Self-Learning Control Algorithms for Energy Systems Integration in the Residential Building Sector

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***Abstract*— This paper provides a research plan focusing on the application of self-learning techniques for energy systems integration in the residential building sector. Demand response is becoming increasingly important in the evolution of the power grid since demand no longer necessarily determines system supply but is now more closely constrained by generation profiles. Demand response can offer energy flexibility services across wholesale and balancing markets. Different applications have focused on the Internet of Things in demand response to assist customers, aggregators and utility companies to manage the energy consumption and energy usage through the adjustment of consumer behaviour. Even though there is extensive work in the literature regarding the potential of the commercial and the residential building sectors to provide flexibility, to date there is no standardised framework to evaluate this flexibility in a customer-tailored way. At the same time, demand response events may affect occupant comfort expectations hindering the utilisation of flexibility that building energy systems can provide. In this research, the integration of machine learning algorithms into building control systems is investigated, in order to unify the monitoring and control of the separate systems under a holistic approach. This will allow the operation of the systems to be optimised with respect to reducing their energy consumption and their environmental footprint in tandem with the maximisation of flexibility, while maintaining occupant comfort.**

Keywords — energy flexibility, demand response, machine learning techniques, energy systems

I. Introduction

Nowadays, demand response (DR) is evolving into a promising technology with numerous services already commercially available. DR will be an inextricable component of the grid operator policies, since it can facilitate the integration of renewable energy resources and cope with rapid and unexpected demand changes, which can threaten grid integrity. Furthermore, DR enhancement can offer market revenues and reduce the need for investment in peak generation capacity as well as reduce the dependence from foreign energy imports and in the same time lower consumer electricity bills [1]. Energy flexibility can enable shifting any discretionary usage away from peak consumption times. This allows electricity system operators to limit using inefficient peaking generation plants.

Nowadays, the availability of dynamic price tariff schemes and the ongoing evolution of thermal and electric energy storage can further foster demand-side energy flexibility as well as enhance the stabilisation of grid demand [2]. To tackle the barriers to flexibility in the residential building sector, the quantification and characterisation of the energy flexibility potential are deemed a priority [3]. Despite its importance, many EU member states lack standardised measurement and baseline methodologies concerning energy flexibility evaluation, although the electricity industry is undergoing a dramatic transformation to ensure consumer benefits, increase the security of supply and reduce carbon emissions [4]. In fact, EU members have paid little attention to these methodologies in order to accurately measure consumption changes resulting in market barriers. This means that consumers may not necessarily receive precise payments for the services they deliver [4].

To address the barriers to energy flexibility procurement, the uncertainties relative to climate, pricing, and behavioral factors should also be considered. Thus, customer engagement with DR services requires systematic communication and interaction between aggregators and the people it serves, with the intent of building trust, respect, and achieving optimal energy usage amongst the heterogeneity of individual households. In fact, the heterogeneity amongst residential consumption patterns poses an additional challenge to the energy service providers. Specifically, energy providers have to learn from customer individual preferences in order to implement the optimal DR actions considering dynamic tariff targeting, as well as consumer

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satisfaction [5]. In order for the DR providers to improve their bidding strategy and efficiency, it is of paramount importance to forecast user consumption behaviour during DR and non-DR periods by targeting households with a high flexibility potential during DR hours. Furthermore, to protect the customer-aggregator relationship and to provide a direct path to the market, energy providers should introduce standardised processes for bi-directional payment of sourcing costs.

Nowadays, the deregulated energy market can incentivise individual customers to widely participate in a DR programme to minimise the electricity bill or even earn a revenue from the procurement of energy flexibility services. Moreover, the evolution of Internet of Things (IoT), along with the availability of building data by smart meters can further foster automated energy management systems in the residential sector [6]. In addition, the availability of various demand-side flexibility end use categories can offer a plethora of control schemes both profitable for service providers and customers. However, the major challenges regarding energy flexibility procurement by households are due to the difficulties to model and estimate in a precise way the residential energy consumption [7].

In Ireland in particular, ancillary services - such as balancing market programmes – as well as the interruptible load programme STAR (Short-Term Active Response) is adequately designed and already in use. This program includes ten to twenty unplanned and instantaneous interruptions per annum typically of the order of 5 minutes duration. Regarding the energy capacity markets, only price-based schemes are commercially available at the moment, while volume-based schemes are still closed. Today, only a meter-before/meter-after system is used, and no common baseline methodology has been agreed upon. In fact, there is room for optimisation in the prequalification procedure for Demand Side Units [1].

The next section of this paper denotes the overall research aim, as well as the identified research gaps and questions. In Section III, the research methodology is described while in Section IV the expected contributions of this research are explained. Finally, in Section V some preliminary results from this work are given.

II. Project aim, Research Gaps and Questions

A. Project Aim

To date, the existing literature regarding automated energy management systems exploit the residential devices flexibility potential to achieve various objectives e.g., financial, environmental, etc. Customer-oriented methods to evaluate the energy flexibility potential and energy management systems with ongoing self-learning capabilities have not been developed for the residential sector. From the above-mentioned, the overall aim of this research can be stated as follows:

"The development of a methodology to assess the energy flexibility of residential buildings, while at the same time ensuring adaptability, scalability and robustness of building flexibility through a self-learning control scheme".

B. Research Gaps

- The existing literature concerning the energy flexibility potential in the residential sector is either confined to individual loads such as HVAC (heating, ventilation, and air-conditioning) systems [8], curtailable devices [9] or thermal and electrical energy storage [10]. Nevertheless, few studies develop baseline methodologies for various energy mixes under a holistic approach. The scope of this paper is to develop a suitable methodology to quantify and evaluate energy flexibility in the residential sector.
- Although extensive research has been carried out concerning habitual behaviour identification in residential electricity consumption [11-13], few studies develop customer tailored methods to assess the energy flexibility potential of residential scale buildings.
- Within existing research, occupancy, pricing policies and weather prediction are taken into account by integrating additional constraints to the optimisation problem [14-16]. Few studies explore the potential of a control scheme to learn and gain more experience in real-time operations under uncertain changes of the building environment.

C. Research Questions

Considering the aforementioned Research Gaps, three key Research Questions (RQ) will be addressed within this research as follows:

1. *RQ1: Is it possible to develop a suitable methodology to quantify and characterise energy flexibility in a residential building?*

   In the context of the above-mentioned question, the most suitable indicators will be identified to evaluate the energy flexibility in a typical residential building. Furthermore, the way by which energy flexibility is influenced by the energy mix and end-use energy components of a dwelling will be examined.

2. *RQ2: Is it possible to develop a methodology to evaluate and optimise the energy flexibility of a household using data-driven approaches?*

   The most suitable variables to develop predictive models for residential consumption will be identified and the most appropriate data driven method to predict energy consumption under different climate, pricing policies, behavioral patterns, and dwelling types.

3. *RQ3: How should a self-learning-based home energy management system be developed in order to optimally integrate demand response strategies?*

The most suitable data-driven methods will be identified to enhance and evaluate the performance of selected DR strategies, the most suitable optimisation techniques to integrate DR events, and the way by which different DR strategies can influence the performance of the control scheme.

III. Research Methodology

To address the research gaps, a calibrated white box model of a smart grid ready residential building is utilised. The selected testbed is a single-storey detached house representing 40% of the Irish building stock and is the most common single building category. It was constructed in 1973 with increased thickness of insulation materials in its opaque elements compared to the contemporary standards. As a result of its construction (two-leaf concrete wall with cavity insulation), it exhibits significant passive thermal energy storage capacity. The space heating system is a 12 kW (thermal output) ground source heat pump (GSHP). The white-box model used to develop and analyse the DR control algorithms was created using EnergyPlus V.8.9 and calibrated using monitored data from the building [2]. Figure 1 shows the case study building and the modelled prototype.

Fig. 1. 3D rendering and picture of testbed house.

Subsequently, a sensitivity analysis under various penalty signals will be carried out to identify the resulting electricity demand changes. To account for the major energy components of the building, their individual characteristics will also be considered as boundary conditions. For example, when it comes to electric vehicles, their boundary conditions can be determined by their required energy and user-defined charging time. The acquired datasets will be used as inputs to the data-driven methods to be developed in RQ2.

To specify strong interrelationships between the input variables, data analysis algorithms will be implemented. This analysis will be used to select the most suitable data-driven methods in order to predict the energy flexibility potential of the residential loads. Current research denotes that energy consumption can be predicted by using artificial neural networks, support vector machine, decision trees, multiple linear regression, ordinary least squares regression and other data-driven techniques [17]. The predictive performance of the designed algorithms will be assessed by the energy flexibility indicators obtained in RQ1. The data-driven approaches developed in this research stage will be integrated into the third and final stage of this work.

In this stage, the most suitable algorithms to solve the optimisation problem will be selected and will be combined with the designed data-driven methods into a unified control scheme. The later will be eventually evaluated under different DR strategies. The schematic diagram of the project structure is depicted in Fig. 2.

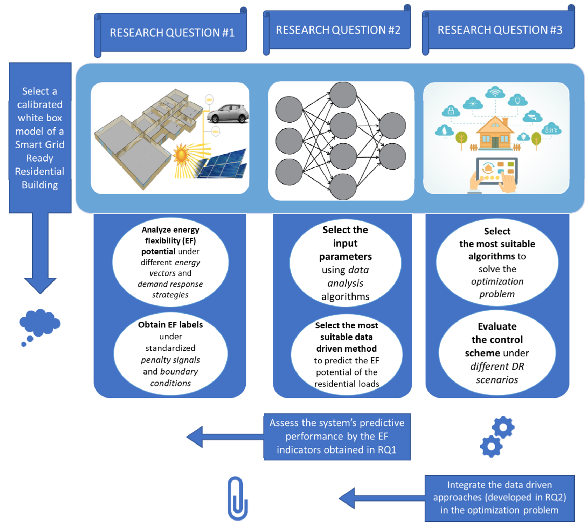

Fig. 2. Research Methodology

IV. Expected Contributions

The expected outcome of RQ1 is the development of a suitable methodology to quantify and characterise the energy flexibility in the residential sector for different residential energy mixes. By taking advantage of the obtained energy flexibility indicators, the data-driven methods determined by RQ2 will enhance the predictability of the residential consumption and the awareness of the energy flexibility potential for all stakeholders. The ultimate scope of RQ2 is to allow for more optimal use of demand energy flexibility under climate, price and behavioural uncertainties. In RQ3, a methodology will be developed to obtain the optimal control strategy for different consumers as well as changing pricing policies, climate and dwelling type, based on the demand and system configuration.

V. Preliminary Results and Discussion

In order to characterise and quantify the flexibility potential of the virtual testbed, the performance of various DR actions is evaluated. Specifically, a sensitivity analysis of two case studies for the testbed was considered with a flat tariff step increase (down-flex) and a flat tariff step decrease (up-flex). These changes were defined as step changes in the temperature setpoint for different DR durations and temperature degrees. A full heating season is considered with a constant temperature setpoint at 22°C. To evaluate these events, the difference $\dot{Q}_{diff}$ between the modulated $\dot{Q}_{\mathrm{mod}}$ and the reference $\dot{Q}_{ref}$ electrical demand $\dot{Q}_{diff} = \dot{Q}_{\mathrm{mod}} - \dot{Q}_{ref}$ is considered. The flexibility indicators used in this study are the available structural storage capacity (C_{ADR}) (equation 1) and the storage efficiency (η) [18].

$$C_{ADR} = \int_0^{L_{DR}} \left| \dot{Q}_{diff} \right| dt \quad (1)$$

The storage efficiency for down-flex and up-flex is given by equations 2 and 3, respectively.

$$\eta_{DF} = 1 - \int_{L_{DR}}^{\infty} \dot{Q}_{diff}\, dt \Big/ \int_0^{L_{DR}} \dot{Q}_{diff}\, dt \quad (2)$$

$$\eta_{UF} = 1 - \int_0^{\infty} \dot{Q}_{diff}\, dt \Big/ \int_0^{L_{DR}} \dot{Q}_{diff}\, dt \quad (3)$$

Figures 3 and 4 illustrate DR efficiency as a function of DR duration for a 1°C and 2°C temperature decrease (down-flex, Fig. 3) or increase (up-flex, Fig. 4). In both cases, the efficiency of the DR events depends on the temperature setpoint change and the DR duration (L_{DR}). Specifically, in down-flex a temperature setpoint reduction of 1°C is more efficient compared to a temperature reduction of 2°C. However, in up-flex a temperature setpoint increase of 1°C is less efficient compared to a temperature increase of 2°C. Further research is currently ongoing to extend this sensitivity analysis to include more energy components (energy storage, curtailable devices, etc.) and the appropriate indicator functions which describe their operation. The obtained results will lead to the suitable categorisation of the residential consumption permitting the controllable demand quantification. This research forms a foundation to develop optimal DR strategies and integrate them in a holistic manner in an Energy Management System. The novelty and the contributions will be proven after the evaluation of the data driven-approaches.

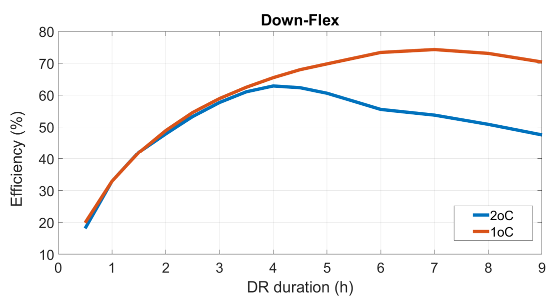

Fig. 3. DR efficiency in Down-Flex.

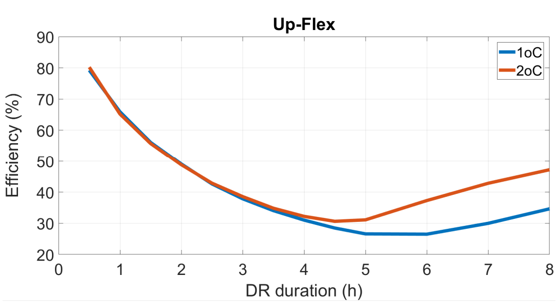

Fig. 4. DR efficiency in Up-Flex.

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