RESIDENTIAL DEMAND RESPONSE IN THE POWER SYSTEM

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Abstract

Demand response (DR) is able to contribute to the secure and efficient operation of power systems. The implications of adopting the residential DR through smart appliances (SAs) were investigated from the perspective of three actors: customer, distribution network operator, and transmission system operator. The types of SAs considered in the investigation are: washing machines, dish washers and tumble dryers.

A mathematical model was developed to describe the operation of SAs including load management features: start delay and cycle interruption. The optimal scheduling of SAs considering user behaviour and multiple-rates electricity tariffs was investigated using the optimisation software CPLEX.

Further, the financial benefits for SA users subscribing to multiple-rates electricity tariffs were investigated. The savings are mainly a result of the appliances' load shifting feature and are sensitive to user settings. The savings averaged at 7% of the household annual electricity bill. For households in the United Kingdom, the SAs had a payback period of less than three years and a net present value of up to £206.

Furthermore, the operation of distribution networks with different uptake rates of SAs was investigated. A simulation containing a load modelling method and a network model determines, through time series power flow analysis, the network branch loading and voltage profile. The thermal ratings and voltage limits were exceeded on the LV network due to deterioration in the temporal diversity of the appliance utilisation. A regional controller for SAs was developed which effectively limited the network peak demand and voltage drop.

A framework was introduced which enabled transmission system operators to access demand response from SAs in a timeframe suitable for operating reserve. A multiple time-step simulation was developed that assessed the load reduction from a number of households as a response to a reserve instruction. The instruction was modelled as a price increase with a short notification period. It was estimated that up to half of the current operating reserve requirements of Great Britain's power system can be obtained with 20% uptake of SAs.

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Table of Contents

Abstract .... **III**

Acknowledgements .... **IV**

Table of Contents .... **V**

List of Figures .... **VIII**

List of Tables .... **X**

Abbreviations .... **XI**

1 Introduction **1**

1.1 Research context 2

1.2 Current demand response practices 4

1.3 Services provided by smart appliances 10

1.3.1 Peak load shifting 11

1.3.2 Balancing services 13

1.3.3 Distribution network support 14

1.4 Modelling of smart appliances operation 16

1.4.1 Optimisation 18

1.4.2 Other methods 19

1.5 Research objectives and thesis structure 21

1.6 Publications and achievements 24

2 Smart Grid ready appliances **25**

2.1 Introduction 26

2.2 Load profiles 27

2.3 Load management 32

2.3.1 Smart timing 32

2.3.2 Cycle interruption 33

2.4 User dependent parameters 34

2.4.1 Activation times 34

2.4.2 Maximum delay 36

2.5 Shifting algorithm 37

2.5.1 Optimisation 37

2.5.2 Execution of the shifting algorithm 42

2.6 Model validation 45

2.7 Overview of the simulation environment 48

3 Financial analysis for smart appliances users **50**

3.1 Introduction 51

3.2 Electricity tariffs ... 51
3.3 Effects of parameters on household savings ... 55
3.3.1 Number of residents ... 56
3.3.2 Maximum delay ... 57
3.3.3 Cycle interruption ... 58
3.4 Annual savings for a group of one thousand GB households ... 59
3.4.1 Electricity cost savings ... 60
3.4.2 Costs of adopting smart appliances ... 61
3.5 Discussion ... 66
4 Reserve services from smart appliances ... 68
4.1 Introduction ... 69
4.1.1 Operating reserve requirement in the GB power system ... 69
4.1.2 Current contribution of DR to the GB operating reserve services ... 72
4.2 Framework for procuring reserve from smart appliances ... 73
4.2.1 Business model ... 73
4.2.2 Simulation ... 75
4.3 Feasibility study of providing reserve services ... 79
4.3.1 One thousand households with single rate tariff ... 79
4.3.2 One thousand households with TOU tariff ... 81
4.4 Potential contribution of appliances to the GB operating reserve ... 82
4.4.1 Effects of reserve instruction parameters ... 82
4.4.2 Financial and environmental achievements ... 86
4.5 Discussion ... 88
5 Distribution network operation with smart appliances ... 90
5.1 Introduction ... 91
5.2 Regional controller ... 91
5.3 Simulation ... 94
5.3.1 Flowchart ... 94
5.3.2 Distribution test system ... 96
5.3.3 Load model ... 97
5.3.4 Pseudo-code ... 99
5.4 Results ... 101
5.4.1 Operation of smart appliances with individual control ... 101
5.4.2 Network support provided by regional controller ... 108
5.5 Discussion ... 115
6 Conclusions and future work ... 118

6.1 Conclusions 119
6.1.1 Smart appliances users 120
6.1.2 Reserve services from smart appliances 121
6.1.3 Distribution network operation with smart appliances 122
6.2 Summary of contributions 123
6.3 Future work 124
6.3.1 Use of smart appliances in operating reserve and frequency support 124
6.3.2 Use of smart appliances in distribution network operation 124
References 126
A. Java code for appliances scheduling algorithm 138
B. CREST domestic energy demand model 142
C. Design of a RTP tariff 143
D. Parameters 147
E. Distribution network 149
E.1 Approximate calculation of voltages for a radial LV feeder 149
E.2 Distribution network parameters 152

List of Figures

Figure 1.1: Demand response categories [22], [23]. 5
Figure 1.2: Smart appliances load management actions: (a) Delay cycle; (b) Interrupt cycle; (c) Modify cycle. 17
Figure 1.3: High level structure of the analyses used and outline of the thesis. 23
Figure 2.1: Washing machine load curve: (a) Average load profile from SMART-A project; (b) Sample of measurements from 3-E Houses project. 28
Figure 2.2: Dishwasher load curve: (a) Average load profile from SMART-A project; (b) Sample of measurements from 3-E Houses project. 30
Figure 2.3: Tumble dryer load curve: (a) Average load profile from SMART-A project ; (b)Sample of measurements from 3-E Houses project. 31
Figure 2.4: Load management features of a smart appliance. 32
Figure 2.5: Scheme of CREST model utilisation. 35
Figure 2.6: Operational diagram of the shifting algorithm. 44
Figure 2.7: Cumulated daily activation times of a washing machine for a single household. 46
Figure 2.8: Savings on the electricity bill from SAs utilization, for 10 houses subscribing to a TOU tariff, each with 3 residents, considering different number of days. 47
Figure 2.9: Energy shifted by SAs over a period of 10 days, for 10 houses subscribing to a TOU tariff, considering different number of residents. 47
Figure 2.10: Process flowchart of the simulation environment. 48
Figure 3.1: Distribution of the residential customers according to the type of electricity tariff [86]. 52
Figure 3.2: Standard, Economy 7 and 10 electricity tariffs. 53
Figure 3.3: Structure of the Ameren Illinois RTP tariff. 54
Figure 3.4: Structure of a RTP tariff specific for GB electricity sector. 54
Figure 3.5: Data flowchart of the simulation used to evaluate the cost savings of a single household from smart appliances. 55
Figure 3.6: Effects of number of residents: (a) RTP; (b) Economy 7; (c) Economy 10. 56
Figure 3.7: Cost savings on the electricity consumed by the appliances (WM,DW,TD) in a household with 3 residents with different values for the maximum delay parameter. 57
Figure 3.8: Additional cost savings on the electricity consumed by the appliances (WM,DW,TD) in a household with 3 residents on account of the *maximum interruption* parameter: (a) RTP; (b)Economy 7; (c) Economy 10. 58
Figure 3.9: Annual electricity bills for 1000 households with regular appliances and with smart appliances (WM, DW, TD). 60
Figure 3.10: Household cash flow and payback periods considering different implementation solutions for smart appliances: (a) Smart Metering solution; (b) IP based solution; (c) HEMS solution. 64
Figure 4.1: Normal distribution of errors (forecast of residual demand and generator output) and the operating reserve, Z x σ, required to secure the NGET reliability criteria [103]. 71
Figure 4.2: Framework for the participation of residential DR to the power system balancing service. 75
Figure 4.3: Flowchart of the simulation model 77
Figure 4.4: Array of decision variables for the optimisation at time step *t*. 78
Figure 4.5: Average household demand simulated for different size groups. 79

Figure 4.6: Aggregated demand from 1000 households with single rate tariff and their response to a reserve instruction: (a) Demand of appliances WM, DW, TD only; (b) Demand of all the loads from households.......... 80
Figure 4.7: Aggregated demand from 1000 households with TOU tariff and their response to a reserve instruction: (a) Demand of appliances WM,DW,TD only; (b) Demand of all the loads in households.......... 82
Figure 4.8: Available reserve from 20% of appliances (WM, DW, TD) in GB for reserve instructions with duration of 2hrs: (a) Reserve instruction notification time 15 min; (b) Reserve instruction notification time 60 min.......... 84
Figure 4.9: Available reserve from 20% of appliances (WM, DW, TD) in GB for reserve instructions with duration of 1hr: (a) Reserve instruction notification time 15 min; (b) Reserve instruction notification time 60 min.......... 85
Figure 5.1: Concept of a regional controller for smart appliances.......... 92
Figure 5.2: Data flowchart of the simulation.......... 96
Figure 5.3: Distribution test network.......... 97
Figure 5.4: Loading of substation transformer T3 in winter season.......... 101
Figure 5.5: Peak demand recorded at transformer T3 with different smart appliances uptake levels: (a) Summer; (b) Winter.......... 103
Figure 5.6: LV feeder branch loading at peak load times with different smart appliances uptake levels: (a) Summer; (b) Winter.......... 104
Figure 5.7: Peak demand at the primary substation with different smart appliances uptake levels: (a) Summer; (b) Winter.......... 105
Figure 5.8: Voltage profile of MV feeder (medium length) and LV feeder at maximum loading: (a) Summer; (b) Winter.......... 106
Figure 5.9: Voltage profile of MV feeder (long length) and LV feeder at maximum loading: (a) Summer; (b) Winter.......... 107
Figure 5.10: Voltage temporal profile at the LV feeder's end for a: (a) Winter day / medium length MV feeder; (b) Summer day / long length MV feeder; (c) Winter day / long length MV feeder.......... 108
Figure 5.11: Performance of the regional controller with thermal limits (nominal rating) at the transformer T3.......... 109
Figure 5.12: Effects of the regional controller with thermal limits on the peak demand recorded at transformer T3: (a) Summer; (b) Winter.......... 110
Figure 5.13: LV feeder branch loading at winter peak load times with different smart appliances uptake levels.......... 111
Figure 5.14: Voltage temporal profile at the LV feeder's end considering 100% uptake of SAs and a regional controller with voltage constraints for a: (a) Winter day / medium length MV feeder; (b) Summer day / long length MV feeder; (c) Winter day / long length MV feeder.......... 113
Figure 5.15: Evaluation of different control strategies for SAs by observing the T3 loading and voltage at the farthest customer from the substation over a time span of a day in winter.......... 115

List of Tables

Table 1.1: Examples of balancing (ancillary) services of the GB trasmission system operator [28]. 8
Table 2.1. Penetration rate of selected appliances in the UK [69]. 26
Table 2.2. Household electricity consumption by load type in the UK [70]. 27
Table 2.3: Evolution of start delay features from regular appliances to smart appliances. 33
Table 2.4: Activation times of WM, DW and TD from 1000 households. 36
Table 2.5: Statistics for user defined *maximum delay*. 37
Table 2.6: Table explaining constraint (2.4). 39
Table 2.7: Table explaining constraint (2.5). 40
Table 2.8: Solving times of the optimisation (Section 2.5.1) for different software programs... 41
Table 3.1: Survey on existing GB electricity tariffs in 2012. 52
Table 3.2: Average number of appliance activations during one month for one household. 56
Table 3.3: Household distribution by number of people living in them in GB [89]. 59
Table 3.4: Annual electricity bill and cost savings for 1000 households resulted from smart appliances (WM, DW, TD). 61
Table 3.5: Additional cost of implementing the smart operation of appliances (WM, DW, TD) in a household. 63
Table 3.6: Example of NPV calculation of investing in smart appliances for a household subscribing to the Economy 10 tariff in the Smart Metering solution. 65
Table 3.7: NPV of investing in smart appliances for a household considering different implementation solutions. 66
Table 4.1: Operating reserve requirement of the GB power system at winter peak. 71
Table 4.2: Estimates of the availability of DR from 20% of appliances (WM, DW, TD) in GB 86
Table 5.1: Impact of the regional controller with capacity constraints on the total financial benefit of smart appliances users in the LV network. 112
Table 5.2: Capability of the regional controller for smart appliances with different network constraints to keep the LV network parameters within the operational limits. 115
Table C-1: Electricity retail price components for domestic sector in UK [123]. 143
Table C-2: Examples of distribution charges designed with CDCM for consumers connected to the LV network. 145
Table D-3: Z-score table [128] (Φ(z) is the probability of normal distributed variables to be bounded by z standard deviations). 147
Table D-4: Parameters used for calculation of the financial benefits of using smart appliances as operating reserve. 148
Table E-5: Verification of the approximate voltage calculation 151
Table E-6. Branches parameters for the MV network (S_B=100MVA) 152
Table E-7. Branches parameters for the LV network (S_B=100MVA) 153

Abbreviations

ADMD	After diversity maximum demand
CCGT	Combined cycle gas turbine
CPP	Critical Peak Pricing
DCC	Data Communication Company
DER	Distributed energy resources
DNO	Distribution network operator
DR	Demand response
DW	Dishwasher
EV	Electric vehicle
HEMS	Home energy management system
HVAC	Heating, ventilation and air conditioning
IHD	In-home display
LOLE	Loss of load expectation
LP	Linear programming
LV	Low voltage
MILP	Mixed integers linear programming
MV	Medium voltage
NGET	National Grid Electricity Transmission Ltd.
NPV	Net Present Value
OCGT	Open cycle gas turbine
OFGEM	Office of Gas and Electricity Markets
OLTC	On-load tap changer
RBT	Rise Block Tariff
RTP	Real Time Pricing
SA	Smart appliance
STOR	Short term operating reserve
TD	Tumble dryer
TOU	Time of Use
TSO	Transmission system operator
WM	Washing machine

Chapter 1

Introduction

Summary:

The current drivers for the development of demand response in the United Kingdom are discussed. An overview of the theory behind residential demand response and programmes implemented by utilities worldwide is summarised. The state of the art on the applications of smart appliances in the power systems is outlined. Furthermore the mathematical methods found in the research literature used to model the operation of smart appliances are reviewed.

1.1 Research context

The Intergovernmental Panel on Climate Change released in 2013 an analysis [1] which confirms with 95% certainty that human activity is the main cause of climate change. The atmospheric concentration of carbon dioxide (CO_2) has increased by 40%, methane (CH_4) by 150% and nitrous dioxide (NO_2) by 20% since pre-industrial times. The European Commission adopted a series of guidelines, such as *Energy Roadmap 2050* [2] and *Roadmap for moving to a competitive low carbon economy by 2050* [3], to assist the European Union (EU) Member States in forming their national legislation to promote the reduction of greenhouse gas emissions. In line with the EU targets, the government of the United Kingdom (UK) has pledged through the *2008 Climate Change Act* and the *2013 Energy Act* [4] to reduce the greenhouse gases (GHG) emissions in the UK by 2050 with 80% from the levels in 1990. Demand response (DR) is amongst the solutions supported by the UK policy mechanism in order to achieve the targets.

The environmental policies are projected to cause the retirement of 11.5 GW of coal and oil-fired plants in the UK under the *EU Large Combustion Plant Directive* [5]. In addition, the low price of coal due to the drop off in United States (US) demand provoked the mothballing of combined cycle gas turbine (CCGT) plants [5]. A *Capacity Market* [6] is being introduced from 2018 in parallel with the energy market to ensure sufficient generation capacity. The *Capacity Market* is designed to accommodate DR, with auctions for DR taking place one year before delivery, in contrast with four years for generation. As a transitional arrangement, until the full implementation of the *Capacity Market*, the national electricity transmission system operator, National Grid Electricity Transmission (NGET), is implementing a new service, Demand Side

Balancing Reserve, starting from 2015 which will reward consumers for reducing their demand in winter weekdays [7].

The *Renewable Obligation* policy mechanism, which supported the installation of 13GW of wind and solar capacity by the end of 2013 [8], is being replaced from 2017 by the *Feed-in Tariffs with Contracts for Difference* (FiT CfD) [6]. The new mechanism is expected to continue to support the installation of generation from renewable sources. NGET expects the level of reserve needed to operate the power system in 2020 to increase by 53% from the 2011 level [9] as more wind power is introduced. The same reference highlights the importance of engaging more DR from the residential sector to meet the required level of balancing reserves.

The *Smart Meter Roll-out* [10], which is set to finish in the UK by 2020, is another initiative with the potential to bring more DR online. The smart meter includes a digital electricity meter, a communication hub and an in-home display (IHD). It is designed to offer more information to the electricity supplier for billing purposes and to enable the customer to manage consumption better through information feedback from the IHD. Apart from connecting the meter with the supplier and the IHD, the communication hub offers the possibility to connect consumer devices [11]. It is expected that consumer devices such as domestic appliances with integrated communication modules will facilitate more DR.

The *Renewable Heat Incentive* [12] supports the adoption of heat pumps by domestic consumers. In *Driving the Future Today* [13], the government has set-up mechanisms through which the adoption of plug-in electric vehicles will be supported in the near future. These policies which aim to decarbonise the heat and transport sector resulted in increasing the electricity demand considerably. As the uptake of low carbon loads in residential areas can be clustered, there is a higher risk of stress to the distribution networks rather than to the transmission networks. The UK energy regulator, Office of Gas and Electricity Markets (OFGEM), is assisting the Distribution Network Operators (DNOs) to prepare for the coming challenges through *Revenue Incentives Innovation Output* regulation and *Low Carbon Network Fund (LCNF)* which supports demonstration projects. DR represents one of the preferred solutions, as revealed by the multitude of *LCNF* projects which include DR trials: Customer-Led Network Revolution [14], Low Carbon Networks [15], Capacity to Customers [16], Flexible Approaches for Low Carbon Optimised Networks [17] and Thames Valley Vision [18].

1.2 Current demand response practices

A history of demand-side management (DSM) programmes is presented in [19]. DSM programes started in the United States (US) in the 1970s in a time when the country was facing an energy crisis. The *National Energy Conservation Policy of 1978* is regarded as the first law to promote DSM programmes. The vertically-integrated utilities were required to provide energy audits to their customers in order to reduce their energy consumption. Utility programmes falling under the umbrella of DSM include load management, strategic conservation, electrification, customer generation and adjustments in market share. Load management is a type of DSM programme that is designed to change the network operators' load shape by influencing how the loads are used at the end-user premises.

With the unbundling of the power sector, the load management was considered under the term Demand Response (DR). The US Department of Energy defines DR as "changes in electric usage by end-use customers from their normal consumption pattern in response to changes in the electricity price over time, or to incentive payments design to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized"[20]. In Europe the Council of European Energy Regulator has given a similar definition, in addition recognizing the role of distributed generators in DR: "Changes in electric usage by end-use customers/micro generators from their current/normal consumption/injection patterns in response to changes in the price of electricity over time, or to incentive payments designed to adjust the electricity usage at times of high wholesale market prices or when system reliability is jeopardised"[21].

DR programmes can be divided into two categories: incentive based and rate-based pricing. A more detailed classification is presented in Figure 1.1.

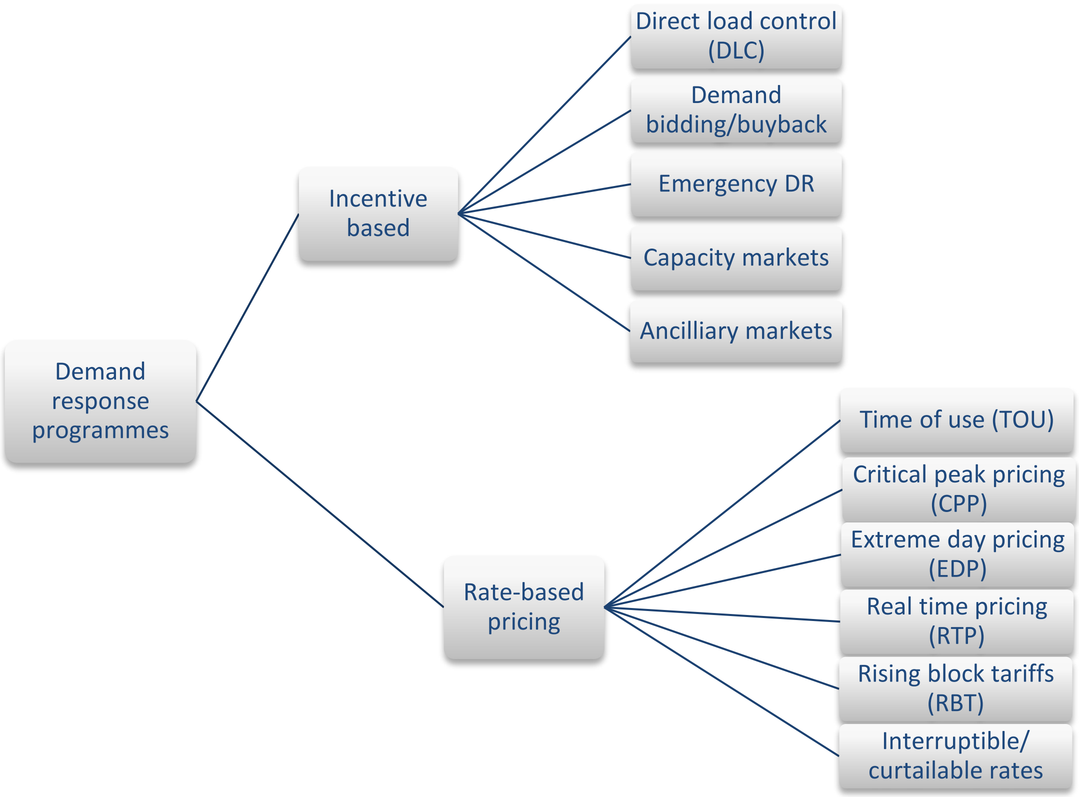


Figure 1.1: Demand response categories [22], [23]**.**

For incentive based programmes customers are financially rewarded for reducing their electricity consumption at times when the power system is under stress.

For direct load control, the DR programme provider remotely switches off the end-users' loads. It is the most popular DR programme in US with 5.13 million participants in 2011 [24]. The programme targets small commercial customers (less than 100kW peak demand) and residential customers. The controlled loads are usually heating, ventilation and air conditioning (HVAC) systems. The residential customer enters into a contract with the DR programme administrator to hand over the control of the air conditioner for a number of hours per year. When a generation shortage occurs, the DR administrator broadcasts a signal to curtail the participants' loads. Upon receiving the signal, controllable loads modify their operations. For example the temperature of the thermostat in air conditioners can be raised by a few degrees resulting in the delay of the cycle start or in the interruption of the cycle for those units which are in operation. In 2014, California Independent System Operator rewards customers who agree to this type of DR programme with 25$ per year for 100 control hours. In the UK, a residential DLC programme was introduced in the 1970s [25]. Three million radio teleswitch meters where installed in households with storage and water heaters. The meters could connect or disconnect the loads at the receipt of a radio signal from long-wave radio transmitters. The loads were supplied for 7 overnight hours with reduced electricity rates; the exact schedule was transmitted using a radio signal. It is estimated that in 2013 there were 550,000 participants enrolled in this programme [26], while the rest of the customers have adopted gas central heating or subscribed to Time-of-Use tariffs. It is expected that this DR programme will be replaced due to implementation of smart meters.

In demand bidding/buyback programmes the participating customers can bid in a market created by the DR administrator for demand reduction. The bid is for day-ahead events or day-of events. There is a minimum duration for the demand reduction. The participating customer receives penalties if the reduction in demand is not delivered.

In the emergency reserve DR, the customers (usually large consumers) are paid for measured load reduction in a generation shortage event. This is a voluntary based program; therefore there are no commitments or penalties.

A capacity market is a type of market running alongside the energy market. It was established to encourage the construction of new power plants and to allow the demand-side easy access to revenues in exchange for its participation. The traded product can be a capacity certificate that represents the available capacity that the power plant or DR aggregator holds. The sellers are generators or DR aggregators and the buyers are the electricity suppliers. A report [27] concluded that in Europe only UK, France and Ireland are developing a capacity market opened for the entire demand side. Spain, Germany and Italy have a capacity market opened only to large consumers and generators. Greece and Poland have a capacity market opened only to generation.

The ancillary markets are used by transmission system operators to procure extra reserve for maintaining the balance of generation and demand in the power system. The participant must commit to reduce load or increase generation when the system operator decides it is needed. Designed initially for the generators, this market is now opened for non-generator resources. Examples of balancing services managed by the Great Britain (GB) transmission operator NGET are given in Table 1.1. More details on the *Fast Reserve* and *Short Term Operating Reserve* are given in Section 4.1.2.

Rate-based pricing DR programmes, shown in Figure 1.1, encourage customers to shift their demand from periods of peak demand to off-peak periods. The concept is widely used in a range of sectors including transport (train tickets are charged differentially throughout the day), and communication (voice calls are charged at different rates depending on the time of the day).

Table 1.1: Examples of balancing (ancillary) services of the GB trasmission system operator [28]**.**

Ancillary service	National Grid Balancing Service	Open to demand	Delivery time	Minimum amount	Spending in 2012 (M£)
Continuous Regulation	Mandatory Frequency Response	No	continuous	-	61.6
Instantaneous Contingency Reserves	Frequency Control Demand Management	Yes	< 2 s	3MW	81.2
	Firm Frequency Response	Yes	< 30 s	10MW	
	Fast Reserves	Yes	< 2 min	50MW	92
Replacement Reserve	Short Term Operating Reserve	Yes	< 240 min	3MW	104
	Demand Side Balancing Reserve	Yes	< 120 min	1MW	-
	BM Start-up	No	< 90 min	-	4.53
Voltage control	Reactive Power	No	continuous	-	55.4

Time of Use (TOU) tariffs incentivise customers to shift their demand from high price to low price time intervals. It has a minimum of two rates: peak and off-peak. The rates can also vary depending on the season. In the EU and the US, TOU tariffs have been available for industrial customers since 1970s. Currently, in the EU and the US, the electricity suppliers offer TOU tariffs for residential and commercial customers. In the EU the most successful TOU tariff was implemented in France, called ‘Heures Pleines / Heures Creuses’ (Full Hours / Hollow Hours) with 10 million participant customers. The electricity rates are reduced by 30% for 8 hrs each day. In the UK, approximately 3 - 3.5 million residential customers are on TOU tariffs. Further details on the UK TOU tariffs are given in Section 3.2.

The critical peak pricing (CPP) rate is applied over the flat rate or TOU rate at hours where the demand is high. Participants are notified the day before if CPP will be enabled. The CPP pilot projects review [29] reported a ratio of three to fifteen between the rates for the most expensive and the least expensive time periods. An average of 14% peak demand reduction for residential customers during the CPP days was recorded in California's Statewide Pricing Pilot. The demand reduction increased to 27% for customers who opted for smart thermostats able to receive the utility's CPP signal and automatically modify their operation.

For extreme day pricing (EDP), the higher rate is in effect for the entire 24 hrs during the days where the demand is predicted to be very high. The participants are notified on a day ahead basis. An example of EDP pricing is the Tempo Tariff, in France. Tempo Tariff has defined three types of days according to the forecasted demand conditions: white, blue and red. The colours, from white to red, correspond to incremental levels of demand and electricity rates. Tempo Tariff also incorporates a TOU tariff. In [30] 300,000 residential and 100,000 small commercial customers are reported to participate in this DR program, giving a peak load reduction of 450MW.

The electricity rate for a customer with real time pricing (RTP) tariff varies hour by hour. The customer receives the tariff on a day-ahead or hours-ahead basis. The hourly rate follows the wholesale electricity cost. This type of programme requires a communication link between the utility and the meter as well as the meter's capability to record energy use on an hourly basis. Home automation can enhance the benefits of adopting RTP. According to [31], RTP is available for large and medium customers in Italy, Spain, Finland and Netherlands. Some utilities from the US have already made available hourly RTP for residential customers [32].

Rising block tariffs (RBT) aim to reduce the overall customer electricity consumption. The electricity price (per kWh) rises after a certain electricity consumption threshold in each month. A study on the impact of RBT on customers in the UK estimated that domestic customers would reduce their consumption between 1 to 7.4% [33].

For the interruptible/curtailable rates, the DR administrator offers lower electricity rates to customers who agree to have a part or the whole load curtailed when an event happens. The number of events per year and their maximum duration is established before the contract is agreed. The targeted customers are commercial and industrial consumers.

Most of the incentive based DR programmes outlined in this section target commercial and industrial consumers. Larger loads are preferred because the incentive is proportional to the load reduction level which requires that each load be metered and monitored. Contrasting with the incentive based DR programmes, the rate-based programmes are widely available for residential consumers. The reward for participating in the programme is embedded in the electricity tariff. The smart metering infrastructure will facilitate the implementation of more dynamic tariffs reflecting the daily changes in the wholesale cost of electricity and in the state of the electricity network. Automation of the response from appliances can make the rate-based programme more efficient for the participant and the administrator.

1.3 Services provided by smart appliances

As shown in Section 1.2, appliances with thermal inertia such as air conditioning and heating units are already used to assist the operation of power systems. There is a recent surge of interest to add other appliances such as washing machines – WM, tumble dryer – TD, dishwasher – DW, fridges and ovens to the residential DR programmes. These appliances, along with controllable distributed energy resources (DERs), are classified by Gellings in [24] as smart energy-efficient end-use devices. Smart devices are equipped with communication capabilities and advanced control strategy to respond to external signals. To differentiate between devices generating power and devices consuming power, the latter are named smart appliances. The Association of Home

Appliance Manufacturers (AHAM) defines smart appliances [34] as: “a product that uses electricity for its main power source which has the capability to receive, interpret and act on a signal received from a utility, third party energy service provider or home energy management device, and automatically adjust its operation depending on both the signal’s contents and settings from the consumer”.

The studies on smart appliances can be classified by topic in three categories:

- Smart appliances which are shifted from peak demand with the goal of reducing the user electricity cost. During the off-peak demand intervals the appliances are powered by power plants with lower marginal costs, such as baseload or renewable generation.

- Smart appliances which are incorporated in the power systems operational procedures such as balancing services.

- Smart appliances which are utilised for distribution network support, i.e. for congestion relief and integration of DERs.

1.3.1 Peak load shifting

A study on smart appliances - WM, DW, TD and plug-in hybrid electric vehicles (PHEV) - responding to utility signals is discussed by Mohsenian-Rad et al. in [35]. The utility signal was a RTP tariff combined with Rising Block Tariff (RBT). The authors began by arguing that the users could not keep track with changing electricity rates in a RTP case, therefore automation was needed to maximize the benefits of adopting such a tariff. The results showed a 25% reduction in the monthly electricity bill. The RTP tariff alone was responsible for lowering the peak-to-average (PAR) ratio of a household by 38% compared with the case with regular appliances, while further reduction in PAR could be achieved by combining the tariff with RBT. For a group of ten houses, the proposed automation had a smaller impact on the PAR of the aggregated demand, reducing it by only 22% as the PAR was already reduced by the load diversity. The authors further explored in [36] the coordination between a group of 10 houses with smart loads using game theory. An RBT tariff, represented by a quadratic cost function, incentivised the group of houses to collaborate to flatten their aggregated demand. The coordination was responsible for a 15% reduction in the monthly electricity bill for the group of houses and a 14% reduction in the PAR of the aggregated demand.

Gottwalt et al. [37] investigated the possible savings for users using smart appliances and multiple-rates tariff. An RTP tariff was introduced by up scaling the wholesale electricity price from the European Energy Exchange. The authors introduced a household load profile generator that utilises statistical data on appliance availability in German households and occupancy profiles. A simulation on a sample of 1000 houses showed household savings of approximately €1300 for space heating, €150 for water heating, €5 for each cold appliance, and between €1.5 and €11.6 per year for each washing appliance. The authors argued that even though the heating load could bring more savings, their penetration rates in Germany were very low. The paper concluded that additional incentives are needed besides TOU tariffs in order to make smart appliances attractive to households.

Dlamini and Cromieres [38] investigated peak reduction in the household load profile by controlling appliances. The activation times of appliances, taken from a survey on 30 households in Japan, were an input of the simulation. Three algorithms were tested: shifting appliances to off-peak intervals, coordinate the appliances in order to avoid the running simultaneously and, thirdly, switching on the appliances only if the house load limits are not infringed. The load profile for the non-controllable loads was assumed to be known. The minimum load reduction across all the algorithms was 6%. The authors underline the importance of the delay allowed by users, between the time the appliance is started and the time the service is delivered, towards reducing load.

In reference [39], the authors introduced a home energy management system (HEMS) capable of receiving TOU tariff and controlling WM, DW and TD. The performance of the HEMS resulted in a 30% reduction on the monthly electricity cost and a 40% peak load reduction for individual households.

1.3.2 Balancing services

Studies in the literature cover the participation of smart appliances in balancing (ancillary) services: frequency response, operating (standing) reserve and transmission network congestions.

System frequency is an indicator of the momentary balance between electricity demand and electricity generation. The concept of using system frequency as an input to controllable residential loads was first introduced in [40]. In the UK, the use of fridges and freezers as dynamic demand was investigated in [41]. The loads stop their cycles at a low system frequency and start at high frequency. The results showed that 40 million appliances are needed to satisfy the 1320 MW of spinning reserve required by the GB power system. In [42] it is reported that 596,299 refrigerators along with 176 bitumen tanks are needed for an aggregator to provide 10 MW of dynamic frequency response to the GB transmission system operator. However it was noted that to meet the system's frequency requirements needs a large number of fridges and freezers due to their small consumption (on average 100W) and to their unavailability to simultaneously respond to a frequency event.

The use of residential DR as operating reserve was investigated in the SMART-A project [43]. A first case study based on the UK power system assumed a 57 GW peak demand, a 25 GW wind generation, and a generic controllable load. The DR helped to reduce wind curtailment and run the system with less part-loaded power plants securing the reserve margin. The reduction in GHG emissions varied between 0.8 to 4.3 $MtCO_2$. A second case study was based on a power system with 19.8 GW peak demand and 5 GW wind generation installed. This considered a detailed shifting algorithm of appliances (WM, DW, TD). The value of appliances as operating reserves was estimated to be between €3.7 for WM, €6.3 for DW and €16.4 for TD per annum. Reference [44], which considered a wider range of household appliances including HVAC and water heater, showed that residential consumers from the US could reduce their annual electricity bill by up to 2% by participating in the operating reserve market.

In the SMART-A project, the use of smart appliances in the congestion management of the transmission network was discussed. The methodology included two steps: economic dispatch and a redispatch using Optimal Power Flow. In this study, an appliance model was not integrated but a generic aggregated controllable load was considered. Two case studies of 2 and 16-bus test systems representing the simplified UK power system were introduced. The benefits for the transmission network operator of using residential DR consisted of the reduction in the cost of disconnecting consumers and avoiding wind curtailment.

1.3.3 Distribution network support

The focus of the studies carried out on the topic of smart appliances for distribution network support can be divided into: congestion relief, and coordination with distributed energy resources (DERs). The studies usually incorporate a network model.

An example of using smart appliances for network congestion relief was investigated in reference [45], where a Spanish distribution network with 700.000 residential consumers was investigated for a summer day. Different correlations between the consumption curve of different types of appliances and the peak demand on a distribution network indicated that some appliances are better suited than others to reduce the peak demand. This is the case in [45], where shifting the WM, DW, TD and water-heaters managed a reduction in peak demand of only 3.2%, as the four appliances have a small contribution to the network's peak demand. Up to 12.6% was obtained from curtailing all the residential and commercial air-conditioning units. However in the case of the UK the residential air-conditioning units may not be the best solution for DR as the ownership of air-conditioning units was estimated at 2.4% [46].

In reference [47], smart appliances of 12 houses belonging to the same feeder were controlled to reduce the peak demand. A reduction of 13.31% was obtained. A similar value, of 14.7%, was obtained in a study [48] on a feeder with 544 houses which investigated the load reduction during the peak pricing of a CPP. It was observed that a significant rebound peak was created after the end of the peak pricing. A release option, in which appliances had their start randomised after the peak pricing interval, reduced the magnitude of the rebound peak. The ending time of the peak pricing is another factor influencing the rebound peak. The most advantageous setting is for the peak pricing of the CPP to end during the off-peak demand period to accommodate the rebound peak. Early measurements taken during a recent trial [14] in the UK also revealed a rebound peak at the end of the CPP peak pricing interval. 150 smart appliances (WMs) were monitored during the trial.

Coordination of smart appliances with DERs can be aimed at different levels: within a house, at Low Voltage (LV) level or High Level (HV) level. In [49], the author investigated the capability of the appliances (WM, DW, TD) to match the generation profile of residential photovoltaic panels (PVs). The argument is that the load shifting of appliances will induce financial savings in the households without net metering or in those where the feed-in tariff from PVs will decrease below the electricity retail price. The results show an increase in household consumption from PV by 200 kWh each year, which converts into a financial benefit of €20 per annum.

Congestion relief and coordination with DERs at HV level were addressed in the SMART-A project [43]. An appliance model of one hour resolution was used in the project. The role of smart appliances for a 30-bus distribution test system with a capacity of 175 MW and 186.4 MW peak demand was investigated. The results showed that smart appliances successfully removed any load shedding and reduced the wind curtailment by 618 MWh.

Another utilisation for smart appliances on distribution network operation indicated in the review on smart appliances [50] is to manage the network in the event of a circuit outage. The demand at HV and higher voltage levels is supplied by at least two circuits, each with a capacity higher than the peak demand. In case of rare one-off events when one circuit becomes faulted the demand is supplied by the remaining functional circuit. There is an opportunity to allow the connection of additional demand, above the capacity of each circuit. The condition is that the DR is required to reduce the post fault demand below the rating of the remaining functional circuit. A trial testing the post fault handling from commercial and industrial loads is under way [16] in the UK; however, there are no investigations on residential loads.

1.4 Modelling of smart appliances operation

According to references [51]–[53] the load management actions implemented in smart appliances are:

- Delay the appliance starting time as exemplified in Figure 1.2 (a) on a tumble dryer load profile.
- Interrupt the cycle of appliances for short periods as shown in Figure 1.2 (b).
- Modify the appliance cycle by reducing the power consumption at the expense of increasing the cycle's duration of operation as shown in Figure 1.2 (c).

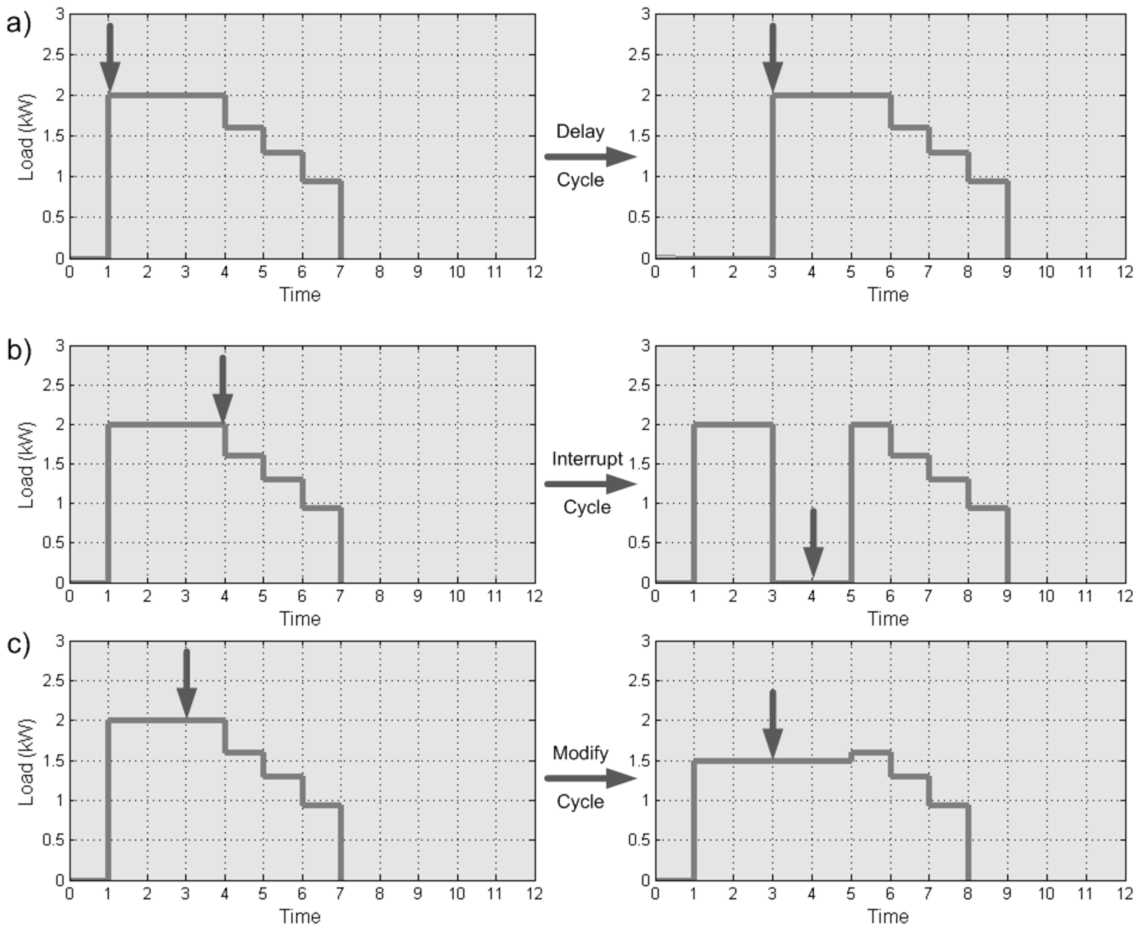


Figure 1.2: Smart appliances load management actions: (a) Delay cycle; (b) Interrupt cycle; (c) Modify cycle.

Mathematical optimisation is widely used by researchers to model the operation of smart appliances. Other methods include: optimal stopping rule, heuristic rules, greedy algorithm and game theory.

1.4.1 Optimisation

Mohsenian-Rad et al. introduced in [35] an optimal load control scheme based on linear programming (LP). In this study the appliance load profile is represented by a vector of continuous decision variables, while the appliance energy consumption is the sum of the variables. The continuous nature of the variable represents an approximation: the appliance power consumption can take any value between zero/minimum and maximum. The authors discussed a more detailed method for modelling smart appliances using discrete energy consumptions and cycle interruption; however, the method was not implemented in the paper. The user behaviour was modelled as a term in the optimisation objective function which weights between the cost reduction and the cost of delaying the appliance.

The smart appliance shifting algorithm implemented by Gottwalt et al. [37] also employs LP-based optimisation. To the list of smart appliances, the authors add fridges and freezers which were modelled as a number of cycles across the day, each cycle being shifted by 30 minutes before and after the initial start time. The appliances are estimated to have constant power during the cycle. LP-based optimisation was also employed to shift appliances in reference [39] by Enrol-Kantarci.

In the references presented until this point the cycles of appliances were modelled as energy consumption. Modelling appliances as a sequence of power phases, each with discrete power consumption, requires decision variables with integer or binary values. This is the case in [54], where a mixed-integer LP (MILP) based optimisation was employed. In order to model each power phase operation, the number of decision variables was multiplied by the number of phases. Additional binary decision variables were added to model the constant power consumption and the order of power phases in an appliance cycle. The binary variables have increased the number of variables by a factor of four. This led to a significant computational time for scheduling even a small number of appliances. The same optimisation problem from [54] was solved in [55] by using dynamic programming, method which required more computational resources than MILP.

LP and Quadratic Programming (QP) based optimisations were utilised in [45] for shifting the smart appliances. The appliances were represented by 2 one hour-long phases with constant power consumption. No interruptions were allowed between the power phases. A two step control strategy was discussed. At the first step, the appliances forecasted to be activated in the next day were optimally scheduled considering a list of control actions, e.g. delay the start by 1 hr, by 2 hrs and so forth. Two optimisation objectives were defined: cost minimisation (LP problem) and error minimisation between the forecasted load and desired load curve determined by the transmission system operator (QP problem). At the second step, users are assigned a control action from the list when they activate the appliance.

1.4.2 Other methods

In reference [56], optimal stopping rule was utilised to schedule smart appliances according to a RTP tariff. Because the considered tariff changes each hour, the authors demonstrated that the optimal schedule for a single appliance is a pure threshold policy. The threshold is a function of the user's waiting cost. If the current price is higher than the threshold, the appliance should start, while if it is lower, the appliance should wait for the next tariff interval. In the case of more than one appliance, an additional step with binary optimisation was added to choose which of the appliances with a higher threshold should start and which should be delayed.

Another control logic based on thresholds for scheduling appliances was introduced in the Active House project, described in [57], [58]. The considered controllable devices were: smart appliances, EV, HVAC, lights and blinds. The RTP tariff received by HEMS was partitioned in a number of intervals. In the interval with the lowest price all the appliances could function unrestricted, while at the interval with the highest cost only the appliances that delivered an essential service were functioning. The loads were started, delayed, or have their operating parameters modified depending on the price interval and according to a logic agreed by the resident. A similar control strategy was described in [48], where the appliances checked the pricing signal at activation. If the price was normal the appliance starts without delay, while if it was high or critical, the start is delayed until the return to the normal price. An override option was given to the appliance user.

The work in [49] proposes a greedy algorithm to shift the appliances. The power consumptions measured at 200 households were processed by imposing a power threshold to identify the appliances cycles. The greedy algorithm finds the interval with the lowest cost of running the appliance by running through each interval of the day, memorising any new minimum and discarding the old minimum. Although the resulting schedule is optimal, the method is suitable to model a small number of appliances. Scheduling a large number of appliances with greedy algorithm takes significantly more computational resources than with optimisation.

A control logic for coordination of appliances based on heuristic rules was introduced in [59], [60]. At activation time, the appliance queries if the electricity rate is high. When it is high, the appliance queries if there is enough power produced by the household small-scale embedded generation or enough energy stored in the EV battery to cover its demand. When there is enough storage, the battery should be discharged while the appliance is operating. The control logic prioritised the use of renewable sources.

Game theory is one of the solutions proposed in the literature as an alternative to centralised control. Each appliance retains its individual control, yet its scheduling is influenced by the other appliances' operations. In references [36],[61], game theory was employed to schedule domestic loads. The load consumption was modelled in terms of energy. The tariff, a quadratic equation function of load, ensured that the lowest cost for the aggregated demand from a group of households was achieved by the collaboration of appliances from all households to avoid a peak. The scheduling was a non-linear convex optimisation problem. Reference [62] introduced an additional game theory concept, of fairness in the billing system. The proposed solution ensures that the households are rewarded according to their contribution. While they showed some advantages over centralised control, such as computational efficiency, the implementations of game theory in smart grids requires high data traffic as all the households have to communicate between each other before reaching a decision. While the current research did not investigate the scalability of game theory in smart grids, the scalability issue was raised in other real world applications [63].

The advantage of using optimisation to schedule the smart appliances is that it will yield the optimal solution. The outcome for other types of models can be suboptimal, or take more resources to reach the optimal solution.

1.5 Research objectives and thesis structure

The goal of this work was to investigate through simulation the effects of adopting smart appliance technology. The implications of this technology were sought for appliances users, transmission system operators and distribution network operators.

A smart appliance model incorporating load management features was needed to carry out the simulations. The smart appliance model had to be accurate enough to make observations at household level, while at the same time, scalable, to be used for system level simulations. A smart appliance model with the above objectives was developed starting from the optimal load control introduced in [35]. The improved model considers cycle interruption and discrete power consumption.

The thesis set out to achieve the following objectives:

- For appliances users:
    - To identify which parameters involved in the operation of smart appliances have the most influence in achieving cost savings;
    - To identify if the smart appliance technology is financially valuable for the UK residents. Multiple electricity tariffs already in use or designed for the UK electricity sector were considered.
- For the transmission system operators:
    - To design a simulation that can assess the response of smart appliances to a reserve instruction from a number of households at each moment of the day;
    - To estimate the level of reserve which can be provided by the aggregated response of the smart appliances towards the operating reserve of the GB power system.
- For the distribution network operators:

- To identify potential detrimental effects of the adoption of smart appliance technology for the MV and LV networks due to the loss in appliances diversity of usage;

- To mitigate the potential detrimental effects by coordinating the operation of appliances and investigate further opportunities for the network operator.

The structure of the thesis follows the research objectives presented, as shown in Figure 1.3. In Chapter 2, the smart appliance model including the shifting algorithm which was used in the simulations of the other chapters is introduced. In Chapter 3, the electricity cost savings for users are calculated through financial analysis tools. In Chapter 4, the current operating reserve requirement of the GB power system is calculated. In addition, the level of reserve from smart appliances and the resulting financial and environmental achievements is estimated. In Chapter 5, the beneficial and detrimental impacts of smart appliance technology on distribution network operation are investigated using power flow analysis. The effects of using appliances for network support on the user cost savings are also evaluated.

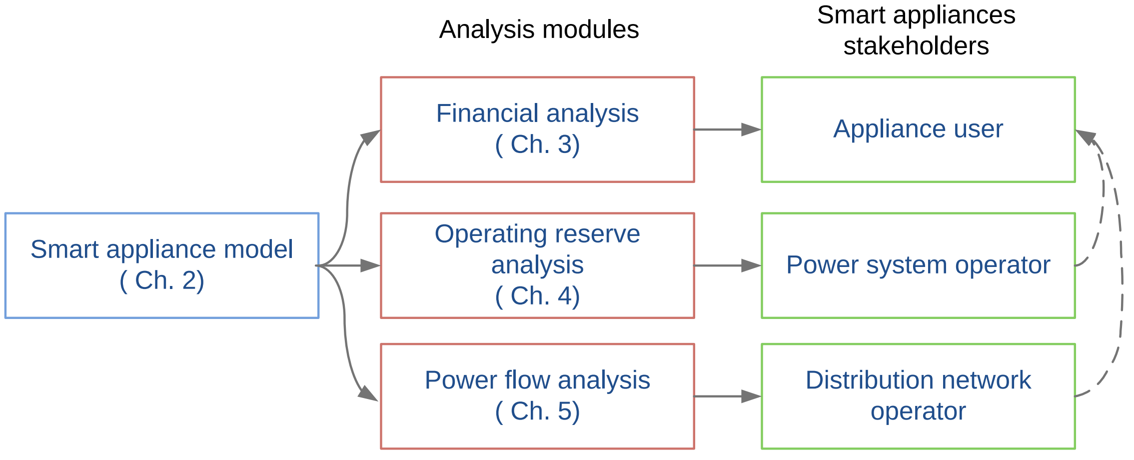


Figure 1.3: High level structure of the analyses used and outline of the thesis.

1.6 Publications and achievements

The following papers are based on the work described in the dissertation.

1. **S. Nistor**, J. Wu, M. Sooriyabandara, and J. Ekanayake, “Capability of smart appliances to provide reserve services,” *Applied Energy Journal*, doi:10.1016/j.apenergy.2014.09.011, Sept. 2014, Accepted for publication.

2. **S. Nistor**, J. Wu, and M. Sooriyabandara, “The impact and opportunities of smart appliances on distribution networks,” *In Proceedings of the 4th IEEE/PES Innovative Smart Grid Technologies Europe Conference*, pp. 1–4, 2013, Copenhagen, Denmark.

3. **S. Nistor**, J. Wu, M. Sooriyabandara, and J. Ekanayake, “Capability of smart appliances to provide reserve services,” Paper presented *at the 5th International Conference on Applied Energy*, pp. 1–6, 2013, Pretoria, South Africa.

4. **S. Nistor**, J. Wu, M. Sooriyabandara, and J. Ekanayake, “Cost Optimization of Smart Appliances,” *In Proceedings of the 2nd IEEE/PES Innovative Smart Grid Technologies Europe Conference*, pp. 1–5, 2011, Manchester, UK.

Chapter 2

Smart Grid ready appliances

Summary:

The objective of the chapter is the development of a tool to model the response from domestic smart appliances to utility signals. A mathematical method to describe the operation of different appliances is introduced. Models to delay and interrupt the operation of appliances are developed. The user behaviour is also considered: the appliance start times are obtained using a residential energy demand model, while the maximum start delays allowed by the user are obtained from statistics reported in the literature. A shifting algorithm that integrates the models and user behaviour is proposed. The algorithm uses optimisation, implemented in CPLEX software, to find the smart appliance actions with regard to the utility signal. The theory behind the optimisation solving algorithm is discussed. A validation of the energy demand model and a verification of the shifting algorithm are performed. The developed tool is generic in that it is capable to model demand response from appliances with predetermined power consumption profile.

2.1 Introduction

The percentage of households in GB that have an Internet connection is increasing: 83% of households in 2013 [64], up from 57% in 2006. An additional communication infrastructure will be deployed with the smart metering roll-out, reaching every household by 2020. Therefore, there is a new opportunity to use this communication infrastructure to send DR signals to a large number of domestic loads for load management actions. This work focuses on small loads, such as appliances that are commonly available. Many of the established appliance manufacturers have introduced Internet connected appliances [65] with new features to increase user comfort such as sending a notification to the user's smartphone when the appliance cycle finishes. Some of the manufacturers are also involved in research [48],[66] on load management. However, trials to demonstrate these features are at incipient stages [67].

The appliances considered in this study - washing machine, dishwasher and tumble dryer (WM, DW, TD) - were chosen due to their high level of ownership shown in Table 2.1. Their electricity consumption makes up approximately 14% of the total household consumption in the UK. Other appliances have similar shares, as shown in Table 2.2. However, the selected appliances are the most likely to allow load management with minimum impact on user's comfort. This is confirmed by the high user acceptance of smart operation for these appliances (95% for WMs, 91% for DWs and 92% for TDs [68]).

Table 2.1. Penetration rate of selected appliances in the UK [69]**.**

	Washing Machine (WM)	**Dish Washer (DW)**	**Tumble Dryer (DW)**
Ownership (%)	95	28	53

Table 2.2. Household electricity consumption by load type in the UK [70]**.**

Load type	Electricity consumption (%)
Washing/Laundry (WM, DW, TD)	13.6
Cold appliances	16.2
Lighting	15.4
Audiovisual	14.4
Cooking	13.8
Others	25.8

2.2 Load profiles

The power consumption of appliances varies with the appliance model, the programme selected, water intake temperature. In this study, the actual load profiles of appliances were averaged for mathematical modelling as proposed in the Smart-A project [71]. During the Smart-A project an average load profile for each type of appliance was constructed by matching the energy consumption measured on appliances from 100 households [71]. The average load profile follows the typical power consumption of the specific type of appliance. For example, the average load profile for washing machines, shown in Figure 2.1 (a), comprises seven processes with constant power, called power phases, each lasting 15 minutes. For a visual comparison real measurements of the appliances, recorded during the 3-E Houses project [72], are also given. For example, the measured power consumption of a washing machine for the duration of one cycle is shown in Figure 2.1 (b).

The main energy consumption elements of a washing machine are the resistive water heating element and the electric motor that spins the drum. At the start of the cycle, the tub, in which the drum with the garments is placed, is partly filled with water and soap. The water is heated by the heating element that has a rated power between 1.8 to 2.5 kW. The heating phase is easily noticeable at the beginning of a washing machine load profile both in the average load profile, shown in Figure 2.1 (a), and in the measured power consumption, shown in Figure 2.1 (b). After the heating phase, the cycle contains a number of spinning and rinsing phases with low power consumption and ends with high speed spinning phase to partially dry the garments. The energy consumption of the average load profile is 0.89kWh per cycle.

(a)

(b)

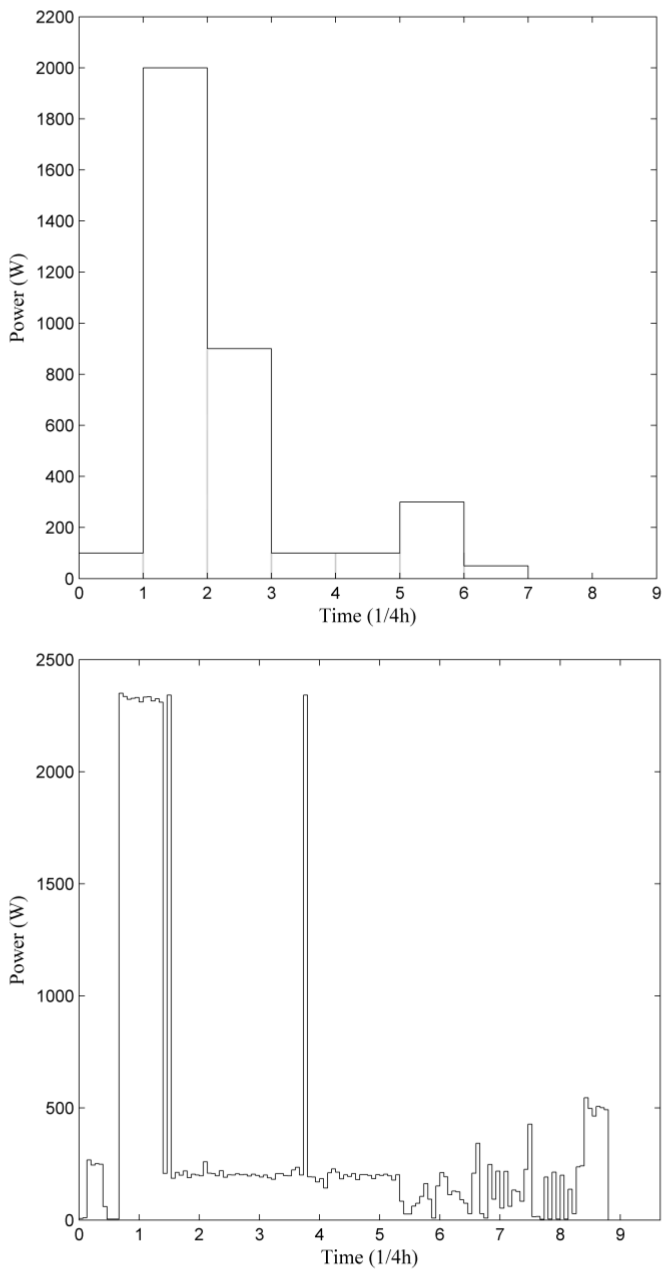
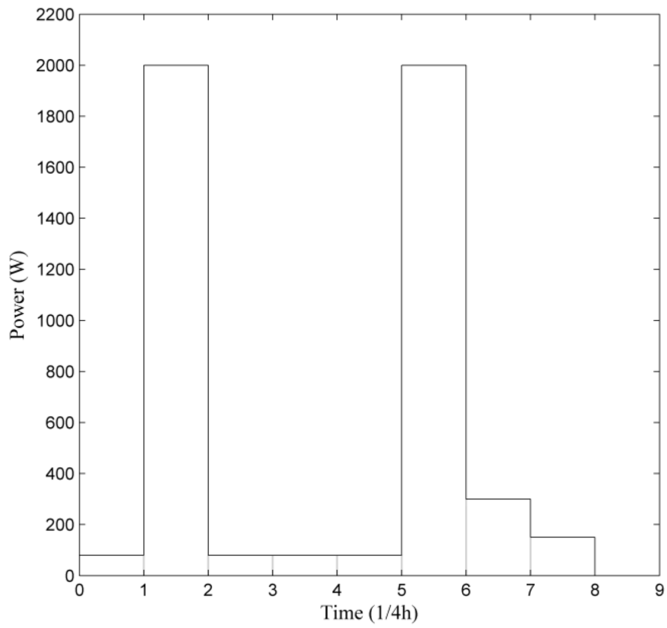


Figure 2.1: Washing machine load curve: (a) Average load profile from SMART-A project; (b) Sample of measurements from 3-E Houses project.

The main energy consumption elements of a dishwasher are the resistive heating element and the electric pump which creates water pressure for the rotating spray arms. At the start of the cycle the tub with the dishes is partially filled with water and heated by the resistive element that has a rated power between 1.8 to 2.5 kW. The water and detergent is sprayed onto dishes followed by a rinse phase. At the end of the cycle the air and the dishes in the tub are heated, facilitating evaporation of the water from the dishes which will condense onto the walls of the tub. These two heating phases can be observed both in the average load profile, shown in Figure 2.2 (a), and in the measured power consumption, shown in Figure 2.2 (b). The energy consumption of the average load profile is 1.19kWh per cycle.

(a)



(b)

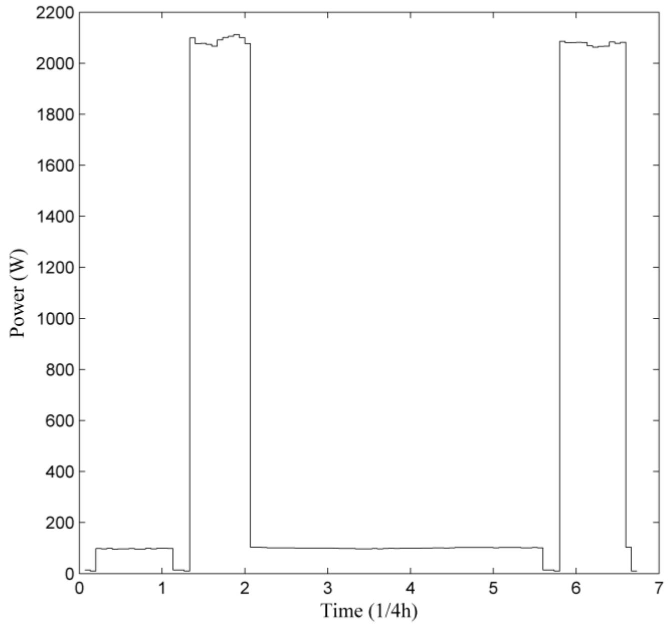


Figure 2.2: Dishwasher load curve: (a) Average load profile from SMART-A project; (b) Sample of measurements from 3-E Houses project.

The main energy consumption elements of a tumble dryer are the resistive heating element and the electric motor that spins the drum. Air is heated by the resistive element with a rated power between 1.8 and 2.5 kW and blown into the rotating drum facilitating evaporation from the wet garments. Depending on the technology used, the humid hot air is either evacuated through a vent duct or circulated through an internal heat exchanger where vapours are condensed. Temperature and humidity sensors set the length of the cycle. The average load profile of a tumble dryer, which is used in this study, is shown in Figure 2.3 (a). The measured power consumption for a tumble dryer recorded during the 3-E Houses project is shown in Figure 2.3 (b). The energy consumption of the average load profile is 2.46 kWh per cycle.

(a)

(b)

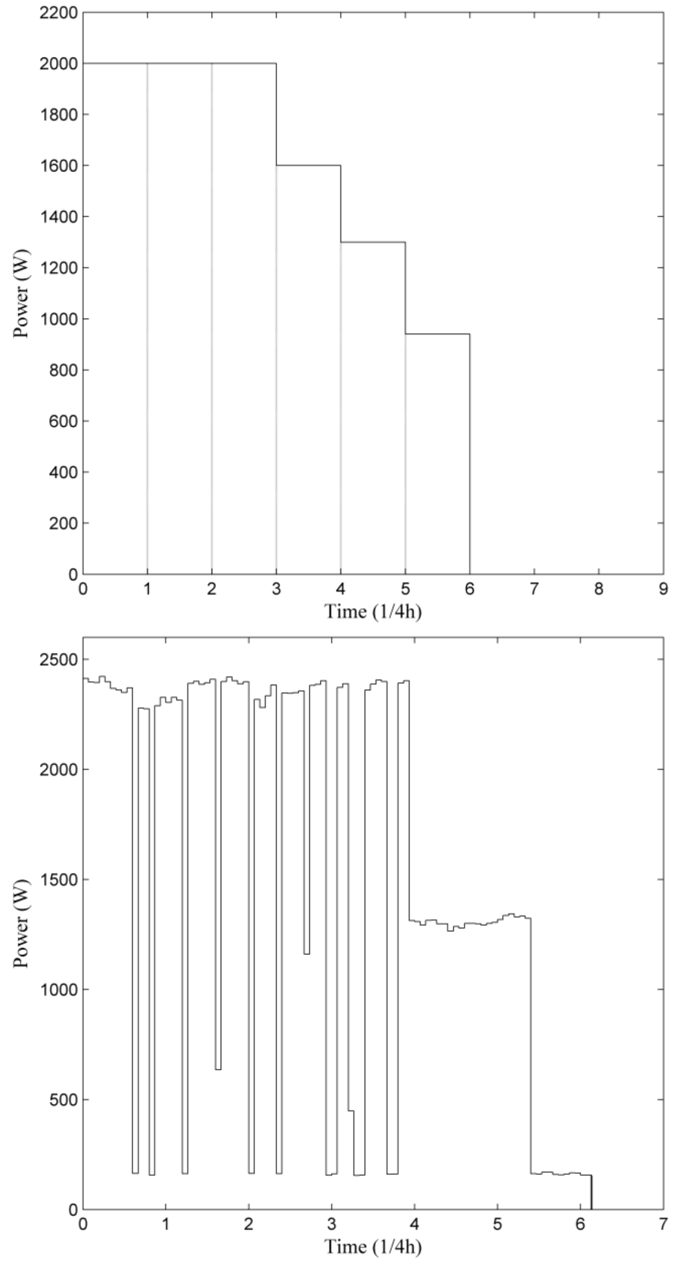


Figure 2.3: Tumble dryer load curve: (a) Average load profile from SMART-A project ; (b)Sample of measurements from 3-E Houses project.

The power phases were used to mathematically model the smart appliances for load management. An example is shown in Figure 2.4, where a tumble dryer cycle is partitioned into six energy phases. For each power phase a binary operation vector was defined over a period of time. The elements of the vector, x_v^t, represent the operation status of power phase *v* at time *t*. A value equal to zero indicates that the power phase *v* is ‘off’ at time *t*, i.e. $x_v^t = 0$, while $x_v^t = 1$ indicates that the power phase *v* is ‘on’ at time *t*.

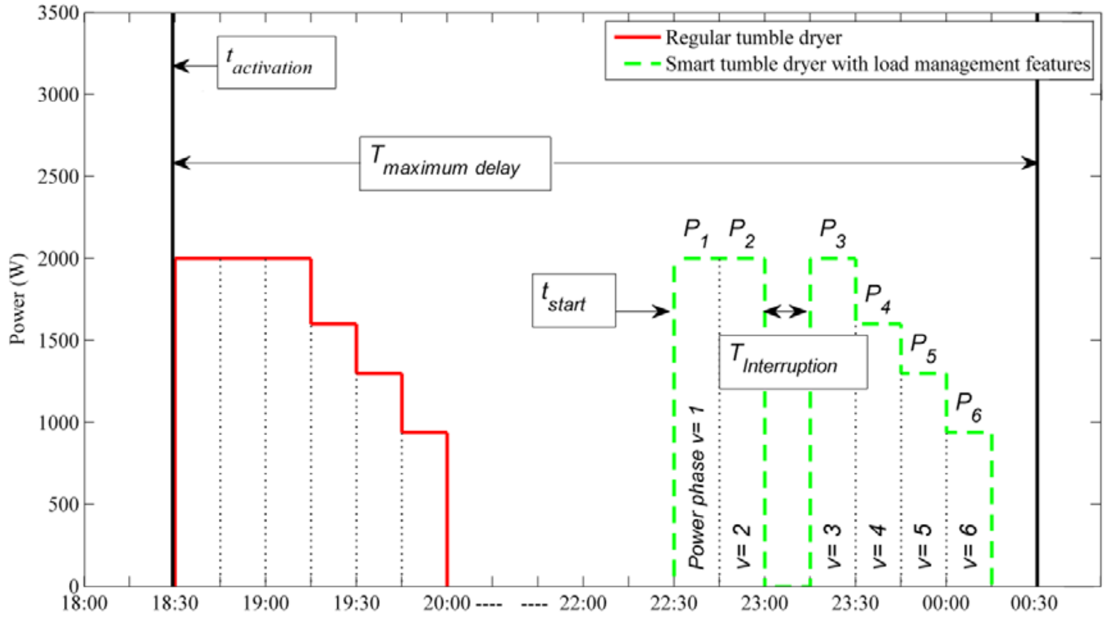


Figure 2.4: Load management features of a smart appliance.

The operation of the smart tumble dryer (Figure 2.4) between 22:30 and 00:15 is described with the help of the binary elements, x_v^t, in Equation (2.1). The binary operation vector for the first power phase of the appliance is highlighted.

$$[P_1 \quad P_2 \quad P_3 \quad P_4 \quad P_5 \quad P_6] \cdot \begin{bmatrix} x_1^{22:30} & x_1^{22:45} & \cdots & x_1^t & \cdots & x_1^{00:00} \\ x_2^{22:30} & x_2^{22:45} & \cdots & x_2^t & \cdots & x_2^{00:00} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ x_v^{22:30} & x_v^{22:45} & \cdots & \boldsymbol{x_v^t} & \cdots & x_v^{00:00} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_6^{22:30} & x_6^{22:45} & \cdots & x_6^t & \cdots & x_6^{00:00} \end{bmatrix} = \begin{bmatrix} P_1 \\ P_2 \\ 0 \\ P_3 \\ P_4 \\ P_5 \\ P_6 \end{bmatrix} \qquad (2.1)$$

where: $$\begin{bmatrix} x_1^{22:30} & x_1^{22:45} & \cdots & x_1^t & \cdots & x_1^{00:00} \\ x_2^{22:30} & x_2^{22:45} & \cdots & x_2^t & \cdots & x_2^{00:00} \\ \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ x_v^{22:30} & x_v^{22:45} & \cdots & \boldsymbol{x_v^t} & \cdots & x_v^{00:00} \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ x_6^{22:30} & x_6^{22:45} & \cdots & x_6^t & \cdots & x_6^{00:00} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}.$$

2.3 Load management

2.3.1 Smart timing

One of the envisioned features of smart appliances that could facilitate DR interventions (e.g. load shifting), is called *smart timing*. For the *smart timing* feature, the starting time

t_{start} of the appliance cycle is determined considering the user preferences and also external signals (e.g. pricing) received from utilities or DR aggregators.

Before introduction of the *smart timing* feature, appliance manufacturers facilitated users to postpone the operation of their appliances to off-peak time through a feature called *start delay*. This feature can be found on 30% of the appliance stock in the UK [71]. The difference between *start delay* and *smart timing* is highlighted in Table 2.3. With the *start delay* feature, after the appliance is loaded with garments at $t_{activation}$, the user introduces, through a user interface, how many hours after $t_{activation}$ the appliance cycle should begin. This duration is noted with T_{delay}. With the *smart timing* feature the appliance selects automatically when the cycle should begin, within the interval ($t_{activation}$,$t_{activation}$ + $T_{maximum\ delay}$), depending on the user input $T_{maximum\ delay}$ and an external signal. If the external signal is an electricity tariff with multiple-rates, the appliance will automatically select the interval that yields the cheapest cost of operation. An example of this feature execution is shown in Figure 2.4, where the tumble dryer's operation is delayed from 18:30 ($t_{activation}$) in the evening until 22:30 (t_{start}) in the night, avoiding peak electricity rates. In the example given, the user allows a maximum delay, $T_{maximum\ delay}$, equal to six hours. This user defined parameter, *maximum delay*, is described in Section 2.4.2.

Table 2.3: Evolution of start delay features from regular appliances to smart appliances.

Appliance type	Feature	User input	Start time
Regular	*start delay*	T_{delay}	$t_{start} = t_{activation} + T_{delay}$
Smart	*smart timing*	$T_{maximum\ delay}$	$t_{activation} \leq t_{start} \leq t_{activation} + T_{maximum\ delay}$

2.3.2 Cycle interruption

Cycle interruption is a second load management feature which is considered in the smart appliance model. The appliance's cycle is interrupted for a period of time to avoid high electricity rates or peak loading. An alternative way of looking at the effect it has on the appliance cycle is that it will increase the cycle's duration. It is important that pausing the operation of the appliance should not affect its service quality. From the selected appliances, the *cycle interruption* feature can be implemented in tumble dryers without any effects on the service quality, as they store little thermal energy during their operations. For washing machines and dishwashers, interruptions at certain times of the cycle could result in the energy, which is stored in the heated water, being radiated through the tub walls. The resulting thermal energy loss detracts from the potential positive effects that interruption brings. However, in this study it was considered that in the near future, research and development efforts of the appliances manufacturers in tub insulation, such as the one in [73], will facilitate the interruption of cycles with close to zero energy loss.

It is envisioned that the *cycle interruption* feature will allow the appliance to be paused at any point during the cycle. In this study, the interruptions of the appliance cycle were considered only at the boundaries between power phases. An example of the tumble dryer's cycle being interrupted for $T_{interruption}$= 15 min, between the power phases v = 2 and v =3, is shown in Figure 2.4. Different values for the parameter *maximum interruption* time, denoted by $T_{off\ v}$, were considered during this study.

2.4 User dependent parameters

2.4.1 Activation times

One of the user dependent parameters is the *activation time*, $t_{activation}$, which is defined as the time the user presses the appliance ON button after he finished loading the appliances with the garments for WM and TD or dishes for DW. In the absence of a large database of appliance measurements a generator of artificial household demand was employed to generate the *activation times* for appliances. The CREST domestic energy demand model [74], described in Appendix A, was selected as it uses time of use data collected in a UK survey [75] to create probabilities from which a infinite number of realistic household demand can be generated. The survey sample is representative for the entire UK population considering the income distribution as shown in [76]. The model outputs 24 hrs load profiles for each house, at a resolution of one minute, depending on the number of household occupants, season and day of the week. The profile of a house distinctly shows the load profiles of all the appliances that constitute it, as can be seen in Figure B-1 of the Appendix A. In this study, it was assumed that the *activation times* of appliances are the start times of the appliances from the CREST model.

A scheme for the utilisation of the CREST model in this study is illustrated in Figure 2.5. For this work, the script of the CREST model, written in Perl programming language [77], was modified[1] to run over consecutive days and to output the activation times of WM, DW and TD and the aggregated demand of the households, excluding the demand from the three appliances. The aggregated demand represents the demand that is inflexible, not capable of responding to external signals.

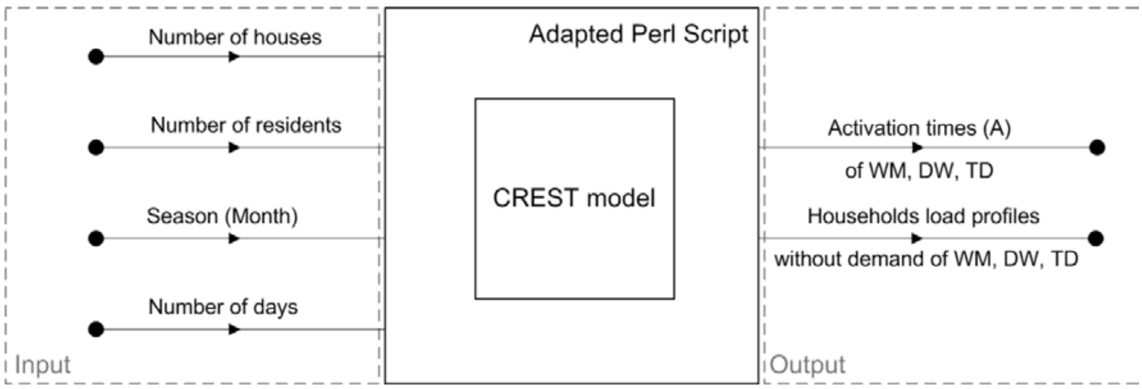


Figure 2.5: Scheme of CREST model utilisation.

[1] The code developed by the author can be found at: https://github.com/hitron/adapted_crest

The activation times of WMs, DWs and TDs were structured as a matrix *A* with three columns, one for each appliance type, and *T* rows; where *T* is the number of 15 minutes intervals within the number of days considered. For example, in the *activation times* matrix from 1000 households shown in Table 2.4, eighteen WM users pressed the ON button in the time interval 18:01 – 18:15. Similarly, nine users pushed the ON button of their TDs in the time interval 18:16 – 18:30.

Table 2.4: Activation times of WM, DW and TD from 1000 households.

Time	Washing machines	Dishwashers	Tumble Dryers
…	…	…	…
18:01 – 18:15	18	2	10
18:16 – 18:30	12	1	9
18:31 – 18:45	8	1	6
…	…	…	…

2.4.2 Maximum delay

The *maximum delay* parameter is a measure of the flexibility offered by the user. It is envisioned that appliances equipped with the *smart timing* feature will require the user to select the *maximum delay*, after pressing the ON button. With the first pilot projects [78] [79] testing a similar type of feature still in progress, there is a lack of real world data on what values will the user select for the *maximum delay*. However, an approximation can be made by observing how the already implemented *start delay* function, described in Section 2.3.1, is used.

The values from a survey completed in the Smart-A project [80] were considered when assigning values for the user defined *maximum delay* parameter. One of the questions that the survey addressed to the users of appliances equipped with *start delay* button was: “How long does your machine remains in the start delay position before the programme starts?” The percentages of the respondents under each number of hours of delay are given in Table 2.5. In this study, a random number generator was used to assign from 1 hr to 7 hrs for the *maximum delay* parameter for each appliance according to the percentages given in Table 2.5.

Table 2.5: Statistics for user defined *maximum delay*.

Maximum delay (hrs)	1	2	3	4	5	6	7
Percentage of respondents (%)	19	19	19	9	9	9	16

2.5 Shifting algorithm

A shifting algorithm was introduced to model the operations of smart appliances with load management features. The shifting algorithm uses optimisation to schedule the appliances operations with respect to user preferences and external signals. The algorithm produces delays in the start times and/or prolonged appliances cycles, due to interruptions.

2.5.1 Optimisation

2.5.1.1 Variables

The mathematical model of the binary operation vectors, introduced in Section 2.2, is given in Equation (2.2). The elements of the vector are the optimisation decision variables. Each appliance $\underline{a}$, from the total of A^t appliances activated at time t (a single row from matrix A), comprises of a number V_a of power phases. Each power phase v has a binary operation vector with the length of the optimisation window H.

$$\mathrm{X}_{\mathrm{v,a}} = \Big(\; x_{v,a}^{h} \in \{0,1\} \;, \qquad \forall h \in (1, \dots, H) \Big) \;, \quad v \in (1, \dots, V_a) \quad a \in (1, \dots, A^t) \tag{2.2}$$

Where h is the time index corresponding to the position of the element $x_{v,a}^{h}$ in the binary operation vector $\mathrm{X}_{\mathrm{v,a}}$.

The number of decision variables needed in the optimisation model is ($A^t \cdot V_a \cdot H$). For example if the optimisation window is eight hours, or thirty-two time steps (quarter hours), then the number of decision variables needed to model the operation of a washing machine with seven power phases is 1 x 7 x 32 = 224.

2.5.1.2 Objective function

The objective of the optimisation is to minimise the cost of operating the power phases. The mathematical formulation of the objective at time *t* is given in Equation (2.3).

$$\min_{x_{v,a}^{h}\in\{0,1\}}\left\{\sum_{a=1}^{A^t}\sum_{v=1}^{Va}\sum_{h=1}^{T_{MaxDel,a}+\mathrm{T_{cycle}}} c^{t+h}\cdot x_{v,a}^{h}\cdot P_{v,a}\cdot\Delta t\right\} \tag{2.3}$$

Where:

$x_{v,a}{}^{h}$	binary decision variables
A^t	the number of appliances activated at time *t* (from the *activation times* matrix)
$\mathrm{T}_{MaxDel\,,\,a}$	user defined maximum delay for appliance *a*
T_{Cycle}	duration of the appliance cycle
V_a	number of power phases of the appliance *a*
c^{t+h}	electricity rate at time $(t+h)$
$P_{v,a}$	power consumption for the power phase *v* of the appliance *a*
Δt	15 minutes time step

2.5.1.3 Constraints

The constraints are needed to model the operation of smart appliances. The constraints can be of two types: inequality and equality constraints. The optimisation introduced in this study has both types of constraints. One inequality constraint ensures that the power phases are supplied in the correct order within the operation of one appliance:

$$\left(\sum_{h=1}^{\substack{T_{MaxDel,a}\\+T_{cycle}}} x_{v+1,a}^{h}\cdot h \quad - \sum_{h=1}^{\substack{T_{MaxDel,a}\\+T_{cycle}}} x_{v,a}^{h}\cdot h\right)\geq 1\,, \qquad \begin{array}{l} x_{v,a}^{h}\in\{0,1\} \\ h\in\left(1,2,\ldots,T_{MaxDel,a}+T_{cycle}\right)\end{array} \tag{2.4}$$

It should be noted that in Equation (2.4) the sum of the products between the decision variables $x_{v,a}^{h}$ and the time index h identifies the operation time of the power phase *v*. Constraint (2.4) can be visualised using Table 2.6. This constraint states that the operation time of the power phase represented by the binary operation vector $X_{v+1,a}$ must be situated on the right side of the previous power phase represented by $X_{v+1,a}$.

Table 2.6: Table explaining constraint (2.4).

Power phase \ Time index (*h*)	1	2	3	4	5	6	7	8	9	10
$X_{v,a}$	0	0	1	0	0	0	0	0	0	0
$X_{v+1,a}$	0	0	0	1	0	0	0	0	0	0

The smart appliance cycle can be interrupted between any two power phases. The interruption time must not exceed a *maximum interruption* time $T_{off\ v}$. Restrictions between the two power phases were modelled using Equation (2.5).

$$\left(\sum_{h=1}^{T_{MaxDel,a}+T_{cycle}} x_{v+1,a}^{h} \cdot h \; - \sum_{h=1}^{T_{MaxDel,a}+T_{cycle}} x_{v,a}^{h} \cdot h \right) \leq T_{off\ v} \;, \qquad x_{v,a}^{t} \in \{0,1\}\,, \quad h \in \left(1,2,\ldots,T_{MaxDel,a}+T_{cycle}\right) \tag{2.5}$$

As for the previous constraint, it should be noted that in Equation (2.5) the sum of the products between the decision variables $x_{v,a}^{h}$ and the time index h identifies the operation time of the power phase *v*. Constraint (2.5) can be visualised using Table 2.7. It shows the case for $T_{off\ v}$ = 4. In that case, the number of time steps between the operation of the power phase *v+1* and the previous power phase *v* cannot be larger than three.

Table 2.7: Table explaining constraint (2.5).

Time index (*h*) / Power phase	1	2	3	4	5	6	7	8	9	10
$X_{v,a}$	0	0	1	0	0	0	0	0	0	0
$X_{v+1,a}$	0	0	0	0	0	0	1	0	0	0

An equality constraint, Equation (2.6) modelled the operation of a smart appliance in relation to the user preference. As part of the *smart timing* feature of the appliance, the user introduces the time when the cycle should end (T_{cycle} +T_{MaxDel}). The constraint in Equation (2.6) requires the appliance $\underline{a}$, and consequently each of its power phases, to operate in the interval bounded by the *activation time* h=1 and *maximum delay*: *(1,* T_{cycle} +T_{MaxDel} *)*.

$$\sum_{h=1}^{T_{MaxDel}+\mathrm{T_{cycle}}} x_{v,a}^{h} = 1\,, \qquad x_{v,a}^{h} \in \{0,1\}, \qquad h \in \left(1,2,\ldots,T_{MaxDel,a} + T_{cycle}\right) \tag{2.6}$$

2.5.1.4 Software implementation

Finding the best schedule for the operation of smart appliances with respect to the electricity price is an optimisation problem. A widely used tool for solving optimisation problems is linear programming (LP). A LP problem where some or all the decision variables are integers and all the variables are non negative is called Integer Programming (IP) problem [81]. If only a part of the decision variables are integers the problem is called Mixed IP problem and if all the decision variables are non negative integers it is called Pure IP problem. In this study all the decision variables can take only two values: 0 and 1, both non negative integers, therefore the optimization problem can be formulated as a pure IP problem.

In order to test DR interventions on power systems, a large number of appliances need to be simulated. A test implementing the optimisation described in Section 2.5.1.2 has been carried out in three optimisation software programs to assess the execution time and the possibility to solve large IP problems. One of the software programs, Open Solver, extends the built-in Excel Solver. Open Solver uses Computational Infrastructure for Operations Research Branch and Cut (COIN-OR CBC) algorithm to solve IP problems. A second software program was Matlab which has an Optimisation Toolbox offering different algorithms to solve optimisation problems. Function *bintprog* can be used for 1-0 pure IP problems. The function uses a Branch and Bound algorithm. The third tested software, IBM ILOG CPLEX, utilises Branch and Cut. The results of the test are listed in Table 2.8.

CPLEX is chosen for the optimisation model implementation, as it gives the best performances from the three of them. CPLEX has application programming interfaces (APIs) for different languages: C, C++, and Java. Because it is widely used as a programming language in the power system sector, Java has been chosen to code the shifting algorithm including the optimisation model and further, run simulations.

Table 2.8: Solving times of the optimisation (Section 2.5.1) for different software programs.

Decision variables	MATLAB	OpenSolver Excel	CPLEX
288	2s	<0.1s	<0.1s
384	4s	<0.1s	<0.1s
576	1300s	1s	<0.1s
768	>10,000s (~3hrs)	3s	<0.1s
2,000	>10,000s	7s	<0.1s
30,000	-	1200s	3.5s
200,000	-	-	68s
400,000	-	-	240s

CPLEX uses the Branch and Cut method to solve the 1-0 pure IP problem. Branch and Cut method is a hybrid between Branch and Bound algorithm and Cutting Plane algorithm [82]. At the beginning of the Branch and Bound method an LP relaxation is performed, meaning that the problem is solved as a LP problem through Simplex algorithm, omitting the integer restriction for the decision variables. In the case of a 1-0 pure IP problem the decision variables will be constrained to: $0 \leq x_i \leq 1$. If the solution of the LP relaxation is constituted only of integers then certainly that is the solution of the IP problem. If the solution is constituted of fractional values the feasible region is split in two regions. This is performed by arbitrary choosing from one of the decision variables to be: either smaller than the smallest integer that is near the fractional LP relaxation solution of that variable or greater than the biggest integer that is near the LP solution of that variable. Thus, if a tree is created starting from the initial LP relaxation solutions two branches have been added. For the 1-0 pure IP problem, one branch is formed by arbitrary choosing one of the decision variables to be zero $x_i = 0$ and the other branch with $x_i = 1$. For each branch, which has a new constraint, the system is solved through Simplex algorithm. The branch that has the smallest solution is kept. If for this solution the resulting values for the decision variables are fractional, then a valid inequality constraint will be generated through Cutting Plane algorithm, constraint that will cut from the feasible region. The new LP problem is solved again, and if there still are decision variables with fractional values, the process is repeated until the candidate integer solutions are found.

2.5.2 Execution of the shifting algorithm

The operational diagram of the shifting algorithm is shown in Figure 2.6. The shifting algorithm runs at each quarter hour time step Δt until t_{final}. At each time step the algorithm schedules a number of A^t appliances that users have activated during the past quarter hour (t- Δt, t). A^t is a time instance of the *activation times* matrix A, described in Section 2.4.1. If no appliances are activated in the time interval (t- Δt, t), $A^t = 0$, then the algorithm moves to the next time step. If $A^t \neq 0$, the shifting algorithm goes through a series of three loops and runs the optimisation model for time step t. The outer loop cycles through each appliance $\underline{a}$ in A^t. The second loop goes through each power phase v of the appliance $\underline{a}$. In the last inner loop, each element of the binary operation vector of power phase v of appliance $\underline{a}$, which are the optimisation decision variables, are added to the optimisation model. The optimisation is performed after all the appliances of time step t are added, followed by a progress of the shifting algorithm to the next time step.

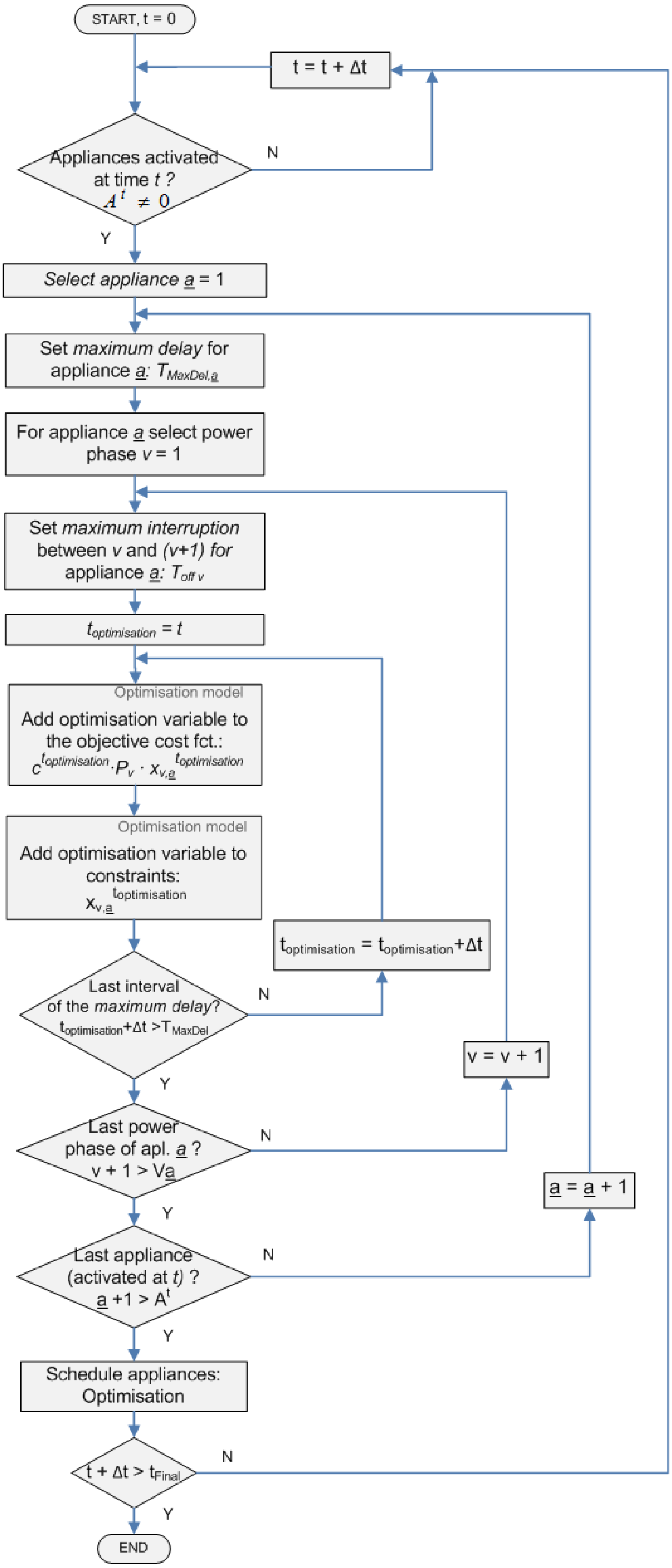


Figure 2.6: Operational diagram of the shifting algorithm.

2.6 Model validation

A two stage verification was performed. At the first stage, a validation of the adapted CREST model against real-world data was done. Furthermore a verification of the entire simulation, including the shifting algorithm, through sensitivity analysis was completed.

The *activation times* of WM, DW and TD are essential for setting the available demand response in the studies carried out during this work. In the absence of a large number of measurements for the three appliances operation, simulated values are generated by the adapted CREST model outlined in Section 2.4.1. The output of the CREST model, which is the aggregated household daily demand, has been validated in [83]. A validation of the adapted CREST model output, which is the individual appliance daily demand, was carried out. The real-world values for the *activation times* were obtained from the 3-E Houses project [72]. The power consumption of a washing machine was recorded with a resolution of one minute using a smart plug. The observed washing machine was in the premises of a social house in Bristol, UK. The power consumption data was processed to show only the *activation times* during the month of June 2012. The CREST model was calibrated to match the conditions when measurements were taken (the household had four residents, measurement period was one month). The simulated and the measured *activation times* recorded during one month are plotted as a cumulative sum over 24 hrs in Figure 2.7. The total *activation times* are 34 for the simulation and 29 for the measured data, while the small difference could be attributed to the fact that the CREST model does not account for the household's income. Another similarity is that no washing machines are activated during the early hours of the morning.

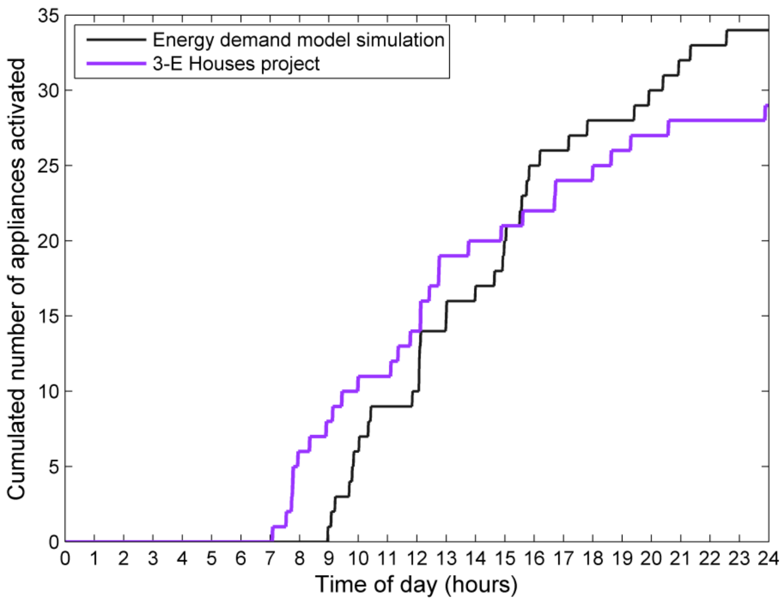


Figure 2.7: Cumulated daily activation times of a washing machine for a single household.

After it was established that the adapted CREST model gives an accurate representation of the appliances utilisation, a verification through sensitivity analysis was performed on the entire simulation, including the shifting algorithm. The objective was to determine whether the algorithm performs as intended. The expectation is that the shifting algorithm will reduce the cost of the electricity consumed in the household. One hundred instances of the simulation were carried out with the resulted savings on the electricity bill from smart appliances shown in Figure 2.8. The savings are a result of shifting the appliances from peak to off-peak time of a Time of Use (TOU) tariff. For each simulation, one of the inputs, the number of days, was randomly chosen from the interval 1 to 30. The rest of the inputs are kept constant; the number of houses is equal to 10, the number of residents in each house is 3 and the month is June. The simulation returns savings for each of the 100 instances. The values tend to converge as the number of days gets higher. This is indicated by the standard deviation shown in Figure 2.8.

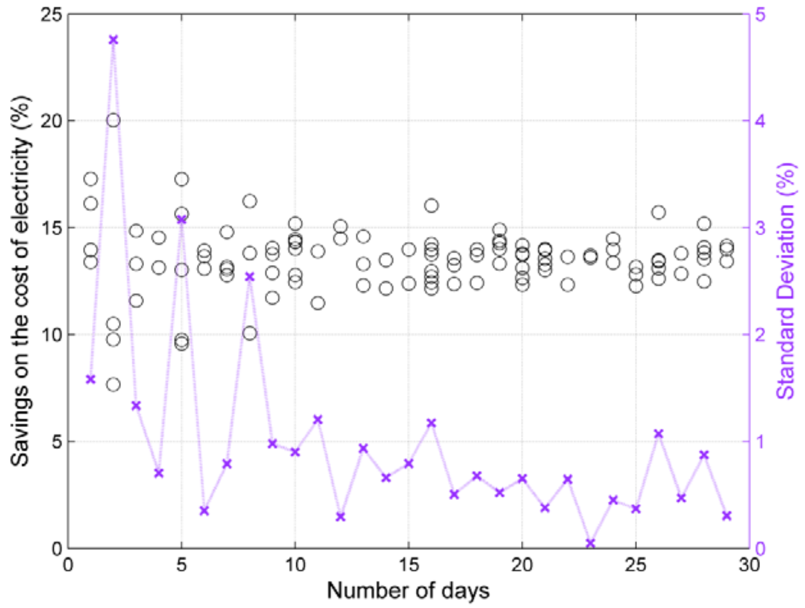


Figure 2.8: Savings on the electricity bill from SAs utilization, for 10 houses subscribing to a TOU tariff, each with 3 residents, considering different number of days.

Figure 2.9 shows the energy shifted by smart appliances in 100 instances of the simulation. At each instance the number of residents was randomly chosen from the interval 1 to 5, while the rest of the parameters were kept constant. As expected, the results vary between instances, while the average increases with the number of residents.

The observations from this section lead to the conclusion that the simulation is fit for the studies that were carried out in this work.

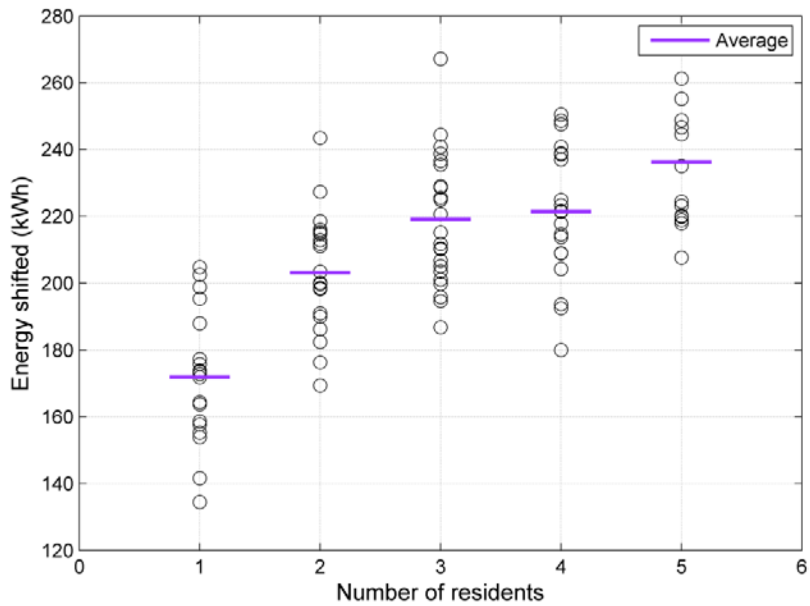


Figure 2.9: Energy shifted by SAs over a period of 10 days, for 10 houses subscribing to a TOU tariff, considering different number of residents.

2.7 Overview of the simulation environment

An overview of the simulation environment used in Ch. 3, Ch. 4 and Ch. 5 is shown in Figure 2.10. The programming language used for the simulation environment is Java. The simulation starts by specifying values for a number of parameters including the number of houses and residents in each house. These parameters are transferred from Java as input data to the adapted CREST model[2], which is written in the Perl programming language. As described in Section 2.4.1, the outputs of the model are the activation times of smart appliances (WM, DW, TD) and the households' load profiles, without smart appliances, over the specified length of time. The output of the adapted CREST model is stored in a comma-separated value (csv) file. At the end of this process, the csv is accessed by the Java simulation environment and passed to the shifting algorithm.

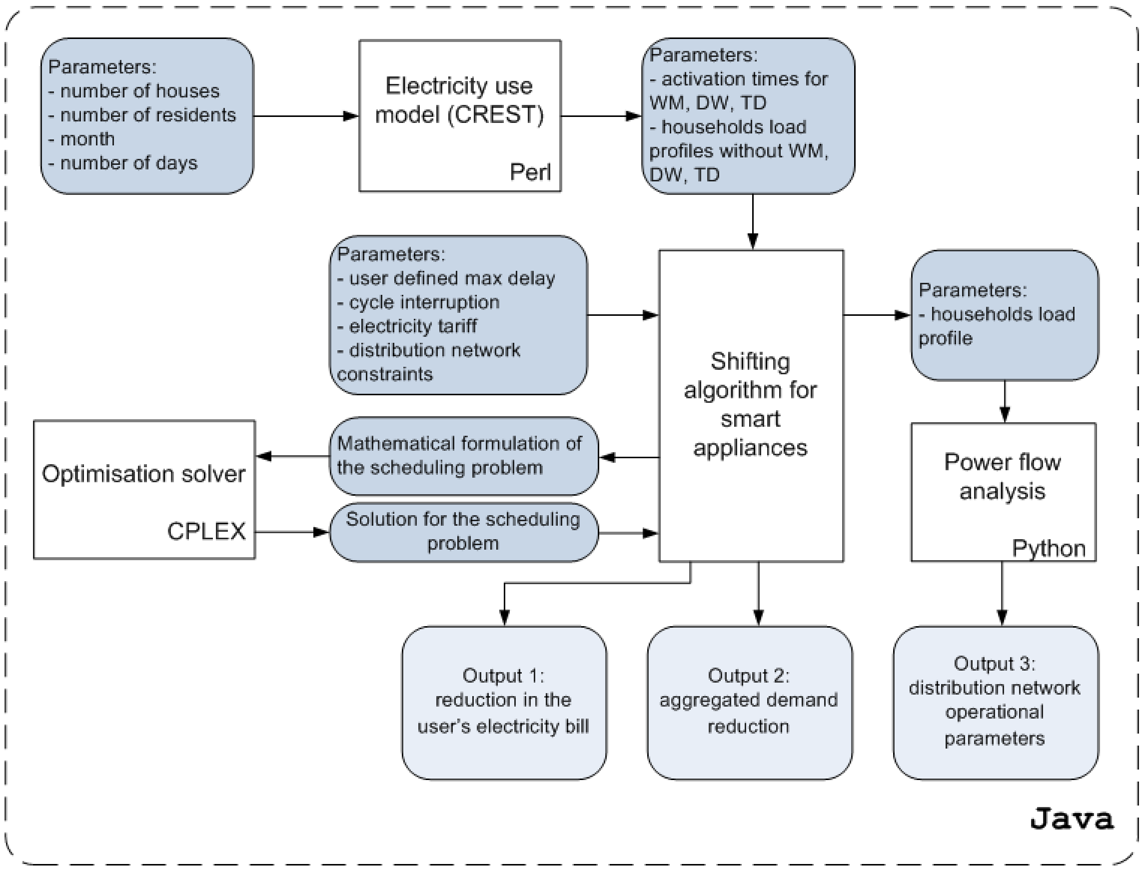


Figure 2.10: Process flowchart of the simulation environment

[2] The code developed by the author can be found at: https://github.com/hitron/adapted_crest

The shifting algorithm is listed in the Appendix A and is described in Section 2.5.2. It generates for each appliance a set of two parameters, user maximum delay and cycle interruption. The user maximum delay, described in Section 2.4.2, is calculated based on statistics from consumer research. The shifting algorithm also reads the electricity tariffs from a csv file. The tariffs, introduced in Section 3.2, have been constructed during this study. Information about the electricity distribution network, i.e. thermal rating of distribution circuits, is part of the input parameters for studies of the operation of distribution networks with smart appliances.

With the input parameters set, the shifting algorithm builds an optimisation model at each time step of the simulation. Building this model includes defining the types of decision variables, constraints, and objective function to be employed in the optimisation. It does this by calling directly CPLEX through an Application Programming Interface (API) for Java which allows the use of Java objects to define the optimisation model. Further, the mathematical formulation is sent and solved by CPLEX. The solution, a binary vector, indicates the optimal time for running the appliances. The binary vector is translated by the shifting algorithm into power demand of appliances and further to electricity cost of supplying the appliances and to load profiles for households. The electricity cost of appliances is an output required in Chapter 3 to calculate the reduction in the user's electricity bill due to the use of smart appliances. The power demand is an output required in Chapter 4 to calculate the aggregated demand reduction of smart appliances. In Chapter 5, the output of the shifting algorithm - load profiles of households - is stored in a csv file which is read by a code developed in the Python programming language. The code accesses IPSA Power software [84] through an API and carries out the power flow analysis. The output is the distribution test network's state variables, e.g voltages and power flows.

Chapter 3

Financial analysis for smart appliances users

Summary:

In this chapter, the reduction in the user's electricity bill achieved by smart appliances and different parameters that influence the reduction are studied. The smart appliance model and the shifting algorithm developed in Chapter 2 are implemented in a simulation used to evaluate the savings resulting due to use of smart appliances with multiple-rates electricity tariffs. The savings are compared against the possible additional costs incurred by users to enable the smart operation of appliances.

3.1 Introduction

Enabling demand response from appliances – washing machine WM, dishwasher DW, tumble dryer TD – relies on the users to buy the Smart-Grid ready appliances and to use their smart capabilities. An outcome of the user survey completed in the Smart-A project [68] was that the users' main incentive for buying smart appliances was the potential financial benefit, while any ecological benefit was viewed as a positive side effect. A straightforward method through which users can gain financial benefits from smart appliances is by using them simultaneously with an electricity tariff that has variable rates throughout the day. With the roll-out of smart meters across the UK by 2020, Time of Use (TOU) and Real Time Pricing (RTP) tariffs will be available to residential customers [10].

3.2 Electricity tariffs

Reference [85] reports an estimate of 3-3.5 million residential customers in the UK with some type of multiple-rates electricity tariff. A survey reported in [86] on 4761 residential GB customers revealed that 620 (13%) were subscribing to multiple-rates electricity tariffs. The most common choices of TOU tariffs were Economy 7 and Economy 10 as can be seen in Figure 3.1. Therefore, these two tariff choices were evaluated in this study.

Economy 7 and Economy 10 were designed for customers with electric storage heaters to incentivise the use of overnight electricity from base load generators and to defer consumption from peak demand times. Economy 7 has seven hours of overnight low electricity rate whereas Economy 10 has ten hours of low electricity rate in the afternoon, evening and night.

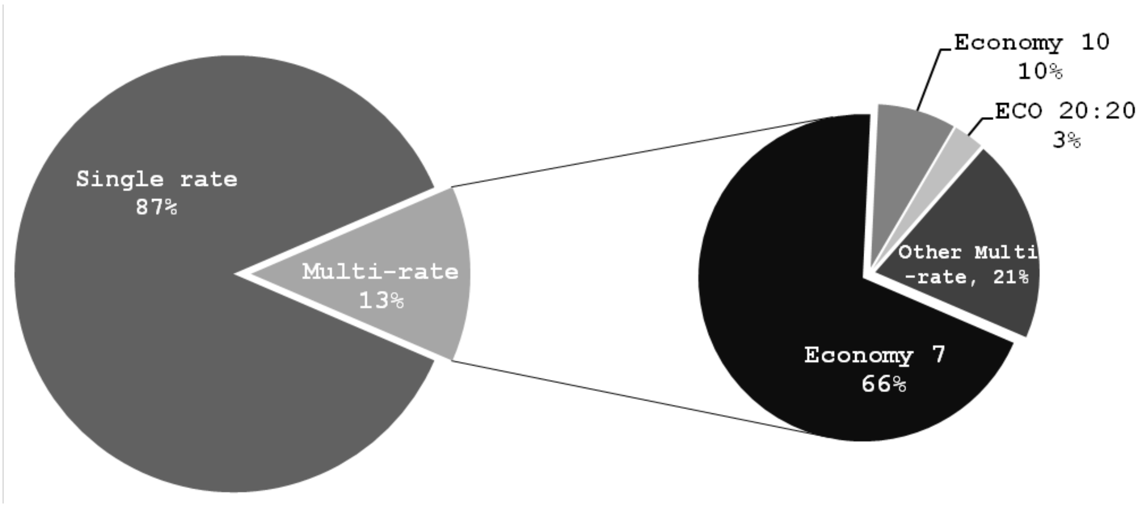


Figure 3.1: Distribution of the residential customers according to the type of electricity tariff [86]**.**

A survey on the standard (single rate) and TOU tariffs from six electricity suppliers in the UK is completed during this study; the electricity rates are listed in Table 3.1. The average electricity rates, illustrated in Figure 3.2, were used in this study.

Table 3.1: Survey on existing GB electricity tariffs in 2012.

Tariff / **Supplier**	**Standard**		**Economy 7**			**Economy 10**		
	Standing charge (GBP pence/day)	*Standard rate (GBP pence/kWh)*	*Standing charge (GBP pence/day)*	*On peak (GBP pence/kWh)*	*Off-peak (GBP pence/kWh)*	*Standing charge (GBP pence/kWh)*	*On-peak (GBP pence/kWh)*	*Off-peak (GBP pence/kWh)*
SWALEC	15	12.8	16.44	16.68	7.7	24.53	17.79	9
Scottish Power	27.39	13.68	27.3	15.73	6.48	26.7	16.46	8.47
EDF	18.9	14.81	18.9	17.94	6.3	18.9	18.36	6.37
E-ON	26	12.8	26	15.78	6.62	-	-	-
British Gas	16.32	13.68	15.34	17.91	6.33	-	-	-
NPOWER	11.5	17.24	8.4	18.85	5.7	-	-	-
Average rate[3]		15.75		18.38	6.85		18.73	8.7

[3] Includes the standing charges for an average consumption of 3300 kWh/year or 9 kWh/day

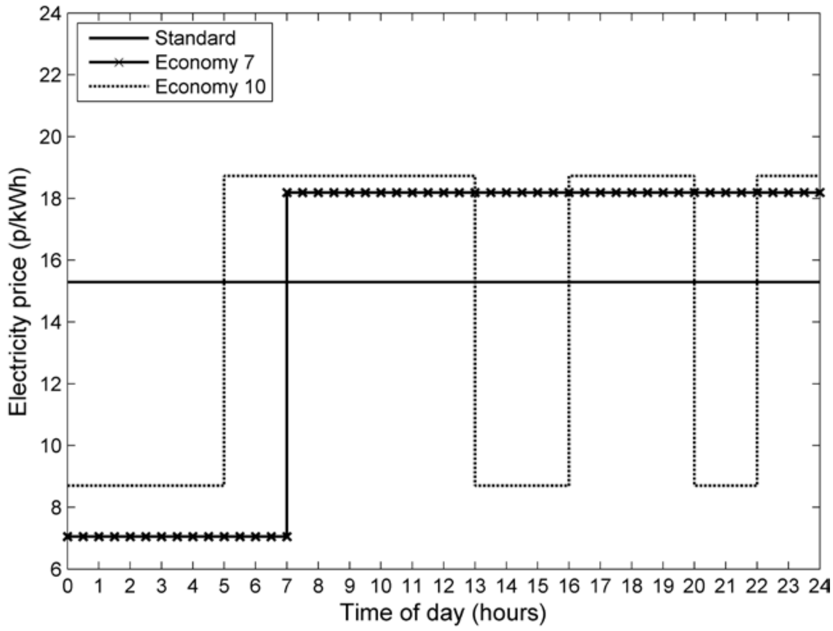


Figure 3.2: Standard, Economy 7 and 10 electricity tariffs.

Another tariff that was considered in this study is Real-Time Pricing (RTP). The electricity rate for a customer with RTP tariff varies hour by hour or with each half hour. The customer receives the tariff on a day ahead or hour ahead basis. Some utilities in the United States (US) have already made available hourly RTP for residential customers, an example is Ameren Illinois utility [32]. A snapshot of the Ameren RTP over a day in April 2012 is shown in Figure 3.3. The price component which varies over the day is the generation costs.

RTP tariffs are not currently available for residential customers in GB. However, the smart meters that will be installed across the UK will have registers capable of storing half-hourly varying electricity rates and half-hourly consumption data [10]. An RTP tariff with half-hourly rates was designed for this study starting from the components of the retail electricity price in GB; details are given in Appendix B. An example from the designed RTP tariff for a weekday is shown in Figure 3.4. As in the case of the US utility, the generation costs vary over 24 hrs, however in the case of the British distribution network operators the distribution charges also vary. The two rate tariff reflects the pattern of loading on the network.

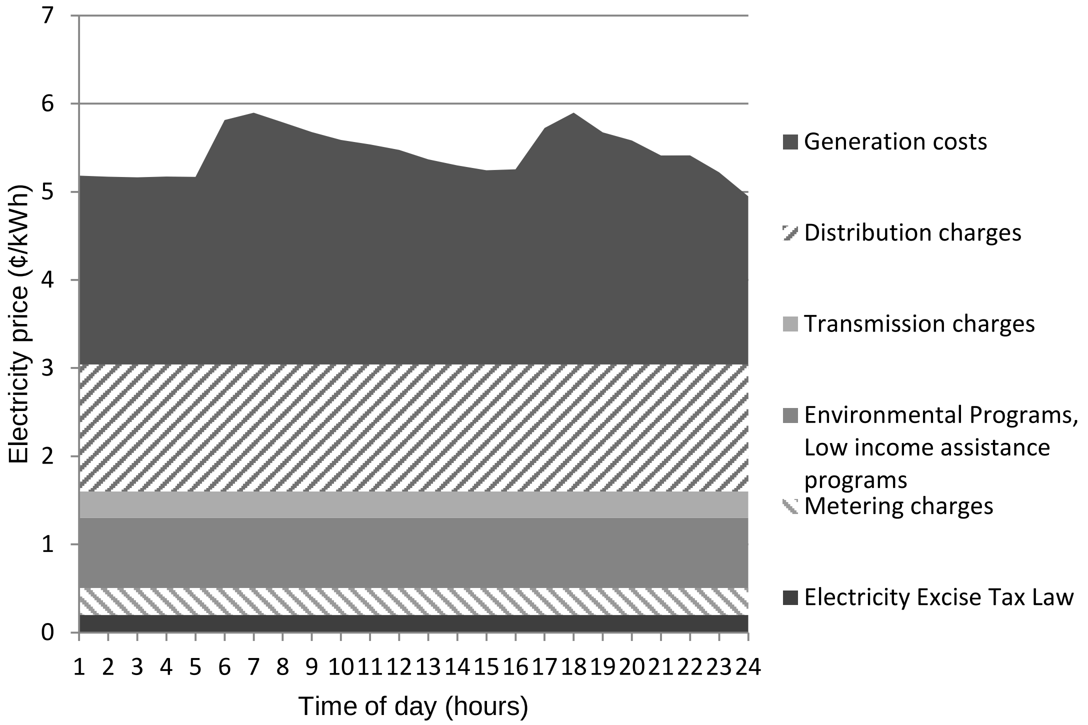


Figure 3.3: Structure of the Ameren Illinois RTP tariff.

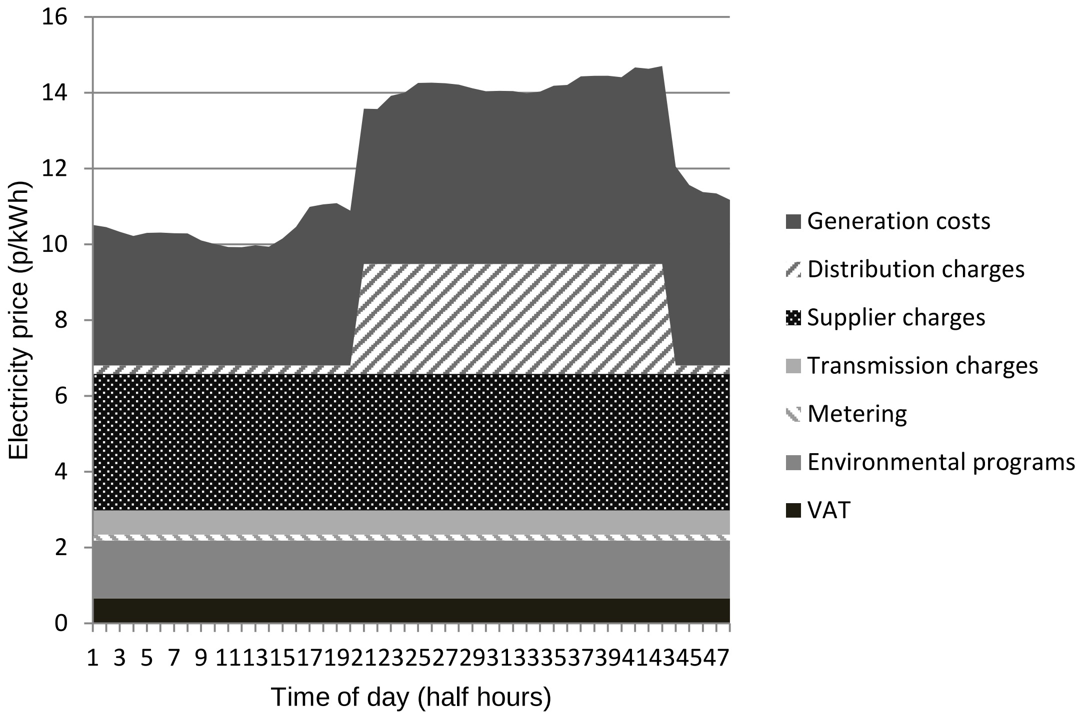


Figure 3.4: Structure of a RTP tariff specific for GB electricity sector.

3.3 Effects of parameters on household savings

A simulation, illustrated in Figure 3.5, was constructed to study the effects of three parameters on the cost savings for a household resulting from operating the appliances. The parameters that were varied are: *number of residents*, user defined *maximum delay* and appliance *maximum interruption time*.

The *number of residents* of the household is an input to the CREST model, described in Section 2.4.1, which outputs the activation times of the appliances (WM, DW, TD). The shifting algorithm described in Section 2.5.2 delays the start time of the appliances and introduces cycle interruptions according to the user defined *maximum delay* and *maximum interruption time* parameters. With the new starting times, the load profile model, introduced in Section 2.2, produces the demand of the appliances. The cost of electricity consumed by the appliances is the product of appliances demand and multiple-rates tariff. The cost savings result from shifting the appliances from time intervals with high electricity price to intervals with low price. The simulation period was thirty days. For each change in the value of one of the three parameters a set of one hundred simulations was carried out to give a clear picture of how the parameters influence the cost savings.

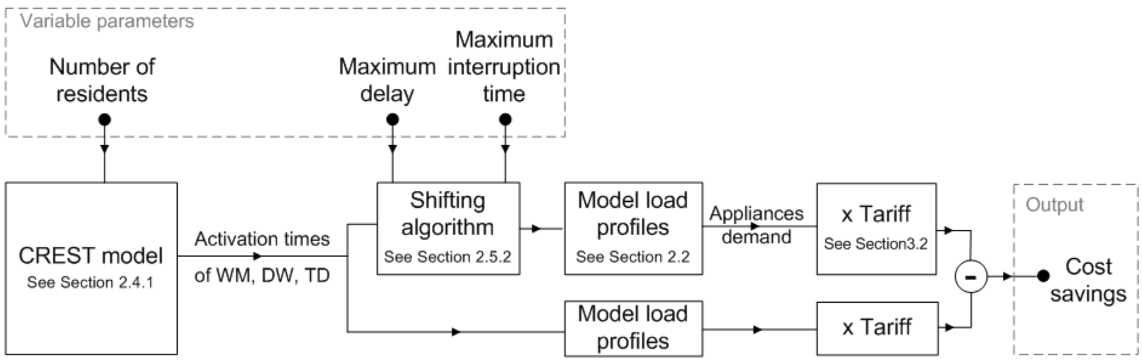


Figure 3.5: Data flowchart of the simulation used to evaluate the cost savings of a single household from smart appliances.

3.3.1 Number of residents

The household's *number of residents* was varied from one to five. The *number of residents* influences the reduction that can be achieved within one household. The results are plotted in Figure 3.6. The highest cost savings are achieved by households with five residents, while the lowest by households with one resident. This is due to the fact that with a higher number of residents more cycles of appliances are activated resulting in additional cost savings. However, since these appliances are shared, the number of cycles doesn't increase at the same rate as the number of residents. The average numbers of appliances cycles for households with different number of residents are given in Table 3.2.

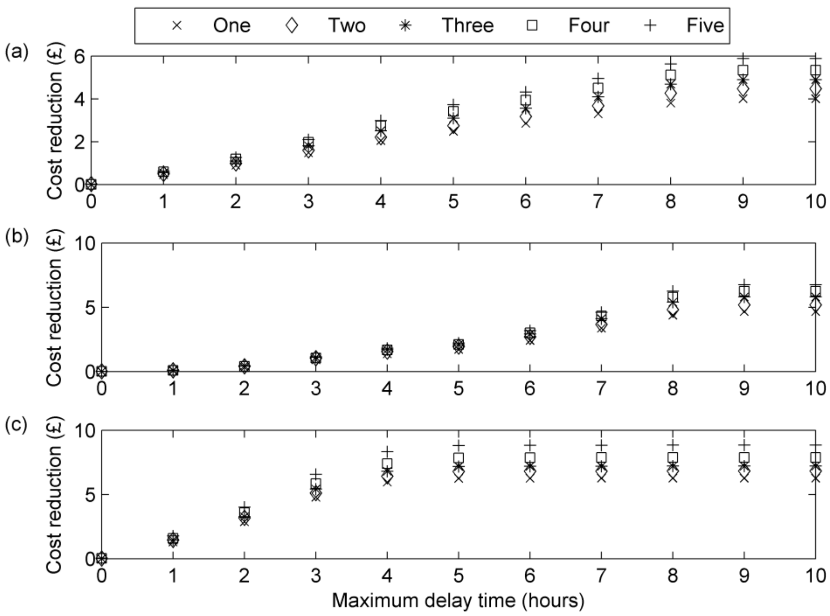


Figure 3.6: Effects of number of residents: (a) RTP; (b) Economy 7; (c) Economy 10.

Table 3.2: Average number of appliance activations during one month for one household.

Household number of residents	Number of WMs activated	Number of DWs activated	Number of TDs activated
1	22.09	2.39	9.79
2	25.24	2.85	12.61
3	27.13	3.28	13.14
4	29.33	3.57	12.58
5	30.24	3.80	14.97

3.3.2 Maximum delay

The *maximum delay* parameter, described in Section 2.4.2, was varied from zero to ten hours. The cost savings on the electricity consumed by appliances as a function of *maximum delay* parameter, for different tariffs, are given in Figure 3.7. If the user decides that the cycles should be started immediately, or *maximum delay* is zero, the cost savings obtained by smart appliances is zero. This applies to any tariff, as can be seen in Figure 3.7.

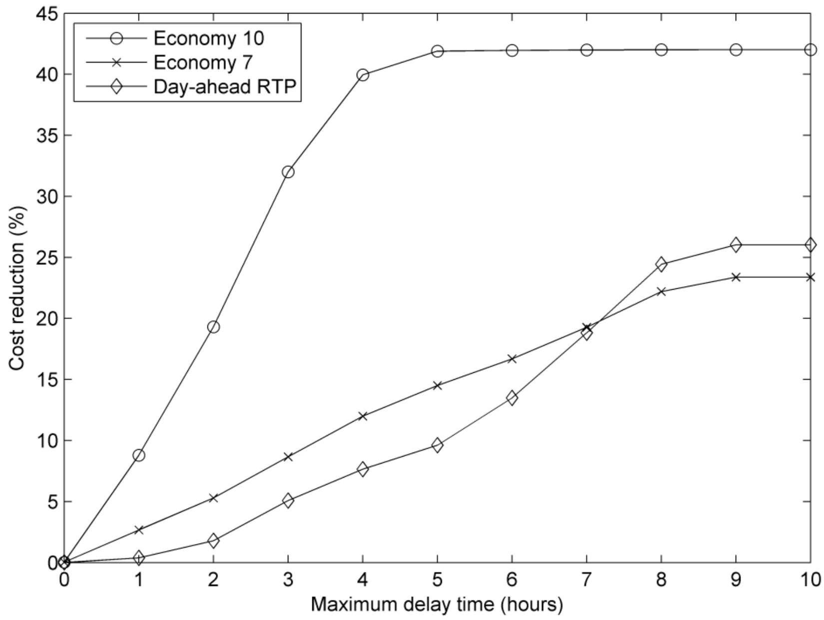


Figure 3.7: Cost savings on the electricity consumed by the appliances (WM,DW,TD) in a household with 3 residents with different values for the maximum delay parameter.

The cost savings obtained with the three tariffs follow a common profile: an increase with the *maximum delay* up to a saturation point followed by a period of constant savings. At the saturation point, the appliances are already in the lowest price interval; therefore an increase in the *maximum delay* will not produce any changes in savings. The values of the cost savings and the saturation point are tariff dependent. For Economy 10 the cost savings reach 42% for *maximum delay* equal to five hours and remain constant from that point. Thus, the users of smart appliances should provide a delay of five hours in order to ensure they maximize the benefits of Economy 10 tariff.

For the other tariffs, the increase in cost savings with the *maximum delay* parameter is at a slower pace and the saturation points are at nine hours.

3.3.3 Cycle interruption

The *maximum interruption* parameter, introduced in Section 2.3.2, was varied from zero to sixty minutes. The results of the simulations are shown in Figure 3.8 and represent the additional cost savings resulting from cycle interruptions.

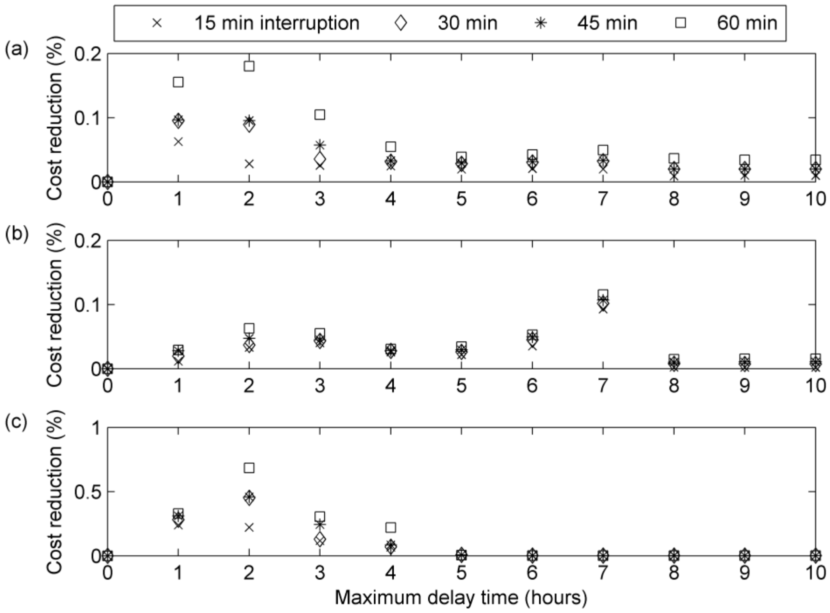


Figure 3.8: Additional cost savings on the electricity consumed by the appliances (WM,DW,TD) in a household with 3 residents on account of the *maximum interruption* parameter: (a) RTP; (b)Economy 7; (c) Economy 10.

The *maximum interruption* parameter has a minor contribution (up to 0.68%) for the cost savings compared with the previous parameters. For Economy 10 tariff, as can be seen in Figure 3.8 (c), a user defined *maximum delay* greater than two hours allows the entire appliance cycle to be shifted away from the interval with peak price, thus mitigating the possible benefits of interruptions.

A tariff that includes more peaks with a high ratio between peak and off-peak rates must be utilised in order for the cycle interruption to have a significant contribution in cost savings. This may well be the case in the future, because, as more wind generation capacity is installed the variation of the electricity spot prices will increase [87]. Potential high price peaks could also arise if tariffs will integrate signals to avoid distribution and transmission networks issues [88].

3.4 Annual savings for a group of one thousand GB households

In this section the financial benefits resulting from adopting smart appliances were investigated for a group of one thousand houses. The simulation from Figure 3.5 has been extended from one household to one thousand households and the simulation period from one month to one year. Furthermore, the three parameters of the simulation presented in Section 3.3 were selected with the objectives of having a representative sample of the GB housing stock and of modelling the behaviour of smart appliances users.

The first parameter is the *number of residents* in each household. The *number of residents* was chosen according to the distribution of the 25.6 million households of the GB housing stock by the number of people living in them as given in Table 3.3 [89]. A number generator was used to assign the number of occupants in each household according to the percentages given in Table 3.3.

Table 3.3: Household distribution by number of people living in them in GB [89]**.**

No. of residents	1	2	3	4	5+
Percentage from total no. of households	29	35	16.5	13	6.5

A second parameter is the user defined *maximum delay*. For each appliance the value of the *maximum delay* parameter was selected according to Table 2.3 in Section 2.4.2. For the third parameter, the appliance *maximum interruption*, two values (zero and 60 minutes) were assessed.

3.4.1 Electricity cost savings

The annual electricity bills with regular appliances and with smart appliances are illustrated in Figure 3.9 for the four electricity tariffs described in Section 3.2. The number of cycles of appliances that were completed during the one year simulation period was approximately 740,000. The difference between the bills with regular appliances for the four tariffs is caused by the aggregated load profile of the 1000 households. The higher bill for Economy 7 compared with the Standard and Economy 10 tariffs indicates that the majority of the customers have a low proportion of their electricity consumption during the off-peak hours of the Economy 7. The RTP tariff has a good correlation with the aggregated load profile, yielding a higher electricity bill compared to Standard and Economy 10 tariffs. It is worth noting that no change in behaviour due to multiple-rates tariffs has been modelled, which is the reason why the Economy 7 and RTP yield higher rates than the single rate tariff.

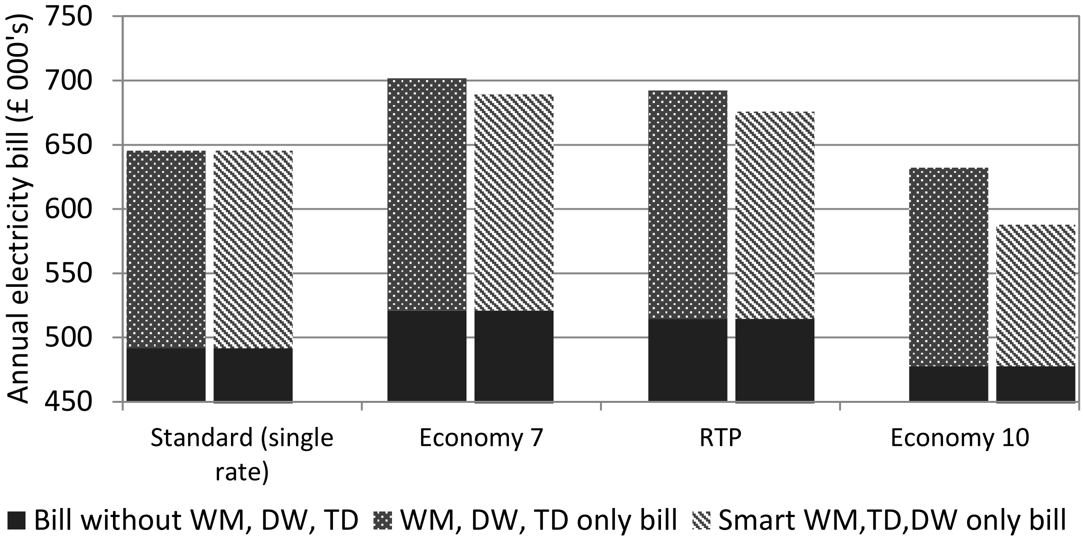


Figure 3.9: Annual electricity bills for 1000 households with regular appliances and with smart appliances (WM, DW, TD).

Table 3.4 gives the annual electricity bills for the 1000 households and the cost savings resulted from using smart appliances with the four electricity tariffs. Under the

Economy 10 pricing scheme the smart appliances can reduce their annual running cost by 28.62% which is equivalent to 6.99% of the electricity bill.

Table 3.4: Annual electricity bill and cost savings for 1000 households resulted from smart appliances (WM, DW, TD).

Tariff	Bill including regular WM,DW, TD (£000's)	Bill including smart WM,DW, TD (£000's)	Cost savings on the bill (%)	Regular WM,TD,DW running cost (£000's)	Smart WM,TD,DW running cost (£000's)	Savings on the WM,TD,DW running cost (%)
Standard (single rate)	645.36	645.36	0	153.82	153.82	0
Economy 7	701.65	689.26	1.76	180.63	168.28	6.83
RTP	692.23	675.76	2.38	177.85	161.4	9.24
Economy 10	632.09	587.86	6.99	154.46	110.25	28.62

The results from Table 3.4 are for the appliances parameter *maximum interruption* set to zero. A repeat of the simulation with the *maximum interruption* set to sixty minutes allowed between the appliances' power phases resulted in almost identical savings as the case where no interruption was permitted. For example running the appliances with no interruption resulted in a 6.99% savings of the electricity bill and allowing them to be interrupted resulted in a saving of 7.01%. The reason for this was discussed in Section 3.3.3.

3.4.2 Costs of adopting smart appliances

In the project Smart-A [90] the cost of implementing the smart operation for a domestic appliance was segmented in three categories. The categories that were identified are: additional appliance cost, additional in-house communication cost and appliance stand-by consumption cost. The values for the three categories were revised for this thesis. As identified in the state of the art, in Chapter 1, there are multiple solutions of implementing the smart operation of an appliance. Three possible solutions were covered in this study, with the cost estimations listed in Table 3.5.

In the first solution, the appliances are connected to the Communication Hub that is part of the future Smart Metering infrastructure. According to the document on ‘Smart Metering Equipment Technical Specification 2’ [10], it is required that a Communication Hub must be able to connect with at least three Consumer Access Devices such as an enhanced energy display, a smart appliance or a home automation controller. The document also specifies that the preferred communication technology is ZigBee Smart Energy Profile (SEP). Therefore, for this solution, the additional appliance cost includes the ZigBee chipset cost and the engineering costs of planning and implementation, which are estimated in reference [91] at £9.5. The additional in-house communication cost is considered to be zero as the cost of the Communication Hub is already included in the smart meters roll-out.

For the second solution each appliance is fitted with an IP/WLAN module and connects directly to the broadband router. According to the Office for National Statistics [64], as at 2013 83% of households have an internet connection. This ensures that the second solution can be applied to a large majority of the consumers. The additional appliance cost consists of the IP/WLAN chipset cost. Also, according to [92], the appliance microprocessor required to control the IP/WLAN chipset demands a higher performance than one for ZigBee, adding £6.50 to the cost of the appliance. The additional in-house communication cost is considered zero because the broadband router is already installed for different Internet services.

For the third solution, the appliances connect to a Home Energy Management System (HEMS). The advantage of a HEMS is that it can collect data from sensors inside the house and offer additional services to the residents such as automatic disconnection of appliances in stand-by when no movement is detected. The additional appliance cost is that of a ZigBee chipset. The additional in-house communication cost includes the cost of the HEMS. The price of an HEMS in 2013 was approximately £100 [93].

The appliance consumption in *start delay* mode, described in Section 2.3.1, was measured in [94]. An average of 3 W was considered. The appliance is in start delay mode only between the moment when the ON button is pushed and the moment the appliance cycle starts. This time interval represents the *maximum delay* parameter and the average value according to Table 2.5 in Section 2.4.2 is 3.61 hours. Assuming the appliance runs each day, the maximum time the appliance is in start delay is 365 x 3.61 hours each year at a cost of approximately £0.60 per annum (p.a).

Table 3.5: Additional cost of implementing the smart operation of appliances (WM, DW, TD) in a household.

Cost category	Smart Metering solution	IP based solution	HEMS solution
Additional appliance cost	3 x £9.50	3 x £16	3 x £9.50
Additional in-home communication	£0	£0	£100
Appliance consumption cost in start delay (p.a.)	3 x £0.60	3 x £0.60	3 x £0.60

The payback period was used to evaluate the value of smart appliances for a household. The payback period is defined as the time required for an investment's cumulative cash flow to reach zero [95]. The cash flow corresponds to the annual savings on the electricity cost from Table 3.4. The initial and annual household costs are given in Table 3.5.

The cumulative cash flows for the three solutions of implementing the smart operation of an appliance are illustrated in Figure 3.10. The payback period for each of the considered tariffs is indicated by a marker at the intersection of the cumulative cash flow with the X-axis. An outcome of the user research completed in the Smart-A project [68] revealed that if the user is to bear the initial cost of enabling the smart operation of an appliance, then the maximum acceptable payback period is three years. The maximum payback period is satisfied for the majority of the scenarios. The only scenarios which will not match the user requirement are for the HEMS solution, when the household is subscribing to RTP or Economy 7 tariffs.

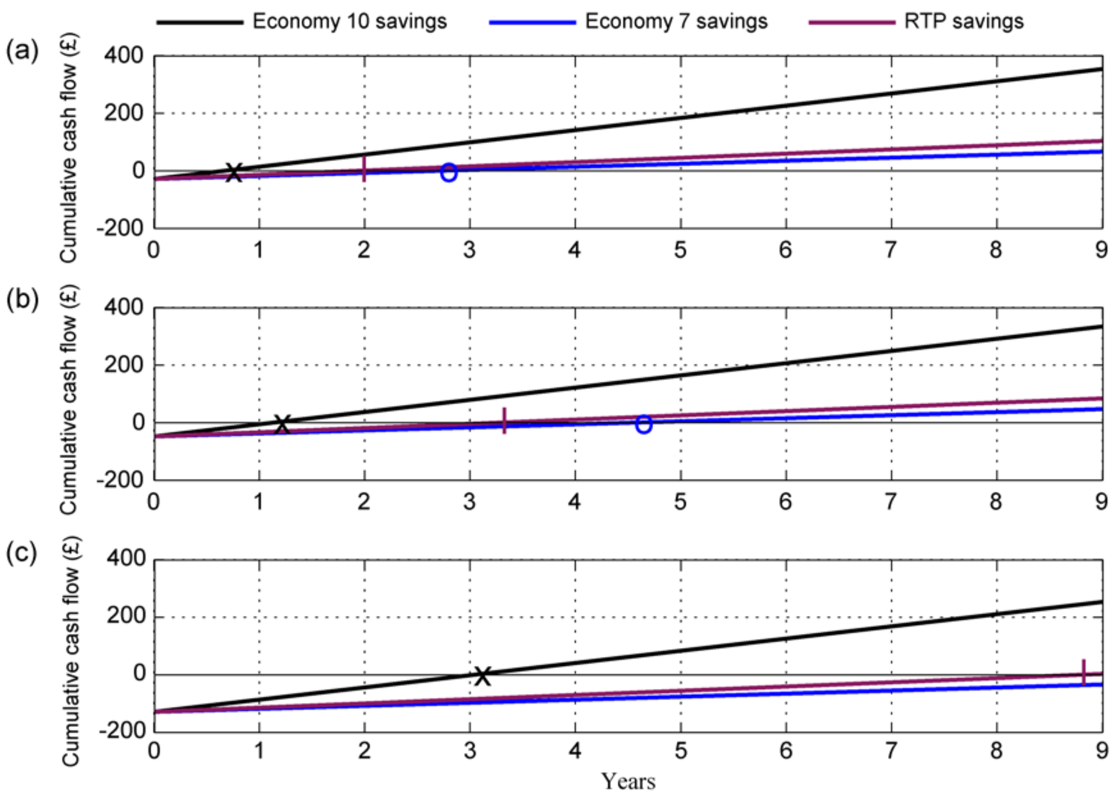


Figure 3.10: Household cash flow and payback periods considering different implementation solutions for smart appliances: (a) Smart Metering solution; (b) IP based solution; (c) HEMS solution.

The Net Present Value (NPV) was also used to evaluate the value of smart appliances for a household. NPV is defined as the investment's discounted cumulative cash flow over its life span [95]. For this study, the life span of the appliances is approximated to 9 years, according to the user research completed during the E-Scope [96] project.

A literature review on consumer discount rate for appliances, reported in [97], indicates that, depending on the households' incomes, a discount rate between 7 percent to 35 percent per year is possible. A discount rate of 20 percent has been considered in the NPV calculation. The formula used to calculate the NPV is given in Equation (3.1). An example of a NPV calculation is given in Table 3.6.

$$\mathrm{NPV} = \sum_{\mathrm{t}=1}^{\mathrm{T}} \mathrm{CF} \times \frac{1}{(1+\mathrm{r})^{\mathrm{t}}} - I \tag{3.1}$$

where,

CF annual cash flow (annual savings on the electricity cost from smart appliances)

r discount rate

T life span

t year number

I initial cost (additional smart appliance cost and in-home communication)

Table 3.6: Example of NPV calculation of investing in smart appliances for a household subscribing to the Economy 10 tariff in the Smart Metering solution.

Year	Initial Cost (£)	Savings (£)	Present Value Factor	Present value cash flow (£)
0	-30.30	-	1	-30.30
1		44.21	0.83	36.84
2		44.21	0.69	30.70
3		44.21	0.57	25.58
4		44.21	0.48	21.32
5		44.21	0.40	17.76
6		44.21	0.31	14.80
7		44.21	0.26	12.33
8		44.21	0.21	10.28
9		44.21	0.19	8.56
NPV				147.90

The NPV of investing in smart appliances for the three solutions described above are given in Table 3.7. A positive value of the NPV signifies that the investment in smart appliances is financially worthwhile for a household.

Table 3.7: NPV of investing in smart appliances for a household considering different implementation solutions.

Tariff Type	Smart Metering solution	IP based solution	HEMS solution
Economy 10	£ 147.90	£ 128.40	£ 47.90
RTP	£ 36.00	£ 16.50	£ -63.99
Economy 7	£ 19.48	£ 0.00	£ -80.51

3.5 Discussion

A sensitivity analysis has examined the influence that the following parameters have on the cost savings of a household: *number of residents*, user defined *maximum delay* and appliance *maximum interruption time.* Out of the three parameters, the user defined *maximum delay* has the highest influence on the financial outcome, while the *maximum interruption time* has the lowest influence.

The annual savings resulted from the smart operation of the three appliances (washing machine, dishwasher and tumble dryer) were calculated. The Net Present Value and Payback Period financial analyses were used to assess if the investment in smart appliances is beneficial for their users. There is a clear correlation between the results of both analyses, highlighting that the cost of the in-home communication technology that will facilitate the smart operation, along with the electricity tariff type, determine if smart appliances are a good investment for their users. It was found that installing HEMS for the single purpose of enabling the appliances to communicate is not financially worthwhile for two out of three electricity tariffs types (Economy 7 and RTP). Using the Economy 10 tariff and the smart metering infrastructure for in-house communication yields the highest return on investment.

The study in this chapter focused on the savings made by the user of smart appliances, savings resulted from shifting their operation from time intervals with peak electricity rates to intervals with off-peak electricity rates. A potential second revenue, resulted from the smart appliances capability to respond at short notice to power system balancing signals, is the focus of Chapter 4.

Chapter 4

Reserve services from smart appliances

Summary:

This chapter addresses the feasibility of using smart appliances as operating reserve in the power systems balancing services. The current operating reserve requirement for the GB power system and the contribution of demand-side are first discussed. A framework outlining the actors and the communication infrastructure that enables appliances to respond to short-term operating reserve instructions from transmission system operators is proposed. A multiple-time-step simulation in Java is introduced, that can assess the response from smart appliances at each moment of the day. The simulation assessed the load reduction from a number of households as a response to a reserve instruction which was modelled as a price increase with a short notification period. The results were used to estimate the available demand response from GB households. Finally, the financial and environmental achievements of the proposed scheme are estimated.

4.1 Introduction

Reserve services, as part of the transmission system operator's instruments to balance the power system, are needed to supply the difference between the actual load or generation and the forecasted ones. In near-term, the Great Britain (GB) power system is experiencing a shortage of capacity margins [5], which prompted the National Grid Electricity Transmission (NGET) to investigate the introduction of a new reserve service designed exclusively for demand side [98]. The studies reported in [9] and [99] confirm that operating the GB power system with large amounts of wind generation requires an increased level of reserve. Therefore, there is now a greater emphasis of obtaining reserve services from demand side response.

4.1.1 Operating reserve requirement in the GB power system

In the NGET's Grid Code [100], the role of the operating reserve is defined as: "to contribute to containing and correcting any system frequency fall to an acceptable level in the event of a loss of generation or a loss of import from an External Interconnection or mismatch between generation and demand". Thus, the operating reserve need to cover for three risks: the risk of generator outages, the risk of generator shortfalls, and uncertainties in load and wind forecasts.

The operating reserve level required for the generator outages is set by the largest power infeed loss. The risk of generator shortfalls is the risk of the generators not being able to output the contracted power. According to [9], the difference between the output and contracted powers can be modelled as Gaussian stochastic variables with a mean μ_s and standard deviation σ_s. The load and wind forecast errors can also be modelled as Gaussian stochastic variables, with means of zero and standard deviations σ_d and σ_w. As the two errors are independent of each other, the forecast error of the residual demand (the demand minus wind generation) has also a mean of zero and standard deviation given by Equation (4.1) [101].

$$\sigma_{r,h}^{t} = \sqrt{\left(\sigma_{d,h}^{t}\right)^{2} + \left(\sigma_{w,h}^{t}\right)^{2}} \tag{4.1}$$

where $\sigma_{r,h}^{t}$ represents the standard deviation of the residual demand forecast for a horizon *h* ahead of time *t*.

The equation used to calculate the operating reserve level required to cover two of the three risks (the risk of outages and forecast error in residual demand) is given in reference [102]. Equation (4.2), used in this study, includes the third risk (the risk of generator shortfalls).

$$r_{h}^{t} = \max\ \{u_{i}^{t} p_{i}^{max}\} + \mu_{s,h}^{t} + Z \cdot (\sigma_{s,h}^{t} + \sigma_{r,h}^{t}) \tag{4.2}$$

Where:

r_{h}^{t}	level of operating reserve for a horizon *h* ahead of time *t*
$\max\{u_{i}^{t} p_{i}^{max}\}$	the capacity of the largest unit committed at time *t* (usually this is set to 1320 MW for the GB power system to cover the risk of an outage at Sizewell B power plant)
$\mu_{s,h}^{t}$	the mean of generator shortfalls for a horizon *h* ahead of time *t*
Z	the number of standard deviations required to cover for the residual demand forecast error and the risk of generators shortfalls
$\sigma_{r,h}^{t}$, $\sigma_{r,h}^{t}$	standard deviations of demand forecast error and the risk of generators shortfalls

Because it is not cost efficient to procure a reserve capacity equal to the maximum possible error, the TSOs adopt a reliability criteria to select the optimal reserve capacity. TSOs use the criterion called Loss of load expectation (LOLE), which is the expected number of days in a year in which demand may exceed available generation (including the operating reserve). For NGET, LOLE is maintained at 1 in 365 days, which can be interpreted as the level of operating reserve must be greater than 99.73% of the forecast errors. Considering this probability, a value for Z = 2.78 was found using Table D-3 in Appendix C. A graphical representation of Z is shown in Figure 4.1.

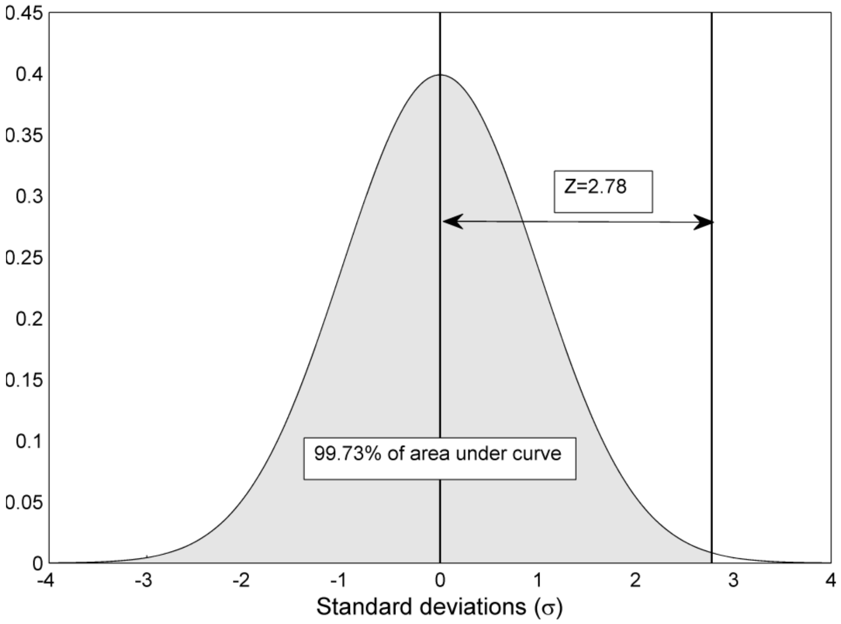


Figure 4.1: Normal distribution of errors (forecast of residual demand and generator output) and the operating reserve, Z x σ, required to secure the NGET reliability criteria [103]**.**

A calculation of the operating reserve requirement, four hours ahead of real time, using Equation (4.2), with NGET's estimates for uncertainties at winter peak demand [9] was performed in Matlab®. The results are shown in Table 4.1. The resulting level of operating reserve 5532MW is in line with the results given in [9], of 5054 to 6163 MW.

Table 4.1: Operating reserve requirement of the GB power system at winter peak.

Uncertainty (Terms in Eq. (4.2))		**Mean (MW)**	**Standard deviation (MW)**	**Operating reserve (MW)**
Generators outages ($\max\{u_i^t p_i^{max}\}$)		-	-	1320
Generators shortfalls ($\mu_{s,h}^t + Z \cdot \sigma_{s,h}^t$)		600	600	2268
Residual demand forecast error ($Z \cdot \sigma_{r,h}^t$)	Demand	0	450	1944
	Wind*	0	535	
			Total	5532

*Note: installed wind capacity of 10.5 GW, load factor 30% and forecast root mean square error (RMSE) of 17% at four hours ahead

4.1.2 Current contribution of DR to the GB operating reserve services

NGET uses Balancing Mechanism (BM) (a spot electricity market) and contracted reserve services to procure the operating reserve. The most important participation of demand side response is in the contracted reserve services: *Fast Reserve* and *Short Term Operating Reserve (STOR)*. The reserve contracted through the *Fast Reserve* service helps control the system frequency in case of sudden demand increase due to unexpected weather change or TV pick-ups. *Fast Reserve* will also be utilised to reinstate the frequency response reserves if a generation loss occurs. The provider's maximum response time[4] is 5 minutes and the delivery should last for 15 minutes. Hydro pump storage are among the main providers. The annual payment for *Fast Reserve* in 2011/2012 was £92 millions.

Demand response (DR) is another technology that has been providing *Fast Reserve* using the radio teleswitch electricity meters which can disconnect consumers' storage heaters when a radio instruction is issued. However, the DR from storage heaters is only available during the night in the off-peak hours of the Economy 7 tariff [104].

Reserve provided through *STOR* covers for the imbalances caused by the errors in suppliers' demand forecast and in wind forecast. Although NGET specifies a maximum response time for *STOR* of 4 hours, 98% of the selected *STOR* providers can respond within 20 minutes [105], as one of the roles of *STOR* is to take over from *Fast Reserve* and to reinstate the committed sources. The *STOR* provider should be able to maintain the response, either increase in generation or demand reduction, for a minimum of two hours. At the moment, the main providers of *STOR* are Open Cycle Gas Turbine (OCGT) power generators and standby diesel generators covering 54% and 18% of the

[4] The maximum time until the provider should start the delivery of the service after receiving the NGET's instruction

STOR market [106]. DR participation in *STOR*, mainly by large commercial and industrial customers, is approximately 200MW [107] from the maximum required of 2800MW. Apart from the utilisation payment (£/MWh), NGET pays the providers for their reserved capacity (£/MW) during the periods – referred to as availability windows [108] - where events are most likely to occur. The annual *STOR* payment in 2011/2012 was £104 millions.

The decrease in communication costs have motivated the appliance manufacturers to provide integrated communication modules for home automation in appliances, such as fridges, ovens and washing machines. At the moment, the communication module is used to remotely turn on/off an appliance or the appliance to send an alarm to the user when the cycle is over or when maintenance is needed. However, there is an opportunity to make appliances automatically interact with the power system towards providing reserve services such as *STOR*, through load shifting, within minutes of receiving instructions.

4.2 Framework for procuring reserve from smart appliances

4.2.1 Business model

The envisioned system to enable reserve from appliances is shown in Figure 4.2. The residential customers participating to the DR programme have smart grid ready appliances such as washing machine, dish washer and tumble dryer (WM, DW, TD). A DR aggregator, in this study the electricity supplier, takes the responsibilities of predicting the available response from the appliances, verifying the response and rewarding the customers. The supplier will enter the *STOR* market, operated by the TSO, to capitalize the response from the appliances.

The communication between the TSO's central server and the electricity supplier is accomplished by an Asymmetric Digital Subscriber Line (ADSL). Through this link the supplier is declaring the available response ahead of real time. If the system TSO decides that reserve is needed from the supplier, it will issue a reserve instruction, e.g. 15 minutes ahead of real time, when the demand reduction is needed. At receipt of the reserve instruction, the supplier will increase the electricity price starting from the next 15 minutes interval for the duration specified by the TSO. The price increase will be delivered through the smart metering communication infrastructure, owned by the Data and Communication Company (DCC) in the UK, which consists of a Wide Area Network (WAN) and Communication Hubs [11]. The smart appliances connected to the hub will receive the increased price and will delay their cycle; thus, a decrease in aggregated consumption will be achieved.

The above solution, where the DR signal is integrated in the price signal, is similar to Critical Peak Pricing (CPP) [109]. CPP is a DR programme that relies on the customers to respond manually, therefore the notification time is on a day-ahead basis and the critical rate is up to eight times higher than the normal rate. In this case, because the response is automatic, the notification time can be shorter, 15 minutes, and the price increase can be small, so that the cost of operating the appliances that are not shiftable to remain roughly the same.

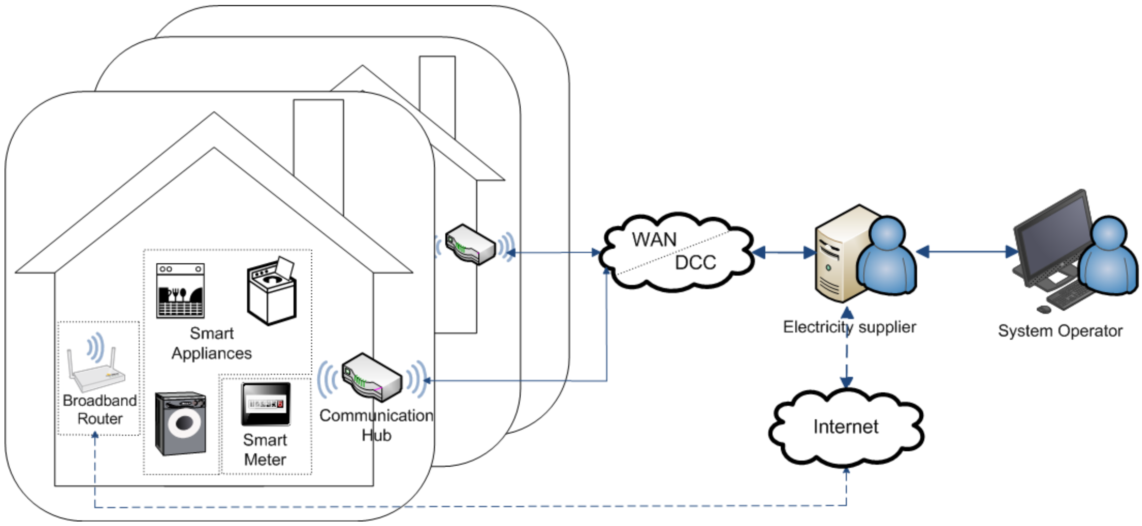


Figure 4.2: Framework for the participation of residential DR to the power system balancing service.

4.2.2 Simulation

In this study the simulation modelled the aggregated consumption of smart appliances from *N* households and their response to a reserve instruction. The response is the load reduction for the duration of the reserve instruction resulted from the difference between the usual consumption and the consumption in the case with instruction. As described in Section 4.2.1, the reserve instruction is converted into an increase in electricity price after the notification time and lasts for the duration of the instruction. The appliances, assumed to be equipped with the load management features such as smart timing and cycle interruption described in Chapter 2, will try to minimise the cost of supplying their power phases. The simulation duration was 24 hrs with a time step Δt of 15 minutes.

The steps involved in the simulation are shown in Figure 4.3. The simulation starts by generating the number of residents living in a single household, according to the statistics given in Table 3.3 of Chapter 3. This number inputs to the CREST energy demand model and that will generate the *activation times* of appliances over 24 hrs. These above steps will be repeated for each of the *N* households. Conveyed to the next step of a simulation is the matrix *A*, which gives the number of WMs, DWs, TDs that are in activation mode in each time step up to 24 hrs.

At time step *t* of the simulation there are A^t appliances to be scheduled. A verification for reserve instructions is made before the execution of the shifting algorithm described in Section 2.5.2. If a reserve instruction is received at time step *t*, the electricity price is increased by 50% at (t + $t_{notification}$) until (t + $t_{\mathrm{notification}}$ + $t_{duration}$); the values of the two STOR parameters have been varied to identify their influence on the simulation's outcome.

The scheduling algorithm, with the flowchart shown in Figure 4.3, is written in the JAVA programming language and constitutes an improvement of the algorithm described in Section 2.5. While the latter has been used in Chapter 3 to investigate the savings that smart appliances obtained from electricity tariffs with fixed rates for the next horizon *H*, the former algorithm is capable of shifting the appliance in response to tariffs that change the electricity rates from one time step Δt to another. This allows the smart appliances to respond to the reserve instructions from the system operator. Therefore, the appliance checks the tariff at each time step for as long as its start is delayed.

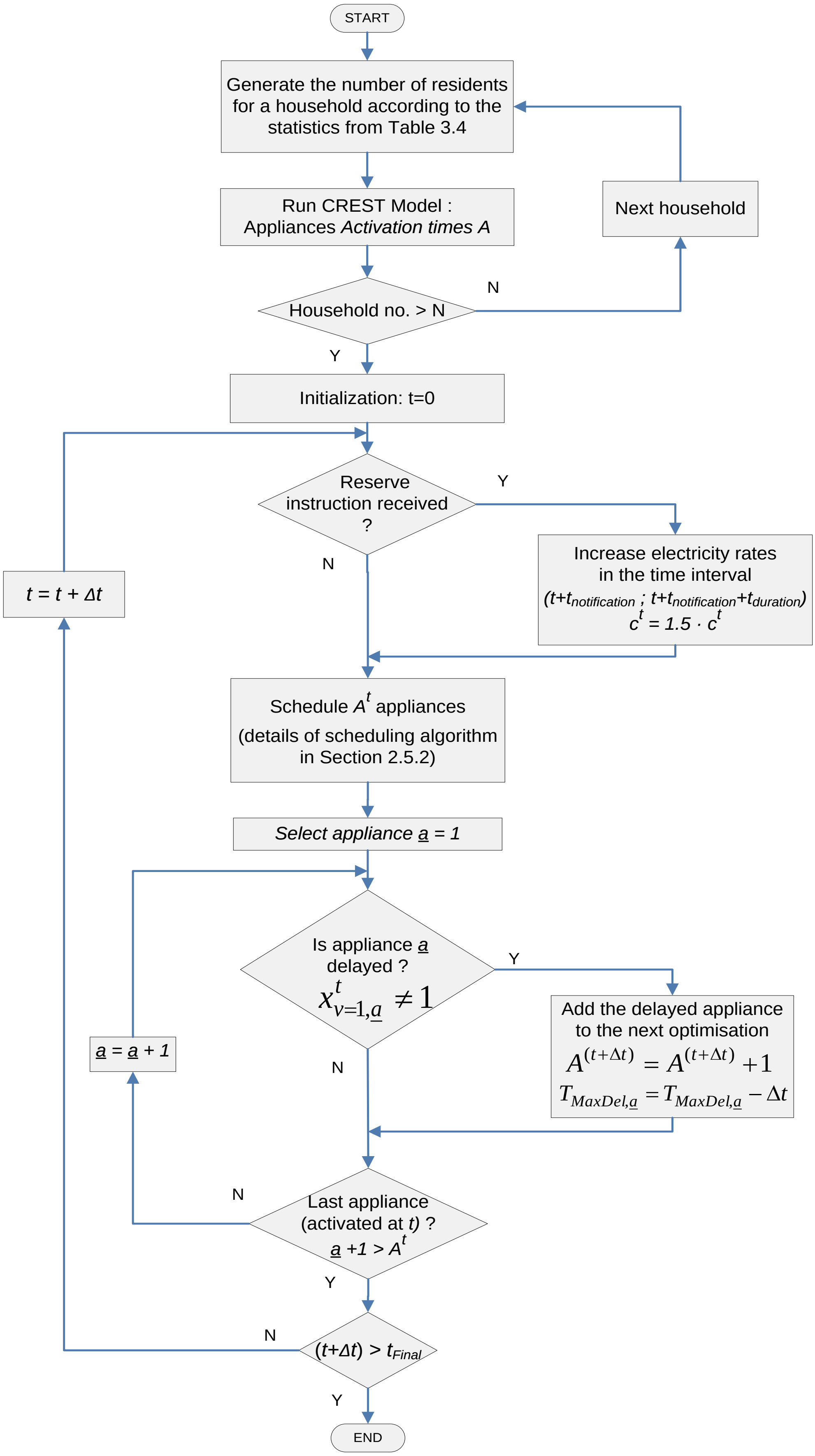


Figure 4.3: Flowchart of the simulation model

The additional procedure identifies delayed appliances in the output of the shifting algorithm. The output at time step t is shown in Figure 4.4 and is constituted of binary elements $x^t_{v,a}$ which represent the operation status of power phase v of appliance $\underline{a}$ at time step t. In the array shown in Figure 4.4, the highlighted element $x^t_{1,a}$ indicates if appliances $\underline{a}$ is delayed: $x^t_{1,a} = 1$ indicates that appliance $\underline{a}$ starts at time t, while $x^t_{1,a} = 0$ indicates that appliance $\underline{a}$ is delayed. The delayed appliance will be scheduled at the next time step: $A^{(t+\Delta t)} = A^{(t+\Delta t)}+1$. The user defined *maximum delay* parameter of the delayed appliance is decremented by Δt, reflecting the decrease in the time interval of the potential start time.

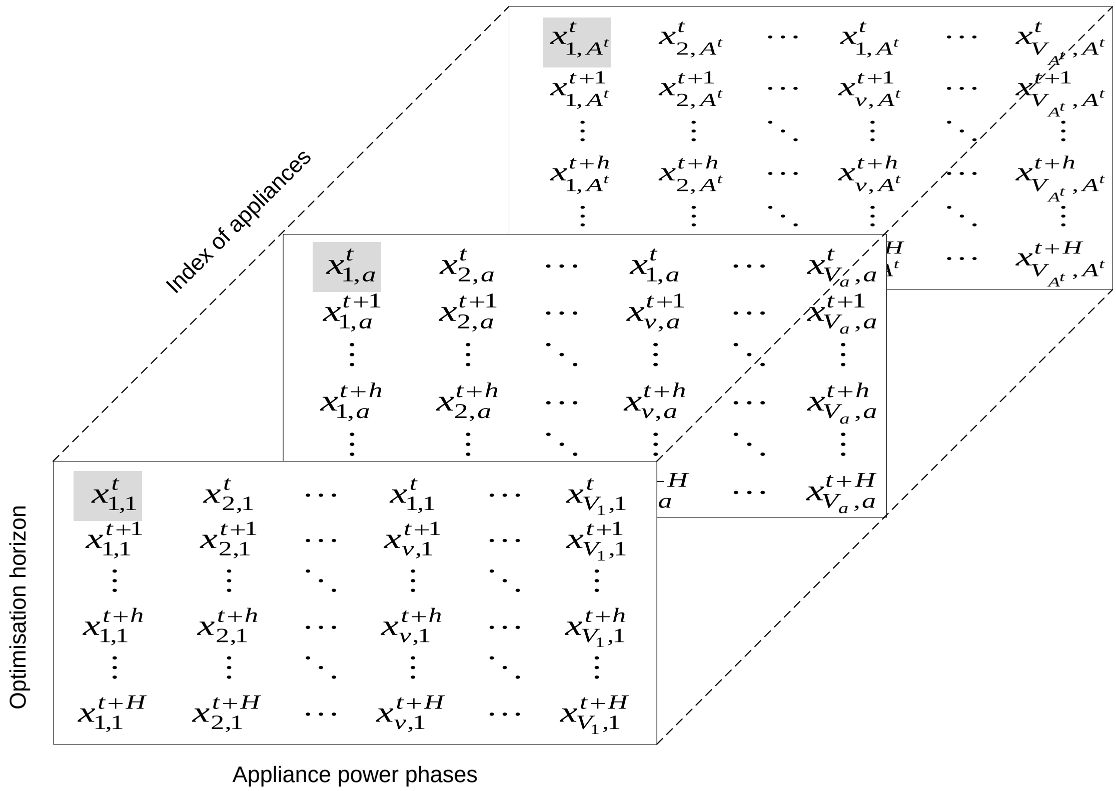


Figure 4.4: Array of decision variables for the optimisation at time step *t*.

In order to assess the potential reserve level that could be obtained by appliances in the GB power system, the user behaviour in each of the 25.6 million households needs to be ascertained. However, considering the limited diversity in the utilization of appliance, a smaller number of customers can be assumed to represent this larger population. As shown in Figure 4.5, the average load profile shows small changes after aggregating a certain number of households. For example the changes seen between the aggregated load profile of 1,000 households and 5,000 households are not significant. For this reason, and also for computational efficiency, 1000 households were used to model the response from the GB residences.

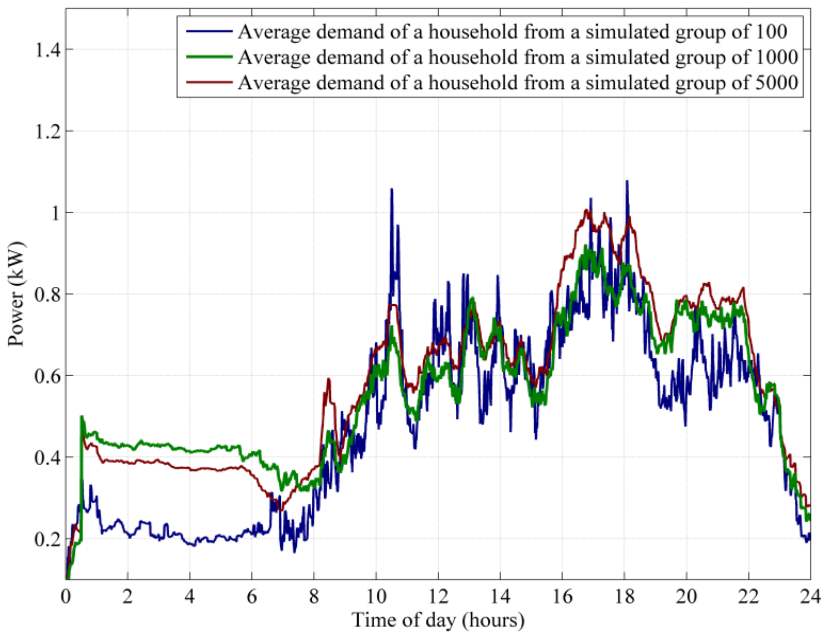


Figure 4.5: Average household demand simulated for different size groups.

4.3 Feasibility study of providing reserve services

4.3.1 One thousand households with single rate tariff

Figure 4.6 (a) illustrates the response of smart appliances (WM, DW, TD) from 1,000 households to a reserve instruction. The response as part of the total aggregated demand is represented in Figure 4.6 (b). In this example the households are subscribing to single rate electricity tariffs. The reserve instruction has the parameters of a *STOR* instruction: 15 minutes notification time and duration of two hours. The appliances receive the increased electricity rates at 9:45 am. The load reduction that was considered as reserve was measured between 10:00 am and 12:00 am. The load reduction obtained from the 1,000 households during the two hours is variable and has a mean of 156 kW.

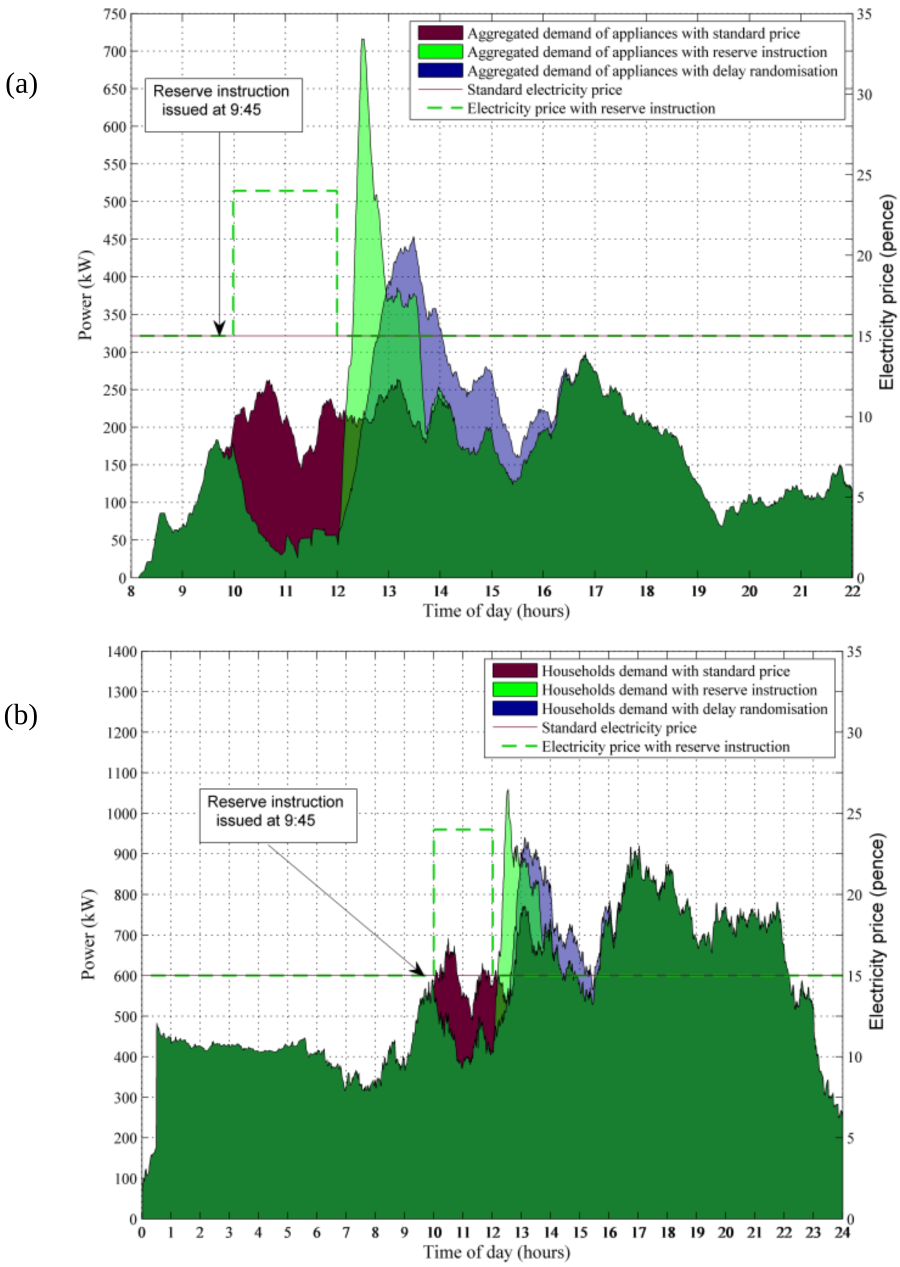


Figure 4.6: Aggregated demand from 1000 households with single rate tariff and their response to a reserve instruction: (a) Demand of appliances WM, DW, TD only; (b) Demand of all the loads from households.

The load reduction is followed by a load recovery period. The load recovery has higher values than the reduction due to the loss in diversity of usage of appliances. The appliances allowed to be delayed or interrupted by the user will start or continue their operations immediately after the instruction ends. The post instruction peak is increased by 270% compared to the original peak. The load diversity was reinstated by delaying the appliances that would otherwise start after the reserve instruction, with a random offset. The random offset takes values between 1 and 60 minutes and is applied to appliances for two hours after the instruction. For this scenario, the new peak, represented in blue in Figure 4.6, is reduced to 170% of the original peak.

4.3.2 One thousand households with TOU tariff

Figure 4.7 (a) shows the response to a reserve instruction of smart appliances (WM, DW, TD) from 1,000 households subscribing to the Time of Use (TOU) electricity tariff. The response as part of the total aggregated demand is represented in Figure 4.7 (b). The tariff with ten off-peak hours, five of them in the afternoon and evening, shapes the aggregated load profile of the appliances. To exemplify the impact of the tariff on the appliances' response, a *STOR* instruction is issued at 12:00. In the first hour of the instruction the load reduction obtained has an average of 42 kW due to the low availability of appliances during the peak price period. For the second hour, the load reduction has an average of 458 kW because the appliances that have been waiting to start at the lower price period will be further delayed at the end of the instruction. For TOU, the random offset between 1 and 60 minutes will reduce the original peak by 47%.

(a)

(b)

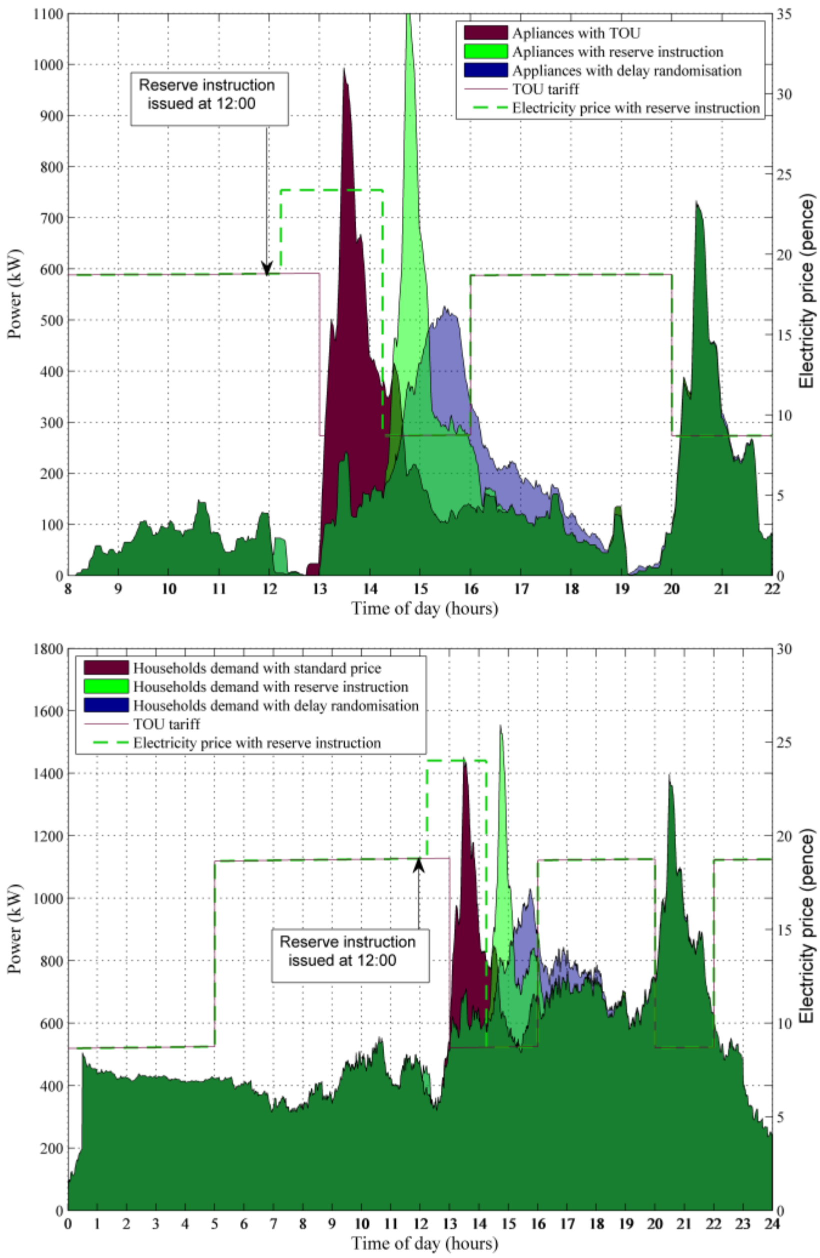


Figure 4.7: Aggregated demand from 1000 households with TOU tariff and their response to a reserve instruction: (a) Demand of appliances WM,DW,TD only; (b) Demand of all the loads in households.

4.4 Potential contribution of appliances to the GB operating reserve

4.4.1 Effects of reserve instruction parameters

The response obtained using the simulations described in Section 4.2.2 was scaled in order to estimate the reserve that smart appliances can provide at the national level. The assumption for this scenario is that 20% of GB households have adopted smart appliances (WM, DW and TD). The response was compared against the maximum required *STOR* level in 2014 of 2,800 MW. As shown in Section 4.3, the response depends on the time of the day when the reserve instruction is issued. Hence, to obtain the available response during a day, simulations were repeated with uncorrelated reserve events over a 24 hrs period. The influence on the load reduction of the reserve instruction parameters - notification and duration - was investigated.

The available reserve in the case where the instructions' duration is two hours is shown in Figure 4.8. To highlight the relation between the available reserve and the time at which the instructions are issued, two lines have been plotted, representing the load reductions if instructions are issued at even or odd hours throughout the day. It is worth noting that even though Figure 4.8 shows a continuous variation of the available reserve, in fact it constitutes of a number of 2 hrs plots shown in a single 24 hrs time axis.

A notification time of 15 minutes for the instructions is considered in Figure 4.8 (a) and 60 minutes in Figure 4.8 (b). The load reduction can cover up to 49% of the maximum *STOR* that NGET requires to safely operate the GB power system. When the appliances are notified one hour prior to the delivery time a higher result is achieved: 54% or 1.5GW. Additionally, the increased notification time means that demand reduction is prompter in its response, similar to a generator with a quicker ramp-up capability, at the times the delivery of the response is required.

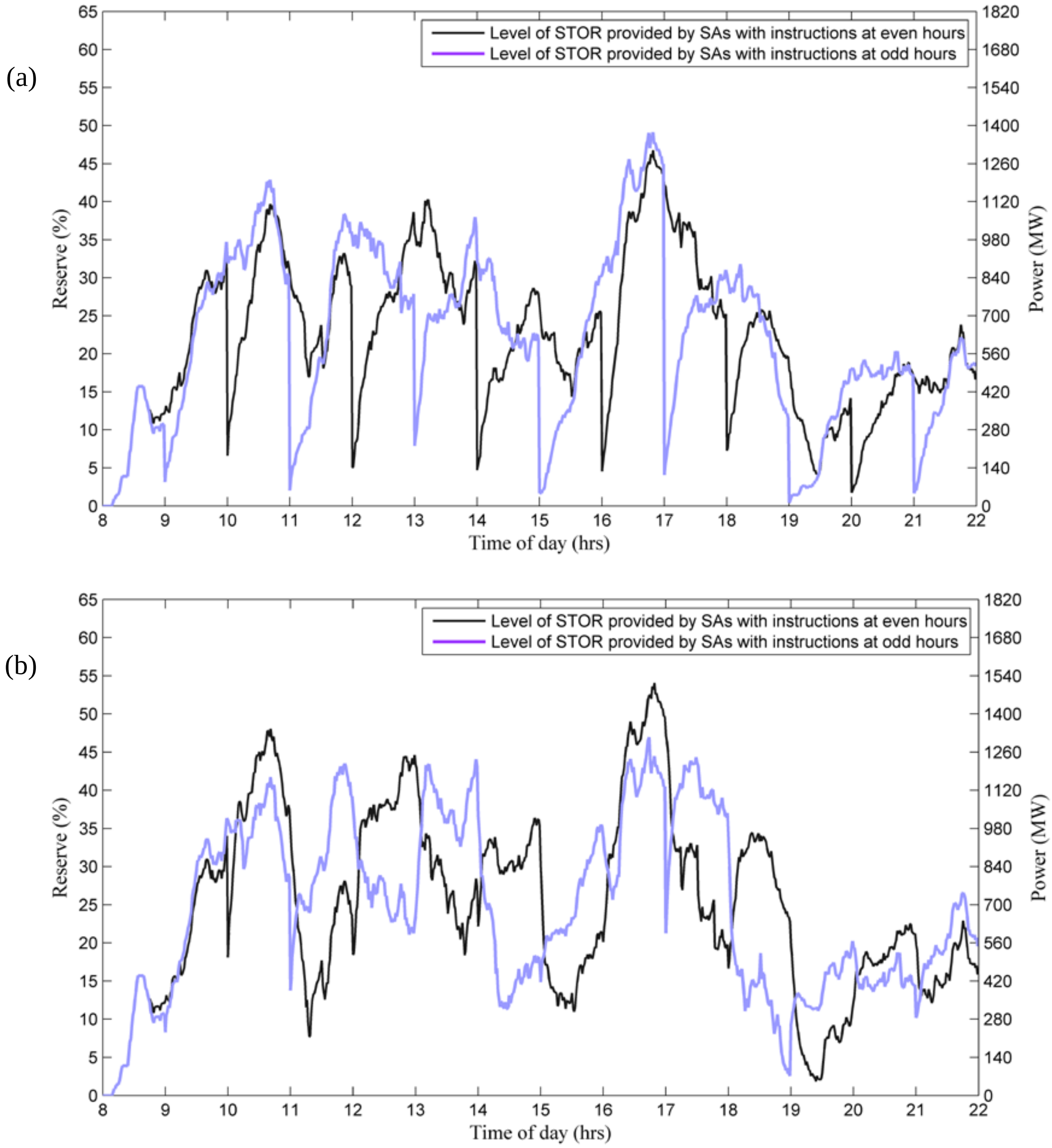


Figure 4.8: Available reserve from 20% of appliances (WM, DW, TD) in GB for reserve instructions with duration of 2hrs: (a) Reserve instruction notification time 15 min; (b) Reserve instruction notification time 60 min.

The available reserve in the case where the instructions' duration is one hour is shown in Figure 4.9. The instructions are issued with 15 minutes notification, in Figure 4.9 (a), at 00' of each hour, with black, and at each 30' of each hour with blue. In Figure 4.9 (b) the reserve instructions have a notification of one hour. By comparing with the previous case it can be seen that the notification of the reserve instruction has a bigger impact on the magnitude of the load reduction than the duration of the instruction.

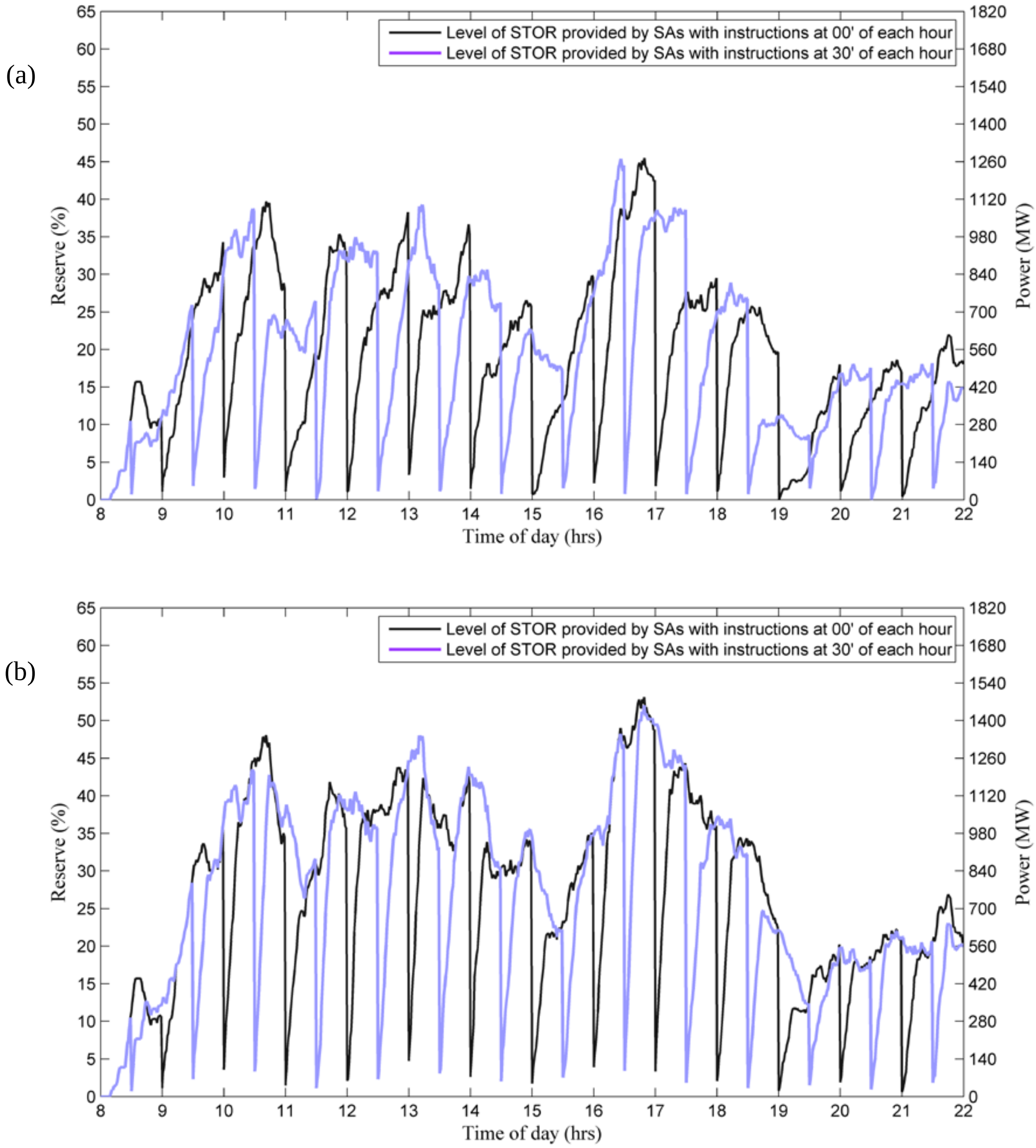


Figure 4.9: Available reserve from 20% of appliances (WM, DW, TD) in GB for reserve instructions with duration of 1hr: (a) Reserve instruction notification time 15 min; (b) Reserve instruction notification time 60 min.

Although the available reserve varies throughout the day, the average values during the availability windows, when events are most likely to appear, could provide a rule of thumb for policy makers. The results for the estimated load reductions with different reserve instruction parameters are summarised in Table 4.2.

Table 4.2: Estimates of the availability of DR from 20% of appliances (WM, DW, TD) in GB

Instruction parameters	**Reserve level available from smart appliances (MW)**					
	Availability window					
Notification / *Duration*	I (07:30 – 14:00)		II (16:00 – 18:00)		III (19:30 – 22:30)	
	Summer	*Winter*	*Summer*	*Winter*	*Summer*	*Winter*
1 h \ 15 minutes	813	856	1097	1250	567	541
1 h \ 60 minutes	989	1059	1324	1516	701	662
2 h \ 15 minutes	843	895	1146	1255	584	576
2 h \ 60 minutes	949	1022	1288	1462	677	642

4.4.2 Financial and environmental achievements

The shifting of the appliances will leave the electricity supplier, acting as the DR aggregator, with volumes of energy different from those contracted. For the period of the reserve instruction, the supplier has its contracted volume suitably adjusted with the response provided to the TSO, thus avoiding imbalance charges. However, the supplier will have to cater for the load recovery period. As the time of the load recovery is predictable, the suppliers can modify their contracted position by trading in the power exchanges as soon as the reserve notification is received.

At a system level, the described solution facilitates the operating reserve to be supplied through more efficient power plants. By delaying the need for extra active power, the smart appliances response can help replace the fast and higher emissions response from OCGTs with the lower emissions combined cycle gas turbines (CCGTs). An estimate of the CO_2 reduction for a period of one year is calculated in Matlab® with Equation (4.3).

$$\Delta\xi = \mathrm{E} \cdot (\epsilon_{\mathrm{OCGT}} - \epsilon_{\mathrm{CCGT}}) \tag{4.3}$$

where

$\Delta\xi$ the annual emissions reduction ($ktCO_2$)

E the annual energy provided by OCGTs in the STOR service

$E \cong 100$ GWh in 2011 [106], [28]

ϵ_{OCGT} carbon emissions factor of operating the OCGTs.

$\epsilon_{\mathrm{OCGT}} = 0.46\ \mathrm{tCO_2/MWh}$ [110]

ϵ_{CCGT} carbon emissions factor of operating the CCGTs.

$\epsilon_{\mathrm{CCGT}} = 0.353\ \mathrm{tCO_2/MWh}$ [110]

The resulting annual emission reduction with the parameter values of 2011 is $\Delta\xi = 10.7$ $ktCO_2$. For comparison the annual emissions from electricity generation in UK 2011 was approximately 150 $MtCO_2$.

Equation (4.4) was implemented in Matlab® to assess the financial benefit of providing STOR service when an uptake of 20% of appliances in GB is considered. The first term of the equation determines the revenues from availability, while the second, the utilisation revenue. It is assumed that the TSO accepts the full availability provided by DR given in Table 4.2 for instruction notification of 15 minutes and duration of 2hrs.

$$V = \left(N_d \cdot \sum_{i=1}^{N_a} r_i \cdot t_i \cdot c_a \right) + \bar{r} \cdot N_u \cdot c_u \tag{4.4}$$

where

V revenue for providing STOR service

N_d number of days in one year

N_a number of availability windows in each day

t_i the duration of the availability window *i*

r_i the available response from smart appliances in the availability window *i*

$\bar{r}$ the average response over the N_a windows

N_u the annual average calling time for STOR providers

c_a availability payment

c_u utilisation payment

The values for the parameters used are representative for the year 2011 and are given in Table D-4 of Appendix C. The resulting availability over one year is 3,572 GW·hrs can bring revenue of £32.62M. Furthermore, a revenue from utilisation of £14.37M was obtained, bringing the total revenue to £47M.

4.5 Discussion

The capability of smart appliances to participate in power system balancing services was investigated. Two new procedures were added to the scheduling algorithm introduced in Chapter 2 in order to model the response from smart appliances to a reserve instruction with a short notification period.

One thousand households in GB participating in the NGET's STOR service were simulated. The shifting and interruption of appliance operation, triggered by STOR instruction, resulted in a fast decrease in consumption. The load reduction, or reserve, varies over 24 hrs and depends on the user behaviour. The electricity tariff, to which the user is subscribing, shapes the availability of smart appliances and, thus, the reserve they can provide over 24 hrs. Furthermore, the STOR instruction parameters influenced the level of reserve obtained. Increasing the time between the moment when the STOR instruction was issued and the moment appliances are expected to deliver the reserve ensures a higher value of reserve from appliances. Following the reduction, a loss in diversity of usage of appliances was observed and was mitigated by the introduction of a random start offset.

The response from one thousand households was used to estimate the available response at system level, considering 20% penetration of smart appliances in the GB residential sector. The results showed that the response of the considered appliances (washing machine, dishwasher and tumble dryer) is well suited to be integrated in the STOR service. A significant share of up to 54% of the maximum STOR level required in the GB power system operation was achieved. The greenhouse emissions savings of the proposed demand side response scheme are relatively small, 10.7 ktCO_2 per year, due to low utilization of the STOR service. The yearly revenue for providing STOR was calculated at £47M.

The results of this chapter show that at system level a peak demand is created when control signals are sent to the appliances, due to the loss in the diversity of usage of appliances. This leads to the question of how this peak would affect the electricity distribution network operation for a scenario where smart appliances are clustered in a residential area. To give an answer to this question a study on medium and low voltage distribution networks is carried out in Chapter 5.

Chapter 5

Distribution network operation with smart appliances

***Summary**:*

In this chapter a study was carried out to identify potential constructive or detrimental effects which the adoption of smart appliance technology will have for the distribution network operation. A generic simulation through which demand response initiatives can be tested on distribution networks is introduced. The simulation contains a load modelling method where each network node is allocated a number of households, while the node's aggregated demand is the sum of the individual household profiles. The branch loading and voltage profile parameters are determined using time series power flow analysis, implemented in IPSA Power software. Two types of control have been considered for smart appliances: individual and regional control. An uptake over 25% of smart appliances with individual control leads to thermal stress on distribution circuits. The regional controller for smart appliances, introduced to assess the network support facilitated by coordination between loads, limits the appliances aggregated demand keeping the network parameters within the operational limits.

5.1 Introduction

The distribution networks have been planned and designed with spare capacity to account for future demand growth and contingency overloads. With the electrification of the transport and heating sectors the load forecasted to connect to the distribution network will require uprating of network components [111]. The capacity allocated to distribution networks for the current demand is estimated by network operators considering temporal diversity in the appliance utilisation, since different appliances are turned on and off at different times. The reduction of temporal diversity in appliance utilisation due to utility signals was discussed in studies [2]-[3]. In GB more domestic consumers will have easy access to TOU type of electricity tariffs through the smart metering infrastructure, which could reduce the diversity factor due to the synchronising effect on smart appliances (SAs). The smart metering infrastructure will enable distribution network operators (DNOs) to send more complex control signals to smart appliances that will result in dynamic changes in consumption. It is thus essential to investigate the implications that the adoption of smart appliances will have on distribution networks.

5.2 Regional controller

A regional controller is introduced to investigate the network support solutions provided by smart appliances: washing machine, dishwasher and tumble dryer (WM, DW, TD). The proposed scheme for the operation of the regional controller is illustrated in Figure 5.1. The location of the controller in this study is the secondary substation. The controller will schedule the operation of smart appliances connected to the electricity network downstream of the controller's location.

The objective of the shifting algorithm implemented in the controller is unchanged from that of smart appliances described in Section 2.5 by Equation (2.3): minimise the cost of operating the appliances' power phases. In addition the controller ensures that the aggregated demand of appliances does not drive the network parameters outside the operational limits. Therefore, in addition to the constraints related to the individual appliance operation from Equations (2.4)-(2.6), network constraints were considered in the shifting algorithm. Three types of constraints were investigated: network thermal limits, network voltage limits, and both thermal/voltage limits.

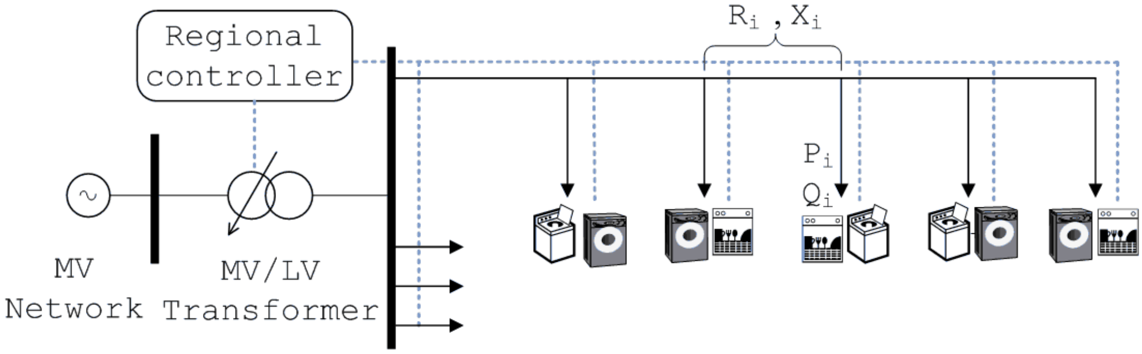


Figure 5.1: Concept of a regional controller for smart appliances.

The thermal constraint, modelled using Equation (5.1), keeps the loading at the secondary substation transformer lower than the transformer rating. The constraint formulation which was implemented in the optimisation model is found by replacing the appliance demand from Equation (5.1) with the expression given in Equation (5.2).

$$\sum_{k=1}^{K} \sqrt{\left({P_D}^t{}_k + {P_A}^t{}_k\right)^2 + \left({Q_D}^t{}_k + {Q_A}^t{}_k\right)^2} \leq S_{transformer}, \qquad \forall t \in (t_0, \dots, \ t_0 + T) \tag{5.1}$$

$${P_A}^t{}_k = \sum_{a=1}^{A^{t_0}} \sum_{v=1}^{Va} x^t_{v,a_k} \cdot P_{v,a_k} \ , \qquad {Q_A}^t{}_k = \tan\varphi \cdot {P_A}^t{}_k \tag{5.2}$$

where:

$S_{transformer}$	MV/LV transformer nominal rating
k	index of the residential consumer

K number of residential consumers connected to the LV network

$P_{A_k}^t$, $Q_{A_k}^t$ power consumption from appliances (WM, DW, TD) for customer k at t

$P_{D_k}^t$, $Q_{D_k}^t$ power consumption from other household appliances for customer k at t

T optimisation window

t_0 current time step

v index of the power phase

V_a number of power phases of the appliance $\underline{a}$

$x_{v,a}^t$ binary decision variables of power phase v of the appliance $\underline{a}$

P_{v,a_k} power consumption for the power phase v of the appliance $\underline{a}$

A^{t_0} number of appliances activated at time t_0

φ phase angle

The voltage constraints keep the voltage across the LV feeder within the declared voltage range of 230 volts +10% and -6%. Because the considered network is passive, it is sufficient to implement voltage constraints for only one node: at the end of the feeder. The constraint, modelled in Equation (5.3), ensures the voltage at the customer connected farthest from the substation is above the lower bound of the voltage range. The formulation of the constraints which were implemented in the optimisation model is found by replacing the appliance demand from Equation (5.3) with the expression given in Equation (5.2).

Calculating the voltage is a non-linear problem and usually involves iterative steps, which cannot be integrated in the optimisation model of the shifting algorithm. Instead, a voltage calculation using linear equation was used as detailed in Appendix D.1. The approximation is possible due to the particularities of a distribution circuit and the radial topology of the LV feeder. In Equation (5.3) a low value of the cable section index indicates the proximity to the secondary substation while a higher value to the end of the feeder (no branches were considered).

$$V_{End\_Feeder} \geq V_{INF}$$

$$V_S - \left[\sum_{i=1}^{n} \left(R_i \cdot \sum_{j=i}^{n} \left({P_D}^t{}_j + {P_A}^t{}_j \right) \right) + \sum_{i=1}^{n} \left(X_i \cdot \sum_{j=i}^{n} \left({Q_D}^t{}_j + {Q_A}^t{}_j \right) \right) \right] \Big/ V_S \geq V_{INF}, \quad (5.3)$$

$$\forall\, t \in (t_0, \dots, \ t_0 + T)$$

where:

V_{INF}	voltage limits for the LV network
V_S	voltage of the LV busbar at the secondary substation
i	index of the cable section across the LV feeder
n	number of cable sections on the LV feeder
R_i	resistance of the cable section i
X_i	reactance of the cable section i
${P_A}^t_j$, ${P_D}^t_j$	power consumption connected to the cable section j at time t

5.3 Simulation

5.3.1 Flowchart

An overview of the simulation constructed to study the impact of smart appliances on distribution network operation is shown in Figure 5.2. There are two sequences of processes in the simulation: one for modelling smart appliances with individual control (without coordination) and the second for modelling smart appliances with a regional controller that coordinates their operation.

Each node of the distribution network was allocated a number of houses according to the node's nominal demand value specified in the network parameters. The CREST electricity demand model described in Section 2.4.1 generates for each node the activation times of WM, DW and TD. It also generates the households' demand P_D and Q_D excluding WM, DW and TD for 24 hrs at a resolution of one minute. The shifting algorithm outputs the appliances power consumption P_A and Q_A at each node. The demand data at each minute throughout the 24 hrs was used to run steady state load flow analyses on the distribution network, a method called time series load flow analysis [113]. The results are the network voltages, loading of transformers and cables at each minute during the time span of a day. A script was developed in Python to run time series load flow analyses. At each time step the script invokes a load flow engine in IPSA Power [84] using an application programming interface. The selected load flow engine uses a fast decoupled Newton-Raphson power flow algorithm.

For the simulation of appliances with individual control the shifting algorithm explained in Chapter 2 was used without any modifications. The model assumes each appliance is independently scheduling its operation to reduce the cost of the consumed energy. For modelling smart appliances with a regional controller, the shifting algorithm requires demand and network information.

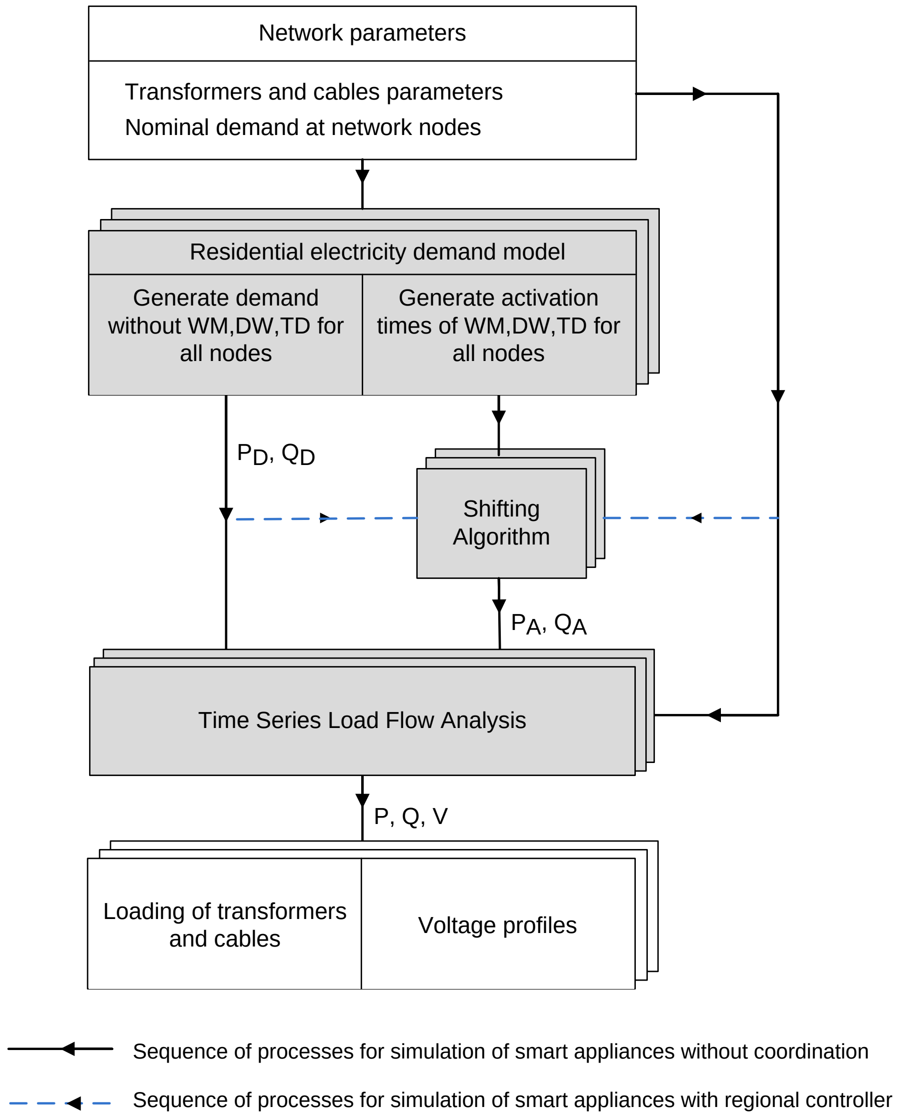


Figure 5.2: Data flowchart of the simulation.

5.3.2 Distribution test system

The voltage levels of the selected distribution networks are medium voltage (MV) and low voltage (LV). The one line diagram of the network is shown in Figure 5.3. Both the MV and LV networks have a radial topology with underground cables. The details of the 33 kV network are specified in the United Kingdom Generic Distribution System (UKGDS) project [114]. At the primary substation there are two 33/11kV transformers operating in parallel on the same busbar, each rated at 26.4 MVA. The transformers are equipped with on-load tap changers (OLTCs) and are controlling the voltage at the MV busbar of the substation. There are eight feeders of different lengths leaving the substation which supply 75 aggregated MV loads, from which one is detailed as a LV network. At the secondary substation the step-down transformer 11/0.4 kV is rated at 500 kVA and is fitted with off-load tap changer. The LV network's design and parameters' values are obtained from reference [115]. The network parameters are given in Table E-6 and Table E-7 of Appendix D.2.

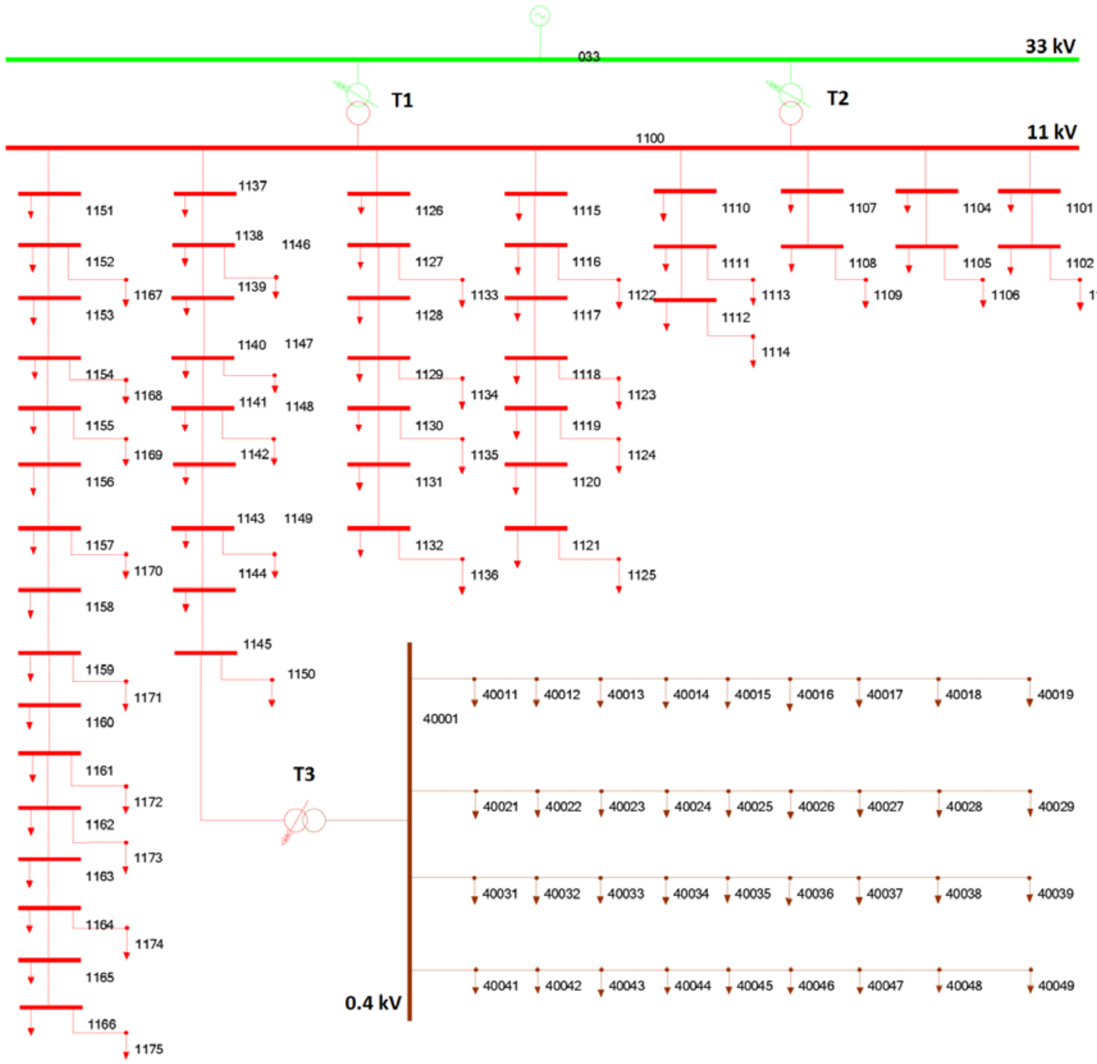


Figure 5.3: Distribution test network.

5.3.3 Load model

The network covers an urban area with high customer density. Demand on the selected distribution network is assumed to be only residential. There are a total of 75 loads at the MV level, each one representing an aggregation of LV consumers. Equation (5.4) was used to assign a number of houses for each of the 75 loads by dividing the nominal demand value to the *after diversity maximum demand* (*ADMD*) parameter. The nominal value is the maximum demand that can be observed in normal operation. The nominal value of the demand at each 11kV busbar is specified in the MV network parameters [114], with values between 100 kVA to 392 kVA. A common value for *ADMD* considered in studies of distribution network operation in the UK is 1.3 kVA [116]. In total, the MV network serves 18,688 residential customers.

$$NH_b = \frac{D_b}{ADMD} \tag{5.4}$$

where: NH_b is the number of houses at busbar *b*; D_b is the nominal demand at busbar *b*; *ADMD* is the after diversity maximum demand parameter.

For the LV network, reference [115] specifies that each of the four feeders serves 97 residential consumers. They were partially lumped into groups of twelve residential consumers connected to eight distribution pillars placed across the feeder. For the last consumer, number 97, the service cable was also included. For example, in Figure 5.3 each load 40011 to 40018 represents twelve consumers, while load 4019 is a single consumer.

The CREST demand model described in Section 2.4.1 was used to model the load curves over one day for each of the residential consumers within the MV and LV networks. Modelling each dwelling gives a more realistic view of the allocation of the demand across the distribution network than using average load profiles. The resulting *ADMD* value for the LV network using the demand model is 1.2 kVA, close to the value considered in Equation (5.4). The daily load factor of the cumulated load seen at the MV/LV transformer, defined as the ratio of the average demand to the maximum demand, is 0.57. This value is close to the daily load factor for residential consumers in the UK (0.55 according to [117]). A lagging power factor of 0.98 was considered for the connected residential loads, value consistent with the average power factor measured by a DNO in [118] . The loads were modelled as constant power loads.

5.3.4 Pseudo-code

The pseudo-codes of the simulation and the shifting algorithm used in this chapter are given in the following two tables. The details of the parameters used in the pseudo-code can be found in the explanations of Equation (5.1)-(5.4), Section 5.2 and Section 5.3.3.

Simulation

Input: No_LVnodes, D_b[No_LVnodes] , ADMD , $S_{transformer}$, $T_{simulation}$, V_S [$T_{simulation}$] , φ

Begin

For each node in No_LVnodes
    NH_b(node)= D_b(node) / ADMD
    P_D (node) = Run adapted_CREST(NH_b(node)), S_D(node)=P_D (node) / cos(φ)
    A = Run adapted_CREST(NH_b(nodes))
End For
For each time step of $T_{simulation}$
    For all each node in No_LVnodes
        Power_limit_apl (time) = $S_{transformer}$ – S_D(time)(node)
    End For
End For
P_A= schedule_algorithm (A, price, V_S, $T_{simulation}$, Power_limit_apl, P_D, φ)
Q_A(node)=tan(φ) · P_A (node)
Run IPSA_software(P_A+P_D, Q_A+Q_D) , **Get** network_state_variables

End

Output: Display network_state_variables

Shifting algorithm (schedule_algorithm)

Input: A, price, V_S , $T_{simulation}$, Power_limit_apl[$T_{simulation}$], P_D[$T_{simulation}$][No_LVnodes], φ

Set: No_power_phase, apl_power_profile[No_power_phase], Volt_lim_inferior,
No_cables = No_LVnodes, R[No_cables], X[No_cables]

Begin

Define decision variable in CPLEX: x[A · No_power_phase · $T_{simulation}$]
For each apl in A
    For each phase in No_power_phase

For each time in $T_{simulation}$
Add to objective_function**:** x(time + $T_{simulation}$ · phase+ $T_{simulation}$ · phase ·apl) ·
·apl_power_profile(phase)· price(time)
Add to power_constraint**:** x(time + $T_{simulation}$ · phase+ $T_{simulation}$ · phase ·apl) ·
·apl_power_profile(phase)
End For
End For
End For
For each cable in No_cables
Equivalent_R (cable)= Equivalent_R(cable-1)+R(cable)+X(cable)·sqrt(1/(ϕ^2-1))
For each apl in A(cable)
For each phase in No_power_phase
For each time in $T_{simulation}$
Volt_fixed_load(time)= Volt_fixed_load(time)+Equivalent_R (cable)
P_D(time)(cable)/ V_S(time)
Add to voltage_constraint**:** x(time + $T_{simulation}$ · phase+ $T_{simulation}$ · phase ·apl) ·
·apl_power_profile(phase)· Equivalent_R(cable)/ V_S(time)
End For
End For
End For
End For
Run CPLEX: power_constraint(time) < Power_limit_apl(time)
voltage_constraint(time) <V_S - Volt_lim_inferior(time) - Volt_fixed_load(time)
Minimize objective_function
For each cable in No_cables
For each apl in A(cable)
For each phase in No_power_phase
For each time in $T_{simulation}$
P_A(time)(cable)= x(time + $T_{simulation}$ · phase+ $T_{simulation}$ · phase ·apl)·
·apl_power_profile(phase)
End For
End For
End For
End For
End

Output: Return P_A

5.4 Results

5.4.1 Operation of smart appliances with individual control

In this scenario the smart appliances (WM, DW, TD) schedule their operation autonomously, without any coordination between them. Each appliance minimises its operation cost according to the electricity tariffs, as described in Chapter 3. In this scenario the focus was to identify if the loss in diversity in the appliance utilisation causes significant voltage drops on the distribution network or the distribution equipment to work in overload conditions.

Figure 5.4 shows the transformer T3 loading with different uptake rates of smart appliances. The smart appliances reacting autonomously to the TOU tariff will decrease the load diversity at the off-peak hours of the tariff. The rating of the transformer is exceeded by the demand, the effect of it being a temperature build-up which could result in deterioration of winding insulation.

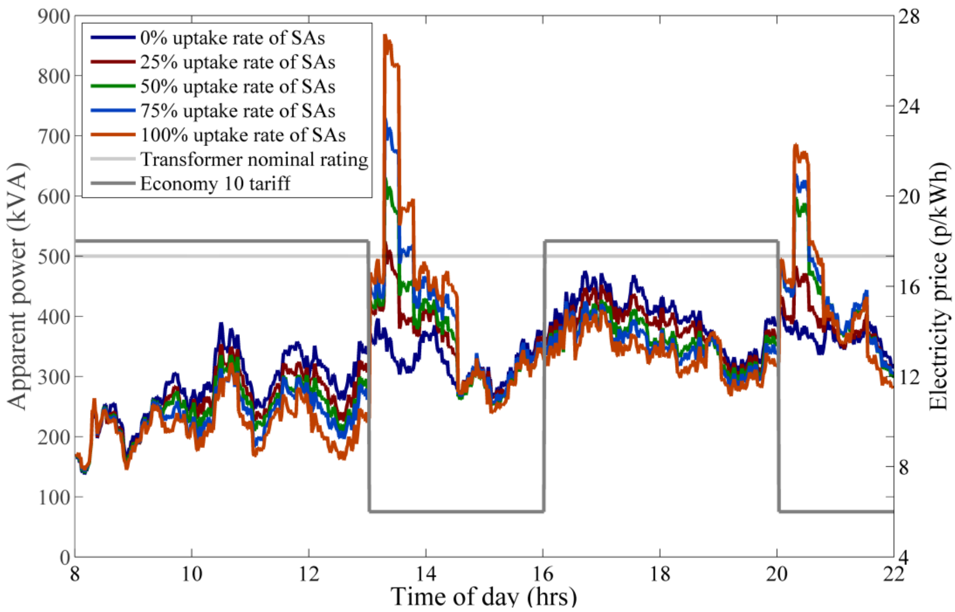


Figure 5.4: Loading of substation transformer T3 in winter season.

Transformer T3 loading was investigated for further circumstances, with the maximum loadings recorded during the time span of a day shown in Figure 5.5. Both Economy 10 and RTP tariffs show a correlation between the uptake rate of appliances and the maximum transformer loading. There are several reasons for the creation of a new peak demand with a higher value than the initial value (without smart appliances). The two tariffs have off-peak intervals during daytime, intervals preceded by periods with high availability of appliances. The appliances are shifted to daytime off-peak intervals where the demand is lower than the initial peak, yet still significant in comparison with night time demand. The appliances which have their start delayed will start their operations immediately after the end of the off-peak interval. Therefore, with the increase in the uptake rate of smart appliances, the new peak demand surpasses the initial peak and the transformer T3 rating. The limitation on the uptake rate of smart appliances is occurring first in winter when the spare capacity of T3 used to accommodate smart appliances is lower than in summer.

For Economy 7 the maximum loading is slightly decreased with the increase of smart appliances uptake. This is because the appliances are shifted from the 17:00-18:00 peak to after 24:00, when the off-peak interval starts. The new peak created by Economy 7 doesn’t surpass the initial peak because the availability of appliances for the hours leading to 24:00 is small compared with the availability during daytime of the other two tariffs (RTP and Economy 10). Another reason is that the initial demand is low during the off-peak interval.

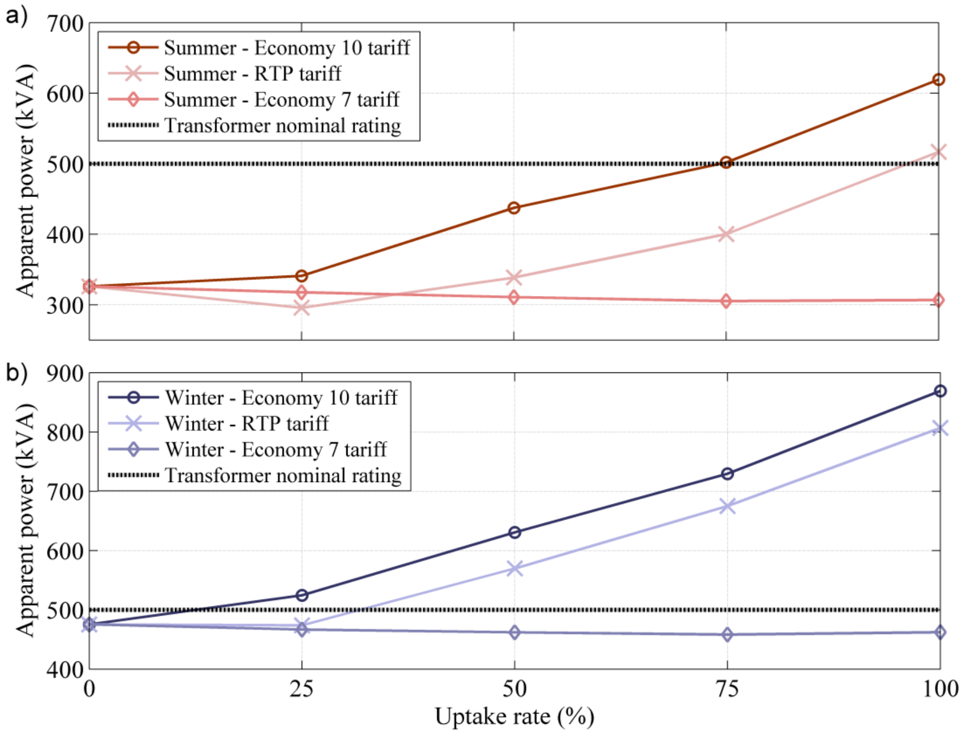


Figure 5.5: Peak demand recorded at transformer T3 with different smart appliances uptake levels: (a) Summer; (b) Winter.

Branch loading is another important aspect in distribution planning and operation. The results showed that the underground cables of MV feeders had enough capacity to carry the loading at peak load times for any of the discussed circumstances. The situation is more problematic for the underground cables of the LV network, where there is a risk of the peak demand exceeding the cable rated capacity. Figure 5.6 shows the maximum loading for Economy 10 and RTP tariffs. Overloads are recorded on the first three cable sections closest to the substation, cable of 185mm^2 cross section, from node 40001 to 40013 and also on the first 95mm^2 section from 40014 to 40015.

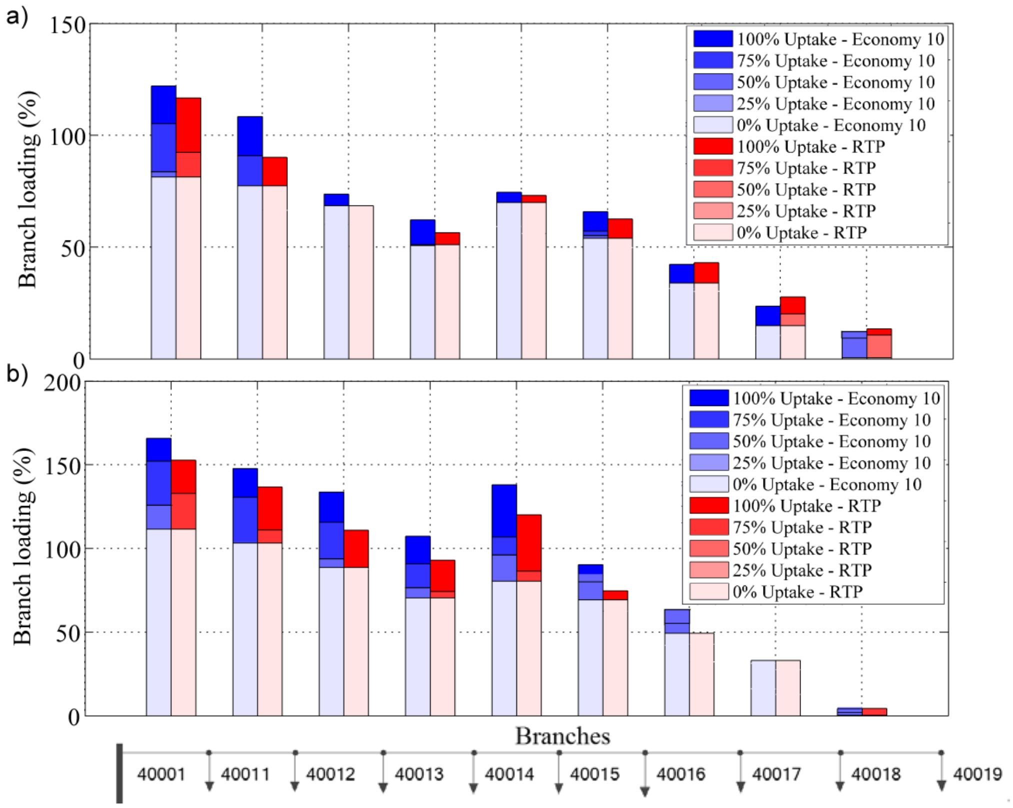


Figure 5.6: LV feeder branch loading at peak load times with different smart appliances uptake levels: (a) Summer; (b) Winter.

The peak demand recorded at the primary substation for the same circumstances as above is shown in Figure 5.7. License conditions require the DNO to supply group demands with a level of redundancy for security reasons. The aggregated demand on the MV network, classified in the range 12MW up-to 60MW, has to be supplied by at least two normally closed circuits [119]. This ensures that in case of a first outage on one of the circuits, situation also called ‘N-1’ single failure, the demand is still supplied by the other circuit. In the test system the aggregated demand is served by the transformers T1 and T2 which are operated in parallel. Therefore, in order to be ‘N-1’ compliant the peak demand seen at the primary substation should not exceed the nominal rating of the transformers. For most of the circumstances the smart appliances do not interfere with this requirement. The nominal rating of the transformers is exceeded only for a smart appliance uptake rate higher than 75% for Economy 10 tariff in winter season.

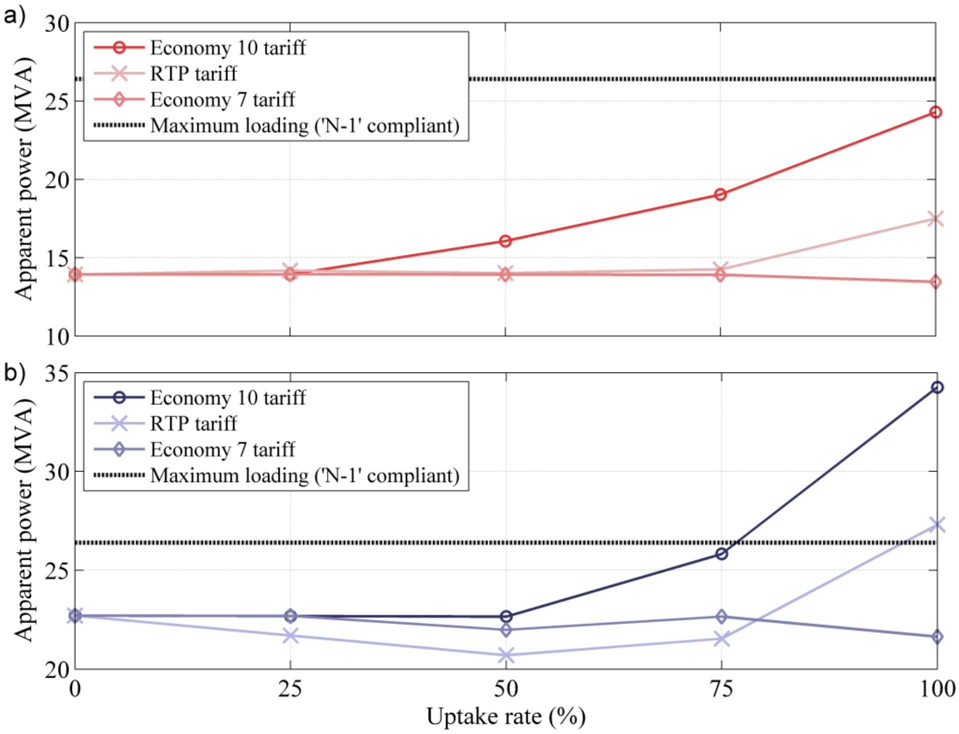


Figure 5.7: Peak demand at the primary substation with different smart appliances uptake levels: (a) Summer; (b) Winter.

The voltage profile across a medium length MV and LV feeder is plotted in Figure 5.8 for different circumstances. Two voltage regulation (VR) practices are considered. For the first practice, the voltage on the MV busbar of the primary substation is set to the upper limit, of 1.06 p.u; while in the second practice the voltage is set to 1 p.u. The voltage is controlled by the tap changers of the two 33/11 kV transformers T1 and T2. The voltage at the LV network is boosted by 2.5% through the off-load tap changer at the 11/0.4 kV transformer. In the summer season the voltage at maximum loading is within the voltage limits for both voltage regulation practices and for all the tariffs considered. In the winter season, most of the values fall within the voltage limits. However, for the second voltage regulation practice the voltage on the last section of the LV feeder falls below the lower voltage limit if the tariff considered is Economy 10.

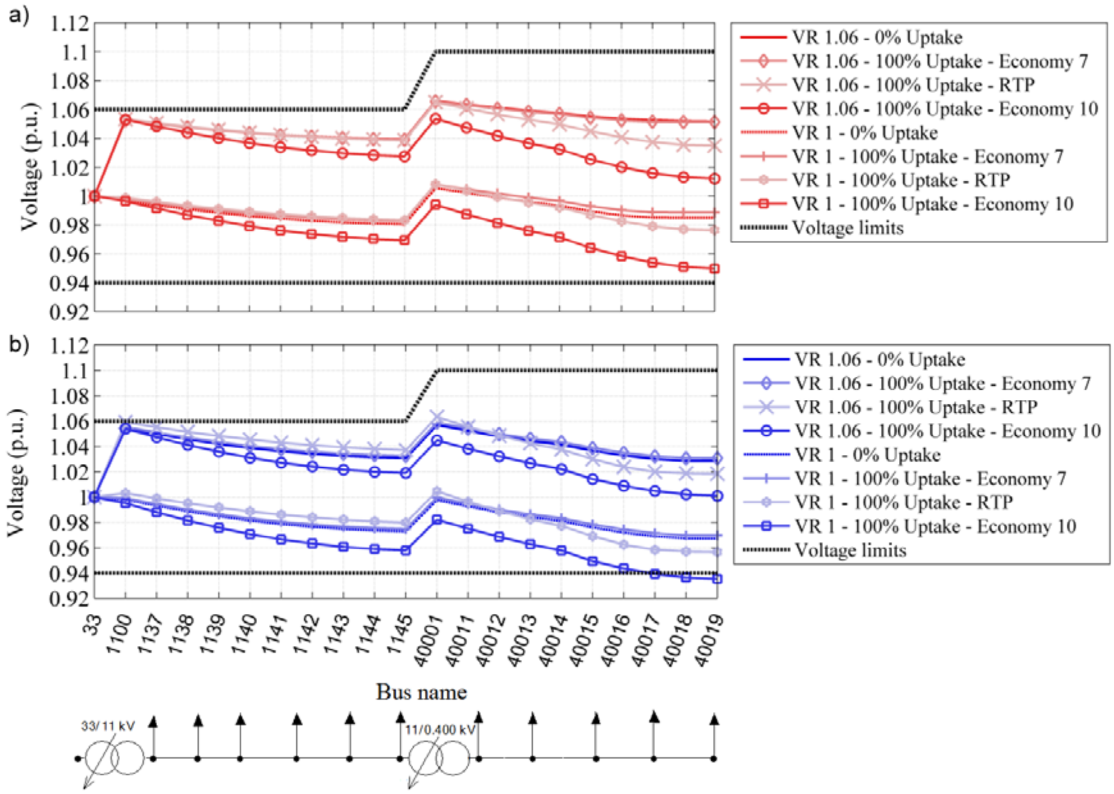


Figure 5.8: Voltage profile of MV feeder (medium length) and LV feeder at maximum loading: (a) Summer; (b) Winter.

Further, the voltage profile was investigated for the LV network connected to the longest MV feeder of the MV network, to consider the most onerous conditions. The voltage regulations practices and tariffs are unchanged from the previous investigation. The voltage profiles, shown in Figure 5.9, have deteriorated compared with the previous case. Yet still the Economy 10 tariff is the only tariff where voltages outside the limits are recorded. In the summer, for the second voltage regulation practice, the last section of the LV feeder falls below the lower voltage limit; while in winter both the MV feeder and most of the LV feeders are below the voltage limit.

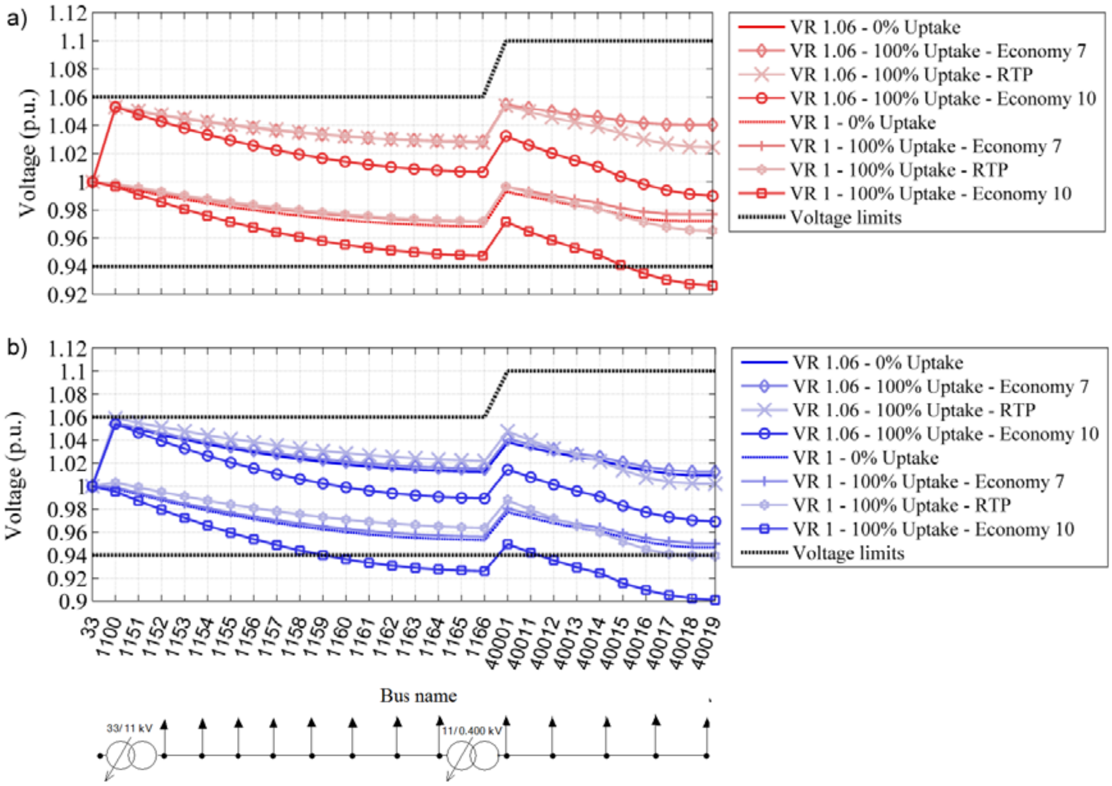


Figure 5.9: Voltage profile of MV feeder (long length) and LV feeder at maximum loading: (a) Summer; (b) Winter.

Three temporal voltage profiles at the LV consumer connected farthest from the substation are shown in Figure 5.10. The profiles correspond to the three situations identified in Figure 5.8 and Figure 5.9 in which voltages are outside the limits. The voltage magnitude suffers significant drops after 13:00 and 20:00, at the start of the Economy 10 off-peak daytime intervals.

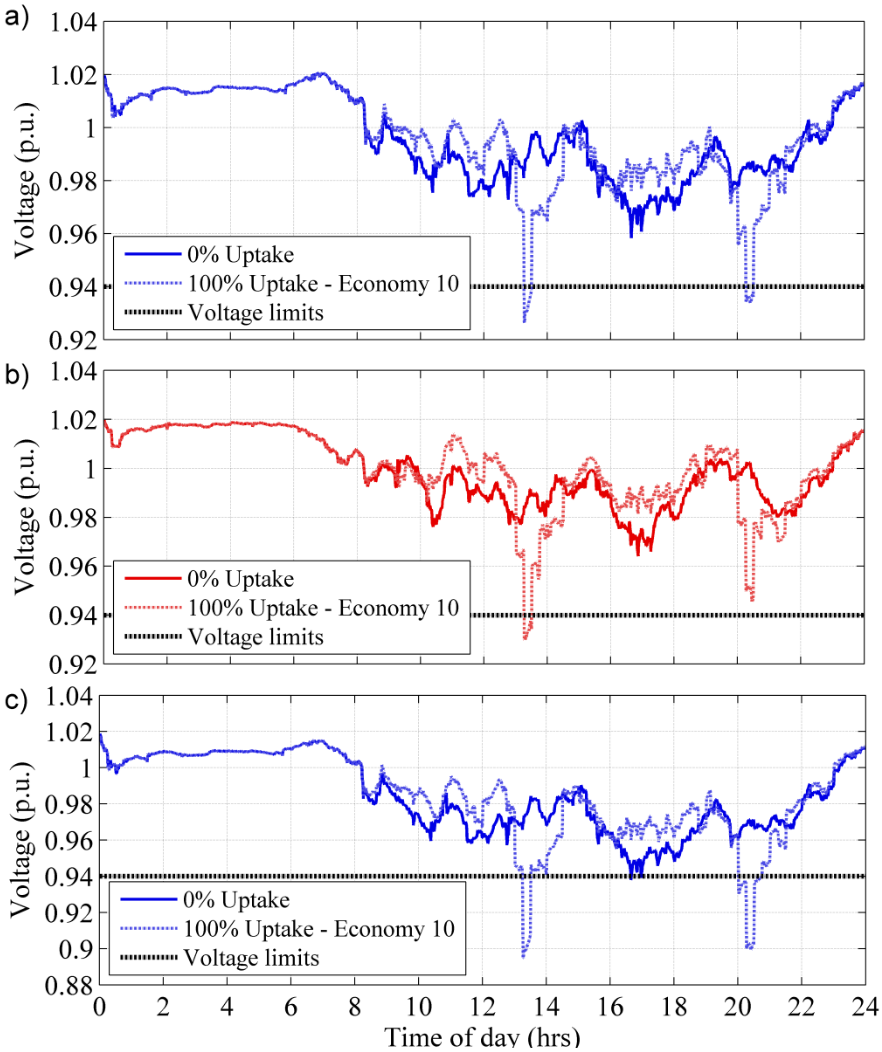


Figure 5.10: Voltage temporal profile at the LV feeder's end for a: (a) Winter day / medium length MV feeder; (b) Summer day / long length MV feeder; (c) Winter day / long length MV feeder.

5.4.2 Network support provided by regional controller

In this scenario the regional controller coordinates the operation of smart appliances (WM, DW, TD) with the objective of maximising the users financial benefits, while ensuring the network parameters remain within the operational limits.

5.4.2.1 Network thermal constraints

In Section 5.4.1 it was shown that one of the elements of the network at risk of overloading is the 11/04 kV transformer T3. Figure 5.11 shows the performance of the regional controller which implements a thermal constraint at the transformer. With the regional controller, the demand recorded at the transformer remains below the transformer nominal rating. For comparison the profile obtained without the regional controller from Figure 5.4 is also shown.

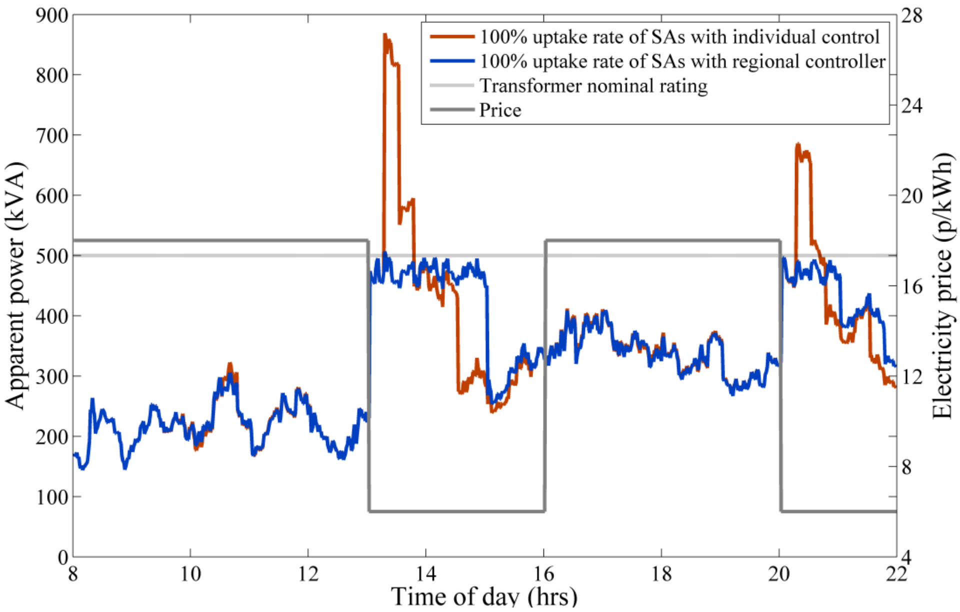


Figure 5.11: Performance of the regional controller with thermal limits (nominal rating) at the transformer T3.

In the case of individual control strategy for smart appliances, the demand at the transformer T3 exceeds its nominal rating for Economy 10 and RTP tariff, as shown in Figure 5.5. For these tariffs, the simulations were re-executed to test the coordinated control strategy, with the regional controller imposing a network constraint equal to the transformer nominal rating. The results, shown in Figure 5.12, demonstrate the regional controller limits effectively the peak demand on the LV network to a value below the transformer rating.

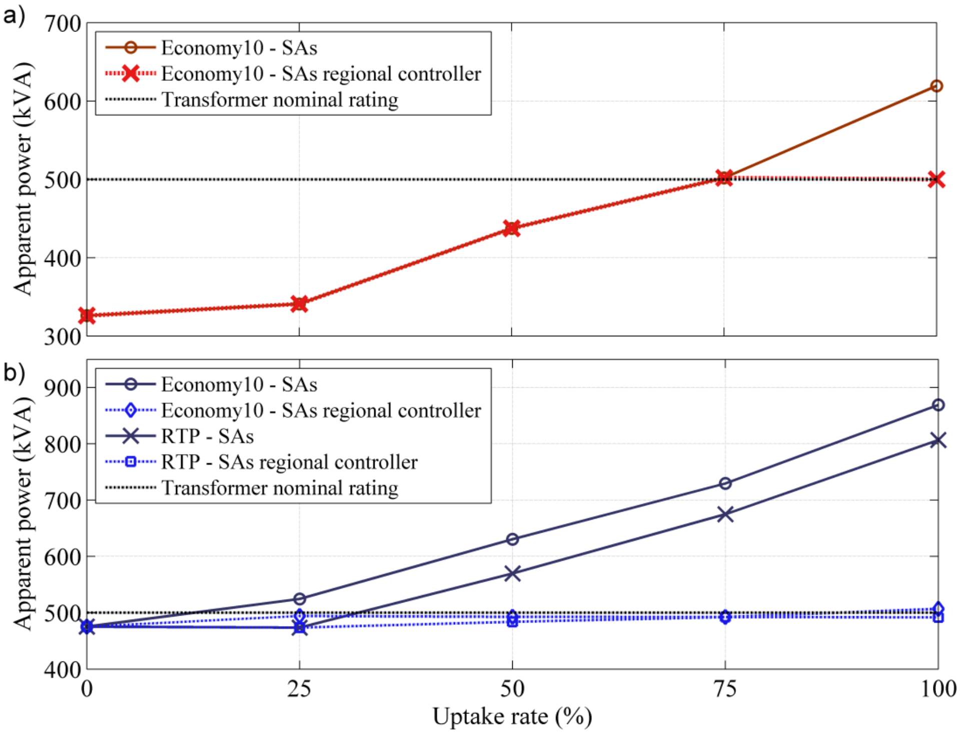


Figure 5.12: Effects of the regional controller with thermal limits on the peak demand recorded at transformer T3: (a) Summer; (b) Winter.

The change in demand due to the capacity constraint at transformer T3 implemented by the regional controller influences the branch loading, as shown in Figure 5.13. Due to the regional controller the maximum loadings of cable sections, from node 40011 to 40015, which were overloaded for the individual control strategy, decreases below their rated capacities. A decrease is recorded for the cable section closest to the substation, from node 40001 to 40002, to a value of 109% of its capacity.

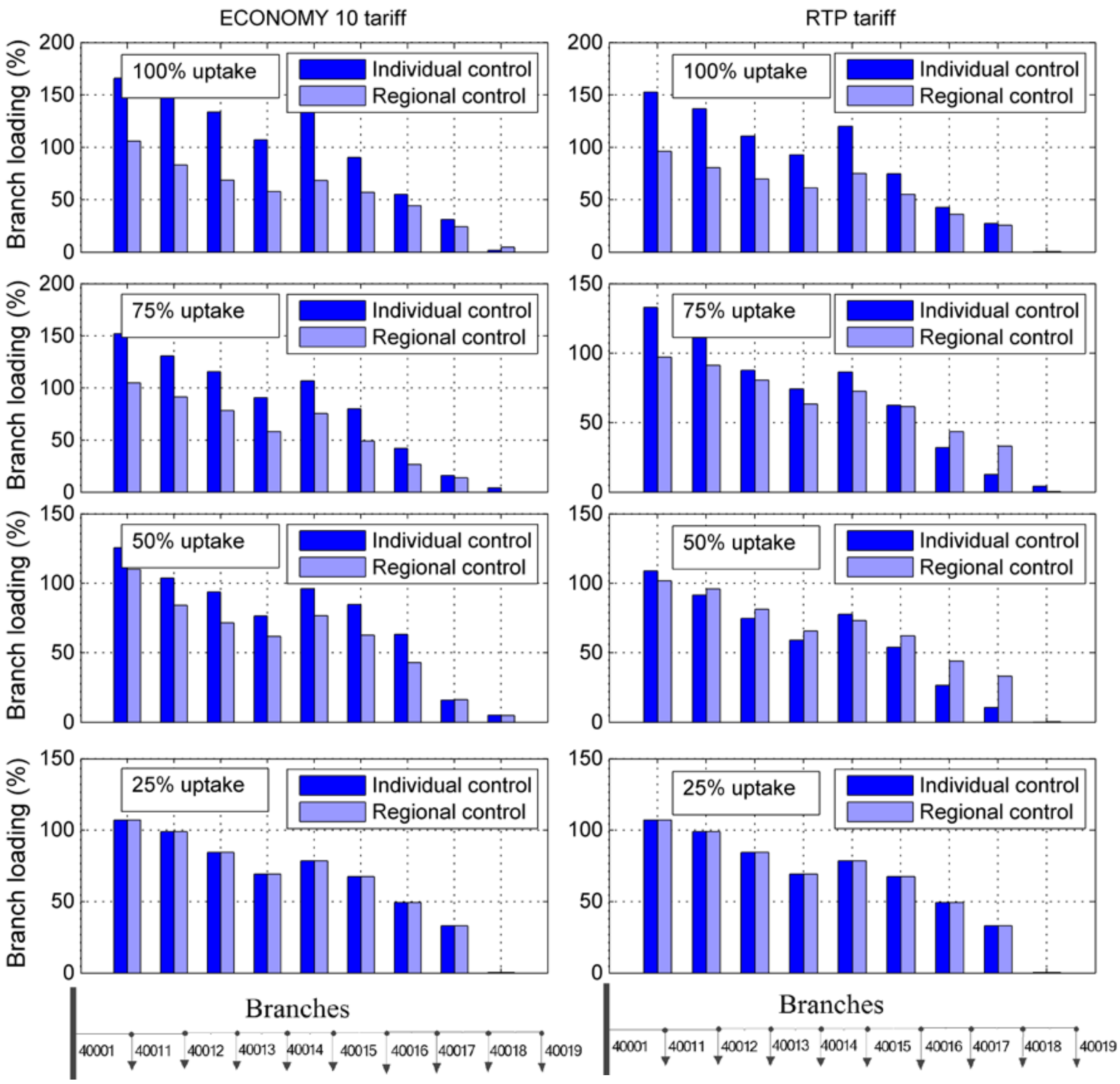


Figure 5.13: LV feeder branch loading at winter peak load times with different smart appliances uptake levels.

The regional controller with capacity constraint delays the cycle of some appliances from the time interval which yields the lowest price. Therefore, a number of users of smart appliances will save less money as compared with the case where no capacity constraint is imposed. Table 5.1 shows the reduction in the total savings on the electricity price for different values of the capacity constraints imposed by the regional controller on the demand at transformer T3. With a capacity constraint equal to the transformer thermal rating of 500 kVA, the reduction in savings is minimal, the users retaining 97.6 to 99.9% of the maximum savings.

The regional controller can impose a capacity constraint (i.e. 450-400 kVA) that will cap the demand at values lower than the initial peak demand (0% uptake of SAs), as shown in Table 5.1. The newly created capacity can be utilised to integrate heat pumps and electric vehicles or accommodate future demand growth on the network. The smooth price curve of the RTP tariff allows the load that cannot be supplied in the time interval which yields the lowest price to be dispersed over the adjacent intervals without a sharp savings reduction. However, for Economy 10 tariff, the steep transitions between off-peak and peak intervals cause a significant reduction in savings.

Table 5.1: Impact of the regional controller with capacity constraints on the total financial benefit of smart appliances users in the LV network.

	Percentage of maximum SAs savings (%)									
Limit (kVA) / **Tariff**	*Summer*					*Winter*				
	-	*500*	*300*	*275*	*250*	*-*	*500*	*450*	*400*	*375*
Economy 10	100	99.9	99.8	85.2 7	66.1	100	97.6	93.1	77.3	67.8
RTP	100	99.9	99.7	98.5	98	100	99.9	99.8	99.1	98.8

5.4.2.2 Network voltage constraints

In Section 5.4.1 it was shown that for a high uptake of smart appliances with individual control there is a risk the voltage magnitude across the network could sustain significant drops. The performance of the regional controller which implements a voltage constraint was investigated for the loading conditions previously found in Section 5.4.1 to trigger voltage drops below the admissible voltage limit.

The scenarios presented in Figure 5.14 have the following assumptions in common: the smart appliance uptake is 100%, the voltage at the MV busbar of the primary substation is set to 1 p.u. and the tariff considered is Economy 10. The regional controller schedules just the smart appliances on the LV network, while the rest of the smart appliances from the MV network have individual control.

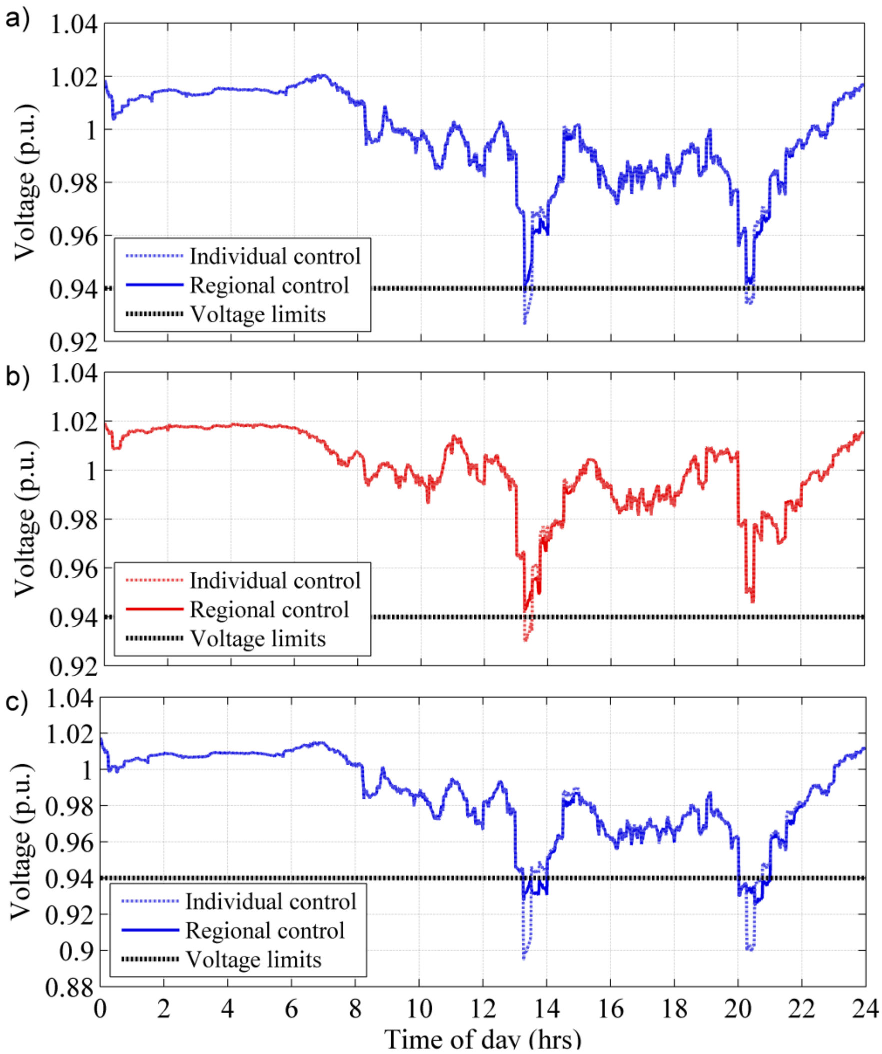


Figure 5.14: Voltage temporal profile at the LV feeder's end considering 100% uptake of SAs and a regional controller with voltage constraints for a: (a) Winter day / medium length MV feeder; (b) Summer day / long length MV feeder; (c) Winter day / long length MV feeder.

In Figure 5.14 (a) the LV network is connected to a medium length MV feeder, and the network demand is representative for the winter season. The controller keeps the voltage magnitude at the LV consumer connected farthest from the substation above the minimum limit. A successful result is also obtained when the LV network is connected to a long length MV feeder, with the demand being representative for the summer season, as shown in Figure 5.14 (b). In the winter season the voltage at the LV busbar of the secondary substation, which is mostly dependent on the voltage of the MV feeder, is significantly deteriorated due to the smart appliances with individual control from the MV network. The regional controller has not enough demand on the LV network to shift from the periods where the substation voltage is low in order to keep the voltage above the minimum limit. However the voltage profile is significantly improved compared to the case without voltage constraint, as shown in Figure 5.14 (c).

5.4.2.3 Network thermal and voltage constraints

The performance of the regional controller which implements both the thermal and voltage constraints was compared in Figure 5.15 with the performances of the previous constraints strategies. Each point characterizes the voltage recorded at the farthest customer from the substation and the corresponding demand at the MV/LV transformer during one minute. The regional controller with both constraints displays similar results with the case when only the thermal constraint is enabled.

In Figure 5.15 the points around the thermal rating are still within the voltage limits, while the points around the voltage limit correspond to a much higher demand than the transformer rating. The thermal rating of the MV/LV transformer is the most limiting constraint in the operation of smart appliances in the network.

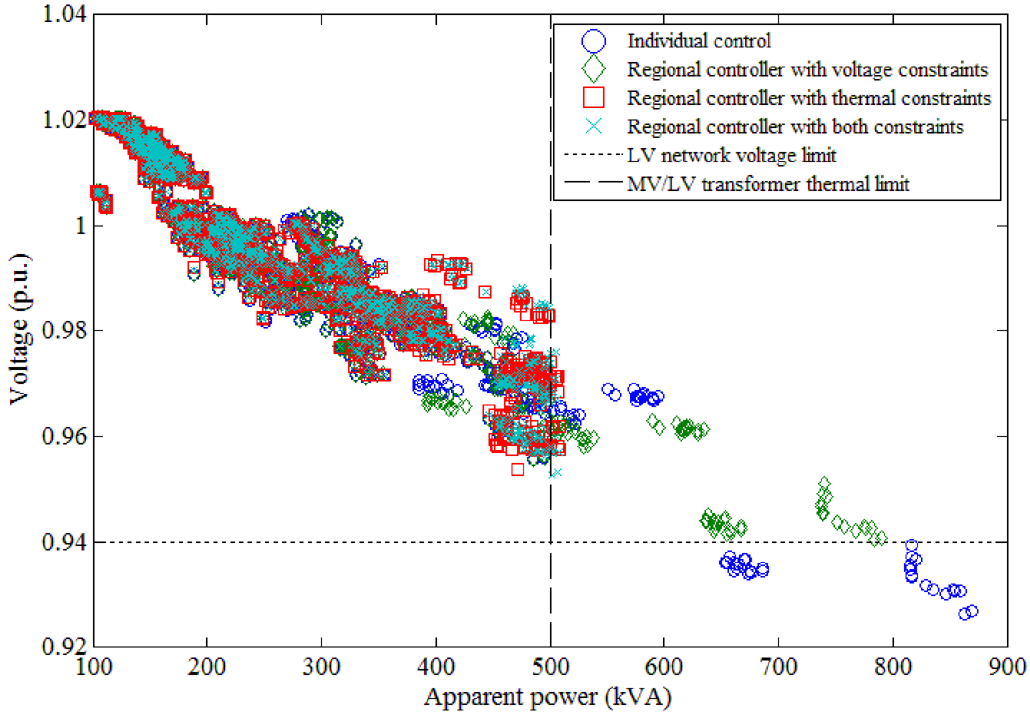


Figure 5.15: Evaluation of different control strategies for SAs by observing the T3 loading and voltage at the farthest customer from the substation over a time span of a day in winter.

A performance outline of the regional controller for smart appliances which implements three different constraints is given in Table 5.2. It has been observed that, while implementing the thermal constraints, the regional controller ensures the voltage remains above the minimum voltage limit. However, the minimum voltage constraint does not guarantee that the thermal ratings are not exceeded.

Table 5.2: Capability of the regional controller for smart appliances with different network constraints to keep the LV network parameters within the operational limits.

Constraints \ Network parameters	*Thermal*	*Voltage*
Thermal transformer rating	√	√
Minimum voltage	x	√
Thermal and voltage	√	√

5.5 Discussion

Smart appliances (WM, DW and TD) reacting to a multiple-rates electricity tariff deteriorate the temporal diversity in the appliance utilisation. The results of the simulation on a high customer density urban network indicate that, starting from an uptake of smart appliances of 25% in winter and 75% in summer, the thermal rating of a number of distribution circuits was exceeded for tariff such as Economy 10 and RTP. Unlike the Economy 10 and RTP, Economy 7 does not create issues for the operation of distribution networks. However, as we've seen in Chapter 3, Table 3.7, it is also the tariff which yields the least amount of savings from smart appliance utilisation. The stressed elements of the network are the MV/LV transformer and sections of the LV underground cable close to the secondary substation. While the duration of the overloads is less than one hour each day, their magnitude can reach 70% of the circuit rating in winter if all the households adopt smart appliances.

During the overloads the network voltage profile deteriorates. However, for most of the situations, the voltage across the network remains above the current admissible minimum voltage of 0.94. In the future, the UK voltage regulation will move towards the wider EU standard of ±10% around the nominal voltage of 230V [120], to which the appliance manufacturers already adhere to. It is only for a situation with 100% uptake of appliances and for the LV network connected at the end of the longest MV feeder that the LV voltage magnitude reaches 0.9 p.u. A concern that the low voltage magnitude raises is the disconnection of the small scale embedded generators (SSEGs), which are required to trip at a voltage lower than 0.9 p.u. [121]. A solution to the voltage issue was to increase the set point of the primary substation tap changer which controls the voltage at the MV busbar from 1 p.u. to the maximum of 1.06 p.u. The solution was tested successfully for the passive network, however further investigation is necessary in the case of MV feeders with high uptake of SSEGs, where the high value of the voltage at the primary substation might cause the voltage on the feeders to rise beyond the allowed range. Other solutions which should be tested in future work include the connection of capacitors at the end of the MV feeders and increasing the voltage rise at the MV/LV substation from the tap changer.

A regional controller for smart appliances is introduced as an alternative to uprating the distribution circuits and voltage regulation. The controller effectively limits the peak demand and the voltage drop on the LV network. For the selected distribution network, the controller imposing a limit on the demand at the MV/LV transformer equal to its rating is sufficient to keep the voltage within the operational limits. The use of a regional controller will reduce the potential savings from smart appliances for some users. Calculated at LV network level, the reduction resulting from a capacity constraint equal to the transformer rating is very small. With so many variables, the process by which the users can incur a reduction in their savings can be classified as random. This could result in the DNO paying a fixed incentive or a rebate to all the smart appliances users to cover the reduction in their savings. The regional controller can also create new capacity on the distribution network. However by doing this the users would have their savings reduced; in the case of the Economy 10 the reduction is significant.

Chapter 6

Conclusions and future work

Summary:

The conclusions of the research carried out are highlighted in this chapter. The key contributions are outlined, and future research possibilities are identified.

6.1 Conclusions

Demand response (DR) is amongst the solutions supported by policies in the UK and across the world aimed at greenhouse gas emission reduction. DR programmes for residential customers have been in use for many years, exclusively targeting large household loads such as heating and air conditioning units. However, with the expected deployments of smart meters, there is an opportunity to reach many more participants and engage a larger range of appliances in more efficient manner.

In this research, the potential roles of smart appliances (washing machines WM, dishwashers DW or tumble dryers TD) in supporting the power system operation were investigated. The main stakeholders of the smart appliance technology: appliance users, transmission system operators (TSOs), and distribution network operators (DNOs), were considered.

A smart appliance model was required to simulate different DR scenarios. A review on the modelling of smart appliances operation revealed a number of mathematical tools, from which an optimisation solution was selected. This work improves on previous research by modelling the operation of appliances with two load management features, cycle delay and cycle interruption. The load profile of the appliance’s cycle is partitioned with constant power phases of 15 minutes each. The shifting algorithm used to find the optimum schedule of one or more appliances employs linear programming implemented in IBM CPLEX software. The smart appliance model is generic and is applicable to any country. However, the user behaviour considered in this work such as the appliances’ *start times* and the users’ *maximum delays* is representative for the UK population.

6.1.1 Smart appliances users

A simulation was developed to determine the electricity cost savings for a household subscribing to electricity tariffs having multiple-rates. The cost savings were obtained by shifting the appliances from time intervals with high price to low price intervals. The electricity prices considered were two Time of Use (TOU) tariffs (Economy 7 and Economy 10) which are offered by suppliers in the UK. In addition, a Real Time Pricing (RTP) tariff was designed based on the wholesale electricity price.

The effects on the cost savings of three parameters involved in the operation of smart appliances were investigated. The simulations showed that the *maximum delay* set by the user for the appliance to be delayed provided the highest influence. For Economy 10, the cost savings varied between 0%, if the user starts the appliance immediately, and 42%, if the user allows five hours of delay. A saturation point is reached after a certain number of hours, from where the cost savings remain constant with the increase of *maximum delay*. The second parameter, *number of residents per household,* influences the cost savings; however, because the appliances are shared between residents, the interdependency was not directly proportional. The third parameter, the *maximum cycle interruption,* provided the lowest impact on the cost savings, that is up to 0.62%.

The annual cost savings for a group of 1000 houses was investigated. The highest value of 28.62% savings from the cost of the electricity consumed by smart appliances, equivalent to 7% of the total household annual electricity bill, was recorded for Economy 10. Two financial tools, payback period and net present value, were used to weight the savings from smart appliances with the estimated costs of implementing the smart appliance technology. In most of the cost scenarios, the payback period was under three years, which is the maximum expected by the users. A positive net present value was also obtained. Both analyses highlighted that smart appliances are considered a good investment.

6.1.2 Reserve services from smart appliances

The level of reserve, either generation or demand reduction, required by TSOs is expected to increase with the connection of more and more renewable sources. The feasibility of using smart appliances as operating reserve in Great Britain's power system balancing services was assessed. The present level of operating reserve was estimated for the GB power system. The current participation of demand side in the *Fast Reserve* and *Short Term Operating Reserve (STOR)* was discussed. A framework outlining the actors and the communication infrastructure required for smart appliances to respond to *STOR* instructions was introduced. Within this framework, the instruction is sent from the TSO to the electricity supplier which will increase the electricity rate for the duration of the instruction. The appliances will receive the increased rates and automatically delay their start, resulting in a demand reduction.

A multi-time step simulation which can determine the aggregated response of appliances from a number of households to a *STOR* instruction was introduced. A case study on 1000 households representative for the UK housing stock was carried out. The results showed that the response varies over 24 hrs and depends on the user behaviour and the electricity tariff to which the households are subscribing. After the reserve instruction ends a load recovery period is generated. Its peak demand is mitigated by a random start offset.

The STOR capacity was estimated at system level assuming that 20% of the households in GB have adopted the smart appliance technology. The level of STOR from smart appliances varies over 24 hrs and can reach up to 54% of the current requirements of

STOR or 1.5 GW. The yearly revenue from smart appliances participating in STOR was estimated at £47M, while the GHG emission reduction was estimated at 10.7 ktCO_2 per year.

6.1.3 Distribution network operation with smart appliances

Distribution networks have been designed considering temporal diversity in the appliances utilisation, since different customers start their appliances at different times. When considering smart appliances, the diversity factor is reduced at low price intervals due to the synchronisation of the appliances starting times. A simulation was developed to study the distribution network operation with smart appliances and multiple-rates tariffs. It incorporates a module which runs sequential power flow analysis in IPSA software to obtain the branch circuit loadings and nodal voltages throughout the day. The distribution test system includes a low voltage (LV) network connected to a medium voltage (MV).

In the case of smart appliances (at an uptake rate of 25% in winter and 75% in summer) with individual control the first network elements which reached their thermal capacity were the MV/LV transformer and the LV underground cables close to the substation. The MV network has enough spare capacity to cope with the full adoption. However, the loading at the primary substation surpasses the maximum imposed by the 'N-1' security condition for an uptake rate higher than 75% during winter days. The voltage on the MV and LV network does not drop below the minimum admissible limits for the majority of the scenarios. However, at 100% uptake rate the voltage at the end of the longest MV feeder and on the LV connected to it reaches 0.9 p.u.

A controller for smart appliances is introduced at the LV network as an alternative to network reinforcement. Three types of control strategies were tested, imposing: a voltage constraint, a capacity constraint, and both constraints at once. The last two strategies are the most efficient since they solve the thermal overloads as well as the voltage issues. The regional controller can also create new capacity on the distribution network by imposing a capacity constraint below the peak demand measured before the uptake of smart appliances.

6.2 Summary of contributions

The contribution of this work includes:

- Advancements were made to the way the operation of smart residential devices is modelled using optimisation, enabling the testing of load shifting and interruption features for devices with complex load profile. (Chapter 2)

- A detailed analysis showed that smart appliances (WM, DW, TD) in conjunction with Time of Use tariffs can offer the user sufficient financial incentive to justify their adoption. (Chapter 3)

- Concepts for the integration of smart appliances in the business models of different actors in the energy sector are introduced. (Chapter 4)

- At system level, the magnitude of the load reduction achieved by the smart operation of appliances is significant, covering, at times, up to half of the current operating reserve requirements of the GB power system. (Chapter 4)

- While smart appliances operated with individual control can overload the distribution network circuits and equipments, when coordinated by a regional controller, they can create new capacity on the distribution network. (Chapter 5)

6.3 Future work

6.3.1 Use of smart appliances in operating reserve and frequency support

This study investigated the maximum level of reserve obtainable from smart appliances. The future work should continue by investigating methods by which the TSO can control the level of demand response obtained from smart appliances. The aim is to obtain from the aggregated demand a similar flexibility to one of a power plant, e.g. output ramp-up or ramp-down capabilities. Segmenting a pool of consumers which own smart appliances by issuing reserve instructions at different times and selecting to how many consumers the reserve instructions are sent could improve the control accuracy of the response. Another important aspect could be to examine if the availability of DR after consecutive reserve instructions decreases, a process known as DR fatigue, and possible remedial actions.

In addition to being utilised for providing operating reserve, smart appliances could be used for frequency support services. However, because of the essential role these services play in the security of electricity supply, they require from the participants not to be involved in more than one service. Further research is needed to investigate the coordination of smart appliances to provide various services effectively.

6.3.2 Use of smart appliances in distribution network operation

In this study a passive distribution network was considered. Future utilisations of the SAs controller could be in the integration of distributed energy resources, such as rooftop photovoltaic panels (PVs). The controller will shift the operation of appliances at the time of peak PV output, reducing the risk of breaches of the upper voltage limit. To be more effective, the SAs control should coordinate its actions with the voltage control strategy of the On-Load-Tap-Changers.

Another service for distribution network operators that smart appliances could provide is post fault handling. The loads connected to HV and MV networks are supplied by at least two circuits, each one capable to sustain the peak demand in case the other becomes faulty. By reducing the aggregated demand of smart appliances after the circuit outage, the extra capacity could be released and used in normal operation.

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A. Java code for appliances scheduling algorithm

```
package homeenergymanagement;

/* Copyright 2015 Silviu Nistor
 * The code schedules appliances according to price using CPLEX software
 */
import ilog.concert.*;
import ilog.cplex.*;
import java.util.Arrays;

public class Schedule {


private double[] powerResultVector;    // output in [Watts] with length of the
optimisation window [15 minutes resolution]


public Schedule( int[] vectorApl, int optimWindow, double[] price, int
interuption ) throws IloException{
  // input vectorApl gives the number of appl to be scheduled e.g. [20 Washing
Machines , 10 Dish Washer , 12 Tumble Dryer]
  // input optimWindow the length of the optimisation window e.g.32=32x15 mins
  // input price has the length of the optimisationWindowInervals
  // input interruption is the maximum interruption parameter between
appliance phases


  /*--------------------------------------------------------*/
  int intrp=interuption;
  int aWm= vectorApl[0]; // number of washing machines
  int aDw= vectorApl[1]; // number of dish washers
  int aTd= vectorApl[2]; // number of tumble dryers
  int virtWmNo=7;  // number of power phases that constitute a washing machine
  int virtDwNo=8;  // number of power phases that constitute a dish washer
  int virtTdNo=6;  // number of power phases that constitute a tumble dryer
  double[] consumption;    // intermediary output
  double[] binaryResult;   // intermediary output
  int[] powerWm= {100, 2000, 900, 100, 100, 300, 50}; // [Watts]
  int[] powerDw= {80, 2000, 80, 80, 80, 2000, 300, 150};  // [Watts]
  int[] powerTd= {2000, 2000, 2000, 1600, 1300, 940};     // [Watts]
  int[]  hour = makeTimeIntervalVector(optimWindow); // subrutine written at
the end of the class
  double[] powerResultMatrix= new double[(aWm*virtWmNo+ aDw*virtDwNo+
aTd*virtTdNo) *optimWindow];// intermediary output: power matrix after
optimization

  IloCplex cpm = new IloCplex();  //new CPLEX optimisation model

  IloNumVar[] x = cpm.boolVarArray((aWm*virtWmNo+ aDw*virtDwNo+ aTd*virtTdNo)
*optimWindow);  //define variables of the optimization model
        /*  ---------the virtual appliance no
         * -       x11  x21 ... xa1_1 next appliance : x(a1+1)_1 ...
         * -       x12  x22 ... xa1_2 xa2_2
         * -       x13  x23 ... ....
         * optim   x14  x24 ... ...
         * inter   .... ... ... ...
         * val     ...  ... ... ...
         * -       ...  ... ... ...
         * -       x1m  x2m ... xa1_m        */

   UserDelayTimes del = new UserDelayTimes(vectorApl); // subroutine
generating the Maximum User delay
  int[] delayTimes=del.getMaxDelayTime(); // vector with the length of
aWm+aDw+aTd and represents the Maximum User delay: [wm1 wm2.....wm_aWm dw1 dw2
dw3....dw_aDw td1 td2....td_aTd]
```

```
  /*--------Washing machine constraints -----------*/
  //  Add washing machines constraints from Eq (2.4) and (2.5)
  for( int aplNo= 0; aplNo<aWm; aplNo++) // Go through each washing machine
     {  for( int v=0; v< virtWmNo-1 ; v++) // Go through each power phase of 
the washing machine
       {   IloLinearNumExpr exprConWm12 = cpm.linearNumExpr();// Build a 
linear expression in the optim model
           for (int i=0; i<optimWindow; i++)// Go through each variable of the 
power phase vector with the length of the optimisation window
              { exprConWm12.addTerm(hour[i],x[i+optimWindow*(v+1)+ 
optimWindow*virtWmNo*aplNo]);   //
                exprConWm12.addTerm(-hour[i], x[i+optimWindow*v+ 
optimWindow*virtWmNo*aplNo]);
               }
           cpm.addGe(exprConWm12, 1); // constraint imposing the order of the 
appliances power model
           cpm.addLe(exprConWm12, intrp); // constraint imposing maximum 
interruption between appliances power phases
        }
       }

 // Add washing machines constraint from Eq (2.6)
 for( int aplNo= 0; aplNo<aWm; aplNo++)
    {  for( int v=0; v< virtWmNo ; v++)
      { IloLinearNumExpr exprConWm3 = cpm.linearNumExpr();
          for (int i=0; i<optimWindow && i<virtWmNo+ delayTimes[aplNo]; i++){ 
//virtWmNo+delayTimes[aplNo]
          exprConWm3.addTerm(1,x[i+optimWindow*v+ optimWindow* virtWmNo* 
aplNo]);          }
          cpm.addEq(exprConWm3,1); // comstraints imposing user maximum delay
              }
       }

 /*---Dish washer constraints: the same commentaries as for washing machine --
--*/
  for( int aplNo= 0; aplNo<aDw; aplNo++)
     {  for( int v=0; v< virtDwNo-1 ; v++)
           { IloLinearNumExpr exprConDw12 = cpm.linearNumExpr();
             for (int i=0; i<optimWindow; i++)          {
                 exprConDw12.addTerm(hour[i],x[i+ optimWindow*(v+1)+ 
optimWindow*virtWmNo*aWm+optimWindow*virtDwNo*aplNo]);
                  exprConDw12.addTerm(-hour[i], x[i+optimWindow*v+ 
optimWindow*virtWmNo*aWm+ optimWindow*virtDwNo*aplNo]);  }
           cpm.addGe(exprConDw12, 1);      //Eq (2.4)
           cpm.addLe(exprConDw12, intrp);  //Eq (2.5)
           }
       }

 for( int aplNo= 0; aplNo<aDw; aplNo++)
    { for( int v=0; v< virtDwNo ; v++)
      { IloLinearNumExpr exprConDw3 = cpm.linearNumExpr();
        for (int i=0; i<optimWindow && i<virtDwNo+delayTimes[aWm+aplNo]; i++){
             exprConDw3.addTerm(1,x[i+optimWindow*v+ optimWindow* 
virtWmNo*aWm+ optimWindow*virtDwNo*aplNo]); }
             cpm.addEq(exprConDw3,1);   //  Eq (2.6)
            }
     }

/*---Tumble Dryer constraints:same commentaries as for washing machine---*/
 for(int aplNo= 0; aplNo<aTd; aplNo++)
    { for( int v=0; v< virtTdNo-1 ; v++)
       {IloLinearNumExpr exprConTd12 = cpm.linearNumExpr();
        for (int i=0; i<optimWindow; i++)
         {exprConTd12.addTerm(hour[i], x[i+optimWindow*(v+1)+ optimWindow* 
virtWmNo*aWm+ optimWindow*virtDwNo*aDw+ optimWindow*virtTdNo*aplNo]);
          exprConTd12.addTerm(-hour[i], x[i+optimWindow*v+ optimWindow* 
virtWmNo*aWm+ optimWindow*virtDwNo*aDw+ optimWindow*virtTdNo*aplNo]); }
```

```
            cpm.addGe(exprConTd12, 1);   //  Eq (2.4)
            cpm.addLe(exprConTd12, intrp);  //  Eq (2.5)
              }
           }

     for( int aplNo= 0; aplNo<aTd; aplNo++) {
         for( int v=0; v< virtTdNo ; v++) {
          IloLinearNumExpr exprConTd3 = cpm.linearNumExpr();
           for(int i=0; i<optimWindow && i<virtTdNo+delayTimes[aWm+aDw+aplNo] ;
i++){
              exprConTd3.addTerm(1,x[i+optimWindow*v+ optimWindow* virtWmNo*aWm+
optimWindow*virtDwNo*aDw+ optimWindow*virtTdNo*aplNo]);
              } cpm.addEq(exprConTd3,1);   //  Eq (2.6)
            }
           }

     /*-------Create objective function Eq(2.3)------------*/
     IloLinearNumExpr exprObj= cpm.linearNumExpr();
     for( int aplNo= 0; aplNo<aWm; aplNo++) // aplNo is an index that shows how
many of the Washing Machines have been integragted
        {for( int v=0; v< virtWmNo ; v++) {
           for(int i=0; i<optimWindow; i++)
              {exprObj.addTerm(price[i]*powerWm[v], x[i+optimWindow*v+
optimWindow*virtWmNo*aplNo] );    }
              }
           }
     for( int aplNo= 0; aplNo<aDw; aplNo++) {
        for( int v=0; v< virtDwNo ; v++) {
             for (int i=0; i<optimWindow; i++)
              {exprObj.addTerm(price[i]*powerDw[v], x[i+optimWindow*v+
optimWindow*virtWmNo*aWm+ optimWindow*virtDwNo*aplNo] ); }
               }
           }
     for( int aplNo= 0; aplNo<aTd; aplNo++) {
        for( int v=0; v< virtTdNo ; v++) {
         for (int i=0; i<optimWindow; i++)
            {exprObj.addTerm(price[i]*powerTd[v], x[i+optimWindow*v+
optimWindow*virtWmNo*aWm+ optimWindow*virtDwNo*aDw+
optimWindow*virtTdNo*aplNo] );}
               }
           }

     /*-------Add objective function to the optimisation model--------*/
     IloObjective obj=cpm.minimize(exprObj);
     cpm.add(obj);
     cpm.setOut(null); //suppresses the output of CPLEX to Java Output

     /*-------Solve the optimisation------------*/
     cpm.solve();
     binaryResult = cpm.getValues(x);
     cpm.end();

     // Code transforms the binary solution to power consumption
     for( int aplNo= 0; aplNo<aWm; aplNo++)
      {  for( int v=0; v< virtWmNo ; v++) {
         for (int i=0; i<optimWindow; i++)
            {powerResultMatrix[i+optimWindow*v+ optimWindow*virtWmNo*aplNo] =
(int) (powerWm[v] * binaryResult[i+optimWindow*v+ optimWindow*virtWmNo*
aplNo]) ;
                           }
                     }
           }
         for( int aplNo= 0; aplNo<aDw; aplNo++) {
            for( int v=0; v< virtDwNo ; v++) {
             for (int i=0; i<optimWindow; i++)
             {powerResultMatrix[i+optimWindow*v+ optimWindow*virtWmNo*aWm+
optimWindow*virtDwNo*aplNo] = (int) (powerDw[v]* binaryResult[i+
optimWindow*v+ optimWindow*virtWmNo*aWm+ optimWindow*virtDwNo*aplNo]) ;
```

```
                    }
                }
            }
        for( int aplNo= 0; aplNo<aTd; aplNo++) {
           for( int v=0; v< virtTdNo ; v++) {
               for (int i=0; i<optimWindow; i++)
                {powerResultMatrix[i+optimWindow*v+ optimWindow*virtWmNo*aWm+
optimWindow*virtDwNo*aDw+ optimWindow*virtTdNo*aplNo] = (int) (powerTd[v] *
binaryResult[i+optimWindow*v+optimWindow*virtWmNo*aWm+optimWindow*virtDwNo*aDw
+optimWindow*virtTdNo*aplNo]) ; }
                }
            }
 consumption  = powerResultMatrix;
 Sumation sumation= new Sumation();// subroutine SummationMatrix.SumMatrix
({1, 2, 3, 10, 11, 12} , 3)= {11, 13, 15}
 powerResultVector= sumation.SumMatrix(powerResultMatrix,optimWindow);
}

    // Subroutine used to create a time vector of the length of the
optimization window [1 2 3 ... 32]
    private int[] makeTimeIntervalVector(int optimWindow)  {
        int[] timeIntervalVector =new int[optimWindow];
        for(int i=0; i < optimWindow ; i++){
             timeIntervalVector[i]=i+1;  }
        return timeIntervalVector;
    }

    public double[] getPowerConsumption(){
    return this.powerResultVector;}   // OUTPUT of the Schedule.java

}
```

B. CREST domestic energy demand model

Realistic load profiles for individual households are used instead of average demand profiles in studies such as demand side response and utilisation of energy from photovoltaic panels [122]. The models that stochastically generate load profiles can be split roughly in two categories, according to the literature survey reported in [37]: 'top-down' or 'bottom-up' approach. For the former category, the simulation starts with an aggregated load profile from a number of houses that is decomposed to the appliance level. The models in the 'bottom-up' category require information about when people are at home, or occupancy, usually constructed from time-use data collected through surveys.

The CREST energy demand model belongs to the second category. Information of occupancy, collected from Time Use Survey 2000 in the UK, is introduced in a Markov-chain model that will stochastically generate occupancy profiles for a number of houses larger than the one in the survey. The Time Use Survey is also used to determine daily probability functions of particular activities, such as cooking and washing. The two stochastic daily profiles, occupancy and activities, are combined to create load profiles for each appliance. An example of a single run of the CREST model is given in Figure B-1.

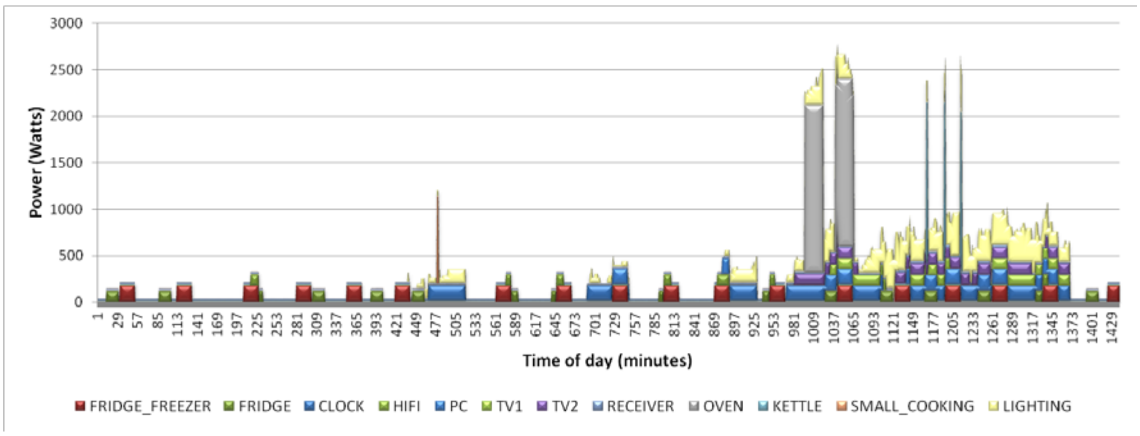

Figure B-1: Plot of a single run of the CREST model.

C. Design of a RTP tariff

There are no electricity suppliers in UK that offer RTP tariffs to domestic consumers at the moment. However, the UK energy regulator, Office of Gas and Electricity Markets (OFGEM), recognises that in a competitive market the consumer should be passed promptly the increase or decrease in the wholesale price of electricity, as in the case of RTP tariffs. Consequently, a RTP tariff was designed for this study starting from the components of the retail electricity price for a typical UK electricity supplier, listed in Table C-1.

Table C-1: Electricity retail price components for domestic sector in UK [123]**.**

Component	Approximate percentage	Description	Variable with time of day
Wholesale costs	63%	Wholesale energy costs;	Yes
		Supply costs: Billing, customer service, debt collections, support services, sales and marketing, staff costs; Profit margin.	No
Distribution charges	17%	Extra HV charges or HV/LV charges depending on the connection point.	Yes
Transmission charges	4%	Transmission Network Use of System (TNUoS) charging.	No
Environmental costs	10%	Carbon Emission Reduction Target (CERT); Community Energy Saving Programme (CESP); The Renewable Obligation (RO); Feed-in-Tariff Scheme (FITs).	No
Meter provision	1%		No
Valued added tax (VAT)	5%		No

OFGEM estimates that the wholesale costs account for 63% of the retail electricity price [123]. This category includes the fuel costs, electricity supplier costs and supplier profit margins. Although for the current arrangements a supplier buys its electricity through long term contracts with generators, in this study the wholesale cost of electricity is obtained from the APX Power UK spot market [124]. APX Power UK is an independent power exchange where day-ahead and within the day energy products are commercialised. The average spot price for 2012 was £45.2/MWh, which represents 28.7% of standard electricity price found in the survey presented in Table 3.1.

There are two types of distribution charges depending on the voltage level at the grid connection point of the consumer. If the connection is point is at a voltage above 22kV, the tariff is established by Extra High Voltage Distribution Charging Methodology (EDCM) [125]. If the connection point is at a voltage below 22kV the tariff is established by Common Distribution Charging Methodology (CDCM) [126]. Both these methods include time of use charging options. For this study the focus being the domestic sector, where the consumers are connected to LV, only the CDCM is of interest. Examples of CDCM charges are shown in Table C-2. For domestic customers DNOs have two tariffs: a flat tariff and a two rate tariff depending on the metering equipment. The two rate tariff reflects the pattern of loading on the distribution network. The “Domestic Two Rate”, the tariff selected for this study, has two rates: one for the time interval 09:00 to 20:30 and the second for 20:30 to 09:00 next day. An average “Domestic Two Rates” DNUoS tariff was calculated from the DNO tariffs published on the Energy Networks Association website.

Table C-2: Examples of distribution charges designed with CDCM for consumers connected to the LV network.

Consumer type	Unit rate 1 p/kWh	Unit rate 2 p/kWh	Unit rate 3 p/kWh	Fixed charge p/MPAN*/ day	Capacity charge p/kVA/day	Reactive power charge p/kVArh
Domestic Unrestricted	2.220	-	-	3.49	-	-
Domestic Two Rate	2.899	0.223	-	3.49	-	-
Small Non Domestic Unrestricted	1.978	-	-	4.42	-	-
Small Non Domestic Two Rate	2.731	0.301	-	4.42	-	-
LV HH Metered	8.847	0.783	0.103	16.79	1.99	0.302
LV Sub HH Metered	6.708	0.482	0.069	5.93	3.80	0.231

*Meter Point Administration Number

The suppliers are liable to pay TNUoS charges to National Grid, the UK transmission network operator, charge that will be passed to its customers. There are two types of charges that a supplier pays: half-hourly (HH) demand capacity charges and non half-hourly (NHH) energy charges. For the first case National Grid establishes the highest three peak average demand periods (equal to a half hour) of its system from November to February with a minimum of 10 days between periods. Then it multiplies the supplier measured demand at those time intervals with a regional rate (£/MW). For the second component of the TNUoS the sum of the energy consumed by the supplier in each day in the time interval 16:00 to 19:00 over one year is multiplied by a regional rate (p/kWh). These charges have the potential to manage the demand, as they offer incentives to reduce the demand at high peak periods. However, at the moment they are passed to the domestic consumer as a fixed charge.

From the tariff components listed in Table C-1 only the wholesale energy costs and the DNUoS charges were used in the variable (with the time of day) part of the RTP tariff, as they can easily be passed directly to consumers. The TNUoS charges are considered fixed.

An example of RTP tariff design is given in [127]. Equation (C.1) shows how the half-hourly rates are being calculated in this study.

$$c^h = \left(\propto + \beta \cdot \frac{c_{spot}^h}{c_{spot\_avg}} + \gamma \cdot \frac{c_{DNUoS}^h}{c_{DNUoS\_avg}} \right) \cdot c_{avg} \tag{C.1}$$

c_{spot}^hrepresents the wholesale electricity price; c_{DNUoS}^h is the DNUoS charge which varies with the time of day and depends if it is weekday or weekend; $\propto$ is a coefficient, equal to 0.53, that reflects the sum of the tariff components, from Table C-1, that are time invariable; c_{avg} is the average standard tariff found in Table 3.1; β is a coefficient, equal to 0.29, the percentage that the average spot market price takes in c_{avg} ; γ is equal to 0.18 and represents the percentage that the distribution charges takes in c_{avg}; $\frac{1}{c_{spot\_avg}}$ and $\frac{1}{c_{DNUoS\_avg}}$ will normalize the RTP tariff so that the average over one year to be equal to c_{avg}. Thus, for loads that are functioning constantly, such as fridges and refrigerators, there will be no changes in the cost of the electricity they consume in one year.

D. Parameters

Table D-3: Z-score table [128] **(Φ(z) is the probability of normal distributed variables to be bounded by z standard deviations).**

z	Φ(z)	z	Φ(z)	z	Φ(z)	z	Φ(z)	z	Φ(z)	z	Φ(z)
	0.		0.		0.		0.		0.		0.
0.01	5040	0.51	6950	1.01	8438	1.51	9345	2.01	9778	2.51	9940
0.02	5080	0.52	6985	1.02	8461	1.52	9357	2.02	9783	2.52	9941
0.03	5120	0.53	7019	1.03	8485	1.53	9370	2.03	9788	2.53	9943
0.04	5160	0.54	7054	1.04	8508	1.54	9382	2.04	9793	2.54	9945
0.05	5199	0.55	7088	1.05	8531	1.55	9394	2.05	9798	2.55	9946
0.06	5239	0.56	7123	1.06	8554	1.56	9406	2.06	9803	2.56	9948
0.07	5279	0.57	7157	1.07	8577	1.57	9418	2.07	9808	2.57	9949
0.08	5319	0.58	7190	1.08	8599	1.58	9429	2.08	9812	2.58	9951
0.09	5359	0.59	7224	1.09	8621	1.59	9441	2.09	9817	2.59	9952
0.1	5398	0.6	7257	1.1	8643	1.6	9452	2.1	9821	2.6	9953
0.11	5438	0.61	7291	1.11	8665	1.61	9463	2.11	9826	2.61	9955
0.12	5478	0.62	7324	1.12	8686	1.62	9474	2.12	9830	2.62	9956
0.13	5517	0.63	7357	1.13	8708	1.63	9484	2.13	9834	2.63	9957
0.14	5557	0.64	7389	1.14	8729	1.64	9495	2.14	9838	2.64	9959
0.15	5596	0.65	7422	1.15	8749	1.65	9505	2.15	9842	2.65	9960
0.16	5636	0.66	7454	1.16	8770	1.66	9515	2.16	9846	2.66	9961
0.17	5675	0.67	7486	1.17	8790	1.67	9525	2.17	9850	2.67	9962
0.18	5714	0.68	7517	1.18	8810	1.68	9535	2.18	9854	2.68	9963
0.19	5753	0.69	7549	1.19	8830	1.69	9545	2.19	9857	2.69	9964
0.2	5793	0.7	7580	1.2	8849	1.7	9554	2.2	9861	2.7	9965
0.21	5832	0.71	7611	1.21	8869	1.71	9564	2.21	9864	2.71	9966
0.22	5871	0.72	7642	1.22	8888	1.72	9573	2.22	9868	2.72	9967
0.23	5910	0.73	7673	1.23	8907	1.73	9582	2.23	9871	2.73	9968
0.24	5948	0.74	7704	1.24	8925	1.74	9591	2.24	9875	2.74	9969
0.25	5987	0.75	7734	1.25	8944	1.75	9599	2.25	9878	2.75	9970
0.26	6026	0.76	7764	1.26	8962	1.76	9608	2.26	9881	2.76	9971
0.27	6064	0.77	7794	1.27	8980	1.77	9616	2.27	9884	2.77	9972
0.28	6103	0.78	7823	1.28	8997	1.78	9625	2.28	9887	2.78	9973
0.29	6141	0.79	7852	1.29	9015	1.79	9633	2.29	9890	2.79	9974
0.3	6179	0.8	7881	1.3	9032	1.8	9641	2.3	9893	2.8	9974
0.31	6217	0.81	7910	1.31	9049	1.81	9649	2.31	9896	2.81	9975
0.32	6255	0.82	7939	1.32	9066	1.82	9656	2.32	9898	2.82	9976
0.33	6293	0.83	7967	1.33	9082	1.83	9664	2.33	9901	2.83	9977
0.34	6331	0.84	7995	1.34	9099	1.84	9671	2.34	9904	2.84	9977
0.35	6368	0.85	8023	1.35	9115	1.85	9678	2.35	9906	2.85	9978
0.36	6406	0.86	8051	1.36	9131	1.86	9686	2.36	9909	2.86	9979
0.37	6443	0.87	8078	1.37	9147	1.87	9693	2.37	9911	2.87	9979
0.38	6480	0.88	8106	1.38	9162	1.88	9699	2.38	9913	2.88	9980
0.39	6517	0.89	8133	1.39	9177	1.89	9706	2.39	9916	2.89	9981
0.4	6554	0.9	8159	1.4	9192	1.9	9713	2.4	9918	2.9	9981
0.41	6591	0.91	8186	1.41	9207	1.91	9719	2.41	9920	2.91	9982
0.42	6628	0.92	8212	1.42	9222	1.92	9726	2.42	9922	2.92	9982
0.43	6664	0.93	8238	1.43	9236	1.93	9732	2.43	9925	2.93	9983
0.44	6700	0.94	8264	1.44	9251	1.94	9738	2.44	9927	2.94	9984
0.45	6736	0.95	8289	1.45	9265	1.95	9744	2.45	9929	2.95	9984
0.46	6772	0.96	8315	1.46	9279	1.96	9750	2.46	9931	2.96	9985
0.47	6808	0.97	8340	1.47	9292	1.97	9756	2.47	9932	2.97	9985
0.48	6844	0.98	8365	1.48	9306	1.98	9761	2.48	9934	2.98	9986
0.49	6879	0.99	8389	1.49	9319	1.99	9767	2.49	9936	2.99	9986
0.5	6915	1	8413	1.5	9332	2	9772	2.5	9938	3	9987

Table D-4: Parameters used for calculation of the financial benefits of using smart appliances as operating reserve.

Parameter	Symbol	Value
Number of days	N_d	365
Number of STOR availability windows	N_a	3
Duration of availability windows	t_i	6.5, 2, 3 hrs
Available response from smart appliances in the availability window i (see Table 4.2)	r_i	843/895, 1146/1255, 584/526 MW
Average available response from smart appliances in the availability windows	$\bar{r}$	883 MW
Annual average calling time for STOR providers	N_u	70 hrs [129]
Availability payment	c_a	9.13 £/MW/hr [129]
Utilisation payment	c_u	232 £/MWh [129]

E. Distribution network

E.1 Approximate calculation of voltages for a radial LV feeder

Voltages on a distribution circuit can be obtained by knowing the active and reactive powers and the line impedance, as explained in [130]. A simple calculation of voltages from a two-busbar distribution circuit, illustrated in Figure E.1, is given in Equation (E.1).

$$V_R = V_S - (R + jX)\left[\frac{P - jQ}{V_S^*}\right] \tag{E.1}$$

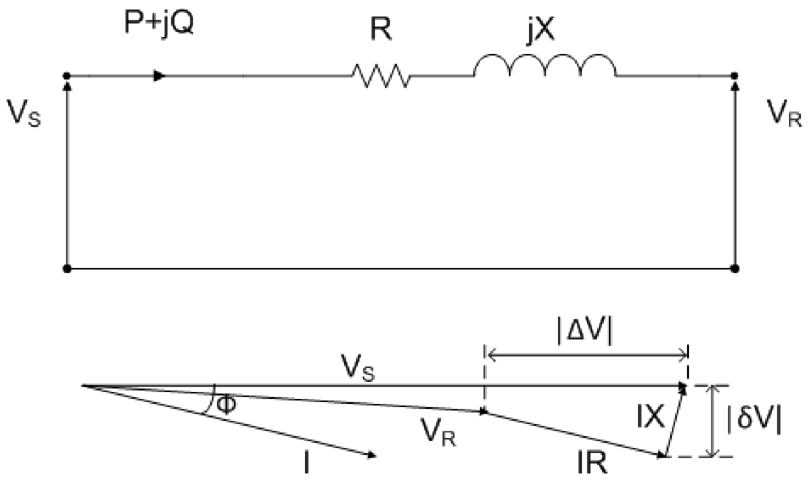

Figure E.1: Two-busbar distribution circuit: network equivalent and phasor diagram [130]**.**

Considering V_S as reference, Equation (E.1) is rewritten:

$$V_R = V_S - \left[\frac{RP + XQ}{V_S}\right] - j\left[\frac{XP - RQ}{Vs}\right] \tag{E.2}$$

For a distribution circuit where $R >> X$ the last term of Equation (E.2) ($|\delta V|$ in Figure E.1) can be neglected [130]:

$$V_R = V_S - \left[\frac{RP + XQ}{V_S}\right] \tag{E.3}$$

A simple radial feeder is illustrated in Figure E.2. To calculate the voltages at the end of the feeder without an iterative procedure an assumption is required. The powers at the sending end, P and Q, are known and can be approximated by Equation (E.4).

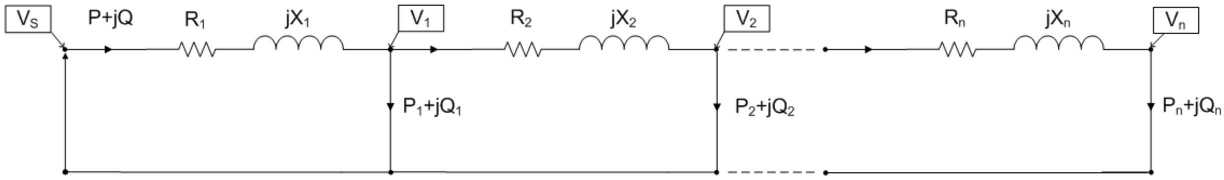

Figure E.2: Network equivalent of a radial distribution feeder

$$P \cong \sum_{i=1}^{n} P_i \ \ , \ \ Q \cong \sum_{i=1}^{n} Q_i \tag{E.4}$$

Applying (E.3) and (E.4) to the radial distribution feeder of Figure E.2, the voltage at Busbar 1 is given by (E.5) and at Busbar 2 by (E.6).

$$V_1 = V_S - \left[\frac{R_1\ (P_1 + P_2 + ..P_n) + X_1\ (Q_1 + Q_2 + ..Q_n)}{V_S}\right] \tag{E.5}$$

$$V_2 = V_1 - \left[\frac{R_2\ (P_2 + ..P_n) + X_2\ (Q_2 + ..Q_n)}{V_1}\right] \tag{E.6}$$

Substituting (E.5) in (E.6), the voltage at Busbar 2 is:

$$\begin{aligned} V_2 &= V_S - \left[\frac{R_1\ (P_1 + P_2 + ..P_n) + X_1\ (Q_1 + Q_2 + ..Q_n)}{V_S}\right] - \left[\frac{R_2\ (P_2 + ..P_n) + X_2\ (Q_2 + ..Q_n)}{V_1}\right] \\ &\cong V_S - \left[\frac{R_1\ (P_1 + P_2 + ..P_n) + R_2\ (P_2 + ..P_n) + X_1\ (Q_1 + Q_2 + ..Q_n) + X_2\ (Q_2 + ..Q_n)}{V_S}\right] \end{aligned} \tag{E.7}$$

Accordingly, the voltage at Busbar *n* can be approximated by the linear Equation (E.8).

$$\begin{aligned} V_n &\cong V_S - \left[\frac{R_1\ (P_1 + P_2 + \ldots + P_n) + R_2\ (P_2 + \ldots + P_n) + \cdots + R_n\ P_n)}{V_S}\right] - \cdots \\ &\quad - \left[\frac{X_1\ (Q_1 + Q_2 + \ldots + Q_n) + X_2\ (Q_2 + \ldots + Q_n) + \cdots + X_n\ Q_n)}{V_S}\right] = \\ &= V_S - \left[\sum_{i=1}^{n}\left(R_i \cdot \sum_{j=i}^{n} P_j\right) + \sum_{i=1}^{n}\left(X_i \cdot \sum_{j=i}^{n} Q_j\right)\right] \Big/ V_S \end{aligned} \tag{E.8}$$

Equation (E.8) was verified against a commercial software, IPSA Power. The value calculated is the voltage magnitude at the end of the LV feeder highlighted in Figure E.3. The error, listed in Table E-5 is acceptable for the objective of this study.

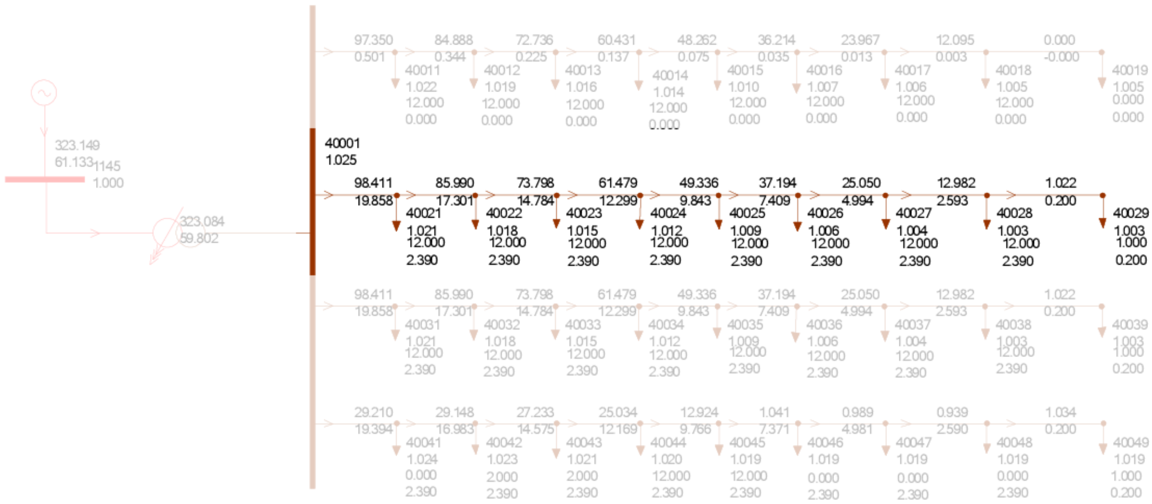

Figure E.3: Radial feeder in a LV network

Table E-5: Verification of the approximate voltage calculation

Method	Voltage at last connection point (p.u.)	Error (%)
IPSA (Fast-decoupled Newton-Raphson)	1.00251	-
Equation (E.8)	1.00297	0.046

E.2 Distribution network parameters

Table E-6. Branches parameters for the MV network (S_B=100MVA)

From Bus	To Bus	R (p.u.)	X (p.u.)	Rating (MVA)	From Bus	To Bus	R (p.u.)	X (p.u.)	Rating (MVA)
33	1100	0.04707	0.654	26.4	1132	1136	0.0542	0.0147	4.84
33	1100	0.04707	0.654	26.4	1137	1138	0.0917	0.0706	8.86
1100	1137	0.0917	0.0706	8.86	1138	1139	0.0917	0.0706	8.86
1100	1151	0.0665	0.0512	8.86	1138	1146	0.0571	0.0155	4.84
1100	1126	0.0745	0.0574	8.86	1139	1140	0.0917	0.0706	8.86
1100	1115	0.0745	0.0574	8.86	1140	1141	0.0917	0.0706	8.86
1100	1110	0.266	0.1378	6.82	1140	1147	0.0571	0.0155	4.84
1100	1107	0.2038	0.1056	6.82	1141	1142	0.0917	0.0706	8.86
1100	1104	0.2038	0.1056	6.82	1141	1148	0.0571	0.0155	4.84
1100	1101	0.2038	0.1056	6.82	1142	1143	0.0917	0.0706	8.86
1101	1102	0.2038	0.1056	6.82	1143	1144	0.0917	0.0706	8.86
1102	1103	0.0624	0.017	4.84	1143	1149	0.0571	0.0155	4.84
1104	1105	0.2038	0.1056	6.82	1144	1145	0.0917	0.0706	8.86
1105	1106	0.0624	0.017	4.84	1145	1150	0.0571	0.0155	4.84
1107	1108	0.2038	0.1056	6.82	1145	40001	0.0125	0.1875	0.5
1108	1109	0.0624	0.017	4.84	1151	1152	0.0665	0.0512	8.86
1110	1111	0.266	0.1378	6.82	1152	1153	0.0665	0.0512	8.86
1111	1113	0.0663	0.018	4.84	1152	1167	0.0729	0.0198	4.84
1111	1112	0.266	0.1378	6.82	1153	1154	0.0665	0.0512	8.86
1112	1114	0.0663	0.018	4.84	1154	1155	0.0665	0.0512	8.86
1115	1116	0.0745	0.0574	8.86	1154	1168	0.0729	0.0198	4.84
1116	1122	0.0542	0.0147	4.84	1155	1156	0.0665	0.0512	8.86
1116	1117	0.0745	0.0574	8.86	1155	1169	0.0729	0.0198	4.84
1117	1118	0.0745	0.0574	8.86	1156	1157	0.0665	0.0512	8.86
1118	1123	0.0542	0.0147	4.84	1157	1158	0.0665	0.0512	8.86
1118	1119	0.0745	0.0574	8.86	1157	1170	0.0729	0.0198	4.84
1119	1124	0.0542	0.0147	4.84	1158	1159	0.0665	0.0512	8.86
1119	1120	0.0745	0.0574	8.86	1159	1160	0.0665	0.0512	8.86
1120	1121	0.0745	0.0574	8.86	1159	1171	0.0729	0.0198	4.84
1121	1125	0.0542	0.0147	4.84	1160	1161	0.0665	0.0512	8.86
1126	1127	0.0745	0.0574	8.86	1161	1162	0.0665	0.0512	8.86
1127	1133	0.0542	0.0147	4.84	1161	1172	0.0729	0.0198	4.84
1127	1128	0.0745	0.0574	8.86	1162	1163	0.0665	0.0512	8.86
1128	1129	0.0745	0.0574	8.86	1162	1173	0.0729	0.0198	4.84
1129	1134	0.0542	0.0147	4.84	1163	1164	0.0665	0.0512	8.86
1129	1130	0.0745	0.0574	8.86	1164	1165	0.0665	0.0512	8.86
1130	1135	0.0542	0.0147	4.84	1164	1174	0.0729	0.0198	4.84
1130	1131	0.0745	0.0574	8.86	1165	1166	0.0665	0.0512	8.86
1131	1132	0.0745	0.0574	8.86	1166	1175	0.0729	0.0198	4.84

Table E-7. Branches parameters for the LV network (S_B=100MVA)

From Bus	To Bus	R (p.u.)	X (p.u.)	Rating (MVA)	From Bus	To Bus	R (p.u.)	X (p.u.)	Rating (MVA)
40001	40011	3.843	1.734	0.142	40027	40028	7.5	1.757	0.094
40001	40021	3.843	1.734	0.142	40028	40029	15.95	0.768	0.048
40001	40031	3.843	1.734	0.142	40031	40032	3.843	1.734	0.142
40001	40041	3.843	1.734	0.142	40032	40033	3.843	1.734	0.142
40011	40012	3.843	1.734	0.142	40033	40034	3.843	1.734	0.142
40012	40013	3.843	1.734	0.142	40034	40035	7.5	1.757	0.094
40013	40014	3.843	1.734	0.142	40035	40036	7.5	1.757	0.094
40014	40015	7.5	1.757	0.094	40036	40037	7.5	1.757	0.094
40015	40016	7.5	1.757	0.094	40037	40038	7.5	1.757	0.094
40016	40017	7.5	1.757	0.094	40038	40039	15.95	0.768	0.048
40017	40018	7.5	1.757	0.094	40041	40042	3.843	1.734	0.142
40018	40019	15.95	0.768	0.048	40042	40043	3.843	1.734	0.142
40021	40022	3.843	1.734	0.142	40043	40044	3.843	1.734	0.142
40022	40023	3.843	1.734	0.142	40044	40045	7.5	1.757	0.094
40023	40024	3.843	1.734	0.142	40045	40046	7.5	1.757	0.094
40024	40025	7.5	1.757	0.094	40046	40047	7.5	1.757	0.094
40025	40026	7.5	1.757	0.094	40047	40048	7.5	1.757	0.094
40026	40027	7.5	1.757	0.094	40048	40049	15.95	0.768	0.048