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A Multi-Level Digital Twin for Optimising Demand Response at the Local Level without Compromising the Well-being of Consumers

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Abstract: Although traditionally perceived as being a visualization and asset management resource, the relatively rapid rate of improvement of computing power, coupled with the proliferation of cloud and edge computing and the IoT has seen the expanded functionality of modern Digital Twins (DTs). These technologies, when applied to buildings, are now providing users with the ability to analyse and predict their energy consumption, implement building controls and identify faults quickly and efficiently, while preserving acceptable comfort and well-being levels. Furthermore, when these building DTs are linked together to form a community DT, entirely new and novel energy management techniques, such as demand side management, demand response, flexibility and local energy markets can be unlocked and analysed in detail, creating circularity in the economy and making ordinary building occupants active participants in the energy market. Through the EU Horizon 2020 funded TwinERGY project, three different levels of DT (consumer – building – community) are being created to support the creation of local energy markets while optimising building performance for real-time occupant preferences and requirements for their building and community. The aim of this research work is to demonstrate the development of this new, interrelated, multi-level DT that can be used as a decision-making tool, helping to determine optimal scenarios simultaneously at consumer, building and community level, while enhancing and successfully supporting the community's management plan implementation.

Key words: Digital Twins, Flexibility, Demand-Response, Energy consumption, Building, Community

1. INTRODUCTION

The digitization of the built environment is becoming increasingly relevant amongst academics and building operators alike as the potential role of Digital Twins (DT) in assisting with the decarbonization of the world's buildings. Buildings are currently responsible for 40% of global energy consumption and 33% of greenhouse gas emissions and are currently the focus of many governments and organizations efforts towards reducing their carbon footprint [1]. A Digital Twin

(DT) is a virtual representation of a physical, real-world asset or group of assets [2]. DTs have the capability to enable building occupants and managers to deeply interrogate the performance of their buildings, forecast their energy consumption into the future, explore the impact of operational and capital improvements and derisk and predict the result of any deep retrofit structures [3]. Despite these benefits, the implementation of DTs, and in particular performance DTs (that facilitate the functionality outlined above in comparison to informational DTs such as BIM models) remain a fringe technology awaiting widespread deployment in the industry [4]. Furthermore, the application of digital tools and the creation of digital assets has not been effectively implemented in the residential market to date. As a result, residential buildings are not recognizing the potential of leveraging digital tools to enable them to decarbonize effectively. As of 2020, there are an estimated 195.4 million households in the European Union alone, a figure that increased by 7.2% over the previous decade [5]. The introduction of DTs for this level of building will provide all building occupants with the ability to track their energy usage, explore performance improvement strategies for their property and even actively engage in the market through engagement in community grid and demand response actions. Currently, many DTs of buildings, communities, grids and their assets primarily rely on static 3D models and data feeds from Building Energy Management Systems and SCADA (supervisory control and data acquisition) models, for example, while any modelling occurs through the use of data-driven techniques such as Artificial Intelligence (AI)[6] . As a result, the relative intelligence that can be gleaned from such models can be somewhat limited and more suited to measurement and tracking of operational energy consumption while failing to unlock the true power of DT. When tools such as physics-based, dynamic simulation modelling (DSM) is integrated into the DT architecture, further capabilities can be unlocked that can empower building occupants, owners and managers to operate their buildings and communities in a more intelligent, energy efficient way [7].

Furthermore, the move towards decentralizing the energy grid is being supported through the development of demand response programs, although these are currently almost exclusively supplied to energy intensive industries such as paper, metal and cement production. Although commercial and industrial demand response is now considered technically and economically viable, residential resources are still not active participants in the market. Despite the slow rollout, residential buildings comprise a large source of flexible energy demand and storage. This flexibility could potentially provide distribution and transmission system operators with the needed services to balance demand and supply, defer grid investments and manage power quality. The net benefit of achieving basic market integration through demand response are in the range of 12.5 to 40 €bn/yr by 2030 [8].

The EU funded TwinERGY [6] project intends to introduce a first of its kind demand response framework that enables the realization of novel business models, allowing electricity retailers and local energy communities to participate in energy markets under the role of an aggregator and, in this way facilitate consumer representation in energy markets and flexibility transactions. Based on this work, the paper presents a novel Digital Twin architecture which integrates optimization algorithms and flexibility to achieved demand response. The main objective is through a multi layer Digital Twin, and the creation of different demand profiles at each level, to manage flrxibility and optimize demand respone on consumer, building and community level. Flexibility is considered as the total calculated capacity of demand response for a set period. In practice, this is the total amount of demand that can be shifted over a given window of time, including all possible demand response actions at either the building or community scale. Furthermore, the predictive power of such tools enables the DT to conduct 'what-if' analyses to explore the impact of altering control strategies and assessing the impact of occupant behaviour, for example, allowing relevant stakeholders to de-risk the operational alterations they make in order to reduce energy consumption in their buildings and within their communities.

2. MULTI-LEVEL DIGITAL TWIN ARCHITECTURE

The TwinERGY Digital Twin seeks to leverage the analytical capabilities of DT technology at three different scales, namely the individual consumer, the building level and the community level. The primary objective is the each stakeholder involved within the community ecosystem is twinned to facilitate the detailed analysis of data and prediction of energy use and behaviour at any energy level within the community. The DTs that will be created for the TwinERGY platform differ from traditional DT assets, which are typically informational or asset registry tools, as they are based on dynamic simulation models and leverage actual data regarding the behaviour of individual citizens, the energy consumption and production of the buildings and commuinbities to create fully calibrated DTs. These performance DTs, while based on physics based modelling principles are enhanced through ongoing calibration with near real-time data that is recorded from the actual buildings of which they are a representation. Based on this approach, the TwinERGY DT technology provides users and stakeholders with a cutting edge DT tool that can be used to support a whole range of energy reduction services, including but not limiting energy optimization, emergy consumption and flexibility forecasting, demand response engagement, maximization of RES (Rwnewable Energy Sources) uptake, minimization of energy costs and simulation based building control.

As mentioned previously, TwinERGY seeks to create a three-leveled interconnected DT tool. The overacrching architecture for this technology is presented in Figure 1. As can be seen from the figure, the creation of the DTs is supported by the iSCAN database, which is used to store data collected from the consumers, buildings and community assets. This data is gathered through a network of IoT and other sensors and used to calibrate and validate the accuracy of the various DTs, ensuring that the virtual assets represent and predict actual behaviour and performance. iSCAN then acts as a data repository, facilitating the transfer of processed data between the different DT assets, as well as to a number of functional modules that will leverage the analytical output of the DTs to perform actionable analysis at the building and community levels.

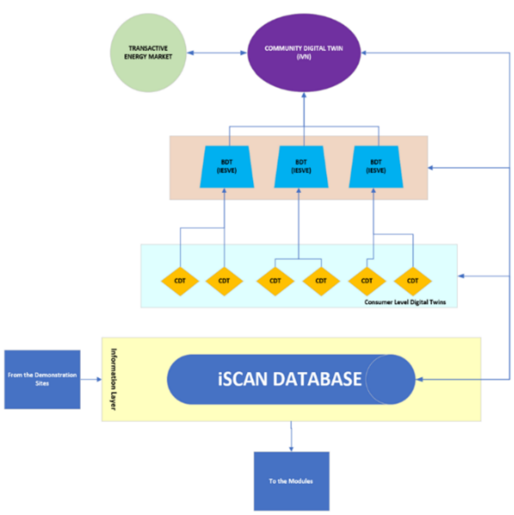

Figure 1. TwinERGY DT Architecture.

2.1. Consumer Digital Twin

Adopting a bottom-up approach to the development and implementation of the DT platform, the Consumer Digital Twin (CDT) is used to virtually represent the behaviour and preferences of the individual building occupant. This particular element of the TwinERGY DT architecture will leverage the individual's physiological data, that will is collected through a novel, wrist-mounted wearable device, as well as other ambient environmental data that is collected through a network of IoT and other sensors located within their building. The CDT will leverage this data, which is supplemented by the collection of qualitative user behaviour metrics and preferences to create dynamic constructs of prosumer energy behaviours, while also establishing consumer preferences with respect to energy usage and openness to engaging in flexibility and demand response actions. With this in mind, the CDT will function as the central element that will facilitate the employment of human-centric demand response optimization strategies, enabling personalized control functions and automation in a non-intrusive manner and without compromising the occupant's comfort, indoor environmental quality or daily operations / schedules for the provision of the required amount of flexibility to aggregators. Furthermore, the CDT will ensure the improvement of demand forecasting at the short and medium intervals through the utilization of the actual data from the building and community to unlock more reliable forecasting of future states of the distribution grid, providing aggregators with improved decision-making metrics and minimizing the potential for DR (Demand Response) strategy overrides that could be initiated by the building occupant and may lead to destabilisation of the grid. The key output of the CDT within the current TwinERGY architecture will be the occupant's preferences regarding participation in demand response actions (acceptance rate) as well as with respect to their comfort preferences. This data will be returned to a dedicated channel within iSCAN and made available to both the Building Digital Twin (BDT) and the Community Digital Twin (CommDT).

2.2. Building Digital Twin

The BDT will be created using the IES Virtual Environment and iCL tools, which currently comprise the market leading performance digital twin platform in use. The TwinERGY project will leverage the BDT as the central digital asset in providing analytical input and forecasting functions to optimize building energy consumption and comfort conditions, predict and forecast energy consumption based on past performance and predicted weather conditions and user preferences and provide analytical and data processing support to other use-cases that are being provided to customers through the TwinERGY platform.

In support of these goals, the TwinERGY BDT is being developed in two distinct but inter-related phases. Initially, a physics based, dynamic simulation model of each of the buildings within the pilot sites is being developed using static information, such as information regarding the components, equipment and systems within each of the residential buildings participating in the project. Once created, these models will then be calibrated using time-series data that is collected from the buildings through the use of the IoT sensors and meters or otherwise. In addition, actual weather conditions from the site is used to ensure that the model is accurately representing the true performance of the actual building. Once fully calibrated, the BDT is then considered to be the BDT and will be used for optimization, scenario testing and forecasting of future performance. This process is supplemented by the output of the CDT to ensure that the occupant preferences and behaviour are accounted for, as well as their willingness to participate in demand response activities. In addition, local energy generation associated with renewable energy sources that are located on the building, such as PV panels, will be forecasted by the BDT.

The key output of the BDT within the TwinERGY architecture is a time-series energy demand profile for each individual building based on the forecasted weather conditions for at least one day ahead. Through the testing period for the tool, the accuracy and practicality of forecasting up to five days into the future will be explored to determine the most accurate prediction period. The demand profile defined through the BDT will be optimized through a dedicated optimization algorithm. The objective function of this algorithm, which represents the parameter for which the profile is being optimized, will be implemented using the preferences from the CDT Similarly the constraints will be defined through the CDT but also through the performance metrics of the components and equipment within the building. For example, if the building occupant defines their preference to be the minimization of energy cost, they have a acceptance rate of 50% (meaning that they are willing to engage in demand response actions some of the time) and they have a 2kW PV installation on their building, the algorithm will function to optimize the demand profile to minimum energy cost, while considering the other constraints on the system. The optimized demand profile will then be returned to iSCAN for use by the CommDT and other services within the TwinERGY platform.

2.3. Community Digital Twin

The CommDT will function to aggregate the demand profiles from each of the BDT to provide a single-pane-of-glass view of the entire community. Further to the building level data, community scale renewable and storage assets, as well as electric vehicles and charging stations will be integrated within the CommDT to accurately represent all energy consuming producing and storage assets within the community. A screenshot of the CommDT of the Hagedorn Community, the German the demonstration site, is presented in Figure 2. As can be seen from the image, each of the buildings within the community are represented on the screenshot, with each of these individual buildings also being connected to its BDT, ensuring that the community grid aggregator has a full representation of the entire community. Furthermore, the characteristics of each individual building can be interrogated to identify the buildings that are consuming most energy, producing the highest level of renewable energy or are most involved in demand response actions in the community.

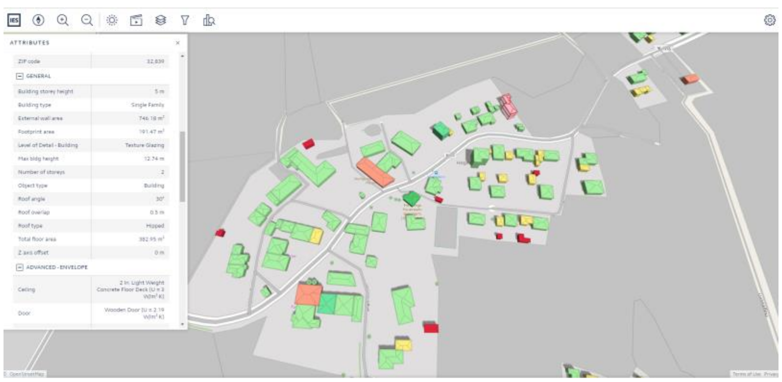

Figure 2. CommDT of the Hagedorn demonstration site.

The CommDT builds on the analytics and forecasted energy demand from the BDT to provide the functionality to analyse the potential for flexibility and demand response actions at the community scale, providing a detailed grid level view of the energy flows within the community network and presenting the community grid operator with the ability and functionality to implement optimization exercises at the grid level. Through the use of optimization algorithms, the CommDT will identify the most appropriate manner in which the forecasted energy demand can be satisfied, based on the level of generation at the community level. The grid view functionality of the CommDT is represented in Figure 3.

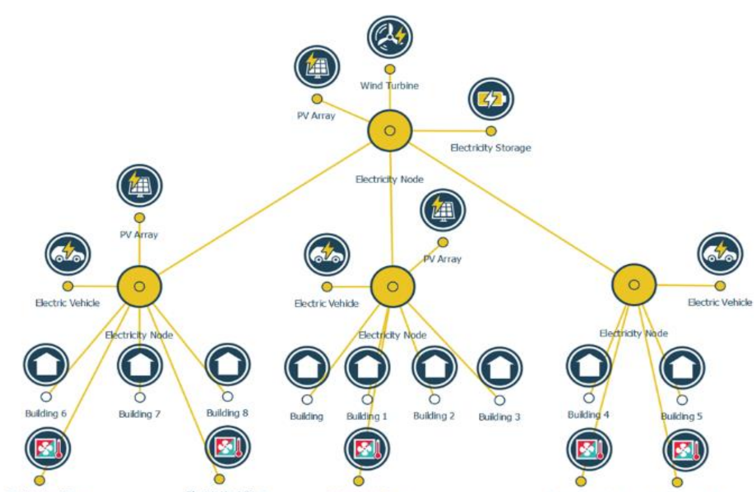

Figure 3. Mock-up of the Grid View functionality provided by the CommDT

Following the completion of the optimization process at the community scale, a set of time-series demand forecasts will be defined for at least one day ahead. These profiles, as well as the forecasted renewable energy forecasts will be returned to the iSCAN platform and made available to the other TwinERGY service providers who will then perform a range of alternative actions, including dispatch of the energy at the community level.

3. FlEXIBILITY AND DEMAND RESPONSE

The forecasting and analytical functionality provided by the TwinERGY DT platform are a crucial component in supporting the implementation of demand response and flexibility algorithms to empower communities to maximize their use of locally generated renewable energy independently of the centralized energy grid. By doing so, communities can not only reduce their carbon footprint and energy cost, but can increase their resiliency to power outages caused for example by increasingly frequent extreme weather events associated with climate change , while also reducing their exposure to increasing energy costs, which will likely have a significant impact on European residents over the coming years [9] [10] [11].

The optimization algorithms utilized in the TwinERGY project are based on the PyGMO library, which is an optimization engine that facilitated multi-objective problem solving [12]. The algorithm is applied to the initial time-series energy demand data that is computed by the DT. Each scale of DT plays an important role in this process, with different inputs, constraints and objective parameters being defined across the entire DT platform. For example, the CDT will define the user preferences with respect to comfort conditions and energy/cost minimization, demand response acceptance level and whether an appliance or load is flexible or non-flexible. The BDT will then develop an initial forecasted energy demand profile based on the next day's weather forecast, as well as the architecture of the building and the performance characteristics of the building's systems and equipment. This profile will then be the main input to the optimization algorithm, which will optimize the time-series demand profile with respect to the user preferences, providing an updated, optimized day-ahead aggregated demand profile for the building. A similar process will occur at the community level, where the community grid energy flows will be optimized based on renewable production and other functions.

As the development of the DT platform remains in progress, the demand response and flexibility algorithms that are to be implemented on the TwinERGY platform have been tested and validated using synthetic time-series data obtained from the open source, StROBe library [13] . Initially, a household comprising three occupants with five flexible and one inflexible load were defined. The flexible loads comprised a dish washer, washing machine, oven and dryer while an iron was presented as an in-flexible loads. The duty-cycles and an acceptable load shifting time period were defined, as well as the number of times the appliance would be used and are presented in Table 1.

Table 1. Appliance Characteristics for Optimization

Appliance Name	Duty Cycle (minutes / job)	Flexible (Y/N)	Potential to Shift (minutes)	# of Jobs
Dish Washer	77	Y	480	1
Washing machine	144	Y	300	2
Oven	25	Y	60	1
Dryer	214	Y	360	2
Iron	10	N	-	1

In addition to the appliance characteristics, a variable pricing structure was imported into the algorithm, with the objective function in this case being the minimization of energy cost. Figure 4 presents the outcome of the validation of this algorithm, with the solid blue line in the figure representing the dynamic energy pricing. The solid red line represents the base case scenario prior to the implementation of the optimization. As can be seen from the chart, there are two durations in which the majority of electrical consumption occurs corresponding with the times between approximately 07:00 and 13:00 and again between approximately 16:00 and 19:00, which is to be expected based on the typical occupancy times of residential buildings.

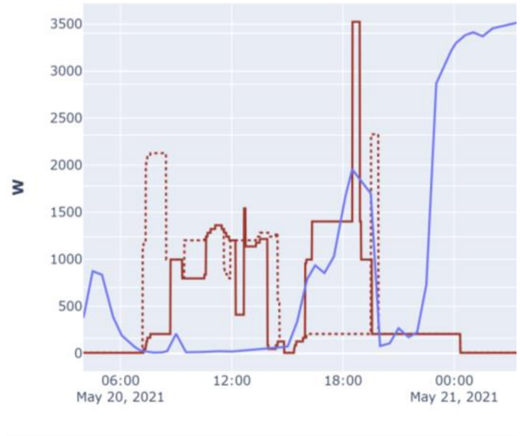

Figure 4. Demand shifting of appliances to minimize energy cost.

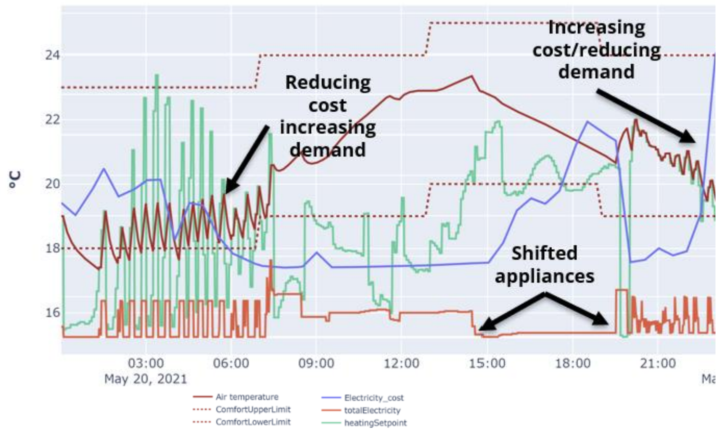

Figure 5. Building performance in terms of air temperature and electricity consumption following optimization.

Moreover, the evening peak corresponds to a time of increased energy costs, meaning that the cost of this energy demand will be higher than the corresponding time in the morning. The baseline energy cost for the operation of appliances in this building for the time period indicated is calculated as approximately £0.77. In order to optimize the energy cost in the building, the flexibility characteristics of each appliance was used as an input to the optimization algorithm along and an updated demand profile was computed for each appliance. This updated profile is represented by the dashed red line in Figure 4. As can be seen from the chart, the energy demand occurring at the time of increased energy cost rate is minimized through demand shifting, with the majority of the demand at this time shifted to times of lower rates, leading to an energy cost during this period of £0.55, corresponding to a 28% decrease in energy cost through the shifting of load alone. By leveraging the analytical and energy forecasting capabilities of the TwinERGY DT platform, optimized appliance scheduling can be implemented in buildings, enabling occupants to decrease their energy bills through leveraging low-cost energy to complete their flexible loads.

The benefit of demand response is not limited to the load shifting of appliances, however, with the use of DTs providing higher resolution insights into building operations, as well as internal environmental conditions. Based on this functionality, optimal HVAC operation can be explored to enable building occupants to reduce their energy consumption while maintaining appropriate thermal comfort conditions. Figure 5 presents the variation in energy consumption and indoor air temperature in the building following its optimization and the implementation of demand response actions. As can be seen, the air temperature setpoint, which is represented by the green line, varies significantly more than shown in the baseline condition. Considering the time period before 09:00 on the chart, it can be seen that the heating setpoint begins to change from approximately 03:00 as the air temperature falls below the lower comfort limit. As the energy cost begins to decrease, the demand increases as the algorithm begins to attempt to increase the air temperature in line with the comfort conditions. As the day progresses, the algorithm, continues to dynamically change the heating set point based on the indoor air temperature and the comfort preferences of the user. As the energy cost begins to increase at approximately 15:00, however, the air temperature begins to decrease as the algorithm starts to reduce the set point in response to the increasing tariffs. This continues until the reduced tariff commences shortly after 18:00, while the temperature is allowed to decay down for the evening, remaining within the comfort preferences of the occupant while also reducing energy consumption inversely with the rising energy cost. One final point of note is that the appliances have been shifted here again to less expensive time periods to further reduce energy cost. Based on this analysis, the energy cost for the day is £0.92, a 25% reduction on the baseline.

The previous use case have assumed that the acceptance rate for demand response actions will be 100%, meaning that the occupant is completely open and willing to implement all demand response actions in their building, an assumption that is typically limited to explicit demand response action and is unlikely to be practical in real residential buildings. As mentioned previously, the CDT plays a key role in defining user preferences, as well as identifying the user's acceptance rate as well as their individual taxonomy of flexible loads. This plays a key role in enabling the BDT to forecast energy demand appropriately while also providing constraints to the optimization algorithms.

Figure 6 presents the results of an analysis of the various acceptance criteria within a community of 39 semi-detached residential homes each with their own solar PV array (4kWp) and demand profiles as described previously. Leveraging the IES DT tools, demand profiles over the course of a single day were calculated for each building and then aggregated across the community. This community demand profile then underwent a multi-criteria optimization against energy cost, renewable generation usage and diversity factor, with the simulation being repeated for four distinct demand response acceptance rates (25%, 50%, 74% and 100%). The base case is represented by an acceptance rate of 0%.

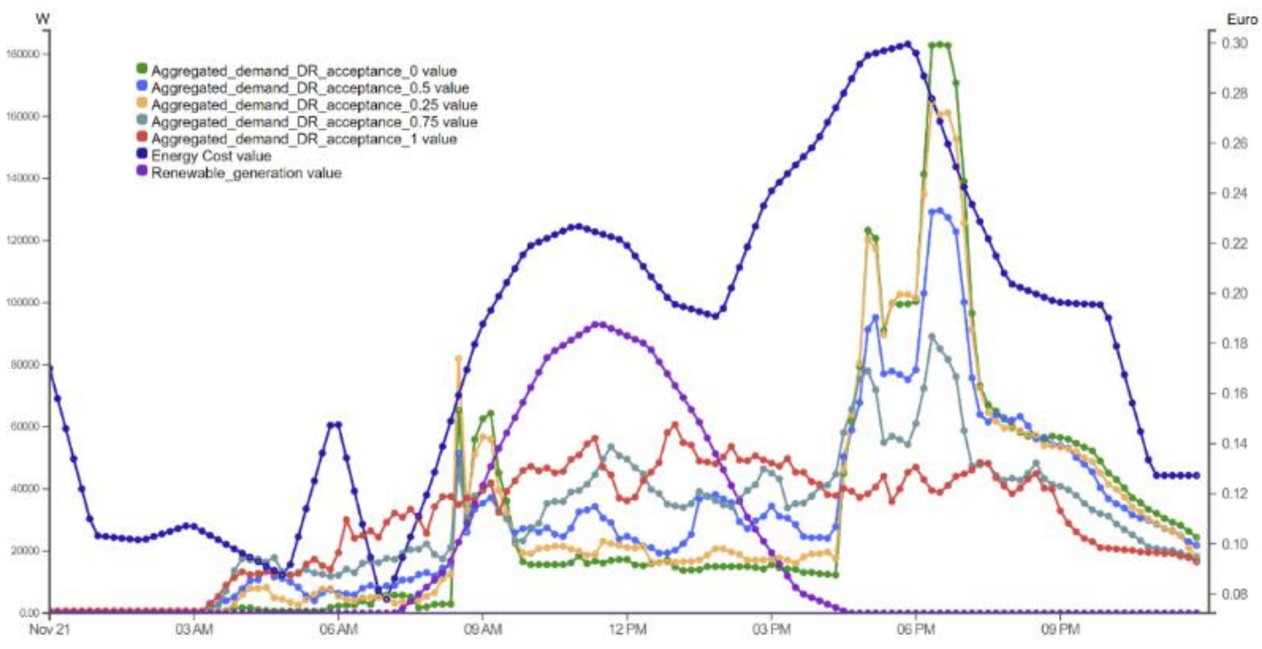

Figure 6. Different acceptance criteria at the community level.

As is clear from the chart and as expected, the higher the level of acceptance towards participating in demand response actions, the smoother and less variable the demand profile. This is most obvious when comparing the green (base case, or 0% acceptance) and red plots (100% acceptance). The unoptimized green profile is consuming the highest proportion of power in the evening, when the renewable energy is unavailable and the time-of-use cost is highest. Compare this then to the most optimal red profile, which peaks during the time of maximum renewable energy generation, when the time-of-use cost is not at a peak and is also the most consistent across the day. It should be noted, however, that this level of acceptance is not necessarily viable for all users, as certain users will not be home during that time of the day, and other preferences will be provided by the consumer digital twin, which will define further constraints, however it is important to note that at this point, prior to the availability of real world data from the pilot sites, the algorithm is performing as expected with increasing acceptance rates of demand response actions corresponding to more optimal demand profiles compared to the base case scenario.

4. CONCLUSIONS AND FUTURE WORK

This paper has presented an overview of the progress to date in the development of the TwinERGY DT platform and associated flexibility and demand response algorithms. Based on the research to date, it can be concluded that the forecasting and prediction functionality of DTs provide a building occupants and managers with a key digital asset to assist in the reduction of energy consumption in their building, particularly when used in conjunction with the flexibility optimization algorithms described within this paper at both the building and community level. This has the potential to create a step change move towards decarbonization and facilitate the proliferation of community grids across the EU, thus reducing the dependency of the residential market on the central grid and providing resiliency in the face of increasing grid stability and rising energy costs. This impact will have on the normal building occupant cannot be understated.Testing and validation of the algorithms, particularly under other objective functions will continue while the DT platform is developed, allowing quick adaption and implementation of the algorithms to the DT platform once ready. This process is ongoing as static data is provided by each of the demonstration sites participating in the project. It is intended that the algorithms developed through the project will be incorporated into the DT platform to create a single tool that can be used to analyse and implement demand response actions at the building and community level.

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