Modelling and Analysis of Demand Response Implementation in the Residential Sector

by

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Declaration

I declare that this thesis is my own account of my research and contains as its main content work which has not been previously submitted for a degree at any tertiary educational institution.

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Abstract

Demand Response (DR) eliminates the need for expensive capital expenditure on the electricity distribution, transmission and the generation systems by encouraging consumers to alter their power usage through electricity pricing or incentive programs. However, modelling of DR programs for residential consumers is complicated due to the uncertain consumption behavious of consumers and the complexity of schedulling a large number of household appliances. This thesis has investigated the design and the implementation challenges of the two most commonly used DR components in the residential sector, i.e., time of use (TOU) and direct load control (DLC) programs for improving their effectiveness and implementation with innovative strategies to facilitate their acceptance by both consumers and utilities.

In price-based DR programs, the TOU pricing scheme is one of the most attractive and simplest approaches for reducing peak electricity demand in the residential sector. This scheme has been adopted in many developed countries because it requires less communication infrastructure for its implementation. However, the implementation of TOU pricing in low and lower-middle income economies is less appealing, mainly due to a large number of low-income consumers, as traditional TOU pricing schemes may increase the cost of electricity for low income residential consumers and adversely affect their comfort levels. The research in this thesis proposes an alternative TOU pricing strategy for the residential sector in developing countries in order to manage peak demand problems while ensuring a low impact on consumers' monthly energy bills and comfort levels. In this study, Bangladesh is used as an example of a lower-to-middle income developing country.

The DLC program is becoming an increasingly attractive solution for utilities in developed countries due to advances in the construction of communication infrastructures as part of the

smart grid concept deployment. One of the main challenges of the DLC program implementation is ensuring optimal control over a large number of different household appliances for managing both short and long intervals of voltage variation problems in distribution networks at both medium voltage (MV) and low voltage (LV) networks, while simultaneously enabling consumers to maintain their comfort levels. Another important challenge for DLC implementation is achieving a fair distribution of incentives among a large number of participating consumers. This thesis addresses these challenges by proposing a multi-layer load control algorithm which groups the household appliances based on the intervals of the voltage problems and coordinates with the reactive power from distributed generators (DGs) for the effective voltage management in MV networks. The proposed load controller takes into consideration the consumption preference of individual appliance, ensuring that the consumer's comfort level is satisfied as well as fairly incentivising consumers based on their contributions in network voltage and power loss improvement.

Another significant challenge with the existing DLC strategy as it applies to managing voltage in LV networks is that it does not take into account the network's unbalance constraints in the load control algorithm. In LV distribution networks, voltage unbalance is prevalent and is one of the main power quality problems of concern. Unequal DR activation among the phases may cause excessive voltage unbalance in the network. In this thesis, a new load control algorithm is developed with the coordination of secondary on-load tap changer (OLTC) transformer for effective management of both voltage magnitude and unbalance in the LV networks. The proposed load control algorithm minimises the disturbance to consumers' comfort levels by prioritising their consumption preferences. It motivates consumers to participate in DR program by providing flexibility to bid their participation prices dynamically in each DR event.

The proposed DR programs are applicable for both developed and developing countries based on their available communication infrastructure for DR implementation. The main benefits of the proposed DR programs can be shared between consumers and their utilities. Consumers have flexibility in being able to prioritise their comfort levels and bid for their participation prices or receive fair incentives, while utilities effectively manage their network peak demand and power quality problems with minimum compensation costs. As a whole, consumers get the opportunity to minimise their electricity bills while utilities are able to defer or avoid the high cost of their investment in network reinforcements.

Dedication

I would like to dedicate this thesis to:

My parents

My wife Sharmin Akter

My sister Farzana Urme

My brother Mostakin Rahman

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Table of Contents

List of Abbreviations and Variables

Abbreviations

AC	Air conditioner
BEES	Battery energy storage system
BPDB	Bangladesh power development board
CPP	Critical peak pricing
OLTCs	On-load tap changers
DLC	Direct load control
DLF	Distribution load flow
DR	Demand response
DG	Distributed generator
DESCO	Dhaka electric supply company Ltd
DSO	Distribution system operator
dSTATCOMs	Distribution static compensators
EWHs	Electric water heaters
ENS	Energy not served
EVs	Electric vehicles
FY	Financial year
kW	kilo-Watt
kWh	kilo-Watt hour
IL	Interruptible load
IHPSO	Improved hybrid particle swarm optimisation algorithm
LV	Low voltage
RESs	Renewable energy resources
RTP	Real time pricing
MPSO	Modified PSO
MW	Mega-watt
MV	Medium voltage
PA	Pattern search

PEVs	Plug-in electric vehicles
PSO	Particle swarm optimisation
PV	Photovoltaic
TOU	Time of use
TSO	Transmission system operator
VRs	Voltage regulators
VU	Voltage Unbalance

Variables

$ADR_{(i,t)}$	Appliance disturbance ratio of the i^{th} candidate consumer at t^{th} timeframe.
$AFI_{(i,t)}$	Appliances disturbed for i^{th} consumer at DR event t
$A_{n(i,t)}$	Switching control/status variable for the n^{th} appliance of the i^{th} candidate
$avg.volt.sens._{(i,t)}$	Average sensitivity of voltage change in all voltage violated buses at time t due load change at bus i
C_{main}	Estimated maintenance cost of OLTC
$cost_{(t)}$	Network power loss (kw) cost ($/kw) at t^{th} timeframe.
$DR_{(i,t)}$	DR contribution in kw from the i^{th} candidate consumer at t^{th} timeframe.
$I_{(l,t)}$	lth line current at t^{th} timeframe.
$I_{\max(l)}$	Maximum current limit of l^{th} line
$incentive_{DRbus(i,t)}$	Incentive rate ($/kwh) at DR candidate bus i at time t
N_{bus}	Number of buses
N_{change}	Maximum allowable number of tap change of OLTC without maintenance
N_{DR}	Total number of DR candidate consumers.
$N_{DR(t)}$	Total number of DR candidate consumers participating in a DR event at time t
$N_{disturb(t)}$	Total number of participated consumers with at least one $A_{n(i,t)} \neq 0$.
N_{DG}	Total number of DG
N_{line}	Total number of lines.
$Network_{losses(t)}$	Total network power loss (kw) at t^{th} timeframe.
N_{phase}	Total number of phases of all buses.
N_v	Number of voltage violated buses
$OLTC_{dep}$	Three phase tap control.
$OLTC_{ind}$	Independent phase tap control.

$P_{DG(i,t)}$	Active power from DG at time t bus i
$\text{Penalty}_{ADR(i,t)}$	Penalty factor associated with $ADR_{(i,t)}$.
$\text{Penalty}_{AFI(i,t)}$	Penalty factor associated with $AFI_{(i,t)}$
$\text{Penalty}_{(\mathrm{I})}$	Penalty factor for the line thermal limit violation.
$\text{Penalty}_{(OLTC)}(t)$	Penalty factor for OLTC tap change at t^th timeframe.
$\text{Penalty}_{(V)}$	Penalty factor for the magnitude voltage violation.
$\text{Penalty}_{(VUF)}$	Penalty factor for negative sequence voltage unbalance violation
$\text{Penalty}_{(VUF_{Zero})}$	Penalty factor for zero sequence voltage unbalance violation.
$P_{n(i,t)}$	Rated kw demand of the n^th appliance of the i^th candidate at t^th timeframe.
$price_{(i,t)}$	Bid price ($/kwh) of the i^th candidate consumer at t^th timeframe.
$P_{T.loss\ (t)}$	Total power loss
$Q_{DG(i,t)}$	Reactive power from DG at time t at bus i
ST1	Smart pricing 1
ST2	Smart pricing 2
ST3	Smart pricing 3
ST4	Smart pricing 4
T	Number of intervals for a DR event in a particular day
$tap_{posi}(t)$	OLTC tap position at t^th timeframe.
$tap_{chng/day}^{total}$	Total tap changed per day
$tap_{chng/day}^{total}$	Maximum allowable tap operation per day
$T.loss.sens._{(i,t)}$	Sensitivity of total network loss at time t due load change at bus i.
Δt	Timeframe duration (hours) of a DR event.
UPQCs	Unified power quality conditioners
$V_{(p,t)}$	P^th phase voltage magnitude at t^th timeframe.
$VUF_{(j,t)}$	Negative sequence voltage unbalance factor for j^th bus at t^th timeframe.
$VUF_{Zero(j,t)}$	Zero sequence voltage unbalance factor for j^th bus at t^th timeframe.

List of Publications

Journal papers

1. **Rahman M.M.**, Hettiwatte S., Shafiullah G.M., Arefi Ali. *An Analysis of Time of Use Electricity Price in Residential Sector of Bangladesh.* Energy Strategy Reviews 18 (2017): 183-198. (Chapter 2)
2. **Rahman M.M.**, Arefi A., Shafiullah G.M., Hettiwatte S. *A New Approach of Voltage Management in Unbalanced Low Voltage Network using Residential Demand Response.* International Journal of Electrical Power & Energy Systems. 2018 Jul 31;99:11-27. (Chapter 5)
3. **Rahman M.M.**, Shafiullah G.M, Arefi A., Hettiwatte S. *A Dynamic Fair Incentive Based Multi-Layer Load Control Algorithm for Managing Voltage Variations in Medium Voltage Networks Considering Consumer Preferences*. IEEE Transactions on Power Delivery, 2018 (submitted). (Chapter 4)
4. Maruf Islam. M. N, Zunnurain. I, **Rahman M.M**, Shafiullah G.M. *Implementation of Advanced Demand Side Management for Microgrid incorporating with Demand Response and Home Energy Management System.* Energy Conversion and Management, Elsevier, 2018 (submitted).

Conference papers

1. **Rahman M.M.**, Shafiullah, G.M, Arefi, A., Hettiwatte, S. *Improvement of Voltage Magnitude and Unbalance in LV network by Implementing Residential Demand Response*. In Power & Energy Society General Meeting, 2017 IEEE, pp. 1-5. IEEE, 2017. (Appendix C)
2. **Rahman M.M.**, A Alfaki, GM Shafiullah, MA Shoeb, T Jamal. *Demand response opportunities in residential sector incorporated with smart load monitoring system*. In Innovative Smart Grid Technologies-Asia (ISGT-Asia), 2016 IEEE, pp. 1183-1188. IEEE, 2016. (Chapter 3)
3. **Rahman M.M.**, Arefi, A., Shafiullah, G.M., Hettiwatte, S., *Penetration Maximisation of Residential Rooftop Photovoltaic using Demand Response*. In Smart Green Technology in Electrical and Information Systems (ICSGTEIS), 2016 International Conference on, pp. 21-26. IEEE, 2016. (Appendix B)

4. **Rahman M.M.**, Van Heerden, C. and Shafiullah, G.M. *Electricity Tariffs Evaluation using Smart Load Monitoring Devices for Residential Consumer*. In Computer Science and Engineering (APWC on CSE), 2016 3rd Asia-Pacific World Congress on, pp. 265-270. IEEE, 2016.
5. **Rahman M.M.**, S. Hettiwatte, and S. Gyamfi. *An intelligent approach of achieving demand response by fuzzy logic based domestic load management*. In Power Engineering Conference (AUPEC), 2014 Australasian Universities, pp. 1-6. IEEE, 2014. **(*Received best conference award*).**
6. MA Shoeb, T Jamal, GM Shafiullah, **Rahman M.M.** *Analysis of remote PV-diesel based hybrid minigrid for different load conditions*. In Innovative Smart Grid Technologies-Asia (ISGT-Asia), 2016 IEEE, pp. 1165-1170. IEEE, 2016.
7. Taskin Jamal, GM Shafiullah, Craig Carter, SM Ferdous, **Rahman M.M.** *Benefits of Short-term PV Forecasting in a Remote Area Standalone Off-grid Power Supply System*. 2018 IEEE PES General Meeting, USA (accepted).

Attribution

In consultation with my supervisors Dr. GM Shafiullah, Dr. Ali Arefi and Dr. Sujeewa Hettiwatte, I was responsible for the development of the innovative concepts, literature review, manuscript writing, interpretation of results and design of the chapters in the thesis. The thesis contains published work which has been co-authored. In particular, Dr. GM Shafiullah provided overall supervision of all the research and the final editing of all manuscripts. Dr. Ali Arefi assisted in developing the concept suggested relevant literature, editing the manuscripts and providing initial programming support presented in Chapter 2, Chapter 4 and Chapter 5. Dr. Sujeewa Hettiwatte provided initial supervision, writing support and proofreading of the manuscripts presented in Chapter 2, Chapter 4 and Chapter 5. Ahmed Alfaki helped to install the load monitoring and control devices at his premises for data collection of electric household appliances for the manuscript presented in Chapter 3. Md Asaduzzaman Shoeb and Taskin Jamal helped to design tables and figures for the manuscript in Chapter 3.

Md Moktadir Rahman

Chapter 1

Introduction and Literature Review

1.1. Background

Consumers generally expect affordable, safe and reliable electricity services. In this context, to guarantee a reliable electricity supply to consumers, retail electricity prices have been increasing in every year. The key factor influencing the retail price of electricity is the increase in distribution network costs. Distribution network costs account for between 40 to 60 percent of a consumer's electricity bill, depending on the jurisdiction. This is primarily due to the replacement of aging assets, the impact of increasing peak demand, increased reliability standards and connection of renewable energy generation sources.

With the rising residential demand for electricity at peak times, utilities are finding it increasingly difficult to satisfy consumer power demands. As the use of energy-intensive appliances such as air-conditioners, dishwashers and new battery electric vehicles (EVs) have grown, network operators have had to invest in additional capacity to accommodate the growing demand for electricity at peak times. It is estimated that the cost of each additional kilowatt of peak load on the power network to be between AU$240 and AU$310 a kilowatt [1]. As recently highlighted in [2], while it costs around AU$1500 to purchase and install a 2-kilowatt air conditioner, such a unit can impose costs on the energy system of around AU$7000 when adding to peak demand, yet peak demand usually lasts for less than 5 percent of the system's operational time (i.e., just a few hundred hours a year). This means that some power plants are only needed during the peak load hours and their productive capacity is utilized only occasionally [3]. One distribution network business has estimated that AU$11 billion in network infrastructure is used for the equivalent of 4 or 5 days a year [4]. Another distribution network business has estimated that around 20 percent of network capacity is used for the equivalent of 23 hours per year [5].

Furthermore, the situation has been aggravated by the increased presence of decentralised renewable energy generation. The existing grid was initially designed for one-directional electricity flows only, but the intermittency associated with renewable power generation greatly compromises the grid stability. Due to global warming concerns, the world's energy system is in transition towards becoming a low-carbon system. As a consequence, the share of renewable energy has increased over recent years, and this has caused challenges for the traditional electricity network. Thus forcing utilities to invest in network upgrades and to install expensive new technologies (such as battery energy storage systems) to allow power delivery to consumers in compliance with power quality and reliability standards. One Australian utility has stated that many of its distribution transformers have already exceeded half of their expected service life and due to increasing intermittent solar photovoltaic (PV) generators being connected to the network resulting in the necessity to replace transformers sooner than had been anticipated [6].

The aforementioned challenges have led the electricity industry to seek to identify and deploy cost-effective techniques for managing its networks in order to efficiently manage the expected increased the decentralised generation and load demand. It is important for utilities to ensure the optimisation of the available power resources. Consequently, the utilities can capitalise on the emerging innovative demand response (DR) programs to reduce peak load and adapt power fluctuations by adjusting consumers loads. DR eliminates or defers the need for expensive capital expenditure on distribution, transmission, and generation systems [3]. DR refers to modifications to electricity usage by consumers, which result from changes in the price of electricity or incentive payments offered to change electricity use at specific periods.

The importance of DR in the residential sector is also quantified, for example in Canada [7], it shows that a slight extension of 10% in the total operation time of residential demands may reduce peak consumption by 125MW. Another study in Australia estimates that the DR could deliver up to AU$2.8 to $4.3 billion in delayed supply-side investments (generation and network) over a ten-year period through to 2022/23 [8].

1.2. Motivation

Despite having many benefits, DR has not been embraced by most utilities and their consumers. There are still some issues that remain to be addressed for residential DR programs to be successful. These include the price unresponsiveness of some residential consumers, fairness issues in electricity pricing rate design and incentive payment to consumers, less prioritisation on consumer consumption decisions and comfort levels and the lack of available DR communication infrastructure. It is essential to get these attributes right and motivate consumers to supply their DR resources to the grid.

DR programs have been previously implemented by utilities through price based and direct load control programs [9]. Price based programs include time of use (TOU) pricing, critical peak pricing (CPP) and real time pricing (RTP) and encourage consumers to adjust their consumption behaviours voluntarily. Amongst all pricing programs, TOU pricing is more popular in terms of simplicity, attractiveness to consumers and it requires less communications between the utility and consumers, thus it has widely been accepted and implemented in many developed countries [10-11]. Researchers have highlighted two important considerations in TOU pricing programs. Firstly, TOU pricing may increase financial risks for some categories of residential consumers especially, low-income consumers if they are unable to shift their peak usages [12-13]. As low-income households typically use less energy than the average consumer, their ability to conserve energy is reduced [14]. Secondly, households demand responsiveness to price decreases as household income increases [15], however, some high-income households may not care about the price of energy as it is only a tiny fraction of their available budget.

Though TOU pricing implementation in developed countries is well established, implementation of this pricing in low and lower-middle income economies is more challenging, mainly because the majority of residential consumers are a low-income bracket. The traditional TOU pricing strategy offers the same pricing structure to consumers of all different income levels, and which invariably results in higher electricity bills for lower-income consumers. Therefore, most of the developing countries commonly use inclining block pricing or flat pricing schemes in the residential sector which do not give incentives or adequate information to consumers to encourage them to change their consumption behaviours during peak periods. The lack of a suitable TOU pricing strategy in such countries results in high peak demand, poor utilisation of network infrastructure and, consequently, higher electricity prices than are necessary. However, offering a same price rate for a specific time period to all consumers of different consumption levels with the traditional TOU pricing approach, is not fair to those who already have a normal or low level of consumption. Therefore, an effective TOU pricing strategy should be developed which is suitable for all categories of consumers in low and lower-middle income brackets, where consumers are charged according to their consumption levels while ensuring minimal impact on consumers' monthly energy bills and comfort levels.

A communication infrastructure is a foundational element in the successful deployment of DR programs [16] in the residential sector. Some consumers cannot economise on their power consumption due to fact that they simply are not aware how much energy each of their appliances consume and their energy usage varies at different times in the day. Innovative use of information technology (such as the use of smart meters, smart load monitoring and control devices) could permit users to access and understand their power usage and increase awareness of efficient energy consumption. They could also benefit by participating in DR programs [17]. To improve power reliability and quality as well as preventing electricity blackouts, access to real electricity consumption data and load profiles of major household appliances is crucial for utility and consumers to incorporate in DR programs implementation. Therefore, it is necessary for there to be a study of the latest communication technologies and smart load monitoring devices and their suitability for use in DR program implementation in the residential sector.

Direct load control (DLC) program is increasingly being adopted by utilities in developed countries due to advances in the construction of communication infrastructure. DLC program is used to monitor and control household appliances remotely in order to measure and regulate a participant's consumption, to manage network voltage, peak demand, PV penetrations, etc. An important barrier which has been identified is the lack of consumers' engagement in DLC programs [18]. This can be attributed to the fact that the volume of load disturbances of each participant, the form of incentive payments, the level of complexity of load control, and the priority provided to participants to maintain their comfort levels. There is a paucity of information available which deals with these necessary aspects of effectively designing and deploying a DLC program. From a distribution system perspective in managing network voltage in large networks, it is crucial to identify the most effective locations for DR activation (i.e., the most voltage sensitive nodes) in the network. DR activation in random locations increases the unnecessary adjustment of load controls and load disturbances to consumers [19-20]. It is interesting to note that consumers located in higher voltage sensitive nodes in the network usually provide more DR amounts and contribute more in voltage improvement than the consumers located in less voltage sensitive nodes [19], [21-22]. This location effect creates a potential fairness issue for incentive payments since the impact of DR on households are not all the same. In the existing DLC strategy, the incentive payments to participants are blunt and inefficient due to participants are typically offered an uniform flat incentive payment [23-24]. Mechanisms to compensate such location discrimination needs to be developed so that participants are fairly incentivised according to their contribution in alleviating network problems. It is also important that in the DLC strategy, an efficient load control algorithm is used and that participants' consumption decisions are prioritised in the load control to maintain their comfort levels.

Another important lacking in existing DLC strategy is that, not considering network voltage unbalance constraints in the load control algorithm. Voltage unbalance is more prevalent in low voltage (LV) networks due to unequal line impedances, unequal distribution of single-phase loads and distributed generators. Asymmetric DR activation between phases may lead to an increase in voltage unbalance and network loss in the LV network [25]. The presence of excessive levels of voltage unbalance may results in overheating and derating of all induction motor loads [26], malfunctioning of protection relays and voltage regulation equipment, and generating non-characteristic harmonics from power electronic loads [27]. Therefore, in the load control algorithm, both the voltage magnitude and unbalance need to be considered, so that network operation standards are satisfied. Furthermore, if the consumer is provided with the opportunity to dynamically bid their participation prices in the DR event at which they are willing to participate, it will motivate more consumers to participate in DLC programs and reduce the inconvenience of entering into a long-term DR contract.

1.3. Literature review on DR programs

Demand Response can be defined more precisely as: a paradigm shift in the power consumption of the final subscribers in response to severe changes in electricity price or incentive payments that are designed to stimulate consumers to use less electricity, when wholesale market prices are high or when the reliability of power system is in danger [18]. On the distribution side, DR is a key component in reducing the peak load and adapting power fluctuations by shaping consumers loads.

In restructured power systems, there are many independent players who benefit from DR. These include transmission system operators (TSOs), distribution system operators (DSOs), retailers, aggregators and end-consumers. These can be categorised as Market perspective, Network perspective and Consumer perspective.

- Market perspective: DR is important for stable wholesale and retail market development. It reduces wholesale power prices; provides an efficient operation of markets; enhances reliability and support the use of renewable energy resources [11], [23]. The energy market value is generally assessed by analysing the effects of using the flexibility to minimise generation costs
- Network perspective: TSO can benefit from DR by improving reliability of the transmission network. Improvement of network reliability results from reducing the probability of forced outages when system reserves fall below desired levels. By reducing electricity demand at critical times (e.g., when a generator or a transmission line is unexpectedly lost), DR dispatched by the TSO can help to return system reserves to pre-contingency levels [28].

  DSO can benefit from DR by managing network constraints at the distribution level. DR increases the capacity of the distribution networks by making the networks more efficient (e.g., by relieving the voltage problems or network congestions). Therefore, distribution networks can accommodate more load and renewable energy sources without the grid operators investing in costly grid expansions [29], [20].
- Consumer perspective: with the deployment of DR, end users have the opportunity to enjoy considerably lower electricity bills due to the efficient use of electricity [29]. By shifting their loads to low peak hours, electricity users can capitalise on reduced

electricity tariffs to minimise their electricity costs. Consumers also receive direct monetary compensation for agreeing to control their loads during peak hours or high renewable energy generation hours. Furthermore, DR increases consumers’ awareness of their energy consumption, thus contributing to an increased use of renewable energy.

DR programs are generally classified in two broad categories, namely; price based and incentive based programs. some of the available DR programs today are presented and discussed below.

1.3.1. Price based DR

Price based DR programs charge consumers with prices which reflect the value and cost of electricity during particular time periods. Electricity generation costs are not constant but vary considerably with time of the day, day of the week, weeks of the month and also seasons of the year. To reflect this, electricity pricing is being structured to indicate the time varying marginal costs of electricity generation [9]. Time of use, real time and critical peak pricings are well-known price based DR programs [30]. Consumers are encouraged with these pricings to individually and voluntarily manage their loads by reducing their energy consumption during peaks hours [29], [10].

- **Time of Use (TOU) pricing**

TOU pricing is well known to consumers and utilities in most of the developed countries, e.g., Australia, USA, UK, Italy and Spain [10-12]. The main feature of TOU pricing is to offer time-differentiated electricity prices to the end-use consumers, for example, having two or three predefined price levels per day, i.e., peak and off-peak and shoulder prices. Hence, the consumers would have incentives to shift their flexible loads from hours with high demand to hours with lower demand. In [31], the authors conclude that effective pricing mechanisms to change consumers' behaviour is one of the most important matters which affect the success of TOU rates. The results of studies concerning varying numbers of consumers in different countries show that TOU pricing potentially reduces peak demand by 8% to 13% [32-33]. There has been a range of empirical work undertaken on estimating the potential benefits of residential consumers moving to a TOU pricing option. For example, in an Australian study comprising 32,000 residential consumers who were already subject to TOU billing, it was found that consumers were able to save an average of AU$64 a year compared to regulated flat prices, with 69 percent of consumers being better off under flexible pricing. It was also found that on average families are using 78 percent of power outside peak times [34].

Despite the growing interest of TOU and its implementation in various countries, the practical experience in using this program showed mixed results. The study in [35] showed that low-income consumers who are able to shift their demand are likely to benefit from TOU pricing. Low-income households have lower levels of use at times of peak demand [14], and introducing TOU pricing would reduce their average bills by 10 to 20% [1]. The percentage of peak load reduction has been found significantly higher for low-income households compared to high-income households [36]. However, there have been mixed opinions about the impact of peak price on low-income households. One opinion is that higher prices discriminate against low-income households [37], where the householder does not have the capacity to take action to avoid paying high peak prices [13]. Furthermore, when confronted with an increase in energy costs, lower-income families tend to make “lifestyle cutbacks” [38]. This was evidenced by the increase in “food insecurity” among the elderly households during periods associated with high heating and cooling demand when they spend a significant proportion of their income on energy [13]. Another finding is that some households demand responsiveness to price decreases as household income increases. A more detailed study shows that a significant proportion of residential consumers are non-responsive to price [15]. This may be due to different reasons. Some ‘rich’ households may not care about the price of energy as it is only a tiny fraction of their available budget. This consumer type is referred to as “selfish consumers”, as all consumers are penalised due to their high level of energy consumption during peak periods, which means the price rate increased for all consumers due to some high consumers [39].

Hence it would be important to develop an alternative TOU pricing structure that charges consumers based on their usage patterns, so that consumers with low energy usages receive low peak prices compared to the consumers with high energy usages. As TOU prices are static and price rates do not vary dynamically, less communication infrastructure is required, and this is suitable for developing countries where there is no DR program in the residential sector.

- **Real Time Pricing (RTP)**

The main purpose of an RTP program is to provide consumers with electricity pricing that reflects the wholesale market or actual conditions in the power system. Consumers could be charged based on day-ahead, hourly, 15-minute or even faster fluctuating prices [40]. RTP has been studied extensively in recent years, and different approaches have been proposed regarding the design of the pricing structure and how to assess the demand side flexibility. A number of studies [41-42] on RTP in different countries indicate that RTP has a significant impact on peak demand reduction. According to [41], the possible cost reduction is achieved by consumers when scheduling their electric heating is around 47%. In [42], dishwashers, laundry and drying machines are considered as flexible loads and shifted according to the day-ahead market prices to reduce the electricity cost for consumers. On average the cost reduction on consumers' bills was found to be AU$9/year.

A critical aspect of the design of an RTP scheme is the time difference between the announcement of the price to the consumers and the actual consumption of power. A long time lag, e.g., using day-ahead price, which has been most commonly used, would result in a price that less accurately reflects the wholesale market and power system conditions [30]. A shorter time lag, e.g., based on the intraday market, would result in a better reflection of demand/supply levels, but would make it more difficult for the consumers to plan their electricity consumption

[41]. Since the market price of electricity depends both on the available production and consumption, the volatility in the electricity price could increase with increased electricity production from intermittent energy sources and may even cause negative electricity prices [43]. Studies in [40] and [44] provide a quantification of the real time relationship between total peak demand and spot market prices. They found a low value for the real time price elasticity, which occurred because not all consumers observed the spot market price. Following price changes at different time periods may also be confusing to consumers [39].

The main barriers to fully utilising the potential benefits from RTP are the lack of knowledge among consumers on how to respond to time-varying prices, the lack of effective automation systems and communication infrastructures [39], [44]. To obtain the full benefits of RTP, consumers need to have in their premises an optimal and automatic residential energy consumption scheduling technique [45] with integrated smart load monitoring and bi-directional communication technologies (e.g., smart meters) [17]. Therefore, an RTP scheme may not be suitable for those countries where there is a lack of communication infrastructure for both utilities and consumers to participate in this program.

- **Critical Peak Pricing (CPP)**

In CPP, the price rate which is designed by the utility is pre-specified for consumption for some peak periods in every year when the transmission/distribution system is congested, or the market price is extremely high. Consumers who participate in CPP programs receive a discounted price, usually during non-critical peak pricing periods. The critical period rates are not common but have been tested for small and large consumers in several areas (e.g., Florida, California, North and South Carolina) [46].

One disadvantage with CPP is that the number of hours available to apply CPP is limited during each year [30], and therefore. it could not be used on a regular basis to improve the overall system performance. As RTP and CPP require electricity consumption measurements of an adequate resolution, it is generally required to have a smart meter at the consumer site.

1.3.2. Incentive based DR

In incentive based programs, consumers change their load consumption (either reduce or increase) for a given period in response to the reward offered by the utilities. Direct load control and interruptible load programs are common types in this group. These programs provide their consumer with incentives or allow them to offer their participation prices to manage their loads, when the utilities think the reliability is at risk or when the market prices are really high.

- **Direct Load Control (DLC)**

In a DLC program, the utility can directly switch consumer loads ON and OFF with the consumer's permission given in advance. The purpose of DLC is to compensate the consumer financially if they permit the utility to remotely control some of their electrical loads during contingencies in the power system, (e.g., domestic hot water boilers, air-conditioners and some white goods (e.g.,dryer, washing machine, etc.). DLC has been studied for a long time and there are many studies available of classical DLC on load management. Many optimisation methods have been proposed to achieve different objectives such as peak load reduction [47], unit commitment problem solving for fuel cost savings [48], power shortage minimisation [49], power quality improvement in distribution networks [20], etc.

With respect to DLC programs, it is important to motivate consumers to participate in the program. Consumers are motivated by a desire to protect their comfort level and to obtain financial benefits from participating in the program. Some studies such as [23-24], [50] proposed a uniform flat incentive payment for all participating consumers regardless of load size to avoid complexity of incentive design. The study in [51] investigated an exponential model for a DLC program to describe consumers' responses to different incentive offers. The results showed that increasing the incentive rate increased the percentage of peak reduction and the consumers' involvement. The DLC program requires advanced communication infrastructure, remote monitoring and control system in the premises of participating consumers. Hence, utilities in developed countries where smart grid technologies are already viable can implement DLC program in cost-effective way.

- **Interruptible Load (IL)**

With respect to IL programs, consumers are asked to (typically manually) adjust their loads to a predefined value. In general, an IL program is used to reduce loads when the power system is under stress [30]. Consumers who do not respond accordingly can face penalties, depending on the program terms and conditions. Participants are offered a discount on the retail tariff or incentive payments. For example, a coupon-based method is formulated in [51] where the incentive offered to consumers is determined according to market prices. A voluntary coupon incentive along with the existing flat rate electricity charge is offered to consumers by a load serving entity through which consumers reduce their usage during price spikes.

Unlike DLC, the loads are not remotely controlled, and IL is traditionally only offered to large industrial consumers [53].

1.3.3. Differences between price based and incentive based DR programs

The primary distinction between price based and incentive based DR programs is the control strategy used for DR. In the case of incentive based DR, the signals and conditions for load adjustment are agreed upon beforehand, while in the case of price based DR, the consumers are free to respond in their own chosen way. Furthermore, an incentive based DR has an advantage over price based program, in that the pricing program is voluntarily based participation and it cannot ensure that a sufficient number of participants will engage to avoid critical or unstable network conditions in a certain period of time [52]. Incentive based DR can guarantee the consumers' participation, as consumers sign contracts with the DR operator. Other advantages of incentive based DR are improved social welfare and the fact that consumers are not exposed to fluctuating wholesale electricity prices. However, the main problem with the incentive based DR is that requirement of the advanced communication facilities.

1.3.4. Main challenges of DR programs implementation

As the number of DR programs continue to grow due to the advancement of communication infrastructures, they face challenges in attracting consumers [18]. Price based DR strategies are still in their infancy and have complications in their implementation. These include price unresponsiveness of some consumers, the fact that some consumer may not have the capacity to respond, a lack of quantitative understanding of consumer consumption behaviour and lack of the metering infrastructure. These factors are significant barriers to the design and deployment of effective pricing programs. The impact on consumers' electricity bills and comfort levels are the main consideration for consumers in whether or not to participate in price based programs [10]. Other factors such as environmental and supply security information together with the price signals provided to consumers can inspire them to participate in price based programs [54].

The success of incentive based DR programs is driven by a number of factors including priority of consumers' consumption preferences and comfort levels, the perceived benefits that the utilities offer consumers in return for controlling their loads, the effort required from consumers to control their loads, and load control optimisation method and strategies. Not many literatures are found that prioritise consumers' preferences or convenience to maintain their comfort levels in optimal manner. Even though consumers receive financial compensation in the incentive based DR programs, the consumers may have subjected to some level of discomfort or inconvenience as these DR programs involve alteration of consumer's preferred or usual electricity consumption patterns.

1.4. Literature review on DR contribution to distribution network problems

The growing peak demand and intermittent supply of the renewable resources affect the way in which the distribution network is planned, operated and controlled. The growth in peak demand causes a strain on the available power generation, transmission and distribution infrastructure, and meeting this peak demand is often associated with high cost [9]. The growth of renewable energy integration in the distribution systems poses several challenges in the safe operation of distribution systems. In particular, renewable energy sources such as wind and solar power have a high degree of unpredictability and time-variation which create complexity in maintaining power quality and reliability standards of the networks [55]. Utility companies are increasingly finding it difficult to cost effectively satisfy both consumers' power demands and network power quality problems.

1.4.1. Peak demand management problems

The demand profiles of residential consumers reflect usage of household appliances at peak times, the prime example being the use of air conditioners on hot days [29]. The stability of the network is usually achieved by having surplus capacity in the system. When peak demand for electricity increases, new infrastructure must be built to carry enough power at peak times and therefore, the cost of an additional unit of peak electricity consumption in the network is very high. The scenarios of peak demand related problems are very great in developing countries (e.g., Bangladesh, Nepal, Myanmar, etc.) [29]. Studies have shown that developing countries will continue to have severe electricity shortages during peak periods [29]. Electricity interruptions due to power shortages and network failures occur more often during peak periods and result in brownouts or blackouts. This is mainly due to the lack of awareness of peak demand, energy management options, and available DR programs in households. In such cases, utilities in these countries have had to build new power generation capacity, run peak capacity generators (mostly diesel based), apply load shedding, and consequently, incur higher electricity production costs than normal. The costs associated with the Energy Not Served (ENS) due to severe electricity interruptions have substantial impacts on the total cost of the power supply to the consumers [56]. For example, a survey of 400 residential consumers in Bangladesh showed that the estimated economic loss due to electricity outages was US$306k in a typical summer month [57].

Residential consumers in most developing countries are currently offered inclining block usage or flat rates for their electricity usage. For example, inclining block usage pricing is available in Bangladesh [58], Indonesia [59], India [60], Nepal [61], Maldives [62], etc., and flat pricing is available for residential consumers in the Philippines [63], Myanmar [64], Cambodia [65], etc. These pricing schemes are not time varying pricing and therefore provide no financial incentive for consumers to shift their electricity usage from peak to non-peak periods. It means that these pricing policies will not necessarily reflect network infrastructure costs during the peak period when the cost of generating electricity is high. As a result, peak demand is high and increases inefficient investment in network capacity and generation [66].

DR programs have the potential to mitigate peak demand by encouraging consumers to consume less energy during the peak periods [20], [10]. This will in turn reduce electricity generation and distribution costs in the long run [29]. Many studies such as [53] and [13], show the importance of undertaking DR studies for residential consumers in order to identify demand periods and help the distribution utilities to reduce both peak demand and their operational costs. A direct load control (DLC) program has been studied in [47] and [48] to ascertain how to reduce consumer demand during peak periods. However, this DR program implementation requires advanced communication technologies (such as smart meter, load monitoring devices, etc.) as similar to a real time pricing (RTP) program. Thus, these DR programs may not be suitable for the low income developing countries, as smart grid technologies are still immature in those countries, which will require significant investment costs to implement. A simple approach is to deploy TOU pricing DR program, which is an effective solution for managing peak demand. This DR program only requires TOU billing meters at consumer premises [29]. Currently, TOU pricing in low and lower-middle income developing countries is less attractive, due to a large number of low-income consumers and the classical TOU pricing approach may increase the cost of electricity for low-income consumers, as observed in [37], [13] and [38]. Therefore, it is necessary to investigate an alternative TOU pricing approach for the residential sector that will be suitable for countries with a high percentage of low-income household consumers.

1.4.2. Power quality management problems

The growing integration of plug-in electric vehicles (PEVs) i.e., battery electric vehicles and plug-in hybrid electric vehicles and intermittent renewable energy sources, such as solar PV and wind power are affecting the operation of distribution network and causing significant power quality problems [20], [42]. The conventional distribution networks have been constructed without taking into consideration the integration of these resources [20]. The voltage control problem is known as one of the biggest obstacles to operate the distribution network at its maximum capacity. If voltage problem can be solved efficiently, higher renewable energy and the PEVs can be integrated into distribution networks. Voltage management problems in both MV and LV networks are discussed below.

1.4.2.1. Voltage management problems in MV networks

The distributed generation (DG) penetration in MV networks creates a new set of challenges for utilities to maintain voltages within an adequate range [67]. In particular, the solar photovoltaic (PV) in the form of DGs has increased considerably in recent years [20], [67]. The output of these DGs is variable and this power variation has a direct influence on voltage profile, which causes both slow and fast variations of voltage in the network due to cloud movement [68]. The main problem is the significant voltage change in the network that forces existing voltage control devices such as on-load tap changers (OLTCs) and line voltage regulators (VRs), to operate continuously. This results in the deterioration of the operating life and increased maintenance/overhaul costs of these voltage regulation devices [6]. Moreover, these devices cannot guarantee that the voltage profile will be within acceptable bounds throughout all connected feeders to the same transformer without any coordination among the voltage regulation devices [69]. One distribution company in Australia states that many of its distribution transformers have already exceeded half of their expected service life and the high intermittent DG generations are shortening the projected time for the replacement of transformers, the cost of which is significant [6].

An alternative to the use of these voltage regulation devices for handling both short and long terms voltage variations is to utilise the DG's power electronic interfaces. In the case of MV distribution systems, especially long distribution feeders with DGs, there could be a significant amount of conflicting operations between multiple voltage regulating devices and DGs, if they are not coordinated optimally [70]. Moreover, the reactive power generation from DGs does not provide any financial benefits in return and instead put more stress to inverters which shortens their lifetime. Installing distribution static compensators (DSTATCOM) can also mitigate voltage problem. The reported price is roughly 66–70 $/kVar for small STATCOM units [71]. Another solution is to reconductor the feeder using larger sized conductors, which can help reduce line voltage drops. This will provide a strong foundation for the distribution network. However, considering the number of feeders that need to be upgraded in distribution networks, reconductoring may not be an economically feasible option. The estimated cost of replacing wires for a single-phase system is in the vicinity of AU$25,000/km [72]. A battery energy storage system (BESS) can be a possible solution to the problem of short and long variations of voltage in the distribution grid, however, this technology is still an expensive solution. For example, a zinc–bromine (ZnBr) flow battery unit with a capacity of 5 kVA–20 kWh costs around $20,000 [72].

If consumers who participate in DR programs are able to alter their load consumption as requested, the utility can bring the voltages of critical nodes within their permissible range. However, the price based DR programs are inadequate to manage voltage critical nodes effectively, as pricing programs are entered into on a voluntary basis and the utility cannot ensure that a sufficient number of participants will engage to solve the network voltage problem within a certain period of time. The incentive based DR programs, particularly, DLC programs, can directly switch ON and OFF household appliances almost instantaneously, thus enabling them to react faster than voltage regulation devices in the network to avoid critical or unstable network conditions [20]. The implementation of a DLC strategy for a large distribution network is very complex and difficult to manage large number of various types of household appliances effectively.

A number of recent studies have explored the potential of household loads to provide voltage control services in different time scales due to variations of power from DGs. These include thermostatic loads to provide fast control in the time-scale of a few minutes [73] and [70], electric vehicle (EV) charging [23], [74] that can provide voltage control service in the time scale of a few hours. In [75] DR is deployed to mitigate forecasting errors due to the integration of DGs, whereas in [76] DR is considered in the context of islanded microgrids where it aims at providing a form of reserve. These previous studies considered only a few selected appliances in the network. A holistic study which addresses the potential of all major appliances to manage network voltage effectively has yet to be undertaken. Furthermore, the importance of consumer comfort has not been considered in the aforementioned load control studies. There are many other studies such as [23], [77], [68], etc. not consider the consumers' consumption preferences to maintain their comfort levels in DR implementation. Moreover, these DR studies were undertaken assuming fixed kilo-watt (kW) consumption ratings for all appliances used in the study. In reality, appliances rated kW power demands may not be exactly the same for all participating consumers in DR. The load control algorithm needs to have the ability to consider the variability of power consumption profiles of each household appliance separately to obtain the accurate optimisation results.

The resulting DR amount using the implemented voltage control technique will vary depending on the location of the particular DR actions. If DR is initiated at less voltage sensitive nodes in a network (where the ratio of voltage change to power change is less), the resulting DR volume will be significantly higher and voltage changes in the voltage violated nodes (where voltages are not within the standard limits) will be insignificant [20]. When DR is implemented in high voltage sensitive nodes of a network, even a small amount of DR may provide a considerable change in voltage violated nodes [19-20]. To minimise the amount of load disturbances, it is crucial to identify the voltage sensitive nodes for DR implementation. The voltage sensitivity method [78-79] can be used for location ranking in the network for load adjustment.

It is interesting to note that load adjustment volume for each participating consumer will vary depending on the consumer’s location in voltage sensitive nodes [21-22]. It means that consumers who are located in higher voltage sensitive nodes tend to provide greater DR amounts than the consumers who are located in less voltage sensitive nodes. For instance, simulation results using IEEE 14 bus system demonstrate that households located far away from the feeder (where voltage sensitivities are usually higher) contribute more DR amounts than households at the buses close to the feeder in the DR events [22]. The reason for this location effect is that both power loss minimisation and voltage regulation are closely related to the length of the line. As the length of the distribution line increases, the impedance of the line increases, leading to a higher power loss and voltage drop. Therefore, the DR optimisation algorithm will disturb more appliances in those locations than the households at the buses beginning of the feeder for effective voltage improvement and loss minimisation. Study in [21] shows that load adjustment at the end of the feeder improves the network voltage significantly when compared with the load adjustment at the beginning of the feeder. This location effect implies a potential fairness issue in DR since the impact of DR on households is not the same. The utility may need to set the DR incentives given to the households differently and based on their locations in the network. Hence, the DR incentives for the consumers located in the higher voltage sensitive nodes should be greater than in other less sensitive nodes of a network [19]. However, DR studies such as [50], [23] and [24] consider equal incentive rates for all participating consumers in DR implementation. For instance, the study in [23] uses a fixed incentive rate for all 2000 participated EVs in the simulation to manage the network voltage and line thermal limits. Hence, a fair distribution mechanism needs to be developed to compensate the participating consumers based on their contribution in DR, in terms of both voltage improvement and network loss minimisation.

Accordingly, a complete approach of DR deployment is required for managing voltage variations in MV distribution networks by using the flexibilities of various types of household appliances, which will minimise excessive disturbances on appliances and consumers' comfort levels, while giving incentives to the consumers fairly based on their contribution in each DR event.

1.4.2.2. Voltage management problems in LV networks

The LV residential networks are usually three-phase, four-wire systems (including neutral lines), supplied by Dyn three-phase transformers (e.g., in Australia, Asia, Europe, and Africa) [80]. Most houses have a single-phase connection (i.e., one of the three phases and neutral) but larger houses may have three-phase connections. When it comes to three-phase, four wires LV network there are significant differences compared to the MV network. Besides the voltage levels, the physical characteristics of the LV network in terms of the length and reactance to resistance ratio (X/R) is lower than in an MV network. Another significant difference is the unbalance of the LV network. Unsymmetrical loads or generation can cause a displacement in the neutral point and cause additional voltage drops in the neutral line, or a voltage rise on the other less loaded phases [80]. The challenge here is that in contrast to the MV network, it can no longer be assumed that the three phases are equally loaded [81]. Voltage unbalance (VU) is one of the main power quality problems in LV networks [82]. The growing penetration of rooftop PVs in LV feeders has increased the VU problem. The output power of the rooftop PVs is intermittent and the PVs are randomly distributed amongst phases as their installation depends on the consumers. Therefore, penetration level and location of PVs in the network significantly affects the VU [80]. The growing penetration of plug-in electric vehicles (PEVs) will contribute to further unbalance. In [83], it is shown that they can lead to high VU in each of the charging and discharging modes.

VU in the three-phase electric system is a condition in which the three-phase voltages (VA, VB and VC) differ in amplitude and/or do not have 120 phase differences between them [80]. Voltage unbalance in a three-phase four wires system can exist in two forms: zero sequence and negative sequence unbalances. Negative sequence unbalance is relatively more significant than zero sequence, as negative sequence currents can flow through the network in a similar way to positive sequence currents which increase the energy loss and reduce the capacity of the transmission/distribution line. The zero sequence current causes eddy current and energy loss as well as the windings heating of the transformer. The presence of excessive levels of VU can result in overheating and derating of all three phase induction motor loads such as squirrel cage induction motors, swimming pool pumps and air-conditioning compressors [74]. A small unbalance in the phase voltages can cause a disproportionately large unbalance in the phase currents [74]. VU also can cause the incorrect operation of protection relays and voltage regulation equipment, and generate harmonics from power electronic loads [84]. In Australia, the distribution code allows for negative sequence voltage of up to an average of 1% and a maximum of 2% (it can go over 2% for a maximum period of 5 minutes within each 30-minute period) [85]. In the UK, VU limit in the whole network is 2% [86] and the max limit of VU is 3% at no-load conditions according to the ANSI standard [87].

Many different solutions tackling VU problems in the LV networks have been put forward in various publications. Traditionally, utilities minimise VU problem by manually changing the connection phase for some consumers in order to equalise the loadings amongst the phases [80]. Some other conventional methods such as feeder cross-section improvement or capacitor installation are investigated in [80]. However, those practices were carried out only once and are not dynamic solutions. Furthermore, the variability of solar PV generation would make it difficult to balance the combined effect of load and solar PV unbalance using the traditional mitigation techniques [88]. To dynamically reduce VU along LV feeders, a distributed intelligent residential load transfer scheme is proposed in [82]. In this scheme, residential loads are transferred from one phase to another through static transfer switches implemented in three-phase connected houses. The central controller, installed at the distribution transformer, observes the power consumption in each house and determines the house(s) to be transferred from an initially connected phase to another. However, the main drawback of this approach is that the consumer requires three-phase connection and the majority of consumers in the LV network have single phase connections. Therefore, this solution may not cost-effective. Similarly, the study [74] requires three-phase consumers, where three-phase balancing PV inverters and EV chargers are proposed to improve the phase balance in LV networks. Furthermore, the proposed three-phase balancing PV inverter or EV charger requires three single-phase inverters. It will increase the size of the inverter which will increase the cost and may not be financially viable for some consumers. In [80], a new control scheme is proposed for single phase and three-phase PV converters to regulate the voltage by providing reactive power for reducing VU in the networks. Since the LV network has a low X/R ratio, the reactive power control has less effect on voltage compared to active power. In addition, there is no rebate scheme currently available that compensates the reactive power support from the PV owners. In cases where high levels of VU are unavoidable, special balancing equipment such as unified power quality conditioners (UPQCs) and distribution static compensators (dSTATCOMs) are proposed in [89] and [90], respectively to improve VU in LV networks. For example, the dSTATCOM in combination with control of on-load tap changer (OLTC) is introduced in [90]. However, all these approaches need additional hardware investment in addition to the associated operational and maintenance costs.

An alternative approach is to use the flexibility of household appliances through a DLC program in order to avoid voltage issues in LV networks. However, most of the studies considering the flexibilities of household appliances have been proposed for three-phase balanced LV distribution networks for managing voltage magnitude. For example, the study in [91] investigates how different levels of DR participation can facilitate the integration of PV in the LV networks. The simulation results show that DR can significantly improve the voltage rise effect at high PV penetration as well as decrease network losses. The study in [92] introduces a distributed, self-organizing approach to load control based on voltage measurement in an LV network. A local voltage measurement defines a Level of Service (LoS), which is balanced with the neighbouring households in order to avoid extreme restrictions of energy use in a single household. The approach distinguishes four criticality classes for devices which suspend themselves at specific LoS thresholds. This method is proposed to handle power under-supply, i.e., the situation where power demand exceeds possible production capability. The above-mentioned studies only consider voltage magnitude improvement in the LV network with DR. However, the effects of load control on VU are not studied. Unequal DR activation among three phases may create unbalance loadings, which can increase the VU. Furthermore, consumers' consumption priorities with respect to maintaining their comfort levels are not considered in the load control.

There are few studies currently available that provide a detailed modelling of various household appliances to maintain consumers' consumption priorities. The authors in [93] propose a local voltage control mechanism for LV networks using white good appliances (i.e. dishwashers, washing machines and tumble dryers), electric domestic hot water buffers, and EVs. The philosophy behind the developed control system is the well-known droop control, which is translated towards ON/OFF switching devices with low reacting times. The control system decides which devices to switch on or off based on a defined merit order. The merit order is based on the measured local voltage and the consumer consumption priority of the appliances to preserve the comfort level. Another study [94], proposes a load control algorithm for the balancing of renewable energy and the mitigation of voltage and power issues in LV networks. This study investigates user behaviour and acceptance to evaluate the developed DR model. The smart appliances are divided into two categories to minimise the comfort impact for the participants. The first type consists of postponable appliances, such as dishwashers and washing machines. The second type are appliances with buffers, such as smart domestic hot water buffers, EVs and tumble dryers. However, none of these studies consider VU improvements in the LV networks.

Therefore, a realistic approach of DR implementation is necessary which can manage both voltage magnitude and unbalance in LV networks while prioritising consumers' consumption preferences to satisfy their comfort levels as well as incentivising participants by allowing them to dynamically bid for their participation prices. Studies in [95-96] show that if consumers are provided with the flexibility to bid for their prices dynamically in the DR event, it motivates them to participate in DR programs and reduces the inconvenience of long-term DR contracts.

1.5. Aims and objectives

The ultimate goal of this thesis is to eliminate or defer expensive capital expenditure on distribution network through optimal implimentation of residential DR along with coordination with other network controlled equipment. It will allow distribution networks to host more decentralised renewable energy generation, utilise networks efficiently, prevent potential blackouts as well as providing an opportunity for consumers to minimise their electricity bills and at the same time maintaining their comfort levels. To this end, this thesis contributes to filling the research gaps of solving the barriers in motivating consumers and utilities to embrace DR programs. Therefore, this thesis proposes effective strategies for two main components of residential DR programs, i.e. Time of Use (TOU) and direct load control (DLC) implementation which distribution operators can capitalize. For each proposed DR program, a detailed problem formulation, operational framework and mathematical model are presented and the benefits of adopting such DR program to both utilities and their consumers are identified.

The main objectives of this thesis are to:

1. Propose an alternative Time of Use electricity pricing structure for low and middle economies for managing their growing peak demand problems by encouraging consumers to change their consumption behaviours with minimum impacts on their electricity bills and comfort levels.
2. Investigate suitable communication technologies for DR implementation in the residential sector, potential DR capacities of major household appliances and the importance of adopting smart load monitoring and control system in consumers' premises.
3. Propose a realistic and effective load control algorithm for managing short and long intervals of voltage variation problems in MV networks by engaging a large number of

household appliances considering consumers' comfort levels and fair incentive distribution to consumers.

4. Propose a realistic and effective load control algorithm for managing network voltage in unbalanced LV networks by optimally switching selected household appliances considering dynamic bidding and comfort levels of consumers.

1.6. Contributions and structure of the thesis

The summary of main contributions of each chapter in this thesis are outlined in Fig. 1.1 The thesis is structured as follows.

Chapter 1 describes the general background and motivation of the study. A comprehensive review of demand response and its implementation for distribution networks is provided. Subsequently, objective and structure of the thesis are presented.

Chapter 2 discusses the proposed model of the alternative TOU pricing DR program for the low and middle incomes developing countries. A case study is presented considering Bangladesh as an example of a low-to-middle income developing country. Four TOU pricing models are analysed and compared. The TOU pricing models are tested through simulations on a real electric distribution network.

Chapter 3 investigates the characteristics of different communication technologies and their suitability for use in DR implementation in the residential sector. Results from a case study using smart monitoring and controlling systems integrated into a household's electric appliances are presented.

Chapter 4 provides a holistic approach of DLC program deployment in MV network. The formulations of the developed multi-layer load control algorithm for DLC program are presented in this chapter for managing slow and fast variation of the network voltage using different categories of household appliances. Consumer consumption preferences are prioritised to maintain their comfort levels as well as a fair incentive strategy is developed in the load control algorithm.

Chapter 5 presents a new load control algorithm of DLC program for managing voltage in unbalanced low voltage networks by optimally switching household appliances. The developed load control algorithm is tested in a real unbalanced three-phase four wires low voltage network. Consumers are provided flexibility in dynamically bidding for their participation price and setting their consumption preferences to maintain their comfort levels.

Chapter 6 provides a summary of the findings of the thesis and concludes by outlining the main contributions. In addition, possible future research is recommended.

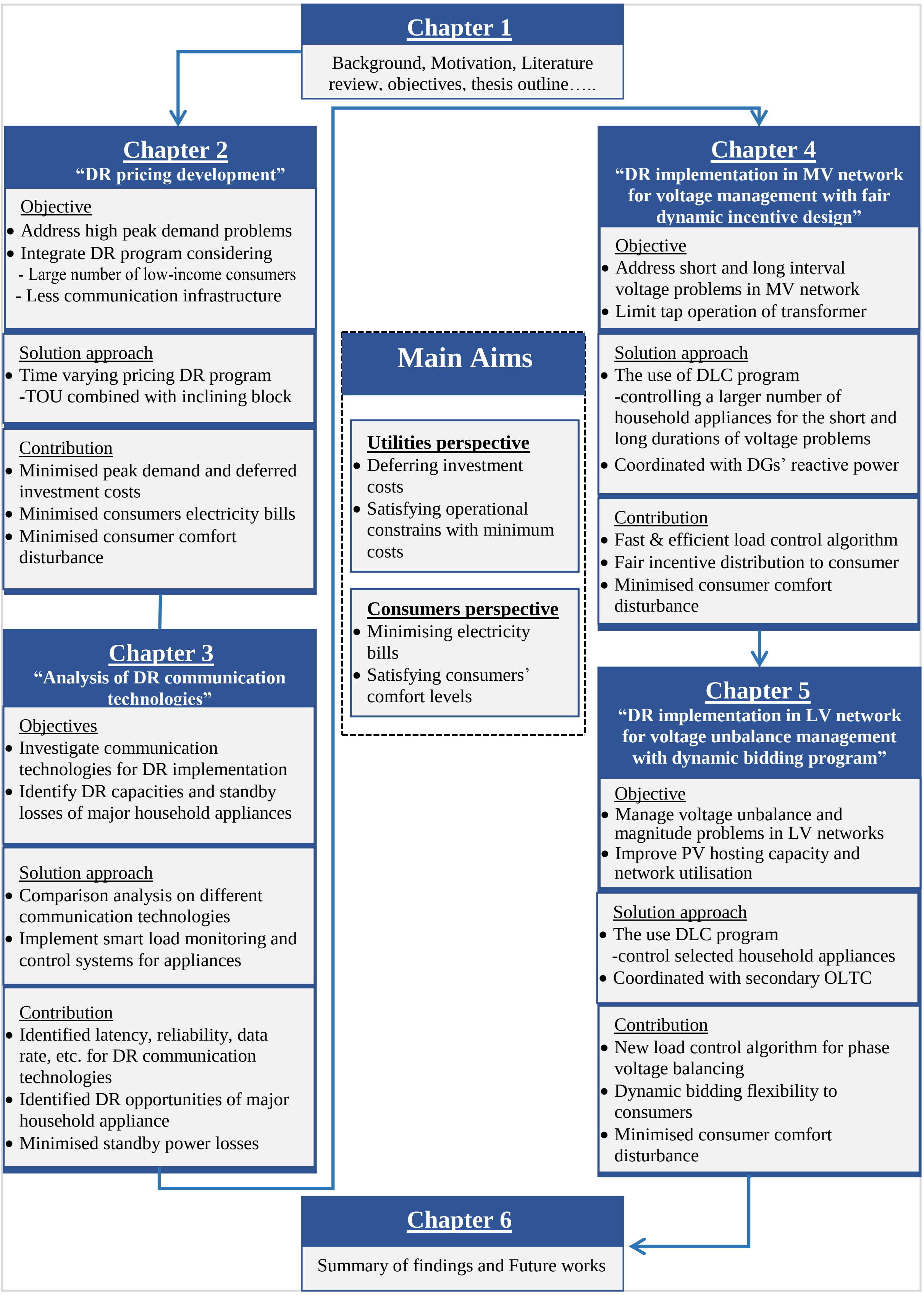

Fig. 1.1. Summary of the main contributions of each chapter of the thesis.

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Chapter 2

An Analysis of the Time of Use Electricity Price in the Residential Sector of Bangladesh♣

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Abstract

Time of Use (TOU) pricing is a cost-reflective electricity pricing scheme; it has proven to be an effective approach for reducing peak electricity demand in the residential sector around the world, especially in developed countries. The implementation of TOU pricing in low and lower-middle income economies is less appealing, mainly because traditional TOU pricing scheme usually increases the cost of electricity for low income consumers. The lack of a suitable TOU pricing strategy for these countries results in high peak demand, poor utilization of network infrastructure and, consequently, higher electricity prices than necessary. The purpose of this study is to analyse and propose a TOU pricing scheme for the residential sector that will be suitable for countries with a high percentage of low income household consumers. In this study, Bangladesh will be used as an exemplar of a lower-to-middle income developing country. In Bangladesh, the residential sector is responsible for half the country's total

♣ The content and structure of this published paper are modified based on the Thesis requirements.

electricity consumption, and constitutes an even greater proportion of the peak demand. Residential consumers currently pay inclining block usage rates that provide no financial incentive for them to shift their electricity usage from peak to non-peak periods. The proposed TOU pricing scheme is a combination of the traditional TOU and inclining block usage pricing schemes, based on a realistic load shifting capacity that is applicable to Bangladesh, and to other similar developing countries. Analysis of this pricing system for different income levels of residential consumers shows that the proposed scheme effectively reduces the peak demand, while ensuring minimum impact on consumer monthly energy bills and comfort levels.

Keywords: Time of use pricing; Peak demand; Inclining block pricing; Low income economies; Bangladesh.

2.1 Introduction

The World Bank has categorized 31 and 52 countries in the World as low income and lower-middle income economies respectively [1]. As in many other low and lower-middle income economies, investments in Bangladesh utility sectors are growing slowly, and often not enough electricity production is available to serve the demand at all times of the year. The residential sector of Bangladesh has a relatively high electricity consumption and accounts for 52% of the total electricity retail sales according to the Bangladesh Power Development Board (BPDB) annual report of 2015 [2]. Distribution companies in Bangladesh have estimated that a significant proportion of the recent growth in peak demand has been due to increased demand in the residential sector. This is mainly due to the lack of awareness of peak demand, energy management options, and alternative pricing structures among households. The electricity demand in Bangladesh is growing at more than 500 MW a year [3] and is expected to double in the period from 1997 to 2020 [4]. The peak demand growth requires high investment in network capacity and peak generation resources. A study by [5] has predicted that Bangladesh will not be able to meet its future energy demand without importing energy. This is due to inadequate oil and natural gas reserves, derated capacities of aging power plants, limited capacity of transmission or distribution networks and severe climate change effects [6]. The efficiency of energy production and consumption in Bangladesh is poor which has consistently strained the power system during peak demand periods [7]. Failure to match supply and demand has resulted in brownouts or blackouts. In such situations, utilities have had to import additional capacity (often at a high-cost premium) from neighbouring countries, switch to peak capacity generators, and apply load shedding schemes.

Electricity interruptions due to power shortages and network failures are common in Bangladesh and occur more frequently during peak periods, especially in peak summer months. The severity of the electricity interruptions was as high as 932 MW, 780 MW, and 535 MW during 2013, 2014 and 2015, respectively [2]. The costs associated with the Energy Not Served (ENS) due to severe electricity interruptions have substantial impacts on the total cost of the power supply to the consumers [8]. For instance, a survey of 400 residential consumers shows that the estimated economic loss due to electricity outages was US $306k (24 million TK)[*] in the residential sector in Dhaka, Bangladesh [9]. According to the World Bank's Enterprises Survey, the economic loss due to electricity outages in Bangladesh was 5.5% of the total electricity sale in 2013 [10].

There is a direct relationship between peak demand and environmental emissions [11]. Most of the peak plants in the country utilize liquid fuel based power plants. The power generation is almost entirely dependent on fossil fuels; specifically, natural gas and coal continue to be the main fuel sources for electricity generation. As a result, the share of CO_2 emissions emanating from these power plants in the national CO_2 inventory is expected to

[*] Taka (TK) Bangladeshi currency (1 US$ = 78.51 Taka, as on 27 July 2016).

grow. According to [12], the electricity sector alone contributes 40% of the total CO_2 emissions of the country.

As a result of these concerns, there is a growing interest in addressing this issue, at least partially on the demand side, through reducing the peak demand for electricity at critical times by consumer engagement. One of the primary methods that can be pursued to reduce the peak electricity use in households is through behavioural modification. For example, introducing high energy prices during peak usage periods should incentivise users to shift their demand to non-peak periods. However, with the current energy policy in Bangladesh, households pay inclining blocks usage rates for their electricity, which divides the electricity price into several consumption blocks. This inclining block pricing scheme is developed so that a low energy usage consumer pays a substantially lower price compared to a high usage consumer, irrespective of the time of use [13]. This means the current pricing policy will not necessarily reflect network infrastructure costs during the peak period when the cost of generating electricity is high. There is no financial incentive for consumers to encourage them to shift consumption from peak to non-peak periods [14]. As a result, peak demand is high and increases inefficient investment in network capacity and generation [15].

From the above discussion, it is apparent that there are still significant opportunities available to improve the electricity sector of Bangladesh, especially involving end-users in the residential sector. Therefore, the objective of this study is to manage the growing peak demand in the residential sector by charging consumers according to a cost-reflective electricity pricing scheme such as TOU pricing. However, in Bangladesh, the total number of low income households (who are mainly low usage consumers) is relatively large. Based on the Household Income and Expenditure Survey 2010 in Bangladesh [16], around 46% of households are low income, 39% are middle income, and 15% are high income. With these large percentages of low and middle income households, the main challenge for a TOU pricing implementation is to motivate all categories of residential consumers to change their consumption behaviour without adversely affecting their comfort levels and electricity bills, while reducing consumption during peak periods. There is no research literature available that discusses the feasibility of TOU electricity pricing for the residential sector in Bangladesh. Therefore, the main contribution of this study will be to answer these research questions: “Is TOU an effective pricing for all categories of residential consumers in Bangladesh to reduce peak demand? If yes, what sort of TOU?” This study developed and analysed four TOU pricing structures for residential consumers that were deemed to be suitable. Based on ensuring low impact on consumers’ monthly energy bills and their comfort levels, an appropriate TOU price structure has been selected for households in Bangladesh. The proposed TOU electricity pricing scheme is tested through simulations of a real electric distribution network, which will demonstrate the scheme’s effectiveness in peak demand reduction and network investment cost minimization. This study will benefit electric utilities in low and middle income developing countries as they explore alternative approaches for capacity expansion to meet their current and future electric power demands. This is especially important in today's conditions, where the capital cost of new generating capacity and environmental concerns over fossil fuel emissions are increasing. In addition, the approach presented in this study will be beneficial to consumers as it prevents electricity price increases in the long-term.

The structure of this study is organised as follows: Section 2.2 provides a review on the challenges of implementing TOU pricing in both developed and developing countries. The methodology of the study is presented in Section 2.3. Section 2.4 describes the analysis steps that are proposed in the methodology of Section 2.3. The analysis results of four different forms of TOU pricing on different groups of consumers’ monthly energy bills are presented in Section 2.5. Section 2.6 presents the impacts of the proposed TOU pricing scheme on the reduction of peak demand, the costs of supplying and delivering electricity to consumers and the costs of ENS. Finally, the paper is concluded in Section 2.7.

2.2 TOU pricing implementation challenges in developing countries

TOU pricing is a cost-reflective electricity pricing scheme in which days are commonly split into two or three time periods, such as, peak, off-peak, and shoulder. The electricity price is highest during peak periods, moderate during shoulder periods and the lowest during off-peak periods. There are many convincing arguments that TOU pricing can reduce peak electricity demand and energy conservation in the residential sector [17, 18]. TOU electricity pricing is widespread in developed countries (e.g., Australia, America, etc.). Several upper-middle income developing countries such as Malaysia, Thailand, etc. have begun to implement TOU pricing to improve their economics [19]. The potential benefits of TOU, which are identified from different pilot studies include: avoided or deferred generation and transmission costs [20]; significant peak reduction [21]; consumers' energy bill reduction [22]; reduced wholesale market prices [23]; improved fairness in retail pricing and facilitating the deployment of distributed generation [24]; and environmental benefits [25].

The applicability of pricing reforms varies across different countries, depending on the level of their economic and the stage of their power sector reform. While there are many potential benefits from TOU pricing in developed countries, the benefits from the TOU pricing in low income household countries (such as Bangladesh, Nepal, Cambodia, etc.) may not be the same due to differences in culture, lifestyle, education level and income level. Due to low per capita income consumers in these countries have a limited affordability to pay for electricity, which limit the electricity rate design for system capacity expansion. There have been mixed opinions about the impact of traditional TOU pricing on low socio-economic households. One opinion is that high prices would disproportionately affect low income households who do not have the capacity to take action to avoid paying high peak prices [26]. Also, when confronted with an increase in energy costs, lower income families tend to make "lifestyle cutbacks" [27]. Introducing traditional TOU may increase low income consumers' financial risks, if they are unable to shift peak consumption [28]. In addition, a detailed analysis in [29] indicates that household demand responsiveness to price decreases, as household income increases. On the other hand, TOU pricing experiments show that low income consumers have been found to be price responsive and thus leading to reduced average peak demand by 13% [30]. Low income households will be able to shift their peak load by the same amount as medium-consuming households if an appropriate design and selection of a TOU pricing scheme is implemented [31].

2.2.1 Scopes of TOU pricing implementation in the residential sector of Bangladesh

The growth in peak demand in Bangladesh requires ongoing investment in network capacity and peak generation. Usually, electricity distribution networks make up the largest component of these expenses and accounts for between 60% to 75% of the total electricity costs [32]. The retail electricity prices for all sectors in Bangladesh increased on average by 7% in the financial year (FY) 2014-2015 and 8% in FY 2015-2016, as shown in Table 2.1. A TOU electricity pricing scheme is already available for commercial and industrial consumers in Bangladesh. However, for residential consumers in Bangladesh, it is a new concept, similar to other low income countries (e.g., Nepal and Cambodia have a block pricing scheme in their residential sector [33], [34]). Table 2.1 shows, the current electricity pricing scheme in Bangladesh for residential consumers, which is inclining block pricing. Inclining block does not price energy according to the time of consumption, rather it prices energy based on the level of energy consumption only. Most residential consumers are not aware of the impact of electricity use during peak periods on the costs of electric networks and the environment. Also, there are no incentives to encourage consumers to shift their use of electricity from peak periods to off-peak periods. Hence, energy usage depends on individual consumer preferences and weather conditions. Many high-use consumers have peak-oriented consumptions for air conditioning, heating, and other temperature-sensitive applications [35], which leads to high peak demand in the network. Analysis in [36] shows that there is almost no peak demand reduction possible from inclining block pricing in the residential sector. However, with TOU pricing, consumers know when and by how much the price varies, and higher prices during peak periods would encourage them to shift their electricity use to off-peak periods. Small responses will have significant effects on marginal peak production costs, reducing investment in expensive peak generation, additional transmission and/or distribution capacity. For example, a study in [37] estimated that a reduction of only 2–5% in system-wide demand at peak times could reduce the spot price for electricity by 50% or more.

Table 2.1

Retail price structures for various categories of consumers [38, 39].

Consumer Category	**Price per unit (Tk/kWh)**		
	FY2013-2014	FY2014-2015	FY2015-2016
Category-A: Residential			
Life Line: From 1 to 50 kWh	Not available	3.33	3.33
First Step: From 1 to 75 kWh	3.33	3.53	3.80
Second Step: From 76 to 200kWh	4.73	5.01	5.14
Third Step: From 201 to 300 kWh	4.83	5.19	5.36
Fourth Step: From 301 to 400 kWh	4.93	5.42	5.63
Fifth Step: From 401 to 600 kWh	7.98	8.51	8.70
Sixth Step: Above 600 kWh	9.38	9.93	9.98
Category-B: Agricultural pumping	2.51	2.51	3.82
Category-C: Small Industries			
Flat Rate	6.95	7.42	7.66
Off-Peak (23 hours to 17 hours)	5.96	6.64	6.90
Peak (17 hours to 23 hours)	8.47	9.00	9.24
Category-D: Commercial and Office			
Flat Rate	9.00	9.58	9.80
Off-Peak (23 hours to 17 hours)	7.22	8.16	8.45
Peak (17 hours to 23 hours)	11.85	11.85	11.98

2.3 The methodology of TOU electricity pricing assessment

A two-stage (analysis and case study) assessment process is deployed in this study for evaluating a suitable TOU pricing scheme for residential consumers and its impact on the network upgrade and the ENS costs. Fig. 2.1 illustrates five steps that are undertaken in the analysis stage for assessing a suitable TOU pricing. The case study stage evaluates the total cost of network upgrades and ENS costs with the proposed TOU pricing. At this stage, different scenarios for network expansion are also examined. Briefly, the two stages of assessment in this study for evaluating the effectiveness of the proposed TOU scheme are as follows:

Analysis stage: Assessment of TOU electricity pricing

$$\text{Subject to: } \begin{cases} \text{Minimum impacts on consumers}'\text{monthly energy bills;} \\ \text{Minimum impacts on consumers}'\text{comfort levels;} \\ \text{Maximum contribution on peak demand reduction.} \end{cases}$$

Case study: Assessment of total network investment costs + ENS costs

Subject to maintaining network constraints, such as voltage and thermal limits at minimum cost.

A scenario-based method is used in each of the two stages. In the analysis stage, the monthly energy bills of different groups of consumers are calculated based on different TOU electricity pricing schemes and compared with the existing inclining block monthly bills. The selection of a suitable TOU pricing scheme depends on minimum monthly billing impacts, comfort levels of consumers, and the amount of peak shaving.

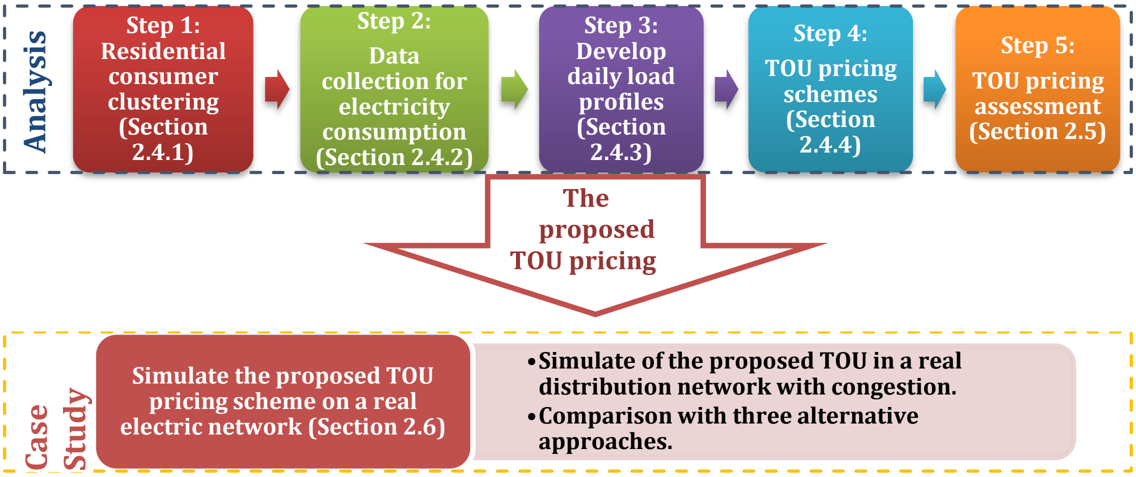


Fig. 2.1. Two-stage assessment process.

In the case study, as detailed in Section 2.6, the effect of peak demand reduction, using TOU pricing on the network capacity upgrade and ENS costs, is evaluated considering different scenarios by simulating a realistic distribution grid. In this stage, network upgrade options (e.g., adding transformers and diesel generators), the cost of ENS due to load shedding and the proposed TOU scheme will be considered. The next section describes the first four steps of the TOU pricing analysis stage.

2.4 Analysis stage: steps 1 to 4

2.4.1 Step 1: Residential consumer clustering

Residential consumers are clustered into six different groups according to their monthly incomes and energy consumption levels, as defined in Table 2.2. The clustering is based on income tax categories and the poverty line in Bangladesh [40]. Consumers with less than 100 kWh monthly energy usages are considered as Low income consumers (monthly incomes less than 10,000 TK). Middle income consumers are divided into four monthly energy groups such as Middle 1 (100-200 kWh), Middle 2 (201-400 kWh), Middle 3 (401-500 kWh) and Middle 4 (501-600 kWh) and their income range between 10,000 and 30,000 TK per month. High income consumers consume over 600 kWh per month (monthly income more than 30,000 TK) and are considered as High energy users.

Table 2.2

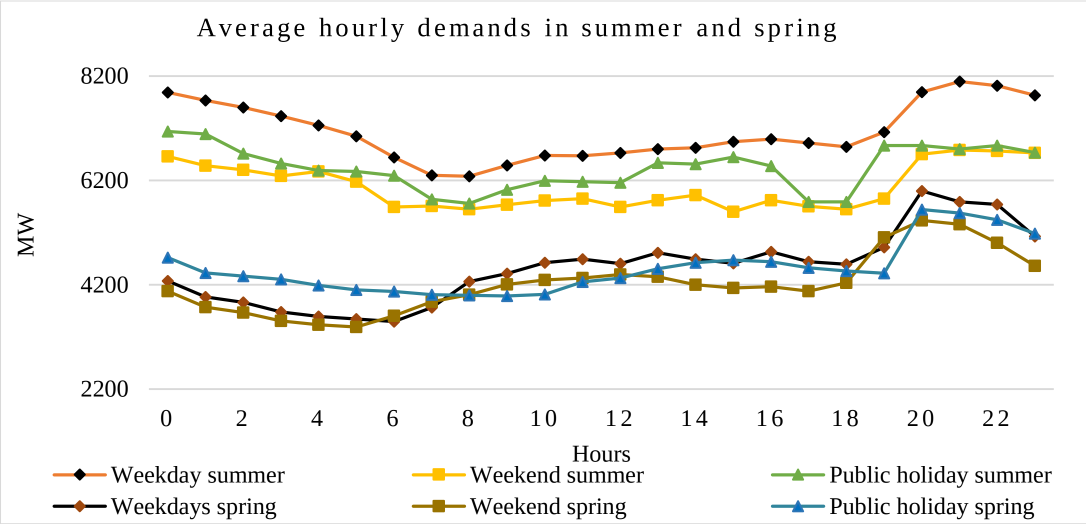
Consumer groups according to income and consumption levels [40].

Income Level	Income (TK/month)	Consumer group	Usage range (kWh/month)
Low	<10,000	Low	<100
Middle	10,000 to 30,000	Middle 1	100-200
		Middle 2	201-300
		Middle 3	301-500
		Middle 4	501-600
High	>30,000	High	>600

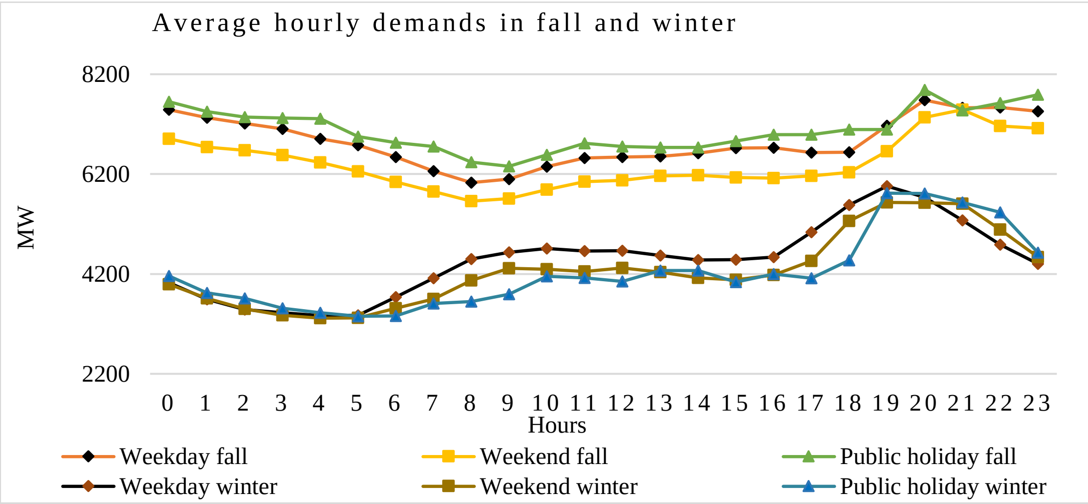
2.4.2 Step 2: Data collection for electricity consumption

As this study aims to consider the practicality of the proposed TOU, residential consumers' monthly electricity bills, available electric appliances and daily usage patterns for each energy consumer group are collected through personal communication [41]. A total of 40 consumers' monthly electricity bills and their appliances' daily usage profiles have been collected; with 15 being from the Low income group, 15 from the Middle income group and 10 consumers from the High income group (the total load profile for each income group during different seasons are presented in Appendix A.3). The collected monthly electricity bills cover energy consumption for four consecutive seasons over the 2014/2015 period, i.e., summer (May-Jul), fall (Aug-Oct), winter (Nov-Jan), and spring (Feb-Apr). Figures 2.2 (a) and (b) show the average hourly load profiles during weekdays, weekends, and public holidays in the four seasons [42]. As seen, the average daily electricity demand in summer and fall are higher than in winter and spring. This is due to the weather being normally pleasant and comfortable in winter and spring seasons (especially in spring), hence there is less use of heating and cooling appliances during these seasons. In Bangladesh, the peak period is considered to be from 17:00 to 23:00 each day. The ratio of peak to off-peak usage during weekdays, weekends and public holidays in the high demand summer season are 36%, 35% and 34%, respectively, while for the low demand spring season, these figures are 41%, 40% and 38%, respectively. It can be seen that these peak to off-peak consumption ratios are quite similar in weekdays, weekends and public holidays. However, the average hourly consumption during weekdays (7124 MW in summer and 6438 MW in spring) and public holidays (6438 MW in summer and 4517 MW in spring) are higher than the consumption at weekends (6075 MW in summer and 4214 MW in spring). Therefore, in the analyses of this paper, public holidays are treated as weekdays.

Table 2.3 shows the typical monthly electricity bills for the all four seasons (i.e. summer, spring, fall and winter) in Bangladesh, which are based on the inclining block pricing rates of FY 2014-2015. These electricity bills represent six different monthly energy consumer groups and are further recalculated using the new inclining block pricing rates for FY 2015-2016 (see in Table 2.1). The percentages of electricity bills increased with the new price rates are then compared against the previous year price rates (FY 2014-2015), as shown in Table 2.3. It shows that with the new electricity pricing rates, the Low and Middle energy consumers are significantly affected with a higher electricity bill compared to the High energy consumers. The calculated electricity bills with the new (updated) inclining block pricing rates are considered as the base monthly bills in TOU pricing assessments. All the energy bills presented in Table 2.3 are excluded from the demand charges (15 TK/kW), value added tax (5%), and late payment penalty fees (2%). The available electric appliances and the daily usages information for each energy consumer group are discussed in the next section.



(a)



(b)

Fig. 2.2. Average hourly demand profile for weekdays, weekends and public holidays in all seasons in 2015 [42].

Table 2.3

Residential consumers' monthly electricity bills based on the current inclining block pricing in different seasons.

Consumer group	Average monthly energy usage (kWh/month)	2014-2015 rates: Average energy bill (TK/month)	2015-2016 rates: Estimated bills with new price rates (TK/month)	% of bill increased	Average monthly energy usage (kWh/month	2014-2015 rates: Average energy bill (TK/month)	2015-2016 rates: Estimated bills with new price rates (TK/month)	% of bill increased
		Summer				***Fall***		
Low	**97**	375	398	6.13	**84**	310	331	6.77
Middle 1	**175**	766	799	4.31	**122**	500	527	5.40
Middle 2	**295**	1384	1437	3.83	**230**	1047	1088	3.92
Middle 3	**491**	2726	2818	3.37	**409**	2029	2105	3.75
Middle 4	**600**	3654	3767	3.09	**556**	3280	3384	3.17
High	**800**	5640	5763	2.18	**734**	4985	5104	2.39
		Spring				***Winter***		
Low	**60**	212	228	7.55	**63**	227	239	5.29
Middle 1	**101**	390	414	6.15	**111**	445	470	5.62
Middle 2	**217**	979	1019	4.09	**227**	1041	1072	2.98
Middle 3	**326**	1551	1610	3.80	**385**	1871	1942	3.79
Middle 4	**510**	2888	2984	3.32	**542**	3160	3216	1.77
High	**651**	4160	4276	2.79	**700**	4647	4765	2.54

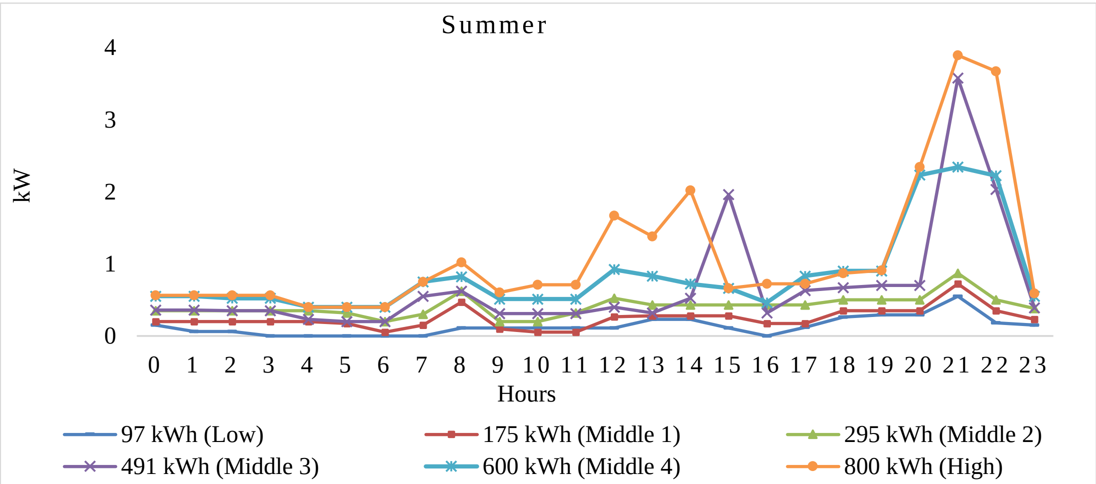
Source: Dhaka Electric Supply Company Limited [38].

2.4.3 Step 3: Daily load profiles

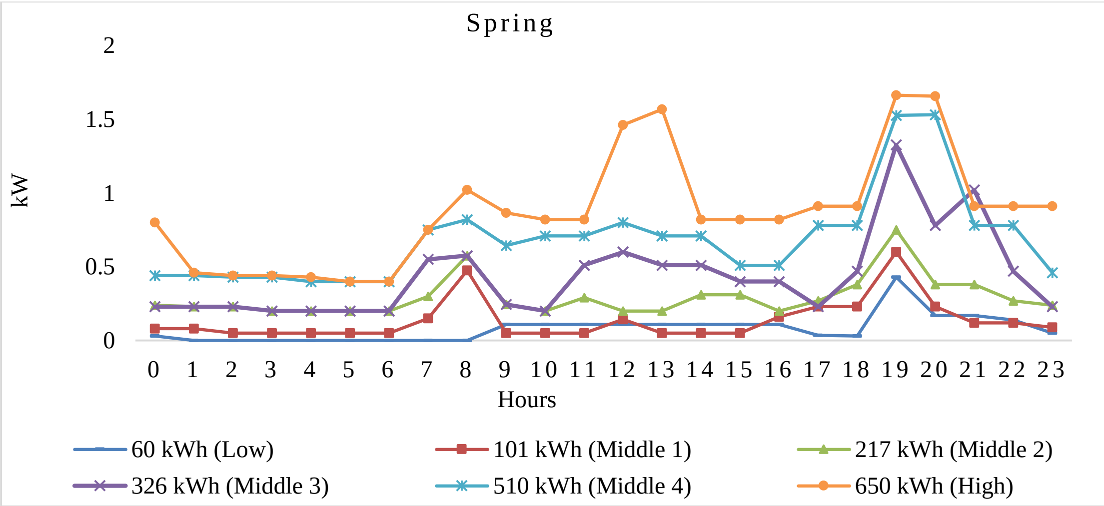
The daily load profile has a critical impact on the evaluation and selection of a pricing scheme. In this step, for each season, six average daily load profiles of six energy consumer groups are constructed, as shown in Fig 2.3. These load profiles are constructed based on the estimation of consumers' available electric appliances and their typical daily usage patterns. The typical consumption ratings (W) and typical daily usage for all appliances are obtained from the Dhaka Electric Supply Company Limited [39], [43]. It is ascertained that, on average, the appliances used each day by a Low consumer group are two or three lights (mostly Compact Fluorescent Lights), a small television, two cooling fans (mostly ceiling fan) and a small pump motor (370W). Additional appliances used by the Middle 1 and Middle 2 consumer groups are an electric iron, microwave oven, grinder, exhaust fan, computer and small refrigerator (180W). Middle 3 and Middle 4 consumer groups can also afford a washing machine (550W), a larger television (200W), one or two larger refrigerators (250W each), a large pump motor

(746W) and an air-conditioner (1500 W). High consumer groups, who consume more than 600 kWh per month, can also afford at least two air-conditioners (1500W each), two refrigerators (350W each) and two televisions (200W).

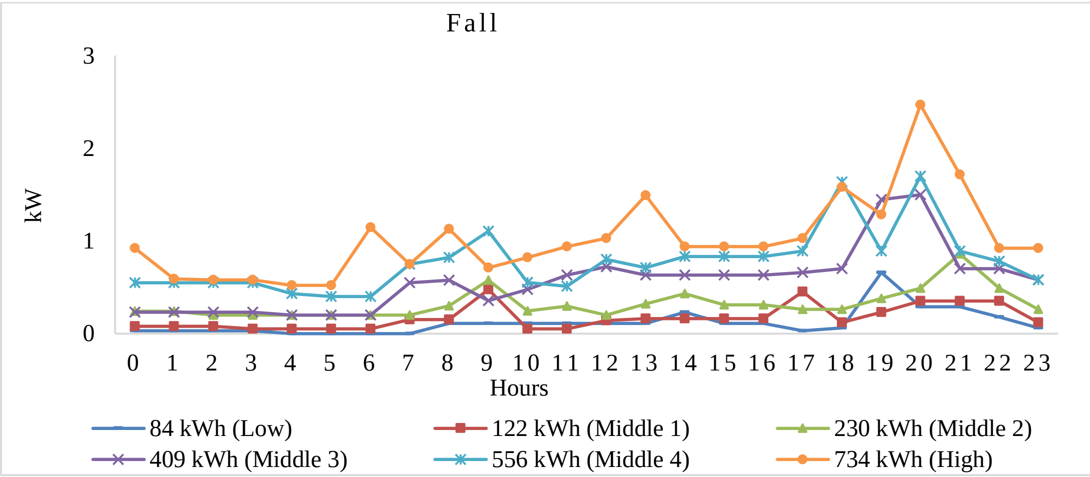
Based on this survey, some of the basic loads, such as lighting, television, and computer, are operated for 8 to 12 hours each day for all consumer groups. The cooling fan and air-conditioner (AC) operations depend on weather conditions. For example, in peak summer months, fans are operated mostly all hours of the day and ACs function for 1 to 5 hours, as seen in Fig. 2.3(a) for weekdays. In the spring, due to comfortable cool weather conditions, these appliances are not in operation, therefore there is less consumption in peak periods, as shown in Fig. 2.3(b). Figures 2.3(c) & (d) present the daily load profiles for fall and winter, respectively. The use of flexible appliances, such as a washing machine and pumps, depends on the consumer preferences. In this study, the daily operation of these appliances is restricted to peak periods, which is the normal behaviour of Middle 3 and 4 and High consumer groups [39]. In addition, the typical load profiles for each season are constructed for weekends based on the collected data, which are not reported here for the sake of simplicity.



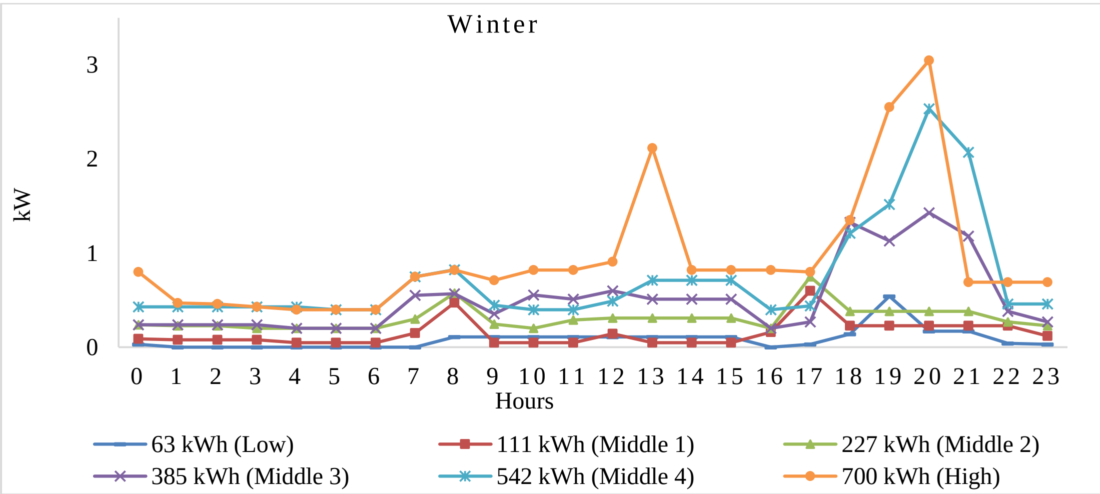
(a)



(b)



(c)



(d)

Fig. 2.3. The representative average daily load profiles for six consumer groups during the four seasons.

Based on the constructed daily load profiles for each season, the monthly energy consumption during weekdays and weekends are calculated for each energy consumption group, as shown in Tables 2.4 and 2.5. These tables also show the consumption during peak and off-peak periods during weekdays and weekends, which are calculated based on the daily load profiles and the number of weekdays and weekends in each season. The "others" in Tables 2.4 and 2.5 include all the appliances total monthly peak and off-peak consumption, except the washing machine and water pump monthly energy usage. In order to minimize the impacts on consumers' comfort, a washing machine and water pump are considered as shiftable loads in all pricings schemes described in the next section.

Table 2.4

Total monthly consumption during weekdays and weekends for each consumer group in summer and spring.

	Summer												Spring											
Energy usages group	Avg. daily	Total mon-thly	Monthly weekday usages		Monthly weekend usages		W.Pump (370/ 746W)		W.mch (550W)		Others		Avg. daily	Total mon-thly	Monthly weekday usages		Monthly weekend usages		W.Pump (370/746 W)		W.mch (550W)		Others	
	kWh	kWh	kWh		kWh		kWh		kWh		kWh		kWh	kWh	kWh		kWh		kWh		kWh		kWh	
	(c1)	(30 × c1)	P	Off P	P	Off P	P	Off P	P	Off P	P	Off P	(c1)	(31 × c1)	P	Off P	P	Off P	P	Off P	P	Off P	P	Off P
Low	**3.23**	**97**	37.2	33.9	13.5	12.3	11.1	0.0	-	-	39.6	46.2	**1.94**	**60**	22.4	22.1	7.8	7.7	11.5	0.0	-	-	18.8	29.8
Middle 1	**5.83**	**175**	50.4	77.9	18.3	28.3	11.1	0.0	-	-	57.6	106	**3.26**	**101**	35.2	39.7	12.2	13.8	11.5	0.0	-	-	36	53.6
Middle 2	**9.83**	**295**	72.6	144	26.4	52.2	11.1	0.0	-	-	87.9	196	**7.00**	**217**	55.9	105	19.4	36.6	11.5	0.0	-	-	63.9	142
Middle 3	**16.37**	**491**	183	177	66.4	64.5	22.4	0.0	16.5	0.0	210	242	**10.52**	**326**	98.8	143	34.4	49.8	23.1	0.0	17.1	0.0	93	193
Middle 4	**20.00**	**600**	207	233	75.4	84.6	22.4	0.0	16.5	0.0	244	317	**16.45**	**510**	142	236	49.4	82.2	23.1	0.0	17.1	0.0	151	319
High	**26.67**	**800**	273	314	99.2	114	22.4	22.4	16.5	16.5	333	389	**21.00**	**651**	160	323	55.7	112	23.1	23.1	17.1	17.1	176	395

Avg. = Average; W. Pump= Water pump; W.mch= Washing machine; P = Peak; Off P =Off-peak.

Table 2.5

Total monthly consumption during weekdays and weekends for each consumer group in fall and winter.

	Fall												Winter											
Energy usages group	Avg. daily	Total mon-thly	Monthly weekday usages		Monthly weekend usages		W.Pump (370/ 746W)		W.mch (550W)		Others		Avg. daily	Total mon-thly	Monthly weekday usages		Monthly weekend usages		W.Pump (370/746 W)		W.mch (550W)		Others	
	kWh	kWh	kWh		kWh		kWh		kWh		kWh		kWh	kWh	kWh		kWh		kWh		kWh		kWh	
	(c1)	(30 × c1)	P	Off P	P	Off P	P	Off P	P	Off P	P	Off P	(c1)	(31 × c1)	P	Off P	P	Off P	P	Off P	P	Off P	P	Off P
Low	**2.8**	**84**	33.2	28.4	12.1	10.3	11.1	0.0	0.0	0.0	34.2	38.7	**2.03**	**63**	25.1	21.6	8.7	7.5	11.5	0.0	0.0	0.0	22.3	29.1
Middle 1	**4.07**	**122**	40.7	48.8	14.8	17.7	11.1	0.0	0.0	0.0	44.4	66.5	**3.58**	**111**	40.3	42.1	14.0	14.6	11.5	0.0	0.0	0.0	42.8	56.7
Middle 2	**7.67**	**230**	60.3	108	21.9	39.4	11.1	0.0	0.0	0.0	71.1	148	**7.32**	**227**	58.4	111	20.3	38.2	11.5	0.0	0.0	0.0	67.3	148
Middle 3	**13.63**	**409**	126	174	45.6	63.4	22.4	0.0	16.5	0.0	132	238	**12.4**	**385**	131	154	45.7	53.6	23.1	0.0	17.1	0.0	137	208
Middle 4	**18.53**	**556**	149	258	54.3	94.0	22.4	0.0	16.5	16.5	165	336	**17.5**	**542**	189	213	65.8	74.0	23.1	0.0	17.1	0.0	215	287
High	**24.47**	**734**	198	340	72.0	124	22.4	22.4	16.5	16.5	231	425	**22.6**	**700**	210	310	73.0	108	23.1	23.1	17.1	17.1	243	377

2.4.4 Step 4: TOU pricing schemes

In this study, four TOU electricity pricing schemes are analysed based on knowledge of existing TOU pricing policies. Considering the characteristics of consumers in Bangladesh, such as a large number of low income and middle income consumers, these four TOU pricing schemes are chosen and evaluated. The proposed TOU schemes are labelled as Smart tariff 1 (ST1), Smart tariff 2 (ST2), Smart tariff 3 (ST3), and Smart tariff 4 (ST4). Table 2.6 presents a brief description of each TOU pricing scheme. ST1 pricing uses two-period TOU pricing rates (peak and off-peak). ST2 and ST3 use peak and off-peak prices in addition to the inclining block pricing. The ST2 scheme applies peak and off-peak price rates when monthly consumption exceeds 200kWh. The ST3 scheme uses these TOU rates when monthly consumption exceeds 300kWh. By comparison, in California, peak, off-peak and shoulder rates are applied from l00 kWh of monthly usages [14]. Finally, the proposed ST4 pricing presented in this study is an integration of inclining block and TOU pricing, which uses five different kWh usage blocks with different peak and off-peak price rates (see Section 2.5.4). The Pacific Gas and Electric Company in California [44] uses a scheme similar to ST4. However, all parameters associated with ST4 including the number of blocks, timing, levels of blocks, and rates are different to those proposed here. These pricing schemes and their impacts on consumer monthly electricity bills are described in Section 2.5.

Table 2.6

The four proposed TOU pricing schemes

TOU scheme	Description
ST1	Two parts fixed period TOU price rates (peak and off-peak price rates).
ST2	First 200 kWh monthly usages will be charged based on inclining block price rates. Usages over 200 kWh will be charged at ST1 pricing rates.
ST3	First 300 kWh monthly usages will be charged based on inclining block price rates. Usages over 300 kWh will be charged at ST1 pricing rates.
ST4 (the proposed pricing scheme)	Energy usages are divided into five inclining blocks. Each block has a different peak and off-peak price rates.

For the first three smart pricing schemes (ST1 to ST3), the duration of peak and off-peak hours in weekdays, weekends and public holidays are shown in Fig. 2.4. During weekdays and public holidays, the peak period is considered from 17:00 to 23:00 and the off-peak period is the remaining hours of a day. During weekends, all the hours of a day are considered as the off-peak period. Peak and off-peak price rates for the first three pricing schemes are calculated as follows:

- Off-peak rate: the off-peak rate is 5.88 TK/kWh, which represents the average electricity generation cost in FY 2014-2015 [2]. The off-peak price rate is excluded from the supply costs of electricity to minimise the high pricing rate for the low and middle incomes' consumers.
- Peak rate: the peak rate is 5.88 × 1.45 = 8.53 TK/kWh, where 1.45 represents the ratio of peak to off-peak price rates of the commercial TOU pricing in FY 2014-2015 (as mentioned in Table 2.1).

For the ST4 scheme, peak and off-peak periods are considered the same as for weekdays, weekends and public holidays to reduce complexity in the pricing scheme. Peak and off-peak price rates for each kWh block of ST4 are calculated from the inclining block weighted average price of FY 2014-2015, as described in Section 2.5.4.

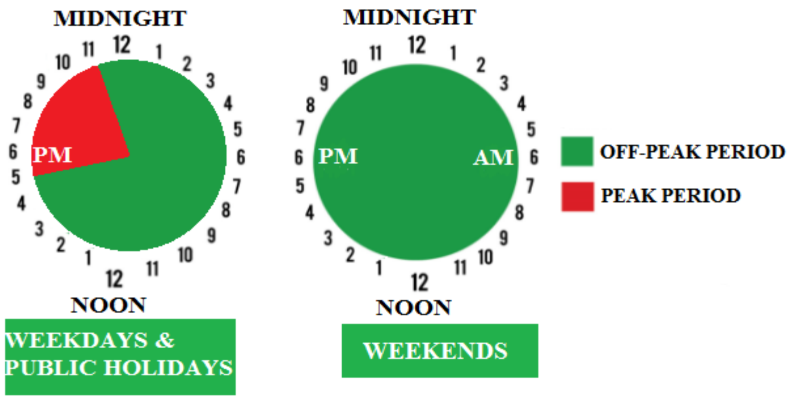


Fig. 2.4. Peak and off-peak periods for ST1, ST2 and ST3 pricing schemes.

The next section describes the step 5 of the TOU pricing analysis stage, in where the impact of all proposed TOU pricing (ST1 to ST4) on different consumer groups are assessed based on their monthly bills.

2.5. Analysis Stage: Step 5 (TOU pricing assessment)

2.5.1 Smart tariff 1 (ST1)

The ST1 scheme offers two fixed period TOU price rates; peak and off-peak. Based on the TOU pricing rates (calculated in Section 2.4.4) and total energy usage during peak and off-peak periods in weekdays and weekends of a month, the electricity bills for all consumer groups are calculated for peak summer and low demand months. The monthly electricity bill is calculated using equation (2.1).

$$\begin{aligned} \mathit{Monthly\ electricity\ bill} \\ &= \sum_{i=1}^{N^{wd}} \left(E_{p,i}^{wd} - E_{shift,i}^{wd}\right) \times C_p^{wd} + \left(E_{off,i}^{wd} + E_{shift,i}^{wd}\right) \times C_{off}^{wd} \\ &+ \sum_{i=1}^{N^{we}} (E_{p,i}^{we} - E_{shift,i}^{we}) \times C_p^{we} + (E_{off,i}^{we} + E_{shift,i}^{we}) \\ &\times C_{off}^{we} \end{aligned} \tag{2.1}$$

where C_p^{wd} and C_{off}^{wd} are peak and off-peak price rates for weekdays, respectively, as calculated in Section 2.4.4; $E_{p,i}^{wd}$ and $E_{off,i}^{wd}$ are the total peak and off-peak periods energy consumption for the *i*th weekday, respectively; $E_{shift,i}^{wd}$ is the total shiftable consumption for the *i*th weekday that can be shifted to off-peak period; N^{wd} and N^{we} are the number of weekday and weekend days in a month; and the indexes '*wd*' and '*we*' represent weekdays and weekends, respectively.

Table 2.7 illustrates the resulting monthly electricity bills from the ST1 pricing scheme, with and without load shifting. In this table, the values for E_p, E_{off} and E_{shift} during weekdays and weekends for each season are obtained from Tables 2.4 and 2.5. As shown in Table 2.7, the resulting electricity bills for each season, for each consumer, are presented in two ways: “ST1 bill” and “ST1 bill included weekend pricing”. “ST1 bill” represents the total monthly electricity bill, which is calculated by excluding the off-peak rate option from weekends. In this analysis, weekends and public holidays are priced the same as weekdays. The “ST1 bill included weekend pricing” represents the total monthly electricity bill, which is calculated based on TOU pricing provided for weekdays, weekends and public holidays (as depicted in Fig. 2.4). These calculated electricity bills provide a further insight into the economic analysis for both the utility and consumers, as the consumption patterns of Bangladesh in public holidays are quite similar to consumption patterns on weekdays (as shown in Fig. 2.2). The calculated monthly bills are then compared to the base monthly bills, which were obtained from the inclining block pricing rates of FY 2015-2016 (see Table 2.3).

Table 2.7 shows that the monthly energy bills based on the ST1 scheme are significantly higher for all groups of consumers compared to the base inclining block pricing bills, even with the load shifting to the off-peak period. The only group who benefited from this scheme is the High consumer group, which includes consumers who consume over 600 kWh per month (as their ‘extra pay’ is negative, as highlighted in Table 2.7).

Table 2.7

Monthly electricity bills for different consumer groups using ST1 pricing scheme in different seasons.

Energy usage groups	Total usage	Base bill	Total Shift-able loads	Without load shifting: ST1 bill	Extra pay	ST1 bill included weekend pricing	Extra pay	W. Pump shifting only: ST1 bill	Extra pay	ST1 bill included weekend pricing	Extra pay	W. Pump & W.mch shifting: ST1 bill	Extra pay	ST1 bill included weekend pricing	Extra pay
	kWh/ month	TK/ month	kWh/ month	TK/ month	%	TK/ month	%	TK/ month	%	TK/ month	%	TK/ month	%	TK/ month	%
							Summer								
Low	**97**	398	11.1	699	75.7%	665	67%	670	68.3%	643	61.6%	-	-	-	-
Middle 1	**175**	799	11.1	411	51.5%	1162	45.4%	1181	47.8%	1140	42.7%	-	-	-	-
Middle 2	**295**	1437	11.1	1996	38.9%	1926	34.1%	1967	36.9%	1905	32.6%	-	-	-	-
Middle 3	**491**	2818	38.9	3547	25.9%	3371	19.6%	3488	23.8%	3328	18.1%	3444	22.2%	3296	16.9%
Middle 4	**600**	3767	38.9	4277	13.5%	4077	8.2%	4218	12.0%	4034	7.1%	4174	10.8%	4002	6.2%
High	**800**	5763	38.9	5690	–1.3%	5427	–5.8%	5631	–2.3%	5384	–6.6%	5587	–3.1%	5351	–7.1%
							Spring								
Low	**60**	228	11.1	433	89.8%	412	80.8%	402	76.5	390	70.9%	-	-	-	-
Middle 1	**101**	414	11.1	720	73.8%	687	66.0	689	66.5%	665	60.5%	-	-	-	-
Middle 2	**217**	1019	11.1	1476	44.8%	1424	39.8%	1445	41.8%	1402	37.5%	-	-	-	-
Middle 3	**326**	1610	38.9	2270	41.0%	2179	35.3%	2208	37.2%	2133	32.5%	2163	34.4%	2100	30.4%
Middle 4	**510**	2984	38.9	3506	17.5%	3375	13.1%	3445	15.4%	3330	11.6%	3400	13.9%	3296	10.5%
High	**651**	4276	38.9	4400	2.9%	4252	–0.6%	4338	1.5%	4207	–1.6%	4293	0.4%	4173	–2.4%
							Fall								
Low	**84**	331	11.1	614	85.5%	582	75.8%	585	76.6%	560	69.3%	-	-	-	-
Middle 1	**122**	527	11.1	864	64%	825	56.6%	835	58.4%	804	52.5%	-	-	-	-
Middle 2	**230**	1088	11.1	1570	44.3%	1512	39%	1541	41.6%	1491	37%	-	-	-	-
Middle 3	**409**	2105	38.9	2858	35.8%	2737	30%	2799	33%	2694	28%	2755	31%	2662	26.4%
Middle 4	**556**	3384	38.9	3809	12.6%	3665	8.3%	3749	10.8%	3621	7%	3706	9.5%	3589	6.1%
High	**734**	5104	38.9	5032	–1.4%	4841	–5.2%	4972	–2.6%	4797	–6%	4929	–3.4%	4765	–6.6%
							Winter								
Low	**63**	239	11.1	460	92.3%	436	82.36%	429	79.6%	414	73.2%	-	-	-	-
Middle 1	**111**	470	11.1	796	69.4%	759	61.5%	766	63%	737	56.7%	-	-	-	-
Middle 2	**227**	1072	11.1	1543	44%	1459	39%	1513	41.1%	1467	36.8%	-	-	-	-
Middle 3	**385**	1942	38.9	2733	40.7%	2612	34.5%	2671	37.6%	2566	32.1%	2626	35.2%	2533	30.4%
Middle 4	**542**	3261	38.9	3863	18.4%	3688	13.1%	3801	16.6%	3643	11.7%	3756	15.2%	3609	10.7%
High	**700**	4765	38.9	4866	2.1%	4672	–1.9%	4805	0.8%	4627	–2.9%	4759	–0.1%	4593	–3.6%

Positive and negative values of % of extra pay represent bill increase and decrease, respectively.

2.5.2 Smart tariff 2 (ST2)

The ST2 scheme uses a combination of inclining block price rates and the two fixed TOU pricing rates from ST1. In the ST2 scheme, the first 200 kWh of consumption will be charged at the inclining block price rates (using FY 2014-2015 price rates) regardless of the consumption time. In order to reduce the high billing impact on small energy consumers, ST1 price rates (peak rate = 8.53 TK/kWh and off-peak rate = 5.88 TK/kWh) are only applied to energy user exceeding 200 kWh a month. The cost for the first 200 kWh block is fixed and equal to 891 TK according to the inclining block pricing. Table 2.8 shows the calculated monthly electricity bills using the ST2 scheme for the four highest energy consumer groups. In this table, monthly bills are calculated using equations (2.2) to (2.6). Based on ST2, the electricity bills associated with the Low and Middle 1 energy consumer groups will remain unchanged, as they are priced at existing inclining block pricing rates because their monthly usage is less than 200 kWh. The results shown in Table 2.8 with the ST2 scheme indicate that consumers from Middle 4 and High energy groups are potentially benefited by receiving lower monthly bills (considering off-peak rate in weekends). Particularly, for consumers from the High energy group, the cost savings are more than 11% compared to the existing block pricing in all seasons. However, consumer from the Middle 3 group experience slightly higher energy bills, even with the load shifting in all seasons. This is due to the Middle 3 consumer group having a higher ratio of peak usage than any other consumer groups (see Table 2.8, column 3). The Middle 2 consumer group experiences a slightly higher bill in the summer season even with the load shifting.

$Monthly\ electricity\ Bill$ =

$$\begin{cases} inclining\ block\ rates, \quad E_T \leq 200\ kWh \\ 891 + (E_T - 200)\ \times \sum \begin{Bmatrix} (R_{Off} \times 5.88 + R_P \times 8.53) \times \\ (R_{weekdays} + R_{weekends}) \end{Bmatrix}, \quad E_T > 200\ kWh \end{cases} \quad (2.2)$$

$$R_{Off} = total\ monthly\ \ offpeak\ \ usage\ (kWh)/E_T \quad (2.3)$$

$$R_P = total\ monthly\ peak\ usage\ (kWh)/E_T \quad (2.4)$$

$$R_{weekdays} = total\ monthly\ weekdays'\ \ usage\ (kWh)/E_T \quad (2.5)$$

$$R_{weekends} = total\ monthly\ weekends'\ usage\ (kWh)/E_T \quad (2.6)$$

where E_T is the total energy usage (kWh) in a month; R_{Off} and R_P are the off-peak and peak usage ratios respectively; $R_{weekdays}$ and $R_{weekends}$ represent ratios of weekdays' usages to total monthly usages and weekends' usages to total monthly usages respectively.

Table 2.8

Monthly electricity bills for different consumer groups using ST2 pricing scheme.

					Without load shifting				W. Pump shifting only				W. Pump & W.mch shifting			
Energy usage groups	Total usage	Ratios from equ. (2.3) & (2.4)		Base bills	ST2 bill	Extra pay	ST2 bill included weekend pricing	Extra pay	ST2 bill	Extra pay	ST2 bill included weekend pricing	Extra pay	ST2 bill	Extra pay	ST2 bill included weekend pricing	Extra pay
	kWh/ month	R_{Off}	R_P	TK/ month	TK/ month	%	TK/ month	%	TK/ month	%	TK/ Month	%	TK/ month	%	TK/ month	%
Summer																
Middle 2	**295**	.66	.34	1437	1533	6.7%	1511	5.1%	1524	6.1%	1504	4.7%	-	-	-	-
Middle 3	**491**	.49	.51	2818	2993	6.2%	2889	2.5%	2958	5.0%	2863	1.6%	2932	4.1%	2844	0.9%
Middle 4	**600**	.53	.47	3767	3743	−0.7%	3609	−4.2%	3703	−1.7%	3580	−5.0%	3674	−2.47%	3559	−5.5%
High	**800**	.53	.47	5763	5158	−10.5%	4961	−13.9%	5114	−11.3%	4929	−14.5%	5081	−11.8%	4905	−14.9%
Spring																
Middle 2	**217**	.65	.35	1019	1007	−1.2%	1003	−1.6%	1004	−1.5%	1001	−1.8%	-	-	-	-
Middle 3	**326**	.59	.41	1610	1768	9.8%	1733	7.6%	1745	8.4%	1715	6.6%	1727	7.3%	1703	5.7%
Middle 4	**510**	.62	.38	2984	3022	1.3%	2942	−1.4%	2985	0.03%	2915	−2.3%	2957	−0.9%	2894	−3.0%
High	**651**	.67	.33	4276	3939	−7.9%	3837	−10.3%	3896	−8.9%	3805	−11%	3865	−9.6%	3782	−11.6%
Fall																
Middle 2	**230**	.64	.36	1088	1096	0.7%	1088	0.03%	1092	0.4%	1085	−0.2%	-	-	-	-
Middle 3	**409**	.58	.42	2105	2351	11.7%	2289	8.8%	2321	10.3%	2267	7.7%	2299	9.2%	2251	6.9%
Middle 4	**556**	.63	.37	3384	3330	−1.6%	3238	−4.3%	3292	−2.7%	3210	−5.2%	3264	−3.6%	3189	−5.8%
High	**734**	.63	.37	5104	4552	−11%	4413	−14%	4508	−12%	4381	−14%	4477	−12%	4358	−14.6%
Winter																
Middle 2	**227**	.65	.35	1072	1074	0.2%	1068	−0.4%	1070	−0.1%	1065	−0.7%	-	-	-	-
Middle 3	**385**	.54	.46	1942	2204	13.5%	2146	10.5%	2174	12.0%	2124	9.4%	2153	10.8%	2108	8.5%
Middle 4	**542**	.53	.47	3261	3328	2.1%	3218	−1.3%	3289	0.87%	3189	−2.2%	3261	0.00%	3168	−2.8%
High	**700**	.63	.37	4765	4367	−8.4%	4229	−11%	4323	−9.3%	4196	−12%	4291	−10%	4172	−12.4%

2.5.3 Smart tariff 3 (ST3)

The ST3 scheme has a similar strategy to that of ST2. ST3 encourages consumers to participate in TOU pricing with a consumption of more than 300 kWh per month. The cost for the first 300 kWh block is fixed and equal to 1410 TK according to the inclining block pricing. Therefore, ST3 specifies that the electricity bills associated with Low, Middle 1, and Middle 2 consumer groups will not change. The Low, Middle 1 and Middle 2 energy consumers will be charged at inclining block pricing for their electricity usages. In Table 2.9, the monthly bills of the three high energy consumer groups with ST3 scheme are calculated using equations (2.3) to (2.7). Table 2.9 shows that all the participated consumer groups in this pricing scheme receive a reduced energy bill even without any load shifting in all seasons. Cost savings are substantially higher for consumers from Middle 4 (more than 7%) and High (more than 14%) energy groups in all seasons.

$$Monthly\ electricity\ Bill =$$

$$\begin{cases} inclining\ block\ rates, & E_T \leq 300\ kWh \\ 1410 + (E_T - 300) \times \sum \left\{ \begin{matrix} (R_{Off} \times 5.88 + R_P \times 8.53) \\ \times\ (R_{weekdays} + R_{weekends}) \end{matrix} \right\}, & E_T > 300\ kWh \end{cases} \tag{2.7}$$

Table 2.9

Monthly electricity bills for different consumer groups using ST3 pricing scheme

			Without load shifting				W. Pump shifting only				W. Pump & W.mch shifting			
Energy usage groups	Total usage	Base bills	ST3 bill	Extra pay	ST3 bill included weekend pricing	Extra pay	ST3 bill	Extra pay	ST3 bill included weekend pricing	Extra pay	ST3 bill	Extra pay	ST3 bill included weekend pricing	Extra pay
	kWh/ month	TK/ month	TK/ month	%	TK/ month	%	TK/ month	%	TK/ month	%	TK/ month	%	TK/ month	%
Summer														
Middle 3	**491**	2818	2790	–1.0%	2721	–3.4%	2767	–1.8%	2704	–4.0%	2750	–2.4%	2692	–4.5%
Middle 4	**600**	3767	3549	–5.8%	3449	–8.4%	3519	–6.6%	3427	–9.0%	3497	–7.2%	3411	–9.4%
High	**800**	5763	4966	–13.8%	4802	–16.7%	4929	–14.5%	4775	–17.1%	4902	–14.9%	4755	–17.5%
Spring														
Middle 3	**326**	1610	1591	–1.2%	1584	–1.6%	1586	–1.5%	1580	–1.9%	1583	–1.7%	1577	–2.0%
Middle 4	**510**	2984	2854	–4.4%	2800	–6.2%	2828	–5.2%	2781	–6.8%	2810	–5.8%	2767	–7.3%
High	**651**	4276	3782	–11.6%	3703	–13.4%	3749	–12.3%	3678	–14.0%	3725	–12.9%	3660	–14.4%
Fall														
Middle 3	**409**	2105	2171	3.2%	2139	1.6%	2156	2.4%	2128	1.1%	2144	1.8%	2119	0.7%
Middle 4	**556**	3384	3164	–6.5%	3097	–8.5%	3136	–7.3%	3077	–9.1%	3116	–7.9%	3063	–9.5%
High	**734**	5104	4385	–14.1%	4272	–16.3	4350	–14.8%	4247	–16.8%	4324	–15.3%	4228	–17.2%
Winter														
Middle 3	**385**	1942	2013	3.6%	1986	2.3%	1999	2.9%	1976	1.8%	1989	2.4%	1969	1.4%
Middle 4	**542**	3261	3134	–3.9%	3056	–6.3%	3107	–4.7%	3036	–6.9%	3087	–5.3%	3021	–7.4%
High	**700**	4765	4191	–12.1%	4080	–14.4%	4156	–12.8%	4054	–14.9%	4130	–13.3%	4035	–15.3%

2.5.4 Smart tariff 4 (ST4)

The proposed ST4 scheme in this study uses a combination approach of inclining blocks structure and TOU pricing rates to encourage all consumer groups to participate in TOU pricing, while ensuring a minimum monthly billing impact. In ST4, off-peak and peak prices vary according to the inclining block kWh usage ranges. These prices increase as usages move to higher kWh blocks. Fig. 2.5 represents the five kWh usage blocks with different peak and off-peak price rates for the ST4 scheme. In this figure, Block 5 is the highest kWh usage block and has the maximum peak and off-peak price rates.

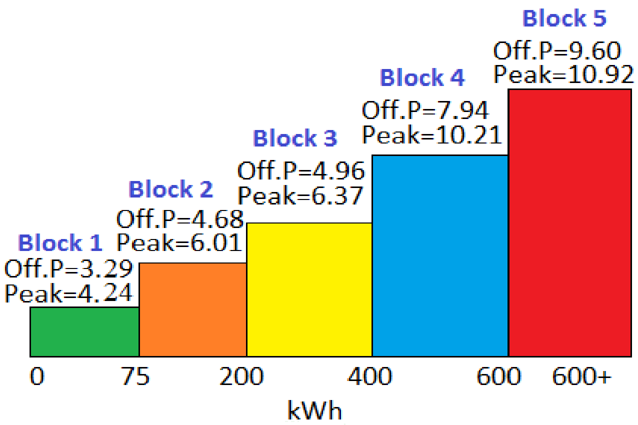


Fig. 2.5. Smart tariff 4 (ST4) pricing scheme.

The peak (*X*) and off-peak (*Y*) price rates for each block are calculated by equations (2.8) and (2.9), where six hours between 17:00 and 23:00 are considered as peak period and the remaining eighteen hours are considered as the off-peak period. In the ST4 scheme, the peak price rate is set 20%[2] higher than the weighted price for each block (except for block 5 which is only 10% higher). The peak, off-peak, and weighted rates for each block are presented in Table 2.10. The weighted price in this table for each block is similar to the inclining block pricing of FY 2014-2015 (see Table 2.2).

[2] In the commercial sector of Bangladesh, electricity price for peak period is set around 20% higher than the off-peak period.

$$Y = (24W - 6X)/18 \tag{2.8}$$

$$X = (1 + k) \times W \tag{2.9}$$

where Y and X are the off-peak and peak price rate (TK/kWh), respectively; W is the weighted price rate (TK/kWh) and k represents the difference between peak and off-peak prices in percent.

Table 2.11 shows the calculated monthly electricity bills using the ST4 pricing scheme for all consumer groups. To distinguish which inclining block is contributing to the electricity bill of each consumer group, the associated block numbers are also reported in Table 2.11. The resulted electricity bills presented in Table 2.11 show that monthly billing impacts from the ST4 scheme on all consumer groups are significantly less compared with ST1, ST2 and ST3 schemes in all seasons. Consumers from Low and Middle (1 and 2) energy groups achieve cost savings in their electricity bills in all seasons by only shifting their daily water pump usages to off-peak. Especially in the low demand season (i.e. spring), these consumer groups receive savings in their electricity bills without load shifting. The remaining groups from Middle 3 to High receive electricity bills that are slightly higher (< 2%) due to their high peak usage ratios in the summer season. However, in other seasons, these large energy usage groups achieve cost savings by shifting their water pumps and washing machines to the off-peak period, except the Middle 4 consumer group who faces a slightly increased bill (< 0.8%) in winter season due to high peak usages compared to rest of the groups (see Table 2.8, column 3).

Table 2.10
The parameters of ST4 pricing scheme

Block (kWh)	**Weighted price (W)** (TK/kWh)	**(1+k)**	**Peak rate (1+k) × W** (TK/kWh)	**Off-peak rate** (TK/kWh)
1-75	3.53	1.2	4.24	3.29
76-200	5.01	1.2	6.01	4.68
201-400	5.31	1.2	6.37	4.96
401-600	8.51	1.2	10.21	7.94
600+	9.93	1.1	10.92*	9.60

*10.92 TK/kWh (1.1× W) represent 10% higher than 9.93 TK/kWh.

Table 2.11

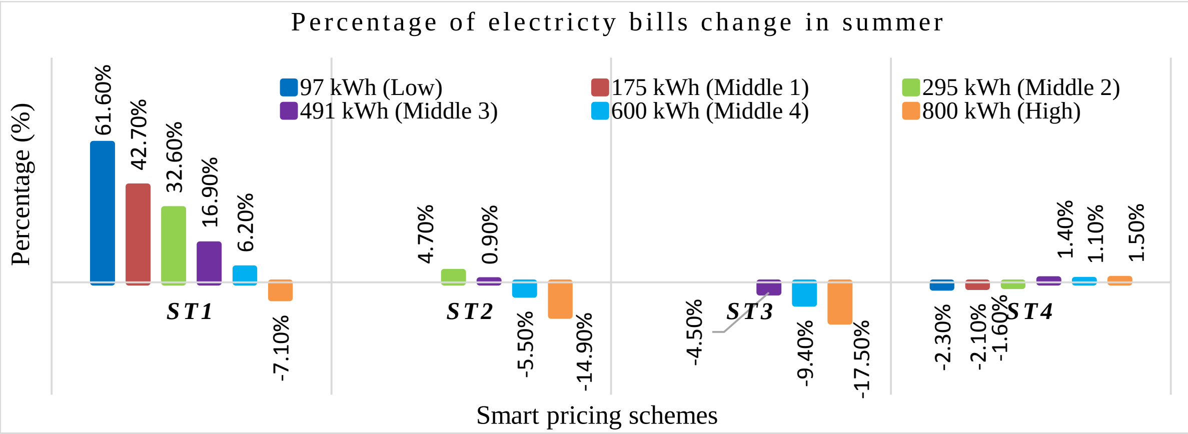
Monthly electricity bills for different consumer groups using ST4 pricing scheme

				Without shift		Pump shift		Pump & W.mch shift	
Energy usage groups	Total usage	Inclining block#	Base bills	ST4 bill	Extra pay	ST4 bill	Extra Pay	ST4 bill	Extra Pay
	kWh/ month		TK/ month	TK/ month	%	TK/ month	%	TK/ month	%
Summer									
Low	**97**	1 and 2	398	400	0.6%	389	−2.3%	-	-
Middle 1	**175**	1 and 2	799	795	−0.5%	782	−2.1%	-	-
Middle 2	**295**	1 to 3	1437	1428	−0.7%	1414	−1.6%	-	-
Middle 3	**491**	1 to 4	2818	2915	3.4%	2882	2.3%	2857	1.4%
Middle 4	**600**	1 to 4	3767	3870	2.7%	3834	1.8%	3807	1.1%
High	**800**	1 to 5	5763	5907	2.5%	5873	1.9%	5847	1.5%
Spring									
Low	**60**	1	228	226	−0.8%	215	−5.6%	-	-
Middle 1	**101**	1 and 2	414	418	−1.0%	406	−1.9%	-	-
Middle 2	**217**	1 to 3	1019	1007	−1.2%	993	−2.5%	-	-
Middle 3	**326**	1 to 3	1610	1626	1.01%	1597	−0.8%	1575	−2.16%
Middle 4	**510**	1 to 4	2984	2986	0.06%	2951	−1.1%	2925	−2%
High	**651**	1 to 5	4276	4236	0.93%	4199	−1.8%	4172	−2.43%
Fall									
Low	**84**	1 and 2	331	334	0.8%	323	−2.5%	-	-
Middle 1	**122**	1 and 2	527	528	0.1%	515	−2.2%	-	-
Middle 2	**230**	1 to 3	1088	1081	−0.7%	1067	−1.9%	-	-
Middle 3	**409**	1 to 4	2105	2121	0.8%	2092	0.6%	2070	−1.7%
Middle 4	**556**	1 to 4	3384	3382	−0.1%	3347	−1.1%	3321	−1.9%
High	**734**	1 to 5	5104	5121	0.3%	5086	−0.3%	5060	−0.9%
Winter									
Low	**63**	1	239	239	0.0%	228	−4.4%	-	-
Middle 1	**111**	1 and 2	470	473	0.7%	461	−1.9%	-	-
Middle 2	**227**	1 to 3	1072	1061	−1.0%	1047	−2.3%	-	-
Middle 3	**385**	1 to 3	1942	1979	1.9%	1949	0.35%	1927	−0.78%
Middle 4	**542**	1 to 4	3261	3348	2.7%	3312	1.6%	3285	0.74%
High	**700**	1 to 5	4765	4819	1.12%	4782	0.36%	4755	−0.21%

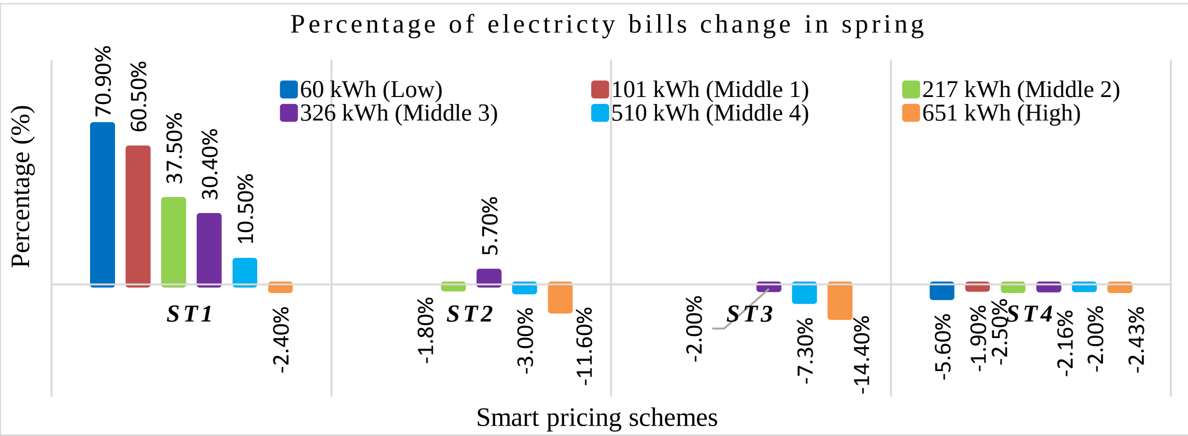
2.5.5 Summary of the electricity pricing schemes and their peak shaving capacities

Fig. 2.6 provides summaries of the analysis of the electricity bills using the four TOU pricing schemes for electricity consumption in all seasons. Fig. 2.6 shows the percentages of change in the electricity bills when considering load shifting for different consumer groups. The analysis and comparison of electricity bills with ST1 show that this pricing scheme only benefits the High energy consumer group (consumers who consume more than 600 kWh) and increase the electricity bills significantly for all Low and Middle energy consumer groups (e.g., > 60% bill increased for Low consumer group). Therefore, ST1 is not a suitable pricing mechanism for residential consumers in low and middle income developing countries like

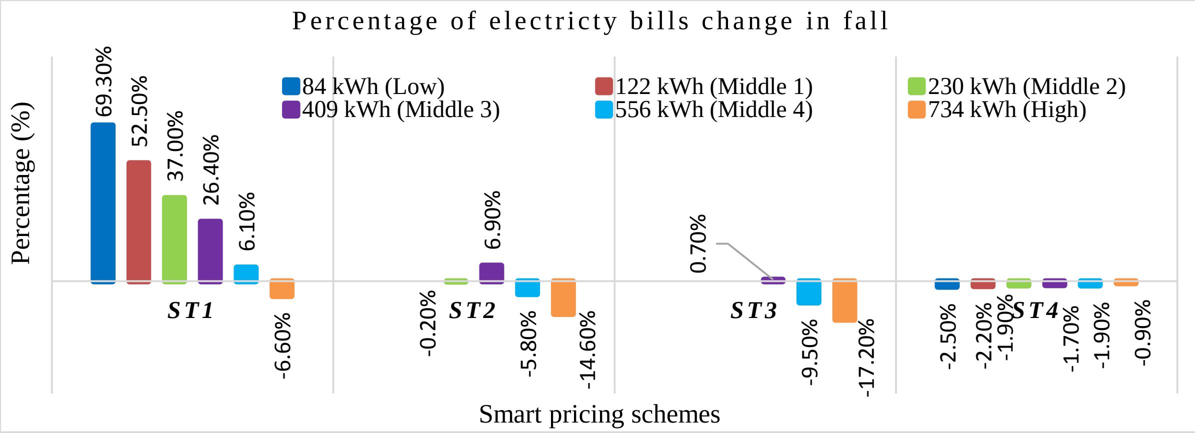
Bangladesh, Myanmar, etc. (who use a block pricing scheme). However, with ST1 pricing, the aggregated daily peak shaving capacity by residential consumers is high (0.64 kW), as shown in Fig. 2.7. This expected value of daily peak shaving capacity for each pricing scheme is calculated based on the weighting factors of 46%, 39%, and 15%, respectively, for Low, Middle, and High income consumer groups. These weighting factors represent the population of Low, Middle, and High income residential consumers in Bangladesh.



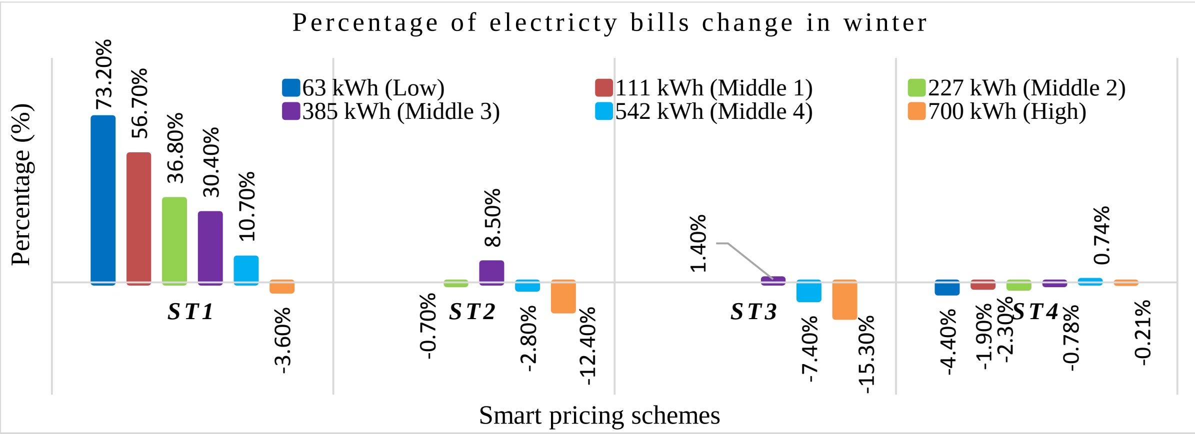
(a)



(b)



(c)



(d)

Fig. 2.6. Monthly electricity bill change (%) with ST1, ST2, ST3 and ST4 compared to the base bills for all seasons.

The results from the ST2 scheme show that it greatly benefits consumers from Middle 4 and High energy groups in all seasons. However, the total daily peak shaving capacity with the ST2 scheme is only 0.43 kW, which is less than that for the ST1 scheme. This is because Low and Middle 1 consumer groups are being excluded in ST2 from participating in peak shaving. With the ST3 scheme, all the participating consumer groups (i.e. Middle 3, Middle 4 and High energy consumer groups) received a significant bill reduction in both peak summer and low demand consumption months. The ST3 scheme has the lowest peak shaving capacity (0.39 kW) compared to the other three pricing schemes. There are two main issues with the ST2 and ST3 schemes, which are: (i) the percentage of cost saving is significantly large in the summer season for both Middle 4 (>5.5%) and High consumer (>14%) groups which may not encourage them to modify their peak period usages; (ii) Low and Middle 1 consumer groups are excluded from contributing in peak shaving, which cover the largest percentages of energy usages in the residential sector of Bangladesh. Therefore, these pricing approaches may not be suitable for Bangladesh considering the low income majority energy user group. However, these pricing schemes may be suitable for upper middle income a developing country such as Maldives [1], where the number of middle income consumers is relatively large. Maldives is currently using a block pricing scheme for residential consumers [45]. By adjusting the pricing parameters The Maldives can use one of these schemes to control the end users' energy usages during peak periods.

Finally, the results from the ST4 scheme in Fig. 2.6 show that the variations of the monthly electricity bill for all usage levels of consumers are reasonably low (<6%) in all seasons compared to other three pricing plans. This pricing scheme provides the opportunity to all consumer groups to reduce their electricity bills by reducing their peak period consumption. Particularly, the low and Middle (1 and 2) consumer groups are benefit more with this pricing scheme, as they can save on their electricity bills in all seasons through their load shifting. The large energy usage groups i.e. Middle 3, Middle 4 and High groups have experienced slightly higher bills (<1.5%) in summer season due to their high energy usages in peak period compared to other seasons (< 0.8% bill increased) (see in Table 2.8). If these consumers can reduce their peak period consumption, then the energy cost will be reduced significantly. The energy cost saving in ST4 depends on the amount of consumers' monthly energy usage and peak period usage. Therefore, this TOU pricing scheme encourages consumers in both energy conservation and peak reduction. In addition, the potential of daily peak shaving is maximum (0.64 kW) with this pricing, as shown in Fig. 2.7.

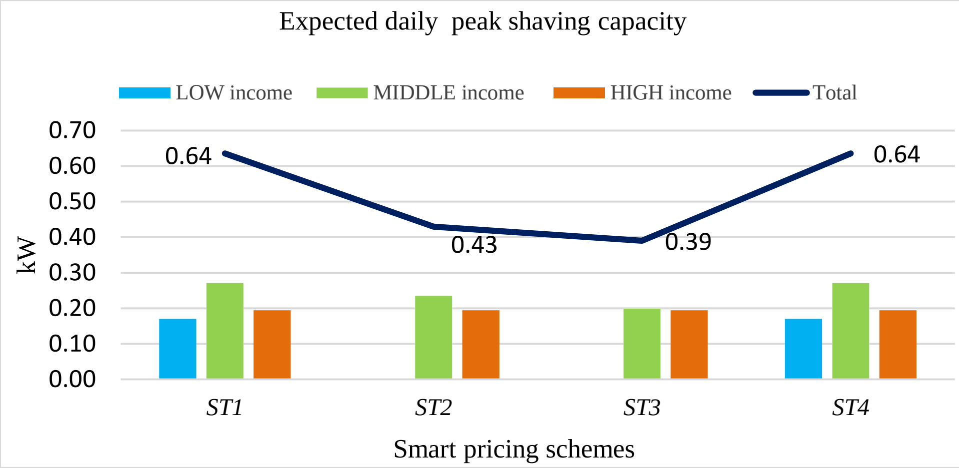


Fig. 2.7. Expected daily peak shaving capacity from three income groups.

Therefore, from the above analysis it can be evident that the ST4 plan provides a better pricing mechanism to influence all consumer groups to reduce peak demand as well as energy consumption for Bangladesh. This electricity pricing scheme may also be suitable for other low and lower-middle economies such as Nepal, Cambodia, Myanmar, etc. The ST4 scheme will not require a smart meter; so the existing residential bi-directional communication prepaid meter with two parts TOU billing software readjustment can be used for consumption measurement in Bangladesh. Finally, the successful development and implementation of ST4 pricing will enable consumers to adopt newer and cleaner technologies such as rooftop solar PV, energy storage, home energy management systems [46], and consumption monitoring technologies [47]. These will allow additional energy savings and peak demand reduction.

2.6 Case study: impact of TOU pricing on a distribution network

Based on the analysis of the results from Section 2.5, only the ST4 pricing scheme is simulated on a distribution network. A DESCO 11kV (50Hz) urban distribution system located at Nikunja, Dhaka is chosen as the test system [48]. A single line diagram of this system is shown in Fig. 2.8. This network is supplied from a 33kV substation with two parallel transformers with sizes of 26 MVA and 28 MVA. The reliability criterion of a single outage contingency specifies that the “N-1” capacity [49] of this substation is 26 MVA. There are nine active feeders in this 11kV urban distribution system, including four Residential feeders, two Residential & Commercial feeders, and three Commercial feeders. Grid modelling and simulations are performed using the DigSILENT PowerFactory power system analysis software [50].

Due to the rapid growth of the peak demand in this network, a total of 26.5 MW demand has been observed at the 33kV substation, which typically occurs on hot summer days during the peak hours between 19.00 and 21.00 in this case [51]. This means that the "N-1" capacity of 26 MVA is exceeded with this level of demand. Consequently, the loads above 26 MVA should be managed differently. The peak demand for each feeder is measured as 2.8 MW for the residential feeder, 4.03 MW for the mixed residential and commercial feeder, and 2.4 MW for the commercial feeder. The total number of residential consumers connected to the Nikunja 33/11 kV substation is around 3700. In this case study, smart meter costs are excluded from the investment costs, as some of the residents are already provided with bi-directional communication meters. Therefore, this study assumes that about 20% of the total number of residential consumers under the test network has smart meters, which is about 780.

At single outage contingencies (N-1) of the network, the existing practice in this system is to apply a load shedding scheme that disconnects the high loaded residential feeder to ensure system stability and load balancing. To avoid frequent load shedding, further investments are required for adding extra capacity to the network (such as upgrading transformers or adding backup generators) [52, 53]. Alternatively, the ST4 pricing scheme (as discussed in Section 2.5.4) can be implemented to alleviate network constraints during high demand periods. The cost associated with network investments, load shedding, and ST4 pricing are described below.

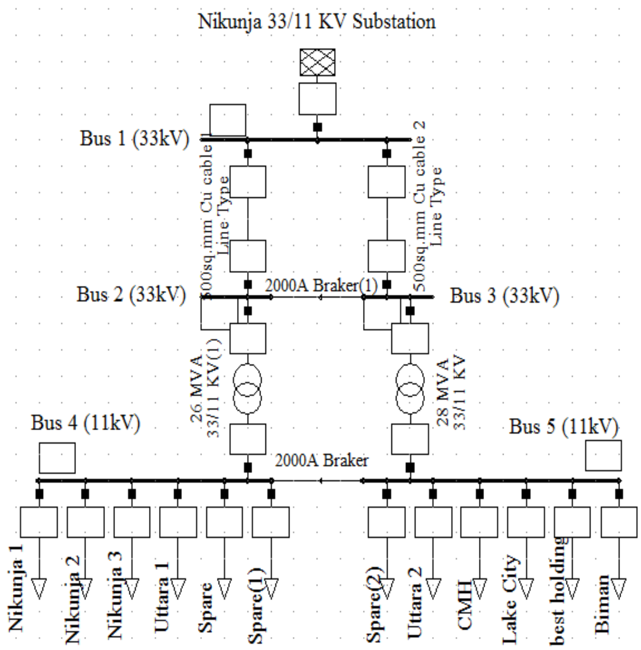


Fig. 2.8. Single line diagram for the Nikunja 33/11kV distribution substation.

- Option 1: *Electric network upgrade/investment*

In order to satisfy the N-1 capacity requirement in this network, the corresponding utility needs to replace the 26 MVA transformer with one of a higher capacity or add another transformer. This approach will cost in order of multi-hundred thousand dollars which is much higher than the approaches given below.

- Option 2: *Apply load shedding*

Considering the load profiles of the six different consumer groups in the summer season, as shown in Table 2.4 (in Section 2.4.3), the coincident peak demand per consumer is about 3.5 kW. Therefore, 143 consumers from those equipped with controllable loads should be disconnected during 2 hours of peak time. Therefore, the total shed load is 500.5 kW. The total expected cost of ENS for two hours of load shedding is considered \$10/kWh (785 TK) [54]. The cost of ENS is a product of the total amount of energy not served (kWh) times the cost per kWh. The cost per kWh of ENS is a measure of the economic impact of not meeting the electricity demand. This cost will be borne by both the utility and its consumers.

ENS cost = (500.5 kW × 2 hours) × $10/kWh

= $10k (≈ 4.4 million TK)

- Option 3: *Install backup generator* (diesel generator)

According to [55] study, diesel generators are widely used for electricity generation during peak periods in Bangladesh. The estimated cost of installation is $600/kW and the operational and maintenance cost of the generator is considered as $0.5/hr for every 10 kW of generator size. The diesel fuel price is taken as $0.6/litre based on the local market price in Bangladesh [56]. If the diesel generator is operated for 100 hours in a year, the optimised total cost to supply the 500 kW is $303k. This will be added to the consumers' energy bills.

Investment cost = 500 kW × $600/kW + (500/10) × $0.5/hr × 100 hours

= $303k (≈ 24 million TK)

- Option 4: *Implementation of ST4 pricing scheme in the residential sector*

Residential consumers are responsible for at least half of the peak demand (13 MW) in this network. The expected daily peak shaving capacity with the ST4 pricing from the six different consumers is 0.64 kW (as depicted in Fig. 2.7) according to 3.5 kW coincident peak demand per consumer (the method for calculating the coincident peak demand is presented in Appendix A.4). Therefore, the maximum number of consumers required to cause the ST4 pricing to reduce the 500 kW of peak demand is 780, which is about 20% of the total number of residential consumers connected to the distribution substation. There are no extra investments and ENS costs associated with this approach. For TOU billing, a readjustment of software settings will be all that is required.

(Investment costs + ENS costs) = 0

In addition to this, the participation of all residential consumers in the ST4 pricing scheme has the potential of reducing at least 2.4 MW of peak demand, which the utility may consider in their future investment planning for the grid. Table 2.12 presents a summary of the costs associated with all four options for satisfying the (N-1) contingency criterion in this network. It shows that option 1 has a significantly higher estimated cost ($364k ≈ 29M TK) than other options, due to the high investment on the transformer upgrade and maintance costs [57]. Option 2 (load shedding) has a lower cost than Option 3 (diesel generator). Whereas with option 4, the total cost is zero due to the consumers' participation in demand reduction, influenced by the ST4 pricing scheme. Hence, with the implementation of ST4 pricing in the residential sector in Bangladesh, costs for extra generation and energy not supplied during peak hours will be reduced significantly.

Table 2.12

Costs associated with four possible options

Costs	Million TK			
	Option1	Option 2	Option 3	Option 4
Total	29	4.4	24	0

2.7 Conclusion

The current pricing approach in the power sector of Bangladesh receives less attention on demand side management, resulting in high retail prices to meet the cost of production. This study analyses four TOU pricing schemes by considering different groups of residential consumers, including low and middle income consumers. The analysis of the results suggest that a combination of an inclining block and the traditional TOU pricing scheme, called ST4 in this paper, is the most suitable pricing scheme for all residential consumers. This pricing scheme caters for low income consumers effectively by lowering their monthly bill. The simulation results showed that the proposed pricing scheme has the potential to defer investment costs on electric generation and the network, while supporting consumers to access electricity during peak periods. With this pricing approach, total electricity costs from the consumer's point of view change slightly, while from the utility's perspective, considerable savings are made, especially when the network operates close to full capacity or has a limited energy supply. Hence, the proposed TOU pricing model is applicable to the Bangladesh electricity supply industry and could be considered by decision makers in Bangladesh in future energy system planning. This pricing model is also applicable for other low and middle income countries, who are facing similar electricity pricing concerns as Bangladesh. Further study is needed to investigate the impact of the proposed TOU pricing scheme on wholesale electricity market prices.

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Chapter 3

Demand Response Opportunities in Residential Sector Incorporated with Smart Load Monitoring System♣

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Abstract

For a successful implementation of demand response in the residential sector, access to real electricity consumption data and load profiles of major household appliances is crucial. With the advancement of the communication technologies and smart load monitoring devices, access to this information become simpler. This study investigates characteristics of different communication technologies and their suitability for use in demand response implementation in the residential sector. A smart monitoring and controlling system is integrated into a household's electric appliances to study their daily energy consumption profiles and identify their potential demand response capacity. This study intends to draw interest on the benefits from using the smart monitoring and controlling system, for instance, it provides real-time energy consumption feedbacks, standby power consumption information and remote load

♣ The content and structure of this published paper are modified based on the Thesis requirements.

control flexibility. Using this information, the total demand response opportunity and standby energy loss are calculated for selected major appliances.

Keywords: demand response, communication technology, ZigBee, peak demand and standby power.

3.1 Introduction

Residential demand response (DR) is gaining more popularity in recent years in reducing peak electricity demand and accommodating more Renewable Energy Sources (RESs) into the grid [1-2]. The power network becomes overstress during the maximum peak demand periods. If a large amount of power generated by RESs, the network experiences overvoltage and frequency rise issues due to imbalance of supply and demand. Additional investment requires in the expansion of power generation, transmission and distribution capacity to avoid equipment failure and service disruptions during these periods. If consumer energy consumption can be controlled using DR schemes during these periods (e.g., shift consumption during peak periods to off-peak or high RES generation periods), it could result in substantial savings on total power generation and distribution costs. DR schemes such as time-varying pricing and direct load control can be actioned in peak demand shifting, changing consumer consumption behavior, and increasing energy efficiency. Fossil fuel savings, lowering average carbon emissions, as well as a permanent fall in electricity prices, are all significant incentives from DR schemes for the residential consumers.

A communication infrastructure is a foundation for the success of the developing DR in the residential sector. To improve power reliability and quality as well as prevent electricity blackouts, communication system helps the utility and customers to cooperate efficiently for load management. When selection of the communication network for DR, factors such as, scalability, security, fast and cost-effectiveness are needed in consideration. Electrical power consumption data and load profiles of major household appliances are crucial elements for DR studies. One of the causes some people cannot economise on their power consumption is that they simply are not aware how much their appliances can consume and their usages impacts during different periods of a day. Innovative use of information technology could permit users to access and understand their power usage as well as encourage to implement smart load management technology [3]. Providing consumers with the right tools to observe their energy consumption together with DR implementation in place will increase in awareness of efficient energy consumption. With advances in technologies, there are many smart energy measuring and controlling devices are available on the market, which can easily install at consumer side. Using the measured realistic load profiles of individual appliances using smart devices will lead the utility to forecaster consumers' demands and understand their consumption behaviours more accurately and precisely.

Fig. 3.1 shows a typical remote monitoring and controlling system for home electrical appliances. The smart energy gateway is the main brain of the system that collects all the data from its connected sensors (clamp reader, meter reader and power nodes). It sends the measured data to central load control center (e.g., the utility) and online, so the both utility and users can remotely monitor and control energy consumption.

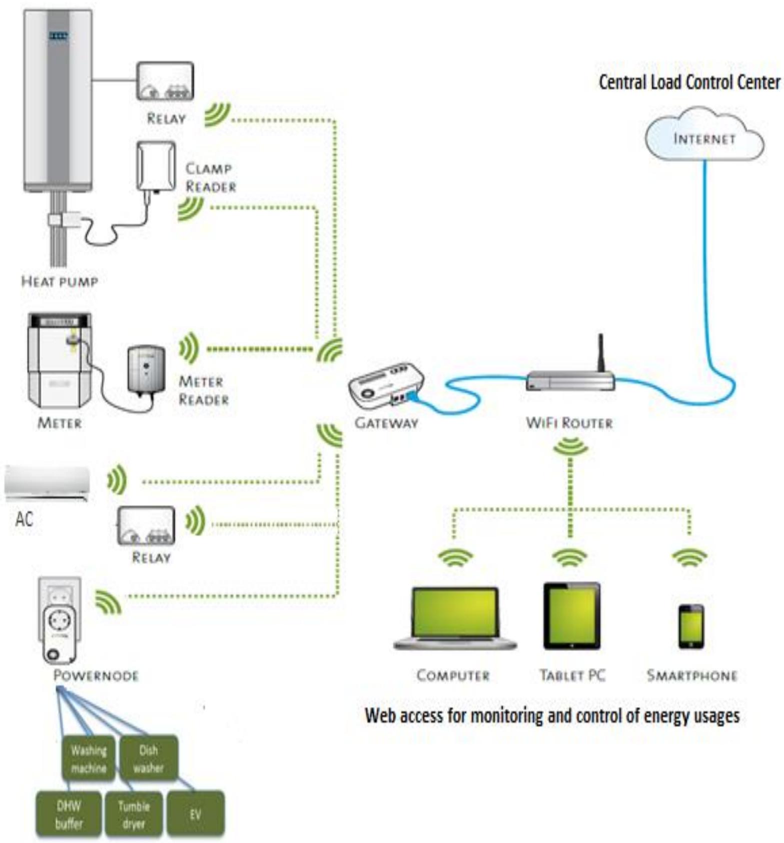

Fig. 3.1. Remote monitoring and controlling devices for home appliances.

The main objective of this study is to investigate the suitable communication technologies for DR implementation in residential sector as well as the importance of using smart load monitoring and control system for the DR studies. The communication technologies for DR, a case study using household electric appliances' load profiles and their DR opportunities and standby power losses are detailed in the following sections.

3.2 Communication infrastructure for residential DR

Two types of communication infrastructure are needed for information flow between an end user and DR interested party such as utility for residential DR [4]. The first flow is from sensor and electrical appliances to smart meter or gateway, the second is between smart meter or gateway and the utility data center (see in Fig. 3.1). For the second information flow, the communication platforms from smart meter to utility can be divided into two types, namely point to point and mesh networks [5]. Point to point communication is an open access communication platform, where authorised entities are able to communicate with smart meters (using existing third-party telecommunication networks) through the use of passwords. Usually, it is used when a limited number of individual metering installations are deployed in a given geographic region using different metering service providers. Mesh communication platform is a comprised of a group smart meters where smart meters communicate with each other to form a meshed radio network. Each meter acts as a signal repeater until the collected data reaches the electric network access point. Then, collected data is transferred to the utility via a communication network. Mesh communication platform is cost-effective, self-healing and capable of providing good network coverage which is generally operated by monopoly service providers (i.e., usually the utility). The main limitation of Mesh are network capacity, interference and fading [6].

The bi-directional information flow between consumer's electrical appliances to utility are mainly supported by two communication mediums, i.e., wired and wireless. Wired communication (fiber, Ethernet, xDSL, broadband PLC) involves the use of a physical link between the transmitter and the receiver. Wireless communication (WiMAX, GPRS, 3G, LTE, satellite) on the other hand eliminates the physical links between the receiver and the transmitter. Wireless communications have several advantages over wired communications examples are the low cost of infrastructure, mobility of wireless communication, and ease of connection of wireless communication to areas that are unreachable. Wired communications, on the other hand, have advantages over wireless communication such as security of transferred data and are not subject to interference during transfer of data [7].

Wired and wireless communication networks can be categorized into: Home Area Network (HAN), Neighborhood Area Network (NAN) and Wide Area Network (WAN). HAN supports low-bandwidth and cost-effective communication between home electrical appliances and smart meters. The primary task of HAN in-home applications is to inform customers about the consumption behaviours via home displays or a web interface. M-BUS, ZigBee, Z-wave, WiFi, Powerline communication (PLC) and HomePlug are some of the examples of HAN systems. NAN directly connects multiple end users (HANs) in specific areas to the data concentrator/substation [8]. Some examples of NAN are ZigBee, PLC, WiFi, etc. WAN communication has a high bandwidth and uses for transmission of data over long distances. It is the category used for provision of two-way communication between utility and concentrators/substations. The WAN connects many NANs to the utility central control unit. Cellular networks, WiMAX, fiber-optic cable, and microwave are some examples of WANs. Fig. 3.2 illustrates the communication network infrastructure between residential consumers and utility data center.

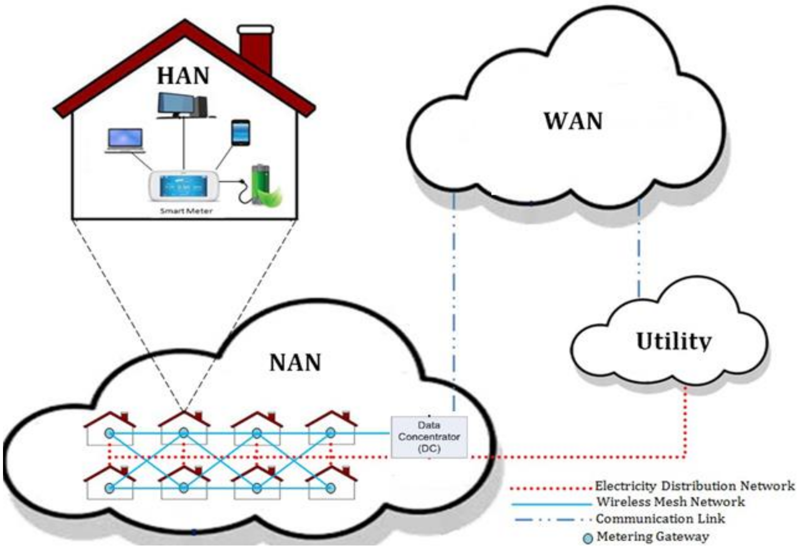

Fig. 3.2. The communication infrastructure between consumers and utility.

The choice of communication technology varies for DR implementation. However, it is always preferable end-to-end reliable and secure communications with low-latencies and sufficient bandwidth. Moreover, the system security should be robust enough to prevent cyber-attacks and provide system stability and reliability with advanced controls. There are key limiting factors that should be taken into account in choosing the communication technologies, such as availability of the technology, time of deployment, operational costs and rural/urban or indoor/outdoor environment, etc. [16].

One of the main goals of this research is to identify a suitable communication technology for HAN communication. For the first information flow between electrical appliances to the smart meter or gateway on consumer, premises can be handled with low-power, short-distance communication technologies. Wireless HAN communication (e.g., ZigBee, Bluetooth, WiFi, etc.) is preferred option because of the advantages it has over wired networks (e.g., PLC, HomePlug, etc.). There is no need for a large amount of bandwidth or communication speed since load monitor and control applications are not counted as mission critical. The bandwidth is required per node/device is 14–100 Kbps and reasonable latency time should be between 2–15 seconds [9].

ZigBee has the most suitable features compare to other wireless HAN communications for managing home appliances, as shown in Table 3.1. ZigBee has a transmission range of up to 175m with a 250 Kb/s data rate and OQPSK modulation [10]. It has the ability to operate in a mesh network topology, which offers some advantages, i.e., some devices in a ZigBee mesh can remain in sleep mode when they are not active in the network, which results in energy conservation [11]. The low complexity makes ZigBee a low-cost wireless communication option that is affordable by the masses. Therefore, the technology based on ZigBee for household load monitoring and control is considered in this study.

Table 3.1

Comparisons of different communication mediums [9], [12], [14].

Technology	Standard	Data rate	Coverage	Latency	Reliability (%)	Application	Medium	Limitation
Communication technologies between utility and smart meter								
Fiber optic	PON,	155Mbps to 2.5Gbps	Up to 60 km	< 15s	> 99.5	WAN	Wired	Costly installation fee.
	WDM,	40 Gbps	Up to 100 km					
	SONET/SDH	10 Gbps	Up to 100 km					
DSL	ADSL	1-8 Mbps	Up to 5 km	200-400 ms	> 98	NAN	Wired	Not available everywhere due to the signal limitations
	HDSL	2 Mbps	Up to 3.6 km					
	VDSL	15-100 Mbps	Up to 1.5 km					
Cellular	2G-4G	Up to 100 Mbps	UP to 50 km	41-80ms	> 99.5	NAN, WAN	Wireless	Costly spectrum fee.
PLC	Narrowband	10-500 kbps	Up to 3 km	< 15s	> 98	NAN	Wired	Harsh, Noisy channel
WiMAX	802.16	57 Mbps	UP to 50 km	1ms	> 98	NAN, WAN	Wireless	Not widespread
Ethernet	802.3x	10 Mbps to 10 Gbps	Up to 100 m	0.3ms	> 98	HAN, NAN	Wired	Short rang
Satellite	Satellite internet	1 Mbps	UP to 100-6000 km	120ms	> 99.5	WAN	Wireless	Costly installation fee, sensitive to heavy rain.
Communication technologies between smart meter to home appliances								
Z-wave	Z-wave	40 kbps	UP to 30 m	< 300ms	> 98	HAN	Wireless	Low data rate, shot range
Bluetooth	802.15.1	721 kbps	UP to 100 m	300ms	> 98	HAN	Wireless	Low data rate, shot range, costly installation
ZigBee	802.15.4	250 kbps	UP to 175 m	30ms	> 98	HAN	Wireless	Low data rate, shot range
Wi-Fi	802.11x	2-600 Mbps	<100 m	> 200ms	> 98	HAN, NAN	Wireless	Noisy channel, shot range, costly installation
PLC	HomePlug	14-200 Mbps	Up to 200 m	< 15s	> 98	HAN	Wired	Harsh, Noisy channel

The most common communication mediums between smart meters and utility are Power line communication, Digital Subscriber Line (DSL) and Cellular networks. PLC has been the first choice for communication between the smart meters and the data concentrator in urban areas where other solutions struggle to meet the needs of utilities [17]. It is preferable choice because, the existing infrastructure decreases the installation cost of the communications infrastructure and PLC provides secure data transmission. However, PLC may be insufficient for some real-time applications requiring high bandwidths [18]. Furthermore, the PLC transmission medium is harsh and noisy. It is sensitive to the network topology, the number and type of the devices connected to, wiring distance between transmitter and receiver, all, adversely affect the quality of signal, that make PLC technology not suited for data transmission [19].

Digital Subscriber Lines (DSLs) is a high-speed digital data transmission technology that uses the wires of the voice telephone network. The widespread availability, low-cost and high bandwidth data transmissions are the most important reasons for making the DSL technology suitable communications candidate for the smart meter communications to utility. The DSL-based communications systems require communications cables to be installed and regularly maintained, and thus, cannot be implemented in rural areas due to the high cost of installing fixed infrastructure for low-density areas. Distance dependence, lack of standardization and reliability are the disadvantages that make DSL technology less appealing. Existing cellular networks are good options for communicating between smart meters and the utility and between far nodes. Widespread and cost-effective benefits make cellular communication one of the leading communications technologies for the smart grid applications. To manage healthy communications with smart meters in rural or urban areas, the wide area deployment of the cellular networks can cover almost 100% areas. Lower cost, better coverage, lower maintenance costs, and fast installation features highlight the cellular networks as the best candidate for the communications of DR applications. However, the services of cellular networks are shared by customer market and this may result in network congestion or decrease in network performance in emergency situations [4]. Hence, these considerations can drive utilities to build their own private communications network. In abnormal situations, such as a wind storm, cellular network providers may not provide guarantee service. In some cases, utilities prefer WiMAX due to proper security protocols, smooth communications, high data speeds an appropriate amount of bandwidth and scalability. However, the WiMAX is not a widespread technology as Fiber optic, therefore the cost of installation will be higher in some areas [20]. Therefore, the choice of the communication technology between smart meter and utility control center varies and it may fit for one environment and may not be suitable for the other.

The requirement of the communication speeds for DR implementation varies based on the DR programs. For example, DR pricing programs (e.g., TOU, real-time pricing, etc.) implementation do not require high speed communication technologies, as in these programs pricing signals are sent to consumers at 5-minute, hourly or day ahead advanced. In DLC program, the requirement of communication technologies depends on the application of DLC. For the primary frequency response services, the communication technologies need to be very fast (<1s) to support the frequency control ancillary services. Other applications of DLC, such as voltage regulation and load flowing, the communication latency between utility load control to consumer devices is expected to between 1s and 10s [15].

3.3 Smart load monitoring and control system

A smart monitoring and control system has been proposed in this study for monitoring the energy consumption behaviours of different electric appliances of a household. The smart system is a ZigBee based wireless technology, developed by Power Tracker [13]. Power Tracker is an internationally reputed company for developing smart monitoring and controlling system which can monitor and control of home electric appliances. Users can access consumption information through online or in-home display. This system can provide near real-time energy consumption information (every sixty seconds), daily, weekly, monthly and yearly historical information, etc. It allows monitoring solar system performance and control of home appliances remotely.

The smart load monitoring system consists of three main units: a Smart Energy Gateway, Smart Clamps and Smart Appliances. Smart Energy Gateway is an all-in-one router which allows secured wireless internet access for real-time power management. The Gateway receives data wirelessly (ZigBee) from the Smart Clamps and Smart Appliances and sends to the server. Smart Clamps allow metering entire home electricity usage by deploying in a power cabinet and they can be connected with the Solar system. Smart Appliances allow to measure and control the consumption of specific home appliances which can be turned on/off remotely. The application diagram Fig. 3.3 shows how the whole system can be connected to home electric appliances.

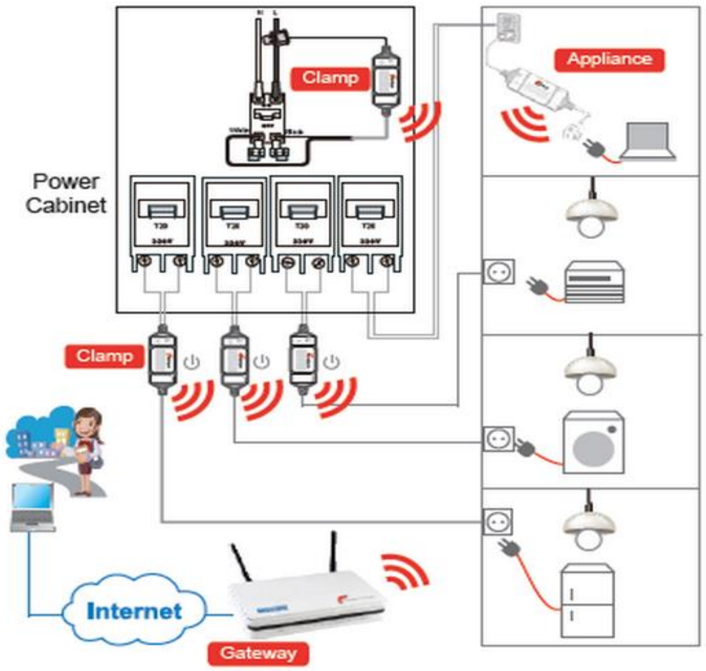

Fig. 3.3. Smart load monitoring and control system from Power Tracker [13].

The Power Tracker's smart load monitoring and control system can be used in different DR schemes. For example, consumers can remotely schedule their consumption preferences throughout the day according to the electricity pricing rates (e.g., real time pricing) or utility and DR aggregator can use direct load control (DLC) technique for DR using this smart system. A case study has been conducted with the Power Tracker's smart monitoring system is detailed in the following sections.

3.4 Case study

The smart load monitoring system is developed in a typical three-bedroom house in Australia. The total number of occupants in this house is three. The Smart Appliances of the smart monitoring system are connected with four major household appliances such as refrigerator, air conditioner (AC), washing machine and dishwasher. A Smart Clamp is installed at the main power cabinet to observe the total household power consumption. The consumption characteristics of the household with the four major connected loads in a typical summer day are observed and measured from the smart devices, which are described in the following sections.

3.4.1 Load profile

Fig. 3.4 shows the monitored load profile with the SMCS on a typical summer day. It shows that the peak demands occur in the afternoon and evening periods. The morning recurring pattern is contributed to the cyclic behaviour of the refrigerator's compressor switching on and off. The afternoon peaks are subscribed to the usage of the AC, oven, kettle, Television and vacuum cleaner. The evening peaks are contributed to the functioning of the refrigerator, washing machine, kettle and two lighting loads.

The consumption characteristics of the major energy contributor loads on this daily load profile are presented in this study. The daily power demand for the refrigerator can be viewed in Fig. 3.5. The refrigerator has a repetitive behaviour due to the compressor switching on and off. The peak in the evening can be attributed to the opening of the fridge which causes the compressor to work harder in lowering the temperature to regain optimal temperature.

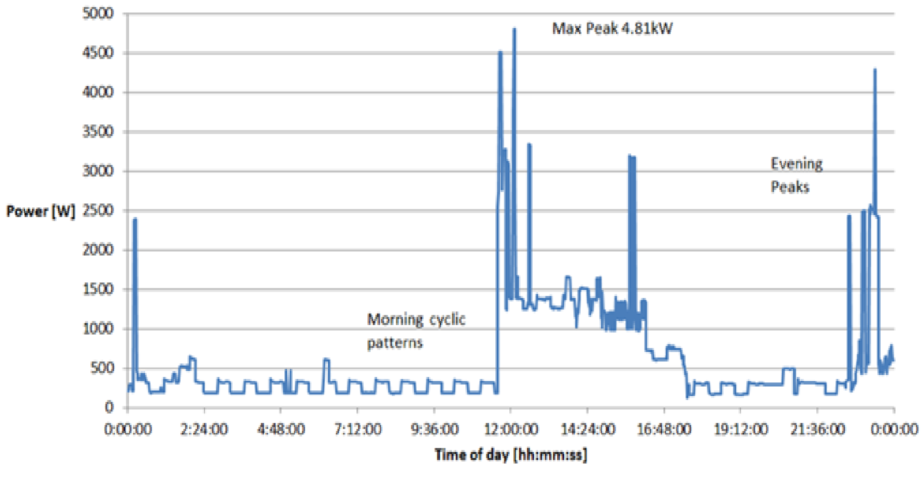

Fig. 3.4. The daily load profile of a tested household in a typical summer day.

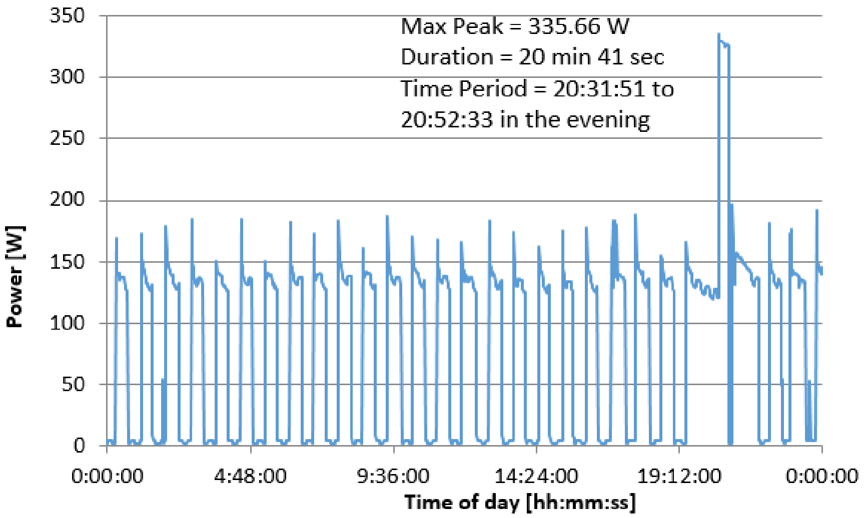

Fig. 3.5. Characteristics of a refrigerator.

The power demand of the AC for this day has depicted in Fig. 3.6. The AC is turned on at 11:45 hr and remained on for four hours twenty-eight minutes. The compressor of the AC continuously cycles and remained on until the room temperate reaches below the nominal set temperature. The AC has stand-by power demand of 7.56W.

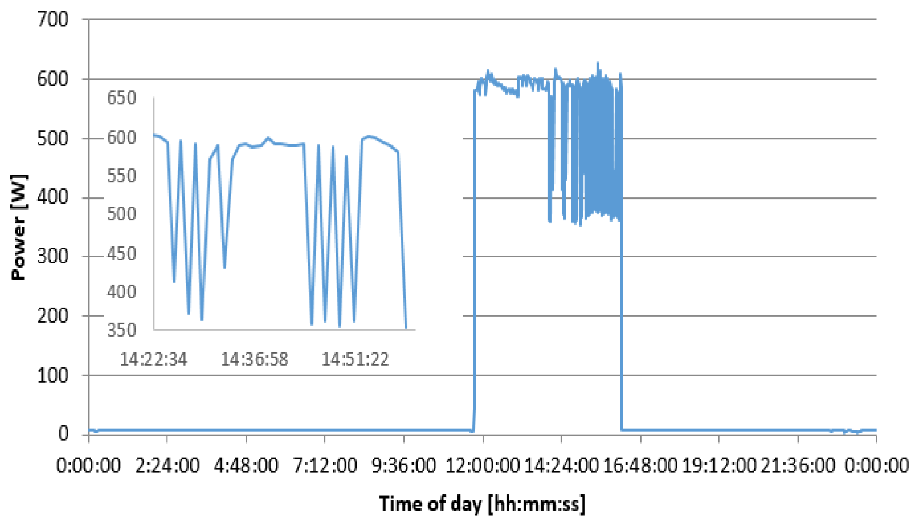

Fig. 3.6. Air conditioner power demand.

Fig. 3.7 presents the daily consumption behaviour of the washing machine. It shows the washing machine is in stand-by mode until it is operated at 20:31 hr and the operation cycle is around 1 hour 27 minutes. The stand-by power demand for the washing machine is 0.58 W.

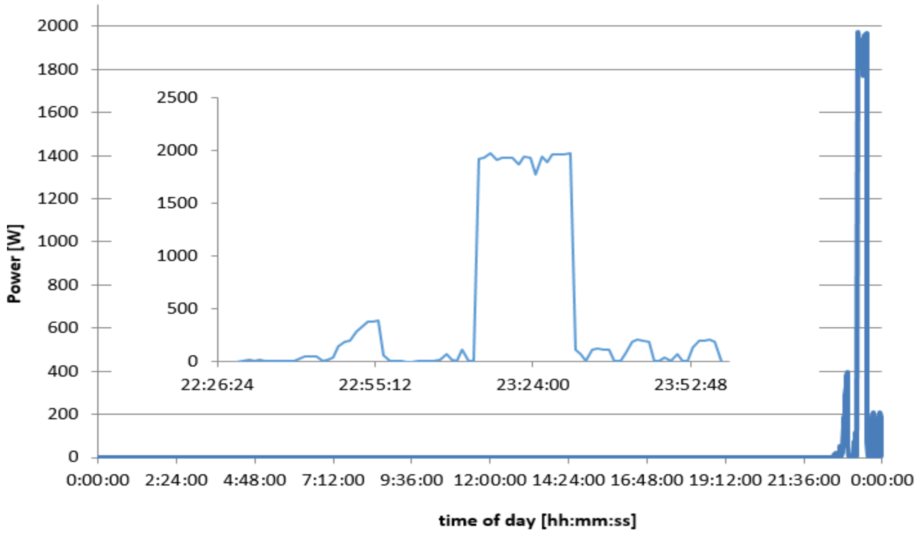

Fig. 3.7. Washing machine power demand.

The dishwasher is not used on that day. To analysis the energy consumption behaviours, Fig. 3.8 represent the consumption patterns of a dishwasher which is taken from a different operation day. The dishwasher cycle lasts for one hour and twenty-five minutes. The first peak in the operation is due to the water being heated for the warm water wash and the second peak is due to the steam cycle. The stand-by power demand is 1.6W.

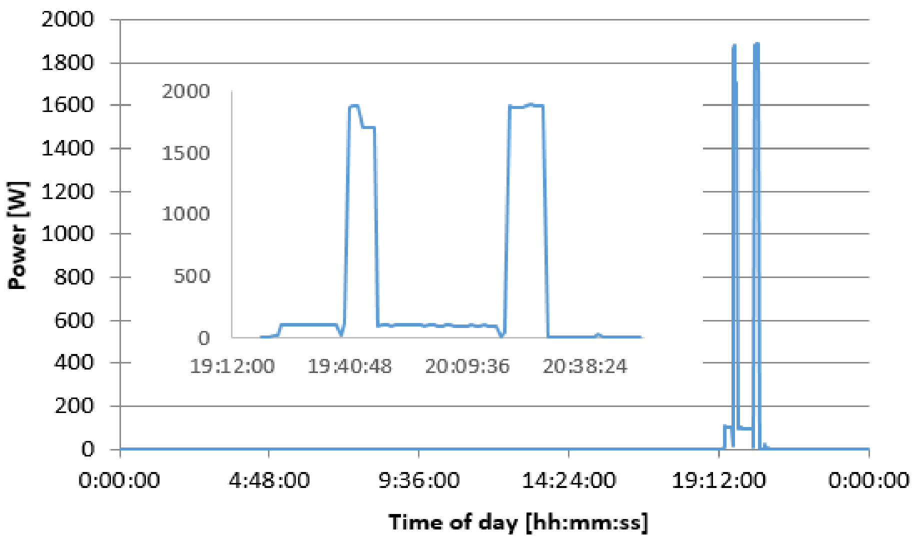

Fig. 3.8. The power demand for the dishwasher.

3.4.2 DR opportunity and standby power losses

Providing priority to the consumer comfort level some of the major appliances are non-interruptible and deferrable, such loads are refrigerator and AC. However, during emergency condition in the grid, the utility operator can switch off the AC compressor for few minutes without violating the consumer comfort. On the other hand, washing machine, dishwasher have high potential for DR participation. During the maximum renewable energy generation periods and peak demand periods, the utility can remotely control these loads by turning on and deferring consumers' consumption to off-peak periods respectively, using a smart system like SMCS. Table 3.2 compares the power consumption, DR potential, DR capacity, possible interruption/deferral period, standby power and potential savings from standby power of the selected appliances in the household.

Considering 100 households take part in DR scheme (e.g., DLC program) by permitting utility to remotely control both their washing machine and dishwasher during peak periods, the total potential peak shaving capacity would be:

$$100\,x(1.9kW + 1.8\,kW) = 370kW\ (or\ 0.37MW).$$

Similarly, for the 100 households, the total daily energy loss in standby mode for AC, washing machine and dishwasher would be:

$$100x21hrs\ x(7.56W + 0.58W + 1.6W)/1000\ = 20.5kWh$$

where, 21 hrs represent the estimated standby time for an appliance during a day. The total daily energy loss from the three standby appliances is significant and it would be more if all the appliances standby power are considered. This contributes substantial increase of consumers' month energy bills. It is therefore recommended that all appliances should be switched off when not in use to save the energy that would otherwise be lost.

Table 3.2

Demand Response and energy savings opportunities for selected major appliances.

Appliance type	Average Peak demand (kW)	DR potential	DR capacity (kW)	Possible interruption/ deferral time	Standby power (W)	Potential Saving from standby power (%)
Refrigerator	150	N/A	150	Up to several hours (defrost cycle)	0	0
AC	580	Low	580	Vary	7.56	100
Washing machine	1900	High	1900	None/up to several hours	0.58	100
Dishwasher	1800	High	1800	None/up to several hours	1.6	100

3.5 Conclusion

This study has investigated the different communication technologies and their suitability for use in residential DR regarding scalability, coverage range and low installation costs. The currently available communication technologies are categorised into two different groups including smart meter to household appliances and smart meter to utility control center. In each group, the suitable communication technologies are compared and analysed according to their data rate, coverage, latency, reliability and limitations. This information is obtained from an extensive literature survey. Based on the compression analysis, a ZigBee based smart load monitoring and control system is proposed and integrated into a typical Australian household to measure and observe the daily load profiles and appliances power consumption behaviors. These obtained realistic load profiles of the selected major appliances including refrigerator, AC, washing machine and dishwasher are useful for any DR study. Furthermore, the potential DR opportunity and standby power consumption of the major appliances are identified and analysed. Finally, the total possible daily peak demand shaving capacity and energy loss in standby mode of the major appliances are calculated for 100 residential consumers.

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Chapter 4

A Dynamic Fair Incentive Based Multi-Layer Load Control Algorithm for Managing Voltage Variations in Medium Voltage Networks Considering Consumer Preferences

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Abstract

The voltage control problem is known as one of the biggest obstacles for increasing the integration of distributed generators (DGs) in distribution grids. Of concern to utilities is when load and solar power move in opposite directions due to the cloud transients cause potential stress on network voltage regulation devices. This study proposes residential demand response (DR) for managing short and long intervals of voltage variations in medium voltage (MV) networks due to intermittency in power generation from solar photovoltaic (PV) based DGs. A multi-layer load control algorithm comprised of 10-minute and 2-hour DR schemes is developed to compensate the short and long intervals of voltage variations in the networks, which is coordinated with DGs' inverters for reactive power support for effective voltage management. The proposed method minimises the cost of DR, network loss, and DG reactive power contribution for voltage management, while prioritising consumers' consumption preferences for minimising their comfort level violations. A dynamic fair incentive mechanism is proposed for each DR event to reward consumers based on their energy contribution and the influence on the network voltage and loss improvement with optimal coefficients obtained through optimisation. This study also presents an improved hybrid particle swarm optimisation algorithm (IHPSO) to solve the optimal switching configurations of appliances and DG reactive power configuration to manage the network voltage. The proposed method is comprehensively examined on a standard IEEE 33-bus network with several scenarios. Simulation results show that the proposed multi-layer load control algorithm coordinated with DG's inverters effectively improves the network voltage while incentivises consumers fairly based on their contributions.

Keywords: direct load control; voltage variation; dynamic incentive; DG; consumer comfort.

4.1 Introduction

In recent years, the use of renewable energy resources (RESs) in the form of DGs has increased considerably [1]. The distribution system operators (DSOs) are facing continuous challenges to maintain the network reliability and power quality within the standard limits, as the conventional distribution systems have not been designed with the consideration of bidirectional power flows from the RESs based DG integration [2]. As their output power varies, which highly depend on weather conditions, the uncertainty in distribution system management is increased and the safe operation of the system becomes more complicated [3]. Cloud-induced transients over solar photovoltaic (PV) based DGs are considered as one of the potential barriers to further expansion when the penetration of PV reaches a high level in distribution systems [4]. If clouds sweep over the solar catchment area within a short time (typically in less than a minute), PV power contribution drops quickly which may cause voltage drop at some remote buses [5]. Such transients can cause voltage deviations beyond the statutory range [3] and excessive operation of the voltage regulating equipment [4].

Conventional approaches, manage voltage in MV distribution systems by using on-load tap changer (OLTC) mechanism of the transformer, step voltage regulators and static VAR compensators [6], [7], [3]. However, these methods cannot guarantee that the voltage profile will be within acceptable bounds throughout all connected feeders to the affected transformer [8]. The lifetimes of operating equipment dramatically reduce from the increased number of operations needed to handle the voltage variations due to sudden changes (on the time-scale of minutes) in supply [7]. Studies in [9-10] proposed that appropriate reactive power control of DG inverter can offset the short variation voltage problems in distribution networks, while reducing or deferring the need for new assets or grid reinforcements. However, if the controlling of these DG units are not properly coordinated, they may conflict with existing voltage regulation devices [11], and may increase the energy losses in the network [12]. Moreover, there is no incentive to DG owner for providing frequent reactive power support. Battery energy storage system (BESS) is a potential solution to the problem of real time variation of voltage in distribution grid [13-14]. However, this technology is still an expensive solution [15]. Moreover, due to several charging/discharging cycles per day to support the intermittent generation, it causes significant challenges for the battery lifespans. In practice, it is highly preferable to utilise the existing infrastructure without additional investments to increase the capacity of existing systems.

One of the promising means of utilising existing infrastructure for managing network voltage is by controlling end-users' loads through demand response (DR) programs [16-17] using direct load control (DLC) approach [18]. In the DLC approach of DR programs, many household appliances can be switched ON and OFF almost instantaneously enabling them to react fast to maintain the network voltage effectively [19]. It can be used as a source of reserve in systems [20], which can postpone investments in generation resources and network upgrades [21]. The DLC programs are becoming increasingly attractive as smart grid technologies, such as smart metering, smart appliances, and home area networks have been developed significantly over the past years [22], [11], [2]. However, the main challenge in the DLC is to optimise the control of a large number of various types of household appliances while maintaining the consumers' comfort levels by prioritising their consumption preferences. In addition, network constraints (such as voltage, current, power loss, etc.) are needed to be taken into account in DLC programs. Inappropriate control of loads may lead to network constraints violations [23] and may unnecessarily increase the volume of load control, which altogether is a complex optimisation problem and requires huge computational efforts. Various analytical and soft computing methods such as evolutionary algorithm (EA) [24], reinforcement learning with q-learning [25], learning automata [26], particle swarm optimisation (PSO) [27] are proposed to address such complex problems for scheduling appliances. Some of these methods are successful in locating the optimal solution, but they are usually slow in convergence and entail heavy computational costs. Moreover, these studies have not taken into consideration the consumption decision priorities of individual consumers to maintain their comfort levels, which is one of the important indices for a successful DR implementation.

The study in [28] provides a large percentage of real time balancing reserve for MV network by aggregating electric water heaters (`s) for load shifting while maintaining consumers' comfort levels. However, that study is limited to control of EWHs only. Multi-layers DR are proposed in [29] using only air conditioner (AC), EWH and cloth dryer to satisfy both utility and consumer preferences. A load shedding optimisation technique is proposed in [4] for utilities to maintain network voltage considering a limited numbers of household appliances. These exampled studies consider only few selected appliances from a limited number of consumers in DLC strategy, assuming all the consumers have similar appliances with fixed kilo-watt (kW) ratings. In reality, the appliances' power consumption ratings and their quantities vary between consumers and may not be exactly the same across all participating consumers in a DR event. A complete study, considering the variability of household appliances of large number of consumers with their different kW sizes in DLC program has yet to be investigated.

Furthermore, the incentives to the participating consumers in a DR event should not be fixed or equal for all conditions of a network; it should be fair based on consumers' locations in the network, and as well as their contribution to each DR event. Study in [27] developed a load control algorithm to manage the MV network voltage and line thermal limits by using 2000 electric vehicles (EVs) with a fixed incentive rate for all EV users. Likewise, in [11] and [30], the DR participation costs are considered similar for all participating consumers in the network. It is important to note that the households located far away from a feeder are usually interrupted more than the households nearer to the feeder during DR events. The reason for this location effect is due to consideration of both the power loss minimization and the voltage regulation in DR optimisation [31]. This location effect creates a potential fairness issue in DR incentive selection since the impacts of DR on the households are not the same. Mechanisms to compensate such location discrimination needs to be developed. A study in [32] developed a reward based load control algorithm to shave network peaks, where houses are ranked with a factor reflecting their impact on voltage due to their load. It shows that rebate of consumer increases towards the end of the feeder due to their significant contribution in network voltage improvement. However, only a limited number of houses are considered in the simulations assuming all have similar controllable appliances of 1 kVA each. Moreover, in this study, the network loss minimisation is not considered in the optimisation. In order to improve the optimality, reliability and life expectancy of the distribution system, the efficiency of the whole system must be kept in the maximum possible value during all operating conditions. An optimum DR implementation reduces the network power loss and improves its efficiency significantly.

Therefore, this study proposes a complete approach of DR deployment considering flexibilities of the most of major household appliances and DG reactive power support in managing both short and long terms variations of the network voltages as well as minimising the network power losses. Consumer consumption preferences are prioritised to maintain their comfort levels as well as incentivised fairly. The main contributions of the proposed study are summarised as follows:

1. A multi-layer load control algorithm is developed to manage the variations of voltage in different time scales in MV networks considering the flexibilities from large number of household appliances with their different consumption ratings and DGs' reactive power support capabilities.
2. The load control algorithm prioritises consumers' consumption preferences as well as performs optimal switching disturbances on appliances to maintain their comfort levels.
3. A dynamic fair incentive mechanism is proposed in the load control algorithm to incentivise participating consumers based on their energy contribution and the influence on the network voltage and loss improvement.
4. An improved hybrid particle swarm optimisation (IHPSO) algorithm is proposed in the load control algorithm to obtain fast convergence with less computational time and robust output.

4.2 DR implementation strategy

This section provides details about the proposed multilayer load control approach, how consumer preferences are defined in load control algorithm, selection criteria for DR candidate bus locations, and mechanism for developing fair incentive distribution to consumers.

4.2.1 Multi-layer load control approach

This study focuses on designing a multi-layer load control approach considering a large number of residential households for handling short and long durations of voltage variations in MV networks due to intermittent PV generation caused by cloud movements. Household appliances are divided into two DR schemes, i.e. 10-minute DR scheme and 2-hour DR scheme respectively for mitigating the voltage variations across the network. The proposed load control algorithm considers a realistic approach of DR implementation, and to fulfill this aim, each appliance's realistic consumption rating and number of available appliances are considered separately for each participating consumer in the load control algorithm. The two DR schemes are as follows:

(1) *10-minute DR scheme*

A 10-minute load control scheme is also a useful tool for grid operators, when fast moving clouds pass through a catchment area of a network. Multiple 10-minute load controls can be applied within an hour for a given site. For this DR scheme, the candidate appliances considered in this study are the air conditioner (AC) and the electric water heater (EWH). These devices can be interrupted for a maximum of 10 minutes while they are operating to avoid consumer discomfort. These appliances can be switched ON and OFF almost instantaneously without prior notification or with short period notification to consumers. Therefore, they can be interrupted multiple times to compensate the fast voltage variations. However, once the control signal for adjustment is sent to these devices, another signal is not sent for the next 10 minutes. The controlling approach of these devices are discussed below:

Electric water heater (EWH)control: In order to calculate the number of EWHs that need to be turned ON or OFF, it is important to calculate how many EWHs are available to turn OFF or ON for next 10 minutes period. Each EWH has a thermostat set point $(T_{i\,(t)}^{set})$ and a dead band (D), the temperature inside the tank of EWH must maintain the thermostat set point range, as given in (4.1). The temperature change of the EWH relates to the required hot water flow rate, tank surface area, insulation resistance and current water temperature.

$$T_{i\,(t)}^{set} - D \leq T_{i(t)} \leq T_{i\,(t)}^{set} \tag{4.1}$$

where $T_{i(t)}$is the current state temperature of hot water inside the tank of EWH at time t.

If the EWH is in the ON state and its current temperature ($T_{i(t)}$) is less than or close to dead band temperature ($T_{i\,(t)}^{set} - D$), it will be excluded in the load control algorithm. Similarly, if the EWH in the OFF state and its temperature ($T_{i(t)}$) is close or equal to the setpoint temperature $T_{i\,(t)}^{set}$, it will be excluded in the algorithm. Only EWH participates in the DR event if the current temperature ($T_{i(t)}$) is within the thermostat set point range. However, if a consumer set consumption preference on a EHW as high, the EHW will also be excluded from the algorithm. It means utility will not control the EHW during the DR event. The thermostat set point of each EHW are considered to vary between 52 °C and 71 °C with a dead band of 12 °C [28]. When the EHW is turned OFF by the DR event for 10 minutes to reduce energy consumption, its temperature should be maintained to 52 °C or above. On the contrary, if the EHW is turned ON by the DR event to increase energy consumption, the temperature of the water should not exceed 71 °C. A brief description of the modelling of an individual EWH and aggregated EWHs are provided in [28], [35].

Air conditioner (AC) control: An AC can be controlled similarly to the EWH control approach. However, an AC will only be controlled when it is in operational mode (ON). Some ACs can run in both heating mode and cooling mode as per requirement of consumers. For each household *i*, the comfortable temperature range that the consumer can bear, is denoted by [$T_i^{comf,min}$, $T_i^{comf,max}$], as shown given in (4.2).

$$T_i^{comf,min} \leq T_{i\,(t)}^{in} \leq T_i^{comf,max} \tag{4.2}$$

where $T_{i\,(t)}^{in}$ is the current state temperature inside the room at time t.

If the AC cycle is in ON state and the current room temperature ($T_{i(t)}$) is less than the minimum comfortable temperature ($T_i^{comf,min}$), it will be excluded from controlling in DR event. Likewise, if the AC cycle is in OFF state and its temperature ($T_{i\,(t)}^{in}$) is close to or equal to the maximum comfortable temperature ($T_i^{comf,max}$), it will also be excluded in algorithm. The comfortable temperature range is considered [21C, 26C] in this study [31]. The consumer can set their consumption preferences on AC, in this case the utility will not control the AC during the DR event. The modelling of AC is provided in [31].

(2) *2-hour DR scheme*

Maximum 2-hour load control scheme is reasonable for managing long interval of voltage variations caused by PV generation [33]. In this scheme, those appliances of consumers are selected for contributing in DR, which have less impacts on consumers' comforts and have reasonable flexibilities for deferring operational time. These appliances are washing machine, dishwasher, dryer, pool pump and electric vehicle (EV). For washing machine and dishwasher, the consumption cycles have to be completed once started by the consumer, however, their operating time can be shifted. EV, pool pumps and dryer can be interrupted during the DR event (modern dryer heating cycles can be interrupted for 30 minutes [34]). Consumer can set their consumption preferences on the appliances, so that utility will not control these appliances during the DR event (discussed in the nest section).

4.2.2 Consumer Preferences in DR

Consumer preferences are taken into account in both of the DR schemes activation process. Utility collects the appliance consumption preferences from each consumer before any DR scheme activation to minimise the impact on their comfort levels. The consumption preference on each appliance can be defined as consumption priority or consumption restriction, so that the appliance cannot be switched OFF or switched ON, respectively, during the DR event. For instance, if an EV's current state of charge is less than the minimum requirement of a user or if their AC is required to operate continuously without any interruption. The user can set consumption priority on these devices so that they cannot be switched OFF during a particular period of a DR event. Likewise, if a washing machine or any other appliance has already been utilised in a previous DR event, the owner may set consumption restriction, so that it will not be controlled in any DR event within 24 hours. Each appliances' current switching and consumption preference status are defined in the proposed load control algorithm using the numerical values 0 to 4, as shown in Table 4.1. These values are collected by the utility before DR implementation. In this study, a switching control variable $A_{n(i,t)}$ is defined for the n^{th} appliance of the i^{th} candidate consumer during a DR event at time t. This parameter for each appliance represents the appliance switching status after optimisation. The value of this switching control variable can be 0, 1, or -1, which is chosen through the optimisation process and defined in [3].

$$A_{n(i,t)} = \begin{cases} 1 & \text{the participating appliance is turned on} \\ 0 & \text{no change (the appliance is not participating in DR)} \\ -1 & \text{the participating appliance is turned off} \end{cases} \tag{4.3}$$

The implication of the appliance preferences on $A_{n(i,t)}$ is presented in Table 4.1. Based on $A_{n(i,t)}$ value for each appliance the proposed algorithm minimises the DR cost, comfort disturbance, and the voltage violations in the network. Appliances which are assigned with the preference 2, 3 and 4, will not be included in the optimisation and their switching statuses will not be changed during optimisation; thus, the corresponding $A_{n(i,t)}$ will be always zero. For example, as washing machine and dishwasher operation cycles cannot be interrupted while they are on, the status of these appliances will be 3 in that operating condition. Therefore, in the optimisation process, the corresponding $A_{n(i,t)}$ of these appliances will not be optimised, so that they cannot be switched OFF. While appliances assigned with the status 0 and 1, their switching status can be changed. The total cost of DR is the sum of the controlled appliances' demands (kW) multiplied by the corresponding incentives ($/kWh) to consumers and the duration of an event.

Table 4.1

Appliance status and the implication on $A_{n(i,t)}$

Preference #	Preference name	Definition	Is the appliance participating in DR?	$A_{n(i,t)}$
0	not restricted mode	the appliance is off and can be switched on	Yes	1 or 0
1	not restricted mode	the appliance is on and can be switched off	Yes	−1 or 0
2	not available (n/a)	appliance is not available for any future DR event	No	0
3	priority mode	the appliance is on and cannot be switched off	No	0
4	restricted mode	the appliance is off and cannot be switched on	No	0

In addition to the appliance preferences, the optimisation algorithm needs to minimise the number of switching operations to reduce the disturbances on the consumer comfort levels. It can be achieved by controlling first those appliances, which have a large power rating among the participating appliances of a consumer. This way the total number of appliance disturbances will reduce. To quantify this as a measure the appliance disturbance ratio (ADR) is defined as a constraint in the optimisation, which will be minimised by the proposed load control algorithm. ADR is the ratio of the total demand change (ΔP) for a consumer to the total number of appliances disturbed for that consumer, as in (4.4).

$$ADR_{(i,t)} = \Delta P_{(i,t)} \Big/ \sum_{n=1}^{N_{A(i,t)}} \left|A_{n(i,t)}\right| \tag{4.4}$$

where $ADR_{(i,t)}$ is ADR, $\Delta P_{(i,t)}$ is the total demand change, | | is the absolute function, and $N_{A(i,t)}$ is the total number of DR appliances. $A_{n(i,t)}$ is the switching control variable of the nth appliance. All the parameters are for ith consumer at time t in the DR event. The total demand change is the resultant demand after turning participated appliances ON and/or OFF, which is calculated as in (4.5).

$$\Delta P_{(i,t)} = \sum_{n=1}^{N_{A(i,t)}} \left|A_{n(i,t)}\right| \times P_{n(i,t)}\,(kW) \tag{4.5}$$

where $P_{n(i,t)}$ is the rated kW demand of the nth appliance. To clearly understand ADR, lets consider a consumer having 3 kW of EV and 0.5 kW of washing machine and the current switching status of these devices are ON and OFF, respectively. In a DR event, if the load control algorithm decides to switch OFF only the EV, the ADR value will be 3/1=3. If in the same time the washing machine is also switched ON then the ADR value would be (3+0.5)/2=1.75. Then the associated penalty factor ($\text{Penalty}_{ADR(i,t)}$) with $ADR_{(i,t)}$ value will be added in the objective function cost, as in (4.6).

$$\text{Penalty}_{ADR(i,t)} = \begin{cases} 10^2 & ADR_{(i,t)} \leq 0.5 \\ 10^2(2 - ADR_{(i,t)}) & 1 < ADR_{(i,t)} < 2 \\ 0 & ADR_{(i,t)} \geq 2 \end{cases} \quad (4.6)$$

As seen in (4.6), the penalty factor of ADR is considered high for $ADR_{(i,t)}$ values less than 0.5 to exclude the corresponding switching solution from the search space. If $ADR_{(i,t)}$ value is bigger than 2, the penalty is zero to relax the ADR constraint. If $ADR_{(i,t)}$ is in between 1 and 2, a linear reduction of the penalty is proposed to relate the penalty to the value of ADR for each consumer. From the above example, where the ADR value is 1.75, the corresponding penalty would be 25, so this switching configuration will be considered as a high penalty cost. For the ADR value 3, the corresponding penalty would be 0, this switch configuration would be an optimal choice. Therefore, the number of appliance disturbances will be reduced. The limit values of 0.5 and 2 can be changed based on the appliances' power ratings available at consumer premises. Next section describes the procedure of the DR candidate locations selection for each DR event.

4.2.3 DR candidate locations selection process

The candidate location selections for DR implementation is crucial for MV networks, as there are many consumers connected in each bus of MV networks. Identifying effective locations for DR implementation which have the maximum influence on network voltage and loss improvement, will reduce the load control volume (DR size), optimisation search space and time, disruptions to consumers, as well as DR costs. The random selection of locations will increase unnecessary load adjustments, increase complexity and the optimisation time and hence increase DR costs [18]. Therefore, in this study, sensitivities analysis for both voltage and network power loss in regards to active power changes are performed to estimate the candidate bus locations for before each DR event. The combination of voltage and loss sensitivities of each bus is considered to rank the DR candidate bus. Higher the combination value of a bus, higher its rank would be in DR candidate bus selection. The number of candidate bus selection will be depended on the consumer availability and estimated load adjustment requirement.

The change of voltage magnitude $\Delta|V_j|$ at each voltage violated bus j due to change active power ΔP_i at each bus i is obtained from inverse Jacobian matrix J [18]. Then the average effect of voltage changes in all violated buses with respect to ΔP_i change at bus i is calculated using (4.7). The buses with the higher average sensitivity values are considered for ranking the DR candidate buses. The benefit of considering this approach for selecting DR locations is presented in [18] (see Appendix B for detail analysis).

$$avg.volt.sens._{(i,t)} = \left(\sum_{j=1}^{N_v} \frac{\partial|V_{(j,t)}|}{\partial P_i}\right) / N_v\,, \quad \forall\ i = 2,3,..,N_b \tag{4.7}$$

where $avg.volt.sens._{(i,t)}$ represents the average sensitivity of voltage change in all voltage violated buses at time t due load change at bus i. N_v is the number of voltage violated buses. $N_b$is the total network buses. $\partial|V_{(j,t)}|$ is voltage change at each violated bus j at time t due to power change ∂P_i at bus i.

The sensitivity of total active power loss change $\Delta|P_{T.loss}|$ with respect to active power change ΔP_i at each bus i is calculated numerically to rank the DR buses. The bus with higher loss sensitivity value has more influence on total network loss change due to active power change in that bus [36]. The total power loss of the network at time t is calculated using (4.8). The sensitivity of total network loss with respect to load change at each bus i, is calculated using (4.9) based on the study in [36].

$$P_{T.loss\,(t)}(\text{total power loss}) = \sum_{l=1}^{N_{line}} \left|I^2_{(l,t)}\right| \times R_l \tag{4.8}$$

$$T.loss.sens._{(i,t)} = \frac{\partial\left|P_{T.loss(t)}\right|}{\partial P_i}, \qquad \forall\ i = 2,3,..,N_b \tag{4.9}$$

where, $T.loss.sens._{(i,t)}$ represents the sensitivity of total network loss at time t due load change at bus i. N_{line} is the number branches, $I_{(l,t)}$ is the current flowing out of branch *l* at time t, R_l is the resistance of branch *l*. $\partial|P_{T.loss}|$ is the total system loss change due to power change ∂P_i at bus i.

The bus with the highest combined value of (4.7) and (4.9) will be ranked as 1; with the second highest value, the corresponding bus will be ranked 2, and so on. The simulation results section (Section 4.5) shows the bus ranking results using this combined approach.

4.2.4 Dynamic fair incentive distribution

Consumers sign for the DR contract due to economic benefits they receive from the utility [28]. Their contributions in each DR event on network voltage and loss improvement depend on the network condition and their locations in MV buses. Consumers who are located at higher voltage and loss sensitive buses are tended to be interrupted more than the consumers who are located at less voltage and loss sensitives buses in the network [31-32]. It means that consumers located in higher sensitive buses contribute more on voltage and loss improvement than consumers in less sensitive buses. If all the participating consumers are incentivised in a same manner (e.g., considered in [11], [30] and [37]), it implies a potential fairness issue in DR incentive distribution. To ensure fairness of incentive distribution to consumers, this study proposes a mechanism of calculating incentive rate ($/kWh) for each DR event and DR candidate bus dynamically. It is a combination of three components: fixed cost (based on time of use energy cost rate ($/kWh)), voltage improvement cost and total loss improvement cost, as shown in (4.10). Equations (4.11) and (4.12) are used to calculate voltage and total loss improvement factors of each bus for rate design, respectively.

$$incentive_{DRbus(i,t)}\ (\$/kWh) = k_1 \times TOU\ rate + k_2 \times TOU\ rate \times volt.improvement\ factor_{(i,t)} + k_3 \times TOU\ rate \times total\ loss\ improvement\ factor_{(i,t)} \quad (4.10)$$

$$where\ \ k_1 = 1 - k_2 + k_3\ , \qquad \forall\ \ k_1 > 0$$

$$volt.improvement\ factor_{(i,t)} = avg.volt.sens._{DRbus(i,t)} \Big/ \left(\left(\sum_{i=1}^{N_{DRbus(t)}} avg.volt.sens._{DRbus(i,t)} \right) \Big/ N_{DRbus(t)} \right) \quad (4.11)$$

$$total\ loss\ improvement\ factor_{(i,t)} = T.loss.sens._{DRbus(i,t)} \Big/ \left(\left(\sum_{i=1}^{N_{DRbus(t)}} T.loss.sens._{DRbus(i,t)} \right) \Big/ N_{DRbus(t)} \right) \quad (4.12)$$

Here, $incentive_{DRbus(i,t)}$ represents the incentive rate ($/kWh) at DR candidate bus i at time t. k_1, k_2 and k_3 are the coefficient factors of fixed cost, voltage improvement cost and network loss cost, respectively relate to incentive rate of each DR bus, which will be optimised by the proposed load control algorithm. The DR cost for per participating consumer is then calculated by multiplying the total controlled demand (kW), controlled duration (hr) and incentive rate ($/kWh) of the corresponding bus. $N_{DRbus(t)}$ is the total number of DR candidate buses considered at time *t*.

In addition to fair incentive distribution to the consumers, the load algorithm needs to fairly interrupt the consumer appliances. As stated before, consumers located in higher voltage and loss sensitive locations are interrupted more compared to less sensitive consumers in the DR event. The excessive interruption on appliances of each consumer can be reduced by limiting the number of appliances interruption to a specific value in the load control algorithm. To address this, a constraint called appliance fair interruption (AFI) is added in the objective function, which will be minimised by the load control algorithm. AFI is used to count the total number of appliances disturbed on each consumer premises using (4.13). The penalty factors of AFI for the two proposed DR schemes are shown in (4.14).

$$AFI_{(i,t)} = \sum_{n=1}^{N_{A(i,t)}} \left|A_{n(i,t)}\right| \tag{4.13}$$

$$\text{Penalty}_{AFI(i,t)} = \begin{cases} 10(AFI_{(i,t)} - 2) & AFI_{(i,t)} > 2,\ for\ 2\ hours\ DR\ scheme\ only \\ 10(AFI_{(i,t)} - 1) & AFI_{(i,t)} > 1, for\ 10\ minutes\ DR\ scheme\ only \\ 0 & else \end{cases} \tag{4.14}$$

$AFI_{(i,t)}$ is the total number of appliances disturbed for i^th^ consumer at DR event *t*. $\text{Penalty}_{AFI(i,t)}$ for 2-hour DR scheme is applied when $AFI_{(i,t)}$ value for i^th^ consumer is greater than 2. For example, if $AFI_{(i,t)}$ value is 3 then the $\text{Penalty}_{AFI(i,t)}$ would be 10. It means the maximum number of appliance of each consumer can be controlled is 2 at any DR event. Similarly, for 10-minute DR scheme, if $AFI_{(i,t)}$ is greater than 1, $\text{Penalty}_{AFI(i,t)}$ would be applied in the objective function. Thus, the excessive interruption of appliances for a consumer will be reduced and will distribute fairly among the consumers.

4.3 Objective function

Two optimisation solutions are applied for the short and long intervals of voltage variations in the network, considering 10- minute DR scheme and, 2-hour DR scheme respectively. Each optimisation problem has two mutually conflicting objectives. The first objective is to satisfy the network constraints including voltage magnitude, line thermal limits, power loss and DGs' reactive power capability ranges. The second objective is to provide fair incentive rates to consumers while minimising the total cost of DR as well as consumers' comfort disturbances.

In both optimisation problems, the decision variables are k_1, k_2 and k_3 factors for incentive rate of each DR bus, the participating appliances switching configurations (ON/OFF) and the DGs' reactive power capability ranges. The outcome of the optimisation is the optimal switching positions (ON/OFF) of the appliances, total DR cost (calculated using optimised k_1, k_2 and k_3 factors) and each DG's reactive power setting. Therefore, the objective function in (4.15) is formulated as a mixed integer nonlinear programming problem as follows:

min: F $(DR_{cost}, P_{T.loss}, Q_{DG})$

$$= \sum_{t=1}^{T} \left\{ \begin{array}{c} \left(\sum_{i=1}^{N_{DR(t)}} DR(kW)_{(i,t)} \times \; incentive_{(i,t) \in eq.(10)} \right) + P_{T.loss\,(t)} \\ + \sum_{i=1}^{N_{DG}} Q_{DG(i,t)} \end{array} \right\} \times \Delta t \qquad (4.15)$$

$$DR(kW)_{(i,t)} = \sum_{n=1}^{N_{A(i,t)}} \left| A_{n(i,t)} \right| \times P_{n(i,t)} \qquad (4.16)$$

Subjected to

$$V_{min} \leq V_{(j,t)} \leq V_{max}, \quad \mathrm{j} = 1, 2, \ldots\ldots, N_{bus} \qquad (4.17)$$

$$I_{(l,t)} \leq I_{\max(l)}, \qquad l = 1, 2, \ldots\ldots, N_{line} \qquad (4.18)$$

$$Q_{DG(i,t)}^{min} \leq Q_{DG(i)} \leq Q_{DG(i,t)}^{max}, \qquad i = 1, 2, \ldots\ldots, N_{DG} \qquad (4.19)$$

$$Q_{DG(i,t)} = \sqrt{S_{DG(i)}^2 - P_{DG(i,t)}^2}, \qquad i \in N_{DG} \qquad (4.20)$$

$$P_{DG(i,t)} = S_{DG(i)} \times PF_i, \qquad (4.21)$$

$$min \left[\sum_{i=1}^{N_{disturb(t)}} ADR_{(i,t)} \times \mathrm{Penalty}_{ADR(i,t)} \right] \qquad (4.22)$$

$$min \left[\sum_{i=1}^{N_{disturb(t)}} AFI_{(i,t)} \times \mathrm{Penalty}_{AFI(i,t)} \right] \qquad (4.23)$$

where $DR(kW)_{(i,t)}$ represents the total kW DR contribution from ith candidate at tth timeframe of a DR event and $incentive_{(i,t)}$ presents the associated incentive rate ($/kWh) from the corresponding DR bus. $N_{DR(t)}$ is the total number of DR candidate consumers participating in a DR event at time t; Δt is the timeframe duration (hours) of a DR event, and T represents the number of intervals for DR events in a particular day. If the duration of the DR event is 15-minute, then the value of Δt is 0.25. $P_{T.loss\ (t)}$ is the total network power loss (kW). The total kW DR contribution ($DR_{(i,t)}$) from ith candidate consumer is calculated by summing all participated appliances rated kW demand at time t, as shown in (4.16). The limits of the distribution voltage at each bus, line thermal limits and reactive power output of DGs' inverters are expressed in (4.17) to (4.19), respectively. The amount of reactive power and active power from a single DG unit can be calculated using (4.20) and (4.21), respectively, considering the limits of power factor (PF_i) between ±0.95. The reactive power generation from each DG is minimised by the objective function as it does not provide any financial benefits to DG owner and instead puts more stress on inverters which shorten its lifetime.

To minimise the number of appliances disturbance of each consumer, $ADR_{(i,t)}$ is included as a constraint in the objective function, as in (4.22). Furthermore, considering fairness on appliances disturbance of a consumer $AFI_{(i,t)}$ is added to the objective function as a constraint, as in (4.23). $N_{disturb(t)}(\leq N_{DR})$ represents the total number of participated consumers with at least one $A_{n(i,t)} \neq 0$. The constraints (4.17) to (4.19) are included in the objective function as penalties. These penalties are selected in such a way to provide minimum cost for the total objective function. If any constraint is not satisfied, the corresponding penalty factor is added to the objective function to exclude that solution from the search space.

4.4 Solution approach

The proposed method is designed in such a way that it first prioritises the use of available residential appliances to manage the voltage variations by optimally switching ON/OFF the appliances. If the load management is not sufficient enough to manage the network voltage within the standard limits then the coordination of DGs' reactive power control is used to manage the network voltage. The proposed method can integrate and coordinate with the network voltage regulation device (i.e. OLTC of a transformer) as in the worst-case scenarios when both approaches fail to maintain the standard voltage levels. However, this study is limited to DR and DG control approaches only.

Consumers who participated in any DR scheme provide their list of available DR appliances to the utility in advance to give permission for controlling their appliances any time with prior notifications. Consumers can predefine their consumption preferences for each day through in-home display or online, based on day ahead DR event notifications. It is assumed that smart remote monitoring and control devices [22] are connected to the appliances of the participating consumers. Fig. 4.1 illustrates the flowchart of the proposed voltage management method. In each day utility forecasts the DG generation and load demand in every 5 minutes in advance and run offline load flow to check the network voltage levels. Satellite images [38] or sky-view cameras [39] can be used to track the cloud movement for forecasting at short timescales. The forecasting of the irradiation and the production of the PV plant is extremely reliable in the short-term [39], therefore reduces the uncertainties of forecasting errors. The offline load flow study for voltage violation identification with the forecasting data is achieved within 1 minute. Fig. 4.2 depicts the time schematic of the voltage management process. Once the voltage violated nodes are identified, the next step is selecting the DR scheme based on the forecasted cloud patterns. After the DR scheme selection (either 2-hour or 10-minute DR scheme), network buses are ranked based on their sensitivities using (4.7) & (4.9) to select the appropriate DR candidate buses. Utility then sends DR event notification (through online, email, text, etc.) to consumers in these selected buses to update their consumption preferences if available. The DR candidate bus selection process is obtained within 25 to 30 seconds in our program. Data sending process to consumer takes less than a second using the communication networks like WiMAX (has bit rate 5 to 25Mbps) and ZigBee (has bit rate 250 kbps). Hence, total 1 minute time frame is considered for this stage. The communication techniques between utility control center and household appliances with their latency, reliability and costs are provided in detail in [22]. The next stage is to collect information such as appliances' current states, consumer consumption preferences and previous history of DR events participation. Data collection and processing in this stage are achieved within 2 minutes. The final stage is to evaluate the objective function to calculate the optimum switching positions of appliances, DGs' reactive power settings and cost of DR by distributing fair incentive rates to consumers. Once the optimum solution is obtained, the control signals are sent to appliances and DGs' inverters to switch ON/OFF and provide reactive power support, respectively. This stage is performed within 1 minute. Hence, the average computational times require for the optimisation process of 2-hour DR scheme and 10-mintue DR scheme are 50 and 20 seconds, respectively using MATLAB software on Intel CORE i7-2600 PC with clock speed of 3.4 GHz and 12GB RAM.

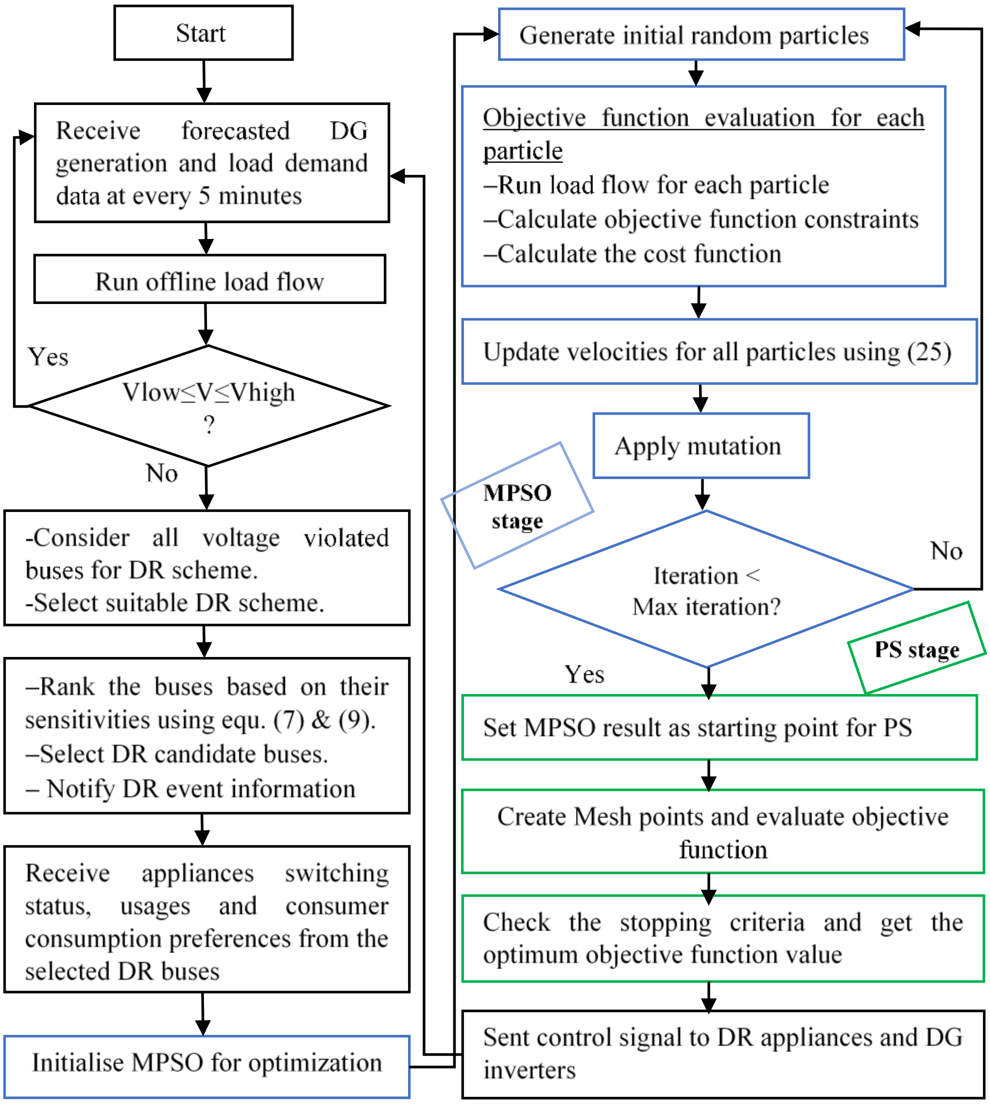


Fig. 4.1. The flowchart of the proposed voltage management method.

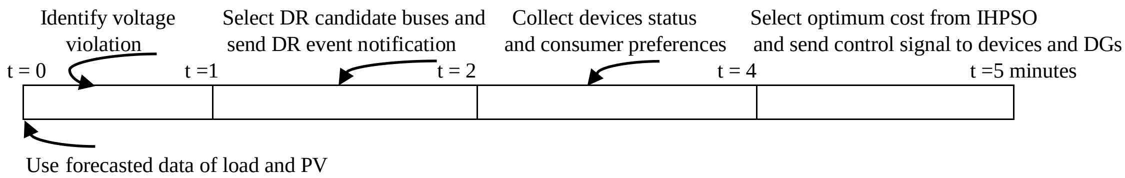


Fig. 4.2. Time schematic of the network voltage management process.

The next section describes the optimisation process based on the modified hybrid particle swarm optimisation (IHPSO).

4.4.1 Optimisation process with the proposed improved hybrid particle swarm optimisation (IHPSO)

Particle swarm optimisation (PSO) based approaches have a proven ability to handle highly non-linear and mixed integer problems and have fast convergence with less computational time [40]. However, the main problems of the standard PSO are premature convergence and lack of guarantee in global convergence [41]. To improve its performance researchers have proposed several methods include: fuzzy PSO [42], modified PSO [21], hybrid PSO, addition of a queen particle [43], etc. In this study, an improved hybrid PSO is proposed which is based on a modified version of standard PSO [21] incorporated with pattern search (PS) algorithm [44] to provide fast convergence and robust output for solving the voltage management problem.

Unlike other heuristic algorithms, such as GA, PSO, etc., PS possesses a flexible and well-balanced operator to enhance and adapt the global and fine-tune local search [44-45]. However, an important drawback of the PS method is that the need to supply a suitable initial point [45]. Where PS hybrids with PSO algorithm, the initial starting point will no longer have to be specified by the user, it will be automatically generated by the PSO phase. However, the standard PSO may not provide a suitable initial starting point for PS in high dimensional problems, as the standard PSO easily converges into local optima resulting in a low optimising precision. In order to improve the accuracy of the solution, in this study a mutation function is applied in the standard PSO particle update rules. The mutation function is conceptually equivalent to the mutation in genetic algorithms (GA) [21]. In addition, the constriction factor approach for PSO is applied, here, because it has a better performance compared to the inertia weight approach [46]. A comparison study in [47], shows that this modified version of PSO (MPSO) outperforms other heuristic methods such as original PSO, GA, and SA in terms of accuracy, robustness and speed. Therefore, an improved hybrid PSO (IHPSO) is proposed in this study which is a combination of modified standard PSO and PS algorithm to improve the optimisation performance as well as minimise the computational CPU time (as shown in simulation result section). The formulation details of MPSO and hybrid process of standard PSO with PS algorithm are presented in [21] and [44], respectively.

The velocity and position update of MPSO particle at iteration k is as follows [21]:

$$V_i^{k+1} = \gamma \times (V_i^k + 0.5 \times \varphi_{max} \times rand \times \left(P_{best_i} - X_i^k\right) + 0.5 \times \varphi_{max} \times rand \times \left(G_{best} - X_i^k\right)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{4.24}$$

where V_i^k and X_i^k are velocity and position of *i*th particle at iteration k, respectively; γ is the constriction factor coefficient; P_{best_i} is the best value of ith particle; G_{best} is the best value among P_{best_i} ; and $rand$ is a random number generator uniformly distributed between 0 and 1. The constriction factor coefficient (γ) is calculated as follows:

$$\gamma = \begin{cases} \sqrt{\frac{2k}{\varphi - 2 + \sqrt{\varphi^2 - 4\varphi}}}, & \varphi > 4 \\ \sqrt{k}, & else \end{cases} \tag{4.25}$$

In (4.25), k ∈ [0, 1] is a coefficient that allows control of exploration versus exploitation propensities. The mutation function is applied when G_{best} is not improving while increasing the number of iterations. In this study, if the G_{best}after 11 iterations does not improve, the mutation function with the mutation probability of 0.8 is applied.

The PS algorithm proceeds by computing a sequence of points called a mesh around the given point. This given point/current point could be the initial starting point supplied by the MPSO phase, or it could be computed from the previous step of the algorithm. The mesh is formed by adding the current point to a scalar multiple of a set of vectors called a pattern. If a point in the mesh is found to improve the objective function at the current point, the new point becomes the current point at the next iteration. The mesh points of the first iteration are:

$$X_0 + [0,1],\ X_0 + [1,0],\ X_0 + [-1,0], and\ X_0 + [0,-1] \tag{4.26}$$

Here, X_0 is the initial starting point of PS that is obtained from MPSO result, which is then added to the pattern vectors [0 1], [1 0], [-1 0] and [0 -1], to form mesh points.

In PS, a sequence of iterates $\{x^1, x^2, \ldots x^k, \ldots\}$ are generated with non-increasing objective function values. There are two important steps conducted in each k iteration, namely the SEARCH step and the POLL step. In the SEARCH step, the objective function is evaluated at a finite number of points on a mesh to improve the current iterate. The aim of the SEARCH step is to find a feasible trial point that yields a lower objective function value than the function value at x^k. If SEARCH step is successful, the mesh size increases and the objective function is evaluated in the next iteration. If the SEARCH step is unsuccessful in improving the current iterate x^k, a second step, called the POLL step, is executed around x^k with the aim of decreasing the objective function value. The poll step generates trial points at the poll set around the current iterate, x^k. If POLL step is successful, then the mesh size increases and the objective function is evaluated in the next iteration. If this step is unsuccessful, the mesh size decreases and the objective function is evaluated in the next iteration. Finally, when the stopping criteria is met, the iteration stops and provides the optimum objective function value.

The decision variables in each particle of IHPSO are different for each type of DR scheme. For 2-hour DR scheme a maximum number of five appliances of each candidate consumer are considered for DR participation. As mentioned in Section 4.2.1, these appliances are the washing machine, the dishwasher, the dryer, the pool pump and the electric vehicle. Each of the appliance is defined with five switching control variables. Therefore, the number of cells (variables) for total N_{DR} candidate consumer is $5 \times N_{DR}$, representing $A_{n(i,t)}$ for $n = 1, \ldots, 5$ and $i = 1, \ldots, N_{DR}$. For 10-minute DR scheme a maximum two appliances are considered in the optimisation and each of the appliance has five switching control variables. These appliances are AC and EWH. Thus, the number of cells (variables) for total N_{DR} candidate is $2 \times N_{DR}$. For coordination approach of DR scheme with DG inverter, one extra cell (variable) for each DG inverter is added with each particle of a DR scheme. The output of the optimisation proposes new switching positions of the appliances and DGs' reactive power size (kVar), which minimise the network voltage violation, network losses, and cost of DR by providing fair incentives to consumers while maintains the consumer consumption preferences and load interruption fairness.

4.4.2 Loadflow algorithm

To accelerate the optimisation process with IHPSO, the direct load flow method [48] is used in this study to calculate the technical parameters include (i), (i,t), and $P_{T.loss\,(t)}$ for each particle at every iteration and evaluate the objective function with the constraints. This approach uses the BIBC, BCBV, and DLF matrices which are implemented in MATLAB as in (4.27) and (4.28). The direct load flow approach reduces the computational burden during the optimisation search and thus it is more time efficient [48].

$$DLF = BCBV \times BIBC \tag{4.27}$$

$$\Delta V = DLF \times I \tag{4.28}$$

Here, DLF is the distribution load flow, BCBV is the branch current to bus voltage; BIBC is the bus injection to branch current; ΔV is the error of voltage matrix; I is the bus current vector. The next section provides case studies to evaluate the performance of the proposed method.

4.5 Simulation Results

This section provides simulation results for two case studies considering multiple worst-case scenarios to show the effectiveness of the proposed load control approach for voltage management. The proposed method is tested on the IEEE 33-bus radial distribution test system shown in Fig. 4.3. Since high intermittent of DG power in the network is a concern, the IEEE 33-bus system is modified with three large solar PV based DGs (each 1.22 MW capacity). The optimal locations of DGs in the 33-bus network as shown in Fig. 4.3 are estimated by the study in [49]. To analyse PV power output, 1-minute interval data was gathered for a 1.22 MW PV system located at the University of Queensland's (UQ) St Lucia campus in Brisbane [50]. The total number of PSO particles in Case 1 is considered 300 and in Case 2 it is 200. The typical TOU electricity pricing structure for the proposed incentive rate development is obtained from [51].

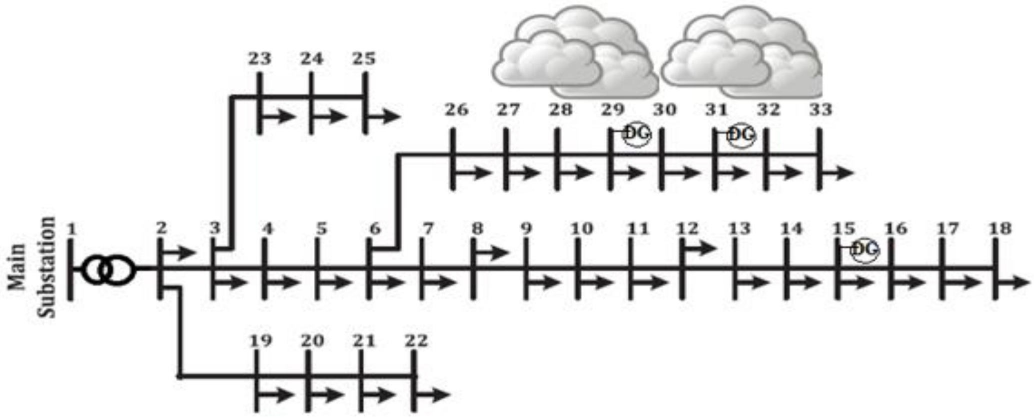


Fig. 4.3. IEEE 33-bus network with multiple DG connections.

4.5.1 Case 1: Long interval of voltage variation

Case study 1 is divided into two scenarios which shows significant voltage drops in a typical hot summer's day due to slow moving clouds. Fig. 4.4 shows the load profile and the DG power generation within a 24-hour time period. It shows that the total output power from the DGs suddenly drops by about 75% at 11:15 hours due to a huge cloud coverage, which persists for about 53 minutes till 12:08 hours. There is another significant power drop occurring (by around 92%) by DGs at 13:09 hours and continues for 69 minutes till 14:18 hours. Fig. 4.5 portrays the maximum voltage drops at far end buses caused by significant DG power variations. It shows that voltages at some remote buses fall extremely below the standard limits. The upper and lower permitted limits of voltages for all network buses are set at 1.05 pu and 0.95 pu, respectively [18]. To overcome the voltage drop conditions, two DR events are initiated as shown in Fig. 4.4.

- DR event 1 (duration: 11:15 hours to 12:08 hours)
- DR event 2 (duration: 13:09 hours to 14:18 hours)

Due to the slow voltage variations in the network caused by slow cloud movements, 2-hour DR scheme is initiated to solve the under-voltage problems. As seen in Fig. 4.4 the DR event 1 is activated at 11:15 hours to compensate the output power drop by DGs until there is an improvement in the total output power from DGs. The initial demand (2828 kW) is reduced optimally by about 10% by DR event 1 to support cloud coverage problems. Due to the significant power improvement from DGs, DR event 1 is released after 53 minutes to allow the controlled appliances to consume the additional power to balance the generation. The DR event 2 is activated at 13:09 hours due to substantial clouds sweeping over the network causing extremely low voltage conditions (see Fig. 4.5). The DR event 2 is coordinated with inverter reactive power support from DGs, as the number of voltage violated buses are high and DR capacity is limited. In DR event 2, the initial demand (2600 kW) is reduced by around 8.6% with DR and a total reactive power of 66 kVar is induced in the network by DGs. The optimised voltage profiles during DR events 1 and 2 are shown in Fig. 4.5.

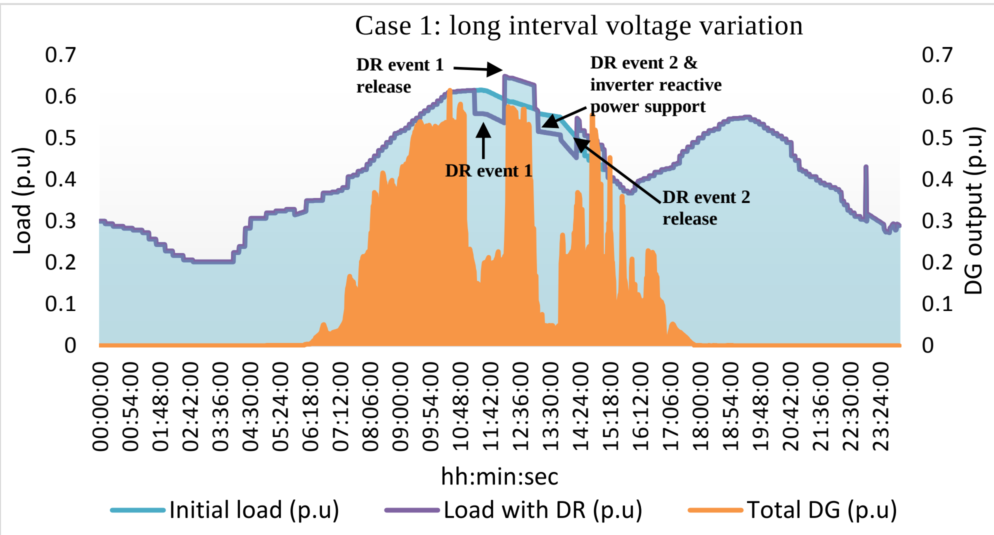


Fig. 4.4. Load profile and DG power generation profile before and after DR events.

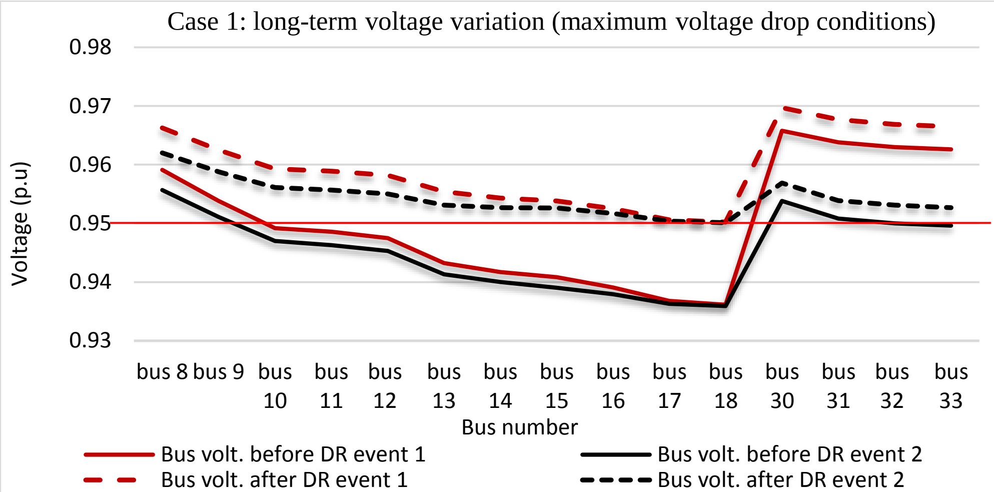
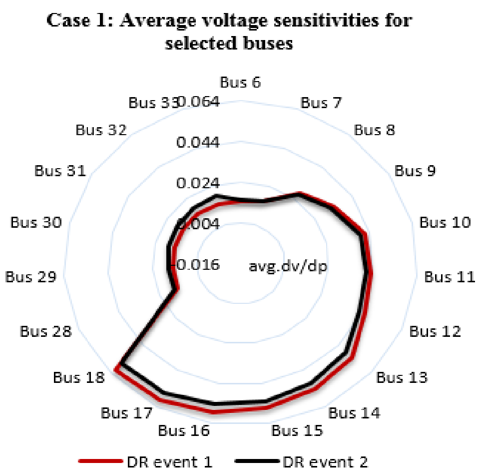


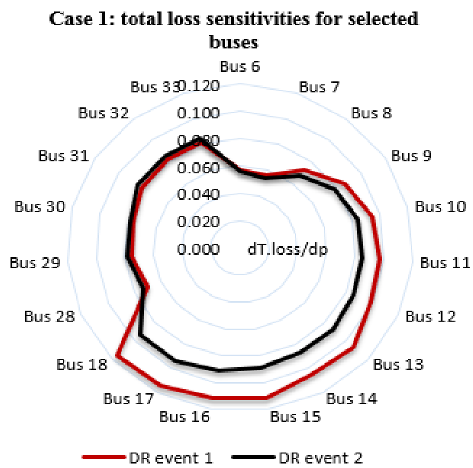
Fig. 4.5. Voltage profiles of remote buses before and after DR events.

The identified DR candidate bus locations for DR events 1 and 2 are the same. The DR candidate buses are identified based on the approach presented in Section 4.2.3. Fig. 4.6 (a) shows the sensitivities of average voltage change on voltage violated buses with respect to load change in some remote buses. The innermost circle in Fig. 4.6 (a) shows an average dv/dp value of 0.004 whilst the outermost circle has an average value of 0.064 for dv/dp. As seen, the voltage sensitivity values are much higher for buses 8 to 18 for both DR events. Similarly, the effect of network loss change with respect to load change in buses 8 to 18 are higher as depicted in Fig. 4.6 (b). In Fig. 4.6 (b), the value of dT.loss/dp is 0.020 for the innermost circle, and 0.120 for the outermost circle. The combination of voltage and loss sensitivity values are higher for these buses compared to the other buses. Thus, buses 8 to 18 (total 11 buses) are considered as DR candidate bus locations for both DR events. The importance of proposed DR candidate locations compared to random locations selection for DR activation is shown in Appendix A.1.

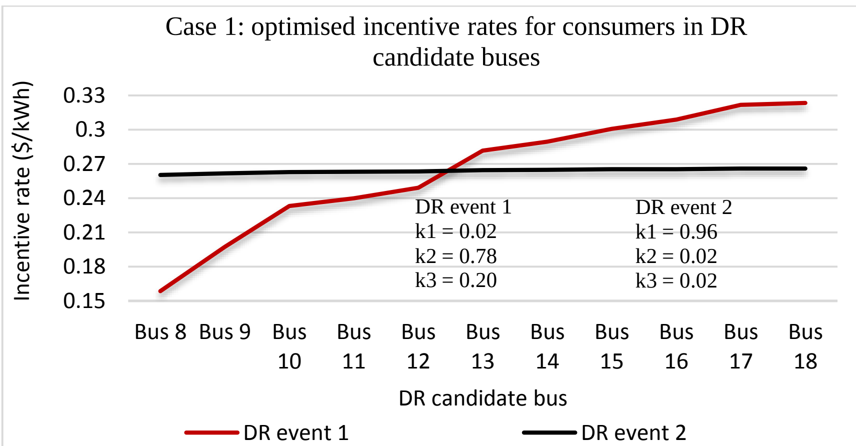
Fig. 4.6 (c) illustrates the optimised incentive rates ($/kWh) using the proposed algorithm for each DR candidate buses. It can be seen that in DR event 1, the incentive rate increases progressively from bus 8 to bus 18, it is due to far end buses have higher voltage and loss sensitivities and contribute more in voltage and loss improvements and therefore, consumers located in those buses receive higher incentive rates. The optimised voltage improvement coefficient k_2 is higher compared to the loss coefficient k_3 for DR event 1, it is due to our primary goal being improving the network voltages. Interestingly, for DR event 2, the incentive rates from bus 8 to bus 18 do not have much differences, it is due to the coordinated control of reactive power from DGs with load control is used in DR event 2. The coordinated control is used due to load adjustment was not sufficient enough to manage the voltage drops. The reactive power injected into the network improves the bus voltages and network losses and thus k_2 and k_3 values of DR event 2 are much lower compared to DR event 1, as shown in Fig. 4.6 (c).



(a) voltage sensitivities



(b) total loss sensitivities



(c) optimised incentives for DR buses

Fig. 4.6. Bus sensitivities to voltage and total network loss and optimised incentives in DR buses.

Table 4.2 shows the optimised results with the proposed load control algorithm for voltage management. It is assumed that total 90 consumers participated in each DR event, consumers are randomly spreaded in the DR buses. It shows that in DR event 1 the optimal DR size required is 261 kW to maintain the bus voltages within the standard limits, while reactive power contribution from DGs is zero. The estimated total DR cost is $67.27 with the optimised incentive rates for each bus (as shown in Fig. 4.6 (c)). The total network loss is reduced by 28%. In DR event 2, the optimised DR size is 222.4 kW and DR cost is $58.81. The reactive power injection from each DG into the network is equal (22 kVar), as presented in Table 4.2. The total network loss is reduced by about 26%. There is no constraint violation in both of the DR events. Therefore, the total objective function cost is minimised.

Table 4.2

Optimised results from the proposed load control algorithm for Case 1

	Before DR events	After DR events								
	Power loss (kW)	Power loss (kW)	Device turned off (kW)	Device turned on (kW)	Total DR Used (kW)	Total DR cost ($)	Penalty ADR	Penalty AFI	Reactive Support (kVar)	Total objective function cost
DR event 1	62.34	44.66	260	1.0	261	67.27	0	0	0	111.93
DR event 2	83.13	61.14	222.4	0	222.4	58.81	0	0	DG_{15} =22 DG_{29} =22 DG_{31} =22	139.8

4.5.2 Case 2: Short interval voltage variations

Fig. 4.7 presents the worst-case scenarios of a typical hot summer's day due to high variability of DG power generations affected by fast moving clouds. The short-term cloud transients create large changes in the net load and create voltage drops in some remote buses to an unacceptably low level, as shown in Fig. 4.8. To compensate the output variations of intermittent power generations, four DR events are initiated as below:

- DR event 1 (duration: 09:50 hours to 09:57 hours)
- DR event 2 (duration: 10:17 hours to 10:26 hours)
- DR event 3 (duration: 10:54 hours to 11:00 hours)
- DR event 4 (duration: 12:15 hours to 14:14 hours)

Due to the short-time variations of the power from DGs, the first three DR events are activated with the 10-minute DR scheme, using AC and electric water heater appliances. The duration of these events are 7 minutes, 10 minutes and 6 minutes, respectively. The DR event 4 is activated with the 2-hour DR scheme for 120 minutes due to long duration variation of voltage in the network produced by a huge cloud coverage. Fig. 4.8 shows the optimised bus voltages after the DR events activation. It shows that the violated bus voltages are improved with the proposed load control algorithm.

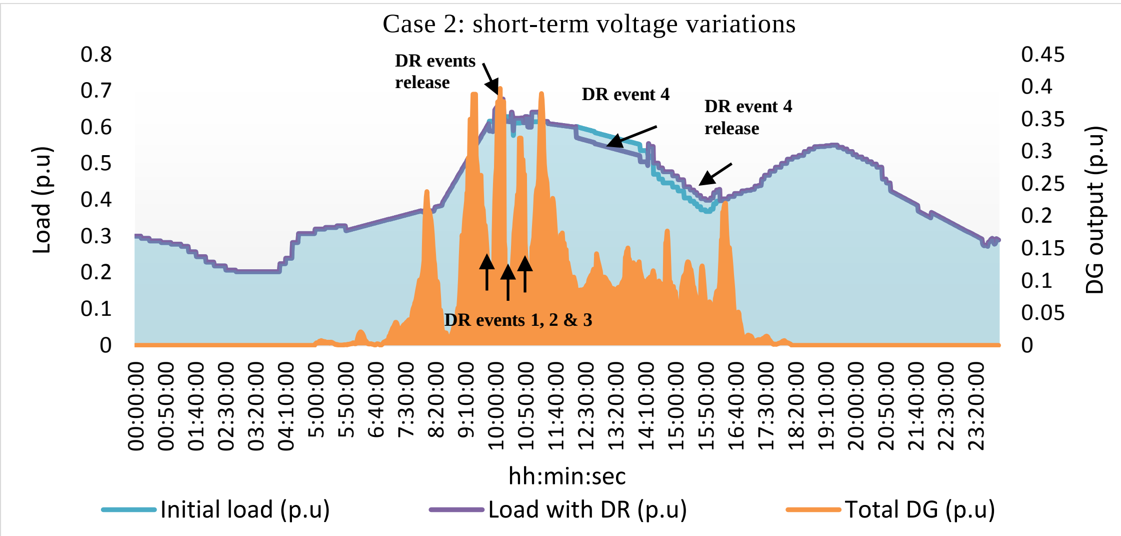


Fig. 4.7. Load profile and DG power generation profile before and after DR events.

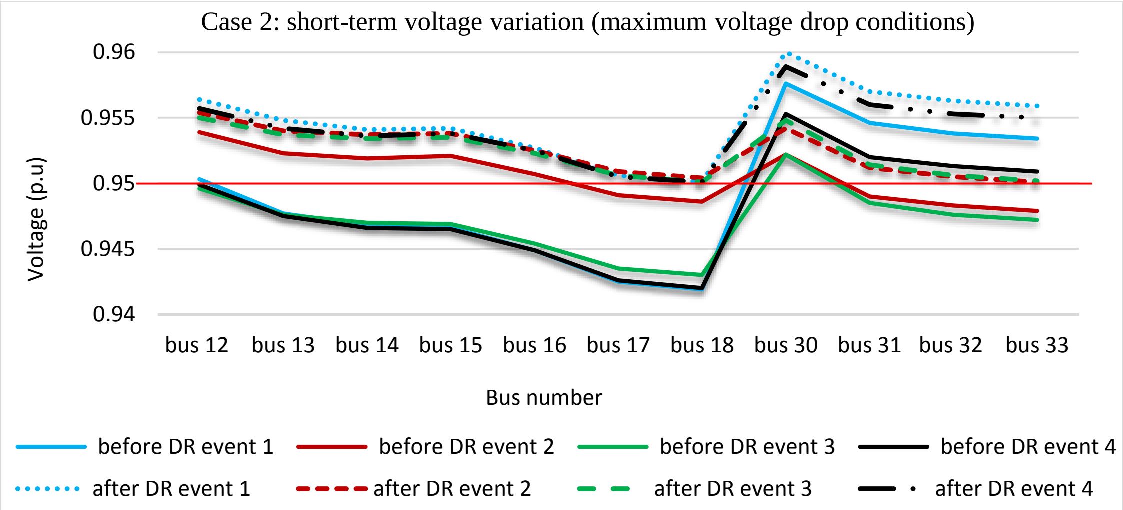
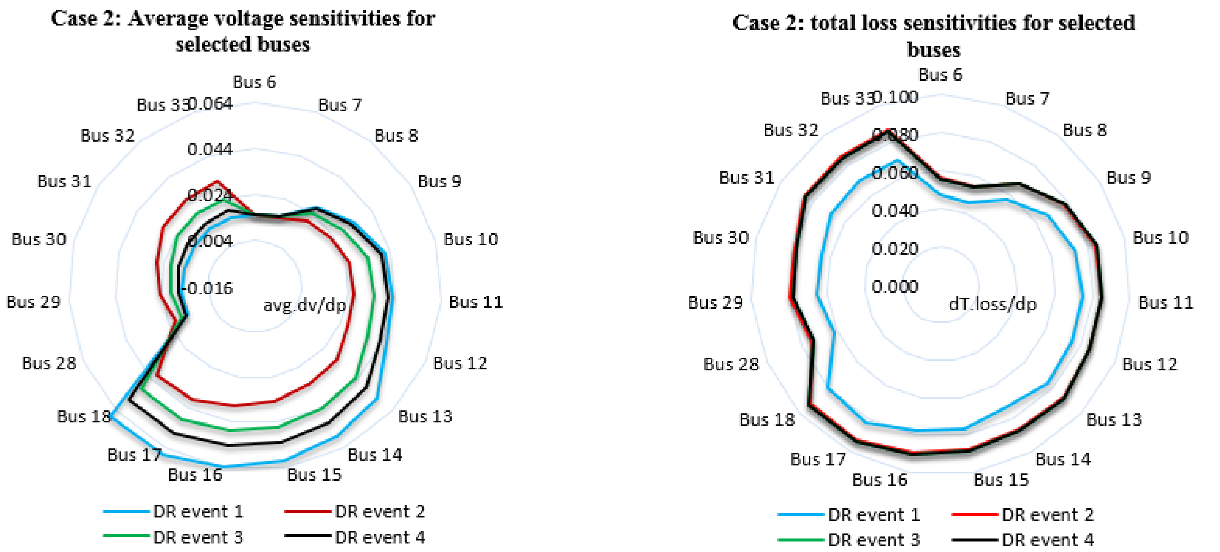


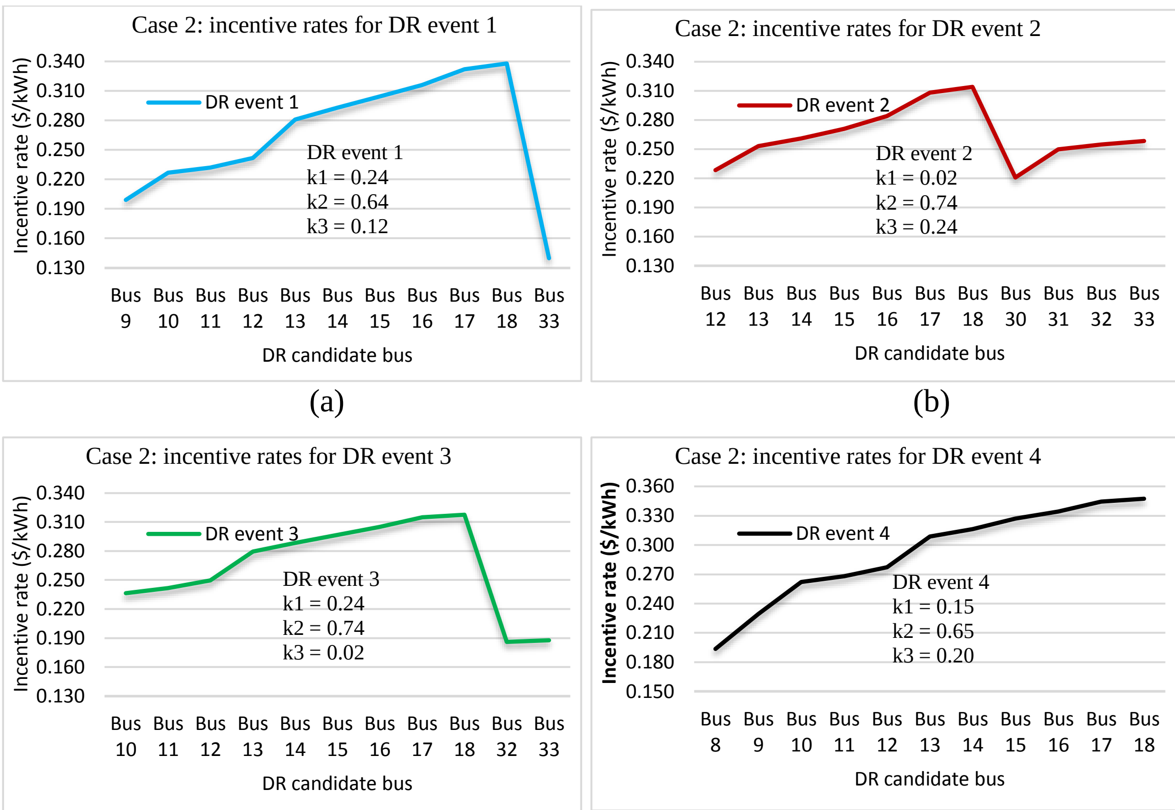
Fig. 4.8. Voltage profiles of remote buses before and after DR events.

The sensitivities of network bus voltage and power loss are presented in Fig. 4.9. It shows that in each DR event, the sensitivity values of each bus are different. For example, in DR event 1, buses 9 to 18 and bus 33 have higher average voltage sensitivities to the violated buses compared to other buses. These buses also have higher network power loss sensitivities. The combination of sensitivities for these buses are higher than the other buses. Therefore, buses 9 to 18 and bus 33 are selected as DR candidate buses for DR event 1. The selection of candidate buses for other DR events are performed using a similar approach. Fig. 4.10 depicts the selected candidate buses for each DR event with their optimised incentive rates. It can be seen that as the sensitivity combination increases for each bus, the incentive rate increases. For instant, in DR event 1, bus 18 has the highest combination of voltage and loss sensitivities (as seen from Fig. 4.9), therefore, the optimised incentive rate ($0.338 /kWh) is maximum for that bus. On the contrary, the bus 33 has the lowest sensitivity combination and thus the incentive rate ($.140/kWh) for that bus is minimum. The voltage improvement cost coefficient k_2 is larger for all DR events than the loss improvement cost coefficient k_3, due to voltage improvement being the primary aim of this study.



(a) voltage sensitivities (b) total loss sensitivities

Fig. 4.9. Bus sensitivities to voltage and total network loss.



(a) (b) (c) (d)

Fig. 4.10. Optimised incentive rates with k values for DR buses in all DR events.

Table 4.3 presents the optimised results with the proposed load control algorithm for solving both short and long durations of voltage variation problems. It shows that the total DR used in each DR event varies and depends on the voltage violation magnitude. For example, the total DR used in DR event 4 is maximum (77.23 kW) due to compensating the highest voltage drop (as shown in Fig. 4.8). In contrast, in the DR event 2 the least DR (17.30 kW) is used, as the voltage drop is minimum to compensate compared to the other DR events. In all DR events no reactive power support is required. There is no violation of appliance disturbance ratio (ADR) constraint. Therefore, the corresponding penalty is zero for all DR events. However, the appliance fair interruption (AFI) constraint is violated for only 6 consumers, in both DR events 1 and 3, and, therefore, a small penalty factor (60) is added into the total objective function cost of those events.

Table 4.3

Optimised results from the proposed load control algorithm

	Before DR events	After DR events								
	Power loss (kW)	Power loss (kW)	Device turned off (kW)	Device turned on (kW)	Total DR used (kW)	Total DR cost ($)	Penalty ADR	Penalty AFI	Reactive Support (kVar)	Total objective function cost
DR event 1	68.87	58.92	146.9	1.8	148.7	4.72	0	60	0	123.64
DR event 2	79.41	73.34	68.4	0	68.4	2.60	0	0	0	76.0
DR event 3	82.08	70.21	144.1	2.5	146.6	3.87	0	60	0	134.1
DR event 4	72.94	55.92	177.9	3.0	280.9	77.23	0	0	0	133.15

4.5.3 Appliances switching configurations for participating consumers

Appliances' initial switching positions (generated randomly) and their optimised new switching positions of randomly selected 18 consumers out of the total participated 90 consumers from DR candidate buses are presented in Table 4.4. It can be seen that the appliances kW demand and their quantities vary from consumer to consumer. For instant, Consumer 1 located at DR bus 8 has no washing machine participating in the 2-hour DR scheme. It is because the consumer did not sign the DR contract for the washing machine. Therefore, that appliance switching position is allocated with number 2 (see details in Table

4.1). The participating appliances from that consumer are the dishwasher (2.0 kW), the dryer (3.0 kW), the pool pump (1 kW) and the EV (3.0 kW), whose initial switching positions are OFF, ON, OFF and ON, respectively. After optimisation these switching positions change to new optimal switching positions.

The consumer number 4 at DR bus 8 provides preference setting restricted mode for pool pump (initial switching position allocated with number 4), which means that consumer is not willing to turn ON the pool pump at the particular DR event 1. Therefore, this appliance is not turned ON in DR event 1 and its new switching position is 0 (OFF). The consumer number 68 at DR bus 16 prefers not to turn OFF EV in DR event 1. The switching position of the EV is defined with number 3 in the optimisation algorithm to avoid switching it OFF. As a result, the EV of consumer 68 is not controlled in the DR event 1 and its switching position remained the same after the optimisation. The DR cost for each consumer presented in Table 4.4 is calculated based on the optimised incentive rate ($/kWh) in their corresponding bus multiplied with the obtained DR size (kW) and the duration of the DR event 1 (about 1 hour) in 2-hour DR scheme. The penalty costs related ADR and AFI constrain are zero, due to these constrained are not violated in the 2-hour DR scheme. Similar approaches are performed for all the participating consumers including those for the 10-minute DR scheme.

Table 4.4

Switching configurations for DR event 1 in both 2-hour DR scheme and 10-minute DR scheme (for details see Appendix A.2)

		2-hour DR scheme										
		Initial switch					New switch					
DR bus	Cons. #	W.mc Pos/kW	Dish.w Pos/kW	Dryer Pos/kW	Pump Pos/kW	EV Pos/kW	W.mc Pos/kW	Dish Pos/kW	Dryer Pos/kW	Pump Pos/kW	EV Pos/kW	DR cost($)
8	1	2/(n/a)	0/1.8	1/3.0	0/1.0	1/3.0	0	0	1	0	0	0.475
	2	0/0.6	1/1.2	2/(n/a)	1/2.0	1/3.0	0	1	0	0	1	0.317
	4	0/1.8	0/2.0	1/3.0	4/2.0	1/3.0	0	0	1	0	0	0.475
	7	0/1.5	2/(n/a)	1/3.0	2/(n/a)	1/3.0	0	0	1	0	0	0.475
	10	4/0.5	0/1.2	0/3.0	0/1.0	1/6.0	0	0	0	0	0	0.951
	11	0/1.9	4/1.8	1/3.0	0/1.0	1/3.0	0	0	0	0	0	0.951
9	15	1/0.5	1/1.5	4/3.0	1/2.0	0/3.0	1	1	0	0	0	0.395
	16	0/0.6	0/2.0	2/(n/a)	1/1.0	13.0	0	0	0	0	0	0.395
10	23	1/0.2	0/1.2	1/3.0	2/(n/a)	0/6.0	1	0	0	0	0	0.699
13	45	2/(n/a)	1/1.5	0/3.0	0/2.0	1/3.0	0	1	0	0	0	0.845
	46	1/0.6	0/(n/a)	0/3.0	1/1.0	1/3.0	1	0	0	0	0	1.127
14	58	1/1.9	0/2.0	4/3.0	0/1.0	1/3.0	1	0	0	0	0	0.868
	60	1/0.5	2/(n/a)	1/3.0	1/1.0	0/6.0	1	0	0	0	0	1.158
16	68	1/1.9	0/2.0	0/3.0	1/1.0	3/3.0	1	0	0	1	1	0
17	79	1/.2	0/2.0	0/3.0	3/1.0	1/3.0	1	0	0	1	0	0.965
18	84	4/1.8	0/2.0	0/3.0	1/2.0	3/3.0	0	0	0	0	1	0.647
	85	2/(n/a)	0/1.5	0/3.0	1/2.0	1/3.0	0	0	0	0	0	1.617
	89	1/0.2	1/2.0	0/3.0	4/1.0	1/3.0	1	1	0	0	0	0.97

		10-minute DR scheme				
		Initial switch		New switch		
DR bus	Cons. #	AC Pos/kW	EHW Pos/kW	AC Pos/kW	EHW Pos/kW	DR cost($)
9	1	3/1.1	0/4.5	1	0	0
	2	1/1.8	4/2.7	1	0	0
	6	0/0.6	1/2.7	0	0	0.063
	8	1/0.2	0/2.7	0	0	0.044
	10	1/0.5	0/2.7	1	0	0
10	13	0/0.2	1/2.7	0	0	0.071
	18	1/1.9	4/4.5	0	0	0.051
11	22	1/1.8	0/2.7	0	0	0.049
12	29	0/0.2	1/2.7	1	0	0.082
13	37	3/1.5	0/4.5	1	0	0
	40	4/0.5	1/2.7	0	0	0.092
14	46	0/0.6	1/2.7	0	1	0
15	57	3/1.5	0/4.5	1	0	0
17	71	1/1.1	0/4.5	1	0	0
18	76	0/0.6	1/2.7	0	0	0.106
	78	1/1.9	4/4.5	0	0	0.075
33	89	0/0.2	1/2.7	1	1	0.047
	90	0/0.5	1/2.7	1	0	0

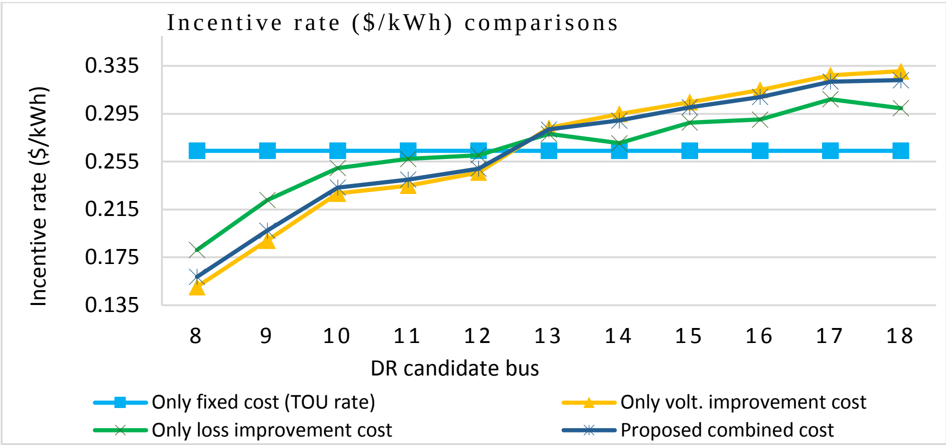
Cons.# = consumer number; Pos. = Switching position; W.mc = washing machine; Dish.w=dishwasher; n/a = not available; EHW = electric water heater.

Cell colour represents device is not available; Cell colour represents device preference setting is not to turn ON;
Cell colour represents device preference setting is not to turn OFF.

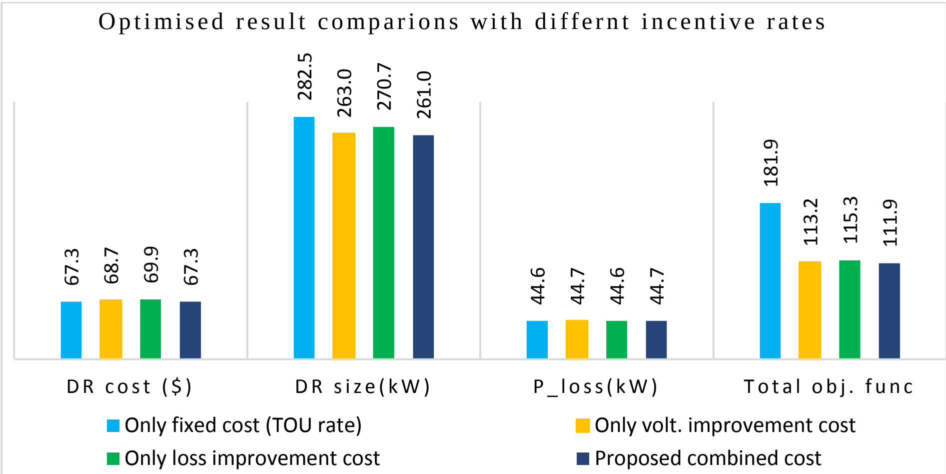
The appliances selection for participating in DR event 1 in 10-minute DR scheme are performed based on equations (4.1) and (4.2). Table 4.4 shows the initial status of the appliances with their consumption preferences. After optimisation the new switching configurations of the appliances presented in Table 4.4 show no violation on consumers' consumption priorities. The DR cost in this scheme is calculated in similar way as 2-hour DR scheme. However, the duration of DR event 1 in10-minute DR scheme is small (7 minutes) and thus the cost of DR provided to each consumer is also less compared to 2-hour DR scheme. In addition, the ADR penalty cost for each consumer in DR event 1 of 10-minute DR scheme is zero. However, for the consumer number 89 at DR bus 33 in the 10-minute DR scheme, the AFI penalty value is 10 based on (4.14), as both appliances of this consumer are interrupted in the DR event.

4.5.4 Validation of the proposed dynamic fair incentive rate design approach

Fig. 4.11 (a) depicts the developed incentive rates for DR buses using only fixed cost (TOU rate), only voltage improvement cost (4.12), only total loss improvement cost (4.13) and proposed combined cost (4.10). Fig. 4.11 (b) presents the optimised results with the four incentive rates shown in Fig. 4.11 (a). It can be seen from Fig. 4.11 (b) that with fixed cost rate and the proposed cost rate, the total DR cost is minimum (at $67.30). The total DR size (in kW) and the total objective function cost is maximum with fixed incentive rate compared to others incentive rates. However, the total DR size (kW) and total objective function cost is least with the proposed incentive rate. There is very little difference in the optimised total network loss between the four incentive rates. Therefore, the proposed incentive approach not only reduces the optimisation parameters, but also fairly distributes incentives among the consumers based on their location and contributions.



(a)

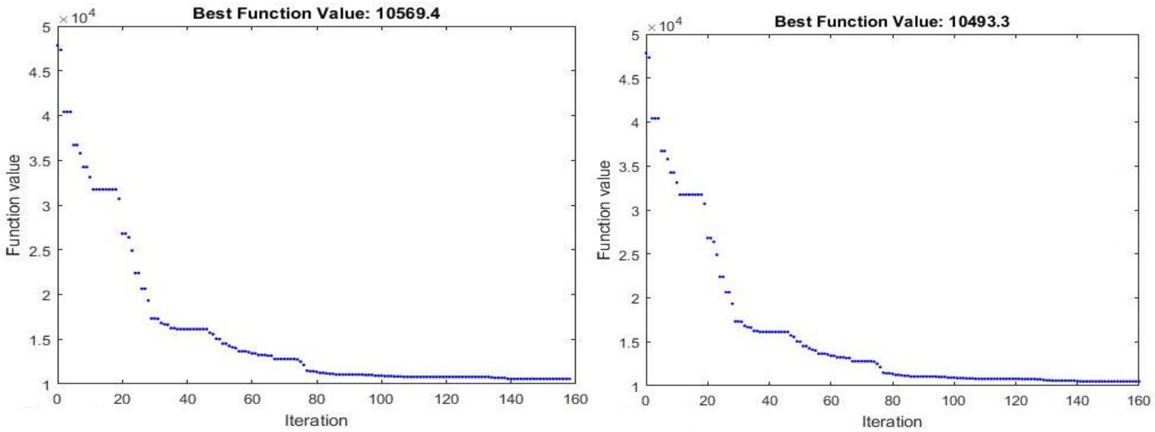


(b)

Fig. 4.11. Results comparisons from proposed incentive rate with different incentive rates.

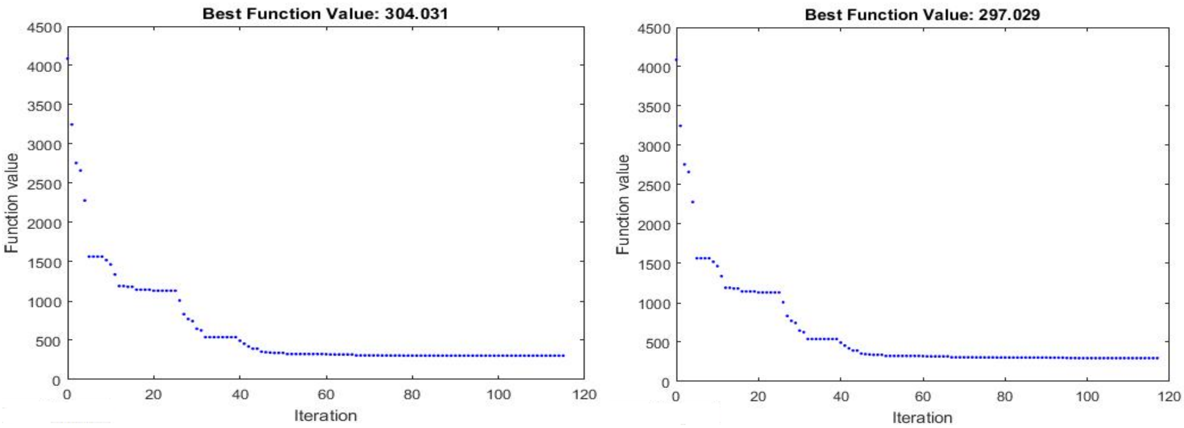
4.5.5 Performance analysis of the IHPSO algorithm

The convergence of optimal solutions (costs) for 2-hour DR scheme using standard PSO and modified PSO (MPSO) are shown in Figures 4.12 (a) and (b), where both PSO versions require about 140 iterations to find the optimal solution. However, with standard PSO the optimum function value (10569.4) is higher than with the MPSO value (10493.3). Similarly, for 10-minute DR scheme, the convergence of optimal solutions using both PSO versions are shown in Figures 4.13 (a) and (b), where they require only about 50 iterations to find the optimal solution. The optimum function value using standard PSO is slightly higher than the MPSO value. Therefore, the MPSO improves the optimal cost and provides a suitable starting point to the PS algorithm.



(a) standard PSO (b) modified PSO (MPSO)

Fig. 4.12. Convergence characteristic of objective function with standard PSO and MPSO for 2-hour DR scheme.



(a) standard PSO (b) modified PSO (MPSO)

Fig. 4.13. Convergence characteristic of objective function with standard PSO and MPSO for 10-minute DR scheme.

Table 4.5 presents the comparisons of optimised results for DR event 1 (in case study 1) using different PSO methods. It shows that the optimisation times obtained with the PSO and MPSO methods are lower which are 37.33 seconds and 32.32 seconds, respective compared with the HSPO (51.02 seconds) and IHPSO (50.13) methods. However, the objective function costs with the PSO ($10569) and MPSO ($10569) methods are is significantly higher than the HSPO ($112.4) and IHPSO ($111.9) methods. Also, the standard deviations (of 10 optimisation runs) are minimum with the HSPO and IHPSO methods. Therefore, the hybrid of PS with PSO (i.e., HPSO and IHPSO) methods provide better optimisation results compared to classical PSO and Modified PSO (MPSO) methods. In particularly, the proposed IHPSO improves the performance and accuracy of the optimisation.

Table 4.5
Result comparisons using different PSO methods

	PSO	MPSO	HPSO	IHPSO
Optimisation time (s)	37.33	32.32	51.02	50.13
Best obj. function	10569	10493	112.4	111.9
Standard deviation	2.2	1.9	1.5	0.70

4.6 Conclusion

This study proposes a multi-layer load control algorithm using residential demand response for managing short and long intervals of voltage variations in MV networks due to power variations of DGs caused by cloud movement. The proposed algorithm considered two DR schemes namely a 10-minute scheme and a 2-hour DR scheme to compensate the short-term and long-term voltage variations, respectively. In each DR scheme, consumer preferences on load consumptions were maintained to minimise their comfort level violations. Furthermore, a dynamic location ranking approach was applied to identify the most suitable DR candidate buses for effective load management. A dynamic fair incentive distribution mechanism was developed to compensate the participating consumers in DR candidate buses for their contribution in load adjustment, network voltage and total loss improvement with optimal coefficients obtained through optimisation. Finally, an improved version of hybrid PSO algorithm was proposed which is a combination of modified PSO (MPSO) and Pattern Search (PS) algorithm to provide a better convergence performance.

The proposed load control method was verified and tested in IEEE 33-bus network with considering high intermittent power generation from DG. The simulation results showed that the multi-layer load control algorithm effectively managed both short and long durations of voltage changes, while minimised the excessive disturbances on consumer loads, reduced the total cost of compensation, prioritised consumer consumption preferences and fairly distributed incentives among consumers based on their location and contributions. The proposed improved hybrid PSO (IHPSO) heuristic optimisation technique significantly improved the accuracy of the optimisation results.

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Chapter 5

A New Approach to Voltage Management in Unbalanced Low Voltage Networks Using Demand Response and OLTC Considering Consumer Preference♣

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Abstract

Voltage unbalance and magnitude violations under normal operating conditions have become main power quality problems in many low voltage (LV) distribution networks. Maintaining the voltage level in an LV network within the standard limits is the main constraining factor in increasing the network hosting ability for rooftop photovoltaic (PV). This study presents a new effective method for voltage management in unbalanced distribution networks through the implementation of optimal residential demand response (DR) and on-load tap changers (OLTCs). The proposed method minimises the compensation costs of voltage management (cost of DR and network loss), while prioritises the consumer consumption

♣ The content and structure of this published paper are modified based on the Thesis requirements.

preferences for minimising their comfort level violations. A modified particle swarm optimisation algorithm (MPSO) is utilised to identify the optimal switching combination of household appliances and OLTC tap positions for the network voltage management. The proposed method is comprehensively examined on a real three-phase four-wire Australian LV network with considerable unbalanced and distributed generations. Several scenarios are investigated for improving the network voltage magnitude and unbalance considering individual and coordinated operations of DR and OLTCs (three phase tap control and independent phase tap control). Simulation results show that the coordinated approach of DR and OLTC, especially, DR integrated with OLTC independent phase tap control effectively improves the network voltage and increases the PV hosting capacity.

Keywords: Voltage unbalance; demand response; on-load tap changers; photovoltaics; consumer comfort; peak demand.

5.1 Introduction

Many low voltage (LV) residential feeders are three-phase, four-wire systems and the majority of the houses have single-phase power supply [1]. In LV four-wire distribution networks, voltage magnitude and unbalance are the main power quality problems of concern to distribution system operators. The three-phase voltage near a strong supply is usually well balanced, however, it can become unbalanced at the consumer side due to many factors such as unequal system impedances, unequal distribution of single-phase loads and distributed generators [2]. The increasing penetration of rooftop photovoltaics (PVs) and new types of loads/appliances such as electric vehicles (EVs) into LV networks, introduce even more network voltage unbalance (VU) and magnitude violations. For instance, in Australia, the widespread installation of residential rooftop PVs have caused the overvoltage problems in the residential LV networks [3]. As distribution networks were not originally designed to accommodate such resources, the consequence is voltage violations in the network [4], which may cause the deterioration of the operating life of distribution system assets (e.g., transformers, voltage regulators, line, etc.) [5]. Furthermore, an unbalanced network can host less PV generation and loads without reaching the critical voltage magnitude limit.

Voltage unbalance occurs due to the asymmetry of voltage magnitude or phase angle at the fundamental frequency between the phases of a three-phase power system [6]. An unbalanced system will have voltage and current that have positive, negative and zero sequence components. The negative sequence component can flow through the network in a similar way to positive sequence currents, which causes energy losses and reduce the capacity of the transmission/distribution line. The zero-sequence current flowing through phase wires results in an extra current in the neutral wire and eddy current energy losses as well as overheating of transformer windings [7]. For a balanced system, both zero sequence and negative sequence components are absent. The presence of excessive levels of VU can result in overheating and derating of all induction motor loads such as squirrel cage induction motors (swimming pool pumps and air-conditioning compressors, elevators, etc.) in residential apartment complexes [1,8]. A small unbalance in the phase voltages can cause a disproportionately large unbalance in the phase currents. VU can cause network problems such as mal-operation of protection relays and voltage regulation equipment, and generate non-characteristic harmonics from power electronic loads [9]. Therefore, it is important to improve VU in LV distribution networks. In Australia, the distribution code allows for negative sequence voltage up to 1% on average and a maximum of 2% (can go over 2% for a maximum period of 5 minutes within each 30-minute period) [10]. In the UK, VU limit in the whole network is 2% [11], and the max limit of VU is 3% at no-load conditions as per the ANSI standard [12].

5.1.1 Voltage control methods

Many different solutions are proposed in the literature to tackle Voltage unbalance and magnitude problems in LV feeders. Some conventional voltage improvement methods are feeder cross-section increase and manually switching the phases to improve the distribution of the loads across the three phases [1,13]. However, these practices are carried out only once and are very costly [14]. Another problem with the phase switching approach is to determine an optimum switching order that allows both reduction of power losses and balancing loads while increasing the renewable energy penetration capacity in the network [15]. Dynamic switching of residential loads from one phase to another using a static transfer switch is proposed in [16] to minimise the VU and network loss along a feeder. However, this approach is only suitable for three phase consumers, but, the majority of the houses in LV networks have a single-phase power supply.

In some situations, special balancing equipment such as the unified power quality conditioners (UPQC) [17] and the distribution static compensators (dSTATCOM) [18] can be useful solutions for improving voltage unbalance and magnitude at LV networks. However, these types of equipment require high installation costs in addition to associated operation and maintenance costs, and therefore, is mainly suitable for medium voltage (MV) networks. Existing MV network equipment such as the OLTC with different types of tap control (e.g., three phase tap control, independent phase tap control) are studied in [19] to improve the voltage in the LV network. The application of OLTC was conventionally limited to MV distribution transformers. As a result of the high growth of intermittent PV generations, recently, various studies [20-21] have proposed secondary distribution transformers with OLTC due to their capabilities and advantages to distribution networks. Nevertheless, they have mostly been studied in three-phase balanced LV distribution networks. One study [5] proposes a coordinated control of PV inverters with an individual phase tap control OLTC to balance the four-wire LV network. It claims that this types of OLTC can minimise the voltage unbalances at some degrees, however, without coordination it can worsen the voltage unbalances in some loading conditions due to the complex nature of positive and the negative sequence components of bus voltages. Furthermore, as the PV generation penetration level increases, OLTC operation might increase the total network losses [5].

Some local control strategies have been proposed using converter control of EVs [4,14] and PVs [2,22] to improve voltage quality in LV networks. One example is, a three-phase balancing PV inverter and EV charger are proposed consisting of three single-phase inverters for improving phase balance in distribution grids [4]. The main drawback of these proposed converter control methods are: the need to increase the capacity of the converter, require three-phase connection to consumers' premises, less influence of reactive power compensation by the converter on LV network voltage control. Another drawback of this approach is the financial losses to PV owners due to curtailing active power generation and currently no incentive scheme available to consumers for supporting reactive power in the network. Recently, due to growing popularity of energy storage devices and vehicle to grid operations, researchers are focusing on improving the charging and discharging conditions of these devices for maintaining network constraints. For instance, authors in [23] present an approach for solving EVs charging coordination (EVCC) problem using Volt-VAr control, energy storage device (ESD) operation and dispatchable distributed generation (DG) in unbalanced distribution networks. An interactive energy management system for incorporating plug-in electric vehicles (PEVs) is developed in [4] to maintain voltage unbalance within acceptable limits. Furthermore, a two-stage control method is proposed in [6] using coordination of OLTC and vehicle-to-grid for voltage management in distribution system. Most of these studies (e.g., [4], [6], [23]) performed unbalance study on three-phase three-wire power networks, which may not provide actual network impacts on voltage management. Since LV networks are generally configured with four-wire cables/lines, the voltage management study including unbalance requires proper modeling of the network parameters as a four-wire network [14]. Moreover, the effectiveness of the proposed EV control methods is limited as their availabilities for a certain area is not guaranteed. For instance, a residential area with a significant amount of rooftop PV would experience overvoltage during the daytime, but the EVs are driven away or less EVs may be available for that area to solve the overvoltage problem. There are other household appliances such as washing machine, dishwasher, pool pump, etc. can provide flexibilities in their consumption and can managing network voltage locally. However, their effectiveness in improving the network voltage are not considered in the aforementioned studies.

5.1.2 Demand response

One of the promising means for improving the voltage quality and network utilisation is participating end-users through demand response (DR) programs [24]. DR programs, such as price-based [25] and direct load control (DLC) programs [26] postpones investment costs in generation resources and network upgrades [2]. The DLC strategy is becoming increasingly attractive [27], as smart grid technologies, such as smart metering, smart appliances, and home area network have been developed significantly over the past years [26]. In DLC strategy, household appliances are monitored and controlled remotely for regulating their consumption to manage network voltage, peak demand, PV penetrations, etc.

The main challenge in the DLC approach is to control a large number with various types of household appliances while consumer consumption preferences are prioritised to maintain their comfort levels, which is a complex optimisation problem and entails huge computational efforts. In addition, DR implementation should consider the network constraints, otherwise an inappropriate DR activation may lead to an increase in network loss and voltage unbalance [28]. Various analytical and soft computing methods such as Evolutionary Algorithm (EA)

[29], Reinforcement Learning with Q-learning [30], Learning Automata [31] are proposed to address this complex problem to schedule appliances in DLC programs. The study in [32] proposed a day-ahead load controlling approach to improve short-term voltage stability using optimal power flow (OPF) problem, which demonstrates another application of DR in stability improvement. In addition, particle swarm optimisation (PSO) is utilised to manage residential load to minimise network operation costs, network loss and voltage violations [33-35]. The results of these studies show the effectiveness of PSO-based algorithm for a large-scale nonlinear optimisation problem. Therefore, several studies propose strategies relating using PSO. However, none of the studies mentioned above have taken into consideration the consumption priorities of individual consumer. Authors in [36] proposes dynamic energy flow control strategy for a residential energy local network with a full consideration of the habits and consumption preference of consumers. However, network operation constraints are not considered in the optimisation process of this study. The use of DR for VU improvement is not considered in the aforementioned literatures. Therefore, this study proposes an approach to integrate DR for improving network voltage magnitude and unbalance considering consumer preferences.

Furthermore, the variability of household appliances with their different kilowatt (kW) sizes and each consumer’s DR participation cost are not considered in those studies. For instance, load control algorithm in [34] uses 2000 EVs with similar kW power rating and a fixed participation cost for all EV users in the simulation to manage network voltage and line thermal limits. Likewise, in [33], the total number of DR appliances and DR participation costs are considered similar for all participated consumers. In reality, the number of DR appliances and their rated kW power demand may not be exactly same for all participated consumers in DR, and the costs of participation may also vary. Study in [37-38] show that consumers are provided with a programmable tool in home energy management systems, which are available in the market. Consumers can program their preferences, availability, and range of bidding prices at which they are willing to participate in a DR event in such systems. These flexible tools help to bid prices dynamically and automatically with a capability of accepting/rejecting events, which motivate consumers to participate in DR program and reduce the inconvenience of long-term DR contract.

To date, there is no study relating to DR implementation for managing both voltage magnitude and unbalance in the LV network, while prioritising consumers' consumption preferences to satisfy their comfort levels as well as providing them the opportunity to dynamically bid their participation prices in the DR event. Additionally, the benefits of coordinating DR with network OLTC for better improvement of VU are not found in the literature.

5.1.3 Contributions

This study fills the current research gaps by proposing a flexible load control algorithm for realistic DR implementation in LV network which takes into account: (i) the variabilities of consumers' appliances with their different kW sizes to estimate accurate DR potential and associated costs, (ii) consumers' preferences to satisfy their comfort levels so that inconveniences of long-term DR contract will be avoided, (iii) consumers' bid prices at which they are willing to participate in DR event, (iv) the benefits of coordinating with network OLTC for better improvement of network voltage. The proposed load control algorithm is developed in such way that it minimises both voltage magnitude and unbalance problems, reduces the network power losses and enhances network PV hosting capacity by optimally switching consumers' appliances and OLTC taps. Two types of OLTC tap control techniques are studied: three phase tap control ($OLTC_{dep}$) which simultaneously operates on the three phases and, independent phase tap control ($OLTC_{ind}$) which independently operates on each phase. The monetary benefits that utility can achieve with the deployment of the proposed model are deferred investment on network equipment, efficient use of network and minimisation of PV power curtailments, while the consumers can benefit from financial incentives for participation in the program. Therefore, the main contributions of this proposed study are summarised as follows:

1. A load control algorithm is developed for voltage magnitude and unbalance management in LV networks using residential DR and network OLTCs including phase dependent and independent tap operation.
2. The proposed load control algorithm has the ability to consider dynamic consumer's bid price ($/kWh), consumption preferences and the number of available DR appliances with their rated kW demand.
3. The load control algorithm satisfies the network operational constraints with minimised cost of compensation while reduces consumers' comfort violations, and excessive switching disturbances on appliances.

5.2 Consumer Preferences in DR

Consumers who participate in a DR program would sign a contract with the utility with their list of available DR appliances in advance to give the utility the permission for controlling their appliances for a period of time. It is assumed that the communication medium (e.g., ZigBee, power line carriers, or WiFi, etc.) and remote monitoring and control devices [26] are connected to the appliances of the participating consumers. In this study, those appliances of consumers are selected for contributing in DR, which have less impacts on consumers' comforts and have reasonable flexibilities for deferring operational time. These appliances are washing machine, dishwasher, dryer, pool pump and electric vehicle. In this study, consumer comfort is maintained in two ways: prioritising consumer consumption preferences and disturbing less appliances during a DR event.

Each participating consumer can place consumption preferences on individual appliance before a DR event. The consumption preference on each appliance can be defined as consumption priority or consumption restriction, so that the appliance cannot be switched off or switched on, respectively, during a DR event. For instance, an EV is charging, and its state of charge is less than the minimum requirement. The owner of EV can set consumption priority on this device so that it cannot be switched off during a particular period of DR event. Likewise, if a washing machine has already been utilised in DR event, the owner can set consumption restriction, so that it cannot be controlled again. Utility collects each DR appliance's rated power demand, consumption preference, and consumer bid price ($/kWh) for participation in each DR event. The accepted bids in $/kWh for each consumer can be for each DR event or all DR events of a year based on the agreement between the utility and consumers. The consumers' bids, their available DR appliances and preference settings are considered in the optimisation algorithm to obtain the optimum DR size and cost for network voltage management (as described in Section 5.4). The appliance preferences for each consumer which may receive by the utility for each DR event are presented in Table 5.1. In this study, a switching control/status variable is defined as $A_{n(i,t)}$ for the nth appliance of the ith candidate consumer during a DR event at time t. This parameter is representing the switching status of appliances when collecting the corresponding data. The values of this switching control variable is 0, 1, or -1, which is chosen through the optimisation process (as described in Section 5.4) and defined as follows.

$$A_{n(i,t)} = \begin{cases} 1 & \text{the participating appliance is turned on} \\ 0 & \text{no change (the appliance is not participating in DR)} \\ -1 & \text{the participating appliance is turned off} \end{cases} \tag{5.1}$$

The implication of the appliance preferences on $A_{n(i,t)}$ is presented in Table 5.1. Based on the preference settings of appliances, the proposed algorithm in Section 5.4 optimises switching control variables to minimise the associated DR cost, comfort disturbance, and the voltage violations in the network. Appliances which are assigned with the preference 2, 3 and 4, their switching status will not be changed during optimisation; that is, the corresponding $A_{n(i,t)}$ is not included in the optimisation. For example, as washing machine and dishwasher operation cycles cannot be interrupted while they are on, the status of these appliances will be 3 in that operating condition. Therefore, in the optimisation process, the corresponding $A_{n(i,t)}$ of these appliances will not be optimised, so that they cannot be switched off. While appliances assigned with the status 0 and 1, their switching status can be changed. The total cost of DR is the sum of the controlled appliances' demands (kW) multiplied by the corresponding bid prices ($/kWh) and the duration of an event (in hours), as discussed in the next section.

Table 5.1

Appliance status and the implication on $A_{n(i,t)}$

Preference #	Preference name	Definition	Is the appliance participating in DR?	$A_{n(i,t)}$
0	not restricted mode	the appliance is off and can be switched on	Yes	1 or 0
1	not restricted mode	the appliance is on and can be switched off	Yes	-1 or 0
2	not available (n/a)	appliance is not available for any future DR event	No	0
3	priority mode	the appliance is on and cannot be switched off	No	0
4	restricted mode	the appliance is off and cannot be switched on	No	0

In addition to the appliance preferences, the optimisation algorithm needs to minimise the number of switching to reduce the disturbances on consumer comfort levels. To reduce excessive switching disturbances on appliances, appliance disturbance ratio (ADR) is defined as in (5.2), which will be minimised by the proposed optimisation algorithm. ADR is the ratio of the effective demand change (ΔP) for a consumer to the total number of appliances disturbed for that consumer.

$$ADR_{(i,t)} = \left| \ \Delta P_{(i,t)} \right| \Big/ \sum_{n=1}^{N_{A(i,t)}} \left| A_{n(i,t)} \right| \tag{5.2}$$

where $ADR_{(i,t)}$ is ADR, $\Delta P_{(i,t)}$ is the effective demand change, | | is the absolute function, and $N_{A(i,t)}$ is the total number of DR appliances. All the parameters are for ith consumer at time t in the DR event. The effective demand change is the resultant demand after turning participated appliances on and/or off, which is calculated as follows:

$$\Delta P_{(i,t)} = \sum_{n=1}^{N_{A(i,t)}} A_{n(i,t)} \times P_{n(i,t)} \, (kW) \tag{5.3}$$

where $P_{n(i,t)}$ is the rated kW demand of the nth appliance. To clearly understand ADR, lets consider a consumer having 1 kW pool pump and 1.5 kW washing machine and the current switching status of these devices are on and off, respectively. In a DR event, if the optimisation program decides to turn on only the washing machine, the ADR value will be 1.5/1=1.5. If in the same time the pool pump is also switched off then the ADR value would be |1.5-1|/2=0.25. Higher ADR value will reduce the switching disturbances on appliances in the DR event and consequently less inconvenience to consumers. Next Section describes how ADR is defined as a constraint in the optimisation problem.

5.3 Problem formulation

The optimisation problem has two mutually conflicting objectives. The first aim is to satisfy the network constraints include voltage magnitude and unbalance, equipment thermal limits, power loss and OLTC tap range. The second objective is to minimise consumer comfort disturbances and the associated cost of appliances utilisation. In this optimisation, the decision variables are the OLTC tap positions and the switching control variable of appliances in the DR candidate locations. The outcome of the optimisation is the optimal size of DR in kW and

OLTC tap position. Therefore, the objective function is formulated as a mixed integer nonlinear programming problem as follows.

$$\text{Minimise Obj. func.}$$

$$= \sum_{t=1}^{T} \left\{ \left(\sum_{i=1}^{N_{DR}} DR_{(i,t)} \times \ price_{(i,t)} \right) + Network_{losses(t)} \times cost_{(t)} \right\} \times \ \Delta t \tag{5.4}$$

Subject to

$$\left\{ \begin{array}{c} Minimum\ ADR \\ VUF_{(j,t)} < 2\% \\ VUF_{Zero(j,t)} < 5\%,\ j = 1 \ldots\ldots N_{bus} \\ 0.95 \leq \left|V_{(p,t)}\right| \leq 1.06,\ p = 1 \ldots\ldots N_{phase} \\ \left|I_{(l,t)}\right| \leq I_{\max(i)}\ ,\ l = 1 \ldots\ldots N_{line} \\ OLTC\ tap\ change\ constraints \end{array} \right\} \tag{5.5}$$

$$DR_{(i,t)} \ = \sum_{n=1}^{N_{A(i,t)}} \left|A_{n(i,t)}\right| \times P_{n(i,t)}\,(kW) \tag{5.6}$$

where $DR_{(i,t)}$ and $price_{(i,t)}$ are the DR contribution (kW) and the associated bid price (\$/kWh), respectively, for ith candidate consumer at tth timeframe of a DR event, represented by Δt. N_{DR} is the total number of DR candidates participating in the DR event. $Network_{losses(t)}$ and $cost_{(t)}$ are the total network power loss (kW) and the corresponding cost (\$/kW), respectively, during tth timeframe. Δt is the timeframe duration (hours) of a DR event, and T represents number of intervals for a DR event in a particular day. The minimum duration of DR event is considered 30 minutes then the value of Δt is 0.5. $VUF_{(j,t)}$ and $VUF_{Zero(j,t)}$ are negative and zero sequence voltage unbalance factors (VUFs) for jth bus at tth timeframe, respectively (the VUFs calculation equations are presented in Appendix C). $\left|V_{(p,t)}\right|$ is the pth phase voltage magnitude at tth timeframe. N_{bus} is the number of buses, N_{phase} is the total number of phases of all buses in the network. N_{DR} is the total number of consumers participated in the DR event.

$|I_{(l,t)}|$ and $I_{\max(l)}$ are the lth line current and the associated limit, respectively. Excessive tap operations of OLTCs reduce their service life and therefore tap operations need to be below the maximum permissible limit. $A_{n(i,t)}$ and $P_{n(i,t)}$ are the switching control variable and rated power demand for nth appliance of ith candidate consumer. Equation (5.6) implies that $DR_{(i,t)}$ is calculated by summing kW demands of all contributed appliances.

- *Constraints*

The objective function optimisation task in (5.4) is subject to few constraints as shown in (5.5), these constraints are included in the objective function as a penalty, which is presented as

$$\text{Penalty} = \sum \begin{pmatrix} Appliances\ disturbace\ penalties + Voltage\ unbalance\ penalties \\ + Voltage\ magnitude\ penalties\ + Current\ magnitude\ penalties \end{pmatrix} \tag{5.7}$$

The penalty factor terms in (5.7) are discussed as follows:

- *Appliance disturbance penalties:*

As discussed in the previous section, for considering the consumer preferences and minimising appliance disturbances, ADR is included as a constraint. ADR is treated as a penalty factor in the objective function using the "*Appliance disturbance penalties*", which is defined as follows:

$$Appliance\ disturbance\ penalties = \sum_{i=1}^{N_{disturb(t)}} ADR_{(i,t)} \times \text{Penalty}_{ADR(i,t)} \tag{5.8}$$

$$\text{Penalty}_{ADR(i,t)} = \begin{cases} 10^3 & ADR_{(i,t)} \leq 1 \\ 10^3(2 - ADR_{(i,t)}) & 1 < ADR_{(i,t)} < 2 \\ 0 & ADR_{(i,t)} \geq 2 \end{cases} \tag{5.9}$$

where $N_{disturb(t)} \leq N_{DR}$ represents the total number of participated consumers with at least one $A_{n(i,t)} \neq 0$ and $\text{Penalty}_{ADR(i,t)}$ in (5.9) is the penalty factor associated with $ADR_{(i,t)}$. As seen in (5.9), the penalty of ADR is high if $ADR_{(i,t)}$ is less than 1 to exclude the corresponding solution from search space. If $ADR_{(i,t)}$ is bigger than 2, the penalty is zero to relax ADR constraint. In between 1 and 2, a linear reduction of the penalty is proposed here to relate the penalty to the value of ADR for each consumer. In the previous section example, where the ADR value is 0.25, the corresponding penalty is 10^3, so this switching configuration will be considered with a high penalty factor. Also, the ADR penalty factor is kept lower compared to voltage and current penalty factors in order to emphasis on the satisfaction of voltage and current constraints. The limit values of 1 and 2 can be changed based on the power of appliances available at consumer premises.

- *Voltage unbalance penalties:*

There are different approaches [9, 15, 39] for calculating the voltage unbalance factor (VUF) proposed by NEMA, IEEE, IEC and CIGRE. In this study, VUF is defined as the ratio of the fundamental negative sequence voltage component (V_2) to the positive sequence voltage component (V_1) [15]. The zero-sequence voltage unbalance factor (VUF_{Zero}) is the ratio of the zero sequence voltage component (V_0) to the positive sequence voltage component (V_1). The VUF constraints at j[th] bus of the network at DR event at time t, namely $VUF_{(j,t)}$ and $VUF_{Zero(j,t)}$, need to be less than 2% [10] and 5% [40], respectively. These limits are updated based on the requirements of each individual utility. Based on the application and the requirement, VUF_{Zero} can simply exclude or include in the objective function considering the utility's goal. The "Voltage unbalance penalties" are calculated using (5.10).

$$\begin{aligned} &Voltage\ unbalance\ penalties \\ &= \sum_{j=1}^{N_{bus}} \left(VUF_{(j,t)} > 2\%\right) \times \mathrm{Penalty}_{(VUF)} + \sum_{j=1}^{N_{bus}} \left(VUF_{Zero(j,t)} > 5\%\right) \times \mathrm{Penalty}_{(VUF_{Zero})} \end{aligned} \tag{5.10}$$

where $\mathrm{Penalty}_{(VUF)}$ and $\mathrm{Penalty}_{(VUF_{Zero})}$ are the associated penalty values for $VUF_{(j,t)}$ and

$VUF_{Zero(j,t)}$, respectively, and " $>$ " is the sign function which produces 1, if the equation statement is true. In this study, $\text{Penalty}_{(VUF)}$ and $\text{Penalty}_{(VUF_{Zero})}$ are considered 10^6 and 10^4 respectively. The penalty factors are considered very high to exclude those solutions from the search space, which violate the corresponding constraints. The differences in penalty factors allow to quickly differentiate the relevant violations of the constraints from the optimised total cost.

- *Voltage magnitude penalties:*

The voltage magnitude of the p^th^ phase of the total phase of all buses in the network is required to be within 0.95 p.u. and 1.06 p.u. [10]. These margins are also chosen based on the requirements of the individual utility. Therefore, “Voltage magnitude penalties” are presented in equation (5.11).

$$\begin{aligned} & Voltage\ magnitude\ penalties \\ & = \sum_{i=1}^{N_{phase}} \left(\left|V_{(i,t)}\right| > 1.06\right) \times \text{Penalty}_{(V)} + \sum_{i=1}^{N_{phase}} \left(0.95 > \left|V_{(i,t)}\right|\right) \times \text{Penalty}_{(V)} \end{aligned} \tag{5.11}$$

where $\text{Penalty}_{(V)}$ is the associated penalty value for the magnitude voltage violation, which is assumed 10^5 in this study. The minimum and maximum limits for each phase voltage magnitude are 0.95 pu and 1.06 pu, respectively.

- *Current magnitude penalties:*

The line current $I_{(l,t)}$ for all branches should be within limits so that thermal limit of the line should not exceed the line current capacity, namely $I_{\max(l)}$, at any time. Therefore, the “Current magnitude penalties” is presented in (5.12).

$$Current\ magnitude\ penalties = \sum_{n=1}^{N_{line}} (I_{(i,t)} > I_{max}) \times \text{Penalty}_{(I)} \tag{5.12}$$

where $\text{Penalty}_{(I)}$ is the corresponding penalty value for the line thermal limit violation, which is assumed 10^5 in this study.

- *OLTC operation penalties:*

Frequent tap-changing of OLTCs, shorten their service life and increase the associated maintenance costs. To minimise the excessive operation of OLTC, a penalty cost, $\text{Penalty}_{(OLTC)}(t)$, of each tap position ($tap_{posi}(t)$) change at time t is calculated by (5.13). The penalty cost of each tap change is comprised of the estimated maintenance cost, C_{main} of OLTC after the certain number of tap change, N_{change} without maintenance.

$$\text{Penalty}_{(OLTC)}(t) = 10^2 \times \frac{C_{main}}{N_{change}} \sum_{t=1}^{24} \left| tap_{posi}(t) - tap_{posi}(t-1) \right| \tag{5.13}$$

Here, C_{main} is assumed to be 20% of the initial investment cost (e.g., \$10,600) of a LV transformer and N_{change} is considered 700,000 [5]. Multifunction factor 10^2 is used to emphasis the OLTC constraint cost. Tap position number and daily maximum allowed tap change of OLTC are expressed by (5.14) and (5.15), respectively, as follows:

$$tap_{posi,min} \leq tap_{posi}(t) \leq tap_{posi,max} \tag{5.14}$$

$$tap_{chng/day}^{total} \leq tap_{chng/day}^{max} \tag{5.15}$$

where, $tap_{posi,min}$ and $tap_{posi,max}$ represent the lower boundary and upper boundary, respectively, of the tap position. $tap_{chng/day}^{total}$ and $tap_{chng/day}^{max}$ represent the total tap changed and the maximum allowable tap operation, respectively, per day. In this study, the lower and upper boundaries of $OLTC_{dep}$ are assumed within of ±10% p.u. limits with 21 operation positions of the tap changer and 1% of voltage regulation per tap is considered. Similarly, for the $OLTC_{ind,}$ each phase tap position can very within 21 operation positions at 1% voltage step per tap change. The average daily tap operation is limited to 10 times per day.

5.4 Solution Approach

In this study, due to non-convexity and non-linearity of the voltage management problem, a heuristic optimisation approach [3], as mentioned in Section 5.4.1, is proposed to solve the voltage management problem. In addition, the heuristic approaches can efficiently manage high computational efforts in a reasonable time as the size of the problem increases [41].

5.4.1 Modified particle swarm optimisation (MPSO)

PSO-based approaches have a proven ability to handle highly non-linear and mixed integer problems [42]. However, the main problems of the standard PSO are premature convergence and lack of guarantee in global convergence [41]. In order to improve the accuracy of the solution, in this study, a modified version of standard PSO [3] is used to solve the voltage management problem. A mutation function is applied in the standard PSO particle update rules, which is conceptually equivalent to the mutation in genetic algorithms (GA). In addition, the constriction factor approach for PSO is applied, here, because it has a better performance compared to the inertia weight approach [43]. A comparison study in [44], shows that this modified version of PSO (MPSO) outperforms other heuristic methods such as original PSO, GA, and simulated annealing (SA) in terms of accuracy, robustness and speed. The formulation details of the MPSO, employed in this study including the corresponding flowchart for the algorithm are detailed in [3]. For example, the velocity and position update of MPSO particle at iteration k is as follows:

$$V_i^{k+1} = \gamma \times (V_i^k + 0.5 \times \varphi_{max} \times rand \times \left(P_{best_i} - X_i^k\right) + 0.5 \times \varphi_{max} \times rand \times \left(G_{best} - X_i^k\right)$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \tag{5.16}$$

where V_i^k and X_i^k are velocity and position of ith particle at iteration k, respectively; γ is the constriction factor coefficient; P_{best_i} is the best value of ith particle so far; G_{best} is the best value among P_{best_i} so far; and $rand$ is a random number generator uniformly distributed between 0 and 1. The constriction factor coefficient (γ) is calculated as follows:

$$\gamma = \begin{cases} \sqrt{\frac{2k}{\varphi-2+\sqrt{\varphi^2-4\varphi}}}, & \varphi > 4 \\ \sqrt{k} \qquad\qquad\quad , & else \end{cases} \tag{5.17}$$

In (5.17), k ∈ [0,1] is a coefficient that allows control of exploration versus exploitation propensities. For bigger value of coefficient k, particles desire more exploration and preventing explosion, derives slow convergence and searching thoroughly the space before collapsing into a point. However, for smaller values, particles care more exploitation and less exploration [41]. The mutation function is applied when G_{best} is not improving while the increasing of the number of iterations. The mutation function selects a particle randomly and then adds a random perturbation to a randomly selected modulus of the velocity vector of that particle by a mutation probability. In this study, if the G_{best} after 11 iterations does not improving, the mutation function with the mutation probability of 0.8 is applied.

In this study, each particle in MPSO is composed of a number of cells as shown in Fig. 5.1, that represent the following decision variables:

1. A maximum number of five appliances of each candidate consumer are considered for DR participation. As mentioned in Section 5.2, these appliances are washing machine, dishwasher, dryer, pool pump and electric vehicle. Each of these appliances is defined with five switching control variables. Therefore, the number of cells (variables) for total N_{DR} candidate is $5 \times N_{DR}$, representing $A_{n(i,t)}$ for $n = 1, \dots, 5$ and $i = 1, \dots, N_{DR}$.
2. Two possible tap adjustment of OLTCs include independent phase tap control OLTC ($\mathrm{OLTC_{ind}}$) and three phase tap control OLTC ($\mathrm{OLTC_{dep}}$) are considered in the

optimisation. Therefore, the total number of cells are 3 for each $\mathrm{OLTC_{ind}}$ and 1 for each $\mathrm{OLTC_{dep}}$. The three cells associated with each $\mathrm{OLTC_{ind}}$ as shown in Fig. 5.1, these will be replaced by one cell in the case of $\mathrm{OLTC_{dep}}$.

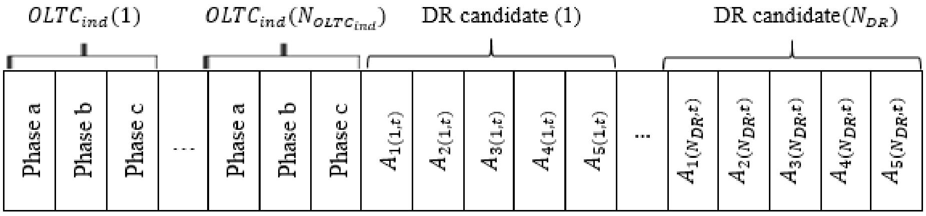


Fig. 5.1. PSO particle structure for voltage management using DR and OLTC.

5.4.2 DR candidate location selection

In theory, all consumers in all phases can be chosen as a DR candidate location. However, in order to reduce the search space, a voltage unbalance analysis is conducted to obtain the most effective DR locations as candidates. Since VU at buses towards the end of a feeder is usually higher than at the beginning of a feeder [2,45], the candidate buses are usually located at downstream side of those buses, whose voltage unbalances are above the limit ($VUF_{(j,t)} > 2\%$). In addition, changing demand in such buses can help in power loss minimisation and voltage regulation [2]. To calculate $VUF_{(j,t)}$, $VUF_{Zero(j,t)}$, $V_{(i,t)}$ at each bus and $I_{(i,t)}$ of each branch at any instance of time, the three-phase load flow equations of direct method [46] are applied. The direct load flow method uses topological characteristic of radial distribution network to calculate load flow directly without computing time consuming Jacobian matrix or admittance matrix. Therefore, direct load flow is time efficient and reduces the computational burden during the optimisation search. This approach uses BIBC, BCBV, and DLF matrices which are implemented in MATLAB as in (5.18) and (5.19). The BIBC matrix is responsible for the relations between the bus current injections and branch currents. The BCBV matrix is responsible for the relations between the branch currents and bus voltages.

$$DLF = BCBV \times BIBC \tag{5.18}$$

$$\Delta V = DLF \times I \tag{5.19}$$

Here, DLF is the distribution load flow matrix, BCBV is the branch current to bus voltage matrix; BIBC is the bus injection to branch current matrix; ΔV is the voltage difference matrix; I is the bus current vector matrix.

5.4.3 System infrastructure

To be able to participate in the proposed DR program, the participated consumer requires smart monitoring and controlling devices connected with home electrical appliances. The smart meter is the main gateway that collects all the data from the connected appliances and makes available for utility control center and an online portal for consumers. Consumers can access real time measured data, take control decisions, receive DR event notification and set consumption preference on appliance as well as place bid prices through in-home display and mobile app. The bi-directional information flow between consumer's electrical appliances to utility can occur via a wide area network (WAN), neighbourhood area network (NAN) and home area network (HAN) as shown in Fig. 5.2. HAN provides communication link between sensors that connected with the electrical appliances, in-home display and smart meters. NAN directly connects multiple smart meters in specific areas to the data concentrator/substation. The WAN connects many NANs to the utility central control unit. The communication platforms can be chosen from any suitable wired and wireless mediums.

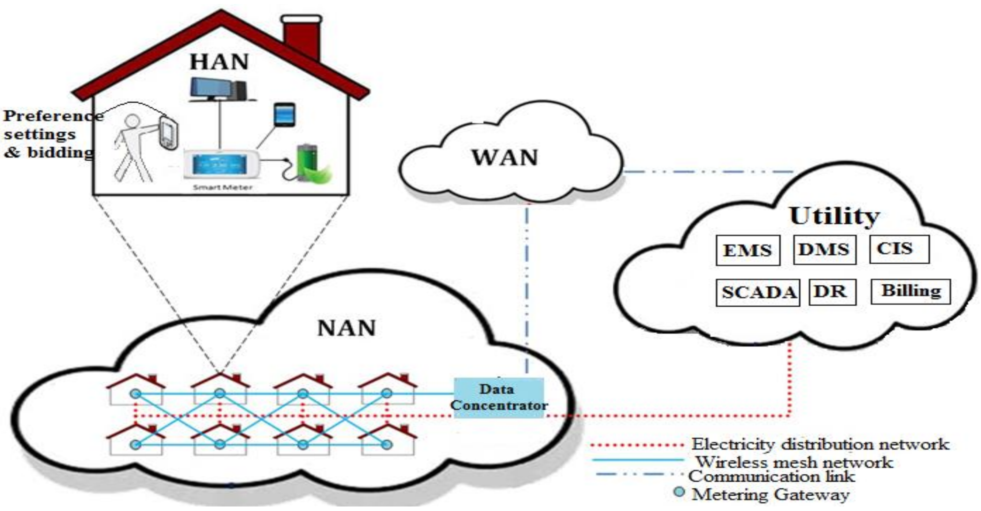


Fig. 5.2. Communication infrastructure between consumers and utility.

The utility control center includes energy management system (EMS) unit, supervisory control and data acquisition (SCADA) unit and distribution management system (DMS) unit perform load forecasting, monitors, controls, optimisation the network performance and response to alarms and/or events. DR participated consumers' information including contract information, bid prices, available appliances and their consumption ratings, participated history in DR events etc., controlled by the customer information system (CIS) unit. The DR unit in the utility control center utilises information (e.g., voltage violation nodes, available DR appliances, accepted bid prices, event duration, etc.) from other units to initiate a DR event. Consumer bid prices and appliances consumption preferences before a DR event are obtained by the DR unit using text, email, phone call etc., or directly from in-home display located at consumer premises. The DR unit optimises the optimum switching positions of appliances for each participated consumer and OLTC tap and then send control signals to smart meters and network OLTC. Consumer billing is performed by the billing unit in the utility control center.

5.4.4 Methodological Approach

The complete flow chart of the proposed approach for voltage management in LV distribution networks is shown in Fig. 5.3. The utility forecasts load demand and performs a three-phase unbalanced offline load flow analysis for a specific interval of Δt (e.g., every 30 minutes), throughout a day to check the network constraints as presented in (5.5). This short-term load forecasting minimises the uncertainties related to forecasting errors and enables near real time management of grid stability. If the network constraints violations are identified, the utility identifies the DR candidate buses based on the approach described in Section 5.4.2. The DR event notifications are then sent to those consumers in the candidate buses in advance within 30 minutes, who have expressed their interest in participating in DR program. The utility collects consumers' bids and their available DR appliances with consumption preference settings as well as OLTC tap positions in the corresponding network for the DR event. The network operator should wait for a response within a time limit for receiving this information, otherwise, the corresponding candidate will be replaced by another candidate consumer or previous information of that consumer, if a permission has granted beforehand. This initial information is considered in the proposed MPSO-based approach to optimise the objective function in (5.4) by switching on and off consumers' appliances and applying new tap positions in OLTCs.

During the optimisation, technical parameters, including $VUF_{(j)}$, $VUF_{Zero(j)}$, $V_{(i)}$, $I_{(i,t)}$, and $ADR_{(i,t)}$ are calculated for each particle at every iteration for evaluating the objective function with the constraints. If a constraint is not satisfied, then a large penalty factor is added to the objective function to exclude that solution from the search space. The optimisation can be terminated when the maximum iteration count has been reached. The output of the optimisation proposes new switching positions of the appliances and OLTC tap positions, which minimise the network voltage magnitude and unbalance violations, network losses and cost of DR while maintain the consumer consumption priorities. After completion of analysis at this time interval and sending the control signal to the associated appliances, again, a load flow analysis will be performed at every Δt interval (i.e. 30 minutes) during the DR event to check if the network constraints are within the limits.

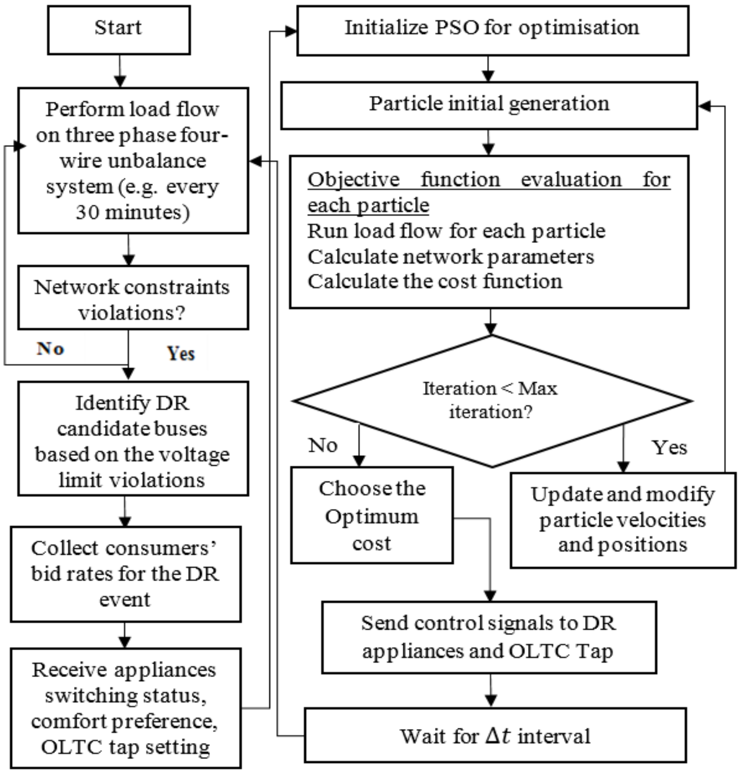


Fig. 5.3. Flowchart of the proposed algorithm.

5.5 Simulation Results

This section provides simulation results on a case study to show the effectiveness of the proposed approach for voltage management and taking into account the consumer preferences.

5.5.1 LV distribution network

The LV network used in this study is a suburban Australian radial LV distribution network consisting of 23 buses (poles), as shown in Fig. 5.4. A 200kVA, 22 kV/400 V distribution transformer delivers power through a 400/230V feeder to 77 residential consumers [40]. The sub-main cables are 7X3.75 AAC (MARS) and 7X4.5 AAC (MOON), whereas the connections from the pole-top to the individual consumers are through 6mm^2 service lines. This feeder has significant current unbalance. This load unbalance is a result of the poor allocation of consumers' loading among the three phases and the growth in PV installations by consumers. The total penetration of rooftop PVs is close to 35% (64 kW), in this case, which helps to study the impacts of both unbalanced loading and PV generation. The feeder is modelled as three-phase, multiple earthed neutral (MEN) for steady-state voltage analysis. Carson's line equations [47] and Kron reduction method [48] are used to obtaining the line/cable parameters for the test feeder, which are used in direct load flow analysis (Appendix C presents the approach of the modelling of the three-phase multiple earthed neutral feeder). In this test network, the number of buses is 23 buses ($N_{bus} = 23$) and thus, the total number of phases is 69 ($N_{phase} = 69$).

5.5.2 Loading specifications

Three phase unbalance load flow analyses were conducted over a year using the residential load profiles collected from smart meters installed at consumer premises in 15-minute intervals [40], [49]. Based on the outcome of these analyses, six representative days are considered which presents the worst voltage unbalances and magnitude violations in the network over the year. The reason for this selection is to show the effectiveness of the proposed algorithm in solving for the worst-case scenarios. If these scenarios are solved, then the proposed method can solve for any voltage violations in the network throughout the year. The representative residential load profiles in this analysis, shown in Fig. 5.5, fall into two operational scenarios:

- Max VUF operating conditions during peak demand periods: Fig. 5.5(a), 5.5(b), and 5.5(c)
- Max VUF operating conditions during peak PV generation periods: Fig. 5.5(d), 5.5(e), and 5.5(f)

As seen, peak demand periods and peak PV generation periods appear in these categories as voltage magnitude and unbalance violations are discussed in Section 5.5.3. It is apparent from Figs. 5.5(a) to 5.5(f) that the blue phase (phase C) is the most heavily loaded phase, while the red phase (phase A) is the least loaded phase. Some load points at specific times are negative due to the power injection of PV units. The majority of the voltage violations can be attributed to the dominant load on phase C. The load points are highlighted with red circles where both maximum voltage magnitude and unbalance violations are occurred.

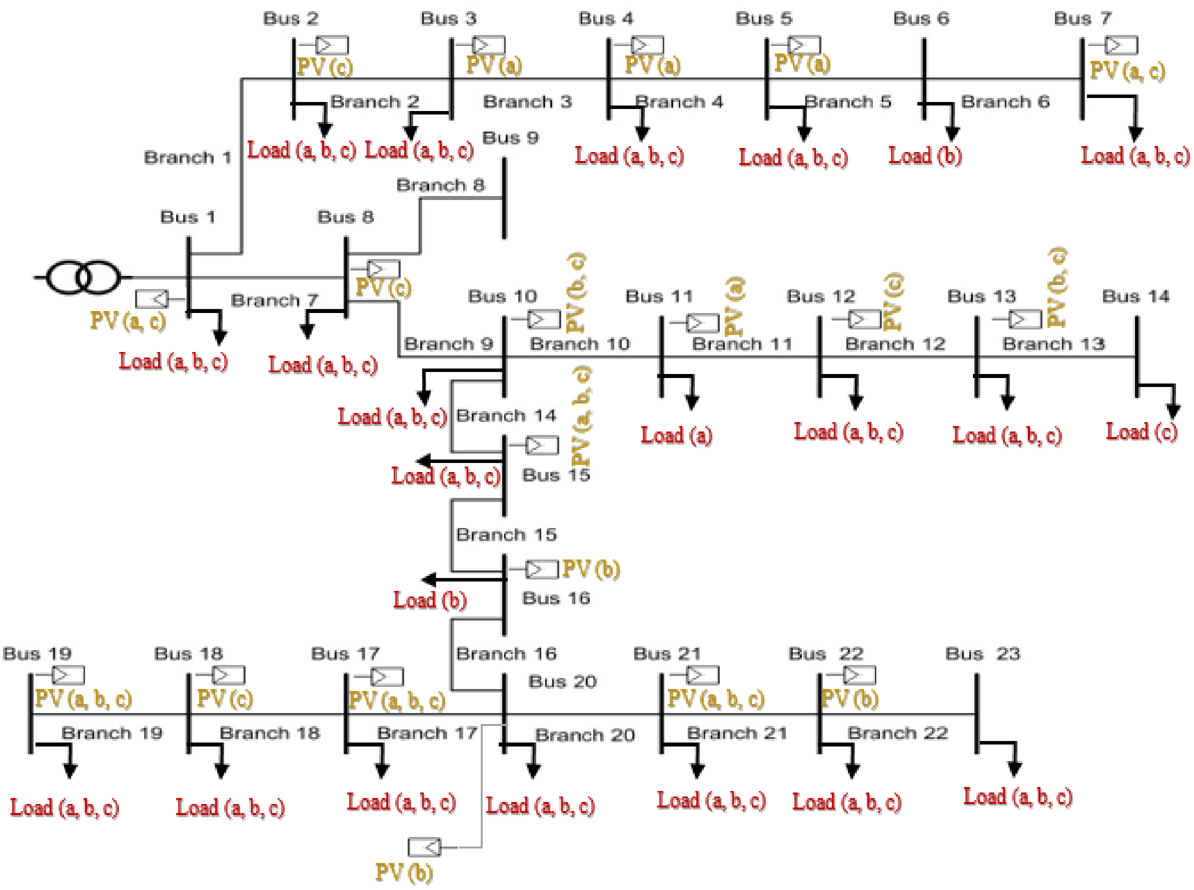
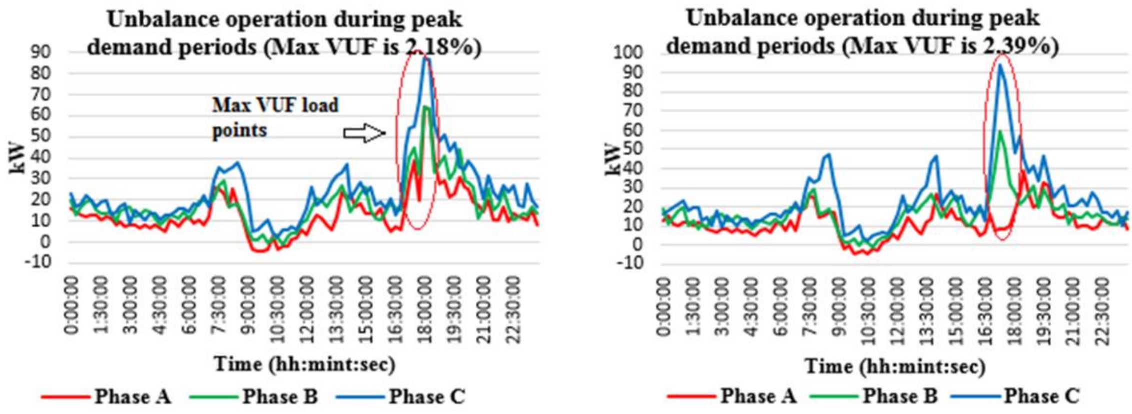
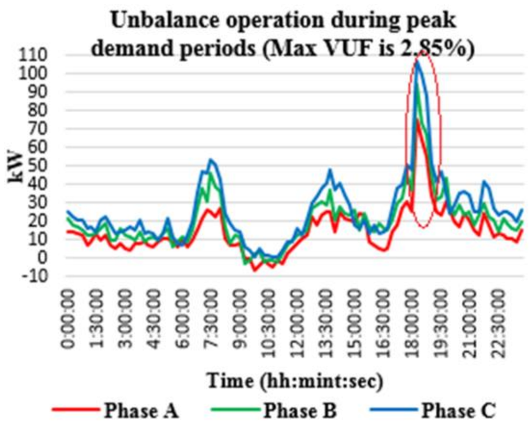


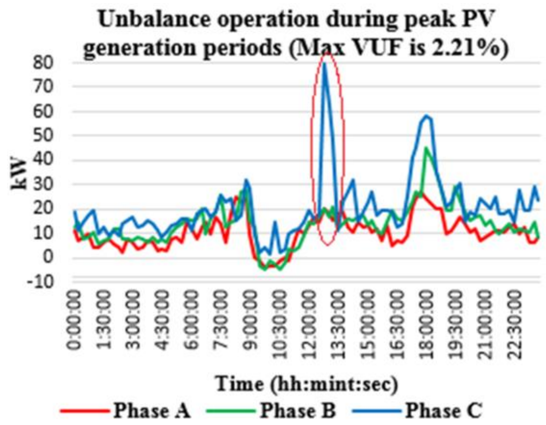
Fig. 5.4. Australian LV aerial network with PV and Load locations [40].



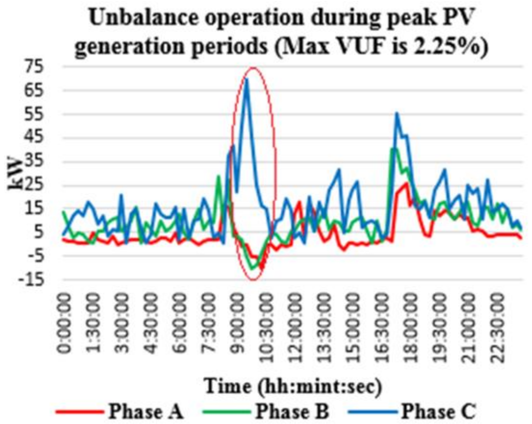
(a) (b)



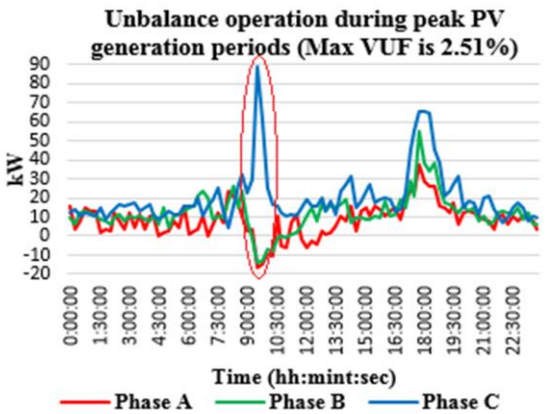
(c)



(d)



(e)



(f)

Fig. 5.5. Six representative load profiles for worst case voltage violations.

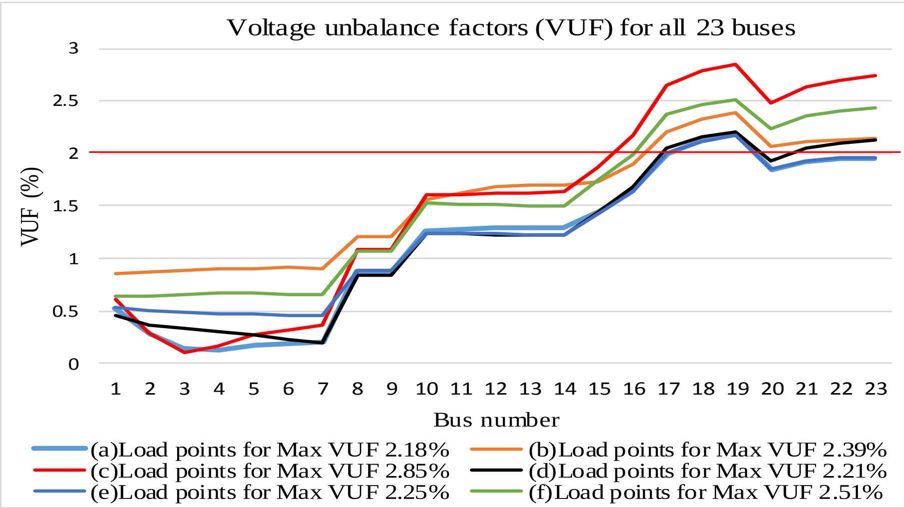
5.5.3 Initial condition of the test network

The technical parameters of the network for identified maximum VUF load condition from each representative daily load profile (shown in Fig. 5.4), are reported in Table 5.2. These parameters are power loss, max VUF, max/min voltage magnitude violation, and the total voltage violated bus and phase of the corresponding max VUF load points. Figures 5.6(a) and 5.6(b) show the VUF results of all buses and voltage magnitude of all phases, respectively, for all corresponding violated load points in Table 5.2. It can be seen from these figures that far end buses have higher voltage unbalance and magnitude problems and occur mostly in the same locations for all identified load points. The DR candidate locations are selected based on the location of downstream buses where VUF is greater than 2%. Fig. 5.6(a) shows that the buses with violated VUF are from bus 16 to bus 23 (totally 8 buses).

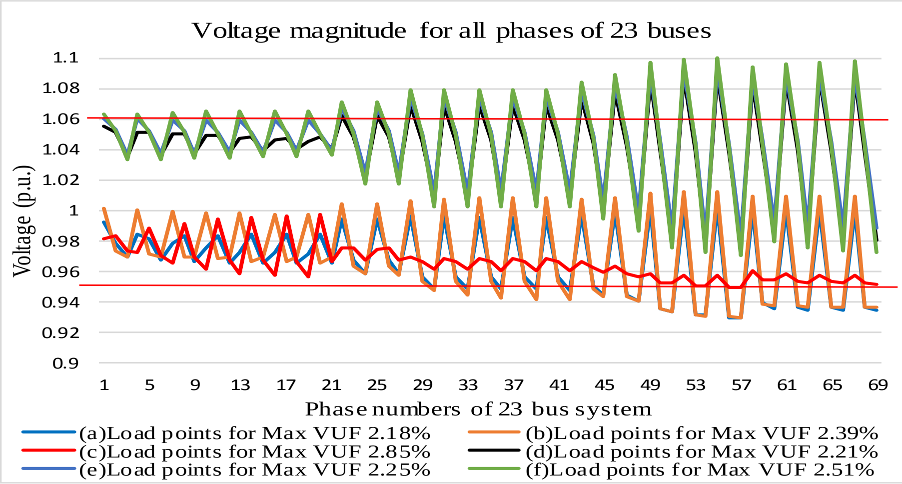
Table 5.2

Max VUF load points of each representative load profile of Fig. 5.5

Max VUF operating load points during peak demand periods											
Load Profile in Fig. 5.5	Max VUF load points Phase A (kW)	Phase B (kW)	Phase C (kW)	Max VUF (%)	Power loss (kW)	No. of buses where VUF > 2%VUF	Max VUF_{Zero} (%)	Total no. of buses VUF_{zero} > $5\%VUF_{Zero}$	Min/Max voltage violation (p.u.)	Total over voltage violation phase	Total under voltage violation phase
(a)	64.22	64.22	87.35	2.18	12.25	2	0	0	0.93	0	22
(b)	8.38	59.83	93.70	2.39	11.46	7	0	0	0.93	0	23
(c)	75.73	94.00	106.94	2.85	26.35	8	5.5	5	0.901	0	28
Max VUF operating load points during peak PV generation periods											
(d)	19.94	19.94	79.94	2.21	9.28	6	5.6	6	1.089	16	0
(e)	-10.0	-10.0	70.0	2.25	7.43	6	5.9	6	1.095	23	0
(f)	-16.9	-13.6	88.65	2.51	10.47	7	6.6	8	1.10	23	0



(a)



(b)

Fig. 5.6. Voltage unbalance and magnitude of all buses and phases of the network for the identified load points.

Table 5.3 shows the identified DR candidate bus locations and selected bid prices for consumers in those candidate bus locations, which are used in the simulation. Taking into account only single phase consumers from 8 DR candidate buses (22 single phase consumers) are participating in DR. In bus 16, only one single phase consumer located at phase B is available for DR, as there are no consumers connected to phases A and C of that. Gaussian random bid prices are generated for all 22 consumers considering a mean value \$0.382/kWh [50], which are used throughout this simulation study. Costs of communication investment and consumer DR availability costs are not considered. However, it can be simply added to the cost function. The following sections analyse the simulation results using the proposed algorithm.

Table 5.3

DR candidate consumers' bus locations and their selected bid prices

DR candidates: bus numbers and participated consumer	Bidding price (\$/kWh) for 22 consumers
Bus 16 to 23 (8 buses), total 22 consumers	0.382; 0.382; 0.275; 0.240; 0.382; 0.350; 0.382; 0.284; 0.30; 0.35; 0.35; 0.382; 0.231; 0.50; 0.274; 0.55; 0.50; 0.382; 0.35; 0.31; 0.41; 0.481

- Voltage and current unbalance dependency

Branch current unbalance (BCU) mainly depends on load unbalance. Fig. 5.7 depicts the branch current unbalance factors of all 22 branches in the network for the representative load points (see Fig. 5.6(a)). The current unbalance is calculated in a similar way as voltage unbalance calculation. It is observed from Fig. 5.6(a) and Fig. 5.7 that there is no direct and strong relationship between current and voltage unbalance. For example, the BCU values in Fig. 5.7 for load points (a), (b), (c) and (d) are relatively equal at the far end branches, however, the VUF values in Fig. 5.6(a) for these load points vary significantly at the feeder ends. In addition, in branches near the distribution transformer, the voltage unbalance is lower than 1%, as shown in Fig. 5.6(a). However, branch current unbalance is varying between 40% and 130%, which demonstrate not very strong dependency between voltage and current unbalance. Another example is voltage unbalance at load point (a) whose VUF is approximately lower than VUF of other load points, depicted in Fig. 5.6(a). However, as seen in Fig. 5.7, sometimes, branch current unbalance at this load point is higher than BCU for other branches. This is because that the magnitudes and angles of load currents influence differently voltage unbalance and current unbalance factors. Detailed analysis on dependency of voltage and current unbalance is required, which will be addressed in the future works.

In the optimisation formulation in this study, only voltage unbalance constraints are considered, as utilities require to maintain the voltage unbalance according to IEC6100-3-13 and EN50160 standards. Since, the network power loss is included in the objective function, it improves the current unbalances indirectly as the current unbalance has a high influence on the network power loss.

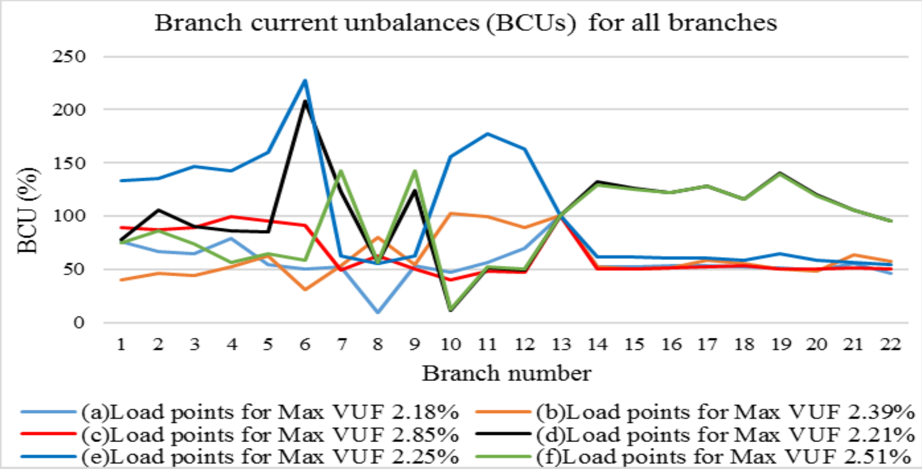


Fig. 5.7. Current unbalance factors for all branches of the network.

5.5.4 Optimisation algorithm results

This section presents the simulation results obtained from the developed algorithm for voltage management in the LV distribution network. The identified max VUF load points (in Table 5.2) from the six representative daily load profiles (in Fig. 5.5) are investigated in five different scenarios. Each scenario is evaluated based on the optimised DR size and cost, OLTC tap positions, power losses and network constraint violations. In the simulation, the loads are assumed to be constant PQ loads and the particle population of MPSO is considered 400. The considered scenarios are:

1. Scenario 1: $OLTC_{dep}$ only.
2. Scenario 2: $OLTC_{ind}$ only
3. Scenario 3: DR only
4. Scenario 4: DR with $OLTC_{dep}$
5. Scenario 5: DR with $OLTC_{ind}$

Table 5.4 presents the summary of the obtained results from five scenarios using the proposed MPSO-based algorithm. For each scenario, the MPSO algorithm is run for 10 times to obtain the mean and standard deviation of the objective function. The standard deviations for DR size and network loss in 10 runs are found to be less than 1 for all max VUF cases, and the mean values are reported in Table 5.4. The computational time of optimisation process for this network is less than 56 seconds in MATLAB 2016 software on Intel CORE i7-2600 PC with clock speed of 3.4 GHz and 12GB RAM. The optimised cost ($) of the objective function for each scenario in Table 5.4 is the sum of DR costs (for 2 hours), power loss cost and penalty cost. The duration of DR event in this simulation is 2 hours, as the average operational time of a DR appliance is around 2 hours [26]. The cost of power loss ($cost_{(t)}$) is considered $235/kW [51]. The constraints violation, as defined in (5.5), in each proposed scenario can be identified by the large penalty factors, added into the optimised cost. For example, if the optimised cost has one of the penalty factors 10^6, 10^5, 10^4, or 10^3, then the corresponding solution contains a constraint violation of $VUF_{(j,t)}$, $V_{(i,t)}$, $VUF_{Zero(j,t)}$, or $ADR_{(i,t)}$, respectively. The grey pattern in Table 5.4 shows the cases with constraint violations.

It can be observed from the simulation results in Table 5.4 that scenario 1 ($OLTC_{dep}$ only), cannot solve all the max VUF cases and therefore, high penalty factors added into the optimised costs. Scenario 2 ($OLTC_{ind}$) and scenario 3 (DR only) solve most of the max VUF cases. However, the network $VUF_{Zero(j,t)}$ is violated with scenario 2 ($OLTC_{ind}$) for max VUF 2.85% case and phase voltage $V_{(i,t)}$ is violated with scenario 3 (DR only) for max VUF 2.51% case. With scenario 4 (DR with $OLTC_{dep}$) and scenario 5 (DR with $OLTC_{ind}$), all the max VUF cases are solved without any constraint violation, as there are no penalty factors in the optimised costs. More specifically, scenario 5 (DR with $OLTC_{ind}$) provides the most cost-effective solution compared to all other scenarios for all max VUF cases, as DR size, power loss and objective function cost are reduced significantly. Therefore, scenario 5 which is an integrated approach of DR with OLTC independent phase tap control ($OLTC_{ind}$) can be an effective voltage management solution for LV distribution networks. The maximum daily allowable tap operations of both $OLTC_{ind}$ (for each phase) and $OLTC_{dep}$ (three-phase) are within limits (less than 10 steps).

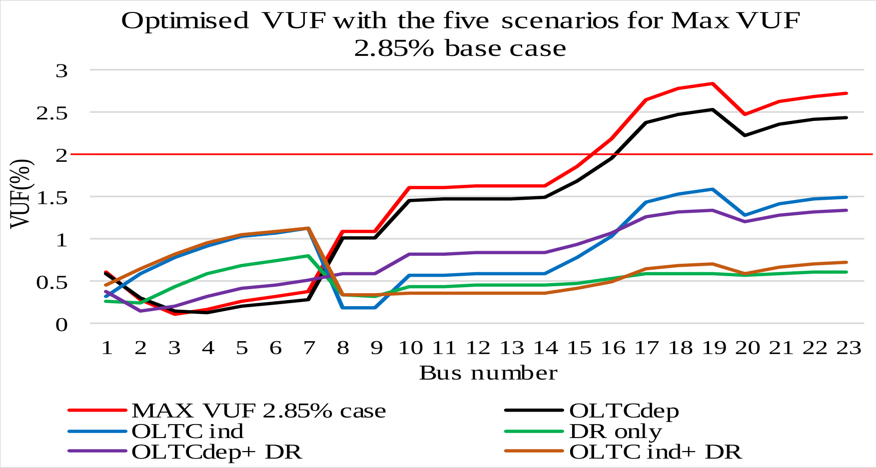
Table 5.4

Optimisation results summary for the proposed five scenarios.

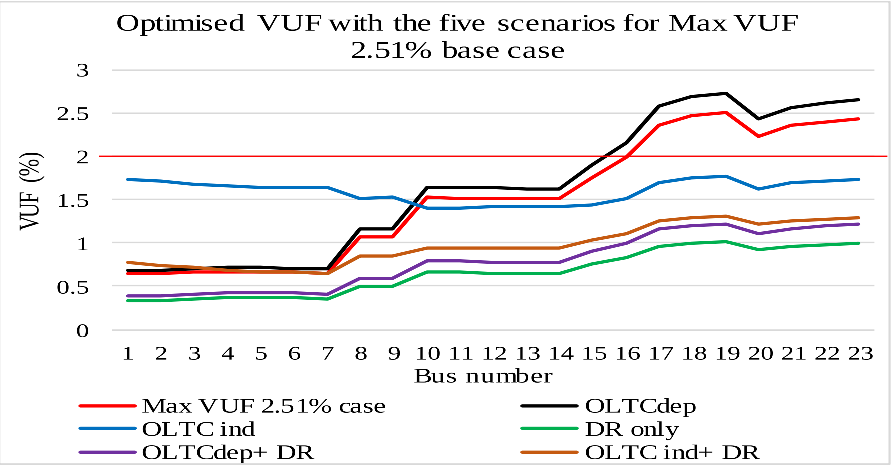
Max VUF cases	1. $OLTC_{dep}$ only			2. $OLTC_{ind}$ only			3. DR only			4. DR with $OLTC_{dep}$				5. DR with $OLTC_{ind}$			
	TAP (p.u)	Loss (kW)	Obj. func. ($)	TAPs (p.u) a/b/c	Loss (kW)	Obj. func. ($)	Size (kW)	Loss (kW)	Obj. func. ($)	Size (kW)	TAP (p.u)	Loss (kW)	Obj. func. ($)	Size (kW)	TAPs (p.u) a/b/c	Loss (kW)	Obj. func. ($)
2.18	1.05	12.77	3010	1.05/1.07/1.09	12.03	2859	60	5.96	1443	61	1.06	5.22	1278	61	1.06/1.07/1.08	5.11	1274
2.39	1.04	10.51	**3×10^6**	1.0/1.03/1.08	9.54	2259	59	6.18	1496	50	1.05	4.27	1048	50	1.05/1.08/1.08	4.02	1015
2.85	1.06	23.09	**7×10^6**	1.06/1.07/1.09	22.17	5243	103.5	14.44	**1×10^5**	90	1.06	8.57	2086	90	1.06/1.06/1.08	8.41	2071
2.21	1.05	8.30	**1.1×10^5**	0.97/0.98/1.01	9.11	2149	65	2.66	672	48	0.99	2.56	640	47	0.99/1.0/1.01	2.47	618
2.25	0.99	7.30	**1.1×10^5**	0.96/0.98/1.02	7.12	1685	72	2.20	567	57	0.99	2.09	534	55.5	0.98/1.0/1.01	2.01	516
2.51	0.96	11.53	**8.3×10^6**	0.95/0.96/1.02	10.04	**1.2×10^4**	89	2.78	684	70.5	0.99	2.64	666	68	0.98/1.0/1.01	2.53	647

To further investigate the optimised results of each scenario in Table 5.4, the resulted $VUF_{(j,t)}$, $V_{(i,t)}$ and $VUF_{Zero(j,t)}$ of the network for the two highest max VUF cases 2.85% and 2.51%, respectively are shown in Figs. 5.8, 5.9 and 5.10. As seen in Figs. 5.8 (a) and (b), the VUF of all buses are less than 2% limit for the all the solution scenarios, except for the $\mathrm{OLTC_{dep}}$ (scenario 1) solution, and therefore, higher objective function cost for $\mathrm{OLTC_{dep}}$ (as highlighted in Table 5.4). For max VUF 2.85% base case in Fig. 5.9 (a), the resulted $VUF_{Zero(j,t)}$ obtained from five scenarios for all buses are within the 5% limit. However, for max VUF 2.51% case, the $\mathrm{OLTC_{dep}}$ (scenario 1) and $\mathrm{OLTC_{ind}}$ (scenario 2) solutions exceed the $VUF_{Zero(j,t)}$ limit, as shown in Fig. 5.9 (b). From Fig. 5.10 (a), it can be observed that the DR only (scenario 3) solution for max VUF 2.85% case cannot limit the phase voltage $V_{(i,t)}$ within 1.06 to 0.95 pu voltage range, and thus there is a voltage magnitude penalty factory added into the cost function (as seen in Table 5.4). Interestingly, the DR only (scenario 3) solution has slightly or equal performance (in) in improving VUF and $\mathrm{VUF_{Zero}}$ for Max VUF of 2.85% and 2.51% cases compared to the DR with OLTC solutions (scenarios 4 and 5), as shown in Figs 5.8 and 5.9. It is due to the fact that the DR only (scenario 3) solution uses higher DR sizes compared to the DR with OLTC solutions (scenarios 4 and 5) for the two Max VUF cases. Thus, the total objective function cost of the DR only (scenario 3) is higher than the DR with OLTC solutions, it is because the OLTC has some degree of voltage magnitude and unbalance improvement capacities which resulted in lower DR size.

Finally, for max VUF 2.51% base case, all scenarios limit the phase voltage $V_{(i,t)}$ within the range, except for the $\mathrm{OLTC_{dep}}$ (scenario 1) solution. Therefore, it can be concluded that individual solution approach such as scenario 1, 2 and 3 may not solve all the network voltage problems effectively. However, with the integrated approach such as scenario 4 and 5, all the network voltage problems can be improved significantly, especially with the scenario 5 (DR with $\mathrm{OLTC_{ind}}$).

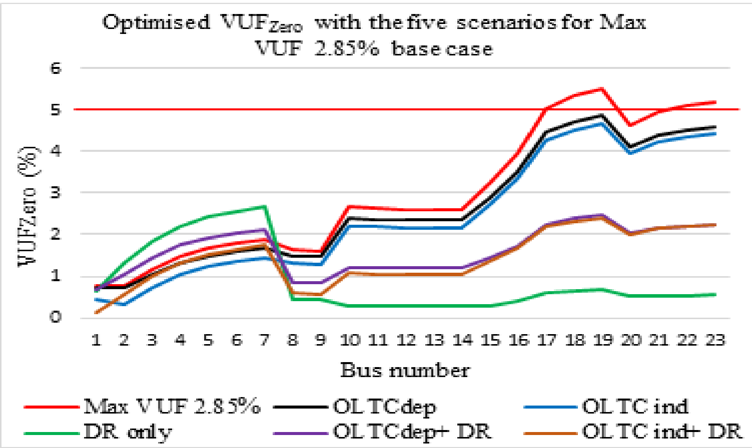


(a)

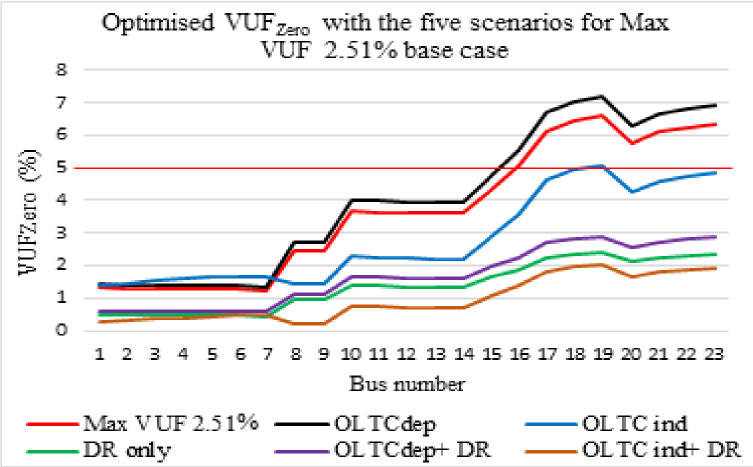


(b)

Fig. 5.8. Resulted $VUF_{(j,t)}$ obtained from five scenarios for max VUF 2.85% and max VUF 2.51% base cases.

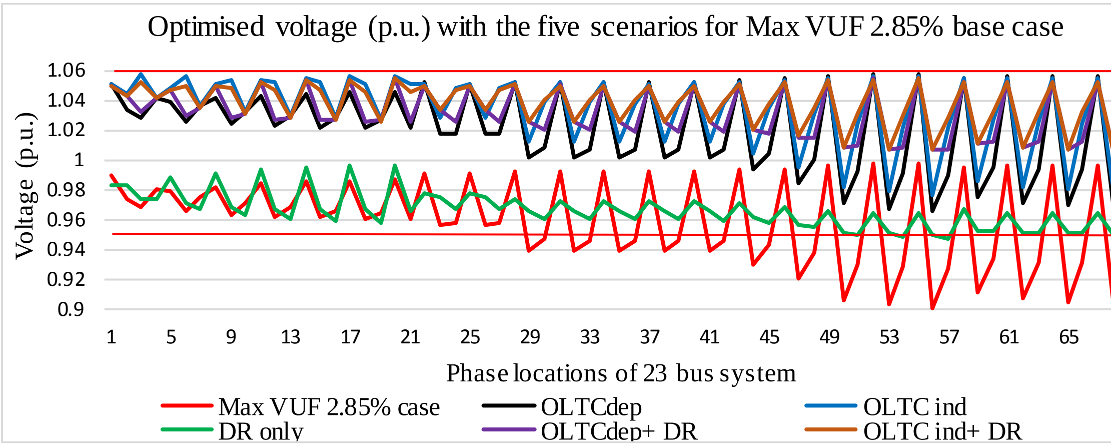


(a)

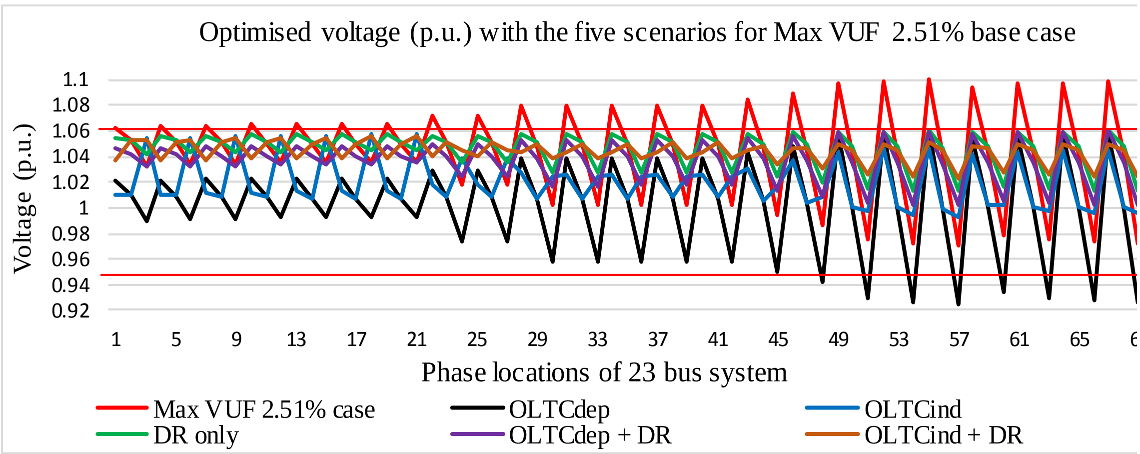


(b)

Fig. 5.9. Resulted $VUF_{Zero(j,t)}$ obtained from five scenarios for max VUF 2.85% and max VUF 2.51% base cases.



(a)



(b)

Fig. 5.10. Resulted $V_{(i,t)}$ obtained from five scenarios for max VUF 2.85% and max VUF 2.51% base cases.

5.5.4.1 Optimised switching configuration for consumers

As seen in the previous section, the integrated approach of DR with $OLTC_{ind}$ (scenario 5) provides significant improvement of network voltage, power loss and DR cost. The optimised switching configurations of each participated consumer for this scenario are detailed in this section for the two highest VU base cases, max VUF 2.85% and max VUF 2.51%, respectively. Appliances' initial switching positions (generated randomly) and optimised switching positions for each participated consumer are presented in Tables 5.5 and 5.6.

Table 5.5

Optimised switching position with DR with OLTC$_{ind}$ (scenario 5) for max VUF 2.85% (peak demand) base case.

	Consumer	Initial switching position						Optimised switching position								
	(phase) location	W.mch Pos./kW	D.wsh Pos./kW	Dryer Pos./kW	P.pum Pos./kW	EV Pos./kW	Total kW	W.mch Pos.	D.wsh Pos.	Dryer Pos.	P.pum Pos.	EV Pos.	Total kW	kW changed	# of load disturbed	T. cost 2hr ($)
Bus 16	47 (b)	3/1.5	3/2.0	1/3.0	2/(n/a)	1/3.0	9.5	1	1	0	0	0	3.5	–6	2	4.58
Bus17	49 (a)	4/1.5	4/2.0	0/3.0	0/1.0	0/3.0	0	0	0	0	0	0	0	0	0	0
	50 (b)	3/1.5	3/2.0	1/3.0	1/1.0	3/3.0	10.5	1	1	0	0	1	6.5	–4	2	2.2
	51 (c)	3/1.5	3/2.0	1/3.0	1/1.0	1/3.0	10.5	1	1	0	0	0	3.5	–7	3	3.36
Bus18	52 (a)	0/1.5	0/2.0	0/3.0	0/1.0	0/3.0	0	0	0	0	0	0	0	0	0	0
	53 (b)	3/1.5	3/2.0	1/3.0	1/1.0	1/3.0	10.5	1	1	0	0	0	3.5	–7	3	4.9
	54 (c)	3/1.5	2/(n/a)	1/3.0	1/1.0	1/3.0	8.5	1	0	0	0	0	1.5	–7	3	5.35
Bus19	55 (a)	0/1.5	0/2.0	4/3.0	0/1.0	0/3.0	0	0	0	0	0	0	0	0	0	0
	56 (b)	3/1.5	3/2.0	1/3.0	1/1.0	1/3.0	10.5	1	1	0	0	0	3.5	–7	3	4.2
	57 (c)	3/1.5	0/2.0	1/3.0	1/1.0	1/3.0	8.5	1	0	0	0	0	1.5	–7	3	4.9
Bus20	58 (a)	0/2.0	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	0	0	0	0	0	0	0
	59 (b)	3/1.5	3/2.0	1/3.0	0/1.0	1/3.0	9.5	1	1	0	0	0	3.5	–6	2	4.58
	60 (c)	0/2.0	0/2.0	1/3.0	1/2.0	3/3.0	8	0	0	0	0	1	3	–5	2	2.31
Bus21	61 (a)	0/1.5	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	0	0	0	0	0	0	0
	62 (b)	0/1.5	3/2.0	1/3.0	1/1.0	1/3.0	9	0	1	0	0	0	2	–7	3	3.84
	63 (c)	3/1.5	3/2.0	1/3.0	0/1.0	1/3.0	9.5	1	1	0	0	0	3.5	–6	2	6.6
Bus22	64 (a)	0/2.0	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	0	0	0	0	0	0	0
	65 (b)	3/1.5	3/2.0	3/3.0	1/1.0	1/3.0	10.5	1	1	1	0	0	6.5	–4	2	3.06
	66 (c)	4/2.0	3/2.0	1/3.0	1/2.0	1/3.0	10	0	1	0	0	0	2	–8	3	5.6
Bus23	67 (a)	0/1.5	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	0	0	0	0	0	0	0
	68 (b)	0/2.0	0/2.0	1/3.0	1/1.0	3/3.0	7	0	0	0	0	1	3	–4	2	3.28
	69 (c)	3/1.5	3/2.0	1/(3.0)	1/2.0	2/(n/a)	8.5	1	1	0	0	0	3.5	–5	2	4.81
	Total						**140.5**						**50.5**	**90**	**37**	**63.57**

Pos. = Switching position; W.mch = washing machine; D.wsh=dishwasher; P.pum= Pool pump; EV= Electric vehicle; T. cost = Total cost of DR for 2hrs

Table 5.6

Optimised switching position with DR with $OLTC_{ind}$ (scenario 5) for max VUF 2.51% (peak PV generation) case

	Consumer (phase) location	Initial switching position						Optimised switching position								
		W.mch Pos./kW	D.wsh Pos./kW	Dryer Pos./kW	P.pum Pos./kW	EV Pos./kW	Total kW	W.mch Pos.	D.wsh Pos.	Dryer Pos.	P.pum Pos.	EV Pos.	Total kW	kW changed	# of load disturbed	T. cost 2hr ($)
Bus 16	47 (b)	0/1.5	0/2.0	0/3.0	2/(n/a)	0/3.0	0	0	0	1	0	0	3	3	1	2.29
Bus17	49 (a)	4/1.5	4/1.5	0/3.0	0/1.0	0/3.0	0	0	0	0	0	0	0	0	0	0.00
	50 (b)	0/1.5	0/2.0	0/3.0	0/1.0	4/3.0	0	0	0	0	1	0	1	1	1	0.55
	51 (c)	3/1.5	3/2.0	1/3.0	1/1.0	1/3.0	10.5	1	1	0	0	0	3.5	–7	3	3.36
Bus18	52 (a)	0/1.5	0/2.0	0/3.0	0/1.0	0/3.0	0	0	0	0	0	0	0	0	0	0.00
	53 (b)	0/1.5	0/2.0	0/3.0	0/1.0	0/3.0	0	0	0	0	0	0	0	0	0	0.00
	54 (c)	0/1.5	3/2.0	1/3.0	1/1.0	1/3.0	9	0	1	0	0	0	2	–7	3	5.35
Bus19	55 (a)	0/1.5	0/2.0	4/3.0	0/1.0	0/3.0	0	0	0	0	0	1	3	3	1	1.70
	56 (b)	0/1.5	0/2.0	0/3.0	0/1.0	0/3.0	0	0	0	0	0	1	3	3	1	1.80
	57 (c)	0/1.5	3/2.0	1/3.0	1/1.0	1/3.0	9	0	1	0	0	0	2	–7	3	4.90
Bus20	58 (a)	0/2.0	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	1	1	0	4	4	2	2.80
	59 (b)	0/1.5	0/2.0	0/3.0	0/1.0	0/3.0	0	0	0	0	0	1	3	3	1	2.29
	60 (c)	0/2.0	0/2.0	1/3.0	1/2.0	3/3.0	8	0	0	0	0	1	3	–5	2	2.31
Bus21	61 (a)	0/1.5	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	0	0	0	0	0	0	0.00
	62 (b)	0/1.5	0/2.0	0/3.0	0/1.0	0(3.0	0	0	0	0	0	1	3	3	1	1.64
	63 (c)	3/1.5	3/2.0	1/3.0	1/1.0	1/3.0	10.5	1	1	0	0	0	3.5	–7	3	7.70
Bus22	64 (a)	0/2.0	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	0	0	0	0	0	0	0.00
	65 (b)	0/1.5	0/2.0	2/(n/a)	0/1.0	0/3.0	0	0	0	0	1	0	1	1	1	0.76
	66 (c)	4/2.0	3/2.0	1/3.0	1/2.0	1/3.0	10	0	1	0	0	0	2	–8	3	5.60
Bus23	67 (a)	0/1.5	0/2.0	0/3.0	0/1.0	2/(n/a)	0	0	0	0	1	0	1	1	1	0.62
	68 (b)	0/2.0	0/2.0	2/(n/a)	0/1.0	4/3.0	0	0	0	0	0	0	0	0	0	0.00
	69 (c)	3/1.5	3/2.0	1/3.0	1/2.0	2/(n/a)	8.5	1	1	0	0	0	3.5	–5	2	4.81
	Total						**65.5**						**41.5**	**68**	**29**	**48.48**

Pos. = Switching position; W.mch = washing machine; D.wsh=dishwasher; P.pum= Pool pump; EV= Electric vehicle; T. cost = Total cost of DR for 2hrs

It can be seen from Tables 5.5 and 5.6 that the appliances kW demand and quantity vary from consumer to consumer. For example, in Tables 5.5 and 5.6, the consumer at the phase location 47 (b) has a washing machine (1.5 kW), dishwasher (2.0 kW), dryer (3.0 kW), EV (3.0 kW) and no available pool pump. However, the consumer at the phase location 49 (a) has all the DR appliances. In the column 'kW changed', positive number means demand increment and negative values represent demand reduction. The total kW changed represents the sum of absolute values of column 'kW changed'.

The appliances initial switching positions are assigned a numerical number from 0 to 4 (as defined in Table 5.1, Section 5.2). Based on these figures, the algorithm optimises the appliances' new switching positions to improve the network voltage and satisfy the consumer preferences. The optimised switching positions for each consumer in Tables 5.5 and 5.6 are represented by only binary number '0' (off position) and '1' (on position). These switching combinations show no violation on consumer's consumption priorities. In addition, the ADR value ($|kW\ changed|$ / number of load disturbed) of each consumer is bigger than 1, which maintains the minimum disturbance on appliances switching positions. The total costs of DR for managing the two highest worst cases voltage unbalance VUF 2.85% and VUF 2.51% are \$63.57 and \$48.48 respectively.

5.5.5 Maximisation of PV hosting capacity

An unbalance network can host less PV generation before the critical voltage limit is reached. The results on the studied network shows significant voltage unbalance at 35% PV penetration level (64 kW). The estimated PV hosting capacity of the network is around 20% (40 kW) without any voltage violations and without any compensations. With the proposed method, the network current PV hosting ability has improved from 20% to 35%. Increasing penetration of decentralised PVs will have more impact on the network voltage, and the proposed algorithm is able to tackle these challenges. To demonstrate this capability, a future scenario is considered in this study by increasing the current PV penetration level (64 kW) to double value (128 kW) to show the effectiveness of the proposed method in managing network voltage. Figures 5.11 (a) and (b) show the initial voltage unbalance and magnitude violations in the network when the PV penetration is reached to 128 kW. These figures also show the optimised voltage levels of the network after using the proposed coordination approaches, which demonstrate the effectiveness of the approach to keep voltage levels within standard limits. Table 5.7 presents the results summary of the proposed coordination approaches for 128 kW PV penetration. As illustrated in this table, DR coordinated with $OLTC_{ind}$ provides better solution results. Therefore, the proposed method can be implemented in any network condition and scenario to improve PV hosting capacity.

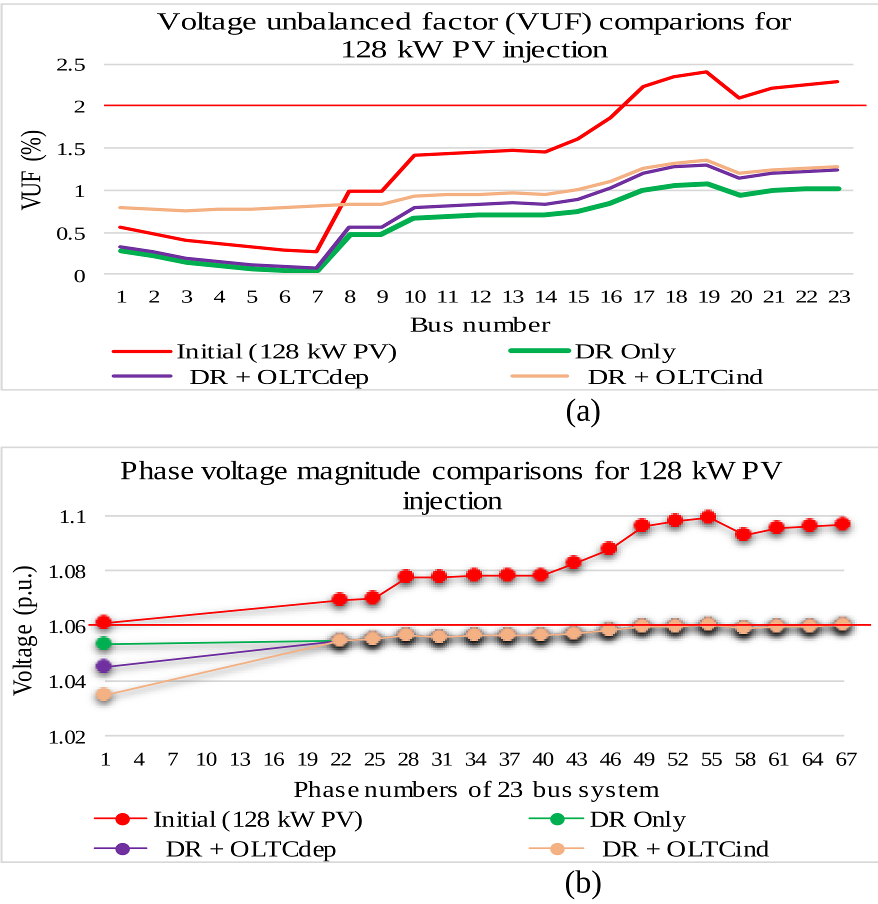


Fig. 5.11. Voltage unbalance and magnitude of all buses and phases of the network at 128 kW PV penetration.

Table 5.7

Optimisation results summary for 128 kW PV penetration.

Options	Loss (kW)	TAP (p.u)	DR Size (kW)	DR cost (kW)	Obj. func. ($)
Initial case	9.36				
DR only	3.56		84	29.61	867
DR + $OLTC_{dep}$	3.43	0.99	66	23.59	830
DR + $OLTC_{ind}$	3.29	0.98/1/1.01	62.5	21.92	796

5.5.6 DR coordination with network capacitor

The proposed algorithm can also be coordinated with the existing network capacitor and voltage regulator to manage the network voltage. The coordination approach of DR with network capacitor or voltage regulator can be achieved by including a variable in the MPSO particle structure, similar to $OLTC_{dep}$ coordination with DR (see Section 5.4.1). For instance, a 15 kVar three-phase capacitor bank, which includes 6 steps with 3 kVar per step, is installed at bus 19 of the test network (Fig. 5.4). The size and placement of the capacitor bank are determined by the highest voltage sensitivity of a bus in respect to reactive power change which is obtained from the inverse Jacobian matrix [52]. Two types of capacitor controls, i.e., switchable and fixed controls are analysed to solve the two maximum VUF cases in Fig. 5.6(a). As shown in Table 5.8, the optimal kVar sizes of the switchable capacitor bank obtained from the load control algorithm are different for two max VUF cases. The results show that DR coordinated with network capacitor results in a higher DR size, network loss and objective function cost compared to those in both OLTC coordination approaches (see Table. 5.4). Furthermore, DR coordinated with fixed capacitor control has a very high objective function cost, due to low voltage violations occur for Max VUF 2.85% case. Therefore, DR coordinated with network capacitor is less effective compared to OLTC coordination.

Table 5.8

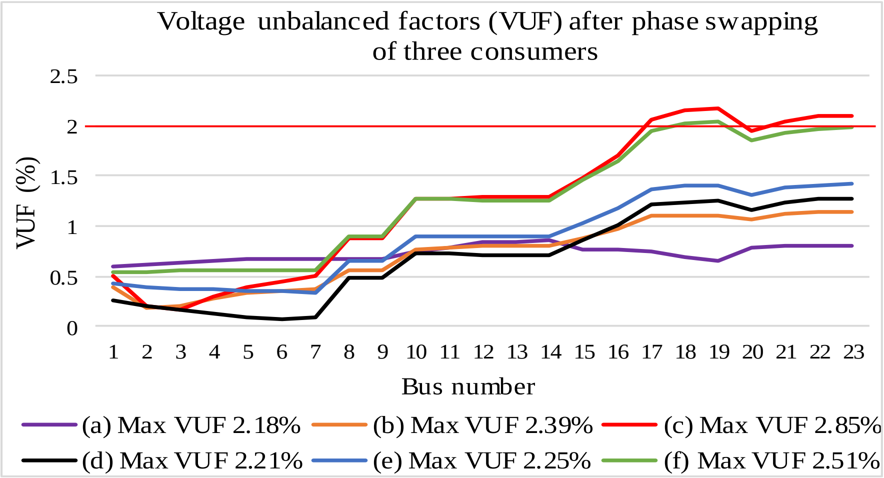
DR coordinatation with network capacitor bank without OLTC.

Capacitor bank operation	Max VUF 2.51%					Max VUF 2.85%				
	kVar used	DR Size (kW)	Loss (kW)	Obj. func. ($)	% Obj. func. increased*	kVar used	DR Size (kW)	Loss (kW)	Obj. func. ($)	% Obj. func. increased*
Switchable	0	86.5	3.16	774	20%	15	104.5	17.5	4161	101%
Fixed	12	91	3.3	807	25%	12	99.5	14.91	**1.04×10^5**	Not acceptable

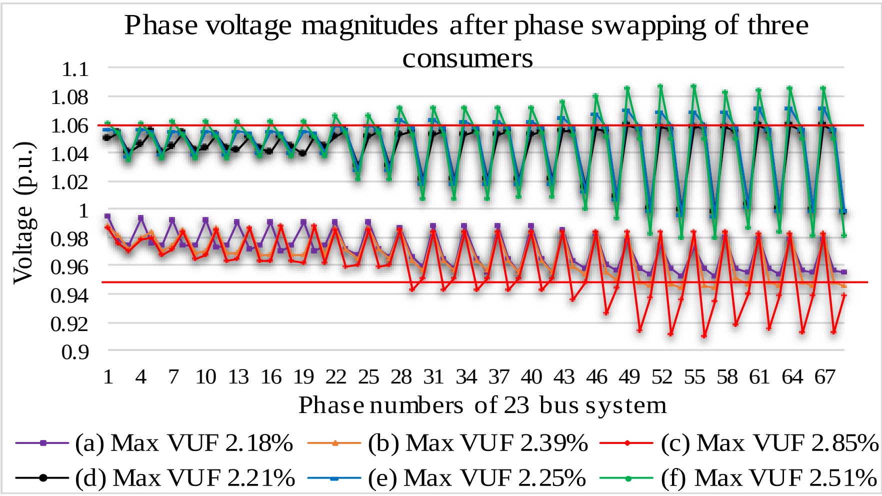
*compared to DR with $OLTC_{ind}$ solution as presented in Table 5.4.

5.5.7 Comparison with existing phase swapping method

One of the solutions for unbalance voltage management is manually switching the supply phases to improve the balance of the load across the three phases [40]. Though this is a mature and effective approach in some cases, however, the intermittent nature of PVs and the variable demand of consumers would result in frequent variations of network operation conditions, rendering the application of manually-controlled strategies and technologies insufficient. Thus, this solution will be costly and labor-intensive when more switching actions are required. In this study, voltage unbalanced improvement is performed by manually transferring the load from the highly loaded phase (phase C) to the lightly-loaded phase (phase A) at that bus. The priority of the phase swap is given to three single phase houses that are located far end of the feeder and have high energy consumption, that is, more than the average consumption of that phase [40]. The number of phase swaps in this analysis are limited to three houses as this would spread single-phase consumers evenly on the three phases of the test network. Figures 5.12 (a) and (b) display the results of voltage unbalances and magnitudes of the six representative load profiles after phase swapping approach. It shows phase swapping considerably reduces the voltage unbalances for all Max VUF violated cases, except for the two Max VUF cases (Max VUFs 2.85% and 2.51%) in which VUF exceeds the limit of 2%. Consequently, the phase voltage magnitudes as shown in Fig. 5.12(b) have improved compared to initial conditions, as presented in Fig. 5.6(b). However, for four load points, which are Max VUF (b), (c), (e) and (f), voltage magnitudes and/or unbalance of some phases are outside the standard limits, as illustrated in Fig. 5.12(b). The associated network power losses of the representative load profiles using phase swapping are depicted in Table 5.9. As seen, with this solution approach, power losses and its related costs are significantly higher than those with the DR only solution approach (see Table 5.4). It can be concluded that the phase swapping method does not result in a better optimum solution compared to the proposed DR based approach in this study.



(a)



(b)

Fig. 5.12. Voltage unbalance and magnitude of six representative load profiles after using phase swapping approach.

Table 5.9

Power loss and the associated costs with phase swap method.

Load points	Loss (kW)	Cost of loss ($)	% Loss increased*	Load points	Loss (kW)	Cost of loss ($)	% Loss increased*
(a) Max VUF 2.18%	7.5	1763	26%	(d) Max VUF 2.21%	5.16	1213	94%
(b) Max VUF 2.39%	11.6	2726	88%	(e) Max VUF 2.25%	4.14	973	88%
(c) Max VUF 2.85%	23.6	5546	63%	(f) Max VUF 2.51%	7.81	1835	181%

*compared to DR only solution as presented in Table 5.4.

5.6 Conclusion

A new effective method for voltage management in unbalanced low voltage distribution networks was proposed. This method integrates residential DR and network OLTC for an effective improvement of network voltage magnitude and unbalance while prioritises the consumers' consumption preferences to reduce their comfort level violations. An MPSO-based algorithm is utilised to identify the optimal locations and size of DR and OLTC tap positions. Five different scenarios were evaluated and simulated in this study using a real low voltage network. Simulation results show that the use of DR integrated with OLTC independent phase tap control (scenario 5) significantly improves the network voltage magnitude and unbalance as well as reduces the overall cost of compensation and consumer comfort level violations. In some distribution networks where the implementation of OLTC independent phase tap control is not feasible, the use of DR integrated with OLTC three phase tap control also can be an alternative solution to manage the network voltage effectively. As a future work, this study will further investigate the coordination approach of DR with the conservation of voltage reduction (CVR) technique for maximum peak demand reduction and energy conservation in unbalanced LV networks. Furthermore, a deep investigation will be carried out to linearize the optimisation problem to be used in a mathematical optimisation instead of heuristic algorithm.

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Chapter 6

Summary and Future Research

Summary

Distribution network operators are currently experiencing many operational challenges, such as ageing assets, increased distributed and renewable generation, anticipated growth of electricity demand, increasingly frequent and severe weather events, increased enormous economic and environmental pressures, causing the operators to invest more in improving their generation and network capacities. Conversely, consumers are facing increased electricity charges, the possibility of financial losses due to onsite generation curtailment and electricity interruptions. These challenges highlight a pressing need to find solutions to identify and deploy. Residential demand response (DR) is an alternative solution to avoid the need for investments in grid reinforcement and generation capacity. Despite the potential economic and technical benefits, DR is still not in widespread use by most utilities and is experiencing difficulty in attracting participants. The research in this thesis provides a detailed understanding of DR implementation challenges and its improvement strategies. The identified key challenges of successful DR implementation are presented below:

Utility's perspective:

- Lack of effective strategies of the modelling and deploying of DR programs to attract more consumers to participate *(Sections 1.3.4 and 1.4).*
- Lack of understanding of DR potential in improving network power quality and its impact on consumers' electricity bills and comfort levels *(Section 1.4).*

- Accurate optimisation methods are required for optimal and fast load control of a large number and various types of households' appliances *(Section 1.4.2.1)*.
- Lack of proper communication facilities for DR implementation. Fast, cost-effective and reliable communication infrastructures are the most desirable *(Sections 3.1 and 3.2)*.

Consumers' perspective:

- Electricity bill increases for some categories of residential consumers with existing TOU pricing program *(Sections 1.3.1, 1.3.4 and 1.4.1).*
- Less priority is given to consumers' consumption decisions to maintain their comfort levels in DR programs *(Sections 1.3.1 and 1.4).*
- Inadequate incentive payment to motivate consumers to alter their consumption behaviours *(Section 1.4.2.1).*

This thesis aims to address these challenges by adopting innovative strategies in modelling and implementing of DR that facilities both utility and consumer to participate. The DR strategies that were undertaken within this thesis include:

1. Modelled an innovative TOU pricing scheme for residential consumers which encourages all categories of consumers to participate in peak demand reduction while minimised their electricity bills with minimum impact on their comfort levels.
2. Identified suitable communication technologies to facilitate consumers to participate in DR programs and to provide the understanding of their appliances' consumption profiles for potential saving opportunity in their electricity bills.
3. Developed a fast and optimal multi-layer load control algorithm for effective management of short and long durations of voltage variations in MV networks considering a large number household appliance. The load control model was developed in such way that it considered each appliance's power consumption rating

and consumption preferences from consumers to maintain their comfort levels. Furthermore, it has the ability to distribute incentives to consumers fairly based their influence in network conditions.

4. Developed an optimal load control algorithm for managing both voltage magnitude and unbalance in LV network. The load control algorithm considered the variability of household appliances with their different consumption ratings to estimate an accurate DR potential and associated cost for each consumer. It prioritised consumers' consumption preferences and accepted dynamic bid prices at which they are willing to participate, so that consumers are motivated, and inconveniences of long-term DR contract are avoided.

The summary of each of the proposed approach are discussed below:

In Chapter 2, an innovative strategy was undertaken to develop an alternative TOU pricing scheme for countries where no DR program is integrated and have a high percentage of low-income household consumers to reduce the peak demand and its associated costs. Bangladesh was used as an example of a low-income country. Based on comprehensive investigations with different pricing models, an appropriate TOU price structure was proposed, having the lowest impact on all categories of consumers' energy bills and their comfort levels as well as having the highest peak shaving capacity. The proposed TOU pricing scheme is a combination of the traditional TOU and inclining block usage pricing schemes. This pricing scheme provided more electricity bill savings to low and middle energy consumer groups compared to the high usage consumer group. It was due to high consumer group usages more electricity during peak demand periods. Therefore, this pricing scheme provided a better electricity pricing mechanism to encourage all consumers in both energy conservation and peak reduction. Furthermore, the proposed pricing scheme was simulated in a real electric distribution network, which demonstrates the scheme's effectiveness in peak demand reduction and network investment cost minimisation.

In order to effective implementation of the proposed TOU pricing and DLC program, a cost-effective communication system is required. In Chapter 3, the different communication technologies and their suitability for use in residential DR regarding scalability, reliability, data rate, cost-effectiveness, etc., were investigated. An identified suitable wireless ZigBee-based load monitoring and control system was implemented in a typical household in Australia to obtain realistic load profiles and consumption characteristics of four major electric appliances. Each appliance's DR potential, DR capacity, possible interruption/deferral period, standby power and potential savings from standby power were estimated for DR study. It was observed that that DR capacity of each appliance was not equal during its period of operation. Therefore, the DR capacity of each appliance was considered based on the average maximum demands in its operation cycles. Furthermore, the standby energy losses of the all the appliances were measured and showed that these energy losses contribute substantial increase on consumer electricity bills.

Since the proposed TOU pricing scheme in Chapter 2 is voluntary based consumer participation, utility cannot ensure that a sufficient number of participants will engage to solve the network power quality problem within a certain period of time. To ensure the effective management of network power quality, DLC program was proposed in Chapter 4 with use of suitable communication technologies identified in Chapter 3. Chapter 4 presented a multi-layer load control strategy to manage the short and long intervals voltage variations in MV networks due to intermittent power generation from DGs. The proposed load control strategy divided larger number of households' appliances into two control schemes namely 10-minute DR scheme and 2-hour DR scheme and coordinated with DGs' reactive power to compensate the associated voltage variations in the networks. In each load control scheme, consumers were provided flexibilities to set their consumption preferences to maintain their comfort levels. In this approach, a dynamic fair incentive distribution mechanism was developed to reward consumers based on their energy contribution and the influence on the network voltage and loss improvement. The average computational times required for the optimisation process of 10-mintue and 2-hour DR schemes were 20 and 50 seconds, respectively. The proposed load control method was verified and tested in IEEE 33-bus network with considering high intermittent power generation from DG.

In addition to MV networks, DLC program can contribute significantly towards improving voltage quality and PV hosting capacity in LV network. In Chapter 5, a new effective load control strategy was developed for managing both voltage magnitude and unbalance in LV networks. The load control strategy considered the flexibilities of selected major household appliances and coordinated with on-load tap changers (OLTCs) of secondary transformer for a better improvement of phase voltages and minimisation of network loss. The proposed method was comprehensively examined on a real three-phase four-wire Australian LV network with multiple scenarios to evaluate the effectiveness of the load control algorithm. The simulation results showed that the proposed load control algorithm satisfies the network operational constraints with minimised cost of compensation while reduced consumers' comfort violations and excessive switching disturbances on appliances.

Several significant contributions were proposed in this thesis which are expected to benefit to the researchers, power utilities, consumers and finally the environment. The proposed combination of TOU and inclining block electricity pricing scheme developed in Chapter 2 is suitable for all categories of residential consumers in both developed and developing countries, as it charges consumers not only based on peak periods usages but also based on the level of their total energy usages. Therefore, this pricing scheme motivates all consumer groups in both energy conservation and peak demand reduction with minimum impact on their comfort levels.

As a result, the excessive investment in network capacity improvement and peak generation resources are eliminated or deferred as well as achieved significant reduction in CO_2 emissions during peak periods. Furthermore, the electricity interruptions due to power shortages during peak periods and its associated economic loss are minimised. With the suitable metering, control and communication technologies proposed in Chapter 3 allow easier response of consumers to time varying electricity price signals and load control signals from utilities. Consumers can receive information regarding state of the grid, environmental conditions, incentive payment or bid data and their appliances usages profiles, which encourage consumers to use their energy efficiently. Since pricing signal proposed in Chapter 2 is voluntary based consumer participation, it may not be able to maintain all power quality problems in the distribution networks. With the help of the identified suitable communication technologies in Chapter 3, the developed direct load control algorithm in Chapter 4 uses the flexibilities from a large number and various types of household appliances and reactive power from DGs to manage the short-term and long-term voltage fluctuations in the large-scale distribution networks due to intermittent of power generation from DGs. The proposed load control algorithm increases the share of the renewable energy generation in the networks without curtailing their generation capacity in critical voltage conditions as well as minimises the excessive operation of the network voltage regulation devices to maintain their operating life. As a result, the investment related to maintaining and upgrading network equipment are reduced. Moreover, consumers are incentivised fairly, and their comfort levels are prioritised in the load control algorithm, which motivates consumers to alter their energy consumption by utilities. Another benefit from this thesis is that, the developed direct load control algorithm in Chapter 5 able to effectively minimises both voltage magnitude and unbalance problems in LV networks with coordinating secondary transformer's OLTC and optimal control of selected household appliances. The proposed load control approach increases the penetration of rooftop

PVs and utilisation of the network capacity during peak demand periods in the LV networks. Thus, it minimises the need for additional hardware investment in addition to the associated operational and maintenance costs in LV networks. The load control algorithm motivates consumers by prioritising their consumption preferences to satisfy their comfort levels as well as incentivising them by allowing dynamically bid their participation prices. Over all, this thesis addresses the fundamental knowledge gap of successful DR implementation in residential sector. It facilities the implementation of the studied DR programs by utilities and consumers. By adopting the proposed approaches in the DR programs implementation, utilities can effectively utilise their existing network infrastructure for managing secure operation in the distribution networks without investing in the network expansion and generation capacity. Concurrently, consumer can gain economic benefits while preserving their comfort levels.

Future Research

To extend the research work presented in this thesis, future research work may consider the following possibilities:

DR coordinated with conservation voltage reduction (CVR) for maximum peak demand reduction and energy conservation: The Voltage reduction technique (i.e. CVR) at consumer terminals is one of the most cost-effective solutions for peak demand and energy reduction. Reducing the supply voltage at consumer terminals reduces the load demand. CVR operates in the lower half of the residential voltage band, (e.g., 216V to 230V, rather than 230V – 253V) without causing harm to consumer appliances. CVR benefits greatly depend on the voltage sensitivity of the loads and the load composition coefficient. CVR effect is measured by “CVR factor” which indicates the reduction in energy consumption for a 1% reduction in voltage [1]. The CVR factors of between 0.7 and 1.0 are most common in different utilities [2]. Residential loads can be classified as constant power, constant current or constant impedance, or a combination of all three. The CVR factor increases when the load changes from constant power type to constant impendence type loads. The voltage control does not affect the constant power type loads such as TV, Printer, electric vehicle charger, induction cooking devices, etc. Experimental results show that the voltage control mode is applicable to 70% of existing household appliances [3].

CVR is usually performed by coordinating network devices such as on-load tap-changing transformers (OLTC), switched capacitors and voltage regulators [16]. Most recently, researchers have proposed some innovative strategies to increase the performance of the CVR. For example, authors in [4] propose the combined operation of battery energy storage (BES) and CVR for load demand reduction and voltage profile improvement simultaneously. The studies [5-6] combine the concepts of CVR and DG placement together for higher energy conservation. The problem with CVR implementation in LV networks is that, LV networks host both single and three-phase users, the different power flow on the phases may result into some voltage unbalance issues that can interfere with the CVR implementation. It may happen that one phase voltage is increasing along the feeder while the others are decreasing, and this can interfere with the CVR control strategy [7]. DR coordinated with CVR can maximise the reduction on peak demand and energy consumption by alleviating the voltage critical nodes on the phases. Therefore, a research needs to be carried out to show the importance of the DR for CVR implementation in unbalanced distribution networks. By curtailing demands using direct load control approach in all voltage critical nodes on the phases, the voltages on those nodes become high, which create scope for the supply substation to reduce the voltage along all feeders with volt/var adjustment for CVR implementation. And thus, the combined operation of DR and CV will maximise the peak demand reduction and energy conservation, which will ultimately benefit both utilities and their consumers.

DR activation coordinated with multiple players in the electricity market: This thesis has studied DR activation by distribution operators for the improvement of the security of distribution networks, to alleviate problems with voltage constrained power transfer, and defer new network investment. There are other players in the electricity market who use DR independently for their benefits such as retailers and transmission system operators (TSOs) [8-9]. There is a lack of data exchange and coordination between the market players in the DR activation process. This unilateral DR activation by one market player may impact on the operations of the other market players. For example, a distributor can produce a plan specifying optimal DR scheduling (e.g., DLC, ILC, Ancillary Services, etc.) to fix reliability problems in the distribution network while, at the same time, the TSO might produce another plan to address a contingency within the transmission network [10]. If there is some overlap in the scheduled DR capacity, serious grid management problems could arise. Similarly, if a retailer activated DR to deal with the spot price volatility, DR activation may conflict with a plan produced by the TSO and distributors to deal with network contingencies [11]. It is important to understand that all players rely on DR capacity provided by the same set of consumers located within a single geographical area. Therefore, coordinated scheduling of DR will increase technical, financial, and social benefits. The distributor plays an important role because the consumers involved in DR are connected at the distribution level. Hence, the highest priority for operating DR is network reliability. A comprehensive approach is required to DR scheduling considering benefits across all players. This approach would be both more reliable and more efficient than any partial approach since it aims to optimise the overall benefit of DR. Similarly, it will reward consumers better by allowing them to deal with multiple DR-involved players.

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Appendix A

A.1 Importance of DR location selection

Fig A.1 shows the impact of DR locations selection on bus voltages. It can be observed that when DR is applied in randomly selected buses (as shown in Table A.1), it is not able to manage the voltages within the standard limits at the load condition of DR event 1 in Case 1 (see Section 4.5.1). However, when DR is applied in the proposed locations (identified by network sensitivity analysis, as shown in Section 4.2.3), it manages the voltages effectively within the standards, as shown in Fig. A.1. As mentioned earlier (in Section 4.2.3), if DR is applied in less sensitive locations, the required DR size will be higher. Table A.1 shows that the total DR size is 26% higher when DR applied in less sensitive buses compared to the high sensitive buses (proposed buses). Moreover, the total DR cost and objective function cost for random DR locations are significantly higher than the proposed DR locations. Therefore, it is important to identify the DR locations to minimise the large disturbances on consumers load as well as the associated costs.

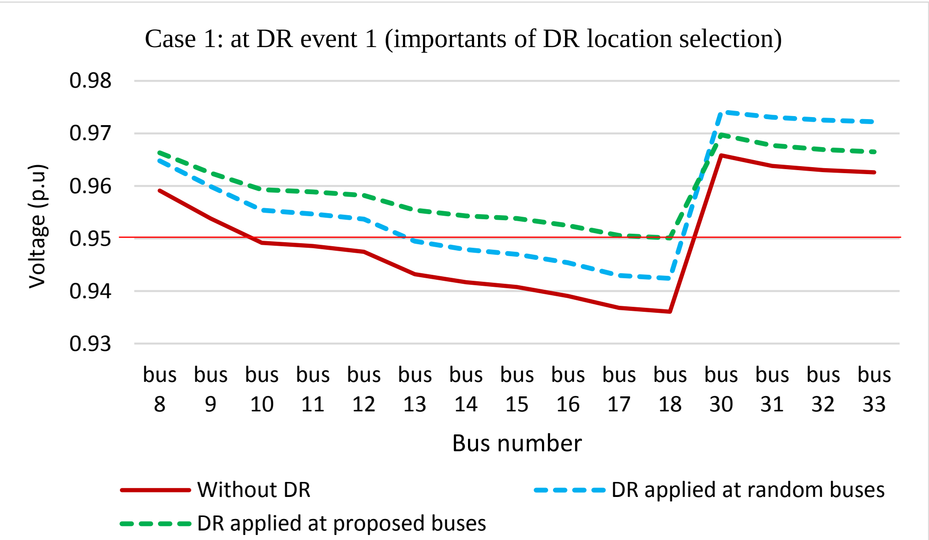


Fig. A.1. DR locations impact on bus voltages.

Table A.1

Optimisation results comparisons after DR applied in different locations

	Without DR	After DR applied (DR event 1)					
	Power loss (kW)	Power loss (kW)	Device turned off (kW)	Device turned on (kW)	Total DR Used (kW)	Total DR cost ($)	Total objective function cost
DR applied at random buses	62.34	47.44	320.4	8.8	329.2	86.2	2.7×10^{3}
DR applied at proposed buses	62.34	44.66	260	1.0	261	67.27	111.93
The random buses for DR (total 11 buses with 90 DR consumers)							
Buses: 8, 9, 10, 26, 27, 28, 29, 30, 31, 32, 33							
The proposed buses for DR (total 11 buses with 90 DR consumers)							
Buses: 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18							

A.2 Appliances switching configurations in DR event 1 (for both 2-hr DR scheme and 10-minute DR scheme)

For 2-hr DR scheme: Table A.2.1 shows the initial switching position of each appliance before DR event 1 and optimised switching position after the DR event 1 for each participated consumer. Appliances switching position 0 represent the appliance is in OFF position and 1 represents the appliance is ON position (operating state). Table A.2.2 presents the total turned on/off power, number of device disturbed, DR size and incentive payment for each participated consumer in DR event 1. It can be seen from that, consumers located at the DR candidate bus 18 receive higher incentive rate (ratio of Total cost to DR size) compared to other DR buses, as this bus has the high voltage and loss sensitivities and therefore contributes more in voltage and network loss improvement.

For 10-minute DR scheme: Table A.2.3 presents initial and optimised switching positions of ACs and EWHs (electric water heater) for all participated consumers in DR event 1. Table A.2.4 shows the details optimisation results for each participated consumer include total on/off power, number of load control, DR amount and DR participation cost. The DR costs for consumers located in bus 18 are higher than other DR buses as similar to 2-hr DR scheme.

Table A.2.1

Switching configurations for 90 participated consumers in DR event 1 (for 2-hr DR scheme)

		Before DR event					After DR event					
DR Bus	Cons. #	W.mc Pos.	Dish.w Pos.	Dryer Posi.	Pump Posi.	EV Posi.	W.mc Pos.	Dish.w Pos.	Dryer Posi.	Pump Posi.	EV Posi.	# of load disturbed
8	1	0	0	1	0	1	0	0	1	0	0	1
	2	0	1	0	1	1	0	1	0	0	1	1
	3	1	0	0	0	1	1	0	0	0	0	1
	4	0	0	1	0	1	0	0	1	0	0	1
	5	0	0	1	0	1	0	0	1	0	0	1
	6	0	0	1	0	1	0	0	1	0	0	1
	7	0	0	1	0	1	0	0	1	0	0	1
	8	0	0	1	0	1	0	0	1	0	0	1
	9	1	0	1	0	1	1	0	0	0	0	2
	10	0	0	0	0	1	0	0	0	0	0	1
	11	0	0	1	0	1	0	0	0	0	0	2
9	12	0	1	0	0	1	0	1	0	0	0	1
	13	0	0	1	1	0	0	0	0	0	0	2
	14	0	1	0	1	0	0	1	0	0	0	1
	15	1	1	0	1	0	1	1	0	0	0	1
	16	0	0	0	1	1	0	0	0	0	0	2
	17	0	0	0	1	1	0	0	0	0	0	2
	18	0	0	0	1	1	0	0	0	1	0	1
	19	0	0	0	1	1	0	0	0	0	0	2
10	20	1	0	1	0	0	1	0	0	0	0	1
	21	1	1	0	0	0	1	1	0	0	0	0
	22	1	0	0	0	1	1	0	0	0	0	1
	23	1	0	1	0	0	1	0	0	0	0	1
	24	1	0	0	1	0	1	0	0	0	0	1
	25	0	1	0	1	0	0	1	0	0	0	1
	26	1	0	0	0	1	1	0	0	0	0	1
	27	1	1	0	0	0	1	1	0	0	0	0
11	28	1	0	0	1	0	1	0	0	1	0	0
	29	0	0	0	0	1	0	0	0	0	0	1
	30	0	0	1	0	0	0	0	0	1	0	2
	31	1	0	0	1	0	1	0	0	1	0	0
	32	0	0	0	0	1	0	0	0	0	0	1
	33	0	0	1	0	0	0	0	0	0	0	1
	34	0	0	0	0	1	0	0	0	0	0	1
	35	0	0	0	0	1	0	0	0	0	1	0
12	36	1	0	0	0	1	1	0	0	0	0	1
	37	1	1	0	0	0	1	1	0	0	0	0
	38	1	1	0	0	0	1	1	0	0	0	0
	39	1	0	0	0	1	1	0	0	0	0	1
	40	1	0	1	0	0	1	0	0	0	0	1
	41	1	1	0	0	0	1	1	0	0	0	0
	42	1	0	0	0	1	1	0	0	0	0	1
	43	1	0	1	0	0	1	0	0	0	0	1
13	44	1	0	0	0	1	1	0	0	0	0	1
	45	0	1	0	0	1	0	1	0	0	0	1
	46	1	0	0	1	1	1	0	0	0	0	2
	47	1	0	0	0	1	1	0	0	0	0	1
	48	1	0	0	0	1	1	0	0	0	0	1
	49	1	0	0	1	1	1	0	0	0	0	2
	50	1	0	1	1	0	1	0	0	0	0	2
14	51	1	1	0	1	0	1	1	0	1	0	0
	52	1	1	0	0	1	1	1	0	0	0	1
	53	1	1	1	0	0	1	1	0	0	0	1
	54	1	0	0	0	1	1	0	0	0	0	1
	55	0	1	0	0	1	0	1	0	0	1	0
	56	1	0	0	1	1	1	0	0	0	0	2
	57	1	0	0	0	1	1	0	0	0	0	1
	58	1	0	0	0	1	1	0	0	0	0	1
	59	1	0	0	1	1	1	0	0	0	0	2
	60	1	0	1	1	0	1	0	0	0	0	2
15	61	1	1	0	1	0	1	1	0	1	0	0
	62	1	1	0	0	1	1	1	0	0	0	1
	63	1	1	1	0	0	1	1	0	0	0	1
	64	1	0	0	0	1	1	0	0	0	0	1
	65	0	1	0	0	1	0	1	0	0	0	1
	66	1	0	0	1	1	1	0	0	0	0	2
	67	1	0	0	0	1	1	0	0	0	0	1
16	68	1	0	0	1	1	1	0	0	1	1	0
	69	1	1	0	0	1	1	1	0	0	0	1
	70	1	1	1	1	0	1	1	0	0	0	2
	71	0	1	0	1	1	0	1	0	0	0	2
	72	1	0	0	1	1	1	0	0	0	0	2
	73	1	1	1	1	0	1	1	0	0	0	2
	74	1	1	0	1	0	1	1	0	0	0	1
17	75	0	1	0	0	1	0	1	0	0	0	1
	76	0	0	0	1	1	0	0	0	1	0	1
	77	0	0	0	1	1	0	0	0	0	0	2
	78	0	0	0	1	1	0	0	0	1	0	1
	79	1	0	0	1	1	1	0	0	1	0	1
	80	0	1	1	0	0	0	1	0	0	0	1
	81	0	0	0	1	1	0	0	0	0	0	2
	82	0	1	0	0	1	0	1	0	0	0	1
18	83	0	1	1	1	0	0	1	0	0	0	2
	84	0	0	0	1	1	0	0	0	0	1	1
	85	0	0	0	1	1	0	0	0	0	0	2
	86	0	1	0	0	1	0	1	0	0	0	1
	87	0	1	0	0	1	0	1	0	0	0	1
	88	0	1	0	0	1	0	1	0	0	0	1
	89	1	1	0	0	1	1	1	0	0	0	1
	90	0	1	1	1	0	0	1	0	1	0	1

Cell colour represents device is not available; Cell colour represents device preference setting is not to turn ON; Cell colour represents device preference setting is not to turn OFF.

Table A.2.2
Each participated consumer's load disturbed amount, DR size and incentive payments in DR event 1 (2-hr DR scheme)

		Before DR event	After DR event				
DR Bus	Consumer Per bus	Initial load (kW)	Turned-on (kW)	Turned-Off (kW)	# of load disturbed	DR size/ consumer (kW)	Total cost/ consumer ($)
8	1	6	0	3	1	3	0.475
	2	6.2	0	2	1	2	0.317
	3	6.2	0	6	1	6	0.951
	4	6	0	3	1	3	0.475
	5	6	0	3	1	3	0.475
	6	6	0	3	1	3	0.475
	7	6	0	3	1	3	0.475
	8	6	0	3	1	3	0.475
	9	6.2	0	6	2	6	0.951
	10	6	0	6	1	6	0.951
	11	6	0	6	2	6	0.951
9	1	4.2	0	3	1	3	0.592
	2	4	0	4	2	4	0.789
	3	4	0	2	1	2	0.395
	4	4	0	2	1	2	0.395
	5	4	0	4	2	4	0.789
	6	4	0	4	2	4	0.789
	7	4	0	3	1	3	0.592
	8	4	0	4	2	4	0.789
10	1	3.5	0	3	1	3	0.699
	2	3.7	0	0	0	0	0.000
	3	3.6	0	3	1	3	0.699
	4	3.2	0	3	1	3	0.699
	5	3.8	0	2	1	2	0.466
	6	3.5	0	2	1	2	0.466
	7	3.6	0	3	1	3	0.699
	8	3.5	0	0	0	0	0.000
11	1	2.9	0	0	0	0	0.000
	2	3	0	3	1	3	0.720
	3	3	1	3	2	4	0.960
	4	2.9	0	0	0	0	0.000
	5	3	0	3	1	3	0.720
	6	3	0	3	1	3	0.720
	7	3	0	3	1	3	0.720
	8	3	0	0	0	0	0.000
12	1	3.6	0	3	1	3	0.748
	2	3.5	0	0	0	0	0.000
	3	3.9	0	0	0	0	0.000
	4	3.2	0	3	1	3	0.748
	5	3.5	0	3	1	3	0.748
	6	3.7	0	0	0	0	0.000
	7	3.6	0	3	1	3	0.748
	8	3.2	0	3	1	3	0.748
13	1	4.8	0	3	1	3	0.845
	2	4.5	0	3	1	3	0.845
	3	4.6	0	4	2	4	1.127
	4	4.5	0	3	1	3	0.845
	5	4.9	0	3	1	3	0.845
	6	4.2	0	4	2	4	1.127
	7	4.5	0	4	2	4	1.127
14	1	4.7	0	0	0	0	0.000
	2	4.8	0	3	1	3	0.868
	3	4.4	0	3	1	3	0.868
	4	4.8	0	3	1	3	0.868
	5	4.5	0	0	0	0	0.000
	6	4.6	0	4	2	4	1.158
	7	4.5	0	3	1	3	0.868
	8	4.9	0	3	1	3	0.868
	9	4.2	0	4	2	4	1.158
	10	4.5	0	4	2	4	1.158
15	1	4.7	0	0	0	0	0.000
	2	4.8	0	3	1	3	0.902
	3	4.4	0	3	1	3	0.902
	4	4.8	0	3	1	3	0.902
	5	4.5	0	3	1	3	0.902
	6	4.6	0	4	2	4	1.203
	7	4.5	0	3	1	3	0.902
16	1	5.9	0	0	0	0	0.000
	2	5.2	0	3	1	3	0.927
	3	5.7	0	4	2	4	1.236
	4	5.8	0	4	2	4	1.236
	5	5.6	0	5	2	5	1.545
	6	5.4	0	4	2	4	1.236
	7	5.8	0	2	1	2	0.618
17	1	4.5	0	3	1	3	0.965
	2	4	0	3	1	3	0.965
	3	4	0	4	2	4	1.287
	4	4	0	3	1	3	0.965
	5	4.2	0	3	1	3	0.965
	6	4.2	0	3	1	3	0.965
	7	4	0	4	2	4	1.287
	8	4.2	0	3	1	3	0.965
18	1	5.2	0	4	2	4	1.294
	2	5	0	2	1	2	0.647
	3	5	0	5	2	5	1.617
	4	5	0	3	1	3	0.970
	5	5	0	3	1	3	0.970
	6	5	0	3	1	3	0.970
	7	5.2	0	3	1	3	0.970
	8	5.2	0	3	1	3	0.970
Total	90	402.5	1	260		261	67.269

Table A.2.3
Switching configurations for 90 participated consumers in DR event 1 (for 10-minute DR scheme)

		Before DR event		After DR event		
DR Bus	Cons. #	AC Pos.	EWH Pos.	AC Posi.	EWH Posi.	# of load disturbed
9	1	1	0	1	0	0
	2	1	0	1	0	0
	3	0	1	0	0	1
	4	1	0	0	0	1
	5	0	1	0	0	1
	6	0	1	0	0	1
	7	1	0	1	0	0
	8	1	0	0	0	1
	9	0	1	0	0	1
	10	1	0	1	0	0
	11	1	0	0	0	1
10	12	1	0	0	0	1
	13	0	1	0	0	1
	14	1	0	0	0	1
	15	1	0	1	0	0
	16	1	0	1	0	0
	17	1	0	0	0	1
	18	1	0	0	0	1
	19	1	0	1	0	0
11	20	1	0	1	0	0
	21	1	0	0	0	1
	22	1	0	0	0	1
	23	1	0	1	0	0
	24	1	0	0	0	1
	25	1	0	0	0	1
	26	1	0	0	0	1
	27	1	0	0	0	1
12	28	1	0	0	0	1
	29	0	1	1	0	2
	30	1	0	0	0	1
	31	1	0	0	0	1
	32	1	0	0	0	1
	33	0	1	0	0	1
	34	1	0	0	0	1
	35	0	1	1	0	2
13	36	0	1	0	0	1
	37	1	0	1	0	0
	38	1	0	0	0	1
	39	0	1	0	0	1
	40	0	1	0	0	1
	41	1	0	0	0	1
	42	1	0	0	0	1
	43	0	1	0	0	1
14	44	1	0	0	0	1
	45	0	1	0	0	1
	46	0	1	0	1	0
	47	1	0	0	0	1
	48	1	0	0	0	1
	49	0	1	0	0	1
	50	0	1	0	0	1
15	51	1	0	0	0	1
	52	1	0	0	0	1
	53	0	1	1	0	2
	54	1	0	0	0	1
	55	0	1	0	0	1
	56	0	1	0	0	1
	57	1	0	1	0	0
	58	1	0	1	0	0
	59	0	1	1	0	2
	60	0	1	1	0	2
16	61	1	0	0	0	1
	62	0	1	0	0	1
	63	0	1	0	0	1
	64	1	0	0	0	1
	65	0	1	0	0	1
	66	0	1	0	0	1
	67	1	0	0	0	1
17	68	1	0	0	0	1
	69	0	1	0	0	1
	70	0	1	0	0	1
	71	1	0	1	0	0
	72	0	1	0	0	1
	73	0	1	0	0	1
	74	1	0	0	0	1
18	75	0	1	0	0	1
	76	0	1	0	0	1
	77	1	0	1	0	0
	78	1	0	0	0	1
	79	0	1	0	0	1
	80	0	1	0	1	0
	81	1	0	1	0	0
	82	0	1	0	0	1
33	83	0	1	0	0	1
	84	1	0	1	0	0
	85	0	1	0	1	0
	86	0	1	0	0	1
	87	1	0	0	0	1
	88	1	0	1	0	0
	89	0	1	1	0	2
	90	0	1	0	1	0

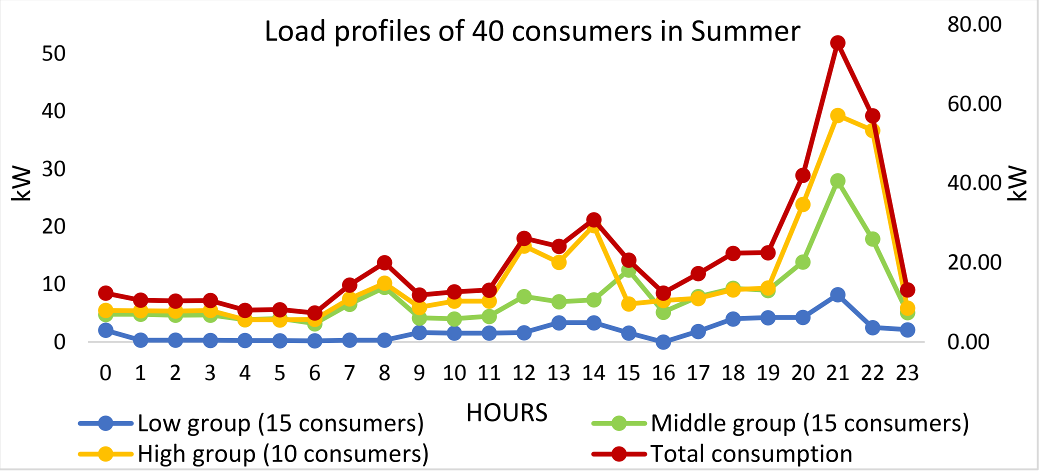
Cell colour represents device preference setting is not to turn ON; Cell colour represents device preference setting is not to turn OFF

Table A.2.4

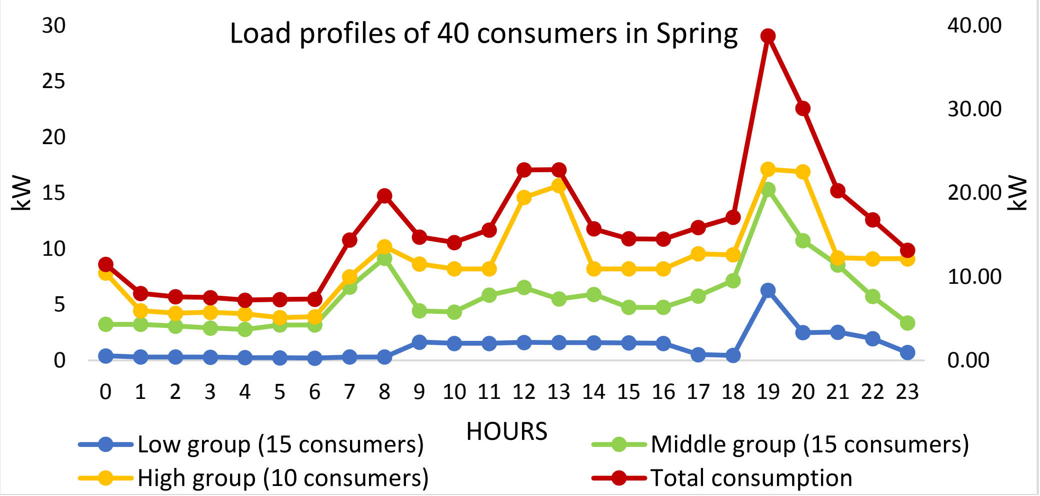
Each participated consumer's load disturbed amount, DR size and incentive payments in DR event 1 (for 10-minute DR scheme)

		Before DR event	After DR event				
DR Bus	Consumer Per bus	Initial load (kW)	Turned-on (kW)	Turned-Off (kW)	# of load disturbed	DR size/ consumer (kW)	Total cost/ consumer ($)
9	1	1.1	0	0	0	0	0.000
	2	1.8	0	0	0	0	0.000
	3	2.7	0	2.7	1	2.7	0.063
	4	1.8	0	1.8	1	1.8	0.042
	5	2.7	0	2.7	1	2.7	0.063
	6	2.7	0	2.7	1	2.7	0.063
	7	1.5	0	0	0	0	0.000
	8	1.9	0	1.9	1	1.9	0.044
	9	2.7	0	2.7	1	2.7	0.071
	10	0.5	0	0	0	0	0.000
	11	1.1	0	1.1	1	1.1	0.029
10	1	1.8	0	1.8	1	1.8	0.048
	2	2.7	0	2.7	1	2.7	0.071
	3	1.8	0	1.8	1	1.8	0.048
	4	0.5	0	0	0	0	0.000
	5	0.6	0	0	0	0	0.000
	6	1.5	0	1.5	1	1.5	0.041
	7	1.9	0	1.9	1	1.9	0.051
	8	0.2	0	0	0	0	0.000
11	1	0.5	0	0	0	0	0.000
	2	1.1	0	1.1	1	1.1	0.030
	3	1.8	0	1.8	1	1.8	0.049
	4	0.2	0	0	0	0	0.000
	5	1.8	0	1.8	1	1.8	0.049
	6	0.5	0	0.5	1	0.5	0.014
	7	0.6	0	0.6	1	0.6	0.017
	8	1.5	0	1.5	1	1.5	0.042
12	1	1.9	0	1.9	1	1.9	0.054
	2	2.7	0.2	2.7	2	2.9	0.082
	3	0.5	0	0.5	1	0.5	0.014
	4	1.1	0	1.1	1	1.1	0.031
	5	1.8	0	1.8	1	1.8	0.051
	6	2.7	0	2.7	1	2.7	0.089
	7	1.8	0	1.8	1	1.8	0.059
	8	2.7	0.5	2.7	2	3.2	0.105
13	1	2.7	0	2.7	1	2.7	0.089
	2	1.5	0	0	0	0	0.000
	3	1.9	0	1.9	1	1.9	0.062
	4	2.7	0	2.7	1	2.7	0.089
	5	2.7	0	2.7	1	2.7	0.092
	6	1.1	0	1.1	1	1.1	0.038
	7	1.8	0	1.8	1	1.8	0.062
	8	2.7	0	2.7	1	2.7	0.092
14	1	1.8	0	1.8	1	1.8	0.062
	2	2.7	0	2.7	1	2.7	0.092
	3	2.7	0	0	0	0	0.000
	4	1.5	0	1.5	1	1.5	0.051
	5	1.9	0	1.9	1	1.9	0.065
	6	2.7	0	2.7	1	2.7	0.092
	7	2.7	0	2.7	1	2.7	0.096
15	1	1.1	0	1.1	1	1.1	0.039
	2	1.8	0	1.8	1	1.8	0.064
	3	2.7	0.2	2.7	2	2.9	0.103
	4	1.8	0	1.8	1	1.8	0.064
	5	2.7	0	2.7	1	2.7	0.096
	6	2.7	0	2.7	1	2.7	0.096
	7	1.5	0	0	0	0	0.000
	8	1.9	0	0	0	0	0.000
	9	2.7	0.2	2.7	2	2.9	0.107
	10	2.7	0.5	2.7	2	3.2	0.118
16	1	1.1	0	1.1	1	1.1	0.041
	2	2.7	0	2.7	1	2.7	0.100
	3	2.7	0	2.7	1	2.7	0.100
	4	1.8	0	1.8	1	1.8	0.070
	5	2.7	0	2.7	1	2.7	0.105
	6	2.7	0	2.7	1	2.7	0.105
	7	1.5	0	1.5	1	1.5	0.058
17	1	1.9	0	1.9	1	1.9	0.074
	2	2.7	0	2.7	1	2.7	0.105
	3	2.7	0	2.7	1	2.7	0.105
	4	1.1	0	0	0	0	0.000
	5	2.7	0	2.7	1	2.7	0.106
	6	2.7	0	2.7	1	2.7	0.106
	7	1.8	0	1.8	1	1.8	0.071
18	1	2.7	0	2.7	1	2.7	0.106
	2	2.7	0	2.7	1	2.7	0.106
	3	1.5	0	0	0	0	0.000
	4	1.9	0	1.9	1	1.9	0.075
	5	2.7	0	2.7	1	2.7	0.106
	6	2.7	0	0	0	0	0.000
	7	1.1	0	0	0	0	0.000
	8	2.7	0	2.7	1	2.7	0.044
33	1	2.7	0	2.7	1	2.7	0.044
	2	1.8	0	0	0	0	0.000
	3	2.7	0	0	0	0	0.000
	4	2.7	0	2.7	1	2.7	0.044
	5	1.5	0	1.5	1	1.5	0.024
	6	1.9	0	0	0	0	0.000
	7	2.7	0.2	2.7	2	2.9	0.047
	8	2.7	0	0	0	0	0.000
Total	90	176.9	1.8	146.9		148.7	4.73

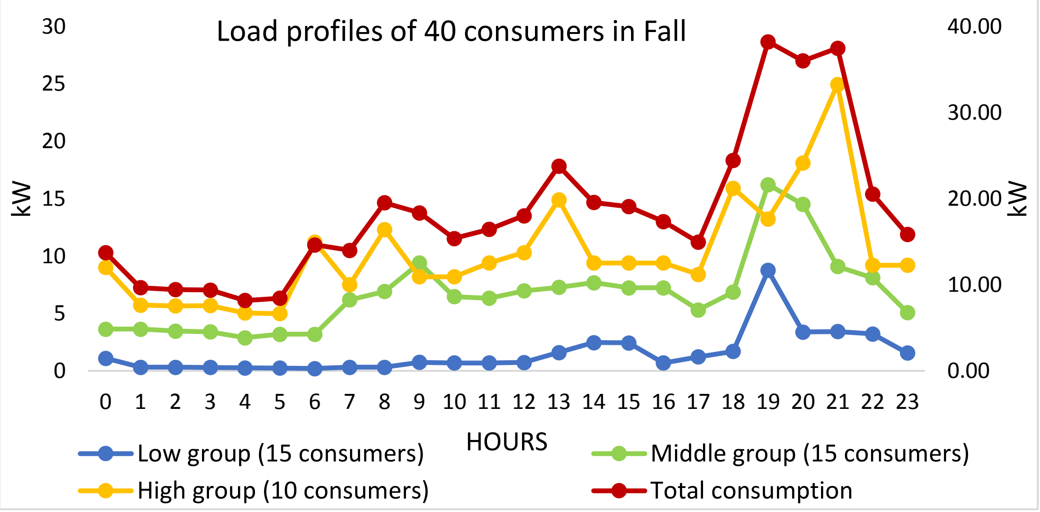
A.3 Load profiles for the test group of 40 consumers during four different seasons in Bangladesh (Chapter 2)



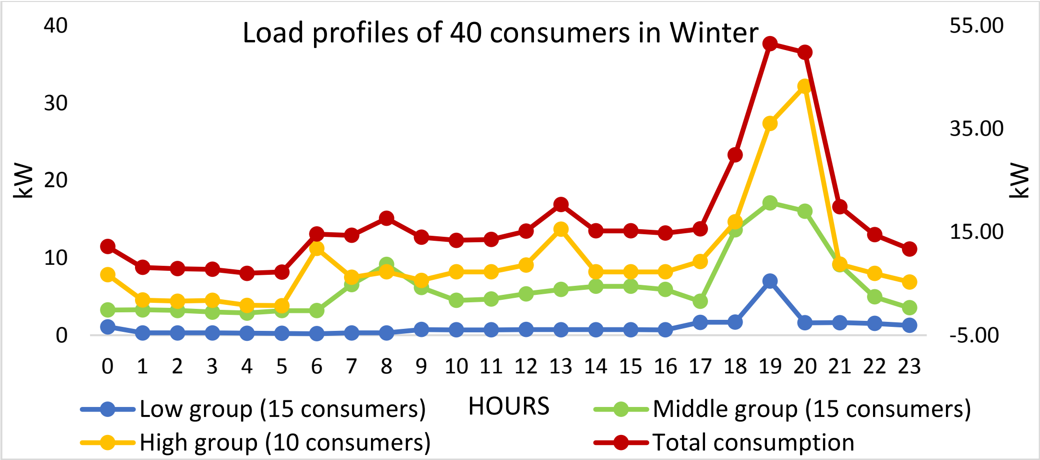
(a)



(b)



(c)



(d)

Fig. A.3.1. Load consumption data from 40 consumers during different seasons in Bangladesh

A.4 Calculation method for coincident peak demand

The following equation is used to calculate the coincident peak demand considering the six different consumer groups in the summer season (as shown in Fig. 2.3 (a)). The maximum power consumption during an hour of a day is considered as coincident peak demand in this thesis.

$$= Max\left\{P_{Low\,(t)} \times 46\% + \left(P_{Middle\,1\,(t)} + P_{Middle\,2\,(t)} + P_{Middle\,3\,(t)} + P_{Middle\,4\,(t)}\right) \times 39\% + P_{High\,(t)} \times 15\%\right\}, \quad t = 1, 2, \ldots\ldots 24h \tag{A.4.1}$$

where,

$P_{Low\,(t)}$ represents load consumption (kW) at each hour (t) for the low income consumer group (97kWh) during summer season. $P_{Middle\,1\,(t)}$, $P_{Middle\,2\,(t)}$, $P_{Middle\,3\,(t)}$ and $P_{Middle\,4\,(t)}$ represent the load consumption (kW) at each hour (t) for the Middle 1, Middle 2, Middle 3 and Middle 4 income consumer groups. $P_{High\,(t)}$ represents the load consumption (kW) at each hour (t) for the High income consumer group. The percentage values 46%, 39% and 15% represent the number of low income, middle income and high income consumer groups in Bangladesh, respectively (as mentioned in Section 2.1).

Appendix B

(Note: Content of this published conference paper shows the DR location ranking approach using voltage sensitivity analysis for Chapter 4).

Arefi, A., Shafiullah, G.M., Hettiwatte, S., *Penetration Maximisation of Residential Rooftop Photovoltaic using Demand Response*. In Smart Green Technology in Electrical and Information Systems (ICSGTEIS), 2016 International Conference on, pp. 21-26. IEEE, 2016.

Penetration Maximisation of Residential Rooftop Photovoltaic using Demand Response

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***Abstract*— The increasing penetration of roof-top photovoltaic system has highlighted immediate needs for addressing power quality concerns, especially where PV generation exceeds the household demand. This study proposes an approach for optimal implementation of demand response in residential sector to eliminate voltage violations, especially during high PV generation periods. The proposed approach uses a load flow sensitivity method to optimise the demand response implementation location and size for PV penetration maximisation in distribution networks. The simulation results on IEEE 13-bus test system show that using the proposed approach every 1 kW of DR implementation increases PV penetration by 2 kW.**

Keywords*— *Demand Response; Distribution network; Load flow sensitivity; Photovoltaic; Voltage violation.

I. INTRODUCTION

Since governments are promoting local renewable green power generation especially generation from solar photovoltaic (PV) at residential premises, the uptake of decentralized PV generation is increasing very fast. The average annual growth rate of PV has been 60% over the last few years, aiming to reduce greenhouse gas emissions and alleviate global warming [1]. Investments in fossil-based plants are being decreased due to low profitability, while, power from renewable energy sources gets the priority. However, as distribution networks traditionally are not designed for high penetration of rooftop PVs, the main challenge regarding the integration of PV units in most cases are maintaining bus voltages within the allowed voltage limits. For example, in Australia, the widespread installation of residential rooftop PV has caused concern about the risk of overvoltage [2]. Since low voltage (LV) networks have a comparatively smaller short circuit impedance and a larger R to X ratio, feed-in PV generations in LV networks often cause voltage violations if the level of PV integration is more than the feeder's PV hosting capacity [3]. The proliferation of PV generation on the distribution networks can result in some adverse impacts, including voltage variation, degraded protection, transient stability issues, reverse power flow and increased fault level [4].

Various control paradigms for voltage control in distribution networks have been developed and investigated [5-9]. These approaches can be classified into the use of existing network elements such as on-load tap-changer (OLTC) transformers, capacitor banks and voltage regulators (VRs) [5], controlling active and reactive power of PV inverters [6], network reconfiguration [8], network reinforcement using energy storage [7] and demand response (DR) [9]. These approaches for controlling voltage are either local control or coordinated central control depending on the network requirements. A coordinated central controller is more complex in nature and requires extra investment on communication technologies. Therefore, the voltage control based on a local measurement is prioritized over coordinated central control.

The presence of PVs on distribution feeders leads to increasing the number of OLTC and VR operations, resulting in a higher maintenance/overhaul cost and deterioration of the operating life [10]. Under specific operational scenarios, this equipment can fail to control voltage of the desired bus while reaching the lowest or the highest tap limit. This phenomenon is widely referred to as "reverse power tap changer runaway" condition [11]. Additionally, the network energy losses would increase slightly for enabling the voltage control capability using OLTC/VR. Voltage control using reactive power compensators such as the static var control (SVC) devices in LV networks are not effective in all cases, as the resistive part of the impedance is prevailing in LV networks. Network reconfiguration solution usually has a quite low impact on voltage control and is limited to areas and voltage levels where switching alternatives exist. Network reinforcement is a relatively high-cost solution and appropriate for a long-term voltage improvement in distribution networks [7]. For example, the small decentralized storages at prosumers' premises can actively contribute to reducing local voltage deviation. However, the economic benefit to the prosumer is limited as it is still a very expensive solution [12]. Voltage problems can be solved by curtailing the PV feed-in power [6]. However, a disadvantage of this mechanism is that this causes a lower yield of the installed PV and thus an increased payback period for the corresponding owner. PV inverters are capable of providing reactive power support for voltage control. The effectiveness of this solution ultimately depends on the impedance of the feeder and is more effective in MV networks than in LV ones. Moreover, the current feed-in policy does not provide any benefits for reactive power generation. Furthermore, this generation may place more stress on power inverters and reduce their lifetime.

Another alternative approach is to use the flexibility of households (smart) appliances in a demand response (DR) context to avoid voltage issues [13]. To cope with the intermittent electricity production from renewable sources, more flexibility is necessary for the power grid, which is found partially on the consumer side in terms of deferrable consumption. The controllable loads in the residential sector are such as dishwasher, washing machine, tumble dryer, electric vehicle, electric domestic hot water buffer, and air-conditioner. Controlling of these flexible loads can be implemented through some low-cost approaches such as DR pricing programs [14] or direct load control systems [15].

While the idea to use flexible demand for PV integration is not entirely new, maximisation of PV penetration using optimal DR has not been addressed. In the residential sector, maintenance of consumer comfort is of prime importance to achieve a sustained participation in DR. Hence, the required DR contribution from consumers should be kept as little as possible. Therefore, this study proposes a framework to optimise the location(s) for implementation of DR, namely location-specific DR, across the network, so that the least amount of consumer loads are controlled to alleviate voltage problems and maximise PV penetration.

II. METHODOLOGY

This section describes the proposed location-specific DR implementation, which includes optimising the location and the contribution of loads to DR program (e.g. direct load control program). After targeting the specific location(s) of DR, the least amount of load that can be controlled to eliminate the steady state over/under voltage problems is selected. Fig. 1 explains the flowchart of managing bus voltages in distribution network using DR. The utility operators forecast the PV generation for a period of time, e.g. for a day, and run offline load flow to check whether PV generation violates the voltage limits. For instance, bus voltage rise appears during off-peak period and high PV generation, resulting in reverse power flow in the network. By finding the DR's optimal locations, which have maximum influence on bus voltages, the management of overvoltage during these periods will be very effective. Also, appropriate sizing of DR reduces the impact on consumer comfort.

A load flow sensitivity method is used in this study to optimise the DR location and the size for reducing voltage violations due to high PV penetration. Sensitivity analysis offers a simpler approach compared to the traditional power flow simulation techniques because it transforms load flow equations into a form that is easier to conceptualize. It has been used for placement decisions of loads, generation and voltage control devices in order to maximise or minimise their effect on system voltages and network losses [16-17]. The sensitivities of bus voltage in respect to loads are computed for the current state of the network and do not remain valid for significant changes in network loading, and thus need to be re-calculated periodically [18]. Sensitivity data is analysed through two main means: 'perturb and- observe', that is, making a small change in network state [19]. In this paper, the well-known Newton-Raphson load flow algorithm [20], within DigSILENT PowerFactory software [20] is utilised for sensitivity analysis,

The Newton-Raphson load flow equations for both active and reactive power flow are:

$$\begin{cases} P_i = \sum_{n=1}^{N}(|V_i|.|V_n|.|Y_{in}|.\cos(\theta_{in}+\delta_n-\delta_i)) \\ Q_i = \sum_{n=1}^{N}(|V_i|.|V_n|.|Y_{in}|.\sin(\theta_{in}+\delta_n-\delta_i)) \end{cases} \quad (1)$$

where P_i and Q_i are the active and reactive powers of i^{th} bus, $Y_{in} \angle\theta_{in}$ is the admittance of the line from i^{th} to n^{th} buses, V_i and δ_i are the voltage magnitude and angle of i^{th} bus, respectively.

The sensitivity of bus voltages with respect to variations of active/reactive power is obtained from the inverse of the standard Jacobian matrix $\boldsymbol{J}$ which is given by (2). The expression of $\boldsymbol{J}$ is also given by (3), which defines the relationship between P-Q and V-δ in a network.

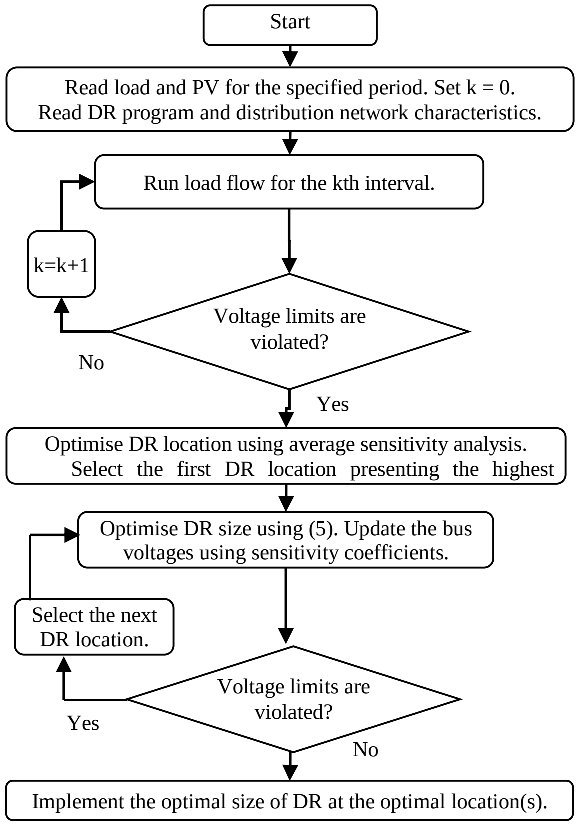

Fig. 1. Flowchart for the proposed location-specific DR.

$$\begin{bmatrix} \Delta\partial_2 \\ \cdot \\ \cdot \\ \Delta\partial_n \\ \hline \frac{\Delta|V_2|}{|V_2|} \\ \vdots \\ \frac{\Delta|V_2|}{|V_2|} \end{bmatrix} = \boldsymbol{J^{-1}} \times \begin{bmatrix} \Delta P_2 \\ \cdot \\ \cdot \\ \Delta P_n \\ \hline \Delta Q_2 \\ \vdots \\ \Delta Q_n \end{bmatrix} \quad (2)$$

$$J = \begin{bmatrix} J_{11} & J_{12} \\ J_{21} & J_{22} \end{bmatrix} = \begin{bmatrix} \frac{\Delta P_2}{\Delta \partial_2} & \cdots & \frac{\Delta P_n}{\Delta \partial_n} & |V_2| \frac{\partial P_2}{\partial |V_2|} & \cdots & |V_n| \frac{\partial P_2}{\partial |V_n|} \\ \vdots & & \vdots & \vdots & & \vdots \\ \frac{\Delta P_n}{\Delta \partial_2} & \cdots & \frac{\Delta P_n}{\Delta \partial_n} & |V_2| \frac{\partial P_n}{\partial |V_2|} & \cdots & |V_n| \frac{\partial P_n}{\partial |V_n|} \\ \frac{\Delta P_2}{\Delta \partial_2} & \cdots & \frac{\Delta P_n}{\Delta \partial_n} & |V_2| \frac{\partial Q_2}{\partial |V_2|} & \cdots & |V_n| \frac{\partial Q_2}{\partial |V_n|} \\ \vdots & & \vdots & \vdots & & \vdots \\ \frac{\Delta P_n}{\Delta \partial_2} & \cdots & \frac{\Delta P_n}{\Delta \partial_n} & |V_2| \frac{\partial Q_n}{\partial |V_2|} & \cdots & |V_n| \frac{\partial Q_n}{\partial |V_n|} \end{bmatrix} \quad (3)$$

Combining (2) and (3) yields a simplified expression for an incremental change in voltage magnitude as:

$$\Delta|V_j| \approx \sum_j \left(\frac{\partial |V_j|}{\partial P_i} \times \Delta P_i + \frac{\partial |V_j|}{\partial Q_i} \times \Delta Q_i\right) \quad (4)$$

where $\Delta|V_j|$ is the change in voltage magnitude at j[th] bus due to change in active (ΔP_i) and reactive (ΔQ_i) power at each network bus i. The sensitivity coefficients, $\partial|V_j|/\partial P_i$ and $\partial|V_j|/\partial Q_i$ are the sensitivities of $\Delta|V_j|$ due to the changes in P_i and Q_i, respectively. This form of equation enables us to calculate the bus voltage change due to power change at each bus. Therefore, all buses in the network are ranked according to their influence on other buses as a result of active and reactive power change. Therefore, the main steps for finding location and size of DR as presented in Fig. 1 are as follows:

- **Optimising DR location:** To this aim, the effect of the injection/consumption of ΔPi at individual bus is evaluated for voltage magnitude change at violated buses ($\partial|V_j|/\partial P_i$). Then the average of the set of sensitivities for individual bus for changing violated voltages is calculated. The bus with the highest average sensitivity is selected as the location of DR. If the voltage problem is not alleviated using the first DR placement, then the next bus with the highest average sensitivity is chosen for the next location of DR and so on. As seen in Fig. 1, this iterative procedure is performed to select the optimal and effective locations for DR. If the PV penetration is higher, the number of DR's locations is also higher. The effect of the injection of ΔQ is not very large compared to ΔP injection in the distribution network, as the ratio of R/X is very high. Therefore, the effect of ΔQ is not considered in this study. Also, reactive power injection from consumers is not yet reimbursed under the DR program in Australia. In this formulation, positive and negative sign of ΔP is translated to the consumption increase and decrease, respectively.

- **Optimising DR size:** This is done using the sensitivity analysis in (5) and target voltage. In this step, first, the target voltage change for the maximum violated bus voltage, namely $\Delta|V_{max}|_{Target}$, is calculated. The $\Delta|V_{max}|_{Target}$ is the difference between the original violated voltage and the maximum limit, e.g. 1±5% p.u. Then, the required ΔP_i change at ith candidate location for DR is calculated. As seen, the contribution of the consumer at each load depends on the location of that consumer and the corresponding sensitivity.

$$P_{DR,i} = \min\left(\frac{\Delta|V_{max}|_{Target}}{\frac{\partial|V_j|}{\partial P_i}}, P_{DR,i}^{max}\right) \quad ,\forall i \in \Omega_{DR} \quad (5)$$

where $P_{DR,i}$ and $P_{DR,i}^{max}$ are the required and maximum amount of DR active power at the DR location at i[th] bus, j is the bus number with violated voltage, and Ω_{DR} is the set of bus numbers of DR locations obtained from the previous step.

In this step, if $P_{DR,i}$ meets $P_{DR,i}^{max}$, the DR power is set to its maximum value at that bus and the updated voltages is calculated using the sensitivity coefficients using the following formula as depicted in Fig. 1. The new voltage magnitude at bus j due to the injected ΔP_i at i[th] bus can be directly calculated by

$$v_{j\,(new)} = v_{j\,(current)} - P_{DR,i} \times \frac{\partial|V_j|}{\partial P_i} \quad (6)$$

where $v_{j\,(new)}$ and $v_{j\,(current)}$ are the voltage magnitude of j[th] bus after and before applying $P_{DR,i}$.

Then, the next preferred DR, which is obtained in the previous step, is selected for the DR implementation. Therefore, DR contribution at the new location is calculated using (5) based on the updated values.

III. Simulation Results

In this section, a modified balanced 4.16 kV IEEE 13-bus test system, as shown in Fig. 2, is modelled with DigSILENT PowerFactory software [20] for the simulation study. The details of network and load data for this case study are provided in [21]. The upper and lower standard voltages are set at 1 ± 5% p.u. The maximum available DR at each candidate bus in this simulation is 0.2 MW. An overvoltage situation appears in this network when the total connected PV generation is high and the kW demand of the network is at a minimum level. PV units of the same size are connected to the buses 4, 5, 6, 9, 11, and 12. Here two cases are investigated in detail as:

Case 1: total PV generation of 4.2 MW,

Case 2: total PV generation of 4.5 MW.

Finally, the PV hosting capacity of this test network is analysed by using optimal level of DR implementation.

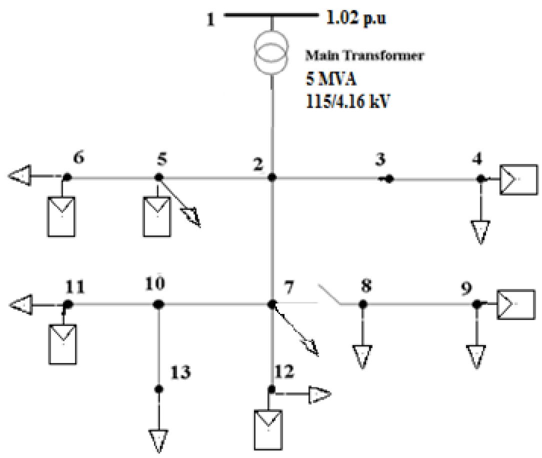

Fig. 2. The modified IEEE 13-bus distribution network.

Appendix B

A. DR location optimisation

The effective location of DR is identified by sensitivity analysis as described in Section II. Table I shows the voltage sensitivity of violated bus voltages with respect to active power change at each bus in the test case. It indicates that bus 13 and bus 11 have the highest average sensitivity coefficients than bus 12. It is important to note that the bus 12 has the largest voltage deviation; however, the average sensitivities for bus 13 and 11 are bigger than that for the bus 12. It is because of the buses, which are far from the main substation, have higher effects on voltage sensitivity coefficient of violated buses. Therefore, bus 13 has the utmost priority for DR applications and then bus 11, 12 and 9. The rank for DR location is presented in the last column on Table I. To minimise the cost of incentive to the consumers and their comfort level violation; it is crucial to optimise the amount of potential DR. The following section describes the process of optimisation of DR quantity. The negative sensitivities in Table I represent that the voltage in the violated buses increase when consumption increases (ΔP positive) at the particular buses.

TABLE I. VOLTAGE SENSITIVITY OF VIOLATED BUS VOLTAGES WITH RESPECT TO ACTIVE POWER CHANGE (PU ×10-3 /MW)

Bus number (i), $\partial\lvert V_{violated}\rvert/\partial P_i$	Bus number of violated voltages					Average Sensitivity	Rank for DR location
	9	10	11	12	13		
2	-0.5	-0.5	-0.5	-0.5	-0.5	-0.50	n/a[a]
3	-0.51	-0.51	-0.51	-0.51	-0.51	-0.51	n/a
4	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	6
5	-0.53	-0.53	-0.53	-0.53	-0.53	-0.53	6
6	-0.54	-0.54	-0.54	-0.54	-0.54	-0.54	7
7	13.33	13.34	13.33	13.31	13.34	13.33	5
8	13.33	13.34	13.33	13.31	13.34	13.33	5
9	15.11	13.28	13.27	13.25	13.28	13.64	4
10	13.3	14.41	14.4	13.28	14.41	13.96	n/a
11	13.26	14.37	15.46	13.24	14.37	14.14	2
12	13.21	13.21	13.20	16.86	13.22	13.94	3
13	13.3	14.41	14.4	13.28	17.36	14.55	1

[a] Bus 2, 3 and 10 are not the load buses and so, not applicable for DR.

B. Case 1: total PV penetration of 4.2 MW

In this part, the situation of the network with the presence of 4.2 MW PV at the locations specified in Fig. 2 is analysed. Fig. 3 shows the voltage profile and the buses with overvoltage during the high PV generation and minimum loading period. It shows that bus 12 with the magnitude of 1.051 p.u. exceeds the voltage limit (1.05 p.u.). Fig. 3 illustrates the distance between the buses and the substation as well.

The calculated optimum DR amount using (5) at bus 13 is 0.075 MW to maintain voltage magnitude at bus 12 within the standard. Fig. 4 shows the bus voltage profile using DigSILENT software. It shows that all bus voltages are brought within the limit range (1.05 p.u.) with the penetration of 4.2 MW PV generation.

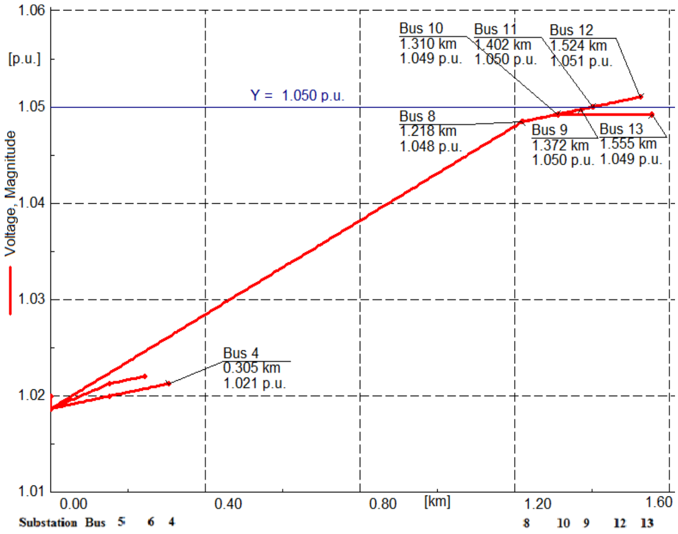

Fig. 3. Voltage profile and the bus voltages above 1.05 p.u. (overvoltage) in Case 1 in IEEE 13-bus test system without DR.

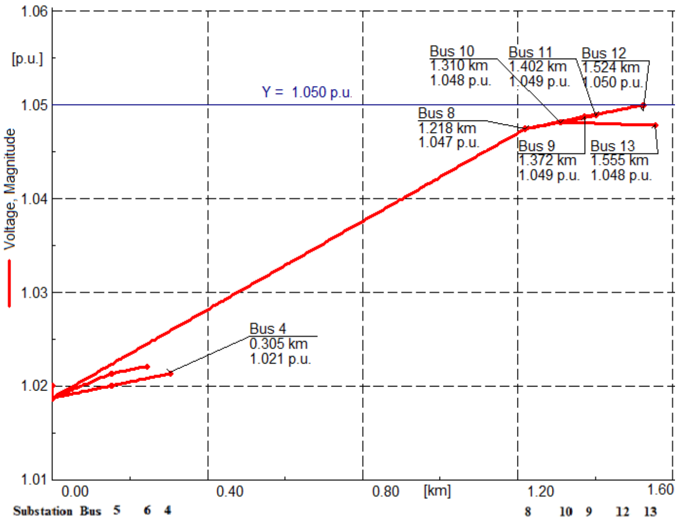

Fig. 4. Voltage profile in Case 1 with optimal location (bus 13) and 0.075 MW of DR.

C. Case 2: total PV penetration of 4.5 MW

Fig. 5 shows the voltage profile of the network in Case 2 without DR. As seen, five buses including the bus 9, 10, 11, 12, 13 have voltage violations exceeding 1.05 p.u. during high generation of PV and low demand period. In this case, first, DR is applied to bus 13 using (5), which yields that the maximum available DR to be 0.2 MW at that bus. Therefore, the next best location for DR is selected using Table I, which is the bus 11. After calculating new voltages in the network using (6), the required DR amount at bus 11 is obtained by (5), which is 0.076 MW. Fig. 6 depicts the voltage profile in Case 2 with optimal location and size of DR in IEEE 13-bus test system. These results show that by optimum implementation of DR in this distribution network, the level of PV penetration increases.

Appendix B

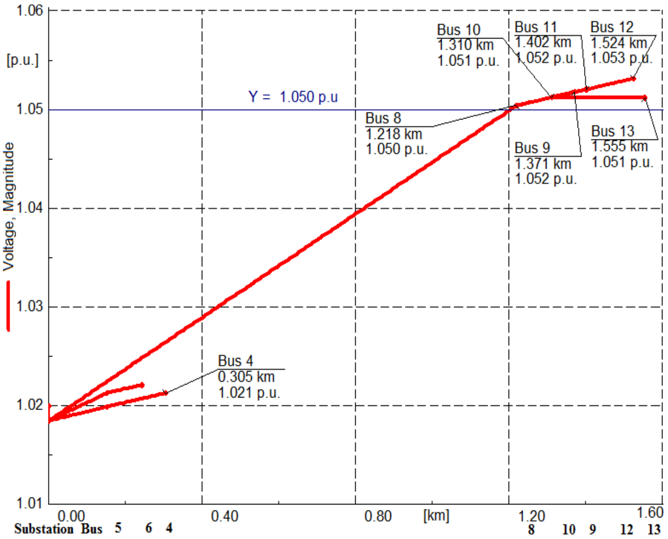

Fig. 5. Voltage profile and the bus voltages above 1.05 p.u. (overvoltage) in Case 2 in IEEE 13-bus test system without DR.

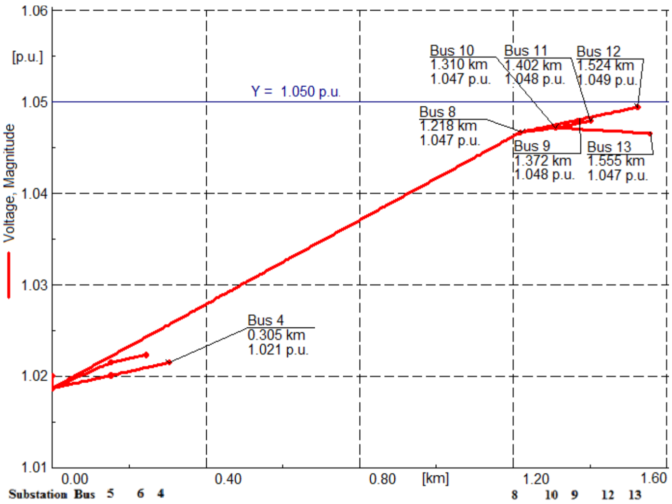

Fig. 6. Voltage profile in Case 2 with optimal location, buses 13 and 11, and the optimal size of DR, 0.2 MW and 0.076 MW, respectively.

D. PV penetration maximisation

This part discusses how DR can maximise PV penetration in distribution network. To this aim, the level of PV penetration increased from 4 MW to 6.5 MW in the network. Then the proposed approach in this paper for optimal locating and sizing of DR is performed. The total available DR in this distribution network is 1.2 MW from the bus number of 13, 11, 12, 9, 8 and 7; and each contributing 0.2 MW. These buses have positive sensitivity coefficients in this case, resulting in a positive impact on bus overvoltage as presented in Table I.

Fig. 7 depicts PV penetration in MW versus the required DR to resolve overvoltage in this network in MW. As shown, DR implementation can maximise PV penetration in distribution networks. In this case, PV penetration increases by 2.5 MW where 1.2 MW DR is applied only during high PV generation and low demand period. This simulation shows that using the proposed approach in this paper; every 1 kW of DR implementation increases the PV penetration by 2 kW. In addition, it shows that the maximum PV penetration is 6.5 MW. This level of penetration can be achieved using optimal use of DR in terms of location and size in this distribution network.

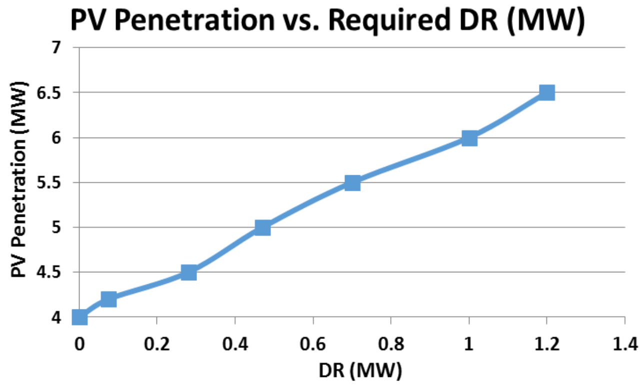

Fig. 7. PV penetration versus required DR implementation

E. Comparing with OLTC approach

To compare the performance of the proposed method, another approach, which is OLTC operation, is assessed in this paper. It is assumed that the 5MVA main transformer in Fig 2 is equipped with OLTC with ±10 tap setting and 1% voltage change per tap. Based on the Case 1 situation with 4.2 MW PV generation, OLTC can resolve overvoltage problem, however, total active loss in the network increases as shown in Table II. As seen, the network loss with OLTC approach even increases. However, DR implementation proposed in this paper not only eliminates overvoltage but also reduces the active losses in the network. This simulation shows that the proposed approach is very effective and economical.

TABLE II. TOTAL NETWORK ACTIVE POWER LOSSES USING DIFFERENT APPROACHES IN CASE 1

Solution	Total active losses (kW)
Initial condition	68.7
Using OLTC	72.6
The proposed DR approach in this paper	64.5

F. Validation of optimal DR implementation

In order to validate the proposed approach for DR implementation in distribution network, the same amount of obtained DR using the proposed approach is applied to other buses. For example, in Case 1 with a voltage violation at bus 12, the optimal location and size of DR is at bus 13 with 0.075 MW. For this evaluation, 0.075 MW DR is implemented at the buses 4, 5, and 6, and the results using DigSILENT software are shown in Fig. 8. As seen, the proposed level of DR is able to resolve overvoltage at bus 12 when it is implemented at bus 13. However, applying the same amount of DR at the other locations such as buses 4, 5, or 6 do not bring the voltage magnitude at bus 12 within the standard limit. These results show that the proposed method can find the optimal location and size of DR in distribution networks.

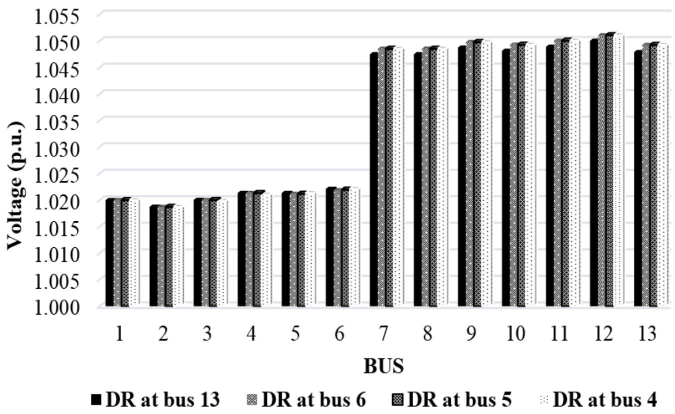

Fig. 8. The effect of DR implementation at the optimal, bus 13, and non-optimal buses 4, 5, and 6.

IV. CONCLUSION

An effective approach for maximisation of PV penetration in distribution network is proposed in this paper. The proposed approach obtains the optimal location and size of DR implementation in a network to keep all bus voltages within the standard limit using sensitivity coefficients. The simulation results on the IEEE 13-bus test system shows that the proposed approach efficiently eliminates overvoltage during high PV generation and low demand period and consequently increases the PV penetration in the network. The results show that every 1 kW optimal DR implementation based on the proposed approach, increases PV penetration by 2 kW. In addition, the study shows that the performance of DR outperforms OLTC approach in term of active power loss in the network.

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Appendix C

(Note: Content of this published conference paper shows the voltage unbalance calculation formulas and LV network configuration methods for Chapter 5)

Rahman M.M., Shafiullah, G.M, Arefi, A., Hettiwatte, S. *Improvement of Voltage Magnitude and Unbalance in LV network by Implementing Residential Demand Response*. In Power & Energy Society General Meeting, 2017 IEEE, pp. 1-5. IEEE, 2017.

Improvement of Voltage Magnitude and Unbalance in LV Network by Implementing Residential Demand Response

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***Abstract*— Maintaining voltage levels in low voltage (LV) distribution network within the standard limits is the main constraining factor in increasing network hosting ability for high penetration of rooftop photovoltaic (PV). Distribution system operator must be able to take corrective approach to avoid critical voltage unbalance and magnitude violations where rooftop PV generation is high. This study presents an effective method for voltage management in distribution networks through implementation of optimal residential demand response (DR) and transformer tap setting using a particle swarm optimization algorithm. The method is comprehensively verified on a real Australian distribution network with considerable unbalance and distributed generations. The simulation results show that PV penetration of the network can be further increased with the proposed approach.**

***Keywords*— Demand response, distribution network, voltage unbalance, photovoltaic, particle swarm optimization.**

I. Introduction

Excessive voltage unbalance and magnitude levels under normal operating conditions have become a power quality problem of concern in many power networks [1]. Since governments are promoting local renewable green power generation especially generation from solar photovoltaic (PV) at residential premises, the rapid uptake of decentralized PV generation is creating power quality concerns for the distribution system operator [2]. The distribution networks traditionally are not designed for high penetration of rooftop PVs and the main challenges are to maintain bus voltage magnitude and unbalance within the permitted limits. For instance, in Australia, the widespread installation of residential rooftop PV has caused the concern of overvoltage and voltage unbalance problems in residential LV networks [3]. The installation of PVs are generally placed randomly in the network, which create unbalance in the network [4]. The consequences are increased voltage unbalance and swells, conductor overloading and losses [5].

Voltage unbalance occurs due to the asymmetry of voltage magnitude or phase angle at the fundamental frequency between the phases of a three-phase power system [6]. There are different kinds of unbalance sources, such as the equivalent voltage source unbalance, the asymmetrical feeder lines and the unbalanced three phase loads [1]. Voltage unbalance can exist in two forms in a three-phase power system: zero sequence and negative sequence unbalances. Negative sequence unbalance is relatively more significant than zero sequence, as negative sequence current can flow through the network in a similar way to positive sequence current which increases the energy loss and reduces the capacity of the transmission/distribution line. The zero sequence current causes eddy current and energy loss as well as the windings heating of the transformer [7].

The presences of excessive levels of voltage unbalance can result in overheating and derating of all three phase induction motor loads such as squirrel cage induction motors, swimming pool pumps and air-conditioning compressors [8]. A small unbalance in the phase voltages can cause a disproportionately large unbalance in the phase currents [9]. Voltage unbalance also can cause incorrect operation of protection relays and voltage regulation equipment, and generate harmonics from power electronic loads [9]. In Australia, the distribution code allows for negative sequence voltage up to 1% on average and a maximum of 2% (can go over 2% for a maximum period of 5 minutes within each 30 minutes period) [10]. In the UK VU limit in the whole network is 2% [11] and the max limit of VU is 3% at no-load conditions according to the ANSI standard [12].

Many different solutions are proposed in the literature to tackle voltage quality problems due to high penetration of PVs [13 -17]. One of these methods is to reconfigure the feeder at the system level and phase swap at the feeder level to balance loads among feeders [13]. The problem consists with this approach is to determine an optimum switching order that allows both reduction of losses and balancing load in the network [14]. In situation where high levels of voltage unbalance are unavoidable, special balancing equipment such as unified power quality conditioner (UPQC) [15] and distribution static compensator (dSTATCOM) [16] can be installed in the network level. For example, the dSTATCOM in combination with control of on-load tap changer (OLTC) is introduced in [17]. However, all these approaches need additional hardware investments in addition to the associated operation and maintenance costs.

One important way to improve the voltage quality and efficiency of the electric power grid is through participating end-users in demand response (DR) programs [18]. DR programs, such as price-based and direct load control programs postpone investments in generation resources and network upgrade costs through active consumer participation [2]. To attain successful implementation of DR, it entails complex optimization problems due to the nonlinearity and nonconvexity of the problems. Researchers have used heuristic-based techniques such as particle swarm optimization (PSO) [19-21] to mitigate the difficulties of solving complex computational time problems and obtain the best solution. PSO algorithm is much faster and very effective in difficult optimization tasks [19] and thus it is used in this study. A PSO-based methodology is proposed in [20] to schedule DR and distributed generation resources to minimize the operation costs of a virtual power plant (VPP). In [21], a Binary Particle Swarm Optimization (BPSO) based load controller is developed for the optimal demand schedule of water heater to minimize the peak load demand. However, none of these studies have taken into consideration the voltage unbalance effect and its improvement.

Since, voltage magnitude and unbalance are the main constraining factors in distribution networks on the hosting ability and capacity to absorb rooftop PV generation, this study presents an effective method for voltage management using a coordination approach of residential DR and OLTC based on particle swarm optimization algorithm. The main goal of the optimization process is to find optimum locations and size of DR (kW) and the tap setting of OLTC to manage voltage across the network.

II. Methodology

Most available unbalance studies only consider the three-phase three-wire power system and concentrate on the unbalance definitions, standards and effects [1], which may not show actual impacts on the network. Since distribution networks are generally configured with four-wire cables/lines, the unbalance study requires proper modeling of the network parameters. Therefore, this study models a realistic LV feeder consists of three-phase, multiple earthed neutral (MEN) for steady-state voltage analysis.

Currently, there are different approaches available [9], [14], [22] to calculate voltage unbalance factor (VUF), for examples, NEMA, IEEE, IEC and CIGRE [14]. IEC considers both phase angle and RMS magnitude and is used in this study to calculate VUF. It is defined as the ratio of the fundamental negative sequence voltage component (V_2) to the positive sequence voltage component (V_1). The percentage voltage unbalance factor (% VUF) is given by (1):

$$VUF = \left|\frac{V_2}{V_1}\right| \times 100\% \tag{1}$$

where, $V_1 = \frac{V_{ab} + a \times V_{bc} + a^2 V_{ca}}{3}$, $V_2 = \frac{V_{ab} + a^2 \times V_{bc} + a \times V_{ca}}{3}$

and $a = 1 \angle 120^{\circ}$, $a^2 = 1 \angle 240^{\circ}$.

V_{ab}, V_{bc} and V_{ca} represent the line to line voltage of the corresponding phases.

A Unbalanced line modeling

For an unbalance three-phase load flow study, an accurate modeling of distribution lines is required. Therefore, Carson's line equations [23] are used for the test three-phase, multiple earthed neutral (MEN) LV line to obtain a series impedance matrix for the line/cable parameters. This 4x4 matrix in (2) considers the self and mutual coupling effects of the unbalanced three-phase line section between bus i and bus j [24]. The obtained 4x4 matrix is then converted to a 3x3 matrix using the Kron reduction method [25], the effect of the neutral or ground wire is still included in the matrix (3).

$$[Z_{ij}^{abcn}] = \begin{bmatrix} Z_{ij}^{aa} & Z_{ij}^{ab} & Z_{ij}^{ac} & Z_{ij}^{an} \\ Z_{ij}^{ba} & Z_{ij}^{bb} & Z_{ij}^{bc} & Z_{ij}^{bn} \\ Z_{ij}^{ca} & Z_{ij}^{cb} & Z_{ij}^{cc} & Z_{ij}^{cn} \\ Z_{ij}^{na} & Z_{ij}^{nb} & Z_{ij}^{nc} & Z_{ij}^{nn} \end{bmatrix} \tag{2}$$

$$[Z_{ij}^{abc}] = \begin{bmatrix} Z_{ij}^{aa-n} & Z_{ij}^{ab-n} & Z_{ij}^{ac-n} \\ Z_{ij}^{ba-n} & Z_{ij}^{bb-n} & Z_{ij}^{bc-n} \\ Z_{ij}^{ca-n} & Z_{ij}^{cb-n} & Z_{ij}^{cc-n} \end{bmatrix} \tag{3}$$

where, $Z_{ij} = R_i + j0.12134 \times f\left(\ln \frac{2h_i}{GMR_i}\right)$,

and $Z_{ij} = R_i + j0.12134 \times f\left(\ln \frac{\sqrt{d_{ij}^2 + (h_i + h_j)^2}}{d_{ij}^2 + (h_i - h_j)^2}\right)$.

To determine candidate locations for DR, a voltage unbalance analysis is performed to obtain most important candidate buses. For this analysis, the load flow equations of direct method [24] are applied. This approach uses the BIBC, BCBV, and DLF matrices which are implemented in MATLAB as in (4) and (5). The VUF of each bus and voltage and current magnitude of each phase in the bus are obtained from the load flow analysis. The direct load flow is time efficient and reduces the computational load during the PSO search.

$$DLF = BCBV \times BIBC \tag{4}$$

$$\Delta V = DLF \times I \tag{5}$$

where: DLF is the distribution load flow; BCBV is the branch-current to bus-voltage; BIBC is the bus-injection to branch-current; ΔV is the error of voltage matrix; I is the bus current vector. The next section describes the optimization process based on PSO.

B Objective function

The core of this study is dealing with a multi-objective problem which is reducing the voltage unbalance, network losses and improving the voltage magnitude while utilizing the least amount of DR cost. PSO is used to solve this nonlinear optimization problem. The optimization variables are the size (kW) and the location of DR as well as the tap position of OLTC. The outcome of the optimization is the cost minimization of DR and network loss costs. The optimization is subjected to some constraints as in (7), which are included in the objective function as a penalty. The objective function is:

$$\text{Min. f(X)} = \sum\left(DR_i \times price_i \left(\frac{\$}{kWh}\right) + Network_{losses} \times 235\left(\frac{\$}{kW}\right) + Penalties\right) \tag{6}$$

$$\text{Subject to}\left\{\begin{array}{c} VUF < 2\% \\ VUF_{Zero} < 5\% \\ 0.95 \leq |V_i| \leq 1.06 \\ |I_i| \leq I_{i,max}\ , i = 1 \ldots .n \\ OLTC\ tap\ range\ \pm 10\%, \text{with setp of } 1\% \\ DR\ per\ consumer \leq 10.5kW \end{array}\right\} \quad (7)$$

where,

$\text{Penalties} = |\text{VUF} - 2\%| \times \text{Penalty} + |VUF_{Zero} - 5\%| \times \text{Penalty} + (|\text{V}_\text{i} - 1.0| > 0.06) \times \text{Penalty} + (|\text{V}_\text{i} - 1.0| > 0.05) \times \text{Penalty}.$

X includes the values of the variables: DR size (kW) and OLTC tap position. Penalty factor is considered very high as 10^6 to exclude the relevant solution from the search space which violates the constraints in (7). $Price_{\ i}$ represents the cost of DR for each participated consumer, which is considered \$0.382/kWh [26]. This cost is excluded from the communication investment cost and consumer DR availability cost. However, it can be simply added into the cost function. $Network_{losses}$ represents the active power loss (kW) and the cost is considered \$235/kW [3].

The VUF and VUF_{Zero} (zero voltage unbalance factor) in all buses need to be less than 2% and 5% respectively [10]. Excessive VUF_{Zero} may cause additional loss in the neutral wire. However, it can simply exclude or include from the objective function based on the utility's goal. The voltage magnitude of per phase requires to be as close as possible to 1.0 p.u. The thermal limit of lines should not be overloaded in the case of high PV penetration. To limit the tap position of the OLTC, ±10% tap settings with 1% voltage change per tap change are applied. A size restriction of DR is also applied to the particles (10.5 kW per consumer). The DR size (10.5 kW) can be achieved from a consumer by adding the flexible appliances of a house such as: washing machine (1.5 kW), dishwasher (2 kW), dryer (3 kW), pool pump (1 kW) and electric vehicle (3 kW).

Consumers who participate in DR event sign a contract with the utility in advance to let the utility remotely control their appliances for a certain period. It is assumed that the communication medium (e.g. ZigBee, power line carriers, or WiFi, etc.) and remote monitoring and control devices are connected with the appliances of the participated consumers. Fig. 1 shows a flow chart of the proposed approach for voltage management in LV distribution network. Load flow analysis will be performed every 30 minutes in a day and network constraints in (7) will be checked. If the constraints are violated, the DR candidate buses will be identified based on worst VUF violation buses located at the far end of the feeder. The DR event notifications are then sent to consumers (e.g. through text, email, phone call etc.) in the candidate buses. Utility collects available flexible appliances and their status (on/off) for the DR event and optimizes the size of the DR for each consumer by switching on and off the appliances using proposed PSO based approach.

During the optimization, distribution parameters are calculated for each particle at every iteration using the load flow

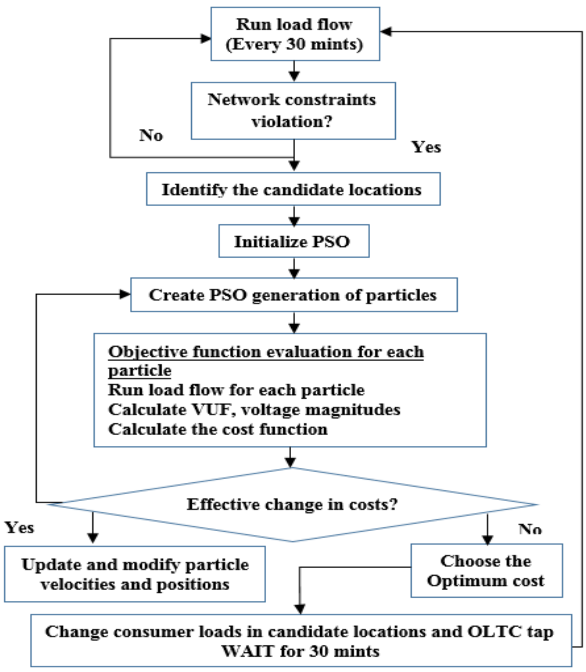

Fig. 1. Flowchart of the proposed algorithm.

equations (4) and (5). After that the objective function is evaluated with the constraints. In this study, PSO particle population member is considered 400 and a self-adaptive iteration size technique is considered. The proposed method can be applied in any LV network where voltage magnitude and unbalance limits are violated.

III. CASE STUDY

The LV network under this study is a suburban Australian radial LV distribution network consisted with 23 buses, as shown in Fig. 2. A 200kVA 22 kV/400 V distribution transformer supplies a 400/230V feeder which includes total of 77 residential consumer [4]. The sub-main cables are 7X3.75 AAC (MARS), 7X4.5 AAC (MOON), whereas, the connection from the pole-top to the individual consumer is through 6mm^2 service line. This feeder has a significant degree of current unbalance. The penetration of rooftop PVs is close to 35% (64 kW). This enables us to study the impacts of both unbalance loading and PV generation.

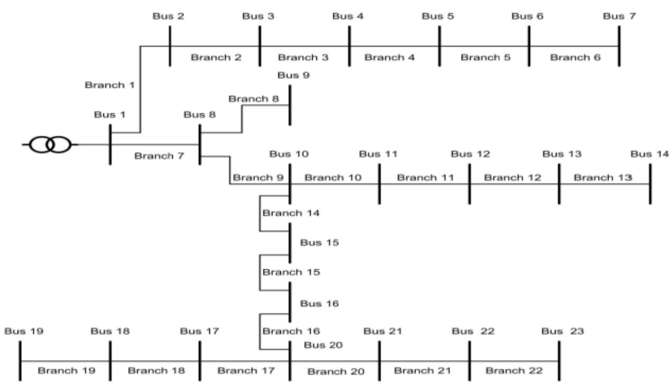

Fig. 2. Australian LV aerial network [4].

Appendix C

Typical load profiles are collected from smart meters installed in consumer premises, which have the highest degree of voltage unbalance and magnitude violations [4]. Based on the collected load profiles, the worst voltage violations cases considering high PV generation are identified and reported in Table I. The last row of the Table I represents a future scenario when the PV penetration is considered to be doubled. This study examines two cases with multiple scenarios. These cases are selected based on two highest voltage violation load profiles from Table I. The reason for this selection is to show the effectiveness of the proposed algorithm for solving the worst-case scenarios. Figures 3 and 4 display the voltage unbalance and voltage magnitude values for the base loading in Case 1 and Case 2. In Fig. 4, node voltages represent the phase voltages of 23 buses (total 69 nodes).

Case 1: 64 kW PV penetration with 122.05 kW demand.

Case 2: 128 kW PV penetration with 169.57 kW demand.

TABLE I. REPRESENTATIVE LOAD PROFILES FOR MAXIMUM VOLTAGE UNBALANCE AND VOLTAGE MAGNITUDE VIOLATIONS

Consumer power demand (kW)	Total PV (kW)	Trns. load (kVA)	Power loss (kW)	Max VUF (%)	Max VUF0 (%)	No. of nodes with over volt.	No. of nodes with under volt.
122.05	64	58.28	10.46	2.51	6.6	23	0
183.74	64	119.89	9.28	2.20	5.6	16	0
282.18	64	218.30	18.88	2.30	6.2	14	0
169.57	128	59.99	9.36	2.40	6.4	17	0

Trns.: Transformer, no: number, volt: voltage.

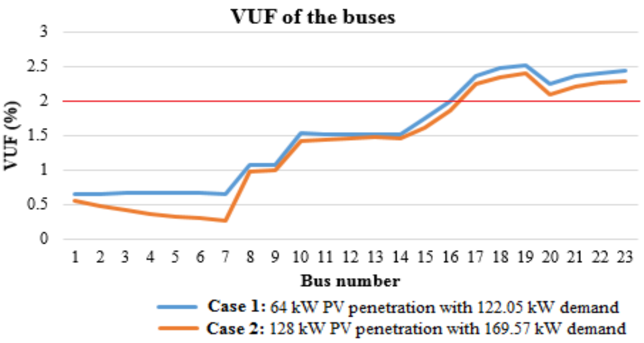

Fig. 3. VUF values of all buses for Case 1 and Case 2.

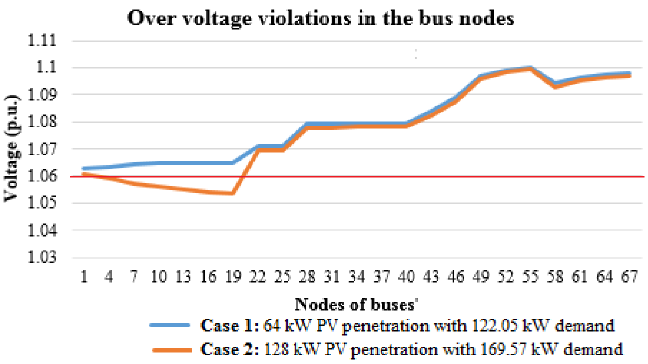

Fig. 4. Selected overvoltage nodes for Case 1 and Case 2.

IV. OPTIMIZATION RESULTS

Two scenarios for each case are considered to show the effectiveness of the proposed voltage management method, which are:

Scenario 1: DR only

Scenario 2: Both DR and OLTC

For each scenario, the PSO particle structure is configured. For example in scenario 1 (without available OLTC), each particle has maximum three cells for a DR candidate bus and each cell represents the phase location of the bus. In this study, we consider only one consumer is participated from each phase location of a candidate bus. In the scenario 2, each particle has maximum three cells for a DR candidate bus and one extra cell representing the OLTC tap position.

In general, the power loss and voltage rise/drop along the distribution line are related to the length of the line and voltage at far end of the line is more sensitive to DR than in the buses beginning of the line. It can be observed from Fig. 3 and Fig. 4 that for both Case 1 and Case 2, voltage magnitude and unbalance are significantly violated in downstream buses from bus 17 to bus 23 (7 buses). Therefore, the DR candidate buses are selected based on the downstream buses whose voltage unbalance is above the standard limit (VUF > 2%). These buses will have higher impacts on voltage and network loss. A total 21 consumer is participating in DR from these 7 buses (considering 3 consumers from each bus). Thus, each particle in PSO has 21 cells for scenario 1 and 22 cells for scenario 2.

Table II shows the results obtained from the proposed PSO based optimization method for the two cases with four scenarios. It can be comprehended that there are no VUF and voltage magnitude violations with this approach, as seen in Figs 5 and 6. For the OLTC+DR scenario of both Case 1 and Case 2, the network loss (kW), total DR size (kW) and transformer loading (kVA) as well as the total cost ($) of the solution are significantly reduced compared to the DR only scenario. It is due to OLTC tap changing provides some degree of voltage regulations in the network [17]. "DR used" in Table II represents the participated consumers' load demand increased and decreased values. The network losses for Case 1 and Case 2 are expressively reduced by 78% and 74% respectively with OLTC+DR solution in comparison with the base cases in Table I.

TABLE II. OPTIMIZATION RESULTS FROM THE PROPOSED PSO BASED VOLTAGE MANAGEMENT SOLUTION

Case 1: 64 kW PV penetration with 122.05 kW demand								
Scenario	Voltage violation	OLTC Tap (p.u.)	Loss (kW)	Loss Cost ($)	DR Used (kW)	DR Cost ($)	Trns. Load (kVA)	Total Cost ($)
DR only	non	n/a	2.78	653	88.5	34	54.8	687
OLTC+ DR	non	1.01	2.64	620	69.5	26.5	35.9	647
Case 2: 128 kW PV penetration with 169.57 kW demand								
Scenario	Voltage violation	OLTC Tap (p.u.)	Loss (kW)	Loss Cost ($)	DR Used (kW)	DR Cost ($)	Trns. Load (kVA)	Total Cost ($)
DR only	non	n/a	2.52	592	86	33	58.61	625
OLTC+ DR	non	0.99	2.47	580	71.5	27	49.93	607

Figures 5 and 6 show the optimized voltage unbalance and voltage magnitude values for all buses and selected overvoltage nodes respectively. It can be seen that VUF and voltage magnitudes for all cases are within the applied limits. Therefore, it is proven that the proposed method improves network unbalance and voltage magnitude, reduces losses and increases the PV hosting ability.

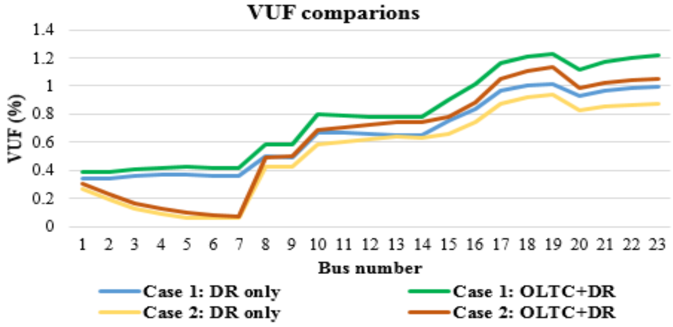

Fig. 5. VUF values of all buses for Case 1 and Case 2 with the optimized DR and OLTC.

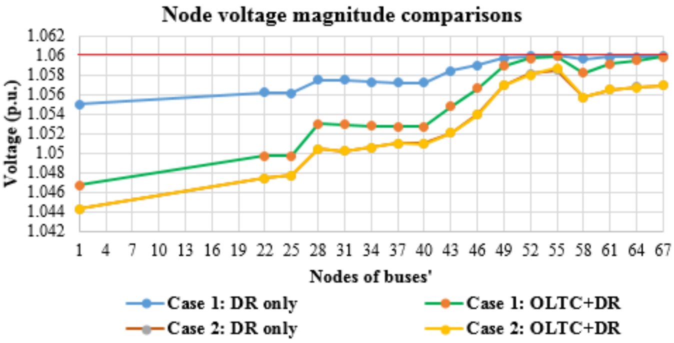

Fig. 6. Voltage magnitudes of selected overvoltage nodes for Case 1 and Case 2 with the optimized DR and OLTC.

V. Conclusion

An effective method for voltage management in low voltage distribution networks is proposed in this study. This method considered a coordination approach of residential DR and OLTC for effective improvement of network voltage unbalance and voltage magnitude. The particle swarm optimization algorithm is utilized to identify the optimal locations and size of DR and OLTC tap. The proposed method has been tested in a real low voltage network. Simulation results show that the proposed method has successfully improved the network unbalance and voltage magnitude as well as increased the PV hosting capacity.

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