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A MULTILEVEL DEMAND RESPONSE PROFILING AND MODELING SOLUTION ENABLED BY DIGITAL TWINS INTEGRATION

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Abstract

This paper presents a novel approach for assessing and optimizing the flexibility potential of electricity consumers in residential buildings using a Consumer Digital Twin (CDT) and a Building Digital Twin (BDT). By leveraging smart devices, cloud-based data processing, and advanced optimization techniques, the proposed methodology integrates CDT and BDT to accurately forecast consumer's energy demand and thermal satisfaction, quantify the consumer's preferences in terms of importance level for specific flexible household appliances, and schedule their optimal operation. The key findings demonstrate the effectiveness of the integrated CDT-BDT framework towards reducing the total energy costs for electricity consumers and enhancing the utilization of local renewable energy sources. The principal conclusions highlight the potential of the proposed method for improving grid stability by reducing the load peaks and shift the load operation off-peak periods. The research contributes to the advancement of digital twin applications in the domain of energy management and optimization, particularly in residential building settings, and the establishment of innovative business models in the electricity market.

Introduction

At present, the growing adoption of renewable energy sources (RES) and the rising demand for electricity in residential buildings underscore the need for effective energy management and optimization strategies. Inherent variability and intermittency of RES present challenges, such as grid instability and inefficiencies, necessitating approaches that harness consumer's flexibility potential and optimize energy consumption patterns for better RES integration. Digital twin technology has emerged as a promising solution, offering real-time monitoring, analysis, and control of energy-related aspects through digital replicas of physical assets and processes. However, applying digital twins effectively in energy management demands a holistic approach that harmoniously combines individual-level consumer preferences and behaviors with building-level energy performance optimization.

The International Renewable Energy Agency (IRENA) projects that renewable resources will contribute to 90% of the global electricity generation by 2050 (IRENA, 2021). Concurrently, electricity demand is anticipated to rise by 30% by 2040, primarily driven by urbanization, population growth, and the increasing number of appliances exerting pressure on existing electricity infrastructure (IEA, 2022). In Europe, buildings are responsible for 40% of energy consumption and 36% of CO_2 emissions, making the promotion of energy-efficient buildings essential for a sustainable and carbon-neutral future (EU Law, 2019). The rising peak demand and integration of renewable energy resources present challenges to grid operators in balancing energy supply and demand (Gan et al., 2020). Furthermore, the stochastic nature of energy generation and demand highlights the need for flexibility in ensuring constant, reliable, and cost-effective energy supply, consequently reducing the expenses associated with remedial actions (Kazempour et al., 2018).

Flexibility refers to the ability to maintain continuous operation despite significant fluctuations in energy supply or demand (El Geneidy et al., 2020). Demand response, a critical form of flexibility in electricity markets, enables consumers to adjust their energy demand in response to incentives and pricing signals. This reduction in peak demand and shift in usage to off-peak periods promotes efficient use of renewable energy and enhances grid stability. Thus, residential flexibility, in this context, can be understood as the potential for consumer demand response.

At the building level, flexibility is primarily provided in three areas: appliance scheduling, heating and cooling control, and electric vehicle (EV) charging. Recent research has explored the use of appliances for flexibility (Rostampour et al., 2020; Vizia et al., 2021; Lezama et al., 2020), with some studies focusing specifically on building heating and cooling systems as a source of ancillary services for the grid. However, user preferences largely determine the constraints for these approaches. Depending on user preferences, appliances such as the washing machine, the dishwasher and the water heater can be preloaded and activated to the determined optimal time interval by a flexibility algorithm. The same approach can be applied to the heating and cooling system in a building by temporarily shutting it off during high-tariff periods and reactivating it before occupants notice any changes. In the case of EV charging, flexibility is derived from the fact that an EV may be plugged in for several hours but typically requires less than an hour to fully charge.

The remainder of this paper is organized as follows: Section 2 presents a detailed description of the CDT and BDT concepts and their integration in the proposed framework. Section 3 describes the methodology for data acquisition, processing, and analysis in the context of CDTs and BDTs. Section 4 presents the optimization framework, including the objective functions and the optimization algorithm used to determine the optimal appliance operation schedules. Section 5 provides the results of the proposed methodology, including a simulation study and a real-world test case from the H2020 TwinERGY project's Benetutti Smart Community pilot site. Finally, Section 6 offers conclusions and future directions for research.

The main contributions of this paper are summarized as follows: the development of a novel integrated CDT-BDT framework for assessing and optimizing the flexibility potential of electricity consumers in residential buildings; the demonstration of the effectiveness of the proposed methodology in reducing total energy costs and enhancing the utilization of local renewable energy sources; the introduction of a novel approach to building energy flexibility that aims to establish the foundation for innovative business models in the electricity market; and the advancement of digital twin applications in the domain of energy management and optimization, particularly in residential building settings.

Literature Review

This section provides an overview of the state-of-the-art in building energy flexibility and highlights the strong attention of digital twin technologies in the energy sector. To start with, CDT serves as a simplified virtual representation of a specific electricity consumer that facilitates the forecast and discovery behavior patterns on individual's energy demand, assesses the consumer's thermal comfort level in a real-time manner, and processes the consumer's preferences regarding the importance of household appliances. BDT captures static information, dynamic characteristics and real-time sensed data regarding a specific building and its occupants to facilitate the building's overall energy performance and efficiency.

Researchers have proposed various applications of digital twins in the energy sector, such as the appliance scheduling, the control of heating and cooling system, and the optimal EV charging (Rostampour et al., 2020; Vizia et al., 2021; Lezama et al., 2020). In addition, several studies have highlighted the potential of building energy flexibility to create new revenue streams and business models in the electricity market (Radenković et al., 2020). A scan-to-BIM-based DT was implemented to improve energy efficiency in an existing building resulting in a 14.1% reduction in energy consumption (Zhao et al., 2021). Another DT was employed to manage heat supply in a smart building and minimize financial costs while maintaining occupants' thermal comfort (Zakharov, 2019). DTs were also utilized to forecast and optimize energy efficiency for historic buildings through AI models (Ni et al., 2021), to deliver personalized energy services to prosumers in a real community (Dembski et al., 2020), and to increase energy savings for the entire infrastructure life-cycle while providing data availability and connectivity for novel services (Bortolini et al., 2022; van Dinter et al., 2022).

Although human-oriented digital technologies hold promises for substantial progress in the energy sector, their realization remains in its early stages due to the intricate and subjective character of human behavior (Shengli et al., 2021). Therefore, a comprehensive approach that seamlessly integrates the individual-level consumer with building-level energy performance optimization remains an open research challenge.

Methods and Materials

The present study introduces a novel approach to building energy flexibility by integrating the Consumer Digital Twin (CDT) and Building Digital Twin (BDT). The approach comprises three optimization problems, namely, the minimization of appliance costs, maximization of Renewable Energy Sources (RES) utilization, and optimization of aggregated demand. The following section commences with an introduction to the components of the CDT and BDT, offering a broad overview of their features and functionalities, followed by an exposition of the framework's strengths, which include seamless data integration of the CDT and BDT, a flexible optimization algorithm, and testing through simulated and real-world test cases.

Consumer Digital Twin

The CDT is a simplified, human-oriented virtual representation of a consumer within the electricity market. The virtual replica encompasses the most discriminative features, behaviors, and actions of the physical counterpart, and ensures seamless bidirectional data exchange between the physical and the virtual entity. To this end, CDT acquires and processes raw data in an automatic way from both physical and digital resources in the consumer's environment, such as smart devices and REST APIs, respectively. Furthermore, CDT obtains and analyzes consumer's preferences, which reflect the individual's energy flexibility priorities in the form of decision criteria.

The key functionalities performed by the CDT focuses on the development of consumer's dynamic constructs to uncover behavioral patterns in energy demand, the determination of relative priorities, versatility in energy flexibility and acceptance in demand response actions, and the assessment of individual's indoor thermal comfort level. In particular, the CDT decomposes historical time-series data related to the energy consumption of specific residential electric appliances to isolate potential trends and seasonality patterns, and evaluates the autocorrelation strength against time lags, aiming to produce an accurate day-ahead forecast for the demand profile of each appliance. Additionally, CDT continuously determines the consumer's thermal comfort level from a wrist-worn wearable device (Gialelis et al., 2022), which expresses the thermal satisfaction associated with indoor thermal environmental conditions to furtherly optimize the forecast of the demand profile for the HVAC load (Andriopoulos et al., 2023).

Another important feature of the CDT is the quantification of consumer's preferences, which are represented as a set of decision criteria that express the individual's prioritized demand response potential. Consumers are requested to define the relative importance for each pair of residential electric appliances in their daily routine using a 9-point balanced importance scale. In this way, the consumer is able to express their level of importance with more precision than a simple binary ranking system. Additionally, the consumer specifies the desired range of operating time window for each appliance and the acceptable demand response rate, selected from the discrete values of 0%, 25%, 50%, 75%, or 100%.

To hierarchically order the appliances based on the determined intensity of importance by each consumer, CDT assigns them weights through the multi-criteria decision analysis framework of Analytical Hierarchy Process (AHP). The weights reflect the subjective importance of an appliance as perceived by the specific consumer. The superior or inferior importance of a specific appliance over the compared one is defined in terms of verbal appreciation. Hence, equal, moderate, strong, very strong, and extreme importance are indicated by the corresponding scale's values of 1, 3, 5, 7, and 9, respectively, whereas the intermediate values are omitted since they evince compromission.

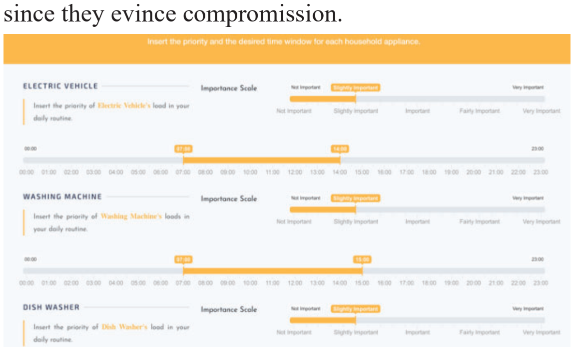

Figure 1. The user interface of CDT from which consumers insert their preferences regarding the importance of each flexible load the desired operation time window.

A graphical interface is implemented in the CDT that serves as a simple and user-friendly end-point from which consumers can insert and update their preferences, as presented in Figure 1. By the time a user has defined the intensity of importance for each pair of residential loads, the desired operation time window and the demand response acceptance rate, the inputs are processed on the back-end of the CDT through AHP method to produce the priority vector of the obtained weights.

With this in mind, the proposed CDT promotes a human-centric DR optimization strategy, which enables personalized, prioritized and non-intrusive control functions of energy assets, and quantifies the consumer's flexibility. Also, it enhances day-ahead forecasts for the energy demand of specific residential appliances to address their stochastic nature.

Building Digital Twin

A Building Digital Twin (BDT) is the digital representation of a physical building that simulates energy-related processes, monitors real-time key energy indicators, and optimizes the building's energy performance. A cloud-native message broker is employed to enable real-time data flows from the CDT in an efficient manner. Additionally, BDT retrieves static information from an external Building Information Model (BIM) and sensed data from smart devices installed in the building's ecosystem. From the stakeholder's perspective, the BDT allows the evaluation of the building's energy performance and execution of data-driven decision making. Also, it schedules and optimizes the operation of electrical appliances based on the aggregated energy flexibility provided by consumers.

During the initialization phase of the BDT, the static building information regarding the architectural drawings, the envelope construction components, the equipment of the building and the geographical coordinates is manually inserted by the owners. In addition, BDT obtains and aggregates real-time data streams regarding energy usage, forecasted data for energy demand and energy production from owned RES facilities, and consumer's preferences.

The schedules of residential electric appliance usage and the disaggregated demand profiles over a specific time period are produced by the building dynamic simulation software (IES-VE). The appliance modeling process within the IES-VE dynamic simulation software comprises six steps, as follows.

1. Building model generation; the users create the initial building model either using the IES SketchUp plugin or the VE software.
2. Determination and evaluation of the model's input parameters; the key input parameters for the dynamic simulation model, such as the internal gains, information on HVAC systems, and schedules of operation, are manually inserted by the users and are furtherly validated by the software.
3. Development of internal gains profiles; The internal gain profiles are established either by following the descriptions in the documentation

or by selecting the most relevant ones based on the consumption associated to each profile.

4. Allocation of a meter to each smart device; meters are VE objects assigned to smart electric appliances by users to associate end-uses to cumulative variables for estimation of energy vectors.
5. Simulation and analysis; A 10-minute simulation is performed for the entire period of analysis. Historical data of the electricity demand for each building is obtained by the CDT to tune the simulation inputs and are compared with the metered data to evaluate the model's performance. The acceptable discrepancy value for the difference between the simulation results and actual electrical consumption is a mean absolute percentage error (MAPE) of 5%.
6. Channel generation: For each residential electric appliance, a single channel is created to store and visualize information.

Another core element of the BDT is the IES Intelligent Virtual Network (iVN), which aggregates and simulates the performance of physical networks including heating and electrical physical infrastructure. The demand of the assets related to the aforementioned networks and the forecasted local weather conditions are inserted into the simulation model to evaluate the minimum local energy generation that satisfies this demand, either by fossil fuels or renewables.

Within the scope of this work, the iVN provides renewable generation forecasts based on the local weather conditions, as acquired by an external REST API service. Additionally, the iVN requires static information of the local renewables, such as the power capacity, the positioning, the angle of installation and the degradation factor.

Optimization Framework

An optimization framework is utilized to determine the optimal solution of a multi-objective optimization problem, which are provided as input into the flexibility model. To this end, the framework utilizes information obtained by both CDT and BDT, including the demand profiles for each smart appliance, the forecasted generation of renewables, and time-series of the day-ahead electricity prices. As a result, the optimized day-ahead aggregated demand profile is produced for each building.

In the scope of this work, the multi-objective optimization problem comprises three objective functions, as follows.

- O1: The objective function for the minimization of the total electricity costs regarding residential electric appliances of a building.
- O2: The objective function of the local renewable's usage maximization.
- O3: The objective function of the diversity's factor maximization of the diversity factor.

O1: Minimization of the total electricity costs

The objective function Oc, described by the Equation 1, minimizes the operational cost of residential electric appliances for the day-ahead.

$$\boldsymbol{O_C} = \sum_{\boldsymbol{\beta}=1}^{\boldsymbol{n_\beta}} \sum_{\boldsymbol{\tau}=1}^{\boldsymbol{n_\tau}} \left(\frac{\sum_{\boldsymbol{\alpha}=1}^{\boldsymbol{n_\alpha}} \boldsymbol{w_\alpha} \cdot \boldsymbol{P_{\beta,\tau,\alpha}} \cdot \boldsymbol{Ep_\tau}}{\boldsymbol{max(Pd_\beta)}} \right)$$

Equation 1. Minimization of total electricity costs

The number of electric appliances, the number of buildings, and the number of time intervals in a day considered by the optimization problem are denoted by the parameters of nα, nβ, and nτ, respectively. The determined relative priority of an electric appliance α by the AHP method is indicated by wα, the average electric power of a building's β electric appliance α in time interval τ is represented by Pβ, τ, α, the electricity tariff in time interval τ is represented by Epτ, and the peak power demand for a building β is represented by max (Pdβ).

O2: Maximization of the local renewables' usage

The objective function OR, described by the Equation 2, maximizes the usage of local renewable resources considering the difference in each time step between the renewable energy generation and the demand for each building.

$$O_R = \left| \sum_{\sigma=1}^{n_\sigma} \sum_{\beta=1}^{n_\beta} \sum_{\tau=1}^{n_\tau} \left(\frac{\sum_{\alpha=1}^{n_\alpha} P_{\beta,\tau,\alpha}}{max(Pd_\beta)} - \frac{G_{\sigma,\tau}}{max(Gd_\sigma)} \right) \right|$$

Equation 2. Maximization of local renewables' usage

Hence, it ensures that only the necessary demand is allocated to meet the generation, while the remaining load will be moved in times of the day to minimize cost and/or maximize the diversity factor.

The number of renewable energy resources is denoted by nσ, the average electric power of a building's β electric appliance α in time interval τ is represented by Pβ, τ, α, the peak power demand for a building β is represented by max(Pdβ), the average generated power from the renewable system σ in time interval τ is represented by Gσ,τ and the peak power generated by the system σ during the day is represented by max(Gdσ).

O3: Maximization of the diversity factor

The objective function ODf, described by the Equation 3, maximizes the diversity factor for the buildings, which indicates the deviation in daily maximum energy demand among buildings. From a mathematical perspective, the diversity factor is defined as the ratio between the sum of the maximum daily energy demand of each building and the maximum daily aggregated energy demand for the group of buildings. The diversity factor quantifies the variability of power demands among different buildings, where a higher diversity factor indicates a more even distribution of power demands, while a lower diversity factor suggests that some buildings may have overlapping power demands. Maximizing the diversity factor can help to mitigate sudden spikes in the aggregated power demand, which is crucial for maintaining a stable and reliable power supply.

Equation 3 defines the diversity factor as the ratio between the sum of the maximum daily power demand of each building and the maximum daily aggregated power demand for the group of buildings. Specifically, the numerator represents the peak power demand for the daily profile of building β, with β being the building index, and Pdβ being the power demand of building β. The denominator represents the peak aggregate power demand for the group of buildings, where τ represents the time interval index and α represents the appliance index.

$$O_{Df} = \frac{\sum_{\beta=1}^{n_\beta} max(Pd_\beta)}{max\left(\sum_{\beta=1}^{n_\beta}\sum_{\tau=1}^{n_\tau}\sum_{\alpha=1}^{n_\alpha} P_{\alpha,\tau,\beta}\right)}$$

Equation 3. Minimization of diversity factor

During the optimization process, the decision vector in each iteration represents the list of starting point in minutes over the day for each smart appliance. Once the starting point has been defined, the reconstructed demand profile will be allocated to that time interval.

Results

The evaluation of the performance for the proposed CDT-BDT integration is divided into two phases; a testing phase, in which synthetic data for residential electric appliances demand and domestic rooftop generation are utilized, followed by a validation phase using real-world data from five buildings in the H2020 TwinERGY project's Benetutti Smart Community pilot site.

Simulation

A simulation of the flexibility algorithm is performed with synthetic daily data for 39 semi-detached houses equipped with a 4kWp solar PV array and their appliance demand profiles generated by StRoBe (Baetens et al., 2016), which models the occupant's stochastic behavior and interaction with appliances in a building. Then, the profile was optimized against energy costs, renewable generation usage and diversity factor, with the simulation repeated for five different DR acceptance rates, namely 0%, 25%, 50%, 75% and 100%. In Figure 2, the results of the simulation are presented. As anticipated, higher levels of demand response acceptance result in better performance of the demand profile. This can be observed by comparing the green and red lines that indicate 0% and 100% demand response acceptance, respectively. The peak of energy consumption for the non-flexible profile, represented by the green line, occurs during the evening, when generation from renewables is low and the energy tariff is high. On the other hand, the energy consumption of the most flexible profile, represented by the red line, peaks when the generation from renewables maximizes, resulting in a more consistent energy consumption during the day and lower time-of-use cost.

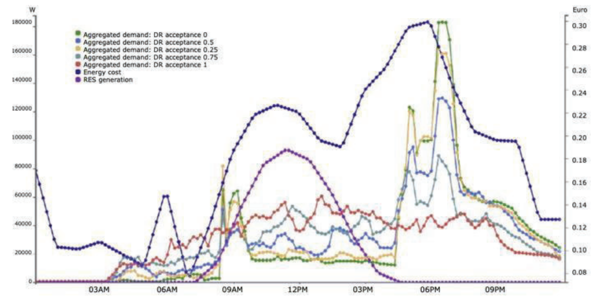

Figure 2: Simulation results

Table 1 confirms that costs decrease as the demand response acceptance rate increases, except in the case of 25% acceptance rate, which shows a slight increase. This deviation is likely due to the optimization of renewable energy use and diversity factor by the algorithm, making it still a more optimal scenario overall.

Table 1: Total energy costs - Simulation results of flexibility algorithm

DR Acceptance	Total Energy Costs
0%	€127.36
25%	€127.65
50%	€120.93
75%	€115.86
100%	€110.48

Real-world test case

To validate the flexibility algorithm, a real-word test case including five residential buildings was conducted within the Benetutti Smart Community. The owners of each building predetermined the required static information and external weather forecasted data of air temperature, solar radiation, plane of irradiance and wind speed for the city of Benetutti retrieved from an external REST API to predict the generation from owned RES facilities. In addition, information on power capacity, angle of installation and degradation factor of each PV considered by the forecast model to furtherly optimize the prediction.

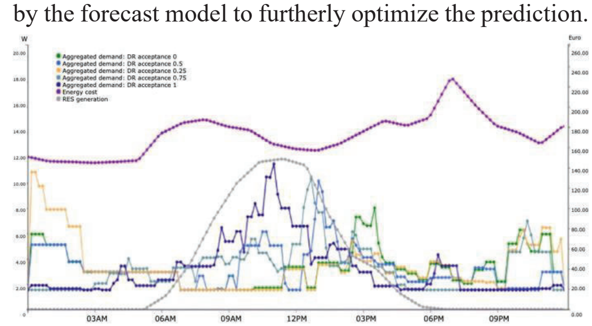

Figure 3: Real-world test case results

As for the energy demand of each household electric appliance, CDT created a demand profile due to the historical consumption patterns of each appliance. Moreover, CDT provided to BDT the user's preferences regarding the relative importance for each appliance, the desired operational time windows and the DR acceptable ratio to produce a time-series output for each load.

The results of the flexibility algorithms in both cases proved to be quite promising. The total energy costs reduce as the demand response acceptance rate increases with the exception of the 25% demand response acceptance rate case which leads to a slight increase. This can be explained by the optimization of renewable energy use and diversity factor by the algorithm, making it still a more optimal scenario on balance.

Table 2: Total energy costs – Real world test case results of flexibility algorithm

DR Acceptance	Total Energy Costs
0%	€8.79
25%	€8.69
50%	€8.75
75%	€5.15
100%	€4.04

Conclusions

In this paper, the proposed integration of CDT and BDT is demonstrated in a real-world test case scenario to evaluate the consumer's flexibility potential and reduce the total costs for each building. The testing and validation of the flexibility algorithm were successful, with results meeting expectations in simulated test cases and verified at the Benetutti pilot site. The next steps include connecting the algorithm to Bristol's, Hagedorn's, and Athens' pilot sites once the modeling is finished.

The future work in the field of distributed energy resources (DER) is expected to involve a comprehensive evaluation of simulation results for shared assets, such as EV charging stations, PV systems, small wind turbines, and batteries. This evaluation will include analysis of associated analytics and operational parameters such as voltage, current flow, and frequency of the electricity grid. Another topic for further research is to enable near real-time flexibility services and develop relevant business models. A recommendation-based solution for modifying end-user performance or behavior is being considered, which will facilitate the implementation of the aforementioned services. Furthermore, evaluating our thermal comfort framework by implementing a quantitative analysis of its impact on the demand response output will provide valuable insights into the effect of demand response adoption on occupant comfort and satisfaction.

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