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The Use of Demand Modelling for Community Energy Analysis

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Abstract—In this paper the challenges of creating accurate, scalable and usable energy demand models are discussed, in the context of existing simulation and data driven energy demand models. Results from high resolution bottom-up data and simulation-based energy demand analysis from a community energy project are provided. A novel Hidden Markov Modelling (HMM) and Generalised Pareto (HMM-GP) methodology for simulating synthetic electrical demand profiles is validated for residential buildings at a temporal resolution of five minutes. The corresponding dynamic thermal demands for the various building archetypes within the community are also modelled. This is achieved using automated externally driven IES-VE (building simulation) models for arrays of control profiles, and is also compared against in-situ thermal measurements.

Keywords—energy demand, thermal modelling, aggregation, data analysis

I. INTRODUCTION

Recent trends in energy demand associated with the residential building sector have stimulated great research interest around the development of accurate computer models. It was reported in July 2017 that UK domestic energy demand showed the biggest increase of any sector, this correlating with fluctuations in temperatures and resulting household consumption for space and water heating [1]. Global building energy demand projections have highlighted a rise in demand for domestic buildings, with the US Energy Information Administration indicating an increase of 32% between 2015 and 2040, as a product of improving living standards [2].

Domestic energy demand models aim to identify primary trends in electricity and gas consumption, but also provide valuable input to energy demand forecasting and policy formulation though an understanding of causation. Such models can be considered part of one of two groups: top-down and bottom-up. Drivers for accurate energy demand modelling capabilities include: improving energy efficiency of buildings (new and legacy); understanding consumer usage; as input data to models examining energy infrastructure investments, energy network control and automation. In terms of the latter, these models can play a role in wider energy system modeling (e.g.

integrating with models such as UKTM [3]), this new approach enabling significant improvements to the present norm, this being predominantly data driven with no causal link to narratives that describe future trends. Long-term planning (typically optimisation based) models form the foundation of the present approach at the administrative level in most developed countries; however, as these are heavily reliant on historic demand data, this overlooks relationships between society (at various scales) with new technologies (e.g. for heating and transport), distributed generation and storage, peer-to-peer energy trading and demand response.

There have been many studies on the subject of building energy demand modeling utilising empirical data, such as: traditional regression methods [4]; Artificial Neural Networks (ANN) [5]; building simulation [6]. Through statistical methods and regression equations, regression models can correlate building energy demand with relevant climatic variables and/or building physical variables in order to predict energy demand. The main advantage of regression models is that they are comparatively simple and efficient. The ANN model is also able to predict the thermal performance of a building, its foundation being based on mimicking the structure and properties of biological neural networks. One of the great strengths of ANN models is their ability to model complex relationships between inputs and outputs. Regression and ANN based models have both been applied successfully in building energy demand prediction. However, regression analysis can become computationally intensive when upscaling to community level, and the “black-box” nature of ANN models can mean that, without contextual analysis, elicitation of the data can produce results beyond what is physically possible.

Such data driven methods are also restricted to the analysis of existing buildings that have in-situ monitoring (e.g. building monitoring systems, sensors and smart meters). While there is great potential for energy systems studies to utilise Big Data Analysis (BDA), the landscape is still dominated by “small data challenges” at the present time. This can include situations where there is no (or limited) in-situ data, this being a significant issue for energy demand in the residential sector. To overcome this limitation, building simulation can provide predictions of building energy performance under various

conditions, relating to the design, material composition, or external factors such as geography or climate. However, these simulation tools do not always perform well in predicting the effect on energy use of occupants' behavioural patterns.

Simulated thermal demand modelling utilises physics-based software models to predict energy performance. This type of approach can provide transient demand time-series for which no data is otherwise available. Moreover, this provides an opportunity to model forecasts informed by changes to future climates, future techno-economic environments and behavioural changes within society. Aspects of this were captured in previous work [7].

The authors of this paper are investigators of the UKs National Centre for Energy System Integration (CESI) project and lead the Energy Demand research theme [8]. The primary objective of this theme within CESI is to explore how bottom-up and top-down energy demand analysis can address the limitations of current energy system models. In this paper, we describe the associated challenges and present findings from our initial investigations into modelling energy demand in the residential sector, with high resolution data gathered from the Findhorn Ecovillage site [9]. In Section II, electrical demand profiles are synthetically generated from a sub-set of five residential properties utilizing Hidden Markov Modelling (HMM) and Generalised Pareto (GP) analysis. The methodology, results and analysis are reported in sub-sections A, B and C respectively. In Section III, the approach to dynamic thermal modelling is described in sub-section A, with results and analysis presented in sub-sections B and C. Finally, Section IV presents conclusions and discusses future work in upscaling energy demand modelling for national energy systems.

II. DATA DRIVEN ELECTRICAL ENERGY DEMAND MODELLING

A. Electrical Energy Demand Modelling

Further to the reasoning already discussed for enhancing the efficacy and efficiency of energy demand models, a range of applications can be identified where the need for highly resolved temporal descriptions of electrical demand are necessary. This includes analyses associated with individual dwellings (disaggregate demand), where, for example, the integration of demand response strategies can be examined. In contrast, aggregated demand data from multiple dwellings (at various scales) provides valuable data which can assist with system design, including transformer sizing, configuration of distribution networks and assessments relating to integrated renewables and storage.

In practice, generating energy demand time-series for an individual dwelling at fine temporal resolution, such as five minutes, is highly complex due to a number of factors, such as climate, building characteristics, behaviour occupants (lifestyle, habits, demographic etc.), with the complex relationships between these factors introducing significant uncertainty. To address this challenge, various stochastic modelling approaches have previously been investigated, such as time-series models

(ARIMA), ANN, genetic algorithms, support vector regression, ant colony, particle swarm optimisation and fuzzy logic [10]. Most of these methods have seen limited application for a number of reasons, such as requiring detailed information on certain input parameters (often not easily accessible in practice) and can have limited applicability with fine resolution data. More recently, the authors have proposed a methodological framework that exploits HMM [11] techniques for synthesising annual electricity demand profiles at one minute resolution [13, 14]. Using the above as a starting point, a novel approach for integrating time-series deseasonalisation in association with extreme value distributions (such as GP distribution) to a single HMM has been developed and detailed below for predicting electricity demand profiles of dwellings at five minute resolution.

B. HMM-GP methodology for simulating synthetic energy demand profiles

For projecting future energy demand profiles, a range of deterministic and stochastic modelling approaches have been investigated in the past. HMM is a popular stochastic modelling approach and has been applied to successfully model a broad range of complex systems, including processes in bio-informatics, speech, molecular evolution, stock market, natural languages, human and animal behaviour [12, 15]. The efficiency of HMM based approaches for generating synthetic electricity demand profiles at one-minute resolution, in parallel to ARIMA based models, has been investigated recently, described elsewhere [14]. Using that approach, the input time-series is considered to be mainly composed of three components: trend, seasonal variation and random component. Time-series deseasonalisation techniques are utilised to segregate these three components. To generate synthetic electricity demand series, the HMM modelling procedure as described in [15] involves deseasonalisation of electricity demand series through a simple but crude approach, described in (1):

$$E_{Deseasonalised}(t) = \frac{E(t) - E_{\mu}}{E_{\sigma}} \quad (1)$$

where, E_{μ} and E_{σ} are the hourly average and standard deviation of the log transformed electricity demand series, respectively. Hourly mean values were taken for one complete year of the demand time-series (containing data at one minute resolution), such that two new time series were created: hourly mean and σ . The one minute resolution demand series $E(t)$ was then processed according to (1). This deseasonalisation procedure segregates the seasonal component from the electricity demand profiles whilst leaving behind the remainder series ($E_{Deseasonalised}$), consisting of trend and random components. The HMM has then been fitted to $E_{Deseasonalised}$, with the simulation generating N synthetic deseasonalised electricity demand series. Finally, this is reseasonalised (by adding the corresponding E_{μ} and then multiplying E_{σ}) to output the synthetic electricity demand series at a resolution of one minute. The model was validated (results presented in Fig. 1) and proved effective up to the 99th percentile of load values. However, the model appears to have limited applicability in simulating extreme load values over the 99th percentile value.

TABLE I. DEMAND CLASSIFICATIONS

Characteristics:	Demand class:		
	Space conditioning (heating and cooling)	DHW	Lighting, appliances and CE
Dependence on weather	Critical (ambient & ground temperatures, solar, cloud cover, wind)	Moderate (ground temperatures, simple to quantify)	Lighting: Critical (solar) Appl.: Moderate (ambient temp.) CE: Weak (behavioural)
Associated temporal lag	Significant lag (construction dependent)	Moderate lag (e.g. HW tank) / No lag (instantaneous heater/combi ^a)	No lag (instantaneous demand) / Moderate lag (refrigeration)
Capacity to include controllable storage technology	Thermal (simple, currently available)	Thermal (simple, currently available)	Electrical (complex, evolving technology, possible links to)
Demand response capacity	Basic time-shifting using storage (Economy 7 ^b)	Basic time-shifting using storage (Economy 7 ^b)	Advanced 'internet of things' control (evolving technology)

^a. Combination boiler (tankless) designed to serve central heating and DHW instantaneously.

^b. "Economy 7" refers to an incentivised off-peak electricity usage scheme currently in place in the UK.

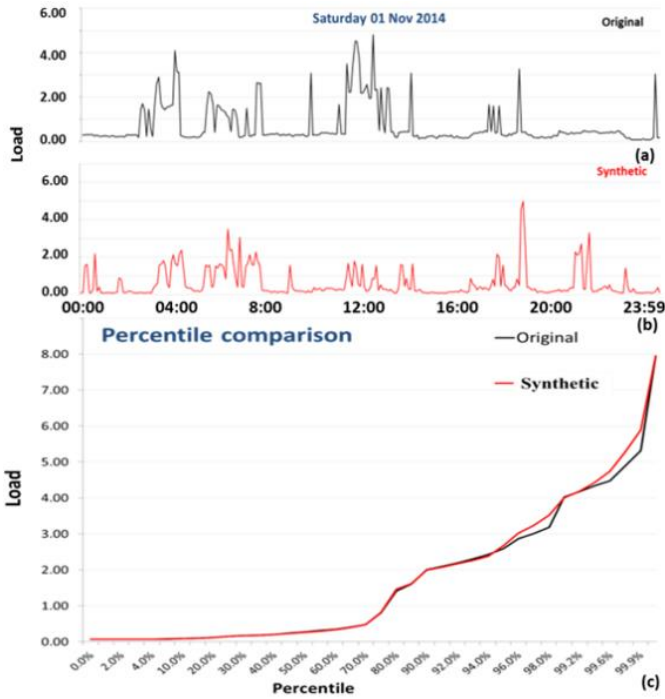


Fig. 1. Individual demand profiles for a typical weekend day for case study dwelling (a) Observed data; (b) Synthetic electricity data simulated using HMM-GP model. (c) Comparing percentile distribution of observed and synthetic electricity time series of case study dwelling A for the time-period from November 2014 to February 2015. Demand classes and characteristics (for the residential sector)

To address this issue, the HMM-GP model, first developed for generating synthetic streamflow sequences [16], has been deployed in this work. Within the framework of HMM-GP, to effectively model extreme values, the Generalised Pareto (GP) distribution has been fitted to the 99th percentile of observed energy demand series, and then the fitted distribution has been used to sample extreme load values for the synthetic energy demand series. This paper demonstrates an innovative approach that replaces the crude approximation (1) for deseasonalising electricity demand series by a more formal approach: the STL process (Seasonal Trend decomposition procedure based on Loess) [10]. The STL process allows a systematic decomposition of electricity demand series into three distinct categories: trend, seasonal and random components. A methodological framework has been developed and detailed below which fits the HMM, integrated with a generalised extreme value distribution, to deseasonalise the time-series (i.e. the STL approach) using five minutely electricity demand profiles:

1. Take the log of the time-series to transform a multiplicative time series into additive series;
2. Apply the STL time-series deseasonalisation procedure, based on the Loess process, to the log series;
3. Fit a single HMM to the random component of the time-series and simulate N distinct synthetic variants of the random component;
4. Add the simulated random components with the appropriately matched seasonal and trend components;

5. Resample extreme values from an extreme value distribution (fitted to observed extreme values, typically over 99th percentile).

C. Preliminary Analysis of HMM-GP methodology for simulating synthetic energy demand profiles

To demonstrate the efficacy of the HMM-GP procedure, a case study dwelling within the Findhorn Ecovillage, located in northern Scotland, is used in this study [8]. For the case study, five minutely data collected over a continuous time-period from November 2014 to February 2015 has been analysed and illustrated in Fig. 1.

III. MODELLING THERMAL ENERGY DEMAND

Demand in the residential sector is split into three categories: thermal demand for space conditioning; thermal demand for domestic hot water (DHW); demand for lighting, appliances and consumer electronics (CE). There is a degree of commonality between certain aspects of these demand classes; however, the discrete nature of each results in three different approaches. Table 1 describes specific characteristics of each class.

Options exist to provide these demands using different energy carriers, which at typically includes natural gas, electricity and heating oil to meet both thermal demands in the current UK building stock. Most appliances use electricity,

however it is common also to use gas for cooking. A significant consideration in the setting of future scenarios is changes to the current norm: the use of electricity for heating and transport is likely to become more widespread in the near future, reinforcing the need for an integrated modelling approach.

A. Thermal Energy Demand Modelling

One of the specific challenges presented by space conditioning demand is the delayed thermal response of building fabric and complex nature of solar gains. Both have an associated memory effect which links to a range of physical variables (notably climate), spanning anywhere from a few hours to a few days. It is therefore useful to have an understanding of transient, dynamic loads when calculating space conditioning demand.

Dynamic thermal building simulation is an established field of computational modelling, with a range of open-source and commercial codes presently available. These bottom-up models provide theoretical representations of physical, thermodynamic processes associated with buildings, i.e. conduction, convection and radiation transfer processes (both gains and losses). Most software programs in current use apply numerical methods to tackle the governing differential equations using finite difference or finite volume schemes. This is the case for the software used in the present work: IES-VE. A comprehensive description of dynamic thermal building simulation is provided in [17].

Such tools are used to assess single buildings or small groups of buildings in a deterministic manner; boundary conditions take the form of inelastic user input profiles dictating occupancy behaviour, lighting/appliance usage and heating/cooling system control requirements (assigning conditional temperature set-points). All climate input data is also deterministic. This lack of stochasticity does not inherently lend the approach to modelling aggregated thermal demand of a diverse building stock. In the following, a process is described in which this bottom-up method, which is typically used for design or energy auditing purposes, can be employed in a stock modeling framework using a probability distribution to describe the temporal variation in a typical daily routine. This is applied to an approximated model representation of the entire Findhorn Ecovillage community.

As an approach to modelling the residential building stock, the following classifications were carried out to develop a set of archetypes for modelling space conditioning demands:

1. Building fabric classification (U-values, thermal mass, infiltration, radiation);
2. Building form classification (detached, terraced, multi-level, etc.);
3. Building orientation;
4. Occupant behaviour (daily routines, working patterns, occupant density, demographic).

Once all combinations were established, simulations were carried out using IES-VE, for each case which exists in the real

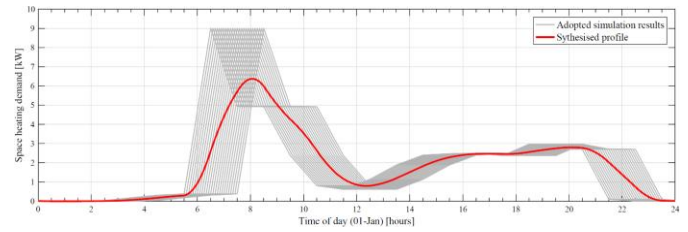


Fig. 2. Diversified space heating demand for an example archetype for a single day, using 25 time-shifted simulation results.

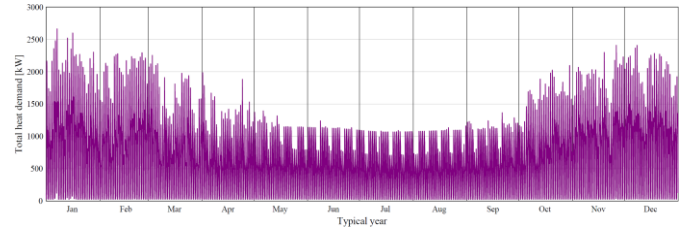


Fig. 3. Total thermal demand for entire stock (space heating and domestic hot water).

village. Using hourly simulation results covering one year, each archetype demand profile was applied a diversity to account for time-shifted behaviour throughout the day in different properties. Each simulation result was regenerated at 5 minute intervals across the range $\pm 1h$. Aggregation of the overall thermal demand requirements of the whole community was achieved by applying a probability to each of the results based on a normal distribution (within the range 2σ at $\pm 1h$). Once repeated for all archetypes in the study, the results were combined to deliver an aggregated demand for the site. Routine evaluations were achieved using the Python API integrated within IES-VE.

In order to provide a complete description of energy use within the community, models describing DHW usage need also to be provided. Despite being associated with the thermal load, the nature of this demand is characteristically similar to the electrical loads described in Section II. In the present work, problems arise from the availability of data describing DHW consumption, which might otherwise allow the use of the HMM-GP approach. In order to estimate DHW demand, a simple parametric model is instead implemented, using daily and annual trends for DHW are taken from elsewhere [18].

B. Results of Thermal Energy Demand Modelling

Fig. 2 shows the underlying time series, along with the regenerated time-shifted series for a sample archetype. Following the diversification procedure described above, synthesised profiles of each archetype were generated, as shown in red. This provides five minutely data throughout the year. This is the modelled thermal requirement for space heating, i.e. this is not based on the usage of a particular fuel.

Where plant load for space conditioning and DHW is shared, the combined thermal demand for the entire site is as shown in Fig. 3. This represents all archetypes, each applied with its specific stock size.

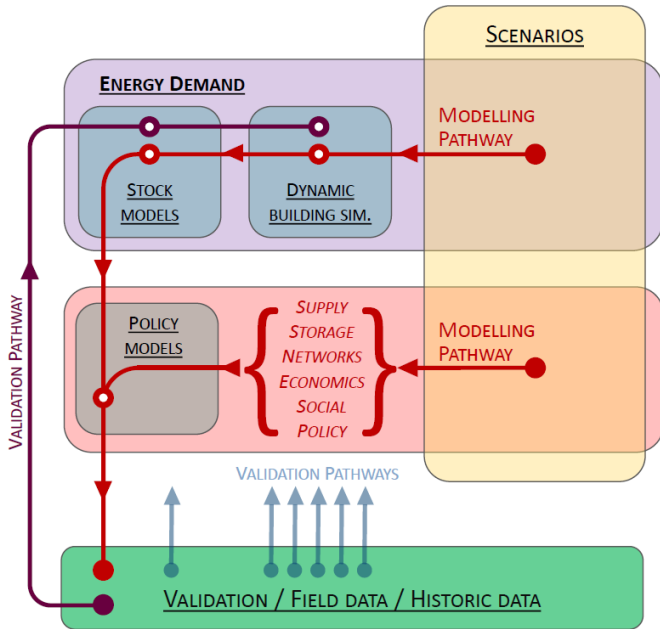


Fig. 4. Overall energy system modelling framework. Dynamic building modelling (as described in this paper), forms one component of a large and complex integrated system, with this intended to represent a range of scales, (i.e. from community level to national energy systems).

IV. ENERGY SYSTEM MODELLING

In the approach described thus far, the main objective has been to generate appropriately aggregated demand profiles to ensure that this adequately represents the diversity of energy demand behaviour of a community (or country). This fits within the wider *integrated energy system modelling* framework, as depicted in Fig. 4, which features a range of inherently diverse models. All of these models are interlinked; however, integration in practice has yet to be demonstrated. As part of the broader concern, the challenges can be reframed as one of adapting existing modelling methods to:

1. fully interpret detailed future scenarios (reducing reliance on historic data);
2. provide active communication links for all relevant interdependent processes and models within the wider energy system, incorporating methods for adapting data temporal resolution as necessary;
3. interface with a common data platform, to allow processing of shared input data and disseminated simulation data to other modelling tools;
4. maintain modularity of the various models, to allow them to be maintained/adapted/enhanced/replaced by their respective user/developer communities (ideally on open-source platforms).

As the different energy system components stem from independent disciplines spanning different fields of science, these links must be carefully considered to ensure that the use of input data is minimised via a common source, or through endogenous calculation where possible. The nature of different modelling practices and requirements implies that a modular model architecture will be of greatest long-term benefit.

V. CONCLUSIONS AND FUTURE WORK

In this work, high resolution data samples of electrical demand data have been combined with detailed thermal energy demand simulation results to explore new applications of bottom-up energy demand modelling. Data driven aggregation of electrical demand using HMM-GP provides an evaluation of how synthetically generated data can be used to represent communities of similar domestic buildings. The dynamic simulation of thermal energy demand allows an evaluation of consequences in varying design parameters of buildings. With respect to an energy system view, such modelling can provide insight to how changes in energy demand for heating within the built environment can impact on the transition to sustainable and affordable low-carbon energy. The electrification of heating systems is a prime example, where renewable systems work in combination with advanced heat pump technology. To be useful for energy system analysis, the modelling methods have to be up-scaled without producing unmanageable complexity and the limits and uncertainties associated with that upscaling must be well understood. Future work will explore the role of decision trees and multi-agent modelling for creating larger regional and national energy demand modelling profiles. This forms part of a much bigger consortium effort, embodied by the five year programme set out in the aforementioned CESI project.

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