A Systems Dynamics Approach to the Bottom-Up Simulation of Residential Appliance Load

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ABSTRACT

Residential demand from real residences can be resource intensive to collect. There is need to generate synthetic residential load in energy research, and new approaches are welcome. Most of the simulation models of synthetic residential load that output realistic loads are tightly coupled to historic correlations. This paper presents a high-resolution simulation model that generates a residential appliance load using the tools of System Dynamics via a bottom-up approach. In addition to being realistic, the model aims to minimise historic coupling. Whilst the intermediary outputs of the modelling process are subjected to systematic scrutiny, the final output is validated by comparing statistical characteristics of the model's output to a validated model and data from real residences. The aims of the model were sufficiently met, and the modelling approach shows potential to simplify; by driving the model on average frequency of appliance use instead of probability distributions of human activities. Other outputs from the model, specifically distribution of appliances' activation and operation, as well as complexity are discussed. Some benefits of the model are also discussed especially with regard to cost of modelling, interpretability of model and potential for transdisciplinary research. This study represents the first attempt to develop a bottom-up simulation model of residential load based on a System Dynamics approach.

Keywords: *System Dynamics, Residential Energy System, Simulation, Residential Load*

1 Introduction

With sustainability a core global agenda, this has afforded many research opportunities to reimagine residential and community energy systems for a sustainable future. Some of the research includes simulations of renewable energy systems, demand side management, smart grids, building simulation, and low voltage grid simulation, all which require residential load as input. However, it can be expensive and time consuming to measure residential loads for use in these simulations. The cheaper and faster alternative is to generate realistic residential loads synthetically via simulations, which provides an opportunity to explore new approaches to generating realistic synthetic load profiles. This paper presents the first attempt to generate synthetic residential load using a System Dynamics approach.

The paper begins by providing a background to behaviour and activities in residential energy use, followed by a deeper look at how residential activities are measured. System Dynamics is subsequently introduced, and existing models are reviewed. The methods section is divided into conceptual model and simulation model. Results are discussed in terms of validation, other model outputs, complexity and evaluation of the model's aims. Finally, some conclusions are drawn and further work is discussed.

2 Background

2.1 Energy Use, Behaviour and Activities

There is agreement that occupant behaviour is a major determinant of residential energy consumption [1–5]. In addition to recognising that occupants are the primary consumers of energy, not buildings [4], occupant behaviour can undermine technological solutions to efficient energy use [2,3]. Behaviour is also recognised as a leverage point in public policy to influence energy use [1,4,5]. Another approach is to focus on energy consuming activities in households as policy levers, as in [6–8].

Whereas behaviour encapsulates actions, patterns of actions, or manners of action, activities (or actions) may be a simpler construct to focus on especially for the purpose of simulating residential load. Everyday activities, in this context, refer to energy consuming activities in residential spaces, which may or may not involve an appliance; e.g. using a kettle or opening windows. There are a variety of theories explaining why individuals participate in everyday activities. In terms of relevance to this study, there are two groups categorised by their disciplines of origin as reviewed in [9]: psychology and time geography.

The psychological theories use concepts that are difficult to measure (or even define) for the purpose of simulation. Concepts – and consequently variables – required to understand behaviour have several definitions across studies which makes it difficult to generalise their findings; e.g. beliefs, values, attitudes and motives [3]. Other challenges include inconsistent and incomplete findings and a lack of a conceptual framework accepted by the majority of researchers [3]. In addition to the complexity that arises from the many and various determinants of human activities [9], their interaction is likely to further complicate it. For example, [10] has shown how multiple psychological subsystems interconnect when participating in an activity. "In psychology, as in the other life sciences, probably the best one can hope for is qualitative laws" [9].

The psychological theories explored are limited to decisions about single activities. For the purpose of simulation of residential energy use, the interest is in scheduling multiple activities. The next section explores theories from time geography, which seek spatiotemporal patterns of activities [9].

2.2 Properties of Activities

Even if we do not know why or how an activity gets to take place, knowing the properties of the activities could facilitate modelling the activities. Three properties of activities have been identified from the literature: activities are routinised but adaptable; activities are periodic; activities have meanings.

2.2.1 Activities are routinised but adaptable

Routinised is the property of being performed in a sequence. Some activities are bundled into a sequence for two reasons: constraints or availability of participants and resources [6]; or in anticipation of a prior or more important commitment [7]. Routines establish normalcy, hence the high reliance on routines to carry out activities [7]. It has also been found that routines get disrupted, but then normalcy returns [6,7].

2.2.2 Activities are periodic

Implied in routine activities is that they are periodic. This is also supported by Time Use Surveys (TUS) which ask respondents about the frequency of their activities [11,12]. Whilst periodicity may not be strictly mechanical and precise, it is a useful way to conceptualise activities that are repeated.

2.2.3 Activities have meanings

The meaning of an activity, or bundle of activities, has been found to be more important than management of energy use [7]. For example, to fulfil the meanings of "family comfort" or "quality family time", families do not mind if this is achieved by increased and expensive energy consumption [7]. Activities have meanings but the same meaning could be associated with different activities for different people, or in different residences or cultures. So while it is important to recognise that an activity may fulfil meanings, the activities – not their meanings – are more concretely associated with energy consumption.

2.3 Time Use Data

Time Use Data (TUD) provides information about how activities are located temporally and spatially with respect to other activities [13]. TUD is commonly collected via time diaries or Time Use Surveys (TUS), but other measurement techniques include Experience Sampling Method, Recall Self-reporting, Activity Checklist, and computer-aided telephone interviewing [13].

Most TUS cover either a 24 hour period, or two 24 hour periods of a weekday and a weekend, per person. In a 2010 discussion paper on valid inferences that can be drawn from TUD [14], only one international TUD covering a seven days period could be identified. This limitation of available TUD has implications on what it can justifiably be used for.

It has been observed that certain properties of TUD make it a poor indicator of any long-run time use of an individual [14]; the properties are the short reference period (in Person-Day), and the large amount in day-to-day variation in time use (since people have different routines). Consequently, TUD is not suitable for policy related questions which require long run time use data [14].

Furthermore, it has been concluded that one person per household provides the same information as multiple persons per household, in a single day of TUD [14]. This is because of the "problem of disentangling the day-to-day covariance of activities from the long-run covariance" [14]. Another conclusion from the same study is that given the designs of multiple day TUS, much cannot be learned about intra-personal variability. The first conclusion may be due to a limitation of information captured by TUD. Moreover, building bottom-up energy demand models from TUD alone has been shown to be problematic because it is difficult attributing energy consumption to an activity, a specific time, or even occupant [15].

The study presented in this paper is interested in the properties of activities that could be used to model a simulation of residential load, intra-personal variability and also activities' interrelationship which has been acknowledged in [6–8]. For these, data covering more than a day or two would be required.

Whilst some studies have proposed methods that could be used to identify influence among activities in TUD using network theory [16] and co-variance analysis [17], these analyses would still lead to inferences about a population, not a person or household. This is similarly the case when TUD is used to extract probability distributions of activities in simulating residential load.

2.4 Models of Bottom-Up Residential Load

2.4.1 The State of The Art

There are many models that predict interaction of occupants with buildings which has impact on energy consumption of the buildings; examples include windows [18–22], blinds [23,24], lighting [25], and air condition [26]. Such predictive models – in addition to occupancy and movement in buildings – can be integrated to Building Performance Simulation software using the obXML schema which is based on the DNAS (Drivers, Needs, Action, System) framework [27,28]. Taking it further, [29] presents a "platform" comprising models of interaction with building, agent-based models of synthetic occupants, stochastic models of activities, and interfaces to integrate with building energy simulation models (e.g. EnergyPlus). However, residential load is not the focus and was not discussed.

A bottom-up simulation model of residential load outputs electricity load of a household based on more elementary load components, which could be a household when dealing with multiple households, or appliances when dealing with a single household [30]. Bottom-up models have been categorised based on scale [30] and include electricity demand models, and end-use models. Electricity demand models output load at utility level, which is multiple residences, while end-use models output load at residential level. These two require different input data, and whilst electricity demand models can be estimated using an accounting method that estimates aggregate residential electricity consumption, it is less the case with end-use models which require simulation to capture the dynamics within a residence. Also, end-use models can be used to build electricity demand models, as demonstrated in [30–32].

Therefore, a bottom-up model at residential level could be broken down into three aspects: the set of appliances in the household, the individual electricity demand of these appliances, and the use of the appliances [31]. The first two can be considered the static aspects, while the last is the driver of model's dynamics because it determines the state of the system in progressive time steps.

Table 2 shows some bottom-up models of residential load highlighting the main model outputs, inputs, drivers and aims. Statistical realism refers to output of the simulation having statistical properties of the real system. A model outcome that is statistically realistic could be used to as input to other simulation models in place of field data; e.g. demand side management, building simulation and low voltage grid simulation [31].

Reference	Outputs	Inputs	Drivers	Aims
[33]	Load of the average residence; conservation effects; weather sensitivity	Appliance stock or saturation; sociodemographic characteristics;	Accounting methods	Forecast; what-if analysis
[34]	Load of residences and community; hot water energy consumption (daily);	Occupancy patterns; energy consumption of appliances (daily);	Accounting methods	Forecast; energy system design
[25]	Lighting	TUD (occupants' activities);	Stochastic modelling	Statistical realism
[30]	Load of residence	Appliance ownership; daily usage pattern of appliances;	Probability distribution	Statistical realism
[32]	Load of residence	TUD (occupants' activities and occupancy); appliance energy consumption;	Probability distribution	Statistical realism
[35]	Load of residence; hot water demand	TUD; mean appliance energy consumption; water tap data; daylight data	Appliance (operation) power conversion scheme;	Statistical realism
[31]	Load of residence; synthetic activity sequence	TUD (occupants' activities); appliance energy consumption; appliance stock or saturation	Markov chain (non-homogenous)	Statistical realism
[36]	Load of residence and community	Appliance energy consumption;	Psychological model of human desire	Statistical realism

Table 2 – Models of energy use at different scales

The models in Table 2 take different approaches. The load of an average residence is estimated which is serviced by a single utility company based on appliance stock and sociodemographic characteristics [33]. Whereas [33] consider itself an end-use model, it is actually an electricity demand model according to the distinction in [30]. Similarly, [34] is a load estimation model for residential and communal load called SMLP (Simple Method for formulating Load Profile) based on occupancy and energy consumption of appliances. On the other hand, [30] provides an end use model based on appliance ownership and appliance usage expressed as probability distributions on different time scales. Similarly, [32] employs probability distribution based on occupants' activities and active occupancy, and energy consumption of appliances to create a realistic residential load. Taking a different approach, [31] focuses on first generating synthetic activity sequences, then using data on energy consumption of appliances and energy-use pattern of the appliances to generate residential load. Finally,

[36] relies on the a model of human desire from Psychology, in addition to other parameters to generate realistic residential load.

2.4.2 Limitations

Most of the models in Table 2 aiming for statistical realism rely on TUD to drive the models. Some of the limitations of TUD have been explored in Section 2.3. TUD captures occupant activities in time, which is then incorporated into the simulation models as a form of probability distribution. Since the probability distributions are historic correlations, the models are tightly fitted to the source field data (TUD) especially given the typical high resolution of 10 minutes. To apply the models to different situations which may have different structural properties and consequently different correlations, the probability distribution would need to be updated, which may lead to new TUS which is resource intensive. To minimise the impact of this limitation, this study aims to model occupant activities based on simpler properties of activities which may not be as tightly coupled to historic correlation. It is therefore expected that the probability distribution of activities can emerge as by-product from the simulation, rather than as an input. It may be less accurate, but it is fit for use.

The second limitation is to do with approach to validation of the models aiming for statistical realism. The models assume that if the output of the simulation model is realistic, then the conceptual model is either realistic or inconsequential. The limitation is that no attention is given to validating the conceptual model, and other intermediary steps. Whilst the models probably undergo several iterations before the final output, a framework to validate the modelling process is not made explicit.

2.5 System Dynamics

2.5.1 Introduction

System Dynamics (SD) is a language to simulate complex systems based on a generic understanding of systems [37,38]. SD provides the vocabulary to describe and analyse a system and it is suitable to describe time-varying variables like electric power. In addition, SD provides a common means of representation and communication across several disciplines and beyond formal disciplines which makes it an interdisciplinary, as well as a transdisciplinary method. Consequently, some of the advantages of using SD includes aiding communication of a model’s dynamics in the language of systems even without expertise in the modelled domain, and also the ease of integration with other SD models of other systems that have a common variable.

2.5.2 Causal Loop Diagram

SD models can be presented diagrammatically using Causal Loop Diagrams (CLD) and Stock and Flow Diagrams (SFD). Figure 1 shows a simple Causal Loop Diagram (CLD) with three components of a system. The arrow shows the relationship between two components which is causal or dependency, depending on the reference component; causal relationship in the direction of the arrow, and dependency in the opposite direction of the arrow. Therefore Figure 1 shows that Production Rate and Shipment Rate cause, or affect, the state of inventory. Alternatively, the state of inventory depends on, or is affected by, Production Rate and Shipment Rate.

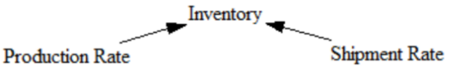

Figure 1 – A simple Causal Loop Diagram (CLD)

2.5.3 Stock and Flow Diagram

Figure 2 shows diagrammatical representation of SFD on the left and a mirrored key on the right. The diagram shows inflow (Production) and outflow (Shipments) to a stock (Inventory); inflows and outflows are flows. The variables in SD are mainly categorised into stocks or flows; others are auxiliary variables and constants. Stocks are represented as rectangles, flows as valves on double arrows, and other variables as text. Links between variables can be material links or information links represented as double arrows or single arrows respectively. The direction of material links indicates the movement of the same quantity between two stocks as well as dependence, but information links simply indicate dependence. Stocks are accumulations, e.g. bank account, product inventory, employed people. Flows are the rate of accumulation, e.g. rate of savings and rate of spending; rate of production and rate of shipment; rate of hiring and rate of quits, firing or retirement. A source or sink is a stock that is outside the model boundary. Mathematically, these symbols are expressed in *Eq. 1*, *Eq. 2*, and *Eq. 3* where x and y can be any variable (stock, flow, auxiliary, or constant) and n is a natural number. Diagrammatically, the terms of integration in *Eq. 1* are connected to the stock via material links (double arrows), whereas the terms in *Eq. 2*, and *Eq. 3* are connected via information links.

Figure 2 – Notation of Stock and Flow Diagram (SFD) adapted from

$$Stock(t) = \int_{t_0}^{t} [Inflows - Outflows]dt + Stock(t_0) \qquad \textit{Eq. 1}$$

$$Inflows\ or\ Outflows = f(x_1, \ldots, x_n) \qquad \textit{Eq. 2}$$

$$Auxillary = f(y_1, \ldots, y_n) \qquad \textit{Eq. 3}$$

2.5.4 Validation in System Dynamics

In SD, the aim of validation is to impart confidence in the users of a model about the model. Building confidence is not focused on the final output of the model only, but also intermediary outputs and processes of the modelling e.g. choice of variables, relationship among variables and parameter calibration. The aim is to adequately describe the model for its purpose, and the output is expected to be valid as a consequence. To interrogate the modelling process and intermediary outputs, validity tests have been developed in SD literature. The validity tests are presented in Table 1 as questions to guide the modelling process based on [38]. Boundary refers to the variables/elements in the system distinguishing between endogenous and exogenous, structure refers to the dependency between elements of the system, dimension refers to units of the variables, parameters refers to exogenous variables (whose values are not dependent on variables within the system boundary), extreme conditions refers to the behaviour of the system when parameters take extreme values, and behaviour refers to the state or properties of endogenous variables over time. The validity tests can be considered a prescriptive framework for validating the modelling process and intermediary outputs, including the final output.

Validity Test	Questions to ask	Positive Validity Result
Boundary Adequacy	• Is the model boundary appropriate to the purpose? • Are the important concepts for addressing the problem endogenous to the model?	All major variables are relevant to the purpose. Major variables are endogenous; as much as possible.
Structure Verification	• Is the model structure consistent with relevant descriptive knowledge of the system? • Is the level of aggregation appropriate? • Does the model conform to basic physical laws such as conservation laws, or contradict common sense? • Do the decision rules capture the behaviour of the actors in the system?	A CLD Conceptual Model justified by the data sources
Dimensional Consistency	• Is each equation dimensionally consistent without the use of parameters having no real world meaning?	Units of variables are consistent and balanced throughout the system. Units should also be meaningful. Choice of units is appropriate and justified.

Parameter Verification	• Are the parameter values consistent with relevant descriptive and numerical knowledge of the system? • Do all parameters have real world counterparts?	Parameters are realistic to the system, and justified by data.
Extreme Conditions	• Does each equation make sense even when its inputs take on extreme values? • Does the model respond plausibly when subjected to extreme policies, shocks, and parameters?	That behaviour in extreme condition matches anticipated or historical behaviour. Model is robust by behaving realistically to the input.
Behaviour Reproduction	• Does the model reproduce the behaviour of interest in the system?	Minimal error/deviation from historical or expected behaviour.

Table 1 – Questions for validity tests and expected positive validity result

Validity tests can be categorised into those seeking to validate the conceptual model, and those seeking to validate the simulation model. Conceptual model validity tests include boundary adequacy and structure verification, whereas simulation model validity tests include parameter verification, extreme condition and behaviour reproduction. That is because a conceptual model identifies the variables and structure of the model, while a simulation model goes further to calibrate the model parameters and run the model to obtain an output behaviour.

Validity tests can address one of the limitations identified in Section 2.4.2. For this study, SD literature provides a framework for validating the process of modelling not just the final output as validity tests (Section 2.5.4) which poses questions that guide the modeller.

3 Methods

3.1 Conceptual Model and Validity Tests

This section looks into the conceptual model and addresses the concerns of validity tests raised in Table 1.

3.1.1 Problem Definition

The purpose of the model is to generate a residential load that aims to be realistic and minimise historic coupling, via a bottom-up approach. Being realistic refers to statistical plausibility when compared to measured data from a real system or a simulation model validated with measured data; which makes it more representative of real systems. Minimising the historic coupling of a model refers to minimising over-fitting between what drives the model and historic correlations like probabilities derived from real residences; which should make the model applicable to wider scenarios.

3.1.2 Model Boundary

Table 3 shows the endogenous and exogenous variables in the system in the Model Boundary Chart (MBC), with their units in parenthesis. The boundary of the model is defined by the endogenous and exogenous variables; the endogenous variables depend on the exogenous. The boundary adequacy of the model is assessed based on whether the variables support the purpose of the model.

Endogenous Variables	**Exogenous Variables**
Activity timer (minutes)	Appliance/Activity cycle per time (dimensionless)
Occupant's attention (dimensionless)	Number of residents (dimensionless)
Appliance activation (dimensionless)	Occupancy of residents (dimensionless)
State of appliance's operation (dimensionless)	Mean duration of appliance operation (minutes)
Power consumption of appliances (kW)	Mean energy consumption of appliances (kW-minutes)
Total power consumption of residence (kW)	

Table 3 – Model Boundary Chart of the model showing the main variables

3.1.3 Conceptual Model

A conceptual model presents the structure of a system. The conceptual model can be understood from four perspectives: aggregation; relationships; constraints; and assumptions on the behaviour of residents. These perspectives were informed by Structure Verification validity tests (Table 1). The conceptual model is presented as a CLD (Figure 3 to Figure 7), and it is the outcome of developing and testing multiple concepts based on the literature and progressive iterations.

Aggregation: At the level of a residence, the main causes/sources of power consumption are appliances, and most appliances operate based on the activities of the residents. Residents are defined by their activities which are influenced by the occupancy and attention of the residents. Activities are conceptualised as timers, appliances as power load, while occupancy and attention as on and off switches but occupancy is exogenous whereas attention is endogenous. Activities have been described as timers because activities have been shown to be periodic and have patterns in [6,7]. Currently, activities are described as tied to only one appliance; e.g. there is no activity "cooking" which may involve multiple devices, but instead there is an activity "use kettle" and another "use microwave". Therefore a conceptual model which describes activities, occupancy, attention and appliances offers an appropriate level of aggregation for modelling residential load demand. Figure 3 shows a CLD of the components at the chosen level of aggregation from the perspective of a single resident. The two types of appliances (Appliance A and Appliance B) relate to the resident's attention differently.

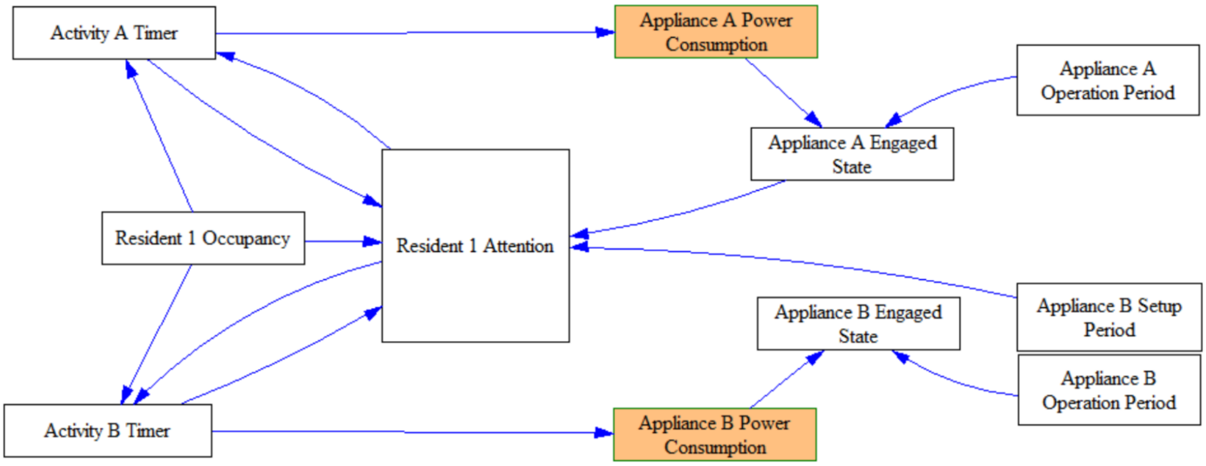

Figure 3 – CLD showing interacting components of a single resident with two types of activities and appliances

Relationships: In the absence of automated scheduling of appliances, a resident commits their attention when carrying out activities, and the attention is influenced differently by type of appliance (see Figure 3); either depending on the appliance's engaged state or set up period. Also, at any time, a resident can either be at the residence or not; and activities in the residence require active occupancy of the resident. Each resident can carry out multiple activities and each power consuming activity requires the operation of one appliance. However, automatic appliances like fridges operate without prompt from a resident and are modelled as periodic power consumption that is ever-present. The standby power consumption of appliances is also modelled (see Figure 4). Therefore the relationships among elements in the system is based on valid observations and the literature.

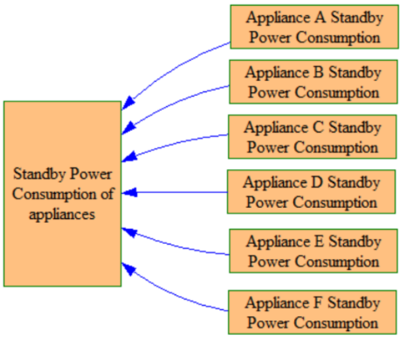

Figure 4 – CLD showing standby power consumption of appliances

Constraints: Attention of residents is finite but residents multitask, as acknowledged in TUS design which distinguishes simultaneous activities as primary and secondary activities, as found in [11,12]. Whilst not all activities are power consuming, residents have also been shown to perform multiple power consuming activities simultaneously [8]. However, a limit to the number of power consuming activities a resident can be engaged in simultaneously shall be limited and reasonable. Some power consuming activities are semi-automatic (e.g. using washing machine) which requires the resident's attention to setup but not for the duration of the operation of the appliance, as acknowledged in [31,35]; for example, the resident's attention in Figure 3 is determined by the setup period of Appliance B which may be shorter than the engaged state. Another constraint is the state of a resident's occupancy determines whether an activity is initiated or not; the resident must be at the residence for an activity to occur, especially the part of the activity that requires the attention of the resident. Finally, appliances in a residence are finite, which means the availability of an appliance is a constraint in a residence with multiple residents who may be ready to use a single appliance while it is engaged by another resident. Assumptions on the behaviour of residents: It has been assumed that residents are able to estimate whether the end of an activity that requires their attention will be outside the time they are scheduled to be in the residence, and consequently, they will refuse to engage in an activity even for the duration of the available time. Also, residents do not share the same appliance concurrently (see Figure 5). Lighting has been modelled based on the assumption that when an appliance is in use, the set of lights in the room is turned on; and lights are turned off when no appliance is in use in a room (see Figure 6). This is the case regardless of the time of day and it should not make a significant difference because LED bulbs are assumed given their ubiquity and low power consumption.

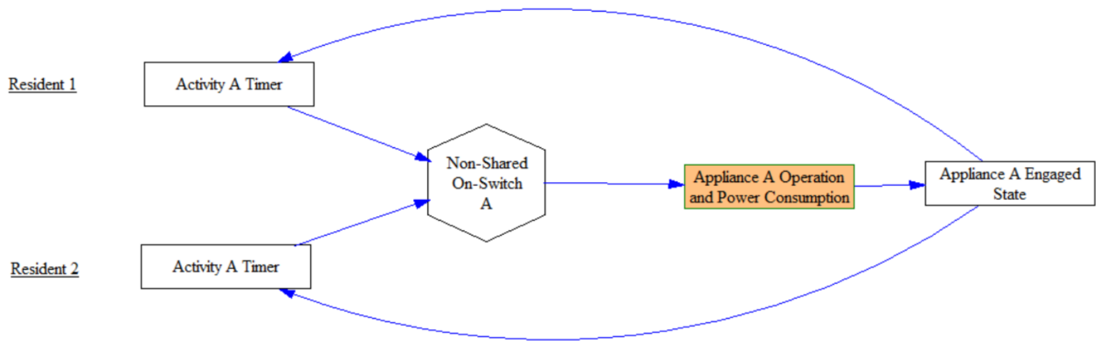

Figure 5 – CLD showing that appliances are not shared concurrently

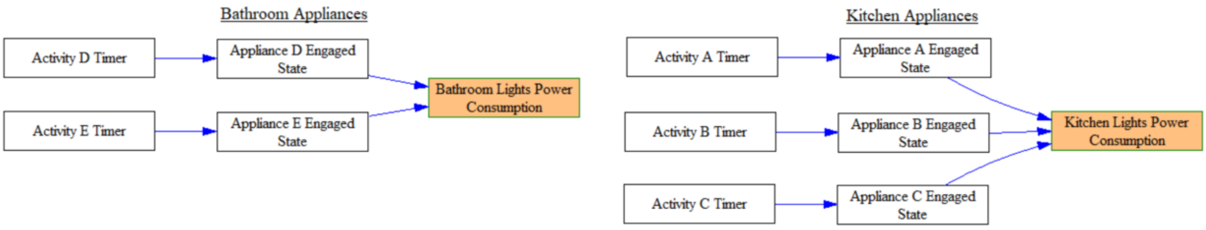

Figure 6 – CLD showing residential lighting

The residential load is an aggregation of all the power consumption of the appliances shown in the diagrams of the conceptual model with orange fill; shown in Figure 7.

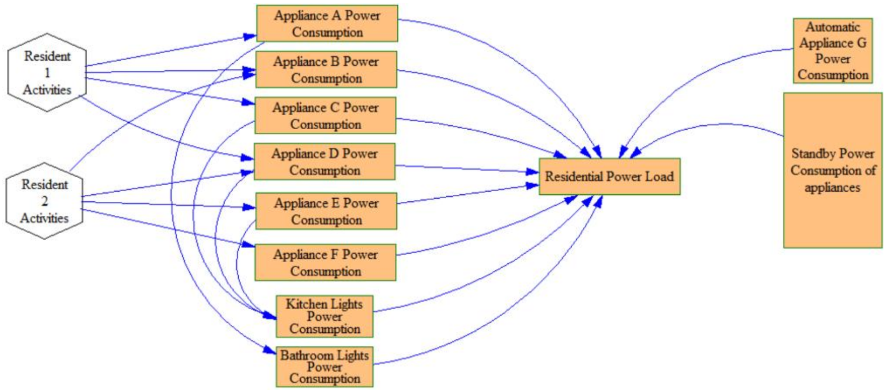

Figure 7 – CLD showing residential power load

3.2 Simulation Model and Validity Tests

This section presents the simulation model (Section 3.2.1) developed from the conceptual model while addressing the concerns of validity tests raised in Table 1. The logic and formulation of the simulation model is explored along with the behaviour outcome (Section 3.2.2). Then the source of values for calibrating parameters are presented (Section 3.2.3) as well as introducing behaviour reproduction (Section 3.2.5).

3.2.1 Simulation Model

Activity has been implemented as a countdown timer in SFD; see Figure 8. As a timer, the following properties of activities are captured (see Section 2.2): periodic and routinised but adaptable. The timer corrects for delays which is tracked by the Due-Time Correction Factor. An activity being due is not sufficient to activate the associated appliance but depends on other variables, as well as resolution of conflict when multiple activities are due at the same time since the available attention of the resident is limited. The necessary conditions for activation of appliances are further discussed in Section 3.2.2. The two types of appliances are shown in Figure 9 and Figure 10: a kettle is modelled as requiring the attention of the resident while on; whereas a washing machine is modelled as requiring the resident's attention only for a setup period, not the entire operating cycle. To model efficiency improvement of an appliance, 'Power per User' can be decreased for more efficient appliances, and increased for less efficient appliances. Figure 11 shows the limited attention of a resident being dependent on the occupancy of the resident as well as the activation and deactivation of appliances.

The simulation was run for three types of residences with one, two and three residents for the duration of a year. Since additional residents lead to marginal increase in residential load [15], the maximum of three residents which is simulated could represent more residents in real residences.

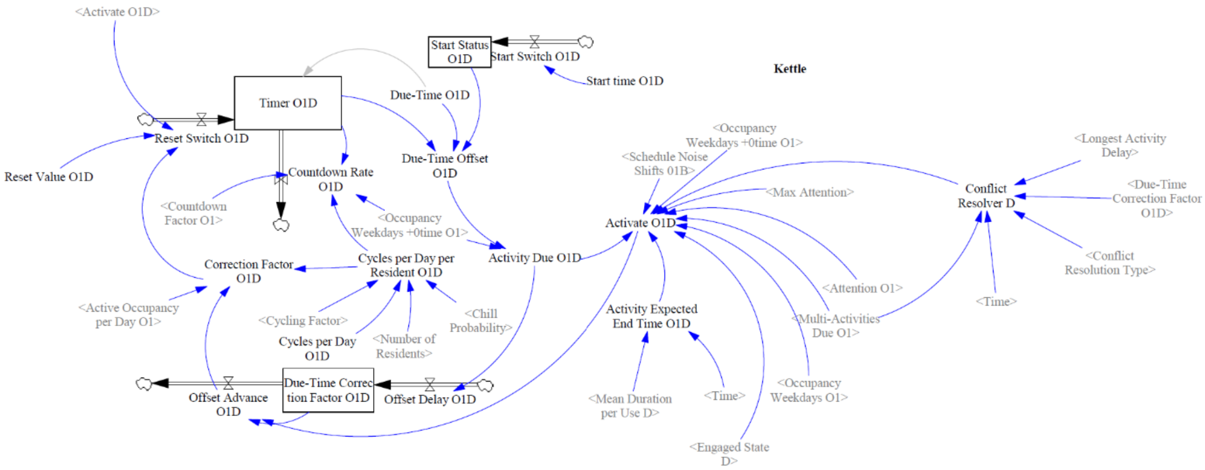

Figure 8 – SFD of an activity for Kettle use

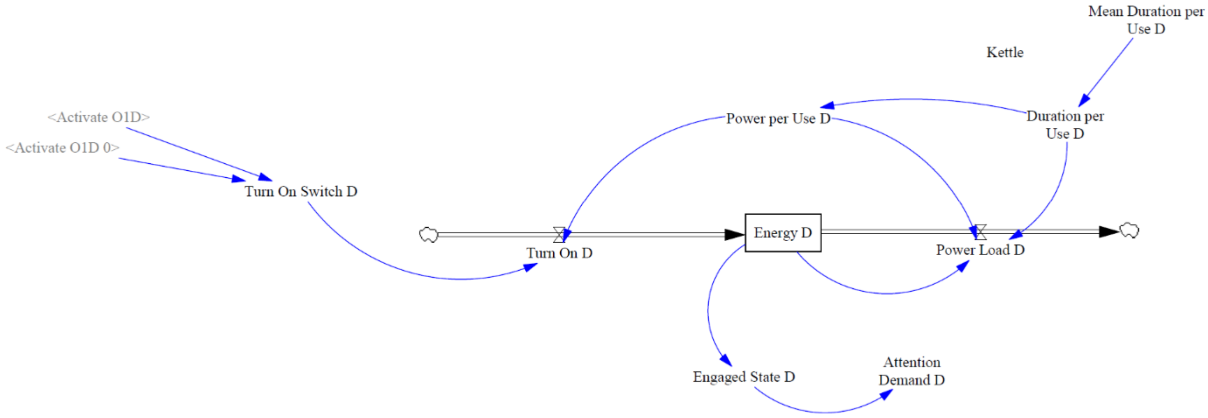

Figure 9 – SFD of an appliance that requires attention while turned on: Kettle

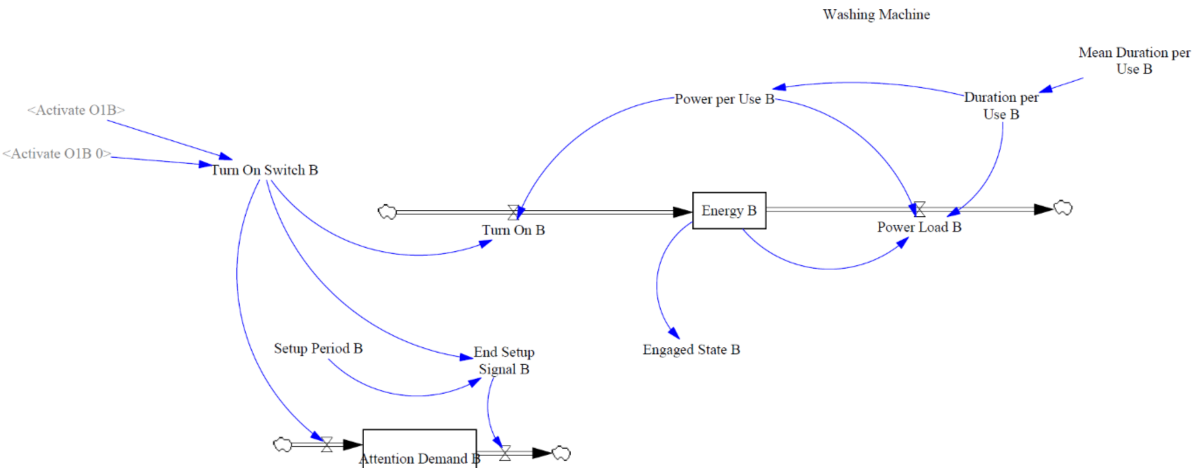

Figure 10 – SFD of an appliance that requires attention only during setup: Washing machine

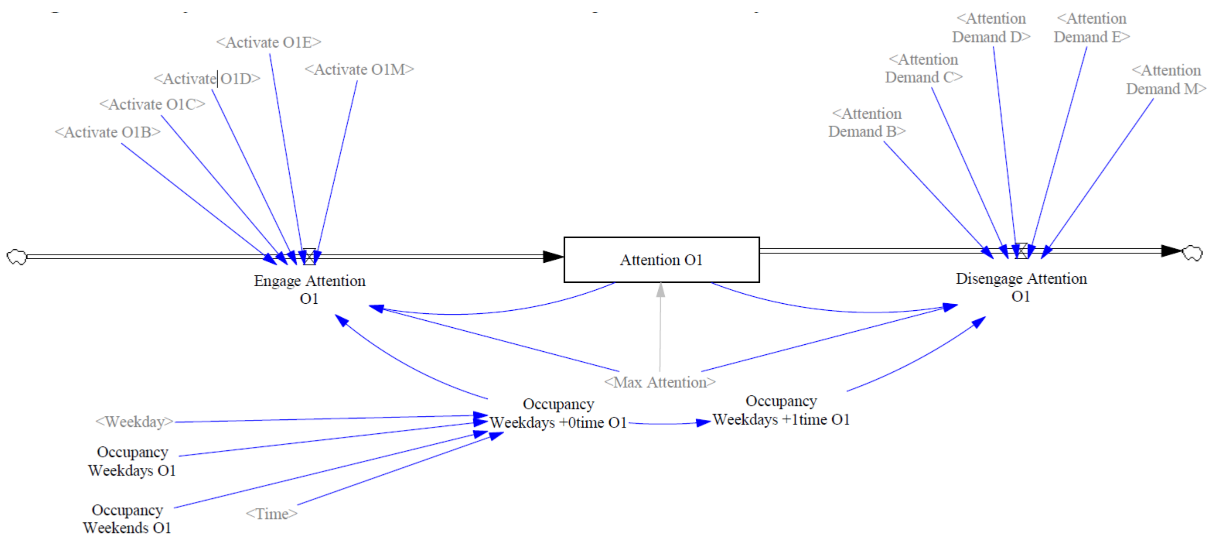

Figure 11 – SFD of attention of a resident

3.2.2 Model Formulation

The simulation model can be further elaborated by looking at the operational logic of the endogenous variables. Figure 12 shows a flowchart of the operational logic of an activity and its related appliance. When resetting the activity timer, the timer is adjusted for the counted delay before the delay counter is reset. There are multiple conditions required to activate an appliance and detailing them would make the flowchart cumbersome; also shown in Figure 8 as the variables pointing to *Activate*. The conditions to activate in the most basic set up of the model are: active occupancy at the start time of the activity; availability of attention of the resident; availability of the appliance; occupancy at the estimated end of activity; and conflict resolved in favour of the activity, in situations where multiple activities are due. Conflict resolution is implemented such that the longest activity due is carried out.

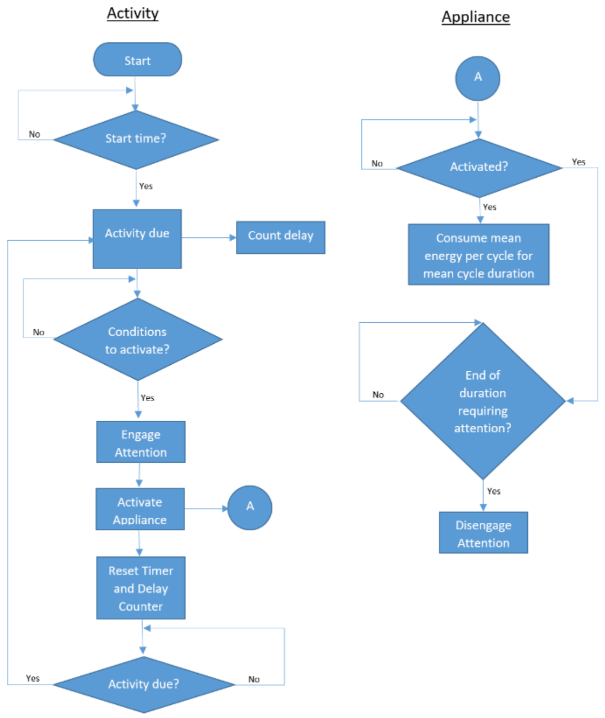

Figure 12 – Flowchart of the operational logic of activities and appliances

The activity timer is implemented as an exponential decay such that the countdown timer is never negative. The advantage of an exponential decay over a linear function is that there is less precision in the activity cycles which makes it perhaps more realistic to human mental model of time tracking. The cycle duration for different active occupancy durations of a resident has been implemented as an exogenous non-linear variable.

Figure 13 illustrates some the behaviour of the timer in three different cycle conditions shown as six full cycles. A cycle is a ramp made of a vertical line and a downward curved slope up to the next vertical line. The first and last cycles are conditions with no constraint which shows a cycle of about 600 minutes. The second and fifth cycles show that the timer pauses during inactive occupancy (occupancy = 0). The third cycle shows a cycle that is delayed by about 200 minutes (because some conditions have not been met) and the delay is adjusted in the fourth cycle by the amplitude of the ramp. Furthermore, Figure 14 shows the behaviour of attention which depends on occupancy (see Figure 11) for the duration of 7 days; attention goes to the maximum available attention (which is set to 2) during inactive occupancy (occupancy = 0) so that no activity can be carried out in the residence, otherwise attention varies between 0 and the maximum depending on activities that are due.

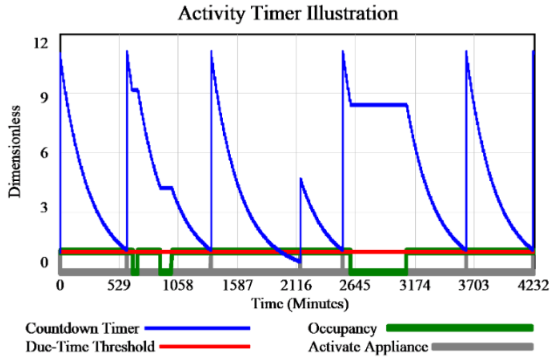

Figure 13 – Behaviour of Activity Timer in 3 conditions

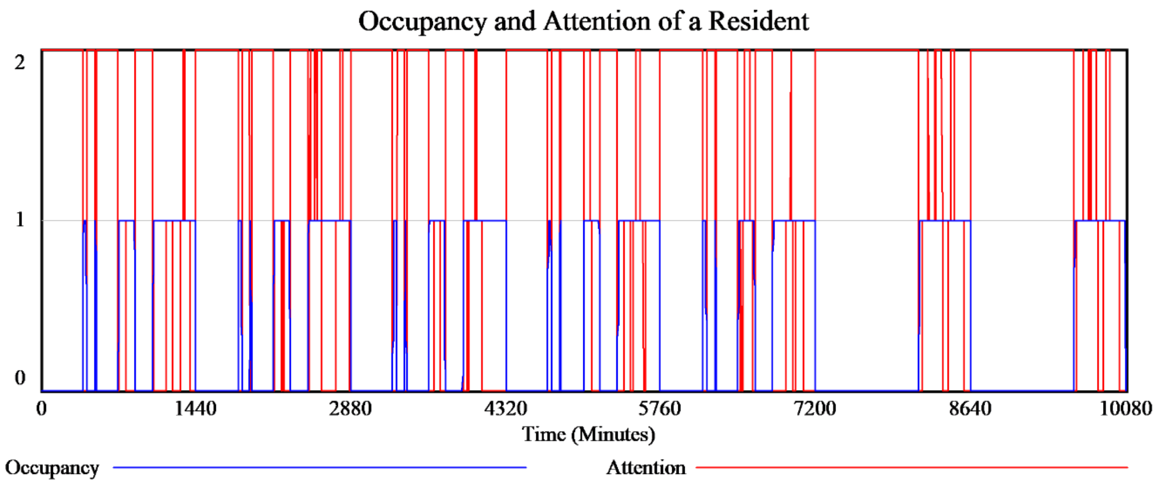

Figure 14 - Occupancy and Attention for 7 days

3.2.3 Parameter Verification and Calibration

Table 4 lists the system parameters and the source of values used to calibrate them; all parameters are exogenous variables. The values of most of the parameters are sourced from the CREST model; which has been well documented [39]; the choice of the CREST model is discussed in Section 3.2.5. In the case of activity frequency (*Mean Base Cycles per Year*), a scaling factor is included which is adjusted until the sum of residential load in the SD model is close to that of the CREST model; because activity frequency in the CREST model is an average from a population of non-homogenous residences which is mediated/adjusted by probability distributions relevant to the residence type. However, the scaling factor is applied to all activities and therefore the proportion of frequencies/cycles among appliances is maintained. Figure 15 shows the annual mean and sum of the models as calibrated with scaling factors of 0.6, 0.75 and 1.2 for residences with one, two and three residents respectively. Figure 15 does not show the monthly trends because available data on appliances from the CREST model are annual averages, not monthly.

Parameter	Source
Mean energy consumption of appliances per cycle	Mean cycle power (CREST model) Standby power (CREST model)

Mean duration of appliances operation cycle	Mean cycle length (CREST model) Delay restart after cycle (CREST model)
Frequency of appliance use (Appliance cycle per time)	Mean base cycles per year (CREST model)
Start times of appliances/activities	Modeller's choice
Appliances available and quantity	Same as parameters set in CREST model being compared
Number of residents	Same as parameters set in CREST model being compared
Occupancy/schedule of residents	Same as parameters set in CREST model being compared
Maximum attention capacity	Modeller's choice; 2 is the default. This allows for multitasking as well as for residents to carry out other activities while their attention is waiting for the most due activity to be performed.

Table 4 – System parameters and sources of calibrated values

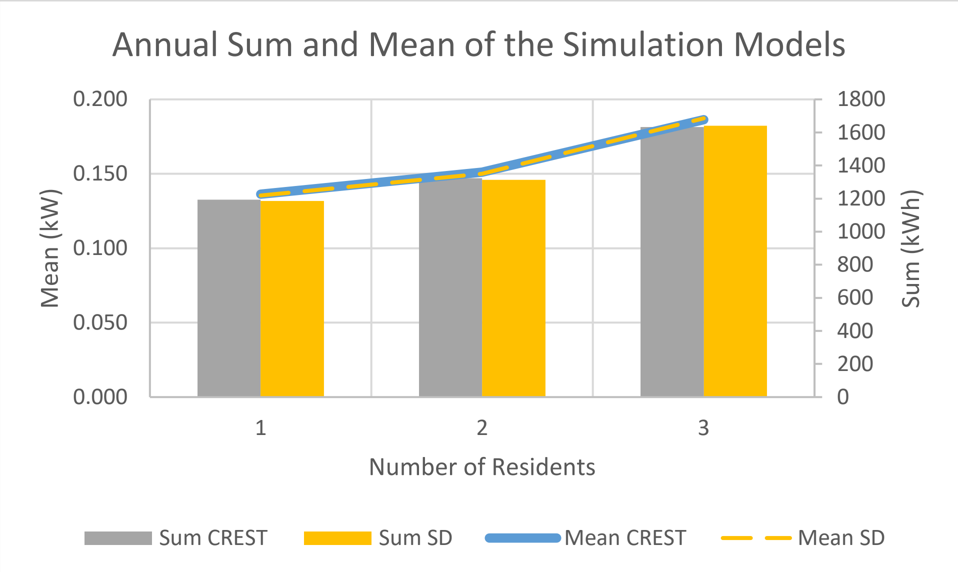

Figure 15 – Calibrated sum and mean of the SD models by adjusting the scaling factor of the activity frequency

There is a secondary group of parameters that add stochasticity to the model; termed the noise parameters. These achieve stochasticity by randomly modifying an associated parameter around its mean value. The noise parameters include: Schedule Shift Noise; and Appliance Duration Shift Noise. Schedule Shift Noise moves occupancy forward or backward every 24 hours, while Appliance Duration Shift Noise changes the duration of the appliance's operation ever cycle. All the noise parameters are based on the Normal Distribution with the mean set as the calibrated value of the associated parameter. The standard deviation for Schedule Shift Noise is set to 8 minutes, while for Appliance Duration Shift Noise, it is 30% percent of the magnitude. Being random noise, the accumulated effect is cancelled out at the end of the simulation of 525,000 minutes.

3.2.4 Extreme Conditions

Most of the extreme and unrealistic conditions that could arise in the model are controlled in the logic of the model; e.g. only one resident can use an appliance at the same time instead of multiple of infinite number. Other controls are specified as parameters e.g. maximum attention per resident set to 2.

3.2.5 Behaviour Reproduction

The aim of behaviour reproduction is to evaluate the similarities of the model's output to a reference dataset. The reference dataset could be a measured residential load or a synthetic residential load which has been validated against measured residential load. Table 5 shows behaviours that will be tested which are based on validations carried out in [31] and [32], but limited to statistical characteristics that apply to a single residence while also excluding characteristics showing the effects of some limitations of the model (e.g. seasons). The simulation model is run at 1-minute time steps for the duration of one year.

Property	Description
Load profile	Plot of the output load of the residence per minute
Annual mean daily load profile	Plot of the annual mean load for every minute of a day
Hourly load duration curve	Plot of the hourly mean load for a year in descending order

Table 5 – Statistical properties for comparison and brief description

High resolution measured data on residential load demand is available like the UK-DALE dataset [40] and the UKDA-6385 dataset [41] but comparing these quantitatively with the SD model's output is challenging because some of the calibrated parameters of the SD model that define scenarios are not specified in the datasets; e.g. active occupancy of residents, number of residents, power consumption of appliances and available appliances. In the UKDA dataset, there are data on available appliances and number of residents, whereas in the UK-DALE dataset, there are data on available appliances and their power consumption only.

On the other hand, the output dataset from the CREST model [39] could be used for validation because many of the model parameters can be extracted from the input parameters of the CREST model. This has been shown in the parameter calibration Table 4. However the CREST model has a limitation, which is that its output represents an average residence from a population because the model is driven by probability distributions generated from TUD which covers many residences in two days (a weekday and a weekend). In contrast, the SD model in this study aims to simulate a single residence across many days. Hence a dataset from a single residence, or simulated based on data from a single residence, would be preferred, and therefore behaviour comparison is carried out in light of this limitation.

Based on the above, there are two aspects to behaviour comparison: a visual-quantitative and a qualitative aspect. Visual-quantitative comparison refers to visual comparison of plots on quantitative axes. The visual-quantitative comparison is between SD and CREST models on how well the former matches the latter on a two dimensional surface of power consumption and time. Purely quantitative comparison is tedious and inconclusive for time series – without qualitative judgement – according to sources like [42–45]. Moreover, all the reviewed literature on synthetic residential load focus on visual comparison to validate at individual-residence level. On the other hand, the qualitative comparison first identifies some qualitative properties of real measurements (UKDA dataset), then compares the two models on how well they exhibit those properties.

Since the CREST model allows for the SD model to be calibrated better for comparison, a few adjustments have been made in the CREST model: maintain the same appliances and occupancy schedule for weekdays and another for weekends, for the simulation period of a year. The appliances selected and their quantity for the residence is provided in Table 6. The main measured residence to be compared with from the UKDA dataset has the same appliances as in Table 6, however the power consumption of the appliances are not available. The residents are assumed not to be children because every resident has access to all the appliances. Children may have access to none or few, which may not be operated by them in reality but would be determined by their routine.

Appliance	Quantity
Fridge freezer	1
Personal computer	1
TV	1
Microwave	1
Kettle	1
Washing machine	1

Table 6 – Appliances in each residence

4 Results and Discussion

4.1 Behaviour Comparison

4.1.1 Load Profile

The load profiles for a 7-day period for the CREST model, SD model and a residence from UKDA dataset are shown in Figure 16, Figure 17 and Figure 18 respectively; all have two residents. Figure 18 is the residence with the same appliances as the CREST and SD models. The three load profiles highlight the similarities of varying and steep peaks resulting from different activities, as well as similar amplitudes between the CREST and SD models. The absence of these similarities would terminate further comparisons.

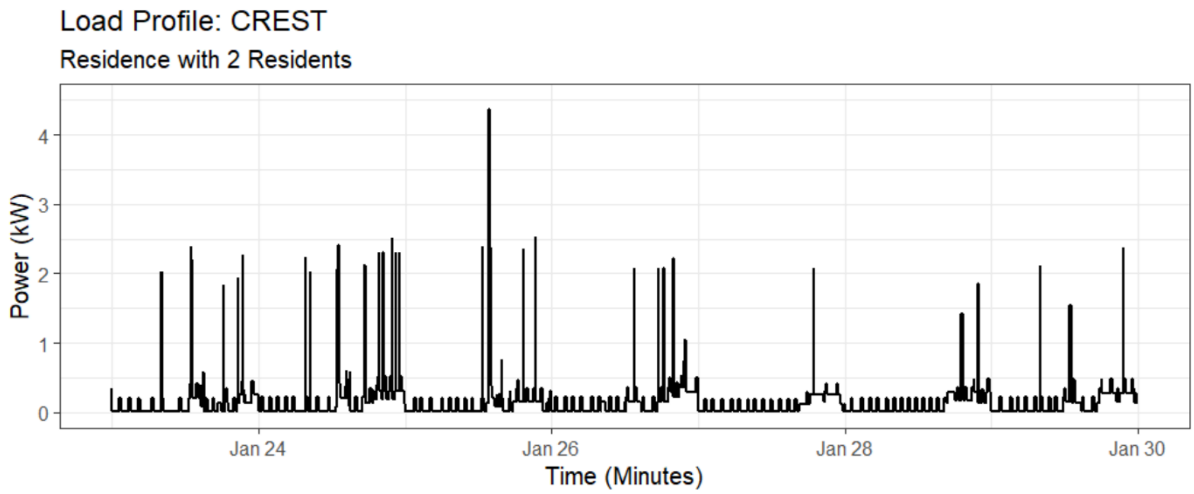

Figure 16 – Load Profile from CREST model

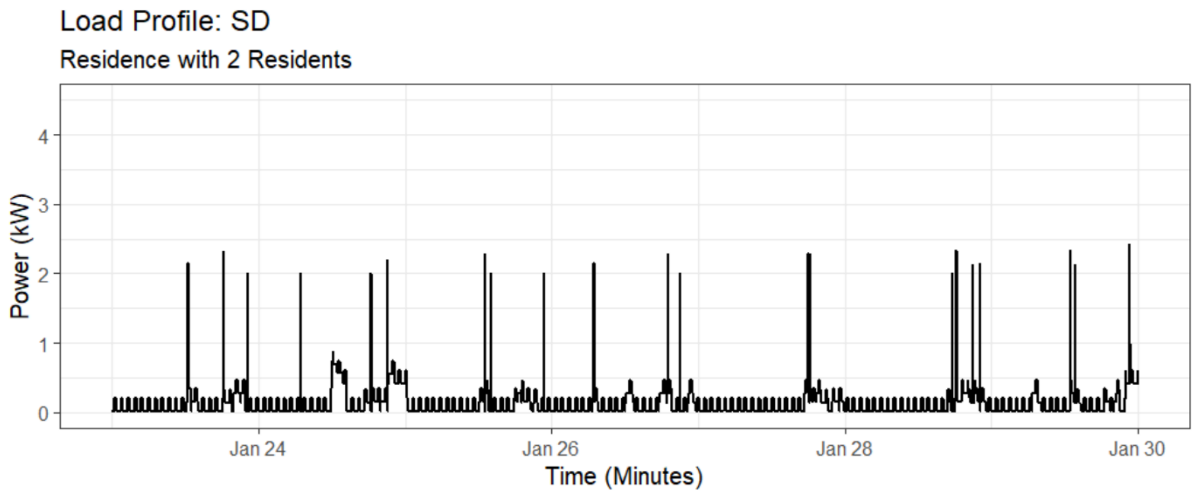

Figure 17 – Load Profile from SD model

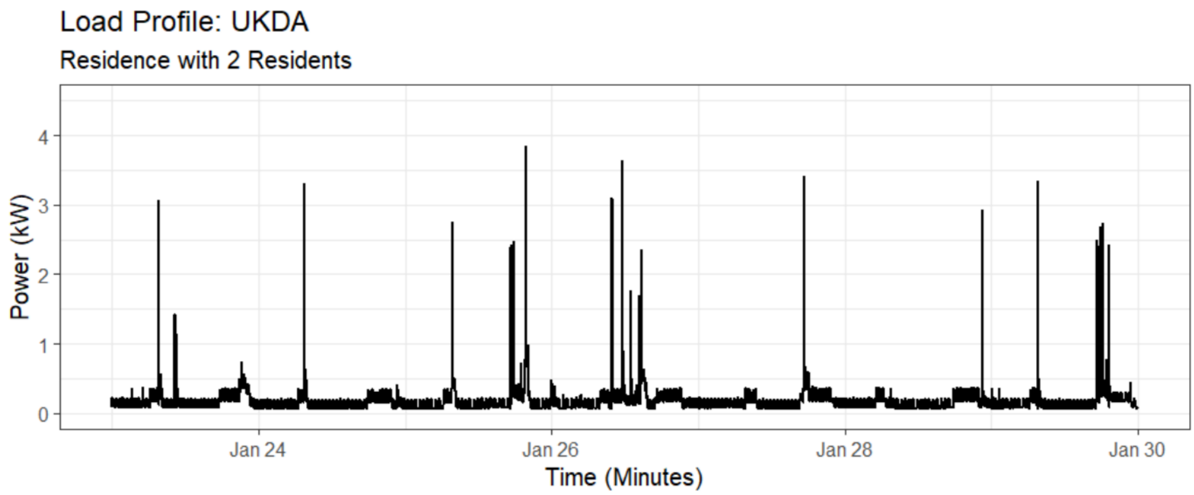

Figure 18 – Load Profile measured from a residence in the UKDA dataset

Looking at the period of a week in Figures 16-18, there is significant difference in peak amplitude between SD and UKDA, but not between SD and CREST. The similarity in average amplitude between SD and CREST is because the parameters of appliances in SD were obtained from CREST. The doubling of peak amplitude in CREST is an outlier which can occur in SD at different time. However, the difference in average peak between SD and UKDA is likely due to higher power consumption of appliances in the UKDA residence, which is not available in the UKDA data. Nonetheless, the three models (Figures 16-18) show similar qualitative properties: intermittent peaks, short but consistent low power cycles, and sparse intermediate power cycles lasting minutes or hours.

The aggregate energy for the period in Figures 16-18 is 24.60 kWh, 27.85 kWh and 30.30 kWh for SD, CREST and UKDA respectively, which indicates that the appliances in UKDA consume the most power and that the difference between SD and CREST would be smaller were it not for the outlier in CREST. However, these values represent a short period of a week and it cannot be generalised for other parts of the year especially given the limitation that SD does not model seasonal variation in residential load. For a more comprehensive qualitative comparison, which should be between SD and CREST, the annual energy consumption for SD and CREST have been shown in Figure 15.

4.1.2 Annual Mean Daily Load Profile (AMDLP)

Residential load profiles are not suitable for comparing the models over a long period of time like a year at 1-minute resolution because the data points are many and the entire dataset is considered a single instance of the data; a year's data could be split into instances of sub-units like weeks or days. The AMDLP summarises a year's load profile by plotting the annual average of every minute in a day, and this addresses the limitations of load profiles. In this section, the AMDLP plots will be explained first, then a visual-quantitative and qualitative comparison, as explained in Section 3.2.5.

Figure 19 and Figure 20 compare the AMDLP of the SD model with the corresponding CREST model having similar parameters, for residences with two and three residences respectively. The plots show clusters of peaks which coincides with the active occupancy for weekdays and weekends; the weighted weekly occupancy of the two residence types are provided in Figure 21. Figure 22 shows the AMDLP of measured residences from UKDA dataset where the number in the name indicates the number of residents; Res2b is the residence with the same appliances as the SD and CREST models, having two residents. The qualitative properties of AMDLP from the real residences (Figure 22) are: gradual transition between trough and peak; at least, visually distinct mountain-like peaks; and continuity between the end of the plot and the beginning. The exception is a steep transition in Res1a which could be due to a scheduled device that operates at the time of day throughout the year.

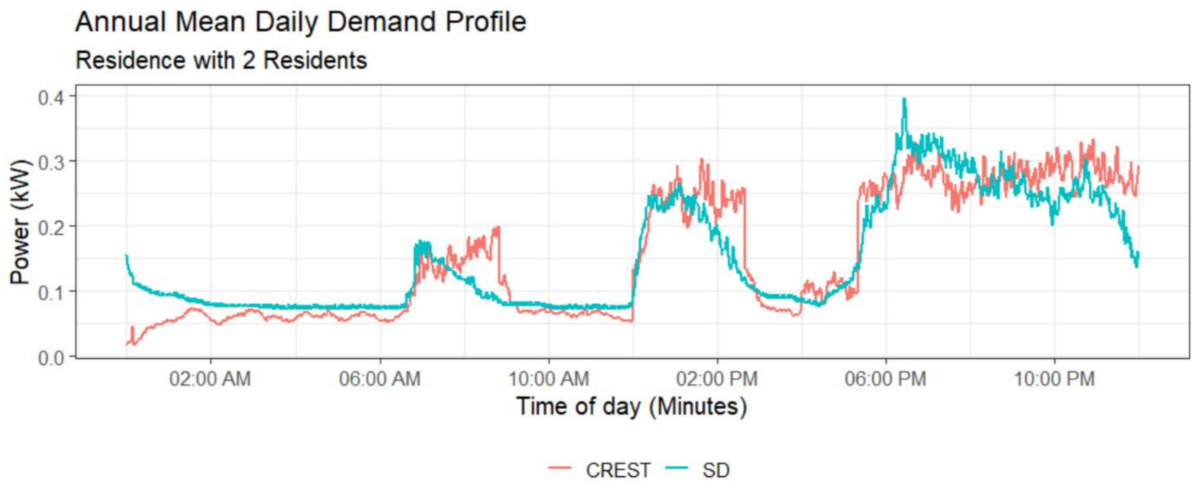

Figure 19 – Annual Mean Daily Load Profile for the CREST model and SD model for residences with 2 Residents

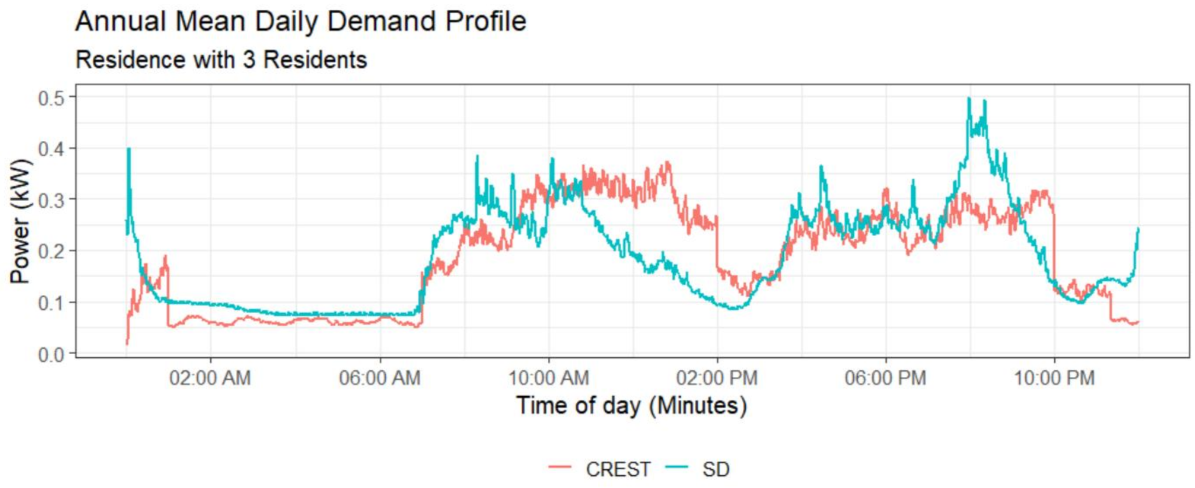

Figure 20 – Annual Mean Daily Load Profile for the CREST model and SD model for residence with 3 Residents

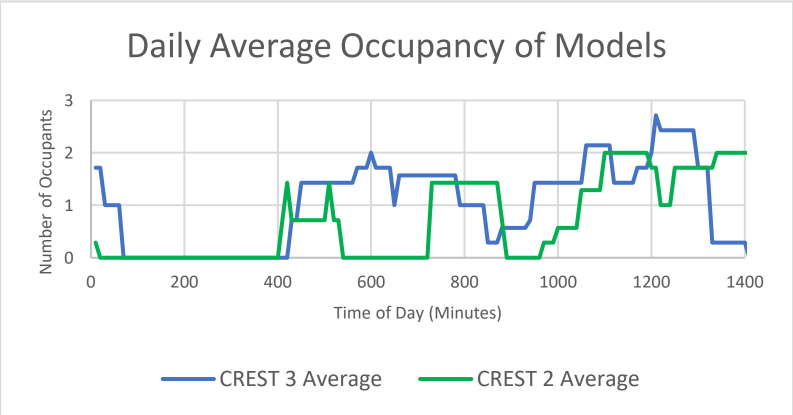

Figure 21 – Occupancy of the residences used in the CREST and SD model; for residences with 2 and 3 residents

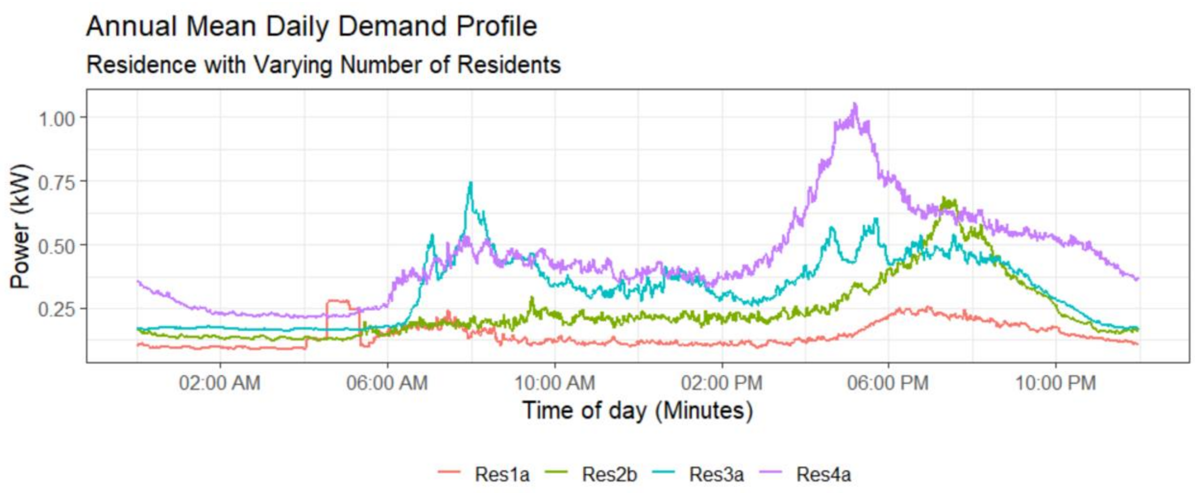

Figure 22 – Annual Mean Daily Load Profile from UKDA dataset for residences with different number of residents

Visual-quantitative comparison of the AMDLP in Figure 19 and Figure 20 are generally similar in terms of power consumption and time. Where the power consumption from the SD model falls short of the CREST model, it compensates for it in other peaks. Moreover, the difference between the two models on total power consumed in a year is less than 1%: 0.67%, 0.78% and 0.5% for residences with 1, 2 and 3 residents respectively (see Figure 15). For qualitative comparison with the identified properties of real residences, the CREST model is steeper during occupancy transition, flatter during active occupancy, and lacks visual continuity from the end to the beginning of the plot. Therefore it seems the SD model behaves more similar to the real residences than the CREST model.

4.1.3 Hourly Load Duration Curve (HLDC)

Similar to the AMDLP, the HLDC is another way to summarise the load profile over a long duration by plotting the average hourly load per time in descending order as shown in Figure 23, Figure 24 and Figure 25. Figure 23 and Figure 24 show the HLDC of residences with two and three residents respectively, while Figure 25 shows the HLDC of real residences from the UKDA datasets. The plots have been separated to aid readability because the pair of plots in Figure 23 and 24 follow each other closely. The qualitative property of the real residences (Figure 25) to be used for qualitative comparison is that the HLDC are smooth, each like a single curved line; not angled straight lines.

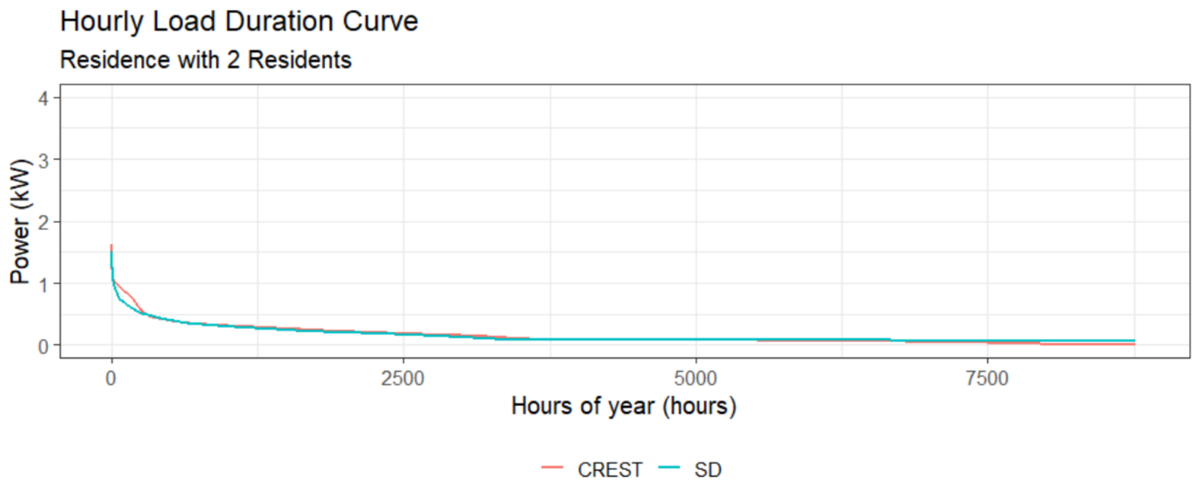

Figure 23 – Hourly Load Duration Curve for the CREST model and SD model for residence with 2 residents

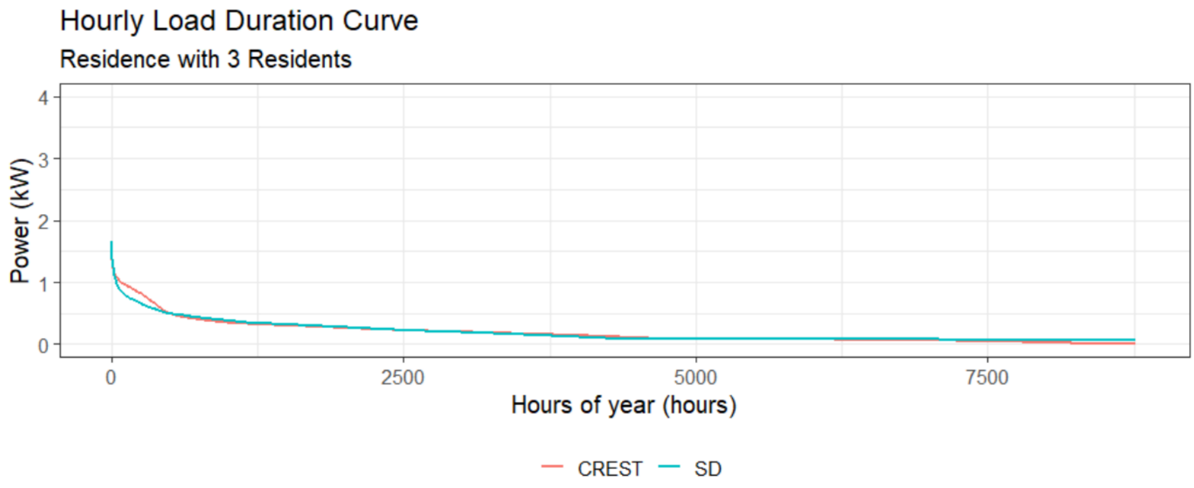

Figure 24 – Hourly Load Duration Curve for the CREST model and SD model for residence with 3 residents

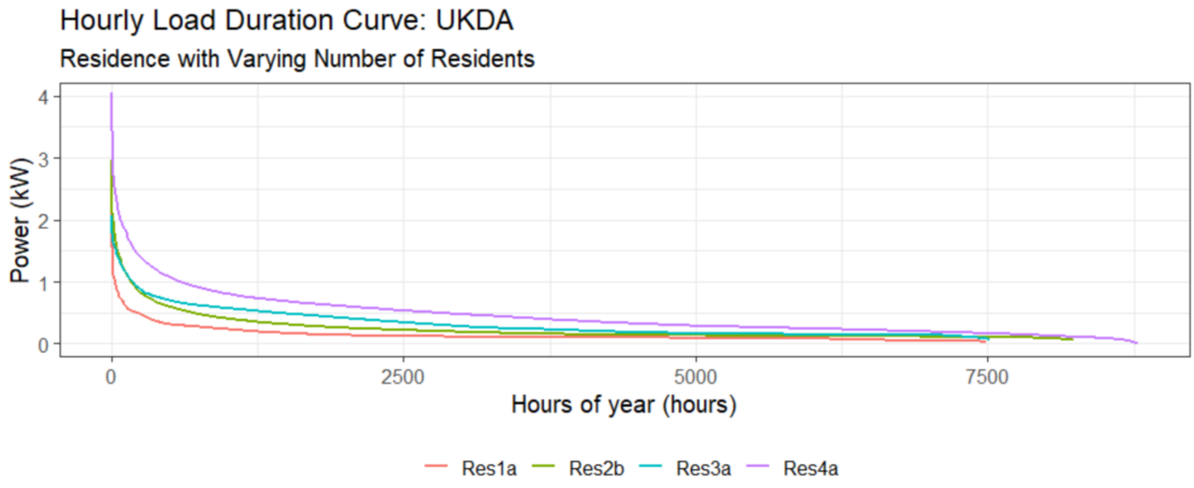

Figure 25 – Hourly Load Duration Curve from UKDA dataset for residence with varying number of residents

For the visual-quantitative comparison in Figure 23 and Figure 24, the SD model approximates the CREST model well. Qualitatively, the SD model appears smoother than the CREST model, and that makes the SD model more similar to the real measurements of Figure 25.

4.1.4 Summarising Behaviour Comparison

In summary, the SD models behave like the CREST models with the same number of residents in terms of load profile, AMDLP and HLDC. Where the SD model deviates from the CREST model, it behaves more like real residences from the UKDA dataset.

4.2 Output on Appliances

In addition to the residential load, other outputs from the simulation include the distribution of appliances' activation and operation. Figure 26 and Figure 27 show the distribution of the operation of appliances in a day over a year from the output of the SD model for residence with two and three residents respectively; and these can be used as probability distributions. The distributions fall within active occupancy period except the washing machine which is semi-automatic and only requires to be setup and started within active occupancy. In other simulation models reviewed (Section 2.6) functionally similar probability distributions are extracted from TUD and provided as input to the models, whereas it is an output in these SD models; Figure 28 shows an example of input to the CREST model. Serving similar function as input in the SD model is a single value: average frequency of appliance use. Having these distributions and their derivatives as input makes the other models more coupled to historic correlations, while the SD model is less coupled to historic correlations. Furthermore, these outputs from the SD model could be used for analysis or as input to other simulations.

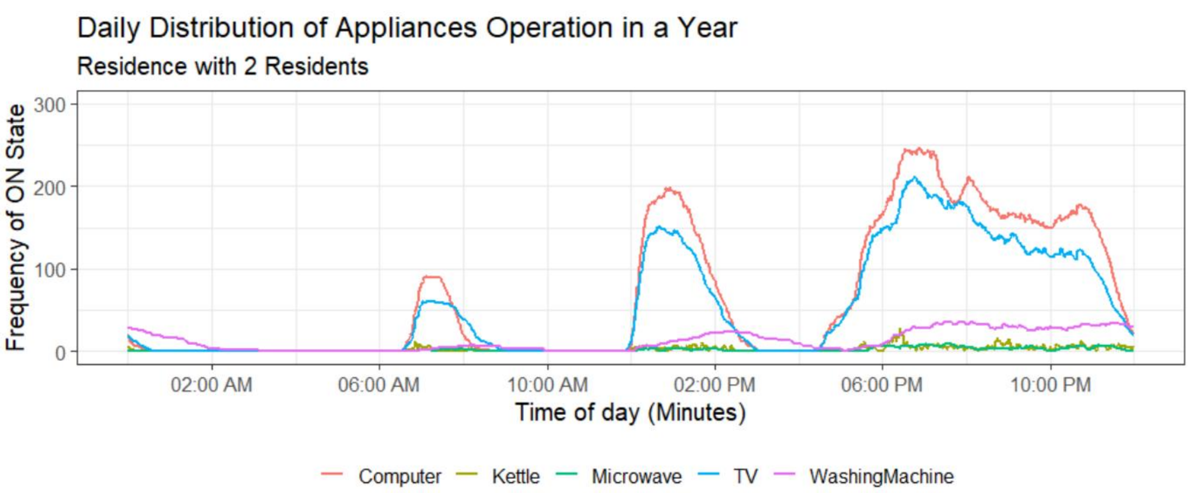

Figure 26 – Distribution of appliance operation in a day over a year, from SD model with 2 residents

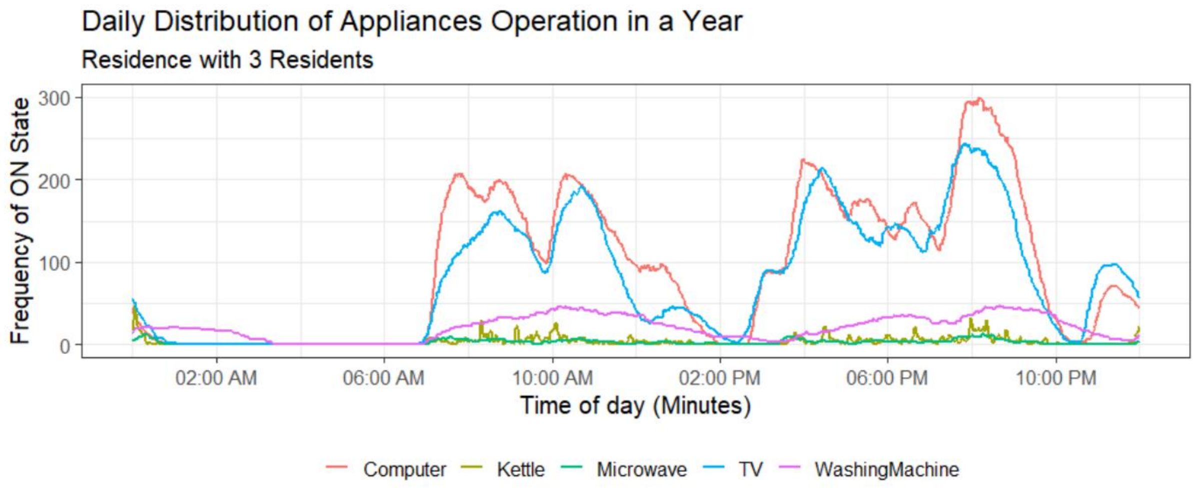

Figure 27 – Distribution of appliance operation in a day over a year, from SD model with 3 residents

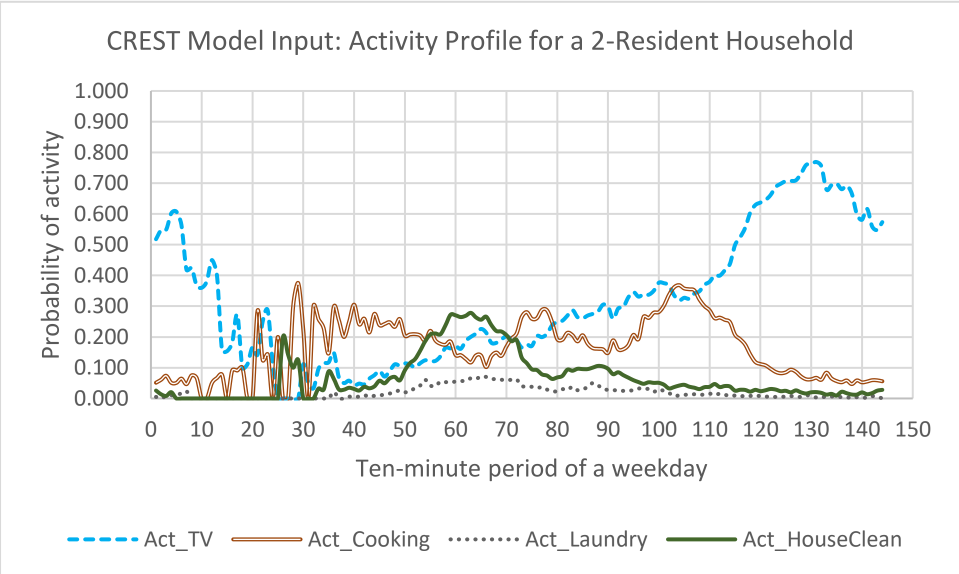

Figure 28 – Input to CREST model showing probability of activities as proportion of households where at least one occupant is engaged in a particular activity during a particular ten minute period

4.3 Complexity

4.3.1 System Complexity

There are two sources of complexity in any system [38]: detailed complexity which arises from aggregation of system components linearly; and dynamic complexity which arises from relationships among system components which are characterised by feedbacks, non-linearity and delays. The detailed complexity of the SD model is proportional to the amount of elements in the system e.g. residents and appliances. On the other hand, the dynamic complexity is determined mainly by the dependencies and constraints within the system as formulated in the system's logic.

The two types of complexity are not necessarily complementary; e.g. when a residence with two residents has one of its two (non-sharable) kettles removed from the system, then one resident would have to wait for the other to finish using the kettle before using it if they both plan to use it at the same time. In this example, the detailed complexity reduced because there are fewer appliances but the dynamic complexity increased because of the increased dependency between the activities of the residents. Therefore the multiple constraints and conditions required before activating an appliance in the SD model can be considered as contributors to dynamic complexity.

Stochasticity from noise parameters could increases complexity in terms of uncertainty about the value of the associated parameter, and this may be considered dynamic complexity because the noise parameters affect time variables (occupancy and appliance operation duration), the effect of which is a delay or advancement of the activation of an appliance in time. Delay or advancement in timing has cascading/ripple effects in time which alters the dependencies in the future, but not infinitely.

4.3.2 Computational Complexity and Cost

Computational cost can be expressed in terms of time taken to run a model, and it is directly proportional to the complexity of the model. There are two levels to evaluate and compare the computational complexity associated with the models. The first is at the level of algorithm, and the second is at the level of the implemented model. Complexity of algorithms can be estimated using the Big-O notation which expresses the rate of growth of run time relative to the size of input. On the other hand, implemented models are impacted by the inefficiencies of the software platforms they are built on, and therefore the actual time taken to run a model can represent the cost.

The Big-O complexity of the algorithms for SD and CREST is linear because the number of operations increase as the input size increases; input could be time duration of the simulation. This is based on the two models ran for duration of 4, 36, and 365 days, being approximate factors of 365. The time taken to simulate a residence (having the same appliances) with three residents for the duration of a year (525,600 time steps) is 186 seconds and 660 seconds for SD and CREST models respectively. The time was measured using a stopwatch and inline python code respectively. It should be noted that while the SD model is implemented in Vensim with some input read from Microsoft Excel, the CREST model was implemented in Microsoft Excel (VBA) for daily simulations and a Python script was written to automate the daily simulations for a year. Therefore, whilst both models are linear, the SD model has a lower rate of growth and is computationally less costly compared to the CREST model in the current implementation.

4.4 Evaluation of the Model's Aims

The two aims of the SD simulation model are to be realistic and minimise historic coupling. The SD model has been shown to be realistic to the extent that it behaves similar to the CREST model and measurements from real residences of the UKDA dataset, in Section 4.1.

Whereas most of the reviewed simulation models (Section 2.6) are driven by historic probabilities of appliance use, the SD model is driven by the average frequency of an appliance use, and that makes the SD model less historically coupled or fitted. This is because the historic probabilities are typically generated from high resolution data of activities (TUD) which makes it sensitive to granular change in the time and individuals/residents in the sample population, whereas average frequency of appliance use is a summary statistic that is less sensitive to granular changes. Moreover, multiple TUD for the same activity (or appliance use) could summarise to the same average frequency of appliance use. Similarly, some of the reviewed models also describe occupancy of residents from historic probabilities derived from TUD, whereas the SD model allows occupancy to be described as a simple binary for times of weekday or weekend.

4.5 Some Benefits of the SD Model

Compared to the some of the reviewed models, the benefits of the SD model include being more cost effective, more interpretable and enabling transdisciplinary research. Interpretability aims to simplify translation of the main variables between the model and real world; which should aid policy research. Enabling transdisciplinary research refers to employing a modelling language that is not discipline-specific.

Compared to models based on TUD, the SD model could be less expensive to collect data on appliance use, assuming data collection is part of the model's cost. Unlike TUD which is resource intensive in terms of cost and person-time, the average frequency of appliance use can be estimated from asking a single question about a household appliance. Since TUD is also scarce, average frequency – estimated or collected – could facilitate empirically grounded models. Computationally, it may also be simpler to calculate average frequency of appliance use compared to generating probability distribution of appliance use from TUD. Furthermore, output from the SD model can be used as probabilities of appliance use as show in Section 4.2.

The SD model is more interpretable than other reviewed models because its driving input (average frequency of appliance use) is easier to translate to the real world than the more abstract driving input (probabilities) of the other models. Being more interpretable could simplify simulating real residences in the model and extracting insight from the model to a residence in the real world; e.g. a limit to average or total use of an appliance in a duration.

Finally, the model enables transdisciplinary research by using the generic language of systems in the form of CLD and SFD. Furthermore, the use of SFD eases integration with other SFD models as long as the models share a common variable, regardless of disciplinary boundaries. Whereas integration between models could be achieved via a common interface (for inputs and outputs), integration among SD models makes the interface seamless while allowing for interaction between variables of the models, including endogenous variables. Therefore common variables are not limited those that are input in one model and an output in the other model.

5 Conclusion and Further Work

The tools of system dynamics have been utilised to simulate a residential load using a bottom-up approach, and the aims of the model have been achieved. The model was conceptualised as a CLD based on literature and reasonable assumptions, and from that, a simulation model was presented as a SFD. Both the conceptual and simulation models addressed the concerns of SD validity tests. The output load from the SD model was compared to output from the well validated CREST model, as well as load measurement from real residences (UKDA), and the behaviour was found to be similar. Therefore, output from the SD model could be used as input to other simulations like other synthetic simulation models. Furthermore, distribution of appliance use was explored as an output from the SD model. In conclusion, the complexity of the SD model and some benefits were discussed.

The novel contributions of this work that are significant to research on synthetic residential models are four. First is that this work represents the first attempt at using SD tools to generate realistic bottom-up residential load in high resolution. The significance of using SD is that integration would be facilitated with other SD models that have a common variable; like top-down residential models. Second is the use of average statistics of appliances as input to the model which is cheaper to obtain or estimate compared to the commonly used TUD. Third is the logic of the SD model which could be adapted and implemented using programming tools. Fourth is the output of distribution of appliance use which could be used as input to other simulations.

A limitation of the SD model includes the lack of modelling seasonal variation in residential demand, which can be achieved by using subannual averages of appliance data instead of annual. Another limitation is that the SD model does not describe different types of residences (e.g. single houses, condominiums) because it does not model envelop or heating and cooling within the building. These limitations can be explored in future work.

Other areas to explore in the future include: calibration of the model parameters using measured data from a single residence; explore further constraints on the total power consumed by appliances like the maximum supply available to a residence; integration of the model with other SD models based on SFD; explore the scalability of the model beyond a single residence to multiple residences; and simulation of a community energy system composed of several residences.

6 Funding

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7 References

[1] C. Wilson, H. Dowlatabadi, Models of Decision Making and Residential Energy Use, Annu. Rev. Environ. Resour. 32 (2007) 169–203. https://doi.org/10.1146/annurev.energy.32.053006.141137.

[2] R.M. Tetlow, C. van Dronkelaar, C.P. Beaman, A.A. Elmualim, K. Couling, Identifying behavioural predictors of small power electricity consumption in office buildings, Build. Environ. 92 (2015) 75–85. https://doi.org/10.1016/j.buildenv.2015.04.009.

[3] E.R. Frederiks, K. Stenner, E. V. Hobman, The socio-demographic and psychological predictors of residential energy consumption: A comprehensive review, Energies. 8 (2015) 573–609. https://doi.org/10.3390/en8010573.

[4] T. Hong, D. Yan, S. D'Oca, C. fei Chen, Ten questions concerning occupant behavior in buildings: The big picture, Build. Environ. 114 (2017) 518–530. https://doi.org/10.1016/j.buildenv.2016.12.006.

[5] M.A. Ortiz, P.M. Bluyssen, Proof-of-concept of a questionnaire to understand occupants' comfort and energy behaviours: First results on home occupant archetypes, Build. Environ. 134 (2018) 47–58. https://doi.org/10.1016/j.buildenv.2018.02.030.

[6] L. Nicholls, Y. Strengers, Peak demand and the "family peak" period in Australia: Understanding practice (in)flexibility in households with children, Energy Res. Soc. Sci. 9 (2015) 116–124. https://doi.org/10.1016/j.erss.2015.08.018.

[7] L. Nicholls, Y. Strengers, Changing demand: flexibility of energy practices in households with children, (2015).

[8] J. Palm, K. Ellegård, Visualizing energy consumption activities as a tool for developing effective policy, Int. J. Consum. Stud. 35 (2011) 171–179. https://doi.org/10.1111/j.1470-6431.2010.00974.x.

[9] T. Gärling, J. Garvill, Psychological Explanations of Participation in Everyday Activities, Adv. Psychol. 96 (1993) 270–297. https://doi.org/10.1016/S0166-4115(08)60047-3.

[10] J. Kuhl, Action Control: The Maintenance of Motivational States BT - Motivation, Intention, and Volition, in: F. Halisch, J. Kuhl (Eds.), Springer Berlin Heidelberg, Berlin, Heidelberg, 1987: pp. 279–291.

[11] Statistical Office of the European Commission, Harmonised European time use surveys, 2008 guidelines, Off. Off. Publ. Eur. Communities. (2009).

[12] Ipsos-RSL and Office for National Statistics, United Kingdom Time Use Survey, 2000 (Computer File), third ed. SN: 4504, (2003).

[13] T. Harms, J. Gershuny, Time Budgets and Time Use, 2009. https://www.ratswd.de/download/RatSWD_WP_2009/RatSWD_WP_65.pdf.

[14] H. Frazis, J. Stewart, How to Think about Time-Use Data: What Inferences Can We Make about Long- and Short-Run Time Use from Time Diaries?, Ann. Econ. Stat. (2012) 231. https://doi.org/10.2307/23646463.

[15] P. Grunewald, M. Diakonova, The electricity footprint of household activities - implications for demand models, Energy Build. 174 (2018) 635–641. https://doi.org/10.1016/j.enbuild.2018.06.034.

[16] E. Mckenna, S. Higginson, T. Hargreaves, J. Chilvers, Exploratory analysis of time-use activity data using network theory, (2016).

[17] T.F. Golob, A model of household demand for activity participation and mobility, (1996) 1–38.

http://escholarship.org/uc/item/5nj1b37b.pdf.
[18] S. Herkel, U. Knapp, J. Pfafferott, Towards a model of user behaviour regarding the manual control of windows in office buildings, Build. Environ. 43 (2008) 588–600. https://doi.org/10.1016/j.buildenv.2006.06.031.
[19] J.F. Nicol, Proceedings of the Seventh International IBPSA Conference, Characterising Occupant Behav. Build. (2001) 1073–1078.
[20] C.F. Reinhart, Lightswitch-2002: A model for manual and automated control of electric lighting and blinds, Sol. Energy. 77 (2004) 15–28. https://doi.org/10.1016/j.solener.2004.04.003.
[21] Y. Zhang, P. Barrett, Factors influencing the occupants’ window opening behaviour in a naturally ventilated office building, Build. Environ. 50 (2012) 125–134. https://doi.org/10.1016/j.buildenv.2011.10.018.
[22] V. Fabi, R.K. Andersen, S. Corgnati, Verification of stochastic behavioural models of occupants’ interactions with windows in residential buildings, Build. Environ. 94 (2015) 371–383. https://doi.org/10.1016/j.buildenv.2015.08.016.
[23] Y. Zhang, P. Barrett, Factors influencing occupants’ blind-control behaviour in a naturally ventilated office building, Build. Environ. 54 (2012) 137–147. https://doi.org/10.1016/j.buildenv.2012.02.016.
[24] V. Inkarojrit, Balancing Comfort: Occupants’ Control of Window Blinds in Private Offices, UNIVERSITY OF CALIFORNIA, BERKELEY, 2005.
[25] C. Kandler, J. Honold, P. Wimmer, Modeling lighting as part of the USER model based on stochastic time budget survey data, Energy Procedia. 78 (2015) 1659–1664. https://doi.org/10.1016/j.egypro.2015.11.247.
[26] V. Inkarojrit, Multivariate predictive window blind control models for intelligent building façade systems, IBPSA 2007 - Int. Build. Perform. Simul. Assoc. 2007. (2007) 787–794.
[27] T. Hong, S. D’Oca, S.C. Taylor-Lange, W.J.N. Turner, Y. Chen, S.P. Corgnati, An ontology to represent energy-related occupant behavior in buildings. Part II: Implementation of the DNAS framework using an XML schema, Build. Environ. 94 (2015) 196–205. https://doi.org/10.1016/j.buildenv.2015.08.006.
[28] Y. Chen, X. Luo, T. Hong, An Agent-Based Occupancy Simulator for Building Performance Simulation, ASHRAE Annu. Conf. (2016).
[29] J. Chapman, P.-O. Siebers, D. Robinson, On the multi-agent stochastic simulation of occupants in buildings, J. Build. Perform. Simul. 11 (2018) 604–621. https://doi.org/10.1080/19401493.2017.1417483.
[30] J. V. Paatero, P.D. Lund, A model for generating household electricity load profiles, Int. J. Energy Res. 30 (2006) 273–290. https://doi.org/10.1002/er.1136.
[31] J. Widén, E. Wäckelgård, A high-resolution stochastic model of domestic activity patterns and electricity demand, Appl. Energy. 87 (2010) 1880–1892. https://doi.org/10.1016/j.apenergy.2009.11.006.
[32] I. Richardson, M. Thomson, D. Infield, C. Clifford, Domestic electricity use: A high-resolution energy demand model, Energy Build. 42 (2010) 1878–1887. https://doi.org/10.1016/j.enbuild.2010.05.023.
[33] R. Bartels, D.G. Fiebig, M. Garben, R. Lumsdaine, An end-use electricity load simulation model. Delmod, Util. Policy. 2 (1992) 71–82. https://doi.org/10.1016/0957-1787(92)90055-N.
[34] R. Yao, K. Steemers, A method of formulating energy load profile for domestic buildings in the UK, Energy Build. 37 (2005) 663–671. https://doi.org/10.1016/j.enbuild.2004.09.007.
[35] J. Widén, M. Lundh, I. Vassileva, E. Dahlquist, K. Ellegård, E. Wäckelgård, Constructing load profiles for household electricity and hot water from time-use data-Modelling approach and validation, Energy Build. 41 (2009) 753–768. https://doi.org/10.1016/j.enbuild.2009.02.013.
[36] N. Pflugradt, U. Muntwyler, Synthesizing residential load profiles using behavior simulation, Energy Procedia. 122 (2017) 655–660. https://doi.org/10.1016/j.egypro.2017.07.365.
[37] J.W. Forrester, Industrial dynamics, Cambridge, Mass.: M.I.T. Press, 1961.
[38] J. Sterman, Business dynamics : systems thinking and modeling for a complex world, Irwin McGraw-Hill, Boston, 2000.
[39] I. Richardson, M. Thomson, Integrated domestic electricity demand and PV micro-generation model, (2011). https://repository.lboro.ac.uk/articles/dataset/Integrated_domestic_electricity_demand_and_PV_micro-generation_model/9513176.
[40] J. Kelly, W. Knottenbelt, The UK-DALE dataset, domestic appliance-level electricity demand and whole-house demand from five UK homes, Sci. Data. 2 (2015) 150007. https://doi.org/10.1038/sdata.2015.7.
[41] I. Richardson, M. Thomson, One-Minute Resolution Domestic Electricity Use Data, 2008-2009 [computer file]. SN: 6583, (2010). http://dx.doi.org/10.5255/UKDA-SN-6583-1.

[42] P. Ellis, How to compare two blackbox timeseries generators?, Free Range Stat. (2015). http://freerangestats.info/blog/2015/09/20/timeseries-differences (accessed October 1, 2020).
[43] J. Yang, J. Chan, Comparison of two time series, Fundam. Stat. Consult. (2019). https://www.maths.usyd.edu.au/u/jchan/Consult/W10_CompareTwoTimeSeries.pdf (accessed October 1, 2020).
[44] Robintw, How to statistically compare two time series?, Stats.Stackexchange.Com. (2011). https://stats.stackexchange.com/questions/19103/how-to-statistically-compare-two-time-series (accessed October 1, 2020).
[45] Moe, Proving similarities of two time series, Stats.Stackexchange.Com. (2015). https://stats.stackexchange.com/questions/172226/proving-similarities-of-two-time-series (accessed October 1, 2020).