Convenience in a Residence with Demand Response: A System Dynamics Simulation Model

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ABSTRACT

Demand Side Management (DSM) is a means to gain more control over energy demand to address some of the challenges of power grids. Demand Response (DR) is an approach to DSM that aims to influence the operation times of appliances; DR is often recommended for residences. Meanwhile, residents can undermine DR if it is not convenient. Therefore, there is need for tools to aid decision-making on the appropriate DR program for residences. Whilst models are used to explore DR programs, most do not measure, visualise or analyse the convenience of residents, although some models make assumptions about convenience. This paper explores convenience of a residence as timeliness by simulating four scenarios of DR programs in a single residence, using the System Dynamics (SD) methodology. In addition to delay in appliance-use that may result from DR, two indicators of convenience are proposed that consider preferences of the residence: Delay Duration Profile (DDP) and Delay Time Profile (DTP). When comparing convenience as delay, it was found that more hours of DR is better than less, earlier hours (from occupancy period) are better, and splitting or distributing DR hours during the day is better than being contiguous. Similar findings apply to DDP and DTP. Furthermore, it was found that DR leads to monetary savings and reduction in daily peak demand. This study represents the first attempt at a DR model from the bottom-up using SD, as well as using the model in decision-making analysis.

Keywords: *Demand Response, Demand Side Management, Convenience, System Dynamics, Bottom-Up Simulation, Delay Duration Profile, Delay Time Profile*

1 Introduction

The effects of many challenges faced by smart grids and traditional grids can be reduced by gaining more control over energy demand. Some of the perennial challenges of power grids include underutilisation of infrastructure (generation capacity, transmission lines, distribution networks) and mismatch between supply and demand especially during peak load [1]. Another major challenge is uncertainty which is introduced by intermittency of renewables, decentralisation of power systems and the emergence of new loads like electric vehicles [2], [3]. A manifestation of these challenges that is critical to the grid is the 'duck curve' phenomenon which is when aggregate demand changes by a large deviation in a short period [4].

Demand-Side Management (DSM) is any measure taken on the demand-side of an energy system to address challenges in the energy system ranging from installing more efficient loads, to sophisticated dynamic load management systems [5], [6]. Whilst DSM has been traditionally driven by (the needs of) utility companies to control customers' energy use [6], (the needs of) customers are also being considered [5]; for example, customer convenience is considered in designing DSM solutions in [7]–[11]. Therefore, the benefits of DSM may be categorised into benefits for utility companies and for customers. Some of the benefits for utility companies include reduction in overall costs (especially investment in capacity), reduction of carbon emissions levels, efficient or optimum utilisation of capacity, and improved resilience to intermittent sources and distributed generation [1]–[3], [6]. The benefits for the customer is mainly monetary savings, though it has not been found to be incentivising [8]; even while [3] posits that smart pricing can encourage more efficient energy consumption. Nonetheless, some customers experience negative financial outcomes from DSM [12].

DSM may be categorised as illustrated in Figure 1 with a focus towards Direct Load Control (DLC) based on [5], [13], [14], because DLC is most relevant to this paper. The top-level categories are Energy Efficiency, Demand Response (DR) and Spinning Reserve. On the second level, Incentive-Based DR refer to DSM techniques that require the customer to opt into an arrangement/contract and often lose control during DSM, whereas Time-Based DR simply provide the customer with price information to act appropriately; the second level can be considered a misnomer. DLC is on the third level. DLC, which aims to shape the load profile, may be further divided (according to the targeted shape and scale) into: load-shifting, peak-shaving, valley-filling, strategic conservation, strategic load growth and flexible load shape.

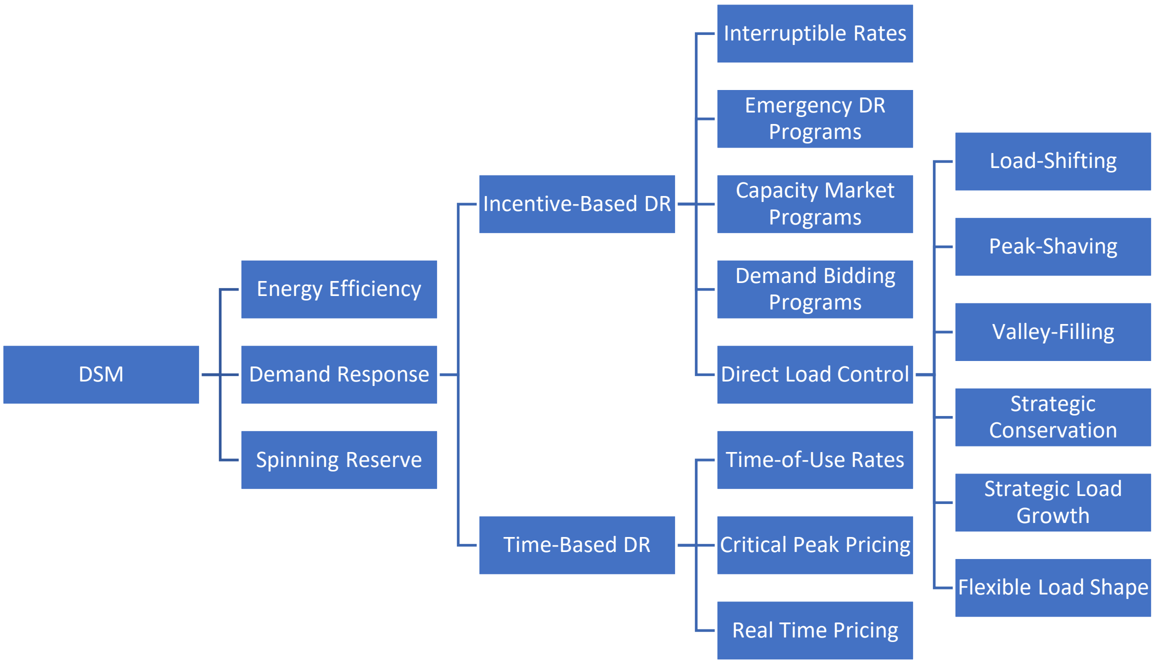

Figure 1 - Classification of DSM focusing on Demand Response and Direct Load Control

Energy Efficiency is the most effective DSM because it saves energy, emissions and reduced impact on aggregate load, while other DSM often focus on management of load operation to minimise impact on aggregate load [5]. However, Energy Efficiency does not preclude other DSM. Among DR techniques, load-shifting was the most widely applied as at the 1980s [14], and it appears to remain so either via Direct Load Control or Time-of-Use (ToU) Rates. Due to the difference between Incentive-Based DR and Time-Based DR, load-shifting can be achieved via automatic control (DLC) as in [15], or via active customer intervention (reacting to ToU rates or penalties) as in [16]. Load-shifting relies on the flexibility to run certain appliances at postponed periods. Consequently, this flexibility is affected by the preferences of the users of the appliances.

DR models explore problems of electric utilities like reducing peak loads [4], [7], [8], [17], reducing the impact of black-outs [7] or system failure [17] and short frequency dips [17]. The benefits for customers can be grouped into economic, social and cultural benefits. The economic benefit is mainly cost savings [3], [6], [8], [18], [19], while the social benefits include fairness of cost savings in a community [18], [20] and privacy [19], [21], and the cultural benefits include customer convenience. There is increasing interest in fairness of economic compensation, not just compensation. Another interesting concern is user privacy. As smart devices become ubiquitous, targeted campaigns and cyber-attacks become more prevalent; user security had been acknowledged as a concern a decade ago in [5]. The complexity of achieving social objectives has been acknowledged in [3], but cultural benefits like convenience can be complex too.

Whilst innovative DR solutions continue to be proposed, convenience of the solution to the end-users/residents is critical to its success, because their preferences can undermine a DR solution in spite of a meritorious assessment of the solution. Convenience can be understood as preferences of end-users which include the two components of comfort and timeliness, as used in [4], [6]–[8], [17]–[19]. These preferences may explain the finding in [8] that monetary savings resulting from DR programs have not incentivised more efficient energy use. Nonetheless, it has been shown that residences decided to use increased and expensive energy so they can have 'quality family time' [22]. In other words, the cheapest, most efficient and most environmentally friendly technology may not be used appropriately if the technology does not align with the users' preferences, and especially if they have an alternative. Convenience has wide-ranging implications, but in the case of DR, end-users would not participate in DR programs that are not convenient.

Therefore, there is need for tools that aid in matching end-users to appropriate DR programs. Moreover, the success of DR programs depends on the willing participation of the end-users, and the collaboration between end-users and suppliers towards mutual benefits [23], [24]. For example, [23] found that there is a potential conflict between the energy consumption goals of residences and the DR policy makers (government or utility companies), and therefore, aligning the two goals increases participation of residences. After all, some consumers experience negative financial outcomes in DR [12]. Furthermore, the success of DR depends on the timings of popular TV programs, timings of family visits, and temperature changes [25]. Similarly, [26] conducted a randomised control trial using data spanning 15 months which showed that the main predictors of energy consumption are time of occupancy in the residence, age and appliance ownership. Whilst different DR programs have been explored and compared in simulation models [17], [18], [27], these models have not been used as decision-making tools for specific residences in deciding on appropriate DR programs based on their impact on convenience.

Some tools to aid decision-making on DR have been proposed, with an aim towards successful DR. Rather than taking direct control of DR loads, or simply incentivising end-users with cost savings at recurring times that may require DR, [28] aids residences by communicating to the residences during peak DR events based on their historic appliance usage; they may act to support the DR or not. In another case, [29] developed a business model-based cost calculator to enable individual residences, as well as utility companies and policy makers, to make decisions about DR programs. Furthermore, [12] uses historical electricity load and household characteristics to identify residences that would financially benefit from DR so that resources can be focused on them. Given the many models that explore various options for DR, none have been found to aid a specific residence in deciding which option of DR programs would be most convenient for them; relevant literature is explored in Section 2.

Consequently, existing models have not attempted to answer questions like how much inconvenience would a residence endure if they subscribe to a particular DR program.

Therefore, the contribution of this study includes:

1. A simulation model of a single residence that explores different DR programs, which can be used for scenario analysis and decision-making about the residence.
2. Novel tools that measure, visualise and compare convenience (as timeliness) of the different DR programs in a specified residence, which can be used for decision-making on DR programs.

In an earlier work, the authors of this study had created demand-side models of single residences that generate realistic load [30]. The models were created using the simulation methodology of System Dynamics (SD), taking a bottom-up approach. Unlike previous models of residential load that use historic probability distributions (like Time-Use Data) to make the models realistic, the SD model is driven by the simpler statistic of mean appliance-use frequency, and dependencies among residents and appliances. This study builds on the SD model. Since Heating, Ventilation and Air Conditioning (HVAC) appliances were not modelled in the SD model, convenience will focus on timeliness but not comfort.

Relevant residential DR models are reviewed next. Then four DR programs are defined, which correspond to five scenarios, including a base-scenario. Next, the indicators for comparing the scenarios are discussed, including the proposed measures of convenience. Thereafter, the earlier SD model of a residence is integrated with a DR subsystem, and the resulting model has DR capabilities. Finally, results from the scenarios are discussed.

2 Literature Review

The focus of the surveyed literature is on DR models of residences. Table 1 highlights dimensions of the literature that were considered relevant to this study. Modelling Approach refers to the mathematical conception of the model, while Modelling Method refers to implementations of the modelling approach, which could be a software package. DR Type refers to the technique of DR, while DR Control refers to how load that is on DR may be turned on and off. Indicators refer to the measures used to compare scenarios in case-studies, and these depend on the aims and research questions of a study.

Model Approach	DR Type	Modelling Methods	Indicators	DR Control	Ref.

Statistical	peak-shaving	-	Area Under the Curve (AUC) index, F1 score index	-	[28]
	load-shifting	-	-	-	[12]
		-	-	-	[31]
Simulation with rule-based management	load-shifting	Load-shifting algorithm considers 3 variables (microgrid energy balance, priority mode of appliance, shifting time which depends on intermittent source of energy)	Self-Consumption Ratio (SCR)	Automatic DR	[15]
	peak-shaving	Autonomous and multi-agent systems; Differential Return of Temperatures (DRT) control strategy	Peak-shaving (at network-level); indoor temperature difference, indoor temperature evolution (at residence-level)	Automatic DR	[32]
	load-curtailing; peak-shaving	-	Energy savings, cost savings, aggregate peak demand	Automatic DR	[18]
	load-shifting; load-curtailing	-	Daily peak load, annual peak load, percentage peak reduction	Automatic DR	[7]
	load-shifting; load-curtailing	-	Peak load	Automatic DR	[17]
	load-shifting	Model Predictive Control (MPC) algorithm, Python (ARX, Gurobi, Dymola/Modelica)	Performance of MPC algorithm, thermal comfort, energy consumption	Automatic DR	[33]
	load-shifting; load curtailing	-	Cost of electricity	Automatic DR	[27]
Simulation with rule-based management; simulation with optimisation management;	load-shifting; peak-shaving	EnergyPlus, OpenDSS, BEopt;	Peak demand (aggregate)	Automatic DR	[4]
Simulation with optimisation management	load-shifting; load curtailing	Python, PVWatts; multi-objective optimisation, then single-objective optimisation.	Consumption cost, load schedule discomfort, Peak-to-average ration (PAR) of aggregate demand profile	Automatic DR	[9]
Simulation with optimisation management	load-shifting; load-curtailing	Hybrid dynamical systems (HDS for load-shifting: continuous-time dynamics, discrete-time	Evolution of battery State of Charge	Automatic DR	[34]

		dynamics), multi-agent systems theory (MAS for load-curtailing);			
	load-shifting; load-curtailing	LINGO; MILP	Aggregate load, utility revenue earning, cost to consumer sector	Manual DR	[16]
	load-shifting	Back-tracking; genetic algorithm (GA)	Electricity cost	Automatic DR	[35]
	load-shifting	MATLAB; MILP	Average indoor temperature, residential power consumption, daily cost, percentage cost reduction	Automatic DR	[10]
	load-shifting	-	Monetary savings; renewable energy surplus	Automatic DR	[36]
	load-shifting	MATLAB; Particle Swarm Optimisation	Electricity cost reduction	Automatic DR	[37]
	load-shifting	MATLAB; MILP, then Artificial Neural Network, then Deterministic Optimisation, then Meta-heuristic Optimisation.	Electricity cost	Automatic DR	[38]
	load-shifting	Residential Electricity Load profile simulation and Optimization (RELO) model	Demand-side flexibility	Automatic DR	[11]
	load-shifting	Indoor temperature model;	Peak load shifting, load management and power saving potential	Automatic DR	[39]
	peak-shaving (via load-curtailing and load-shifting)	MATLAB; Constrained Non-Linear Programming (CNLP)	Compliance to DR timings	Manual DR	[24]
	load-shifting	PL-Generalized Benders Algorithm (MINLP problem)	Cost of electricity	Automatic DR	[19]
	load-shifting	-	Cost of electricity, peak load	Automatic DR	[8]

Table 1 – Surveyed literature of DR models

The modelling approaches can be categorised into three, based on Table 1: statistical; simulation with optimisation management; and simulation with rule-based management. Statistical models aim to make predictions about the future state of the system based on historic data. For example, [31] used smart meter data (historical electricity load) to forecast the load of residences based on assumptions about lifestyle. In contrast, [12] uses historical electricity load and household characteristics to identify residences that would benefit financially from DR. In another approach, [28] predicts which residences need to act during a DR to achieve the aims of the DR.

Simulation has also been used to predict load profile of residences in [40], but on a regional scale. However, most applications of simulation are in demonstrating the effectiveness of DR strategies for management of the energy systems; simulations are used to model the systems in case-studies. However, the management logic of the systems is achieved via either optimisation or rule-based management. Most of the proposed DR management strategies are optimisation problems (with defined objectives and constraints), and they correspond to the modelling approach 'simulation with optimisation management' in Table 1. On the other hand, there are DR models with the modelling approach of 'simulation with rule-based-management', like [15] which aims to propose a method of analysis using historic data, or the system in [32] that responds to a single variable like temperature. In some cases, the two modelling approaches may be combined e.g. simulation with optimisation management is implemented at district-level, while simulation with rule-based management is implemented at residence-level in [4]. Furthermore, a simulation with rule-based management could call upon optimisation as in [33], [41].

The most common DR type modelled is load-shifting. Whilst load-shifting moves load operation in time, load-curtailing (also load-shedding) may interrupt the power to a load, or move the load to another source [34]. Consequently, the DR type is often related to the properties of the load; whether the load's operation can be postponed or interrupted without undermining the utility of the load. Loads have been categorised into shiftable/interruptible and non-shiftable/non-interruptible [1], [3], [4], [6], [8], [18], [19], [21], [42]. For instance, the operation of 'white appliances' may be postponed, while lighting and cooling may be turned off periodically [7], [8], [17]. Appliances were also grouped according to priorities of operation in [7], and an agnostic approach to appliances was adopted by focusing on an attached control unit which controls an appliance in [17]. Typically, load-shifting and load-curtailing are not ends in themselves, but are means to achieve peak-shaving, as in [9], [24], [34], [39]. Load-shifting and load-curtailing are typically applied at the residence-level, whereas peak-shaving is the aggregated effect at higher scales like microgrid; though peak-shaving may be achieved via other means.

There are a variety of indicators used to evaluate and compare model scenarios, but none of the indicators can be considered a measure of convenience, except [9] which measures 'load schedule discomfort'; load schedule discomfort is basically the timeliness component of convenience. At first, [9] models customer preferences in terms of preferred times of operation, minimum required power for appliance, and maximum curtailable power for an appliance. Since optimising (minimising) cost could lead to discomfort, a second objective function was added to minimise discomfort, which would lead to an optimal load schedule that would have lower cost and lower discomfort than otherwise. If this were applied to a real residence, the residents would be able to modify their preferences (in terms of time and appliance power) a day in advance because the assumed tariff is day-ahead tariff. It would then be possible to also measure the inconvenience (schedule discomfort) experienced by the residence by comparing the preferred schedule and implemented schedule. Furthermore, to make decisions about a DR program, the customer preferences and tariff could be assumed for a duration into the future (e.g. a year), and the impact on inconvenience could be measured. However, the model was not used to make decisions about DR programs.

Nonetheless, the way in which the DR loads are controlled should be considered before measuring convenience, because that can affect the complexity of the measurement. The two ways of DR Control are automatic DR [10], [11], [39], [15], [32]–[38] and manual DR [16], [24], [28]. Automatic DR is when the load is not controlled by the end-user, e.g. centrally by an algorithm or the suppliers. Manual DR is when the end-user is incentivised to add or remove load at required times, e.g. via Time of Use (ToU) tariffs, or [24] which uses a credit function to reward residences for shifting loads away at peaks, and increasing loads at off-peak times. Automatic DR is preferred by suppliers because load can respond to infrastructure status more efficiently and timely [5]. Measuring convenience can be more challenging in the case of manual DR, because considering the incentives and penalties associated with the decisions of end-users could affect what they consider convenient. Whilst it is reasonable to assume that those under automatic DR are willing participants (for a duration) in free markets, the type of DR control should be considered when measuring convenience.

Having noted that convenience, as comfort or timeliness, is not a common indicator in the surveyed models, it is considered in some optimisation problems with assumed values that are used as constraints in optimising for other objective functions like cost; after all, most of the surveyed models are automatic DR, and simulation with optimisation management. Convenience has been modelled as a range of indoor temperature [4], [6], [11], [18], [33], temperature of cold appliances [11], customer-defined priority of appliances [7] or appliance runtime. As appliance runtime, it has been modelled as either a maximum time window [8], [17], or latest time [8], or crossing a specific time of day (e.g. 6 am) [8], or preferred times of operation [9], [37], or allowable load per day [24]. Furthermore, comfort (or discomfort) has been modelled as utility functions (not assumed constraints) in [9] and [24]. However, in most cases, the objectives of the utility functions are to minimise monetary cost to residents as in [3], [6], [8], [10], [18], [19], [21], [35], [37], [38], to minimise aggregate and peak demand [4], [42], or even generic objective functions [1].

Given the above, this study presents a simulation model of a single residence with rule-based management, automatic DR, and attempts to measure convenience as timeliness such that the residence can make decisions about the more appropriate DR program for their schedule and frequency of appliance-use. Although, the model in [9] could be used by a residence to make decisions about the appropriate DR program for a residence, it requires representing the schedule discomfort of the residence as an objective function in an optimisation problem; thereby the energy management system of the residence is actively trying to 'comfort' the residents. In contrast, the model presented in this study presents a simulation of a residence with rule-based management, which considers residents' awake-occupancy (which could be preferred times of operation), but does not seek to actively 'comfort' the residents. Also, the implementation of the rule-based management is such that the DR management is exogenous to the model, and so the model can be applied on (or interfaced with) any existing system, in theory.

3 Methodology

3.1 Study Design

3.1.1 Study Objectives

Based on the above, the focus of this study is on the exploration of residents' convenience in a DR simulation model of residential demand. Additionally, other indicators like peak load and money saved shall be explored briefly to demonstrate the versatility of the model. Therefore, the objectives of this study are four:

1. Create a valid DR simulation of a residence where interdependence among appliances, residents and DR programs is modelled;
2. Measure, visualise and analyse residents' timeliness convenience in different DR programs;
3. Briefly analyse peak load in a year by different DR programs;
4. Briefly analyse money saved by different DR programs.

3.1.2 Scenarios and Indicators

The model (and its parameters) is based on a residence with three occupants, which is the 3-person residence from an earlier work [30]. The appliances are shown in Table 2, which shows the quantity of appliances, which appliances are on DR, dependency among the appliances, mean cycle duration, and cycles per day. Mean cycle duration refers to the average duration an appliance remains in operation when turned on, while cycles per day refer to the average frequency of the appliance per day; average is taken over a year [30]. Each DR appliance runs about once in two days on average. Whilst 2-person residences are the most common in the UK as at 2020 [43], a residence with three occupants provides more dynamic complexity because of more dependency relationships between the appliances and the residents. Three (semi-automatic) appliances are on the DR program: washing machine, drying machine and dishwasher.

Appliance	Quantity	On DR	Dependency	Mean Cycle Duration (minutes)	Cycles per Day
Fridge freezer	1	No	-	22	28.8
Personal computer	1	No	-	60	7.2
TV	1	No	-	73	4.8
Microwave Oven	1	No	-	30	0.4
Kettle	1	No	-	3	5.0
Washing machine	1	Yes	-	138	0.6
Dryer	1	Yes	Washing machine	60	0.6
Dishwasher	1	Yes	-	60	0.6
LED Lights	5	No	-	Depends on room occupancy	

Table 2 - Appliances in the simulation model and highlighting the appliances on DR

A baseline scenario where DR is not active was simulated. Then four DR scenarios were defined based on the four DR programs, corresponding to four tariffs: Economy 7 [44] which is cheapest between 00:00-07:00; Economy 10 [45] which is cheapest between 22:00-08:00; Economy 10 Split [45] which is cheapest between 20:00-22:00, 00:00-05:00 and 13:00-16:00; and TIDE Tariff of Green Energy UK [46] which is cheapest between 23:00-06:00.

There are two groups of indicators to compare the scenarios. The first group compares among the four DR scenarios, and the focus is on comparing residents' convenience which are Delay, Delay Duration Profile and Delay Time Profile. The second group compares the baseline scenario to the four DR scenarios, and the two indicators are Daily Peak Demand and Money Saved. See Table 3 for summary.

<table>
<tr><th>Scenario</th><th>Indicators</th></tr>
<tr><td>Economy 7</td><td rowspan="4">Group 1
• Delay;
• Delay Duration Profile;
• Delay Time Profile;</td></tr>
<tr><td>TIDE</td></tr>
<tr><td>Economy 10</td></tr>
<tr><td>Economy 10S</td></tr>
<tr><td>Baseline</td><td>Group 2
• Daily Peak Demand;
• Money Saved</td></tr>
</table>

Table 3 - Simulation scenarios and indicators

3.2 Convenience

Based on the reviewed literature, convenience has been defined in terms of time in two categories. The first is as a 'delay' or duration between when the appliance is set up and when the appliance is turned on, for instance, a dishwasher may take 3 hours after being loaded compared to 5 hours, when comparing two DR programs. The second is in terms of whether the appliance crosses specific times of day between set-up and turn-on, for instance, whether the dishwasher runs by 6:00 am after it had been loaded. However, as noted in Sections 2, previous simulation models of DR were not designed in a way that residents' convenience can be measured. Instead, convenience was assumed a value and incorporated into the models as a parameter. This study proposes a way to measure, visualise and analyse residents' convenience.

In this study, convenience was measured using three indicators over a duration. The first is as a delay between when an appliance is set up and turned on. Delay is a constant measured in minutes, which makes it one-dimensional, however the other two indicators of convenience are two-dimensional because they are a function of time. The other two proposed indicators are Delay Duration Profile (DDP) and Delay Time Profile (DTP). Like Delay, DDP and DTP quantify the inconvenience of using an appliance resulting from the DR programs, and therefore convenience would be the reciprocal. DDP quantifies the number of times a specific duration of the delay is exceeded in the simulation period, by plotting delay duration against frequency of delays that exceed the delay duration. On the other hand, DTP quantifies the number of times a particular time of day falls during a delay, by plotting time of day against frequency of delays at that time of day. DDP and DTP can be used to make decisions about DR programs based on residents' convenience, because both are mathematical functions of the residents' preferences. Residents' preferences are defined in terms of maximum tolerable delay duration for DDP, and intolerable time of day to have a delay for DTP. Functions for DDP and DTP are generated per appliance per residence, and therefore, can be considered properties of an appliance in the particular residence in which they are generated.

To illustrate the indicators, consider a single-occupant residence where the washing machine can only turn on when tariff is cheapest and it has been loaded (set up). Also assume that the cheapest tariff is between 12am and 6am, but the resident wakes up 7am and leaves for work by 8am, then returns by 6pm. After work, the resident loads the washing at 7pm, but since the tariff is not cheap, the washing machine delays until 12am to turn on. Therefore, there was a delay of 5 hours. If the same sequence of activities is repeated for a year (365 days), then the following can be said about the indicators for the washing machine: there will be an average delay of 5 hours per day; DDP would be 365 for the first 5 hours, then 0 afterwards; DTP for the washing machine would be 365 between 7pm and 12am, but 0 at all other times of day. In realistic simulations, these indicators can be used to compare convenience of DR programs.

Alternatively, the indicators can be used by residents to decide on whether a DR program is convenient for them: for example, a resident that can tolerate a 4-hour delay would find the example above inconvenient due to DDP being greater than 0 (365) at 4 hours, but would be half as inconvenient if DDP was 182. On the other hand, if they have a tolerance of 6 hours, they would find the above example convenient. In terms of DTP, the same resident would find the DR program inconvenient if they do not want a delay between 7pm and 12am, but would be half as inconvenient if DTP was 182 (rather than 365) during the period. However, the resident would find it convenient if they do not mind delay between 7pm and 12 am. Essentially, given an appliance under a DR program, DDP asks how much delay a resident is willing to tolerate at any time of day, while DTP asks how much delay a resident can tolerate at specific times of day. Both DDP and DTP can be used to decide on whether a DR program is convenient or inconvenient in the first place, and if inconvenient, the degree of inconvenience can be compared.

3.3 System Dynamics

System Dynamics (SD) is the simulation methodology used in this study. All SD models have at least one of two general aims: to improve understanding of a system by explaining its dynamics; and to virtually simulate and analyse possible configurations of the system [47]. These aims can be achieved via different architectures which include, but not limited to, Ordinary Differential Equations, Agent Based Modelling, Discrete Event Simulation, or a combination thereof [47], [48].

SD has two diagrammatic languages used to describe a model. They are Causal Loop Diagram (CLD) which is used for conceptual models, and Stock and Flow Diagram (SFD) which is used for simulation models. Therefore, there are equation equivalents of SFD. CLD uses arrows between variables to indicate direction of causation, or direction of dependency in reverse. SFD is more complicated. 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 [48]. The direction of material links indicates the movement of the same quantity between two stocks as well as dependence, but information links simply indicate causation (or dependence in reverse). Stocks are accumulations, e.g. electric energy stored in a battery. Flows are the rate of accumulation, e.g. electric power charging a battery. A source or sink is a stock that is outside the model boundary, and both are represented by a cloud. More details of CLD and SFD are provided in [30].

3.4 Model Conception

3.4.1 Residence without DR

This subsection summarises the conceptual model on which the DR model for this study is built on. The DR model is based on the high-resolution model of residential appliance load from [30], which is a bottom-up demand-side SD simulation that generates realistic residential load based on interaction between the activities of residents and appliances, and the intricate feedbacks that exist among them. Figure 2 is a CLD showing the interaction between activities of a resident and two types of appliances: Appliance A requires the resident’s attention for the duration of its operation (e.g. cooker), while Appliance B requires the resident’s attention only while setting up the appliance (e.g. washing machine). Only a limited number of feedbacks are shown in the diagram; refer to [30] for more details. The residence used in this study is the 3-person residence from [30].

The time of set up is determined by Activity X Timer in Figure 2, which represents a resident's readiness for activity X. Activity X Timer is affected by (or depended on) an appliance’s mean cycle duration and cycles per day, as well as a resident's occupancy and resident's attention. Occupancy refers to times of day when the resident is in the residence, whereas attention refers to the limited mental resource of a resident to focus on an activity (set to maximum of 2 simultaneous activities). Attention is affected by appliances but differently depending on the type of appliance which may require the resident's attention throughout the operation, or only during set up; semi-automatic appliances are assumed to require attention only during setup. At the start of the simulation, the appliances are set up in the evening, but subsequent set up times are determined by the dependencies of Activity X Timer. Furthermore, the aggregation of appliances that result in the residential load are shown in Figure 3. To simulate DR for this study, the model will be modified by integrating a DR subsystem, which is discussed in the next subsection.

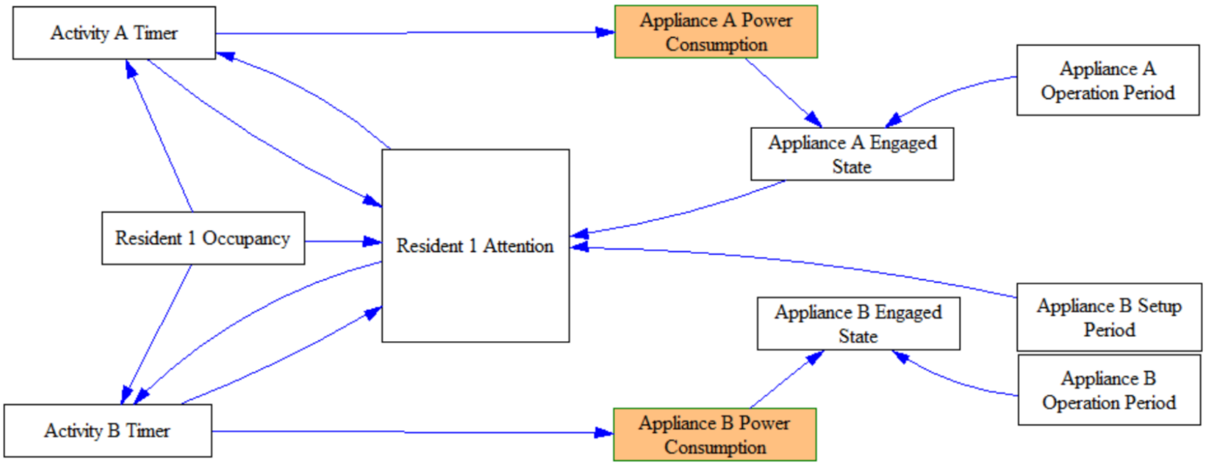

Figure 2 – CLD showing interacting components of a single resident with two types of activities and appliances

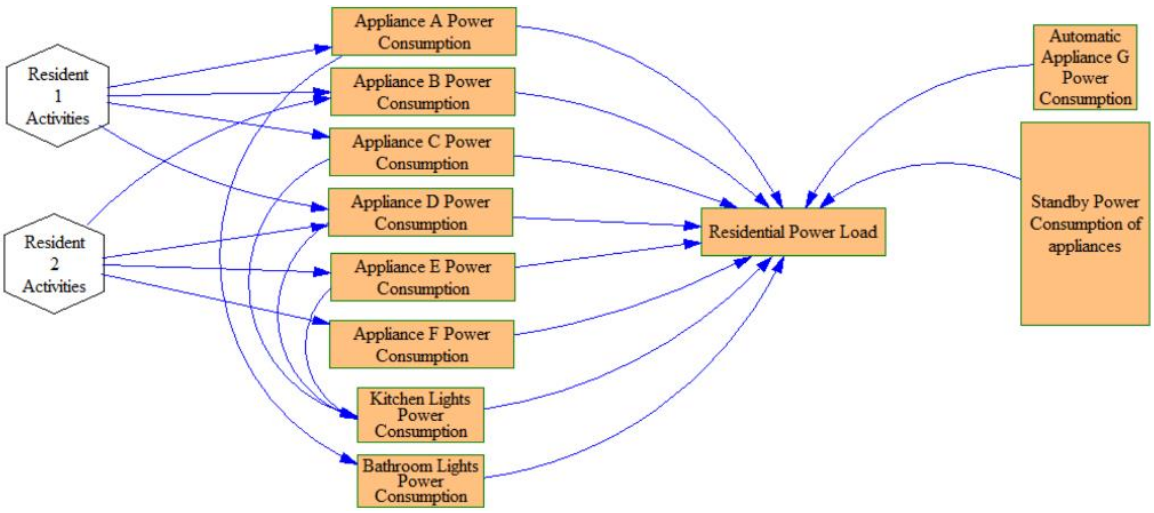

Figure 3 – CLD showing residential power load

3.4.2 DR Subsystem

Semi-automatic appliances (like washing machine, dishwasher and drying machine) are subjected to DR because of their flexible operation times without compromising residents' comfort, as discussed in Section 2. Whilst consumer electronics with batteries (like laptops) could be charged at flexible times without compromising comfort, they are not considered for DR in this study because the focus is on DR that is controlled exogenously (to the residence), rather than by volition of individual residents, as one would decide when to use battery or mains. Furthermore, consumer electronics with battery were not included in [8] because their energy impact is considered low. Whilst the energy impact of appliances for heating, ventilation and air conditioning is high, they are not included in the model because of their high impact on residents' comfort, which may be compromised by an exogenously determined DR. Moreover, the focus of this study is not on the appliances.

The DR control is achieved via a generic DR Signal which could represent the DR signal in the OpenADR framework as in [49], [50], or feedback from the network or local controller as in [17], or a generic objective function as in [1] or even off-peak times in Time-of-Use (ToU) tariff. Being exogenous to the residential model, a DR signal could be generated by feedback from an electricity network or other algorithms which determine the optimal times to operate the DR appliances. In other words, DR Signal can represent a top-down energy policy.

The DR subsystem can be divided into exogenous and endogenous variables. The exogenous variables are DR Signal and DR Mode, while the endogenous variables include DR Schedule X, DR Signal X and DR Agent X; where X is an appliance to which the variables are modelling. Therefore, exogenous variables are common to all appliances in a residence, while the endogenous variables are specific to appliances. Consequently, the endogenous variables can conceptually model a physical DR device dedicated to an appliance. Figure 4 illustrates the relationship between the DR subsystem and other system components (Activity Timer nX and Appliance X) from the existing load generation model (from [30]). Specific variables that are boxed are endogenous while those that are not boxed are exogenous. The DR subsystem groups all the endogenous DR variables in a larger box as a conceptual unit.

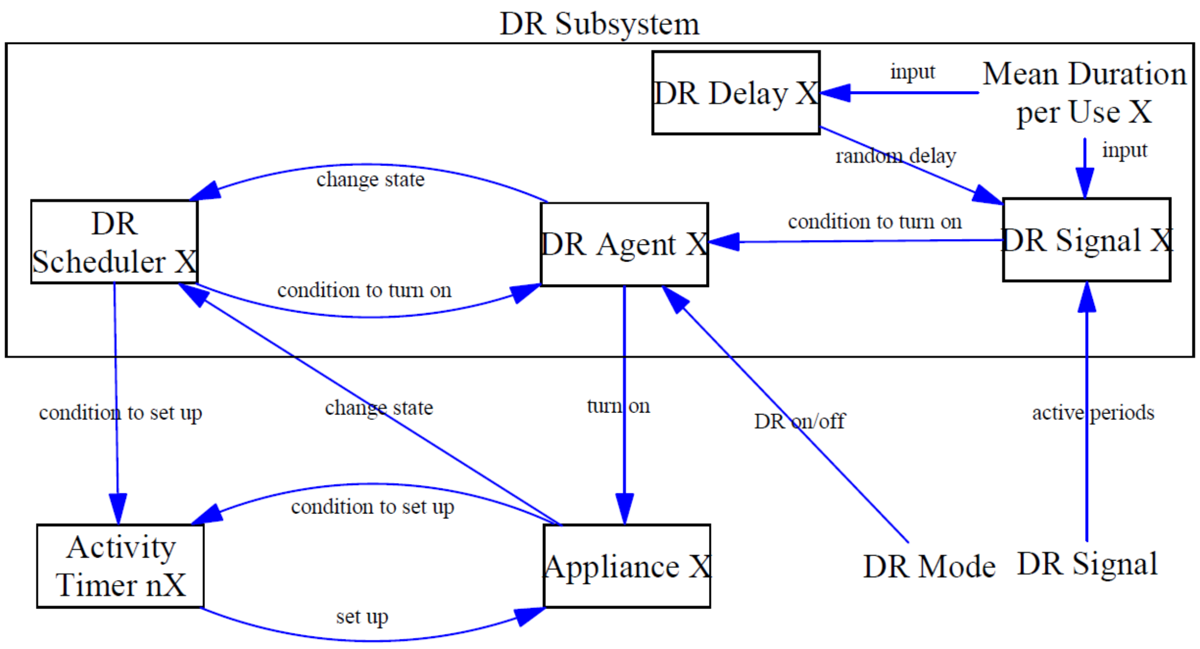

Figure 4 - CLD of components that form the DR subsystem and other system components

DR Signal indicates periods when DR is active. DR Mode indicates whether DR is activated or not. DR Delay X for each appliance X generates a random delay (per day) which delays DR Signal and results in DR Signal X; therefore, DR Signal X is DR Signal plus DR Delay X. DR Signal X is utilised by DR Agent X in deciding whether appliance X can be turned on within the period/duty-cycle of DR Signal. DR Scheduler X keeps track of whether Appliance X has been set up (by a resident via Appliance X) for DR or not, DR Agent X turns on Appliance X at the appropriate time if X has been setup for DR, while DR Signal X indicates periods when it is appropriate for DR Agent X to turn on appliance X. DR Signal X considers DR Signal, the duration of appliance operation cycle, and a random delay for DR Agent from the earliest time to turn on X. These constitute the DR subsystem.

As a whole, the DR subsystem interacts with residents and appliances which are modelled as Activity Timer and Appliance respectively; where Activity Timer nX is an abstraction of the desire of Resident n to use Appliance X (from [30]). The activity timers consider the occupancy of the resident and other constraints like available attention, but these dependencies are not shown in Figure 4. Therefore, for each appliance, there is an Activity Timer per occupant, a DR subsystem per appliance and the DR subsystem interacts with all the residents.

The structure in Figure 4 is consistent with a real feasible implementation of DR because the DR subsystem is similar to the control device discussed in [17] which connects to an appliance and controls the behaviour of the appliance based on external signals and the appliance’s state; hence the feedback between the appliance and the

DR subsystem. There is also feedback between the Appliance and the Activity Timer because the timer sets up the appliance (for DR Agent to turn on) and the state of the appliance (engaged or not) determines when Activity Timer can set it up and then reset Activity Timer. However, there is no direct feedback between the DR subsystem and Activity Timer (Resident), instead the feedback is via Appliance; DR subsystem provides the condition/state required by the Activity Timer to set up, Activity Timer sets up appliance, and Appliance eventually changes the state of the DR subsystem (via DR Scheduler).

3.5 Model Formulation

3.5.1 Simulation Model

DR Signal is implemented as a binary time-series input, where 1 indicates the earliest instance/period when it is permissible to operate a DR appliance; similar to a non-delayed DSM mode in [17]. DR Signal represents the DR programs, which are based on a simple algorithm where DR is active when the ToU tariff is cheapest in a day. Other algorithms and objectives could be used to generate DR Signal.

Figure 5 shows a SFD where part of the DR subsystem attaches to an appliance and determines when the appliance turns on; Figure 5 is an elaboration of the concept in Figure 4, without Activity Timer X. Activate O1B*m* are the output/decision of Activity Timer B (where *m* is the resident number) indicating when to activate Appliance B. The simulation runs without DR when DR Mode is 0 (inactive), and in that case, activating an appliance simply turns on the appliance. On the other hand, when DR Mode is 1 (active), activating an appliance sets up the appliance for DR instead, and DR Agent eventually turns on the appliance at the appropriate time.

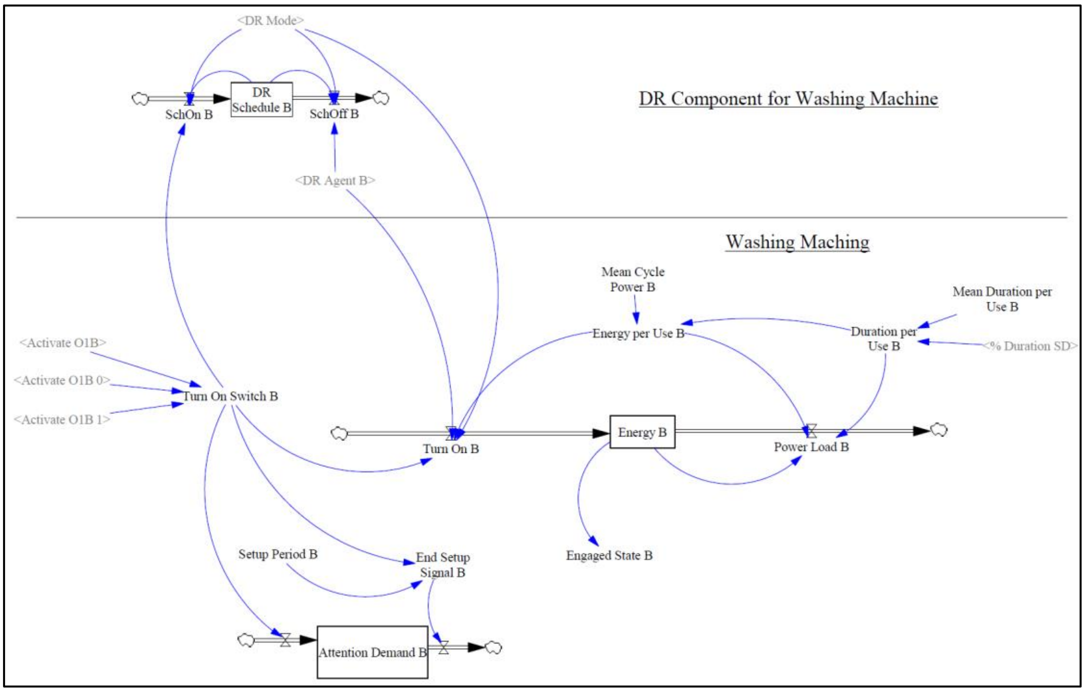

Figure 5 - SFD of appliance and DR subsystem with a horizontal demarcation between the two

The Scheduled State B was implemented as a binary switch which is set to 1 when an appliance has been set up (by Turn On Switch B), and set to 0 by DR Agent after the appliance has been turned on by DR Agent. Therefore, when DR Mode is 1 (active), there are two steps before an appliance turns on; the first step sets up the appliance then changes Scheduled State B to 1, and the second step runs the appliance then changes Scheduled State B to 0. These are the real-world equivalents of loading (or setting up) a washing machine to operate at the best time, as a first step, and then the machine 'automatically' (by DR Agent) operates when the 'best time' arrives, as a second step. Therefore, setting up the appliance still requires the attention and time of the resident, as is the case in the pre-DR model in [30]. Figure 6 shows the flowchart of the process.

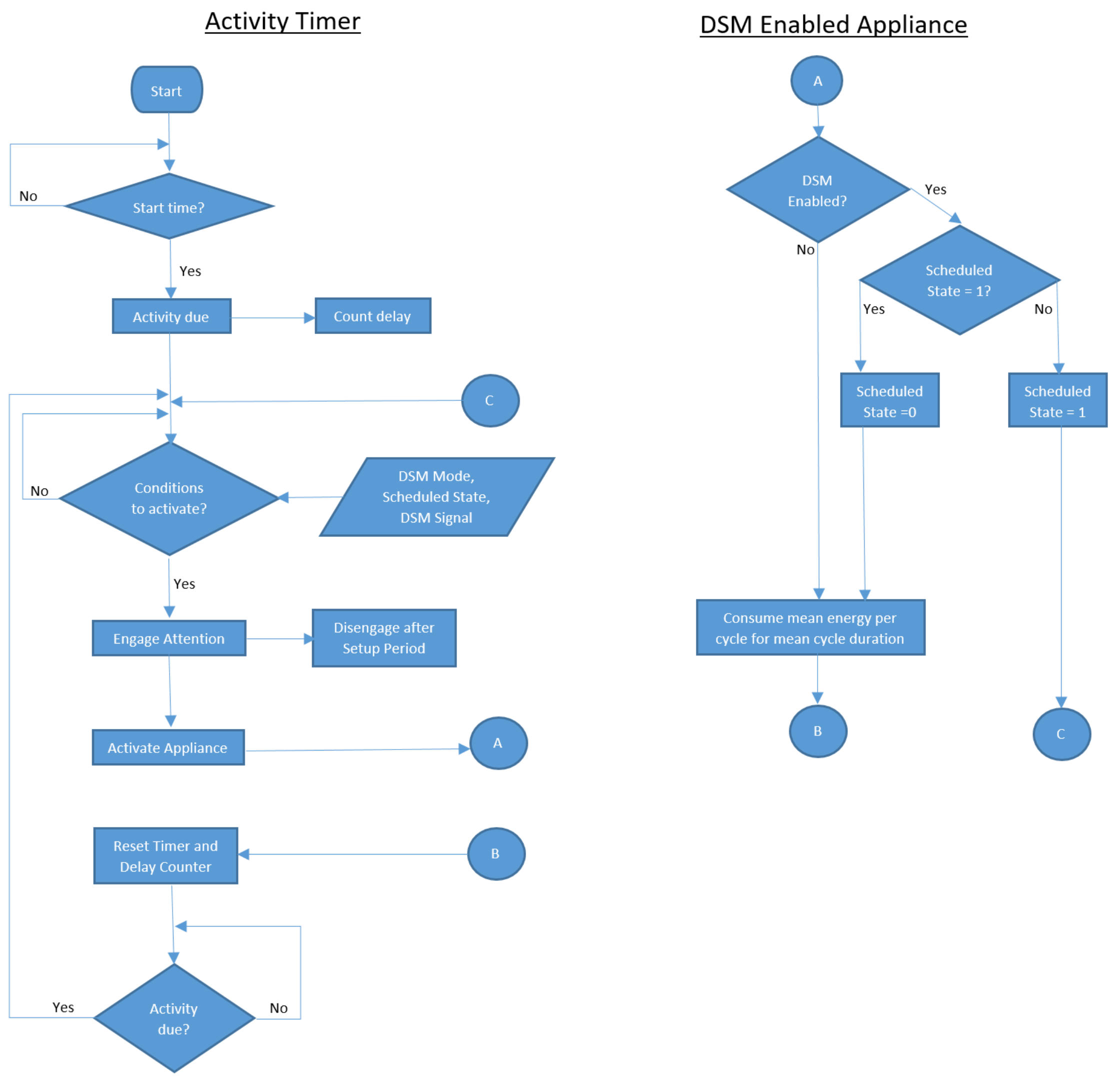

Figure 6 - Flow Chart of the DR Process. A, B and C are flowchart connectors between the Activity X Timer and the appliance for activity X.

Whilst DR Signal is exogenous and shared by all appliances in a residence, DR Signal X is endogenous and specific to appliances. DR Signal X represents what the DR Signal could be for Appliance X after considering a random delay and the duration of the appliance cycle, which then enables DR Agent X to decide whether to turn on an appliance that has already been set-up for DR. Therefore, DR Signal X is also a time-series variable (like DR Signal) bound at the earliest by the delayed DR Signal (or DR Signal if DR Delay = 0), for the duration of DR Signal. Adding a random delay prior to activation of the appliances is important in DR to avoid situations where an electricity supplier may be overloaded with demand from residences at the beginning of the DR period, which could undermine the DR. However, there is no need to simulate scenarios without delay because the model is at residential level not at the level of the supplier, where the effect cannot be adequately simulated.

The operation of some appliances (e.g. drying machine) can be implemented to be dependent on the operation of other appliances (e.g. washing machine). It has been assumed that a drying machine will only be used if there is load that had been washed by the washing machine but not dried yet. A variable monitors the completed uses of the washing machine and it is used as a condition to turn on the drying machine, and this variable is reduced by 1 after a completed use of the drying machine. When Activity Timer and other conditions are due for the drying machine to turn on but there are no washing sets that requires drying, Activity Timer is reset.

3.5.2 Parameters

The setup period for an appliance has been maintained from the original model at 15 minutes, and this was assumed to be reasonable because it represents the duration of attention a resident commits to setting up rather than the actual time interacting with the appliance during the setup. All the semi-automatic appliances (washing machine, drying machine and dishwasher) use the same value. To generate DR Signals, the simple rule is for DR to be active when energy cost is cheapest in a tariff plan; after all the aim of variable price tariff plans is to encourage energy usage when it is cheapest. The DR Signals and tariff names have been summarised in Table 4 .

Tariff Name	Time of Day																							
	am												pm											
	1	2	3	4	5	6	7	8	9	10	11	12	1	2	3	4	5	6	7	8	9	10	11	12
Economy 7																								
TIDE																								
Economy 10																								
Economy 10 (Split)																								

Table 4 – Tariff names and corresponding DR Signals showing time of day when a DR Signal is active (green)

Economy 7 and Economy 10 are common tariff names across electricity providers with 7 and 10 indicating the number of hours where price is cheapest per day; also known as off-peak hours. Economy 10 Split is also an Economy 10 tariff but split into time chunks; 'Split' was appended to differentiate. As mentioned, the resulting DR Signal is implemented as a binary time-series signal, where value of 1 means DR is active and 0 means DR is inactive.

Furthermore, to make the comparison between DR scenarios more comparable, the same random delays are generated in all the scenarios by using the same seed in the random number generator. The random delay, which is the variable DR Delay X, is generated daily. DR Delay X has been implemented as a random variable from a normal distribution with a mean of 0 and standard deviation of a third of the mean appliance cycle time, bounded by a minimum of 0 to avoid negative delays. Since DR Signal X is DR Signal shifted into the future by DR Delay X (See Section 3.4.2), and DR Signal is the earliest possible time for DR appliances to turn on, DR Delay cannot be negative, otherwise appliances will be turned on earlier than DR Signal. Positive values of DR Delay X are achieved by returning 0 where the distribution returns a negative value; therefore, the mean of DR Delay X is positive, not 0. A third of the appliance cycle time was chosen as standard deviation for the distribution so that the delay almost never exceeds the cycle time; 99.7% of the time or at 3 standard deviations.

4 Results and Discussions

4.1 Convenience

4.1.1 Delay

Figure 7 shows the annual distribution of delays from the three DR appliances, each in the four DR scenarios. The x-axis shows appliances and corresponding DR scenarios: D for Dishwasher; DM for Drying Machine; WM for Washing Machine; Eco7 for Economy7; TIDE for TIDE ToU; Eco10 for Economy10; Eco10S for Economy10 Split. The fill-colour of the boxplots, which are the rectangles with possible vertical lines above or below, also represents the appliance: red for Dishwasher; green for Drying Machine; and Blue for Washing Machine. For each Appliance-Scenario combination, Figure 7 shows the mean (yellow points), the boxplot and the individual observations (blue points); the boxplot shows the interquantile range and the horizontal line in the box is the median. The shortest of the mean delay is 124 minutes on the Dishwasher (Eco10S), while the longest is 608 minutes on the Drying Machine (Eco7). All the upper quantiles are less than 1000 minutes.

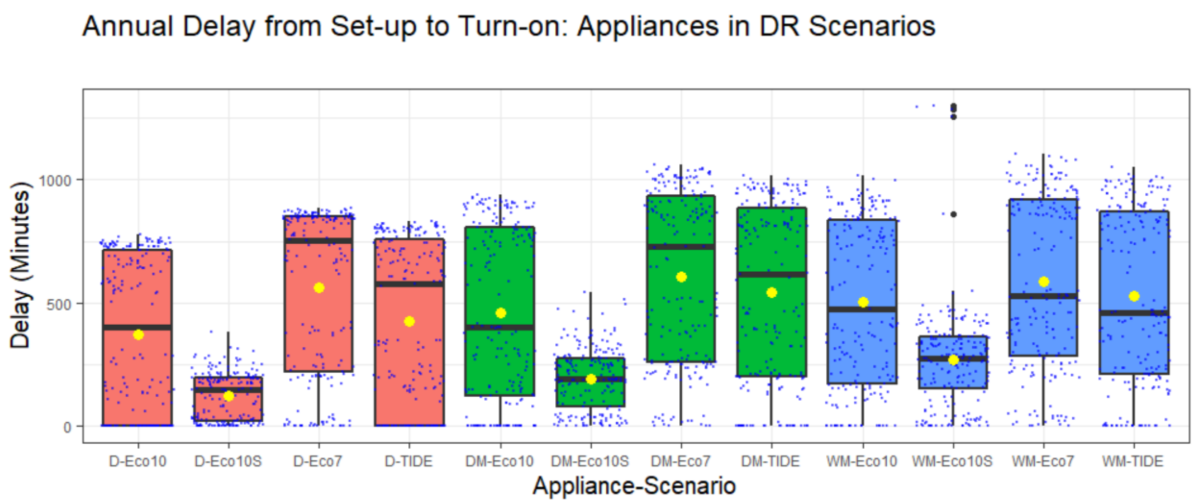

Figure 7 – Boxplots showing distribution of annual delay of Dishwasher (Red), Drying Machine (Green) and Washing Machine (Blue) in the four DR scenarios

Eco7 and TIDE have a DR period of 7 hours each, while Eco10 and Eco10S are 10 hours each. Therefore, three comparisons can be made: between individual scenarios of different hours; between scenarios of equal hours; and between appliances. Between scenarios of different hours, the mean and third quantile delays decrease as active DR hours increase; the delay increases from Economy 10 Split and Economy 10 with lower delay, to TIDE and Economy 7 having higher delay. This follows intuitively that it should take less time on average from setting-up/loading an appliance to having the appliance turn-on automatically if more time in a day is allotted for the appliance to be turned on. However, it does not explain the order observed when comparing between scenarios with the same DR hours.

Between scenarios of equal active DR hours, the result shows that earlier start coincides with lower mean_delay: TIDE (23:00-06:00) has consistently lower mean delays than Economy 7 (00:00-07:00). Delay is lower because there is a shorter period between the occupancy period (which remains the same across the scenarios) when DR appliances are set up, and DR hours when the appliances are tuned on. Furthermore, splitting the DR hours during the day results in lower mean delay: Economy 10S (20:00-22:00, 00:00-05:00, 13:00-16:00) also consistently has lower mean delays than Economy 10 (22:00-08:00). This is because the delay accumulates over time, and splitting DR hours provides more opportunities to terminate the delay during the course of a day, closer to occupancy periods. In other words, delay is less when DR hours are closer to a resident's return at the end of the day or any time during the day.

Finally, between appliances, the Dishwasher consistently shows lower delay (mean and upper quantile) than the Washing Machine and Drying Machine, but the latter two are not consistent in relation to each other. Whilst

Drying Machine has the same mean cycle duration as the Dishwasher (60 minutes), it is operationally tied to Washing Machine cycles (138 minutes) before it gets set-up, and the mean frequency of cycles for all three appliances is about once in 2 days. Therefore, the faster Drying Machine is often set-up after the active DR hours where the slower Washing Machine was turned on, then delays until after the next active DR hours to be turned on.

More appliances would be required to determine whether mean cycle duration affects the delay, because whilst the Drying Machine and Dishwasher have the same mean cycle duration of 60 minutes, the Drying Machine depends on the Washing Machine for its operation which has a mean cycle duration of 138 minutes. Nonetheless, the distribution of delays may not be very useful for making decisions about convenience of residents.

The distribution in Figure 7 is bimodal, about 10-12 hours apart. Data from the survey of domestic appliances in the UK was found to be bimodal for some resident-types, with about 7-10 hours apart especially for washing machine and dishwasher [51]. Unlike the model in this paper, the appliances of the surveyed residences are not determined by DR. The explanation of the surveyed distribution is that it reflects the occupancy and habits of the residents. Similarly, the bimodal distribution in this model can be explained by the occupancy of the 3 residents which are represented by a binary square wave for each resident (1 indicating presence and 0 indicating absence) [30], because the difference between the centre of two consecutive peaks (of active occupancy) prior to the DR period (which is when set-up appliances are turned on) is about 10 hours on weekdays and 5-8 hours on weekends. In other words, the bimodal distribution is the result of either setting up the washing machine before leaving for work or after work.

4.1.2 Delay Duration Profile

Figure 8, Figure 9 and Figure 10 show the Delay Duration Profile (DDP) of the three appliances, each in the four DR scenarios. The DDP quantifies convenience as the inverse of the number of times a specific duration of the delay is exceeded in a year. The plots cover the delay duration of up to a day (1440 minutes), while each of the appliances runs once every two days on average (see Section 3.1.2). For instance, taking the dishwasher in Figure 10, a delay of 750 minutes was exceeded more than 50 times in TIDE and more than 100 times in Economy 7, while it was exceeded less than 15 times in Economy 10 and not exceeded in Economy 10S. For each appliance, DR scenario with Economy 10S resulted in the least delay, followed by Economy 10, then TIDE, and finally Economy 7.

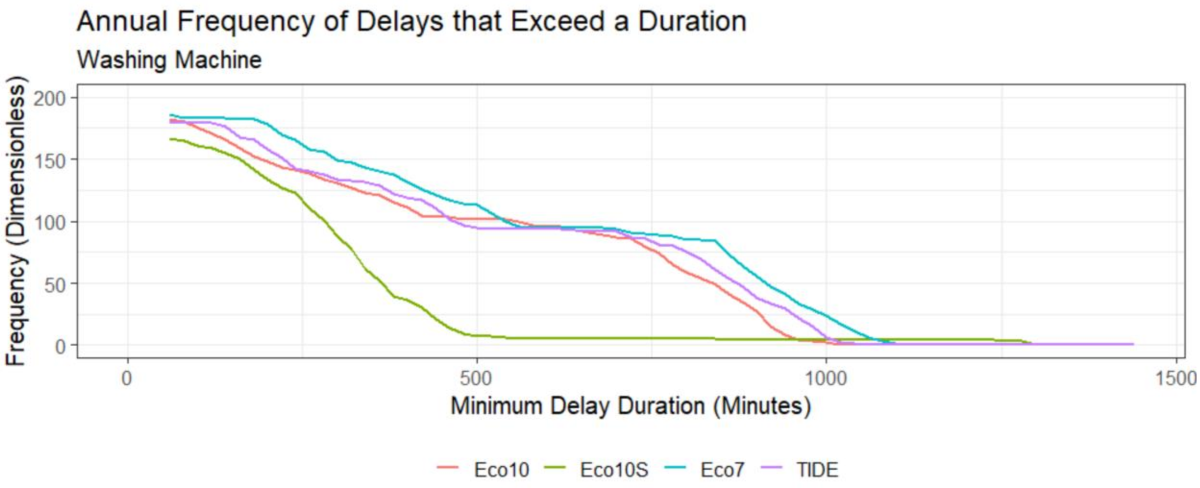

Figure 8 - DDP of Washing Machine

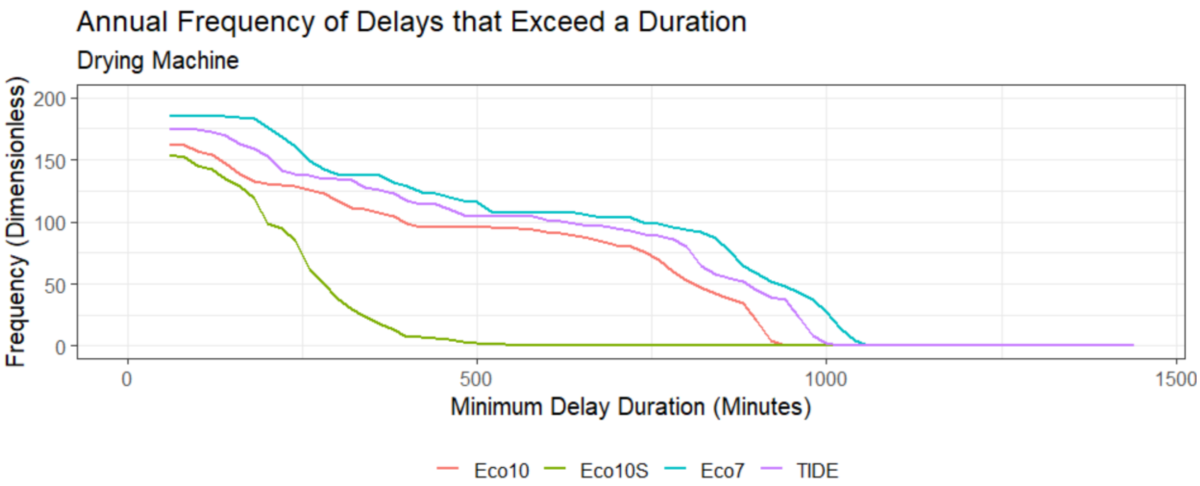

Figure 9 - DDP of Drying Machine

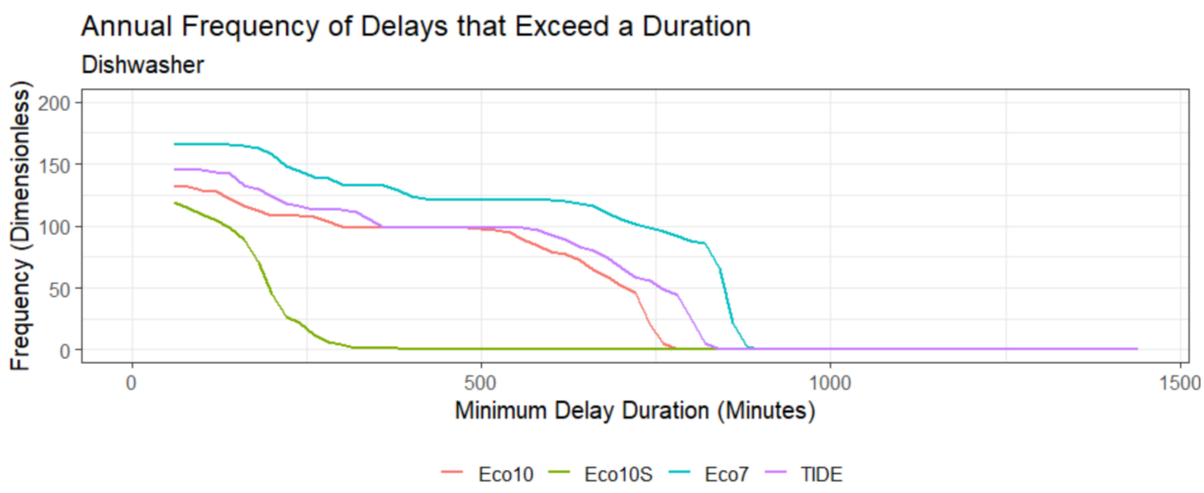

Figure 10 - DDP of Dishwasher

The plots of DDP share a common behaviour: downward slope with occasional plateauing. The steeper the slope between any two durations, the more the difference in frequency of occurrence, and thus, the more difference in convenience. Individual residents can be located on the x-axis based on their preferences on how much delay they can tolerate, then their convenience can be estimated as the frequency on the y-axis such that lower frequency is higher convenience. Two residents with different delay tolerance can estimate about the same 'convenience' where the DDP plateaus; e.g. two residents with delay tolerance of 400 and 500 minutes for dishwasher (TIDE in Figure 10) measure about the same convenience. Also, a resident may opt for a different DR scenario to improve their 'convenience'; e.g. a resident with a delay tolerance of about 500 minutes for their Dishwasher can reduce the frequencies of 'inconvenience' by approximately 25 instances of delay (or 20%) in a year, by changing from Economy 7 to TIDE. At durations where the DDP of two DR scenarios coincide, the scenarios estimate the same level of convenience, and this means that a resident may not improve the convenience of using an appliance depending on their tolerance for delay. At a delay tolerance of about 620 minutes for Washing Machine, Figure 8 shows no preference for any of the DR scenarios, except for Economy 10S.

4.1.3 Delay Time Profile

Figure 11, Figure 12 and Figure 13 show the Delay Time Profile (DTP) of the three appliances, each for the four DR scenarios. The DTP quantifies convenience as the inverse of the number of times a particular time of day falls during a delay in a year. Consequently, the x-axis represents the times of day. Taking the case of the Dishwasher, for instance in Figure 13, there is no delay observed at 6:00 am whereas there are about 100 instances of delays experienced (Economy 10 and TIDE) at 4:00 pm. Like the DDP plots, DR scenario with Economy 10S result in the least frequency of delays per time of day.

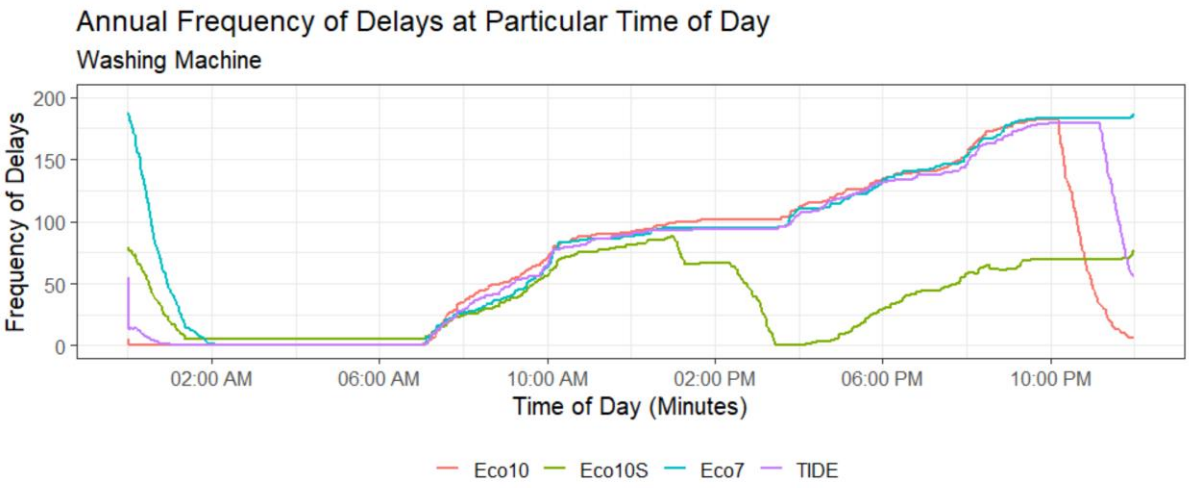

Figure 11 - DTP of Washing Machine

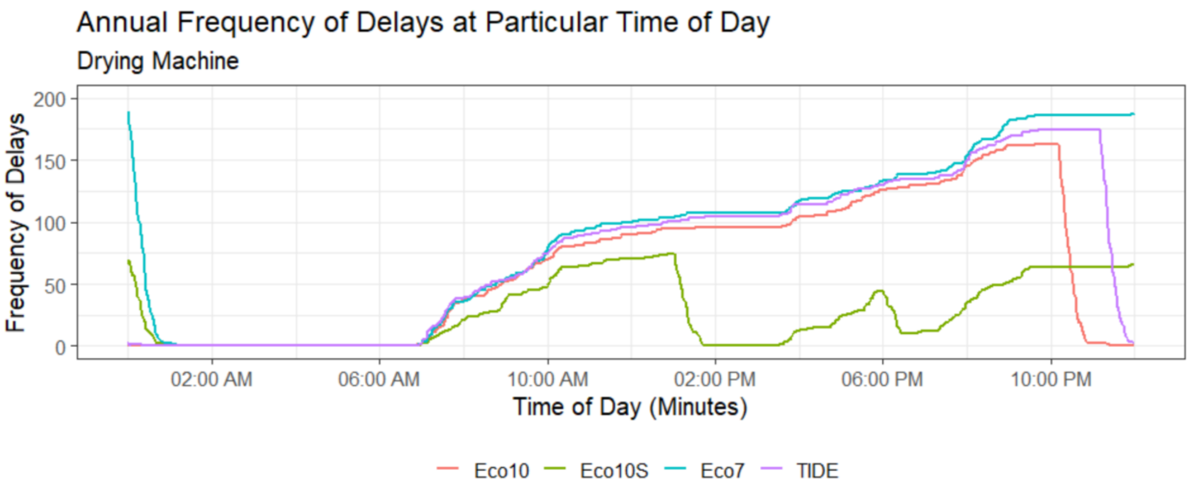

Figure 12 - DTP of Drying Machine

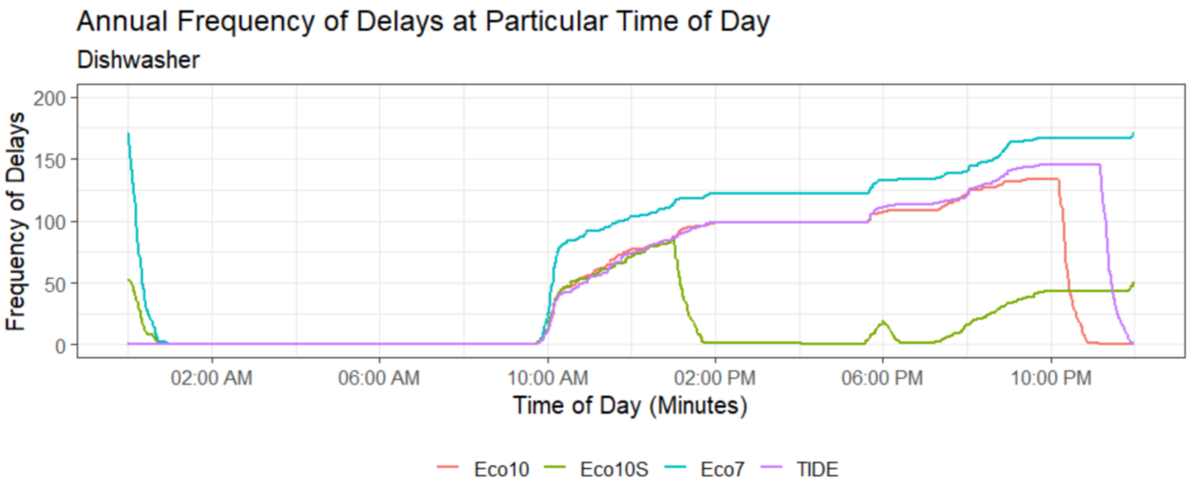

Figure 13 - DTP of Dishwasher

As expected, the DTP plots show no instances of delays during the daily periods where DR is active for each of the DR scenarios. Generally, the DTP of Economy 10S stands out from the other three. The instances of delay increase as the day progresses, remaining fixed (approximately) for significant periods in the day. The continuous increase follows the intuition that the closest time before DR is active is affected by all the delays since the last time DR was active. The flat periods represent times of equal convenience, for example, between 2:00 pm and 5:00 pm in Figure 13. DTP for Washing Machine and Drying Machine show little difference in convenience for most part of the day among the scenarios, but there is significant difference in the case of Dishwasher especially between Economy7 on the one hand and Economy 10 and TIDE on the other hand. Barring the different start of DR active hours, Economy 10 and TIDE have similar DTP for all the appliances. Looking at the Economy 10S, the DTP indicates lower delay – better convenience – for all appliances.

The flat periods indicate moments between an appliance turning on and the subsequent setting up. The flat periods coincide across the scenarios because all other parameters that determine the time to turn-on an appliance and when to set up have been kept the same across the scenarios for comparison, where the only parameter that changes is the DR program (DR Signal). Having the same seed for the random number generator makes the declining slope similar for scenarios with about the same frequency of delays e.g. Eco10 and TIDE in Figures 11-13.

To estimate convenience, individual residents may have a specific time in the day where it is most inconvenient to have a delay. Such a resident may reduce their inconvenience from the Dishwasher at 2:00 pm, if the residence moves from Economy 7 to TIDE or Economy 10, by about 25 instances of delay (20%) in a year, or by 125 instances (100%) if the residence moves to Economy 10S. The assumption in all the applications of convenience plots (DDP and DTP) is that the resident is not flexible in their preference of convenience for the duration of the simulation.

4.1.4 Decision-making and Plotting Convenience

The best performing DDPs and DTPs are in the same descending order: Economy 10S; Economy 10; TIDE; and Economy 7, which aligns with the mean and upper quantile delays in Figure 7. This also implies that the mean and upper quantile of the distributions may be sufficient to know which DR strategy performs better. When all else is equal, the results provide preliminary evidence that having more DR hours, earlier hours (relative to occupancy period), and splitting the active DR hours leads to less delays, and better DDP and DTP, which is better convenience.

Both DDP and DTP apply to an appliance in the specific residences from which it is plotted; that is the residence whose parameters are input to the simulation. Therefore, DDP or DTP cannot be applicable when any of the parameters of the residence changes (e.g. number of residents or addition/removal of an appliance in the residence), and they cannot be used to represent the same type of appliance in a different residence. However, comparing between two appliances in the same residence could be generalised for comparison between the same types of appliances in a different residence, assuming other variables in any residence remain proportionally the same. Furthermore, when residents change their habits (e.g. occupancy or frequency of use of appliance) which are parameters of the model, that would affect the applicability of the model because the underlying assumptions have changed.

The measurement of residents' convenience can be generalised beyond the model in this study. The main requirement is to track two variables for every time an appliance is controlled by DR: time when an appliance would have operated in the absence of DR; time when the appliance operated during DR. Time includes the day and time of day. The variables necessitate that appliances are modelled in sufficient detail. Therefore, models that can keep track of these variables would be able to measure and visualise Convenience as DDP and DTP.

4.2 Other Applications of the Model

4.2.1 Daily Peak Demand

Figure 14 shows the boxplot of daily peak demand in the residence for a year in five scenarios which include the Baseline scenario where DR is not active, and the four scenarios where DR is active. Interestingly, the median peak is the same in all scenarios at 2507 W. But the Baseline scenario is consistently higher than all the other scenarios in terms of the first quantile, third quantile, mean and maximum. Interestingly, the observed difference among the DR scenarios is not explained by the number of active DR hours or whether the active DR hours are split or not; this may be further investigated in the future. However, this section compares the scenarios with DR on the one hand, and the scenario without DR (Baseline Scenario) on the other hand. The result shows that any of the DR programs reduces the distribution (especially the interquantile range in Figure 14) of the daily peak demand noticeably in a residence, compared to having no DR; although the difference in mean is reduction by 6% for Economy 7, and 4% for the other three scenarios. Reduction in the daily peak demand confirms previous studies.

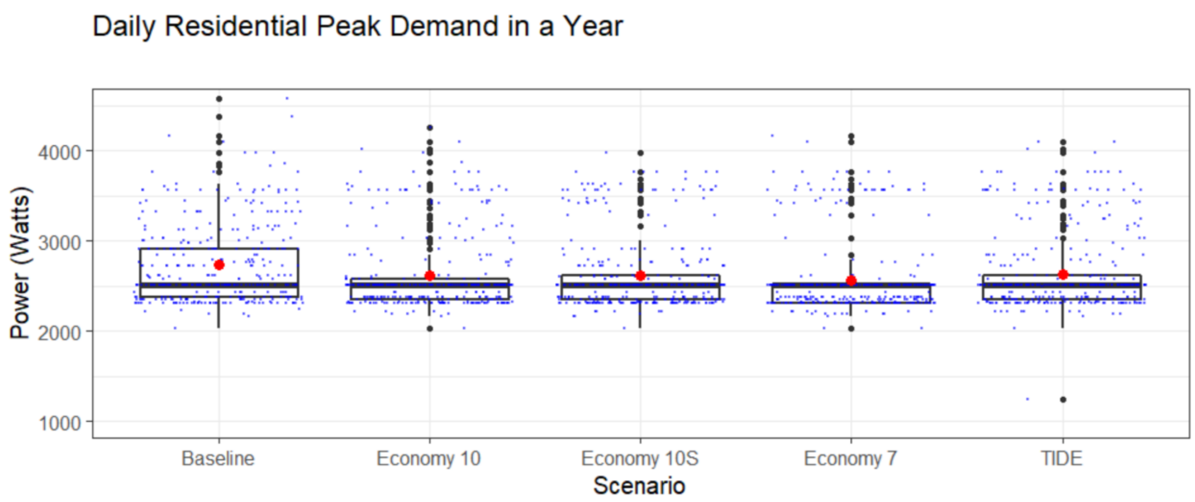

Figure 14 - Boxplot showing distribution of Daily Peak Demand in a residence in all scenarios

4.2.2 Money Saved

Table 5 shows the annual frequency of appliance use in all the scenarios and the cost per unit of energy (kWh) during operation. Given that the frequency of appliance use is almost the same across the scenarios, it can be safely assumed to be the same to ease estimation of cost savings per scenario. Since the energy consumption is the same in every cycle, the only changes to the operation of the appliances are time of operation and energy cost, but energy cost during DR is the cheapest for the ToU tariff. Therefore, the money saved from the operation of the three appliances in the different scenarios can be estimated in terms of the variable energy costs during DR.

Scenario	Annual Frequency of Use			Energy Cost (p/kWh)	Tariff Name
	Washing Machine	Drying Machine	Dishwasher		
Baseline	205	205	204	21.6	npower Standard SC
Economy 7	205	203	197	11.8	
TIDE	205	203	198	4.9	TIDE
Economy 10	205	204	195	13.5	Ovo Energy Simpler Energy
Economy 10S	205	203	192	13.5	

Table 5 - Annual Frequency of appliances and energy unit cost for all scenarios

Given the assumptions above, there can be money saved or lost between scenarios only if the unit cost in energy is different. Table 6 shows a matrix to compare the percentage savings between any two scenarios, which in this study are any two tariffs. The table should be read as the savings when moving from column to row is x. For example, changing from Baseline to TIDE leads to a saving of 77%, whereas from TIDE to Economy 7 leads to a cost increase of 141%. Furthermore, any change to TIDE leads to savings because TIDE row is all positive, whereas all change to Baseline lead to cost increase because Baseline row is all negative. Therefore, the main determinant of savings when changing DR program is the unit cost of energy during DR (off-peak hours).

	Baseline	Economy 7	TIDE	Economy 10	Economy 10S
Baseline	0%	-83%	-341%	-60%	-60%
Economy 7	45%	0%	-141%	13%	13%
TIDE	77%	58%	0%	64%	64%
Economy 10	38%	-14%	-176%	0%	0%
Economy 10S	38%	-14%	-176%	0%	0%

Table 6 - Matrix of money savings and losses by changing tariff from column to row

4.2.3 Beyond a Single Residence

Beyond a single residence, there may be interest in indicators like estimate of aggregate Money Saved by multiple residences. Utility companies are interested in aggregate Daily Peak Demand from multiple residences. There are two ways to aggregate the demand from the residential models, at least: brute-force aggregation and statistical aggregation. Brute-force aggregation would be to create a separate model for each residence then sum their residential demand per minute. The peak demand can be obtained as the maximum of the aggregated demand. On the other hand, a statistical aggregation could estimate the demand of multiple residences based on a single or few residences, which are representative of the population.

In both ways of aggregation, the DR Signal can be shared by all residences, assuming it is generated by a utility company. However, the brute-force approach would be cumbersome, where every appliance in every residence, as well as every resident, must be defined with parameters and simulated, while there is interdependency among appliances and residents in each residence. On the other hand, the statistical approach is less demanding but could be reasonably representative. Comparing brute-force and statistical aggregation, and their accuracy, can be explored in future work.

5 Conclusion

The aim of this study was achieved by exploring the effects of different DR programs on residents' convenience, peak load, and money saved. Building on an existing demand-side SD model of a residence, a DR subsystem was integrated. Four DR programs were generated based on ToU tariffs, and three appliances were identified for the DR program. Each DR strategy was simulated as a DR scenario, and the scenarios were compared in terms of residents' convenience, which included indicators like distribution of annual delay between appliance set-up and operation, DDP and DTP. Furthermore, other indicators were also compared, like Daily Peak and Money Saved.

When comparing residents' convenience as delay in the four DR scenarios, it was found that more hours of DR is better than less, earlier hours (from occupancy period) are better, and splitting or distributing DR hours during the day is better than being contiguous. Similar findings apply to DDP and DTP. Furthermore, it was found that DR leads to monetary savings and reduction in daily peak demand.

Possibilities for scaling the model was also discussed, and two ways of aggregating the residential models were discussed. Future work could implement and compare brute-force and statistical aggregation of the residences. More generally, the created model could be used in future works, because the use of a generic and binary DR Signal to represent the DR strategy allows for integration with many other algorithms for DR strategy that may have different objectives. After all, the binary DR Signal can represent several top-down energy policies. Other future work to explore is to update the underlying demand-sided model with HVAC loads, and then measure thermal comfort, in addition to timeliness; both being convenience.

This study represents the first attempt at a DR model from the bottom-up using SD, as well as using the model in decision-making analysis. Other novel contributions are the proposed indicators for evaluating the convenience of a DR strategy to a resident, which are DDP and DTP. Moreover, the importance of residents' convenience has been emphasised as capable of undermining the purpose of a DR system.

6 Funding

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