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Orchestration of Renewable Generation in Low Energy Buildings and Districts using Energy Storage and Load Shaping.

P. Tuohy[a]*, J-M. Kim[a], A. Samuel[a], A. Peacock[b], E.Owens[b], M. Dissanayake[b], D. Corne[b], S. Galloway[a], B. Stephen[a], S. Santonja[c], D.Todoli[c]

[a]ESRU, University of Strathclyde, Glasgow G1 1XJ, UK
[b]Herriot-Watt University, Edinburgh, EH14 4A , UK
[a]ITI, Instituto Tecnológico de Informática, Valencia 46022, Spain

Abstract

There is increasing penetration of renewable generation in buildings and districts. There are challenges in making the effective use of this generation. The objective of the ORIGIN project (Orchestration of Renewable Integrated Generation In Neighborhoods) is to shape loads so that the fraction of energy consumed that is from local renewable generation is maximized, and energy imported from outside sources is minimized. This paper presents the overall approach taken in the ORIGIN project and explores building physics aspects of solar thermal storage system orchestration. The case study districts are briefly introduced and characteristics of their generation, buildings, districts and shiftable loads described. The orchestration approach taken in ORIGIN is then presented. At the core of the ORIGIN system is the orchestration algorithm which generates informational and control outputs to shape future loads to best meet the objectives. The model based approach used to quantify thermal and electrical load shifting opportunities for pre-charging, coasting or avoiding loads, while meeting thermal comfort and other demands, is described using a solar thermal storage system as an example. The future steps for the ORIGIN project; retrofit of the ORIGIN system into existing districts and potential for other future applications is briefly discussed.

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Keywords: DSM; Load shifting; Renewable; Districts; Demand response;; Predictive Control; Forecasting; ORIGIN concept; eco-communities;

* Corresponding author. Tel.: +44-141-548-2083 ; fax: +44-141-548-4851 .
E-mail address: paul.tuohy@strath.ac.uk

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1. Introduction

There have been many efforts worldwide focused on load shaping and demand side management through real time pricing, storage and control schemes [1,2,3]. The ORIGIN project [4] takes three existing eco-communities with high local renewable integration and seeks to develop advanced algorithms and methodologies that can significantly increase the extent to which use is made of the local renewable resources and reduce the extent to which energy resources need to be imported. The ORIGIN concept is that algorithms can be developed to: (i) stimulate occupants to change behaviors and (ii) to take remote control of systems, and achieve the project aims.

The ORIGIN system is cloud based, inputs are received from monitoring and control devices, algorithms use this data to generate informational and control outputs which are delivered back to the communities. The ORIGIN informational feedbacks are through a library of widgets which provide specific information and viewed through web or phone. ORIGIN direct control is through remote switching of smart plugs either directly powering loads or powering relays inserted into existing control circuits.

This paper is intended to give an overview of the ORIGIN system development and deployment and then to give details of the approach taken to load shifting and control, using a solar thermal storage system as an example.

2. ORIGIN case study districts.

The ORIGIN project is engaged with three eco-communities with high renewable generation: Findhorn in the north of Scotland, Damanhur in the north of Italy and Tamera in central Portugal. These sites have very different characteristics; Findhorn has a local wind farm with 4 wind turbines and 750kW capacity, a private wire electrical network, over 75 buildings including 15 non-domestic buildings, high penetration of solar thermal systems, a range of heating systems including heat pumps, stand alone and district biomass, generally well insulated buildings including some approaching Passivhaus, some photovoltaic generation, and some electric Vehicles; Damanhur has high levels of public grid connected photovoltaic, biomass and solar thermal systems serving a large commercial and retail building plus a number of 20 person communal residences; Tamera has a large islanded photovoltaic and battery storage system, solar thermal systems, electric vehicles and water pumping loads. For reasons of brevity in this paper the focus is primarily on Findhorn.

The 750kW of wind generation at Findhorn allows the community to be around 'net zero' in terms of its electricity supply from the grid but the actual supply / demand balance is highly variable. Figure 1 shows the renewable supply to demand matching for 4 days in February 2015 illustrating periods when surplus is exported to the grid and shortfall when grid electricity is imported. An aim of ORIGIN is to re-shape the load to make more use of the local renewable generation and reduce imports.

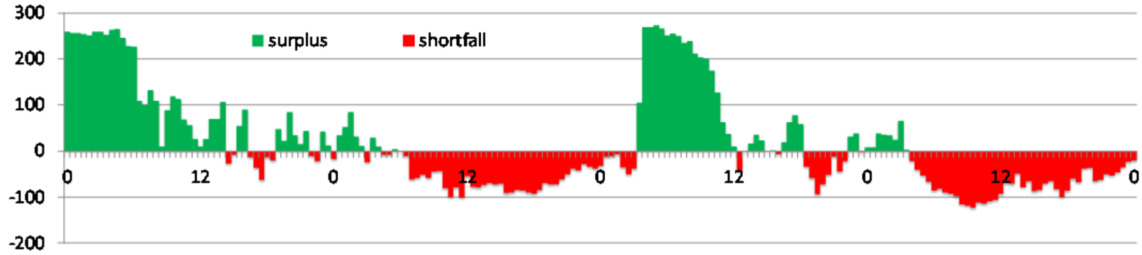

Fig. 1. Findhorn Supply / Demand surplus and shortfall in kWh per 30min period.

3. Audit, Monitoring, and Identification of Load Shift Opportunities.

A starting point for the ORIGIN process was to audit the communities to map the energy flows, establish renewable and non renewable energy system characteristics and identify potential load shaping opportunities. The next step was to establish energy monitoring to support performance quantification and algorithm development.

Based on review of the works of others and brainstorming at the start of the project 24 different load shift opportunities were identified, these can be grouped under three categories: thermal controllable loads, electrical controllable loads, and personal behavioral loads. Thermal controllable loads are those where some heating or cooling demand is to be met and there is some potential for thermal storage that can be related in some way to a temperature measurement and controlled directly through the ORIGIN system. Electrical controllable loads are those that are not related to a thermal measurement but can be directly controlled. Personal behavioral loads are those that can only be indirectly controlled through ORIGIN but rely on human interventions.

Three building types at Findhorn were adopted as focus buildings for automated control within the project. These were picked based on the available load shift opportunities and also due to their being representative of increasingly common building types, maximizing the potential for replication elsewhere.

The first building type identified is the 'Centini' which is a terraced domestic building with high insulation, a large solar thermal panel feeding a 500litre thermal store with backup direct electrical heating supplied with night time reduced tariff electricity, there are 14 of these dwellings at Findhorn. This type was picked due to the large thermal store and high building time constant. The second type is the 'Whins' which is a dwelling constructed in 2012 to close to Passivhaus standards, serviced with an air-sourced heat pump with backup electric boost heater and a solar thermal system, there are 25 of these dwellings at Findhorn. Several of the Whins also have large photovoltaics. This type was picked as being representative of a building type becoming more common in the EU with a high load shift potential due to the presence of a 210litre hot water storage tank and high building time constant. The third focus type at Findhorn is the 'Soillse', there are 6 of these dwellings constructed with high thermal mass and insulation standards, these are serviced by a biomass district heating system with central thermal store feeding individual dwelling hot water tanks with solar thermal panels and electrical backup. Again thermal store and high building time constant led to this type being selected. Figure 2 shows the three focus house types.

Fig. 2. Focus Building Types: (a) Whins; (b) Centini; (c) Soillse.

4. ORIGIN Orchestration: Algorithms and Outputs.

The approach taken in ORIGIN has been first to provide performance feedback widgets to inform and engage the communities. A range of user selectable performance feedback widgets has been provided, a selection of these is shown in figure 3, these can display feedback from the previous day, week, month or since ORIGIN start. The 'Green-O-meter' shows the percentage of consumed electricity that is from the local wind generation and the goal of the project is to maximize this. Widgets can be selected that represent either the total community performance or a specified individual building performance.

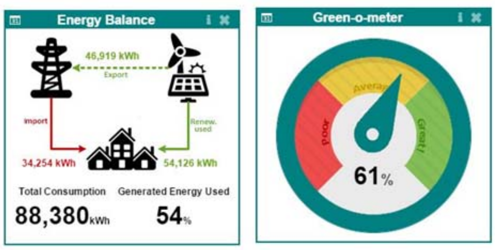

Fig. 3. Historical Performance Feedback Widgets: Energy Balance; Green-O-meter (% of consumed that is from renewable);

To drive performance improvement an algorithm has been developed to deliver future load shaping to best match with predicted generation. The algorithm consists of the following component parts: (i) a weather prediction algorithm, (ii) a renewable generation algorithm, (iii) a demand prediction algorithm, (iv) a gap analysis, (v) a load shift opportunity quantification algorithm, and (vi) an optimization algorithm. The weather, generation, demand and gap analysis components are used to feed widgets to stimulate user behavioral responses to forecast surplus or shortfalls (Figure 4). Behavioral response stimuli include flexible electricity tariffs. The weather and behavior forecasting algorithms and the widget design process are reported on elsewhere [5]. The optimization algorithm also outputs the control schedule to automatically shape the future load. The time-step between iterations of the algorithm is currently set to 30 minutes although different time horizons are used to inform different aspects e.g. tariff commitments remain fixed for a 24 hour horizon etc.

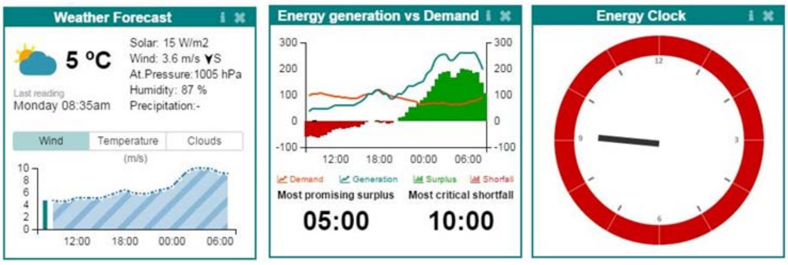

Fig. 1. Behavior Stimulus Widgets: (a) Weather; (b) Gap forecast; (c) Energy availability clock.

5. ORIGIN Orchestration: Opportunity Prediction, Storage and Actuation.

Load switching hardware based on smartplugs has been implemented to give remote control of space heating, hot water heating, electrical vehicle charging and kitchen appliances. For space and water heating the smart plugs power relays that override standard on/off control signals, thermostats are not affected and users can switch off the ORIGIN controls and resume normal operation if desired. The heating and hot water loads have the largest potential for load shifting, figure 7 (a) and (b) show the total daily profile of heating and hot water load for the 14 Centini and 25 Whin types over the same period as in figure 1. The total shiftable load is around 600kWh per day, enough to make a significant impact. Figure 7 (c) shows the top and bottom storage tank temperatures in ^{o}C for a Whin for a period including 4 normal morning charging and bathing cycles, on the second the charge cycle is boosted with the impact that no charge is then required for day 3, illustrating the potential for load shifting on a day to day scale.

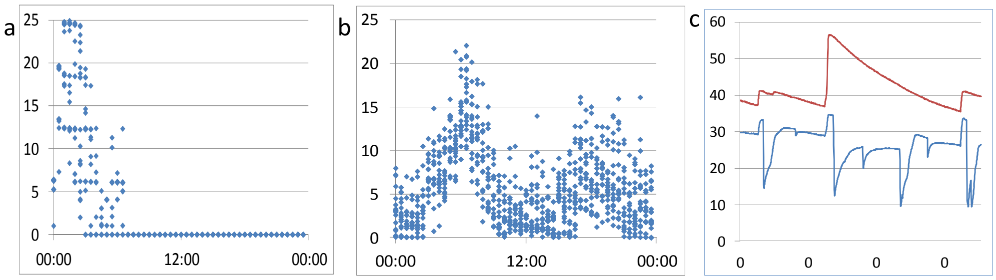

Fig. 1. Shiftable heat loads: (a) Centini in kWh per 30min; (b) Whins, kWh per 30min; (c) Whin top and bottom tank ^{o}C.

At each iteration of the algorithm a forecast is made of the future gap between renewable generation and local demands for the upcoming 48 hour period. The load shift opportunity quantification algorithm produces a vector set capturing forecast load flexibility for each of the potential opportunities. These vectors capture potential for pre-charging or delaying 'coasting' the load beyond the normal load times. The optimization algorithm then selects the most appropriate control actions to take, and these control actions are implemented through the cloud and switching hardware. The opportunity quantification vector is of the following form: [timestamp (48hrs @30min steps): F_Q_load, F_Qprecharge, F_Qcoast, F_h_coast, F_h_prech_coast, F_Cost] where F_Q_load is the forecast load were the load to occur at the standard time, F_Qprecharge is the forecast capacity for absorbing surplus and reducing the standard load by pre-charging, F_Qcoast is the energy that would be required to charge the load if it were to be coasted , F_h_coast is the predicted hours that a load can be coasted for and still meet the comfort requirements, F_h_prech_coast is the hours that the load could be coasted if it were to be charged at this timestep, F_cost is the cost factor taking account of the extra energy that may be used due to increased losses or lower efficiencies if a load is pre-charged or coasted. These vectors are then sifted by the optimisation algorithm and an optimal schedule of actions established.

6. ORIGIN Orchestration: Opportunity prediction for a solar thermal storage system.

To predict the vectors associated with a solar hot water storage tank it is necessary to capture system characteristics in a model for use together with forecasted weather and user demand. The ideal model is one detailed enough to represent system behavior but able to be informed by a relatively simple monitoring set. The approach taken was to initially use a superset including heat meters (figure 5 (a)) and investigating a reduced set.

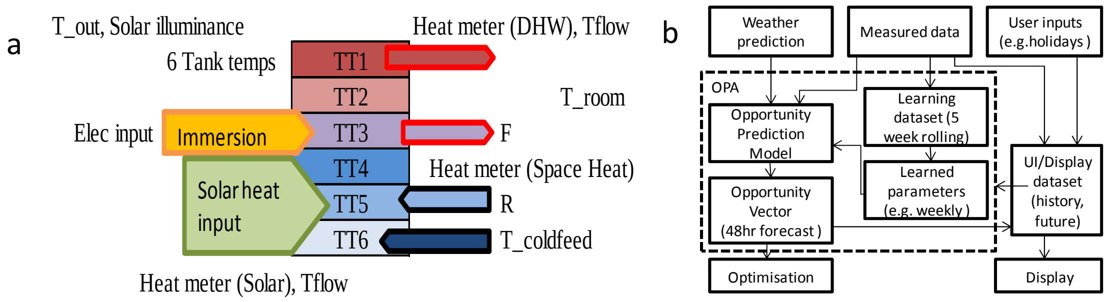

Fig. 5. Hardware and Software for load shifting (a) Monitoring superset; (b) Algorithm flowchart.

After considering a range of possible physical models a 6 segment energy balance model adapted from that of Duffie and Beckman [6] was selected where each segment has an energy storage associated with its temperature and these temperatures are modified based on relevant energy inputs and outputs. The 6 segment temperatures can be easily measured, and then future temperatures predicted for each timestep using the model and weather and demand forecasts. These measured and predicted temperatures allow vector parameters to be determined.

Necessary inputs to the model energy balance are: physical parameters (volume, geometry e.g. position of inflows and outflows etc), heat loss and de-stratification characteristics, standard heating times and setpoints, desired comfort temperatures, space heat and hot water demands, and solar inputs. These are informed by the system audit and periodic analysis of a 'learning' dataset of the rolling previous 5 weeks. User inputs can also be gathered to inform the system of changes in behaviors e.g. holidays, visitors etc.

The underlying heat loss and de-stratification characteristics of the tank are determined as a function of segment temperature by regression analysis in periods without other energy inflows and outflows. Standard heating times and setpoints are inferred from the learning dataset or from user inputs. The desired comfort temperatures are set at standard values or can be inferred or adjusted based on user inputs. Domestic hot water demands are set based on the pattern established from the learning dataset and user inputs, process control statistics are established (mean, sigma) and may be used to detect and respond to changes in behavior e.g. query the occupant. The comfort level and level of service can be adjusted by altering the statistical safeguard used on demand forecasts. Where space heating demands are also met from the storage tank then the pattern of use is a function of the outdoor temperature and solar radiation. Solar inputs to the tank are established in a three step process: first the threshold illuminance below which no solar input occurs is established; then the solar flow temperature dependence on solar illuminance, tank bottom temperature, and outdoor temperature determined; finally the solar energy input is determined as a function of the temperature difference between the solar flow and tank segment temperatures for the given timestep. The model based prediction methodology has so far been investigated for the Centini, Soillse and Whins solar thermal storage systems with promising results. Figure 6 shows an example of solar heat input regression output and the predicted and actual performance of the model for a Centini water tank for a winter period. The regressions in this case gave R-squared values for the solar flow temperature and solar heat inputs greater than 0.95 and 0.9 respectively. It should be noted that in this case the panel had an uninterrupted southerly aspect, where there is shading at some times of day then this also needs to be included. The predictions for the warmer top of the tank temperatures are most important for the delivery of heat to meet demands and for quantification of the ability to precharge and coast the load. The largest discrepancy seen is for the lower temperature nodes due to the influence of the timing of the occupant water draws being different to that predicted, the opportunity quantification algorithm corrects for these offsets by re-forecasting based on the measured tank temperatures at each future time-step.

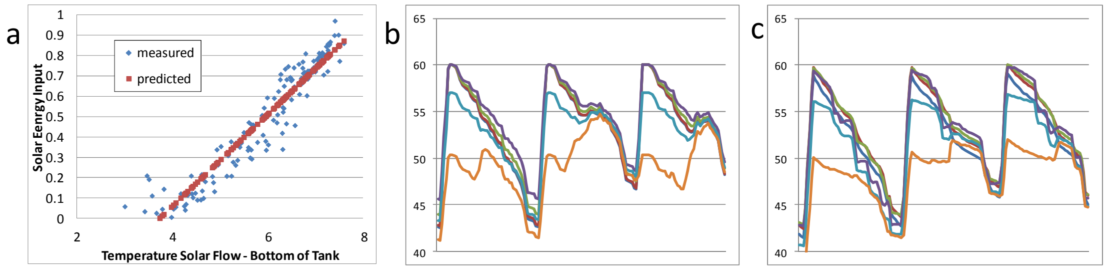

Fig. 6. Model Prediction (a) Solar Energy Regression; (b) Measured Tank Temperatures; (c) Predicted Performance.

7. Discussion and further applications of the ORIGIN concept.

The ORIGIN project is ongoing until November 2015 and this paper describes the overall concepts and methods being applied and gives the example of load shifting methodology applied to a solar thermal storage system of a type becoming increasingly common. Further progress and results will be forthcoming. The availability of weather forecasting and relatively inexpensive monitoring and IT infrastructure makes this approach increasingly applicable. The cloud based approach of the current deployment of the ORIGIN concept could equally be deployed in a more local IT infrastructure.

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