine supports deployment of isolated bundles. However, it allows services to communicate through well-defined channels. The mongoDB listens to all linked services within the docker environment on the default port. Thus, data analysis components can access household information directly through the database. However, it is possible to extend the API provided by the flask web service for remote database access.

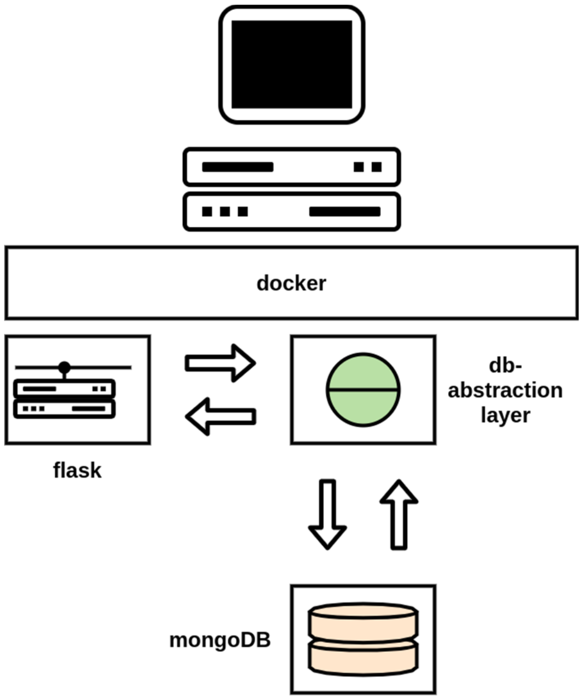

Figure 6. Schematic view of the server.

CONCLUSION

Active consumer participation is valuable to the operation of smart energy systems. Accurate predictions of load profiles provide the basis for numerous energy services such as flexibility identification, demand response, model predictive control or peer-to-peer trading. Active participation allows researchers to improve the accuracy of energy consumption models beyond the accuracy of standard load profiles, models based on socio-demographic characteristics or historic consumption data alone.

The user-centered energy management system (EMS) developed within the GameOpSys project collects behavior data which can be used in prediction models and energy services. Consecutively, prediction models and usage statistics are used to provide consumers with detailed information about their energy system. Simultaneously, the EMS can act as a means to deliver behavior change interventions. Identifying and highlighting behavioral consequences, providing feedback and highlighting the differences between actual and ideal outcomes can support consumers in adapting more sustainable habits.

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