ASSESSMENT OF RESIDENTIAL LOAD PROFILES AND DEMAND RESPONSE POTENTIAL FOR A RENEWABLE-BASED MICROGRID: A CASE STUDY OF AUROVILLE TOWNSHIP IN INDIA

by

Yogitha Miriyala

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Examination Committee:	Dr. Jai Govind Singh (Chairperson)
	Prof. P. Abdul Salam (Member)
	Prof. Weerakorn Ongsakul (Member)
Nationality:	Indian
Previous Degree:	Bachelor of Science in Physics, Chemistry, Mathematics, Solar Science and Environmental Sustainability Sri Aurobindo International Centre of Education Puducherry, India
Scholarship Donor:	Energy Faculty - AIT Scholarships

Asian Institute of Technology
School of Environment, Resources and Development
Thailand
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AUTHOR'S DECLARATION

I, Yogitha Miriyala, declare that the research work carried out for this thesis was in accordance with the regulations of the Asian Institute of Technology. The work presented in it are my own and has been generated by me as the result of my own original research, and if external sources were used, such sources have been cited. It is original and has not been submitted to any other institution to obtain another degree or qualification. This is a true copy of the thesis, including final revisions.

Date: May 2023

Name: Yogitha Miriyala

Signature:

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ABSTRACT

High capacities of variable renewable energy are expected to be grid-integrated in India by 2030 to mitigate climate change. This will pose new challenges for grid operators and, among other strategies, will call for high demand flexibility. Demand response (DR) has the potential to provide these flexibility services. With the projected increase in appliance ownership, residential energy consumption will increasingly contribute to peak load. Thus, this study aims to estimate the generation, storage and distribution capacity benefits of introducing residential DR to achieve 100% integration of net renewable energy in a community's microgrid. The case study is a region in Auroville, India, comprising 100 households.

Firstly, the distribution transformer (DT) and appliance-wise load profiles are generated for 2022 using metered time-series data and a survey conducted in Auroville. Then, based on future appliance ownership rates, population growth, and appliance efficiency improvements, the DT and appliance-wise load profiles are projected for 2030. Secondly, using a DR algorithm that considers appliance-specific DR factors and appliance-wise load profiles, the modified DT load profiles with DR are generated and the technical potential of DR is assessed. Lastly, the microgrid is designed for the DT load profiles with and without DR and a financial analysis is conducted.

The technical potential of DR under the highest and lowest DR potential scenarios were 20.7%, and 8.1%, respectively. The DR scenario, including only air conditioners and electric vehicles, termed DR_EV&AC, was the most financially attractive scenario with a technical potential of 15.2%. The reduction in NPC between DR_EV&AC and the scenario without DR was 3.2%. The LCOE for DR_EV&AC was 11.49 ₹/kWh and 10.38 ₹/kWh, respectively, for maximum and minimum system capital cost (SCC) scenarios. The avoided cost of energy from DR_EV&AC was 0.27 ₹/kWh. ROI for maximum and minimum SCC scenarios were 30.93 and 35.26, respectively. Supposing these benefits were translated into incentives paid to the customers enrolled in DR programs, the share of the incentive to their average monthly bill was estimated at around 20.3%, which is attractive. Thus, this study demonstrated the potential of residential DR in Auroville, India.

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LIST OF ABBREVIATIONS

AC	= air conditioner
AREA	= Australian Renewable Energy Agency
AVC	= Auroville Consulting
AVES	= Auroville Electrical Service
CAGR	= compound annual growth rate
CAPEX	= capital expenditure
CDD	= cooling degree day
CERC	= Central Electricity Regulatory Commission
CF	= capacity factor
C&I	= commercial and industrial
CPI	= copy paste imputation
CPP	= critical peak pricing
DF	= diversity factor
DLC	= direct load control
DR	= demand response
DSO	= distribution system operator
DT	= distribution transformer
EDRP	= emergency demand response program
EV	= electric vehicles
EWH	= electric water heater
FERC	= Federal Energy Regulation Commission
GHG	= greenhouse gas
ICS	= interruptible/curtailable service
ICT	= information and communications technology
IEA	= International Energy Agency
IRR	= internal rate of return
ISEER	= Indian seasonal energy efficiency ratio
ISO	= independent system operator
LCOE	= levelized cost of energy
MAP	= maximum achievable potential
NPC	= net present cost

NPV	= net present value
O&M	= operations and maintenance
OPEX	= operating expenditure
PV	= photovoltaic
PWh	= peta-watt hour (10^12 kWh)
RAC	= room air conditioner
RAP	= realizable achievable potential
RLPM	= residential load profile models
RMSE	= root mean square error
ROI	= return on investment
RTP	= real-time pricing
SO	= specific objective
SOC	= state of charge
SLP	= standardized load profile
STEPS	= Stated Policies Scenario
TANGEDCO	= Tamil Nadu Generation and Distribution Corporation
TPDDL	= Tata Power Delhi Distribution Limited
TNERC	= Tamil Nadu Electricity Regulatory Commission
TOD	= time of day
TOU	= time-of-use
TR	= refrigeration ton
TSC	= total system cost
TUS	= time use survey
VACS	= vapor absorption chiller system
VPP	= variable peak pricing
VRE	= variable renewable energy

NOMENCLATURE

B	= baseload, the average DT load during the night hours – 12 am to 7 am
CC_p	= present value of capital costs
$D_{app,\,t}$	= demand of an appliance at timestep t
D_DR_t	= DT demand after demand response
$DR_{app,\,t}$	= load reduction from demand response
$D_{shift}\_DR_t$	= DT demand after demand response from shiftable appliances at timestep t
D_t	= demand of the distribution transformer (DT) at timestep t in a day
E_DR	= total energy reduction during the peak period in a day
$E_{export,\,grid}$	= energy exported to the grid annually
$E_{import,\,grid}$	= energy imported from the grid annually
$E_{non\text{-}RE}$	= non-renewable energy produced annually
EP_p	= present value of emission penalties
E_{served}	= total energy serving load and grid exports annually
f_{app}	= appliance DR factor based on the selected scenario
FC_p	= present value of fuel costs
F_{RE}	= renewable fraction
GC_p	= present value of grid costs
GSR_p	= present value of grid sales revenue
n	= number of hours typical storage water heater can store water for DR
N_{HH}	= number of households
n_{shed}	= number of sheddable or curtailable appliances
n_{shift}	= number of shiftable appliances
$O\&MC_p$	= present value of operations and maintenance cost
$P_{BESS,\,t}$	= power from the battery at time step t
P_h	= the subset of hours in a day when the DT load is greater than 10% of the baseload
$P_{g,\,max}$	= maximum power imported from the grid
$P_{g,\,min}$	= minimum power imported from the grid
$P_{g,\,t}$	= power imported from the grid at time step t
P_{max}	= maximum charging/discharging power of EV battery
P_{min}	= minimum charging/discharging power of EV battery
$P_{RE,\,max}$	= maximum power generated by renewable energy sources

$P_{RE, min}$ = minimum power generated by renewable energy sources

$P_{RE, t}$ = power generated by renewable energy sources at time step t

RC_p = present value of replacement costs

SoC_{int} = initial state of charge of the battery

SoC_{max} = maximum state of charge of battery

SoC_{min} = minimum state of charge of battery

SV_p = present value of salvage value

t = timestep in a day 0 <= t <= 23

V_h = the subset of hours in a day when the DT load is less than 10% of the baseload

CHAPTER 1
INTRODUCTION

This chapter provides an overview of the current and future trends in the electricity sector in India, with a particular focus on Auroville, a township in South India. Exploring the emerging issues and discussing the concept of demand response, it identifies the research questions, objectives, expected outcomes, scope and limitations of the study.

1.1 Background of the Study

As of 2021, India was the third-largest electricity-consuming country in the world (Statista, 2023). Its installed capacity and electricity generations are 416 GW and 1.62 PWh, respectively (Ministry of Power, 2023). In 2017, its per capita electricity consumption was only 1,122 kWh (Statista, 2021), less than 40% of the world average of 3,000 kWh (U.S. Energy Information Administration, 2017). By 2030, the electricity demand and consumption are set to increase to 792 GW and 2.46 PWh, respectively, due to expanding economy, urbanization, industrialization, population, etc. (International Energy Agency, 2021b).

The share of the residential sector in India's final electricity consumption in 2021 was 26% (Statista, 2022). This sector's electricity use will triple over the next two decades because of the abovementioned factors, leading to rising cooling demand, electric vehicle (EV) penetration, and increasing appliance ownership (IEA, 2021b). For instance, room air conditioner (RAC) stock is projected to grow more than 20 times by 2040 (IEA, 2021b). In forecasting the penetration of electric two-wheelers in India, Niti Aayog, the Government of India's policy think tank, expects a penetration rate above 75% by 2035 in 4 out of 8 scenarios (Niti Aayog, 2022). Since these appliances are typically used or charged in the evenings, the early evening electricity demand is expected to increase drastically (IEA, 2021b).

India's power sector is responsible for around 50% of the country's carbon emissions (IEA 2021b), with a generation mix consisting of fossil fuels (57.6%), hydro (11.4), nuclear (1.7%) and other renewables (29.3%) in 2022 (MoP, 2023). Though, on the one hand, these emissions must reduce to tackle climate change, on the other hand, the country must be able to cope with its growing electricity demand needs. This challenge needs to be addressed through both supply and demand side interventions. On the supply side, this can be done by increasing the share of renewables in the generation mix, while on the demand side, this is possible through various ways such as lifestyle and behavioral changes, increasing the energy efficiency of systems, and using demand response (DR) to reduce peak demand by curtailing or shifting the demand to off-peak periods. According to the Australian Renewable Energy Agency, "DR is the voluntary reduction or shift of electricity use by customers, which can help to keep a power grid stable by balancing its supply and demand of electricity" (Australian Renewable Energy Agency, 2022).

On the supply side, India has an ambitious renewable energy target of meeting 50% of its electricity requirements from renewable energy by 2030 (Government of India, 2021) or 450 GW from solar and wind, and 50 GW from hydro (Carboncopy, 2021; Ministry of New and Renewable Energy, 2021). On the demand side, there are various energy efficiency and conservation initiatives from the Government of India (GoI) for different sectors, such as the Perform, Achieve and Trade (PAT) scheme for the industrial sector, Energy Conservation Building Code (ECBC) for commercial buildings, Eco Niwas Samhita for residential buildings and Standards & Labelling programme for end-use electrical appliances. The PAT scheme is a market-based and regulatory instrument for achieving energy efficiency in selected energy-intensive industries (Bureau of Energy Efficiency, 2020a). ECBC lays down the minimum energy efficiency levels for large commercial buildings (BEE, 2017) and Eco Niwas Samhita is a similar code for residential buildings (MoP, 2020). The Standards & Labelling programme is a scheme to provide customers with the required information regarding the energy performance of energy-intensive end-use appliances before purchasing them. Currently, it targets 29 appliances or equipment (BEE, 2020b).

While the country has various energy conservation and efficiency initiatives, DR is in its nascent stage. DR has several benefits such as generation, transmission and distribution capacity deferral (Advanced Energy Economy Institute, 2017), reduction of the peak-to-average ratio (Nair & Rajasekhar, 2014; Pal et al., 2018), ability to integrate renewable energy (Srivastava et al., 2021) and reduction of renewable energy curtailment (McPherson & Stoll, 2020) among other benefits. A few pilots in the commercial and industrial (C&I) sectors were run by Tata Power electric utility in Mumbai in 2014, Tata Power Delhi Distribution Limited (TPDDL) in Delhi in 2016, and Jaipur Vidyut Vitran Nigam Limited in Rajasthan in 2013 (Hale et al., 2018; Sarkar & Mukhi, 2016). TPDDL launched the first-ever residential DR pilot in India in 2021, which involved 4,000 residential customers in Delhi who had smart meters (TPDDL, 2021). Details of these pilots are provided in Appendix A. The peak load reduction potentials were 18 MW, 12 MW, 22 MW and 7.68 MW, respectively, for the pilots run in Mumbai, Delhi (2016), Rajasthan, and Delhi (2021).

India's electricity demand is increasing. At the same time, the country aims to increase the share of renewable energy – mainly solar and wind – to 50% in its generation mix, which could potentially lead to supply-demand gaps during the peak demand hours in the evenings. The residential sector's electricity demand is also growing, mainly due to the increasing ownership of ACs, EVs and other home appliances. It would contribute in a major way to the evening peak loads. Therefore, managing the residential demand by shedding or shifting some non-critical loads to other off-peak hours in the day is important to avoid forced outages due to supply-demand gaps. It is a service that DR provides, and as its adoption is almost non-existent in the residential sector in India, this study will focus on DR in the residential sector in India.

The research will be conducted in Auroville, a universal township in Tamil Nadu, India, with a population of around 3,305. Its electricity demand grew from 3.6 to 5.9 GW from 2010 to 2017 (Auroville Consulting, 2018). As of 2020, Auroville's per capita electricity consumption was 2,367 kWh and had grown by 47% in the previous 8 years (AVC, 2021). Since Auroville's residential sector's share in the final electricity consumption was as high as 57% as of 2017 (AVC, 2018), both the total increase in demand and per capita electricity consumption could be due to increasing household appliance ownership rates, especially due to energy-intensive appliances such as air conditioners and electric vehicles; along with a population growth rate of 3% per annum (many people join township as it is in the making for a population of up to 50,000 people from around the world to experiment with human unity in diversity).

Currently, the township's generation mix consists of rooftop solar energy (23%), wind wheeling (25%), and grid energy (52%). 700 kW of rooftop solar energy is installed. Under Phase 1 & 2 of the Smart Mini Grid project in Auroville, along with solar, 60 kWh of lithium-ion battery storage and 85 smart meters including data management systems have been installed using a corporate social responsibility grant (AVC, 2021a, 2021b). A long-term renewable energy sourcing plan was prepared considering various renewable capacities, energy storage capacities, and energy efficiency scenarios. The report points out that a 100% sourcing of Auroville's electricity demand through renewable energies could be achieved by 2030 (AVC, 2021a). This is mainly because the cost of solar energy in the region, which is at 3.10 ₹/kWh (TNERC, 2021), is currently lower than the cost of grid supply at 6.75 ₹/kWh (TNERC, 2022), and cost reductions in energy storage are expected in the near future (AVC, 2021a).

1.2 Statement of the Problem

Auroville's increasing electricity consumption and demand will pose challenges, especially as the township plans for 100% renewable energy sourcing.

- As Auroville's electricity demand increases, there is a possibility that the secondary distribution transformers (DT) in the township must be upgraded and Auroville would bear its cost.
- Despite battery storage, solar energy surplus is exported to the grid and not credited to Auroville by the Tamil Nadu Generation and Distribution Corporation (TANGEDCO) (AVC, 2021a). As planned, when more rooftop solar will be installed in the community to achieve its 100% renewable energy sourcing plan, the un-credited surplus exported to the grid will also increase, incurring financial losses to the township.
- When the electricity demand is low during periods of high renewable energy availability, as more renewable energy capacity is installed, more storage will be required to reduce the surplus exported to the grid, requiring higher storage capacities.
- As storage is an expensive option, there is a need to find and assess alternative cheaper options for optimal sizing of the generation and storage technologies.

Noting the residential sector's contribution to the growing electricity demand, there is a need to manage its demand by curtailing and shifting residential loads from peak hours to periods of high renewable energy availability. This reduces the peak load resulting in DT capacity deferral, and instead, the demand increases during periods of high renewable energy availability, resulting in a reduction of the surplus exported to the grid and the storage capacity. Therefore, as the appliance ownership rates increase contributing to the evening peak loads, it is important to assess the future potential of DR in the residential sector in Auroville to see to what extent it can reduce the generation and storage capacities, as well as defer DT upgrades in the future. The learnings from this study would be relevant for India and other developing countries, which aim to increase the share of renewable energy in their generation mix and simultaneously face the challenge of increasing electricity demand and consumption, especially from the residential sector.

1.3 Research Questions

According to the problem statement mentioned above, the research questions of this study are:

1. Considering the increasing cooling demand, EV penetration, and appliance ownership in the residential sector in Auroville/India, what will be the domestic load profile of Auroville by 2030?
2. How much is the technical DR potential of the residential sector in 2030 in Auroville?
3. What are the costs and benefits to the microgrid with 100% net RE generation (based on a constraint on net import and export to the grid)?

1.4 Objectives of the Study

Auroville has set a target to achieve a 100% net sourcing of its electricity needs from renewable energy by 2030. In this context, the overall objective of this study is to find out the generation, storage and distribution capacity benefits of introducing residential DR, through a forecast of appliance-wise domestic load profiles, to the achievement of 100% integration of net renewable energy (based on a constraint on net import and export to the grid). The specific objectives are:

1. To forecast the distribution transformer and appliance-wise domestic load profiles for the residential community in Auroville in 2030.
2. To assess the residential community's appliance-wise and aggregated technical DR potential.
3. To find the technical and financial feasibility of sourcing 100% renewable energy in scenarios with and without residential DR in the community.

1.5 Scope and Limitations of the Study

- The community microgrid referred to in this study is only for all loads connected to the 250 kVA secondary distribution transformer (DT) named "Admin DT" in Auroville, India.
- Only the residential loads connected to the "Admin DT" are referred to as the residential community in this study.
- The scope of the DR analysis is only for the residential community, whereas the projected load in 2030, the renewable energy sourcing, and the costs and benefits of the DR scenario are considered for the entire community microgrid.
- The DR potential is assessed only for technical potential.
- In the residential community, the DR potential is assessed only for air conditioners, water heaters, electric vehicles, washing machines and refrigerators, and the rationale for choosing only these appliances will be explained in the next chapter.
- The DR assessment is only for managing the power demand and doesn't include voltage and frequency regulation.
- The timeframe of 2030 is chosen due to Auroville's plans to install a community microgrid by 2030 that can run with 100% renewable energy but uses the grid for balance. At the same time, since it is quite close to the future, many projections for the residential demand based on which future DR potential will be estimated could hold true to a large extent.

1.6 Organization of the Study

Chapter 1 introduced this study by presenting the background of the study, the problem statement, research questions, study objectives, and the scope and limitations of this study. The literature reviewed to conduct this study is provided in Chapter 2, where the main concepts of DR, DR potential assessment framework, a review of studies that assessed DR potential, among other topics, are discussed. Chapter 3 explains the methodology of this study, where the several steps for addressing each specific objective are explained in detail. Chapter 4 provides the results of each specific objective of this study, followed by a discussion of the results. Chapter 5 will conclude this study and discuss future recommendations.

CHAPTER 2
LITERATURE REVIEW

This chapter provides the literature reviewed to conduct this study. The first sections, 2.1-2.3, provide the main concepts of demand response (DR) – a primer on DR including its definition, origins and services; the different categories of DR potentials; and the different types of DR programs. Section 2.4 lays the framework to assess all the categories of DR potentials and identifies the major steps that need to be viewed in detail to conduct this study. The subsequent sections 2.5 - 2.8 elaborate on these major steps – identification of appliances suitable for DR, approach for estimating residential appliance-wise load profiles and a review of studies that assessed theoretical and technical DR potentials – and highlight the kind of inputs required for the assessment. Finally, sections 2.9, 2.10 and 2.11 deal with the sizing of a microgrid, the various cost and profits of DR, and the policies and regulations enabling DR in India.

2.1 Demand Response: A Primer

2.1.1 Definition of Demand Response

Table 2.1 provides the definitions used by different organizations or authors. Australian Renewable Energy Agency (AREA) considers DR as a voluntary action to change (reduce or shift) the electricity usage of customers (AREA, 2022). Federal Energy Regulation Commission (FERC) also considers DR as a change in the electricity usage of demand-side resources while specifying how these changes are triggered – due to changes in electricity prices or incentive payments. Both sources consider DR as a way to reduce supply-demand gaps ("keeps a power grid stable by balancing its supply and demand of electricity" or "system reliability is jeopardized") (FERC, 2022). However, Albadi & El-Saadany (2007) don't discuss DR as a way to reduce supply-demand gaps but specify the actions that will modify the electricity usage – "alter the timing (shifting the demand), level of instantaneous demand, or the total electricity consumption (shedding load)" (Albadi & El-Saadany, 2007).

Table 2.1

Definitions of demand response from various sources

Source	Definition
Australian Renewable Energy Agency (AREA)	"Voluntary reduction or shift of electricity use by customers, which can help to keep a power grid stable by balancing its supply and demand of electricity."
United States Federal Energy Regulation Commission (FERC)	"Changes in electric usage by demand-side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized."
Albadi & El-Saadany (2007)	"All intentional modifications to consumption patterns of electricity of enduse customers that are intended to alter the timing, level of instantaneous demand, or the total electricity consumption."

2.1.2 Origins of Demand Response

Historically, the power industry was mostly a monopoly, with state-owned companies performing generation, transmission and distribution (vertically integrated). This was mainly due to economies of scale, where it was viewed that one large entity catering to electricity demands would be more efficient than several smaller ones in competition. However, during the 1970s, due to technological advances, smaller generation units (less than 500 MW) also became economically viable. During the same period, awareness of the consequences of GHG emissions was also growing. Furthermore, due to the 1973 oil crisis, electricity security was questioned and the need to diversify the power generation mix was identified (Lotfi et al., 2019).

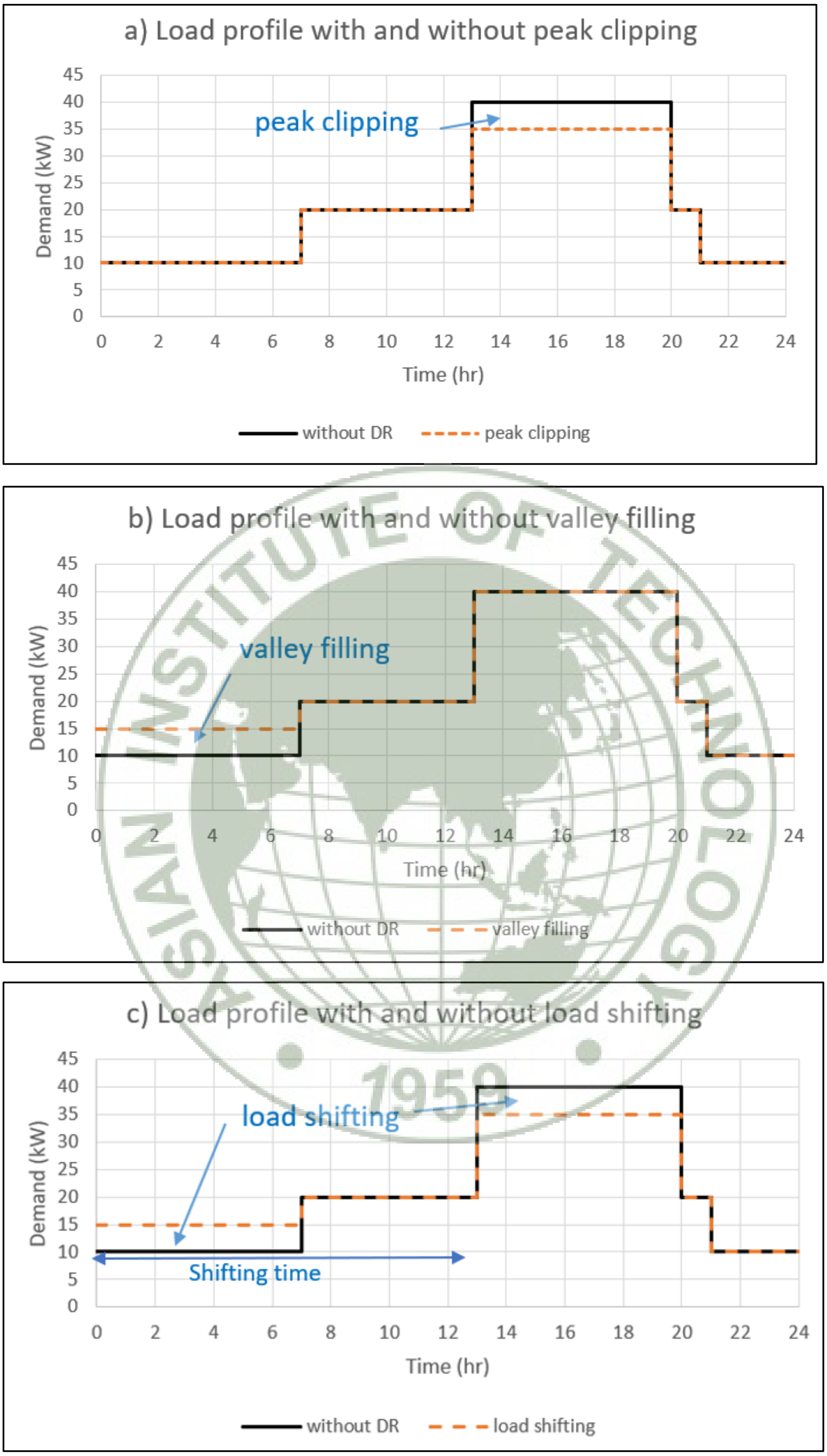
Due to the socio-economic aspect and the environmental sustainability of power systems, the above events caused a global electricity market reform. They resulted in two parallel movements: a) unbundling and deregulation of the power industry and 2) including clean and renewable energy into the generation mix. Unbundling of the power industry means separating the generation, transmission and distribution activities (Florence School of Regulation, 2021), and deregulation means including private entities in the electricity market (Raikar & Jagtap, 2018). Renewable energy is intermittent and non-dispatchable, which makes it unreliable (Lotfi et al., 2019). Thus, in contrast to the classical philosophy of being able to supply all demand whenever and in whatever quantity, as the power industry was restructuring, a new philosophy emerged which says that if the fluctuations in demand are minimized, the system will be the most efficient (Albadi & El-Saadany, 2007). Hence, the demand side also started participating actively in the power industry, and demand response originated. The United States, the United Kingdom and European Union were the first to implement DR programs by including DR in their legislation (Lotfi et al., 2019). Australia, Singapore, Chile, China, and Colombia are also implementing or adopting important measures to implement DR (IEA, 2021a).

2.1.3 Demand Response Program Services

DR can provide different services to the system by peak clipping, valley filling and load shifting. They are typically behaviours that are managed by the utilities. Peak clipping is a service that reduces the peak load demand through curtailment of some loads when the supply cannot meet the demand effectively. Valley filling is a service that increases the off-peak load by increasing the load, such as battery storage charging, EV charging, thermal storage for water heaters, etc. Often, this service increases electricity consumption without increasing the electricity bill. Load shifting is a service that shifts the loads from one period to another, generally from peak to off-peak hours. This duration between these two periods is known as the shifting time. These services are illustrated in Figure 2.1a - Figure 2.1c.

Figure 2.1

Peak clipping, b) valley filling and c) load shifting services offered by DR



Note. Adapted from Li et al. (2017).

2.2 Categories of Demand Response Potentials

DR potential is the potential of the DR programs to provide DR services. Therefore, it is crucial first to assess the DR potential in a location so that we can size the other generation resources and know whether an investment in this field would be profitable or not. Different terms have been used in the literature for demand response potentials, such as demand-side flexibility, flexible demand potential, flexible load potential, and load flexibility potential (Dranka & Ferreira, 2019). The potential of DR can be either theoretical, technical, economic, or achievable, depending on the assumptions used (Müller & Möst, 2018). While there is a general agreement in how most authors define the theoretical and economic DR potentials, it is not true with technical and achievable DR potentials. So, the following section will provide the different definitions of these DR potential categories and the definitions that will be used in this study (Dranka & Ferreira, 2019).

2.2.1 Theoretical Demand Response Potential

There is a consensus on the definition of theoretical DR potential. It is the overall DR potential that is available in the power system. It is the absolute maximum potential and comprises all the facilities and devices of the customers suitable for DR (Dranka & Ferreira, 2019; Gils, 2014; Müller & Möst, 2018).

2.2.2 Technical Demand Response Potential

The technical DR potential is smaller than the theoretical potential because it considers technical restrictions (Müller & Möst, 2018). There is no consensus on the way these restrictions are defined. For example, according to Gils (2014), only the equipment that is currently controlled by information and communication infrastructure is considered in the technical DR potential assessment. According to Grein & Pehnt (2011), only the load that is temporally available for time shift considering "technical peculiarities and legal regulations" is considered for technical DR potential assessment. According to Dranka & Ferreira (2019) the technical DR potential is defined as the potential derived from the theoretical potential by considering technical restrictions such as shifting time, duration and the number of interventions.

2.2.3 Economic Demand Response Potential

There is again a consensus on the definition of economic DR potential. It is smaller than the technical potential and depends on the type of DR program – price-based or incentive-based (Müller & Möst, 2018). It also depends on the capital costs (smart meter, information and communication technologies (ICT), etc.) and operational costs (Dranka & Ferreira, 2019).

2.2.4 Achievable Demand Response Potential

Achievable DR potential is smaller than the economic DR potential. Dranka & Ferreira (2019) consider it as the customers' acceptance level and load interventions. It is further divided into maximum achievable potential (MAP) and realizable achievable potential (RAP). MAP is derived by considering the restrictions from consumers' resistance and market and societal barriers limiting consumers from participating in DR programs. RAP is derived from MAP considering regulatory, financial and political barriers (Dranka & Ferreira, 2019).

Table 2.2 shows the results of some studies that have estimated the theoretical, technical, economic and achievable DR potentials either for or including the residential sector in different regions. An overview of the studies that assessed the theoretical and technical DR potentials will be provided later. An overview of the studies that estimated the economic and achievable DR potentials are provided in Appendices B and C, respectively.

Table 2.2

Theoretical, technical, economic and achievable potentials estimated by different authors for different regions, including the residential sector

Authors	DR potential category	Country/region	Sectoral coverage	Results
Grein & Pehnt (2011)	Theoretical	Germany	C, I & R[a] refrigeration systems	4.2 GW (6% of the maximum power demand in the country)
Söder et al. (2018)	Theoretical	Denmark, Estonia, Finland, Latvia, Lithuania, Norway, & Sweden	C, I & R	12 – 23 GW with a peak load of 77 GW

Authors	DR potential category	Country/region	Sectoral coverage	Results
Gils (2014)	Theoretical	34 countries in Europe	C, I & R	61 GW load reduction & 68 GW load increase potential
Dranka & Ferreira (2020)	Theoretical	Brazil	C, I & R	12.8 GW in 2017 & 25.6 GW in 2050
Babrowski et al. (2014)	Theoretical	Germany, Denmark, Finland, Netherlands, Switzerland, & United Kingdom	residential	24% of the vehicles are constantly available for load shifting when only home charging is allowed
Kwon & Østergaard (2014)	Technical	Denmark	C, I & R	2.48 GW in 2h & 2.11 GW in 24h time frame in 2050
Stötzer et al. (2015)	Technical	Medium-sized German city[b]	Residential & Commercial	8 GW (16% of the peak demand in the residential & commercial sectors) in 2030
Müller & Möst (2018)	Technical	Germany	Industry, tertial & residential sectors	2.5 GW for 2035 (RE - 60%) & 2.3 GW for 2050 (RE - 80%)
Alfaverh et al. (2021)	Technical	United Kingdom	Residential	23% and 15% reduction in the morning and evening peak loads, respectively
AEE Institute (2017)	Economic	Michigan, United States	Residential	382 MW for CPP & 151 MW for DLC[c]

Authors	DR potential category	Country/region	Sectoral coverage	Results
Nair & Rajasekhar (2014)	Economic	India	5 households	2.8 kW
Medha et al. (2019)	Achievable	United States	Mass market[d]	4.3 GW
TPDDL (2022)	Achievable	Delhi, India	4,200 residential customers	7.68 MW during 16 events called in a span of 3 months

Note. a - commercial, industrial and residential is abbreviated as C, I & R; b – a hypothetical city with 500,000 citizens; c – CPP is critical peak pricing and DLC is direct load control (will be explained in the following section); d – mass market consists of AC, thermostat control, water heater and other behavioural DR.

2.3 Types of Demand Response

In general, customers alone will not be motivated to provide DR services to the utility, as seen in the earlier section. So, there are a few ways in which they can be motivated to participate in DR programs. Depending on the motivation method used to encourage the customers to participate in DR programs, DR programs can be categorized as price-based or incentive-based. In price-based programs, the customers voluntarily change their load in response to price signals. In incentive-based programs, they are paid for the achieved load reduction over a specified period (Paterakis et al., 2017). This section will elaborate on both these types of DR programs.

2.3.1 Price-Based DR

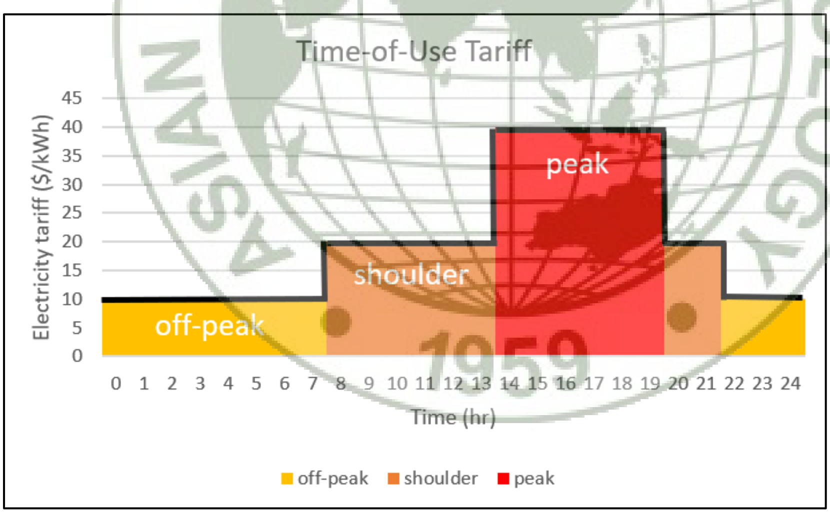
Electricity can be priced statically or dynamically. Static prices do not change when the demand changes, but dynamic prices change when the demand varies and depends on the demand (Dutta & Mitra, 2017). So, under static pricing schemes such as flat or block rate tariffs, the customers are not encouraged to shift some of their electricity consumption to off-peak periods, thereby reducing the peak load. However, with dynamic pricing, such as time-of-use (TOU) tariffs, critical peak pricing (CPP), variable peak pricing (VPP), and real-time pricing (RTP), the customers are encouraged in different ways to participate in DR services. Typically, price-based DR programs are suitable for residential customers (Li et al., 2017). The following sections elaborate on these different price-based programs.

2.3.1.1 Time-of-Use (TOU)

TOU tariffs reflect, to an extent, the variations in electricity provision costs. Electricity provision costs also vary within a day and season depending on the demand and market conditions. TOU tariffs typically include a peak rate, an off-peak rate and sometimes, a shoulder rate (Paterakis et al., 2017). They are pre-determined tariffs that are high during peak hours and low during off-peak hours. Shoulder time is when electricity demand is ramping up or down, and shoulder rate is the tariff associated with this period. Figure 2.2 shows the off-peak, shoulder and peak TOU rates (the tariff rates are only for illustration and not real). TOU tariffs are also called the time of day (TOD) tariffs (Dutta & Mitra, 2017).

Figure 2.2

Illustration of TOU tariff



Note. Adapted from Guerrero et al. (2018).

2.3.1.2 Critical Peak Pricing (CPP)

In CPP, the prices are very high during a few peak hours in a season or year, known as critical peak events, and discounted rates are applied during the remaining periods to compensate for the high prices occurring at these peak events (Energysage, 2021). The utility informs the customers about these events on short notice, ranging from even minutes to hours before the event (Paterakis et al., 2017). In TOU pricing, the prices and the periods when the different prices are applied are known well in advance. However, in CPP, the price applied during peak events is the same for all peak events and is known in advance, but the periods when these rates are applied are known only on short notice.

2.3.1.3 Variable Peak Pricing (VPP)

VPP is similar to CPP, except the prices for critical peak events vary. In some cases, the prices are chosen from a set of pre-determined tariffs, and in some cases, they depend on the wholesale electricity market prices (Badtke-Berkow et al., 2015). Again, the customers are informed beforehand about the peak events and the corresponding rates.

2.3.1.4 Real-Time Pricing (RTP)

As the name indicates, in RTP, the prices are updated frequently to reflect the true electricity supply costs more accurately. Typically, they are updated hourly. Here, the prices and the periods when these will be applied are not known in advance; therefore, this pricing scheme is the riskiest and most uncertain for consumers. And since the prices change at such short intervals, it is necessary to have advanced communication technologies and robust databases to inform the customers of the changing prices and to store and transfer high data rates (Dutta & Mitra, 2017).

2.3.2 Incentive-Based DR

Unlike price-based DR programs, in incentive-based DR programs, the customers are offered incentives, typically monetary incentives, to change their usual consumption patterns. Once the commitment from the customers is made through contracts, or any other form, with the utility or grid operators, they are expected to reduce the load as defined in the contracts. Failure to do so usually results in a penalty for the customers.

Direct load control (DLC), interruptible/curtailed service, demand bidding, capacity markets, emergency demand response, and ancillary service markets consist of incentive-based DR programs (Sharifi et al., 2017). Typically, these programs suit industrial and big commercial customers, and the residential sector can participate through aggregators (Li et al., 2017). The following section will elaborate on these different incentive-based DR programs.

2.3.2.1 Direct Load Control (DLC)

The utility or an aggregator can remotely control customers' appliances in the DLC program. The customers must have a remote-control switch system so that the appliance can be rescheduled, turned on and turned off. The type of appliance, the duration of the interruption and the number of such interruptions in a year are all defined in the contract. These programs typically target many small customers. The participants are compensated through extra payments or electricity bill discounts. Since these programs are managed by the utility, active involvement of the customer is not needed and they are often not notified in advance of the interruption (Li et al., 2017; Paterakis et al., 2017).

2.3.2.2 Interruptible/Curtailable Service (ICS)

The utility notifies customers to reduce loads to some level when the grid is congested or during peak periods. Unlike DLC, the typical customers are from the industrial or large-scale commercial sectors. The participants are again compensated through discounted electricity bills. However, a penalty is applied when the load reduction from the customer is not enough in the specified period because this is a mandatory program (Aalami et al., 2010). There is no penalty in the DLC program because the participant is not involved. However, since the result depends on the participant in ICS, a penalty is applied for non-compliance (Li et al., 2017).

2.3.2.3 Demand Bidding

In demand bidding, the utilities do not notify the customers. Instead, they announce the quantity of electricity that must be reduced and the customers bid on the reduction they can make. If the bid is accepted, the customers must provide the necessary curtailment, and if not, they are penalized. Again, this is suitable for industrial and large commercial customers (Krarti, 2018).

2.3.2.4 Capacity Markets, Emergency Demand Response, & Ancillary Service Markets

Wholesale market providers usually offer capacity market programs. In capacity markets and emergency demand response programs (EDRP), the curtailed load from the customers is treated as system capacity because they reduce the generation capacity. EDRP is a voluntary program; thus, the customers are not penalized if they fail to curtail load (Aalami et al., 2010). They are called only during emergencies (Contreras et al., 2016). In ancillary service markets, the customers bid for electricity reductions, similar to demand bidding. However, these bids are used as operational reserves and to maintain the system reliability by the independent system operator (ISO). Like the other incentive-based programs, the customers are penalized for non-compliance and are awarded for compliance. The customers are from the industrial or large-scale commercial sector. However, small customers can also participate in these programs through an aggregator (Mansouri et al., 2021).

Table 2.3 summarizes the key information from the above sections. As noted earlier, price-based DR programs are more suitable for residential customers and incentive-based DR programs are more suitable for large commercial and industrial customers. Sometimes, residential customers can also be included in incentive-based programs through aggregators. In price-based programs, the risk to the customer increases with increasing uncertainty in the rates and the periods when these rates are applied. In incentive-based programs, the risk to the customers is through the penalty factor and loss of convenience. The DR potential will depend on the selected DR program; therefore, identifying a suitable DR program will be important for assessing DR potential and its success when implemented.

Table 2.3

Summary and comparison of different types of DR programs

DR program	Category of DR program	Type of customer	Penalty	Risk to customer
TOU	Price-based	industrial, commercial, residential	no	low
CPP		industrial, commercial, residential	no	medium
VPP		industrial, commercial, residential	no	medium to high
RTP		industrial, commercial, residential	no	high
DLC	Incentive-based	residential	no	low
ICS		industrial, commercial, aggregator	yes	medium
Demand bidding		industrial, commercial, aggregator	yes	medium

Capacity markets, EDRP, and ancillary service markets		industrial, commercial, aggregator	yes	medium

2.4 Demand Response Potential Assessment Framework

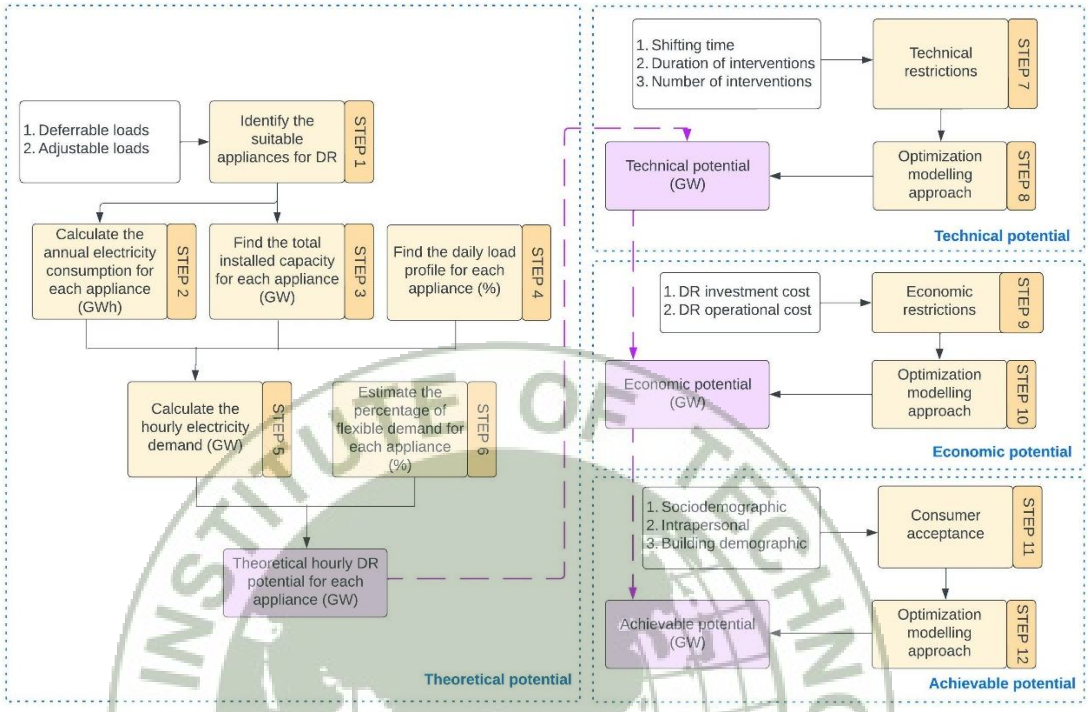
As seen in the previous section, there are various DR potential categories, and hence have different assessment methodologies. However, depending on whether the electricity demand is seen at an aggregate or decomposed level, these methodologies can be classified broadly into these two methods. In the aggregated approach, the potential is assessed using market mechanisms and needs price elasticity of demand as input data. In the second approach, the electricity consumption is decomposed into many end-use processes and using certain technical criteria specific to each process, the DR potential is assessed (Kwon et al., 2014). The price elasticity of electricity in the residential sector is complex due to the varied consumption patterns of domestic customers. Furthermore, it is difficult to obtain or derive this data for India. Therefore, the decomposition method will be used in this study to estimate the DR potential.

Dranka et al. (2019) noted that an increasing number of studies focused on assessing different categories of DR potentials with different assumptions. They pointed out that a general procedure for estimating the different DR potential categories was missing. Therefore, they reviewed the literature and developed a framework for estimating the different categories of DR potentials. Since their work was found to be comprehensive, their framework based on the decomposition method will be used in this study and is described below.

Figure 2.3 shows the steps in estimating different DR potential categories, starting with the theoretical potential till the achievable potential. These steps can be followed to estimate the DR potential in any sector – industrial, commercial and residential, and are explained below. Sections 2.4.1 to 2.4.4 explain briefly the steps in the flowchart related to theoretical, technical, economic and achievable DR potentials for the residential sector.

Figure 2.3

Process and framework for estimating the various DR potential categories



Note. Adapted from (Dranka et al. (2019).

2.4.1 Theoretical Demand Response Potential

Step 1: To identify the suitable appliances for the DR program depending on the characteristics of the appliance to shift or shed loads, or whether it is classified as deferrable or adjustable loads. Note that the term "appliance" in the flowchart can be replaced with "process" for industrial or commercial sectors.

Step 2 – 4: To estimate or calculate the aggregated annual electricity consumption (GWh), maximum aggregated installed capacity (GW), and the typical load profile (%) of each appliance identified in Step 1.

Step 5: To calculate the hourly electricity demand (GW) using the following equation for each appliance:

Hourly electricity demand = (Annual electricity demand x Load profile) / Full load hours (GW) Equation 2.1

Step 6: To estimate the share of flexible demand for each appliance so that the theoretical hourly electricity DR potential can be derived from the hourly electricity demand.

The sum of all hours from each appliance will result in the total theoretical DR potential (Dranka et al., 2019).

2.4.2 Technical Demand Response Potential

Step 7 – 8: Technical restrictions typically depend on the shifting time, duration, and the number of interventions. The technical DR potential is assessed using an optimization modeling approach such as linear or stochastic programming (Dranka et al., 2019).

2.4.3 Economic Demand Response Potential

Step 9 – 10: Economic restrictions typically depend on the DR investment and operational costs. Again, using an optimization modeling approach, the economic DR potential is assessed (Dranka et al., 2019).

2.4.4 Achievable Demand Response Potential

Step 11 – 12: Depending on a few qualitative variables, such as informational, technical, legal, financial, and organizational barriers, the consumer's level of acceptance is determined. Combining this with technical or economic optimization models, the achievable potential is assessed (Dranka et al., 2019).

2.4.5 Discussion

The scope of this study is the assessment of technical DR potential. For this purpose, the major steps in this framework can be condensed and are 1) identification of appliances suitable for DR, 2) estimation of the load profiles for each appliance selected for DR, 3) assessment of the theoretical DR potential and 4) assessment of the technical DR potential. Thus, the subsequent sections will elaborate on each of these major steps to assess the technical DR potential in the context of the case study region.

2.5 STEP 1: Identification of Appliances Suitable for Residential Demand Response

The starting point of DR potential assessments is to identify the set of appliances suitable for the DR programs. Generally, appliances can be classified in two ways depending on their operational characteristics:

1. Deferrable and non-deferrable loads
2. Adjustable and non-adjustable loads (Li et al., 2017).

Deferrable and non-deferrable loads are distinguished by their ability to shift or change their operating times. Deferable loads can be shifted to other time slots, stopped, or restarted, allowing interruptions and time shifts – for example, washing machines, EVs, dishwashers, etc. Deferrable loads can reduce the peak load demand and are fit for DR programs. Non-deferrable loads must operate at their specified schedule – for example, lights, kitchen appliances, etc. Non-deferrable loads are generally unsuitable for DR programs (Arteconi et al., 2018; Li et al., 2017). Deferrable loads are also referred to as shiftable loads.

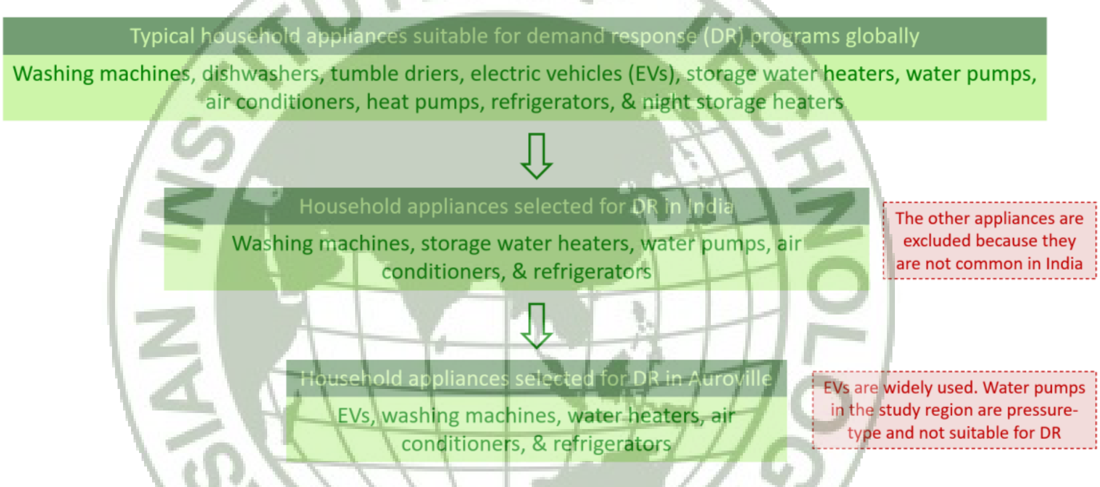
Adjustable and non-adjustable loads are distinguished by their ability to adjust to a lower level of power consumption. Typically, adjustable loads are thermal loads and, therefore, even called thermostatically controlled loads or also referred to as sheddable loads. Examples are air conditioners, heat pumps, refrigerators, etc. Adjustable loads can reduce their total electricity consumption and are suitable for DR programs. Non-adjustable loads are loads that cannot reduce their total electricity consumption, such as televisions and computers. Non-adjustable loads are not suitable for DR programs (Arteconi et al., 2018; Li et al., 2017).

The appliances selected for DR programs vary depending on location and usage. For example, heat pumps are night storage heaters offer good DR potentials in Germany Müller et al. (2018), while dishwashers, tumble driers, and heat circulation pumps are used in a study by Gils (2014) to assess the DR potentials of 34 countries in Europe. Some authors have worked on residential DR in India and identified a few appliances for their studies. For example, Nair et al. (2014) included water heaters, water pumps, electric vehicles, washing machines, and vacuum cleaners, while Mohammad et al. (2019) included water heaters, air conditioners, washing machines, and clothes driers. Some studies have focused particularly on single appliances, such as ACs (Eapen et al., 2019; Srivastava et al., 2021) or a couple of them, such as ACs and refrigerators (McPherson et al., 2020).

Among the appliances chosen for DR studies in India, a few appliances commonly used in Auroville are ACs, EVs, water heaters, refrigerators and washing machines. Therefore, the appliances selected for DR in this study are ACs, EVs, water heaters, refrigerators and washing machines. Figure 2.4 illustrates the identification process of household appliances for the DR program in Auroville.

Figure 2.4

Illustration of household appliances selection for the demand response program



2.6 STEP 3: Approach for Deriving Load Profiles of the Residential Sector

The next step after identifying the appliances suitable for DR is estimating the load profiles of each appliance so that their temporal availability is known, i.e., only the load that is switched on can be shedded or shifted. Therefore, this section focuses on literature that has estimated residential load profiles.

Typically, the residential load profile models (RLPMs) can be categorized into bottom-up and top-down models. Bottom-up RLPMs calculate individual building electricity consumption and extrapolate the results to a target area such as a city or country. On the other hand, top-down RLPMs derive relationships between the total electricity consumption and other macro-variables and then use those relations for modeling the results (Proedrou, 2021). Compared to the top-down models, bottom-up RLPMs provide detailed results due to end-use appliance modelling. Therefore, several studies use this method. Firstly, the end-use appliances are identified, and load profiles for each appliance are generated. Next, all the load profiles are aggregated and in the final step, the model is validated by comparing the results to measured data (Proedrou, 2021). The load profile generation of individual appliances can be characterized according to the input type, i.e., time use survey (TUS) data or metered appliance time series data.

TUSs provide detailed information about the duration and time at which people do various activities such as household work, food preparation, etc., and are recorded through residents maintaining personal dairies (Torriti, 2014). Since the type of equipment used depends on the occupant activity, a relation between activities and energy use is created to develop activity-specific profiles for each end-use appliance. For example, food preparation can be assigned to appliances such as hotplates, ovens, refrigerators, etc. Markov Chains are used to model the probability of transitioning from one state or activity to another (Johnson et al., 2014). Several studies have used TUSs to create synthetic appliance-wise residential load profiles. Pachanapan (2021) combined Thailand appliance ownership rates with TUS data from the UK to simulate high-resolution residential load profiles in Thailand. Irish national TUS activity data was used to create occupancy, appliance and lighting load profiles (Neu et al., 2015). Johnson et al. (2014) combined the occupant behavior model and residential load models to simulate the residential load profiles. The occupant behavior model is derived from the US TUS, and the residential appliance-wise load models are developed and validated. It requires several inputs such as ambient temperature, solar irradiation and thermal conductivities of building mass.

Using metered appliance-wise time series data as the model input is another category of bottom-up RLPMs. The load profiles can either be from any organization's database or from intrusive appliance monitoring through measurement campaigns when metering devices are connected to household appliances (Proedrou, 2021). Several authors monitored different household appliances during measurement campaigns. Besagni et al. (2020) measured the appliance-wise load profiles of Italian households, which were divided into several groups based on a sociodemographic analysis. For each group, the usage probabilities of several household appliances were derived from the time-series data. Gao et al. (2018) extracted similar days to the prediction day from historical days. The operational probability of the 5 most similar days was averaged to obtain the operational probability for the prediction day for each appliance, which was multiplied by each appliance's average power consumption. Clemente et al. (2021) generated appliance-wise load profiles for office buildings. However, their methodology can also be applied to residential buildings. The appliance-wise load profiles were generated based on measurement campaigns. The appliance stock N in the office building was estimated based on a survey and a load curve was randomly selected from the measurement data for N appliances, and those load curves were summed.

While the above studies use either TUS data or metered time-series data to generate load profiles for the current day, a few additional factors must be considered while doing long-term forecasting. Lindberg et al. (2019) reviewed methodologies to do long-term forecasting for hourly electricity demand in a regional scale. They recommended considering factors such as GDP growth, population growth, technological developments and appliance penetration. For constructing the domestic load profile for a future year, Müller et al. (2018) decomposed the domestic load into flexible and inflexible components. The flexible component consists of all appliances suitable for DR and the inflexible component consists of the remaining appliances. The inflexible component was simply scaled up using a scaling factor for the future year. The flexible component was constructed using a bottom-up approach considering the number of households, the market penetration rates of appliances, the average power consumption of each appliance type and the load shapes of each appliance (assuming that the load shape of each appliance remains the same in the future).

In this study, monthly average daily load profiles for each appliance will be constructed for 2022 and 2030. Constructing an hourly load profile for each appliance for each day of the year in 2030 is beyond the scope of this study as the quality of data required for that purpose is not available. The study will consider factors such as future appliance ownership rates, population growth, efficiency improvements and the typical load shapes of each appliance for the long-term forecast. However, apart from the efficiency improvements in air conditioners, the technological developments for other appliances will not be considered as they are already mature technologies. An important assumption is that there is no emergence of technology for the services provided by the selected appliances in the study. Furthermore, the effect of climate change on the future usage of appliances dependent on weather conditions, such as ACs and electric water heaters, is difficult to determine as it is complicated to do a long-term forecast for temperature and other weather factors in a specific region. Thus, this study does not consider the cooling demand change in the study region due to climate change in 2030.

2.7 STEP 3: Theoretical Demand Response Potential Assessment

Once the appliances suitable for DR are selected and their load profiles estimated, it is possible to assess the theoretical DR potential of each appliance. Many authors estimated the theoretical DR potential of various sectors, including the residential sector, to understand the potential of DR to increase the power system's flexibility. This section provides an overview of these studies and concludes with the methodology common to most of them.

Grein et al. (2011) assessed the theoretical DR potential of refrigeration systems in Germany. The theoretical potential was considered as the variable load of the refrigeration systems. To assess the potential of DR, the installed capacities of existing facilities were obtained from the administration of Mannheim city and used as the baseline. Since it was necessary to know when the refrigeration systems are available for load shifting, for example, the time of the day and the season of the year, they investigated the typical usage patterns of refrigeration systems from the literature. The theoretical DR potential was estimated at 4.2 GW, about 6% of the maximum power demand in the country. The DR potential was first estimated for Mannheim city and then extrapolated to the whole country. About 10% of the total theoretical potential in Mannheim city was from households or the residential sector.

Babrowski et al. (2014) studied how load increases brought about by electric vehicles (EVs) could influence the national energy system in six European countries. EV load curves were extracted from mobility studies obtained from the literature. The DR potential of EVs was obtained by defining upper and lower bounds. The upper limit for the DR potential was derived from the total number of EVs at the charging facilities in a given hour. Since some vehicles must be charged daily due to high daily trip distances, it would not be easy to control their charging profiles, so they are excluded from contributing to the DR potential. So, the lower limit is the fraction of EVs that must not be charged daily to be available for DR when needed in a day. The study found that at least 24% of the vehicles were available when charging was allowed at home (Babrowski et al., 2014).

Gils (2014) also assessed the theoretical DR potential in Europe, including the residential sector. They concluded that overall, the minimum load reduction and increase potentials available in each hour of the year are 61 GW and 68 GW, respectively. The residential sector contributed to around 17% and 97% of the load reduction and increase potentials, respectively. The residential sector's high contribution to the load increase potential was due to the restrictions considered in the industrial and commercial sectors for advancing loads (Gils, 2014).

While the above studies are all located in Europe, Dranka et al. (2020) assessed the theoretical DR potential in a developing country, Brazil. Their methodology was based on Gils (2018) and Müller et al. (2018). The study found that although a large share of the potential was from the industrial sector, a lower but substantial share is found for both commercial and residential sectors. In 2017, the overall theoretical maximum hourly potential was assessed as 12.8 GW, and it is expected to almost double to 25.6 GW in 2050.

The methodology to estimate the theoretical potential is similar in all the above studies. Typically, the hourly electricity demand of each appliance is estimated. Then, a fraction of this hourly electricity demand is considered as the theoretical potential of that appliance. This fraction, which differs for each appliance, is termed the flexible component, according to Dranka et al. (2019). The percentage of flexible demand used by some authors is listed in Table 2.4. It can be noted that the values vary a lot. For example, in Germany, Stötzer et al. (2015) assumed the flexible demand for heat pumps and air conditioners as 2% and 4.8%, respectively, compared to Müller & Möst (2018) who assumed these values as 100% and 75% respectively. Another study developed scenarios for this flexible demand and assumed 33%, 67% and 100% for all the appliances selected for DR in each scenario (McPherson & Stoll, 2020). For electric vehicles, Babrowski et al. (2014) assumed that all the EV load is available for DR, and therefore the share of EV flexible demand is 100%. Since the flexible component of each appliance is specific to the location, climate, and usage of the residents, they may be different in the context of India.

Table 2.4

Percentage of flexible demand for different appliances used in the literature

Appliance	Percentage of Flexible Demand (%)			
	Stötzer et al. (2015)	**Müller & Möst (2018)**	**McPherson & Stoll (2020)**	**Babrowski et al. (2014)**
	(Germany)	**(Germany)**	**(India)**	**(6 European countries)**
Refrigerator	18.5	-	33; 67; 100	-
Washing machine	5.0	-	-	-
Heat pump	2.0	100	-	-
Air conditioner	4.8	75	33; 67; 100	-
Cold storage	-	71	-	-
Warm water heating	-	25	-	-
Night storage heater	-	100	-	-
Air supply	-	50	-	-
Electric vehicle	-	-	-	100

2.8 STEP 4: Technical Demand Response Potential Assessment

Theoretical DR potential is the absolute maximum potential possible and therefore doesn't consider the limitations of technical constraints. Therefore, some studies proceed further to derive the technical potential from the theoretical potential so that DR may be modelled in future power systems to assess the value it provides to the system. The following section provides an overview of the studies that assessed the technical DR potential.

Stötzer et al. (2015) assessed the technical DR potential in the residential and commercial sectors in a typical medium-sized German city (500,000 citizens) in light of the current power system that faces high renewable energy penetration. The technical constraints used in the model include the start and end time of appliances, shifting time, minimum break required after shifting a load to start another DR event, and daily duration of the appliance usage. They considered the time-dependent patterns of different loads and optimized the load profile using the genetic algorithm to find the maximum demand shift. A shifting potential of 8 GW was determined for the residential and commercial sectors in the region in 2030 (Stötzer et al., 2015).

Due to similar reasons as in the above study, Kwon et al. (2014) assessed the technical DR potential in the residential, commercial and industrial sectors in Denmark. The EnergyPLAN model was used to simulate a 100% renewable energy scenario in 2050, with input parameters such as electricity production capacities of each technology, heat pump and vehicle to grid capacities, and the electricity demand for heating and other end uses in 2050. Then considering the technical constraints, such as the shifting time of each appliance, the technical DR potential was assessed for two timeframes. In the first time frame of 2 hours, the maximum hourly potential of flexible demand was 2.48 GW and in the second time frame of 24 hours, it was 2.11 GW (Kwon et al., 2014).

Alfaverh et al. (2021) proposed a DR approach for energy management for vehicle-to-grid (V2G). The EV model is interfaced with Google Maps using MATLAB to estimate the driving distance, the battery energy needed for the trip, and each trip's arrival and departure times. Q-learning, a reinforcement learning (RL) strategy of machine learning, was used to model the EV charging and discharging schedules. RL strategies deal with taking actions or decisions in an environment to maximize rewards. Here the charging, delaying charging, discharging (V2G), etc., are the decisions made by the Q-learning strategy. This model was applied to evaluate the effect of EV participation in peak shaving within a residential area of 100 households, with half of them owning an EV. The simulation results showed a 23% reduction in the morning peak load and a 15% reduction in the evening peak load (Alfaverh et al., 2021).

Müller et al. (2018) assessed the technical potential in Germany considering the technical restrictions such as shifting time, number and duration of DR events. Two scenarios were developed for 2035 and 2050 with different shares of renewable energy generation at 60% and 80%, respectively. The peak load with DR decreased by 3% for both scenarios, while the renewable energy curtailment reduced by 77% and 35% for 2035 and 2050, respectively (Müller & Möst, 2018).

To summarize, certain aspects considered to estimate the technical DR potential in the above studies are the shifting time and the number and duration of each DR event. However, it is important to note that there isn’t a general consensus among authors about the exact definition and factors considered in assessing the technical DR potential (Dranka & Ferreira, 2019). In this study, the technical DR potential is assessed by shifting a share of the demand from the residential appliances selected for DR from peak hours to off-peak hours to minimize peak load. The details of the DR algorithm are provided in the next chapter.

2.9 Microgrid Sizing

Next, the modified load profile with DR is derived when the technical DR potential is assessed. The microgrid generation capacities for load profiles with and without DR will differ. So, for both cases, it is important to size the microgrid or to determine the installed capacities of each generation component in the microgrid. There are various approaches to sizing a microgrid; however, a few aspects can be considered as the main considerations for microgrid sizing problem formulation (Mathew et al., 2022). These include:

- Consideration of load demand – Since the aim of sizing a microgrid is to meet the local demand, estimation of the load demand is essential to sizing the microgrid (Mathew et al., 2022).
- Technical considerations – Technical considerations vary depending on the microgrid generation components. For example, for PV-based microgrids, these include rating of PV modules, tilt angle, PV efficiency, efficiency of converters, etc. (Mathew et al., 2022).
- Economic considerations - A few metrics, such as total system cost (TSC), levelized cost of energy (LCOE), and net present value (NPV), are used to find the financial viability of the microgrid. While TSC includes the cost of installation, maintenance, operation and replacement (Mathew et al., 2022), LCOE is the ratio of TSC and total energy generated (El-Bidairi et al., 2018). NPV is the value of all future cash flows incurring during the lifetime of a project discounted to the present year (Corporate Finance Institute, 2022).
- Reliability considerations – The microgrid's reliability can be considered as its ability to meet the demand when grid power is unavailable. Loss of load probability (LLP) is the ratio of total energy deficiency and required demand in a particular period (Sarhan et al., 2019).

For microgrid sizing or optimization, one or a few objective functions are typically optimized with a set of constraints imposed on them. Some objectives functions that are commonly considered are economic, reliability and environmental objectives. The economic objectives include minimizing TSC (Mathew et al., 2022), minimizing LCOE

(El-Bidairi et al., 2018) or maximizing NPV (Talent et al., 2018). The reliability objectives include minimizing LLP (Sarhan et al., 2019) and the environmental objectives include minimizing the GHG emissions from the microgrid (Mathew et al., 2022). Some constraints that are commonly considered are renewable energy fraction in the energy produced (Bukar et al., 2019), boundaries of the sizes of generation components, and grid purchase allowed (Mathew et al., 2022). While there are various optimization approaches, such as linear programming, non-linear programming, artificial intelligence-based methods, etc. (Mathew et al., 2022), there are many software platforms that can be used to size the microgrids. Some software include are HOMER, RETScreen, HYBRID2, TRNSYS (Sinha et al., 2014), PLEXOS (Energy Exemplar, 2022), etc.

Some studies assessing the financial viability of DR have used HOMER software to size microgrids that are partially sourced from renewable energy. HOMER is a tool to design microgrids with several renewable energy sources such as solar, wind, biomass, hydro, etc. and can even include sourcing energy from the grid. Kumar et al. (2019) optimized the size of a residential microgrid for a village in India with DR. They created different DR scenarios by varying the share of controllable load participating in DR. A financial analysis showed that the LCOE reduced by 2.5% in comparison to the scenario without DR. Montuori et al. (2014) also optimized the size of a microgrid that was powered by a biomass gasification power plant in the U.S. They generated DR scenarios according to the different incentive-based DR programs available in the U.S market and found that the avoided cost of energy was 33%. Yu et al. (2021) optimized the size of a residential microgrid in Iran using DR. The DR scenarios varied according to the price-based DR programs such as TOU and RTP. For the RTP DR program, the net present cost of the system was reduced by 16%. Shadman et al. (2020) assessed the feasibility of DR for peak shaving in a microgrid including battery storage and a natural gas generator in Texas, U.S. The TOU utility tariff structure was used as the DR program and the reduction in peak load from the scenario without DR was 19.7%. Ma et al. (2019) sized a residential microgrid with DR in Delhi, India, consisting of 100 households. Assuming 40% of the load to be deferrable and participating in DR, they found that the LCOE reduced by 7%.

This study also uses the HOMER Pro software to size the microgrid in scenarios with and without DR. If any capacity benefits result from DR, the benefits will be estimated in monetary value. However, capacity benefits are not the only cost benefits of DR programs. To evaluate the financial feasibility of the DR program, it is necessary to account for other costs and benefits, which are discussed in the section below.

2.10 Profits and Costs of Demand Response

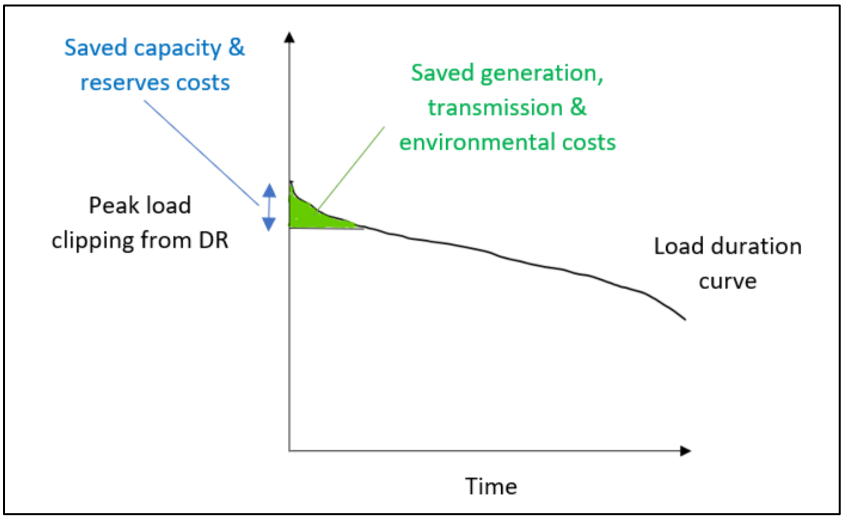
There are various profits and costs of DR programs to different stakeholders. Therefore, in this section, the different profits and costs to the utilities (microgrid operators in the case study context) and customers are identified from the literature and discussed.

2.10.1 Types of Profits from Demand Response

Implementing DR has cost reductions on the power system. Chen et al. (2022) developed a framework to quantify the economic and environmental benefits of implementing DR for peak load shaving in China. The hourly load curves were transformed into load duration curves, as shown in Figure 2.5. The cost savings were from saved installed capacity costs, avoided reserve costs, reduced generation costs, and saved transmission and carbon emissions costs. Among these, their study found that the avoided capacity costs were the major cost savings of DR implementation. Srivastava et al. (2021) and Heffner (2009) discussed the generation, transmission and distribution capacity deferral potential of DR. The deferral cost is the time value of the investment being deferred. Furthermore, combining DR in a system with high VRE penetration can reduce the VRE curtailment and save the associated costs (McPherson et al., 2020; Stötzer et al., 2015).

Figure 2.5

Illustration of demand response benefits from peak clipping



Note. Adapted from Chen et al. (2022).

The cost benefits of DR are not only to the utilities. When the costs of the power system are reduced or avoided, these benefits can translate into customer bill savings since the customers share the cost of the power system. Customers can also get financial benefits by participating in incentive-based DR programs. Eapen et al. (2019) showed how DR for peak clipping could save organizations from penalty costs for exceeding contractual limits set by utilities. Price-based DR programs could also provide bill savings, as shown by Nair et al. (2014) – with TOU and RTP tariffs, the customer bill reduced respectively by 4.35% and 5.69% from flat tariff bills.

2.10.2 Types of Costs from Demand Response

Implementing DR programs also has associated costs. Based on the literature review, Woolf et al. (2013) identified different costs of DR programs. These include the costs of information technology and communication equipment; operations and maintenance (O&M); replacement marketing and outreach; labor or people cost; evaluation, measurement and verification of the DR program; financial incentives to the participants; participant value of lost service; and costs associated with increased energy consumption as a possible rebound effect. During a DR event, when there is a reduction in supply, the participant may incur productivity losses, i.e., some loss of comfort during an event targeting ACs. The participant value of lost service could be challenging to estimate since the loss has to be accounted for in terms of monetary value (Woolf et al., 2013). Despite these various costs, some studies simplify all the costs to only DR programs' equipment acquisition and operating costs (Eldali et al., 2016; Xiang et al., 2020).

2.10.3 Discussion

In the context of the community microgrid, the profits to the microgrid operators due to DR are 1) generation, storage and distribution capacity deferral, 2) reduction of VRE surplus exported to the grid (currently, this is not being credited to Auroville by the Tamil Nadu Generation and Distribution Corporation (TANGEDCO) (AVC, 2021a), and 3) reducing the penalty costs by not exceeding the contractual limits set by TANGEDCO. The costs to the microgrid operators due to DR are hardware cost, O&M, and financial incentives to participants. Currently, the appliances available in the market are not enabled with IoT. However, retrofits such as smart plugs can be used to control them remotely and are available in the market costing around 2000 INR per unit (Kiot, 2022). Apart from this, all the buildings in the residential community already have smart meters installed. The benefits to the residential community are the financial incentives provided by the microgrid operators, while the costs are the possible value of lost service. It is important to note that while all the benefits listed above are monetarily countable, other environmental benefits are not considered, such as reducing GHG emissions and improving resource efficiency by reducing generation capacities.

2.11 Policies and Regulations for Demand Response in India – Time of Use Tariffs

This section provides an overview of the status of the policies and regulations enabling DR in India. Besides a few pilots of DR programs in the C&I sectors in India and recently a pilot in the residential sector, DR hasn't yet received considerable attention (Srivastava et al., 2021). However, DR exists in nascent stages in the form of TOU tariffs (price-based demand response) in almost all the Indian states for large commercial and industrial sectors. Kerala is the only state in India to follow TOU for domestic customers. Customers whose six-month average monthly consumption is above 500 kWh must follow the TOU structure (Talhar et al., 2020; KSEB, 2013).

The TOU tariffs for the C&I sectors are typically similar for all states in India, with minor differences. The periods for peak hours, off-peak hours and normal periods vary from state to state. In some states, these periods are different in winter and summer, while in others, the periods are different for different consumer categories (Forum of Regulators, 2010). In Tamil Nadu, the time of use or time of day (ToD) tariff is mandatory for high-tension industrial customers. During the peak hours – 6:00 to 9:00

and 18:00 to 21:00 – the energy charges are 20% above the normal hours and during the off-peak hours – 22:00 to 5:00 – there is a 5% rebate on the energy charges (Tamil Nadu Electricity Regulatory Commission, 2013).

While no policies currently aim at integrating DR programs in India, the Forum for Regulators recommended introducing TOU to the LT and domestic consumers phase-wise. The suggested TOU structure is 3 slabs with normal, peak and off-peak periods, where the peak periods are priced 20-30% higher than normal tariffs and the off-peak periods are priced 15-20% lower than normal tariffs (Forum of Regulators, 2010).

2.12 Summary

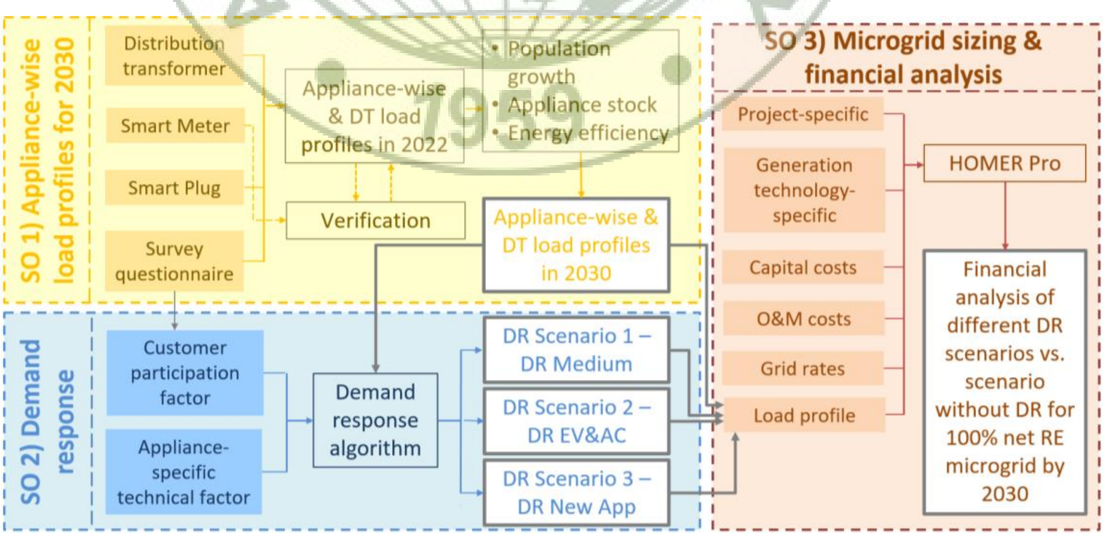
In this chapter, many important concepts to understand DR were introduced. Next, a framework for assessing all categories of DR potentials was described. Based on this, a few major steps were highlighted and elaborated, such as the identification of appliances suitable for DR, assessment of the load profiles of appliances selected for DR, and theoretical and technical DR potential assessment methods. Finally, microgrid sizing, the various costs and benefits of DR programs, and the policies enabling DR in India were explored. The methodology of conducting this study will be explained in the next chapter.

CHAPTER 3
METHODOLOGY

This chapter provides the overall methodology of the study, as illustrated in Figure 3.1. First, using several input data such as distribution transformer (DT), smart plugs and survey data, the appliance-wise (air conditioner, water heater, refrigerator, washing machine and electric vehicle) and DT load profiles are estimated for 2022. The appliance-wise load profiles are verified using aggregated smart meter data of the residential sector. Once verified, based on population growth, future appliance ownership rates and appliance efficiency improvements, the appliance-wise and DT load profiles are projected for 2030 (specific objective (SO) 1). Next, the demand response algorithm is applied to the DT load profile and based on the customer participation factor and appliance-specific technical factor (which will be explained later), a few DR scenarios are created (SO 2). Finally, the microgrid is sized with cost minimization as the objective function for the base case scenario without DR and for the three DR scenarios. A financial analysis is conducted to compare the scenarios with and without DR (SO 3). Each specific objective's detailed methodology is provided in Sections 3.1 - 3.3.

Figure 3.1:

The overall methodology of the study



3.1 Distribution Transformer and Appliance-wise Load Profiles for 2030

This section describes the detailed methodology for specific objective 1. It starts with an overview of the whole methodology and then details all steps in the process. The case study region is Auroville, an international township in Tamil Nadu, South India. The geographical and sectoral scope of the study includes all residential buildings connected to the distribution transformer (DT) in Auroville with the highest rooftop solar PV penetration, as illustrated in Figure 3.2. The appliances suitable for DR are ACs, e-cycles, e-scooters, washing machines, refrigerators, and electric water heaters (EWH) and are termed as the flexible component of the DT demand. The rest of the DT demand, including other residential and sectoral loads, is termed as the inflexible component. Figure 3.3 shows how the flexible and inflexible components of the DT demand are projected for 2030. While the inflexible component's demand in 2030 is projected by scaling the current demand according to the historical growth rate factor, the flexible component's demand is projected according to the specific development of each appliance.

Figure 3.2:

Geographical and sectoral scope of the study

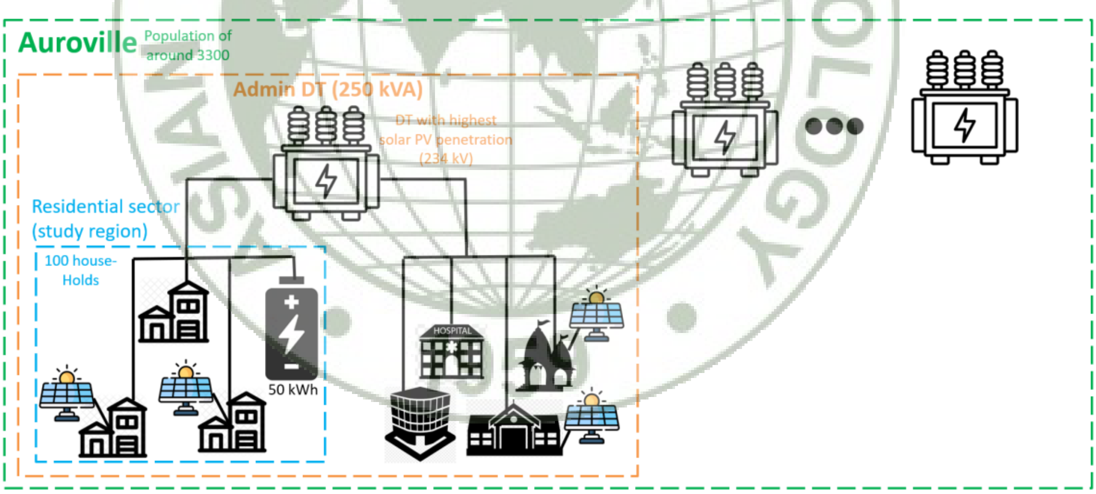
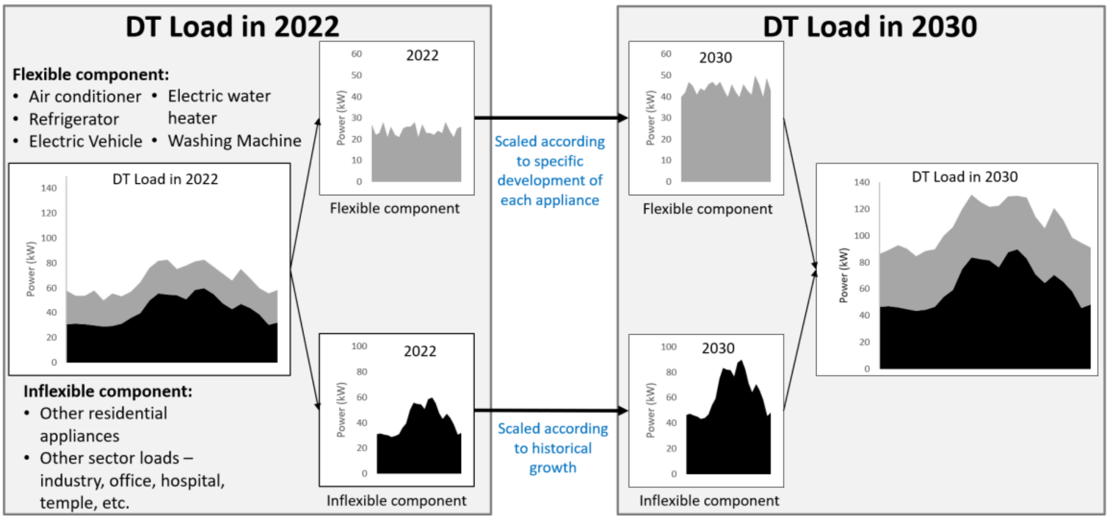


Figure 3.3:

The overall methodology of specific objective 1

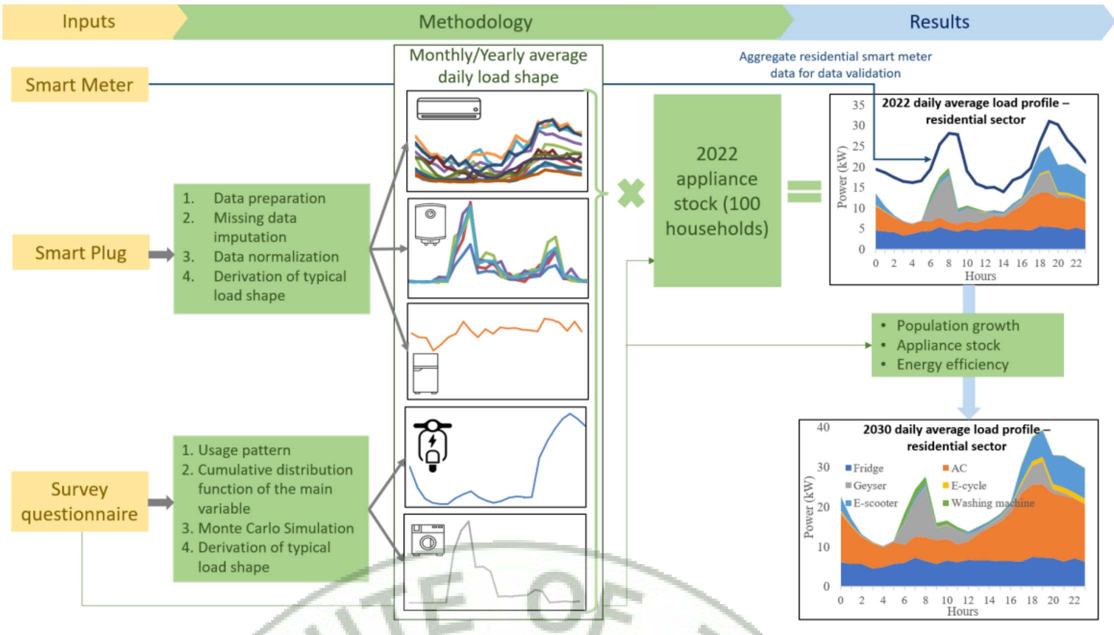


Note: Adapted from Müller & Möst (2018).

Figure 3.4 shows the overall methodology to estimate the current and future load profiles of the flexible component of the DT demand. From the smart plug and survey data, the load shapes of ACs, EWHs, refrigerators, EVs, and washing machines are generated. Then, from the appliance ownership rates determined from the survey data, the current aggregated appliance-wise load profiles – flexible component – are obtained and verified using the residential sector aggregated smart meter data. Then, based on the appliance-specific developments such as future appliance ownership rates, energy efficiency improvements and population growth, the appliance-wise load profiles are projected for 2030.

Figure 3.4:

Methodology to estimate the current and future demand of the flexible component of the distribution transformer



Next, the inflexible component of the DT demand is estimated. The current inflexible component of the DT demand is obtained as the difference between the current DT load profile and the flexible component's load profile. It is then scaled up to 2030 based on the historical electricity consumption growth rate factor. Finally, the future flexible and inflexible components of the DT demand are summed to obtain the DT load profiles in 2030.

The following sections will describe the data sources collected in this study, the methodology of load profile construction for each appliance type, the current and future appliance stock derivation in the study region, the construction of current and future aggregated residential load profile and their validation, and the construction of DT load profile in 2030.

3.1.1 Data Sources

The input data to carry out the study come from two sources - time series power data during measurement campaigns and a survey conducted in Auroville. The following section details the methodology used to obtain these data sources.

3.1.1.1 Metered power consumption data acquisition

Several types of power consumption metered data were monitored during the study's campaign period or were obtained from Auroville Electrical Service (AVES), an electricity service provider in Auroville. These include appliance-wise smart plug data, building-wise smart meter data, aggregate rooftop solar PV generation and DT demand data. Smart plugs were used to obtain the minute-wise power consumption data of ACs, EWHs, and refrigerators during the measurement campaigns ranging from 4 weeks to 12 months. Due to several issues, such as privacy concerns of residents, lack of 24/7 wi-fi, and physical restrictions to place smart meters, a restricted number and type of appliances were monitored. Smart meters were already installed in all the residential buildings by AVES. However, only the aggregate residential demand data was provided by AVES to maintain the privacy of individual households. AVES also provided rooftop solar PV generation and DT demand database. The data range, resolution and measurement sources are provided in Table 3.1.

Table 3.1:

Different types of metered data and their characteristics

Data type	Range	Resolution	Source
Smart plug – AC	4 to 12 months	1 minute	Own, 10 metered appliances
Smart plug – EWH	3 months	1 minute	Own, 3 metered appliances
Smart plug – refrigerators	4 weeks	1 minute	Own, 3 metered appliances
Smart meter	6 months	30 minutes	AVES
Solar PV generation	6 months	15 minutes	AVES
Distribution transformer	2 years	1 hour	AVES

3.1.1.2 Survey data acquisition

The second type of data source in this study is the survey conducted in Auroville. It aimed to estimate the current and future appliance stocks of all appliances and the appliance usage patterns of the appliance types that were not metered, i.e., washing machines and EVs – e-cycles and e-scooters. The respondents were asked to select all the appliances they use for obtaining the current appliance stock. For future appliance stock estimation, they were asked whether they were likely to purchase an appliance in the next 5 to 8 years, and the responses consisted of “yes”, “maybe,” and “no”. Since

EWHs were monitored only during the monsoon months (when the usage is the most), additional questions were asked regarding their frequency of usage per week during the monsoon and the rest of the year. The typical usage hours in a day and the number of washing rounds done per week were included for washing machines. For EVs, the number of users per vehicle, the typical distance traveled in a day, and the charging hours were asked. Furthermore, the duration of a typical charge (in hours) and the charging frequency per week were asked to verify the typical distance traveled in a day since that is the most important input for the charging profiles.

3.1.2 Load Profile Extraction Methodology

The two data sources are used to extract typical appliance-wise daily average load profiles. While the meter data is used to construct AC, EWH and refrigerator load curves, the survey data is used for EV and washing machine load curves. The following sections describe the load profile extraction methodology for each appliance.

3.1.2.1 Load profile extraction methodology from metered data

There are several steps to process the power consumption data so that it may be used to generate load profiles. In the first step, data was obtained from campaigns or AVES. In the second step, the data was pre-processed, i.e., data cleaning, preparation and outlier removal. In the third step, the missing data was imputed when significant and deleted when negligible. Smart plug data was imputed since significant missing data resulted from unstable wi-fi connections and power outages. Missing data imputation techniques depend on the gap size of missing data (Cho et al., 2020; Luo et al., 2022; Pazhoohesh et al., 2021). The linear interpolation technique performs best for small gap sizes or gap sizes less than 2 hours(Cho et al., 2020). Since power consumption time series has periodicity, several studies dealing with such data use copy paste imputation (CPI) technique, where missing data blocks are copied from the previous week’s data and pasted into the gaps (Debnath et al., 2020; Weber et al., 2021). So, the CPI technique was used for gap sizes greater than 2 hours. In the fourth step, data was sampled at a 1-hour sampling rate. In the final step of data preparation, the AC consumption data was normalized to one ton of refrigeration, and the data was ready to be processed to generate load profiles. Water heater and refrigerator data were not normalized since they represented the typical capacities in the region (2 kW and 120 W, respectively).

Once the data was processed, it was used to derive the monthly average daily load profiles. Since several appliances for the same appliance type were metered, average demand data for each type of appliance was derived by doing a point-wise average of all appliances of the same type. Finally, monthly average daily load profiles were derived for each appliance type – AC, refrigerator, and EWH. One year's data was available for ACs. Therefore, monthly average daily load profiles for an entire year were obtained directly. Refrigerators were monitored for only 4 weeks. However, since their usage is not dependent on the season and can be assumed to be representative of the whole year, the same daily average load profile was used for all the months in the year (Müller & Möst, 2018). This is not the case with EWH, whose usage is weather dependent. The measurement campaign for EWHs lasted during the monsoon months of the year in Auroville; hence their usage was maximum. Therefore, a capacity factor (CF) was introduced to extend the load profiles of EWHs for the rest of the year. CF is dependent on the frequency of EWH usage and is calculated as in Equation 3.1, where n is the number of respondents and F_r is the number of days in a week hot water for bathing is used by respondent r. For example, if all respondents use hot water daily during the monsoon months, CF is 1. If everyone uses hot water only twice a week, the CF is 2/7 or 28.6%. CF was then multiplied by the average EWH load profile obtained for the monsoon months to extend it to the rest of the year.

Capacity Factor (CF) = $\frac{\sum_{r=1}^{n} F_r}{7}$, Equation 3.1

3.1.2.2 Load profile extraction methodology from survey data

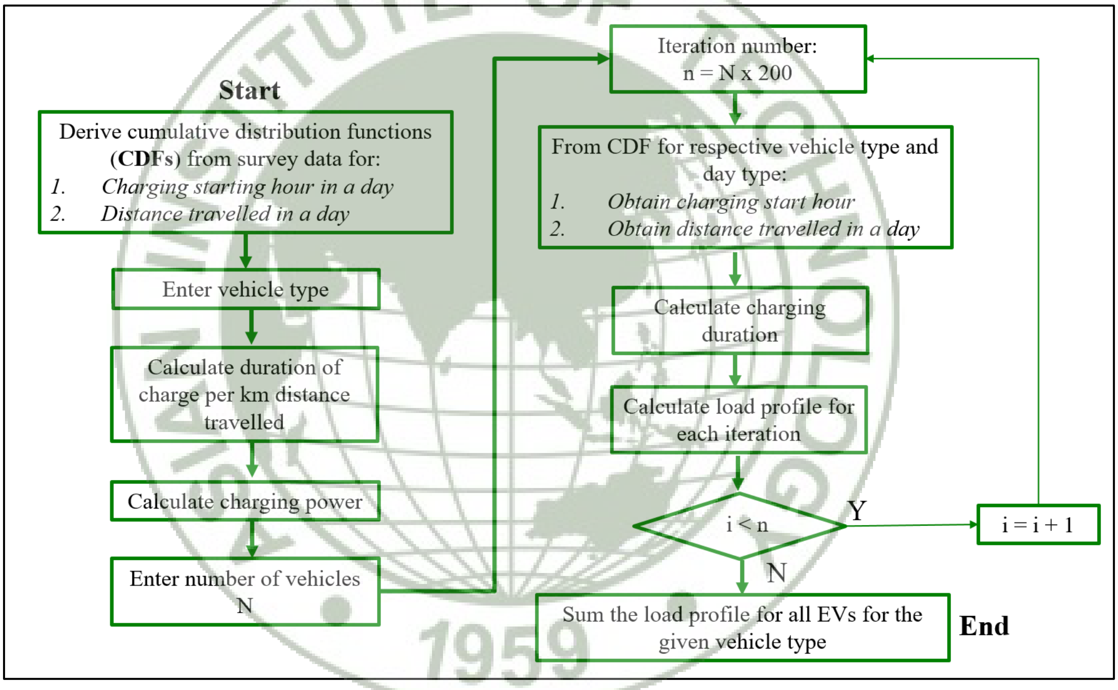
For the remaining appliances, i.e., EVs and washing machines, the load profiles were generated based on the usage pattern from the survey data. Since their usage is not dependent on temperature or seasons, a single load curve representing a typical day in a year was derived. For EVs, cumulative distribution functions of the daily travelled distance and charging starting hour in a day were obtained from the survey. EV specifications such as battery capacity; battery charging and discharging efficiency; charger input current and voltage; charger efficiency and vehicle fuel efficiency (km/kWh) were obtained from an EV rental and sales shop in Auroville. Monte Carlo simulation was done to pick a specific charging starting hour and distance travelled in a day for one iteration. The charging duration was estimated from Equation 3.2. The simulation was run for several iterations, i.e., 200, and the typical charging profile for EVs was derived as illustrated in the flowchart in

Figure **3.5**.

Charging duration = $\dfrac{\frac{\text{Battery capacity}}{\text{Vehicle fuel efficiency}} \times \text{distance travelled in a day}}{\text{Depth of discharge} \times \text{roundtrip efficiency}}$ / (Charger input current x voltage) Equation 3.2

Figure 3.5:

Flow chart to derive charging load profiles of electric vehicles



For washing machines, the methodology of deriving load profiles is similar to that of EVs. The cumulative distribution function for the starting hours for washing machine usage was also derived from the survey. The typical duration and washing machine power consumption ranges were obtained from secondary data. These values were randomly chosen in each iteration.

3.1.3 Appliance Stock in 2022 and 2030

The load profile construction methodology for each appliance type is discussed above. The next essential input to simulate the current and future appliance-wise residential load profiles is the current and future appliance stock in the study region. For the current appliance stock, the residential building caretakers in the study region were approached to find values from their inventory, and when this direct method was not possible, the appliance stock was derived from the survey conducted in Auroville.

For future appliance stock, the current appliance stock is expected to remain till 2030. The new appliance stock by 2030 is due to two factors – the existing population installing new appliances and population growth. For the existing population, the future appliance ownership rates were derived from the survey conducted in Auroville. The respondents were asked whether they owned an appliance type currently (“yes” or “no”) and whether they were likely to install another one in the next 5 to 8 years (“yes”, “maybe”, or “no”). The ownership rates were derived per household based on these two questions. For additional appliance stock from population growth, the historical population of Auroville was obtained from Auroville Archives, and the compound annual growth rate (CAGR) was estimated. The future population in the study region was obtained by using the CAGR. The appliance stock in the future due to population growth was calculated similarly to the existing population purchasing new appliances. The future stock for refrigerators and washing machines is expected from only population growth as almost all households already have them.

Unlike the current appliance stock, there can be variability in predicting future appliance stock. Thus, three scenarios were considered since while some respondents were surely going to purchase an appliance in the future, some “might” install one. In scenario A (maybe 0%), all those who might install one in the future are assumed not to install one in reality. In scenario B (maybe 50%), only 50% of those who might install one in the future are assumed to install one in reality. In scenario C (maybe 100%), all those who might install one in the future are assumed to install one in reality. Of course, all the respondents who will (“yes”) purchase an appliance in the future are expected to do so in reality in all the scenarios. Furthermore, when available, secondary data from the literature was used to predict the future appliance stock in the study region in 2030 to compare the values to the scenario results obtained from the survey.

3.1.4 Current and Future Residential Appliance-wise Load Profile Simulation and Validation

Once the individual appliances' load profiles and their respective appliance stocks were derived, they were used to obtain the current and future residential appliance-wise monthly average daily load profiles – the flexible component of the DT demand. The appliance load profiles derived from the metered data were multiplied by their respective appliance stock for load aggregation. The appliance load profiles derived from the survey data were aggregated by appliance type by setting the appliance stock input to their respective values. Finally, the load profiles of all appliance types were aggregated to obtain the current and future residential load profiles. For the new air conditioner stock to be purchased by 2030, the load profiles were scaled down based on the efficiency improvement projections.

The simulated monthly average daily load profiles were compared with smart meter aggregated residential active power data to validate the results. Since the latter data was only measured from June to November 2022, only the simulated load profiles for the respective months were compared. Furthermore, the simulated load profiles don't consider other non-controllable appliances such as lights, fans, etc. and thus are not expected to be the same as the smart meter aggregated residential active power data. The validation is only possible to a certain extent and is a visual method.

3.1.5 Distribution Transformer Load Profile in 2030

The previous sections detailed all the steps to estimate the flexible component of the DT demand in 2022 and 2030. Next, if the inflexible component of the DT demand is estimated, the DT load profile in 2030 can be generated. The inflexible component in 2022 is obtained by subtracting the flexible component demand in 2022 from the DT demand in 2022. Next, the historical compound annual growth rate of electricity consumption in Auroville was used to scale this demand to 2030. Finally, the flexible and inflexible components of the DT demand in 2030 are summed to obtain the DT load profile in 2030.

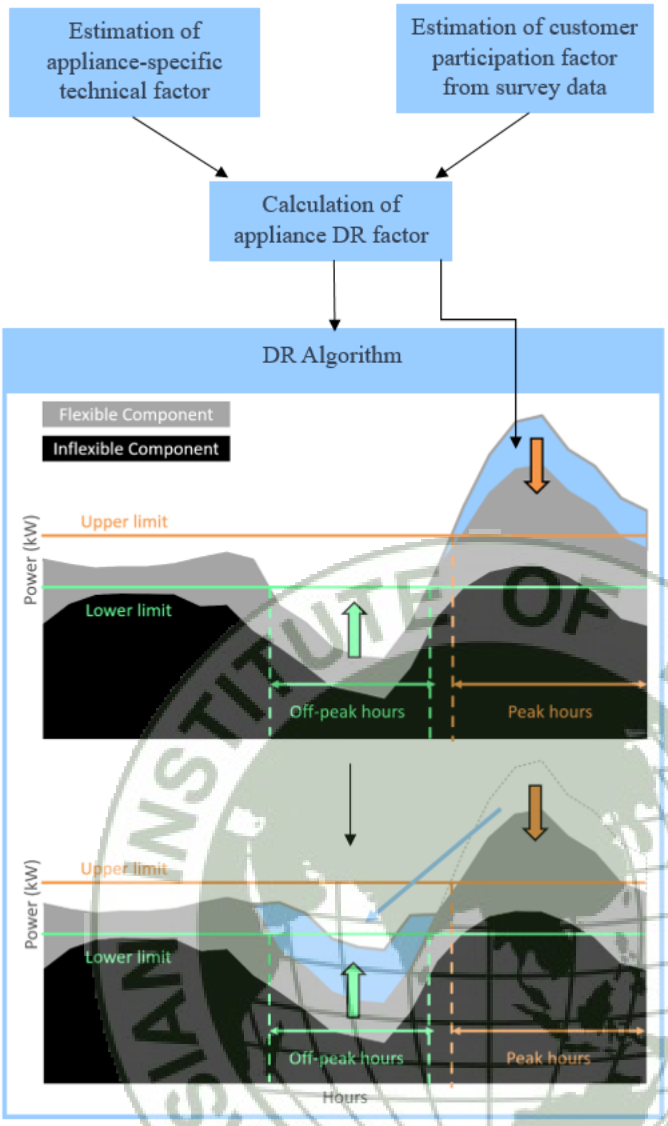
To summarize, this section provided the detailed methodology of the data sources required for specific objective 1, the load profile extraction methodology for each appliance selected for DR, the appliance stock estimation for 2022 and 2030, the construction of aggregated appliance-wise load profiles (the flexible component of the DT demand), and finally the DT load profiles in 2030. Thus, the appliance-wise load profiles and the DT load profiles for 2030 are now available to use as inputs in the next specific objective of this study.

3.2 Modified Distribution Transformer Load Profiles with Demand Response

This section describes the detailed methodology for specific objective 2 and its overview is illustrated in Figure 3.6. Firstly, a couple of factors, such as appliance-specific technical factor and customer participation factor are estimated to determine the share of the demand of the appliances selected for DR that is available for DR, and is termed appliance DR factor. This value represents that not all the load from the appliances selected for DR is available or participates in DR. Then, the share of appliance demand according to its DR factor is curtailed/shifted from the peak hours to the off-peak hours. The following sections will describe the factors considered to estimate appliance DR factors and the DR algorithm to shift load from peak to off-peak hours to estimate the technical DR potential.

Figure 3.6:

The overall methodology of specific objective 2



3.2.1 Appliance Demand Response Factors

This section describes appliance DR factors. The flexible component of the DT demand is from controllable or non-critical loads. Thus, it can be considered as the theoretical DR potential according to the definition provided in section 2.2.1. However, it is necessary to refine this potential further as not all the demand from the appliances selected for DR is available to participate in DR. Firstly, all customers will not participate in the DR of all appliances; therefore the customer participation factor has to be accounted for each appliance. Secondly, even if a customer participates in the DR program of an appliance, all of the appliance's demand must not be available to participate in DR to ensure the customer's comfort. For example, the air conditioner must not be curtailed for 2 hours continuously so that the customer doesn't lose their thermal comfort. Furthermore, load shifting must occur within the same day. These aspects, such as the duration of the DR event and shifting time, are considered in the appliance-specific technical factors. Thus, the appliance DR factor is the product of customer participation and appliance-specific technical factors.

This study develops different DR scenarios based on the appliances selected for DR, the customer participation factor, and whether or not the current stock is considered for DR, as described in Table 3.2. In DR Maximum, DR Medium and DR Minimum scenarios, all appliance types and existing and future appliance stock are assumed to participate in DR. Only the share of customers participating in DR varies. As electric vehicles' and air conditioners' share in the residential demand is high, a scenario with only these two appliances is created. The last scenario, DR New App, is the scenario where only the new appliances to be bought by 2030 are considered to participate in the DR program and are enabled with smart features for DR implementation. This scenario is interesting due to zero investments in hardware costs for DR implementation in 2030, as the new appliances are already assumed to be enabled with smart features.

Table 3.2:

Assumptions of different DR scenarios

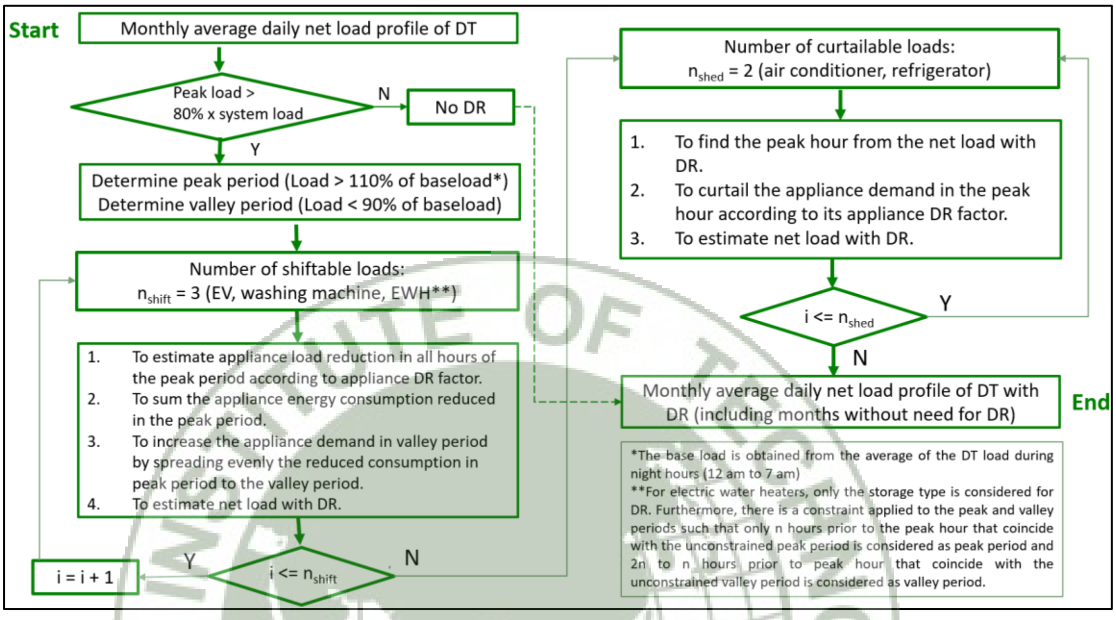
Scenario Name	Appliances selected for DR	Customer Participation	Current appliance stock	Future appliance stock
DR Maximum	All	High	Yes	Yes
DR Medium	All	Medium	Yes	Yes
DR Minimum	All	Low	Yes	Yes
DR EV&AC	ACs and EVs	Medium	Yes	Yes
DR New App	All	High	No	Yes

3.2.2 Algorithm for Obtaining Load Profiles with Demand Response

The previous section described how to obtain the load available for participation in the DR program from each appliance type using its respective appliance DR factor. This section will provide the algorithm to implement DR on the DT monthly average daily load profiles and the algorithm is shown in Figure 3.7. First, the peak load of each month is checked to determine whether or not DR has to be implemented in that month. Next, for shiftable appliances - electric vehicles, washing machines and electric storage water heaters, a share of their demand is reduced in the peak hours and shifted evenly to the off-peak hours based on their respective appliance DR factor. For sheddable appliances - air conditioners and refrigerators, a share of their demand is curtailed during the peak hour based on their respective appliance DR factor.

Figure 3.7

Algorithm to obtain monthly average daily load profiles of DT with DR



First, if the peak load of the monthly average daily net load profile of DT is greater than 80% of the system peak load, DR is applied. The baseload B for each month is the average DT load D_t during the night hours – 12 am to 7 am (Equation 3.3). The hours in a day when the load is 10% greater than the baseload and 10% less than the baseload are considered peak and valley periods, respectively and denoted by the sets P_h and V_h, respectively (Equations 3.4 & 3.5).

$$B = \sum_{t=0}^{7} \frac{D_t}{8} \qquad \text{Equation 3.3}$$

$$P_h = \{t \mid D_t > 1.1 \times B\} \qquad \text{Equation 3.4}$$

$$V_h = \{t \mid D_t < 0.9 \times B\} \qquad \text{Equation 3.5}$$

Next, for each shiftable appliance, $DR_{app,t}$ denotes the load reduction from DR. The appliance load reduction in the peak period is obtained by multiplying the appliance's demand $D_{app,t}$ with its DR factor f_{app} (Equation 3.6). The appliance's load increase in the valley period is obtained by dividing the sum of the energy consumption reduction during the peak period E_DR (Equation 3.7) with the number of valley hours in a day $n(V_h)$ (Equation 3.8).

$DR_{app,t} = D_{app,t} \times f_{app}$ (for $t \in P_h$) Equation 3.6

$$E\_DR = \sum_{t \in P_h} DR_{app,t}$$ Equation 3.7

$$DR_{app,t} = -\frac{E\_DR}{n(V_h)} \text{ (for } t \in V_h\text{)}$$ Equation 3.8

The DT demand after DR from n_{shift} number of shiftable appliances $D_{shift}\_DR_t$ is the difference between the initial DT demand and the sum of load reduction from all shiftable appliances (Equation 3.9).

$$D_{shift}\_DR_t = D_t - \sum_{app=1}^{n_{shift}} DR_{app,t}$$ Equation 3.9

Now, DR from sheddable loads is considered. Let the DT demand from demand response D_DR be equal to $D_{shift}\_DR_t$ initially (Equation 3.10). For each appliance that can shed its load, the peak hour h_{max} is determined where the D_DR load is the maximum. The load is curtailed according to the appliance DR factor at that peak hour, and D_DR is modified for that peak hour (Equation 3.11). This process is repeated until all sheddable loads are considered and finally, the DT demand from demand response D_DR is obtained.

$D\_DR = D_{shift}\_DR_t$ Equation 3.10

For app in n_{shed}:

$h_{max} = t$ for $\max(D\_DR_t)$

$D\_DR_{hmax} = D\_DR_{hmax} - (D_{app,hmax} \times f_{app})$ Equation 3.11

To note that for electric water heaters, only the storage type is considered for DR. Storage water heaters can only store hot water effectively for a few hours n. Thus, a constraint is considered on P_h and V_h such that only n hours before the peak hour that coincide with the unconstrained peak period are considered as P_h (Equation 3.13) and 2n to n hours before the peak hour that coincide with the unconstrained valley period are considered as V_h (Equation 3.14), as illustrated in Figure 3.8.

$t_{max} = t$ for $\max(D_t)$ Equation 3.12

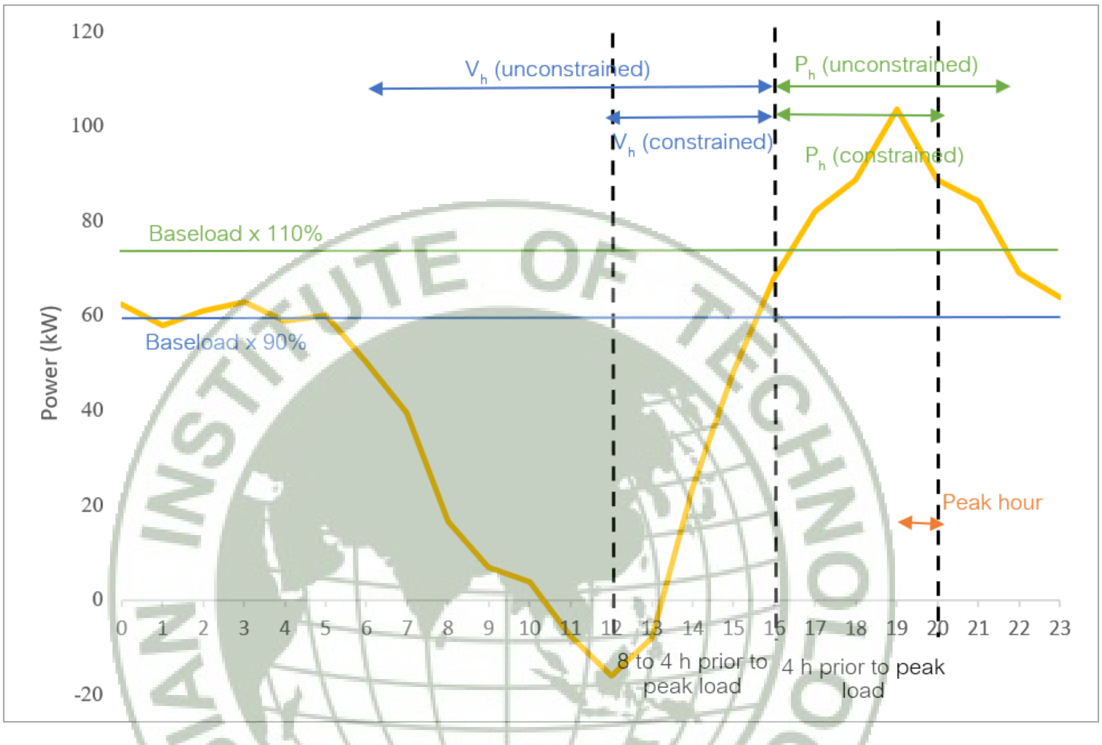
$P_h = \{t \mid D_t > 1.1 \times B\} \cap [t_{max} - n + 1, t_{max}]$ Equation 3.13

$V_h = \{t \mid D_t < 0.9 \times B\} \cap [t_{max} - 2n + 1, t_{max} - n]$ Equation 3.14

Furthermore, to model the losses from storing the hot water for n hours, Equation 3.8 is modified to increase the demand by a small factor.

Figure 3.8:

Illustration of constraints on peak and valley periods for a storage water heater with n = 4 hours



To summarize, this section provided the detailed methodology to generate DT monthly average daily load profiles after applying DR. This is based on customer participation (varies according to the DR scenarios) and appliance-specific technical factors. Their product is the appliance DR factor and thus, accounts for the share of customers participating in the DR program and ensures customer comfort. The technical DR potential is the difference between the system peak load with and without DR. The modified DT load profiles from each DR scenario are now available to use as inputs in the next specific objective of this study.

3.3 Microgrid Sizing and Financial Evaluation

As a final step in this study, the microgrid is sized in the HOMER Pro software for the different DR scenarios' modified DT load profiles generated in the previous section. Then, a financial analysis is conducted and the different scenarios with and without DR are compared. The objective function, constraints and performance metrics for financial evaluation are discussed in the subsequent sections.

3.3.1 Objective Function

The objective function for sizing the microgrid is minimizing the net present cost (NPC), which is the discounted value of all the future cash inflows and outflows to the present year, as given in Equation 3.15.

$$NPC = CC_p + RC_p + O\&MC_p + FC_p + EP_p + GC_p - SV_p - GSR_p \qquad \text{Equation 3.15}$$

Where,

CC_p = present value of capital costs
RC_p = present value of replacement costs
$O\&MC_p$ = present value of operations and maintenance cost
FC_p = present value of fuel costs
EP_p = present value of emission penalties
GC_p = present value of grid costs
SV_p = present value of salvage value
GSR_p = present value of grid sales revenue (HOMER Pro, 2023).

Salvage value is the value of a component at the end of the project's lifetime. It is proportional to the component's remaining life at the end of the project's lifetime and its replacement cost (HOMER Pro, 2023).

3.3.2 Constraints

The constraints that are considered in the software are power balance, boundaries of energy sources, minimum renewable fraction F_{RE}, and maximum net grid purchases. The power balance ensures the demand is always met (Equation 3.16). The boundaries of energy sources ensure that the system always operates under the boundaries of each component, such as renewable energy technologies, grid, and battery (Equation 3.17 – 3.19). The minimum renewable fraction is the minimum fraction of energy supplied to the load in a year that is sourced from renewable energy (Equation 3.20). The maximum net grid purchases are the maximum net energy purchased or imported from the grid annually (Equation 3.21) (HOMER Pro, 2023).

$P_{RE,t} + P_{g,t} + P_{BESS,t} = P_{D,t}$ Equation 3.16

$P_{RE,min} \leq P_{RE,t} \leq P_{RE,max}$ Equation 3.17

$P_{g,min} \leq P_{g,t} \leq P_{g,max}$ Equation 3.18

$SoC_{min} \leq SoC \leq SoC_{max}$ Equation 3.19

$F_{RE} = 1 - E_{non\text{-}RE}/E_{served}$ Equation 3.20

$E_{import,grid} - E_{export,grid} \leq 0$ Equation 3.21

Where,

$P_{RE,t}$ = power generated by renewable energy sources

$P_{g,t}$ = power imported from the grid

$P_{BESS,t}$ = power from the battery

$P_{D,t}$ = demand

$P_{RE,min}$ = minimum power generated by renewable energy sources

$P_{RE,max}$ = maximum power generated by renewable energy sources

$P_{g,min}$ = minimum power imported from the grid

$P_{g,max}$ = maximum power imported from the grid

SoC_{min} = minimum state of charge of battery storage

SoC = state of charge of battery storage

SoC_{max} = maximum state of charge of battery storage

$E_{non\text{-}RE}$ = non-renewable energy produced annually

E_{served} = total energy serving load and grid exports annually

$E_{import,grid}$ = energy imported from the grid annually

$E_{export,grid}$ = energy exported to the grid annually.

According to the objective of this study, the maximum net grid purchases are set to zero. Next, the minimum renewable fraction constraint is used to ensure that only a small share of the load is met by grid imports and to encourage renewable energy self-consumption in the microgrid.

3.3.3 Performance Metrics for Financial Evaluation

The performance metrics for financial evaluation that will be used in this study to compare the outcomes of each scenario are NPC, levelized cost of energy (LCOE), capital expenditure (CAPEX), operating expenditure (OPEX), avoided cost, and return on investment (ROI). LCOE is the ratio of the annualized cost of generating electricity to the electrical load served, as shown in (Equation 3.22) (HOMER Pro, 2023). Avoided cost is the difference between the LCOE of the scenario of interest to the base case (Montuori et al., 2014). ROI is a measure to understand the profitability of an investment. It is the ratio of the difference between the final and initial values of investment to the initial value of investment (Equation 3.24) (Beattie, 2022).

$$\text{LCOE} = \frac{\frac{i(1+i)^n}{(1+i)^n-1} \times \text{NPC}}{E_{served}} \qquad \text{Equation 3.22}$$

Where,

i = real discount rate
n = project lifetime
NPC = total net present cost
E_{served} = total energy serving load and grid exports annually.

The real discount rate is calculated from the nominal discount rate i′ and inflation rate according to ():

$$i = \frac{i' - f}{1 + f} \qquad \text{Equation 3.23}$$

$$\text{ROI} = \frac{\text{Final value of investment} - \text{Initial value of investment}}{\text{Initial value of investment}} \qquad \text{Equation 3.24}$$

To summarize, in this section, the objective function and constraints to size the microgrid in HOMER Pro software were discussed. The several performance metrics to compare the outcomes of each DR scenario were also described. A sensitivity analysis will be done on the capital cost of the microgrid and DR hardware equipment as it is difficult to project their costs in 2030.

3.4 Summary

This chapter provided the detailed methodology of the three specific objectives of this study. In Section 3.1, the methodology to project the load profiles of DT and all appliances selected for DR was discussed. Section 3.2 described the algorithm to modify the DT load profiles with DR based on the appliance DR factor. The technical potential is the difference between the system peak with and without DR. Finally, Section 3.3 provided the objective function and constraints considered in the microgrid sizing software, HOMER Pro, and the several performance metrics used in this study for financial analysis to compare the outcomes of each DR scenario. The next chapter will provide the results of this study.

CHAPTER 4
RESULTS AND DISCUSSION

This chapter provides the results of this study.

4.1 Distribution Transformer and Appliance-wise Load Profiles for 2030

This section presents the results of specific objective 1 – DT and appliance-wise monthly average daily load profiles for 2030. The survey results, typical load profiles for each appliance, appliance stocks for 2022 and 2023, yearly average appliance-wise residential load profiles for 2022 and 2030, and DT monthly average daily load profiles for 2030 are discussed in the subsequent sections.

*4.1.1 **Survey Description***

The survey conducted in Auroville was divided into two parts. The first part consisted of the general household appliances such as ACs, EWHs, and washing machines, referred to as the 'general survey' in this study, while the second part consisted of only EVs and is referred to as the 'EV survey'. The general survey was conducted in the township community dining space and mainly aimed to find the current and future appliance stocks and some appliance usage patterns. The EV survey was conducted at the EV rental and sales shop in Auroville. Specific questions related to deriving the EV charging profile, as mentioned in section 3.1.1.2, were asked of the customers who visited the shop for EV servicing. The respondents answered all the questions directly, and an assistant was provided in case any respondent needed the question to be rephrased (the survey questionnaire is provided in Appendix D). Eighty-seven responses were recorded for the general survey, representing around 10% of households in Auroville (assuming 4 residents per household) and 71 responses for the EV survey, representing around 11% of EVs in Auroville. This has a sample error of less than 10%, according to Yamane's method of sample size determination (Chaokromthong & Sintao, 2021).

4.1.2 Monthly Average Daily Load Profiles of Domestic Appliances

This section provides the typical monthly average daily load profiles of the appliances selected for DR. Monthly average daily load profiles for ACs and EWHs are shown in Figure 4.1 and Figure 4.2, respectively. Since the usage of both these appliances is weather-dependent, monthly average load profiles for the whole year were derived. The overall pattern for ACs is such that the usage peaks between 6 pm and 8 pm and is the lowest between 3 am and 12 pm. May, June and July are the months with the highest usage coinciding with the hottest months in Auroville. Similarly, December, January and February are the months with the lowest usage, corresponding to the coolest months in the region. EWHs were not monitored for an entire year, so only the monsoon months' average daily load profiles were available. The CF for non-monsoon months (January to August) was found to be 46% from the survey data. Thus, a daily average load profile for all the non-monsoon months was used. Hot water for showers is mainly used during the mornings and peaks around 8 am, while there is a smaller peak in the evenings at around 7 pm.

Figure 4.1:

Typical air conditioner (single unit) monthly average daily load profiles

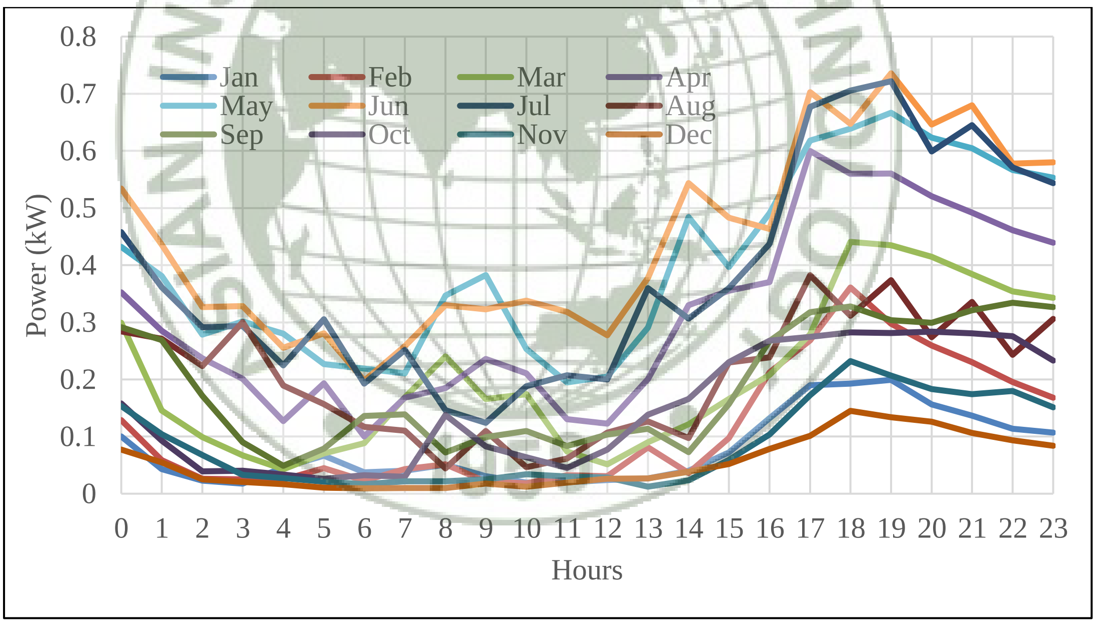
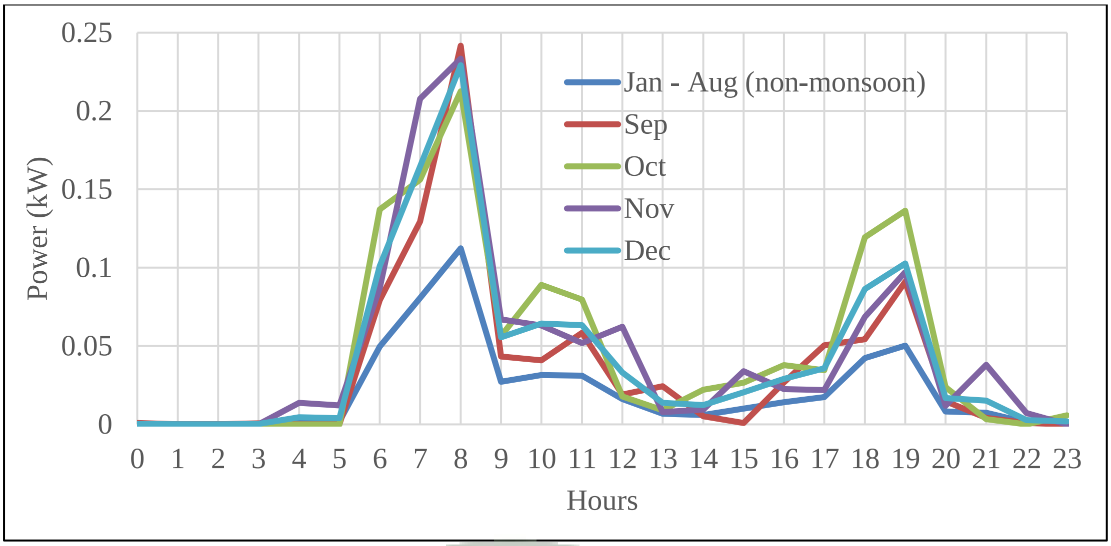


Figure 4.2:

Typical electric water heater (single unit) monthly average daily load profiles



While the usage of ACs and EWHs is weather dependent, it is not the case for EVs, refrigerators and washing machines. Thus, yearly average daily load profiles were derived and shown in Figure 4.3 and Figure 4.4. Most EV charging happens during the evenings and peaks around 9 pm. The refrigerator load is constant throughout the day and peaks between 6 pm and 8 pm. Washing machines are mainly used in the mornings and the maximum demand is around 8 am.

Figure 4.3:

Typical electric scooter (single unit) yearly average daily load profile

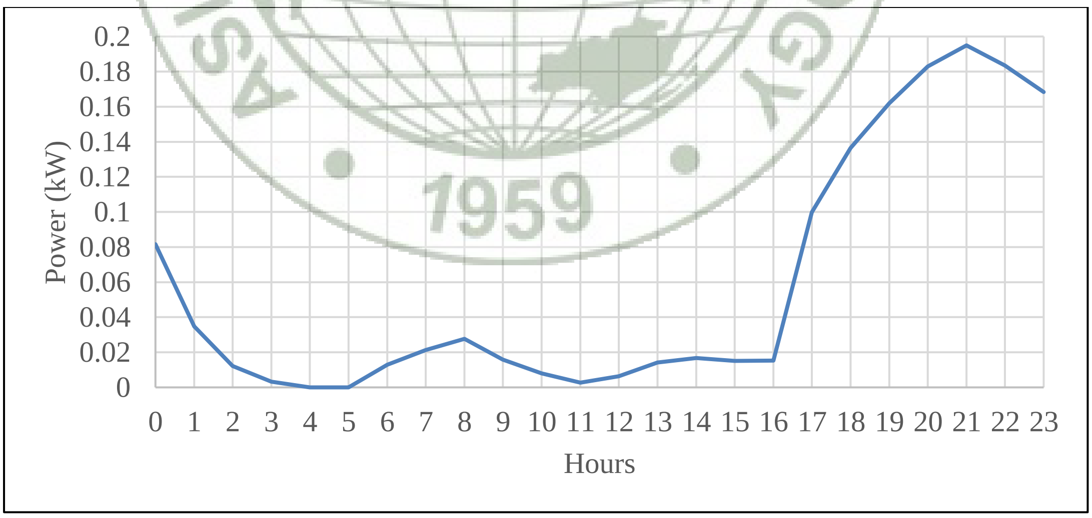
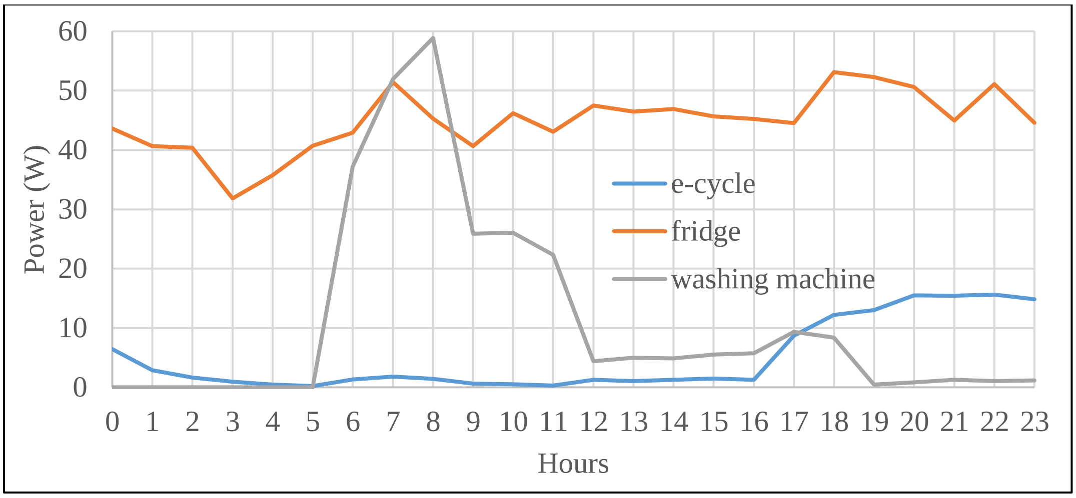


Figure 4.4:

Typical electric cycle, refrigerator and washing machine (single units) yearly average daily load profiles



4.1.3 Appliance Ownership Rates in the Study Region in 2022 and 2030

This section provides the results of the appliance ownership rates in the study region in 2022 and 2030 using the survey conducted in Auroville. Different scenarios for appliance ownership rates in 2030 were created and compared with secondary data from the literature. The current appliance ownership rate was obtained by asking the respondents whether or not they own the appliances listed in Table 4.1. The likelihood of buying an appliance, i.e., AC, EWH and EV, in the next 5 to 8 years was assessed using their confidence in buying the appliance as provided in Table 4.2. Different rates were derived based on whether the respondent already owned the appliance or not and whether they responded "yes" or "maybe".

Table 4.1:

Auroville-wide appliance ownership rates in 2022

Appliance	**2022 appliance ownership rate (Auroville-wide)**
Air conditioner	0.31
E-cycle / e-scooter	0.39
Water heater	0.49
Refrigerator	0.89
Washing machine (decentralized)	0.60

Table 4.2:

Likelihood of buying appliances in the future based on those who currently own or don't own the appliance

Current ownership of appliance (yes/no)		Appliance purchase by 2030 (%)	
		Yes	Maybe
Air conditioner	Yes	11.1	11.1
	No	10.0	8.3
Electric water heater	Yes	16.3	7.0
	No	2.3	9.1
Electric vehicle	Yes: e-cycle	30.4	0.0
	Yes: e-scooter	20.0	0.0
	No	41.5	18.9

However, the general survey was Auroville-wide, whereas the scope of the study is only a few residential buildings connected to one DT, as mentioned in Section 3.1. In the study region, there were three apartments consisting of 83 households and 17 individual households, totaling 100 households. Therefore, for first-hand data, instead of using Auroville-wide survey results, the caretakers of the apartments were approached to get the number of residents and some appliance ownership rates. Among the 17 individual households, the appliance ownership rates from the general survey were used for those that could not be approached. Accordingly, the current appliance ownership rates for the study region are provided in Table 4.3. Based on the current ownership rates and the projected rates from Table 4.2 for the existing and new population in the study region by 2030, scenario-wise appliance ownership rates were derived for 2030 in Table 4.3.

Table 4.3:

Appliance ownership rates in 2022 and 2030 in the study region

Appliance	Appliance ownership rate 2022 (study region)	Appliance ownership rate 2030 (study region)			
		Scenario A (maybe 0%)	Scenario B (maybe 50%)	Scenario C (maybe 100%)	Selected
Air conditioner	0.22	0.34	0.39	0.43	0.39
E-cycle	0.34	0.55	0.59	0.63	0.59
E-scooter	0.36	0.40	0.42	0.43	0.42
Water heater	0.61	0.69	0.72	0.74	0.72
Refrigerator	1.05	-	-	-	1.02
Washing machine (decentralized)	0.17	-	-	-	0.25

Since the appliance ownership rates for 2030 consist of three scenarios, they were compared with secondary data when available to verify the validity of the results and for scenario selection. According to IEA (2021), India's AC ownership rate in 2030 is set to increase to 60%. MEFCC (2019), on the other hand, projects it to be 25.2% and MOP & AEEE (2018) estimates a value of 44%. Thus, the values estimated from the survey in each scenario fall under this range. Therefore, Scenario B ("maybe 50%) was chosen since it was neither optimistic nor pessimistic. For EVs, according to JMK Research and Analytics (2022) and IEA (2021), the electric two-wheeler ownership rate is estimated at 12.6% and 19%, respectively. As Auroville's current EV ownership rate was already higher than this, Scenario B was again chosen since it was neither optimistic nor pessimistic. Details regarding AC and EV stock projections for 2030 from secondary data are provided in Appendix E.

Furthermore, the historic EV sales data from the rental and sales shop in Auroville were utilized to predict EV stock in 2030 in Auroville, and the ownership rates were comparable. For electric water heaters, no secondary data was available for comparison. Therefore, Scenario B was chosen for the same reason. The refrigerator ownership rate in 2030 remained similar to the current rate, as the additional stock was expected from only population growth. Similarly, new washing machine stock was also expected from only population growth. However, since the new population is expected to use decentralized washing machines, in contrast to the current centralized system used, the future ownership rate was greater than the current value.

4.1.4 Aggregation of Load Profiles and Data Validation

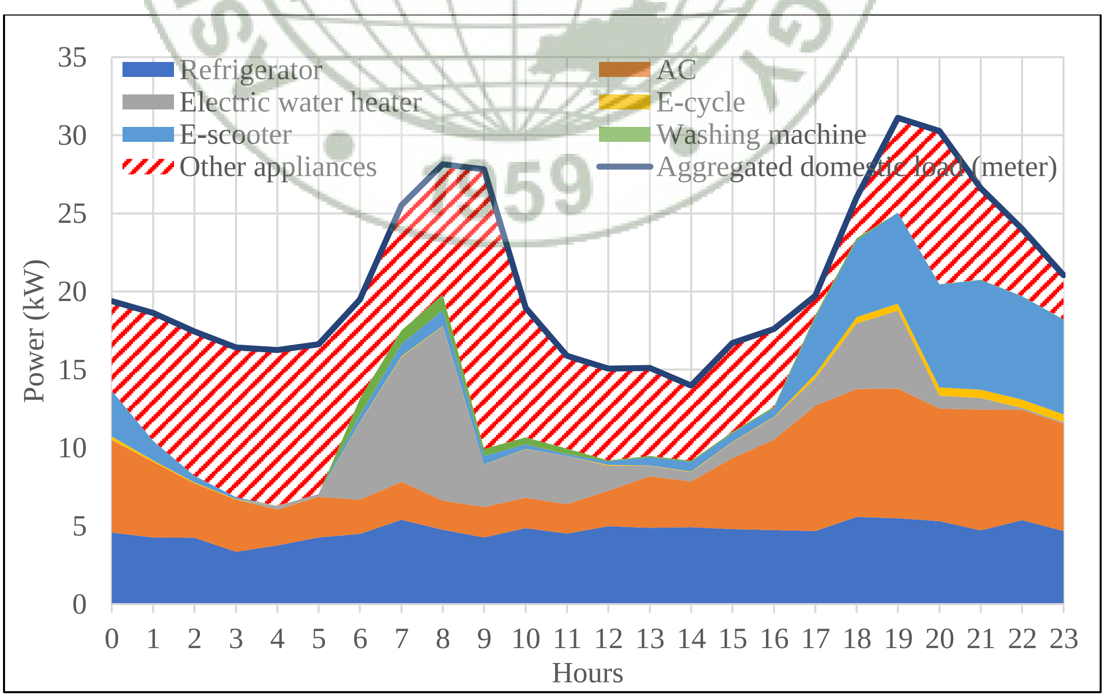
The typical load curves of each appliance and the current appliance ownership rates were used to construct the aggregated appliance-wise residential load profiles for the study region, also termed as the flexible component of the DT demand, from June to November 2022. Since smart meter aggregated residential active power data was available for only this period, the simulated profiles corresponding to this period were compared as a validation step and shown in Figure 4.5.

The aggregated appliance-wise load curve and the aggregated smart meter load curve follow a similar pattern. They peak at 7 pm, with a second significant peak at 8 am. The lowest demand hours are in the afternoons and nights. The non-critical or controllable appliances contribute to around 81% and 67% of the evening and morning peaks, respectively. The red hashed surface is the difference between the aggregated appliance-wise load and the aggregated residential load, representing other domestic loads. These include lights, fans, kitchen appliances, community laundry and kitchen, water pumps, iron, 50 kWh lithium-ion battery storage, and other electronic appliances. Water pumps are pressure-type pumps; therefore, they constantly operate, contributing to the baseload. Other domestic loads consume the most at night, probably due to fans, lights, and lithium-ion battery charging. Community laundry and kitchen contribute to the other loads in the mornings and afternoons, while in the evenings, it is likely through the usage of fans, lights, and other electronic appliances. Therefore, the generated appliance-wise load profiles follow the smart meter building data and thus be validated.

The diversity factor (DF) – the sum of the peaks of the individual components in the load profile divided by the peak of the entire system – represents to what extent the individual components are peaking at the system's peak. The closer the DF is to one, the more the individual components are peaking at the time of the system's peak. In Figure 4.5, the individual components are the appliances, and the DF is 1.08.

Figure 4.5:

Appliance-wise daily average load profile from June to November 2022 in the study region



4.1.5 Yearly Average Appliance-wise Daily Load Profiles for 2022 and 2030

Once the aggregated appliance-wise residential load profile was validated with the smart meter data in the previous step, the monthly average appliance-wise daily load profiles were simulated for 2030. However, in this section, only the appliances' yearly average daily load profiles for 2022 and 2030 are provided and used for the discussion. The monthly profiles are provided in Appendix F.

The 2030 load profiles were forecasted based on the appliance stock estimated for 2030 in the study region. According to MOP & AEEE (2018), the average Indian Seasonal Energy Efficiency Ratio (ISEER) value for air conditioners is currently 3.2 and is projected to increase to 5.9 by 2030. ISEER is a metric to evaluate the performance of air conditioners and is the ratio of cooling load to electric power consumption. Therefore, it was assumed that the power consumption would be reduced by a factor of 3.2/5.9 = 54% from the current value for all new air conditioner stock by 2030. Figure 4.6 and Figure 4.7 show the yearly average appliance-wise daily load profiles for 2022 and 2030, respectively.

The responsibility factor (RF) – the load of the individual component at the time of the system's peak divided by the individual component's peak – indicates the share of each individual component's peak load contributing to the system's peak. When RF is one, that individual component's peak is at the time of the system's peak. Table 4.4 provides the RFs of all appliances for 2022 and 2030, assuming that the aggregated appliance-wise profile's peak coincides with the system's peak, as was the case for June to November 2022. RFs are similar for both years. ACs' peak coincides with the system's peak, whereas refrigerators' and EVs' peak almost coincides with that of the system. The share of these appliances to the aggregated appliance-wise peak load (the flexible component of the DT demand) was around 45%, 19% and 21%, respectively. This indicates that ACs, refrigerators and EVs might have a significant DR potential during the system's peak. While the system peaks in the evening, there is a second significant peak in the morning, with around 75% of the system's peak load. Here, EWH's coincides with the morning peak, while refrigerators' and washing machines' peaks almost coincide. These appliances' DR potential is the most significant during the morning peak.

Figure 4.6:

Yearly average appliance-wise daily load profiles for the study region in 2022

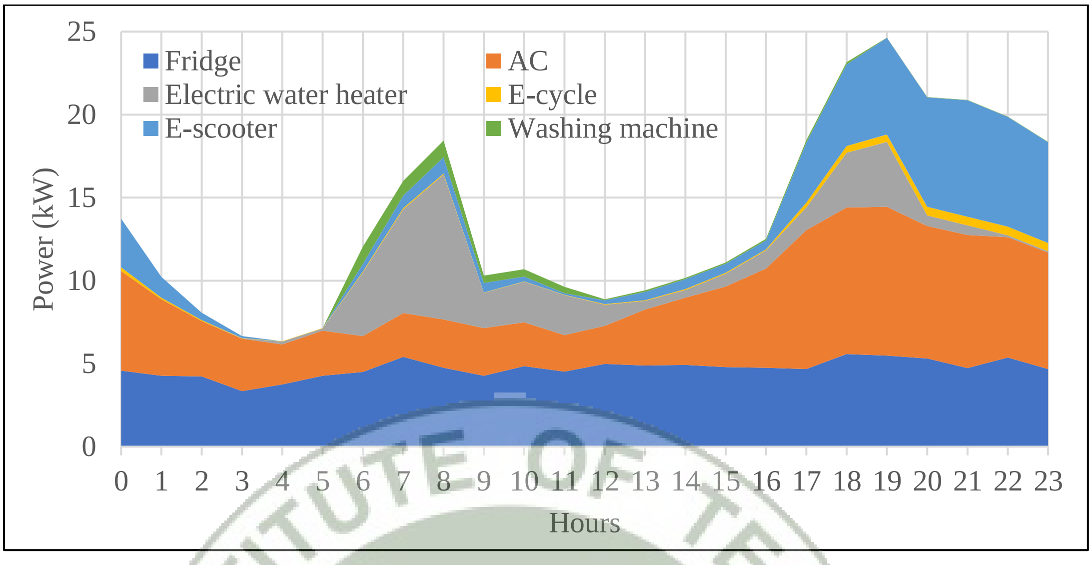


Figure 4.7:

Yearly average appliance-wise daily load profiles for the study region in 2030

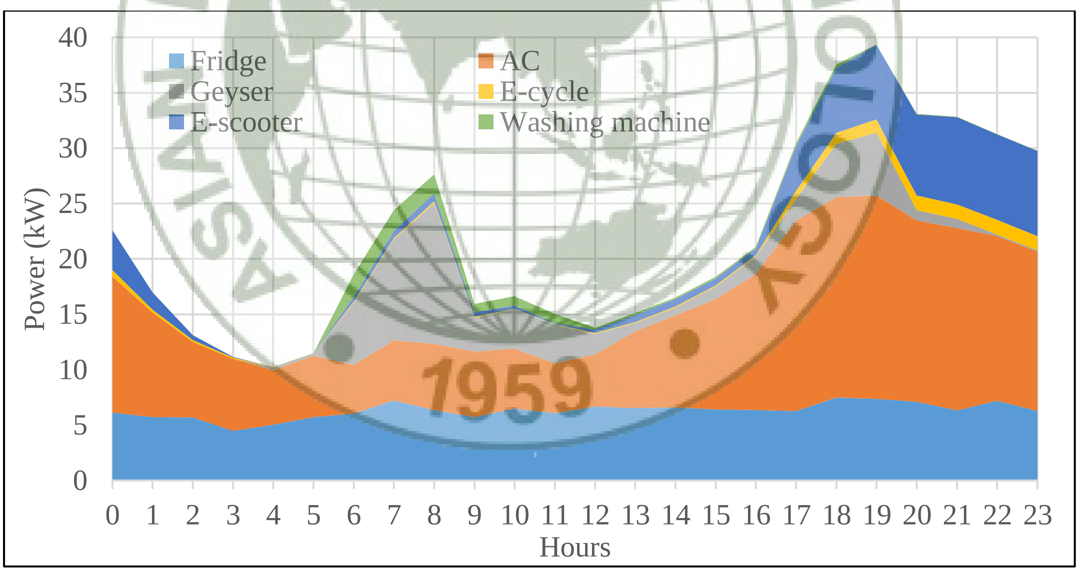


Table 4.4:

Responsibility factors of appliances for yearly average daily load profiles for 2022 and 2030

Appliance	2022		2030	
	RF (evening or system peak)	RF (morning peak)	RF (evening or system peak)	RF (morning peak)
Fridge	0.98	0.85	0.98	0.85
AC	1.00	0.33	1.00	0.33
Electric water heater	0.45	1.00	0.45	1.00
E-cycle	0.83	0.09	0.89	0.12
E-scooter	0.83	0.14	0.86	0.09
Washing machine	0.01	0.96	0.01	0.84

The aggregated appliance-wise peak load is set to increase from the current demand by almost 60% or 14.7 kW, from 24.6 kW to 39.3 kW. This forecasted growth is due to population growth in the study region as well as the existing population purchasing new appliances, mainly ACs and EVs. This data was obtained from the survey conducted in Auroville and didn't use secondary data from the literature for forecasting. An important assumption is that there is no emergence of technology for the services provided by the selected appliances in the study. Furthermore, as these technologies are already mature, energy efficiency improvements are not considered except for ACs. While ACs and EWHs are weather sensitive, the effect of climate change on the usage of these appliances in the future is difficult to determine as it is complicated to do a long-term forecast for temperature and other weather factors in a specific region. Thus, this study did not consider the cooling demand change in the study region due to climate change in 2030.

4.1.6 Distribution Transformer Load Forecast for 2030

The flexible component of the DT demand was forecasted for 2030 in the previous section. The inflexible component, which consists of residential appliances such as fans, kitchen appliances, etc. and other non-residential loads such as office buildings, commercial buildings, hospitals, etc. was forecasted by assuming the historical CAGR of 0.065 (AVC, 2018) as done by Müller et al. (2018). Finally, the flexible component of the DT demand for 2030 is added together with the inflexible component of the DT demand for 2030 to obtain the DT actual and net load profiles in 2030, as shown in Figure 4.8 and Figure 4.9. The solar generation from the existing rooftop solar PV was assumed to remain the same by 2030.

Figure 4.8:

Distribution transformer actual load forecast for 2030

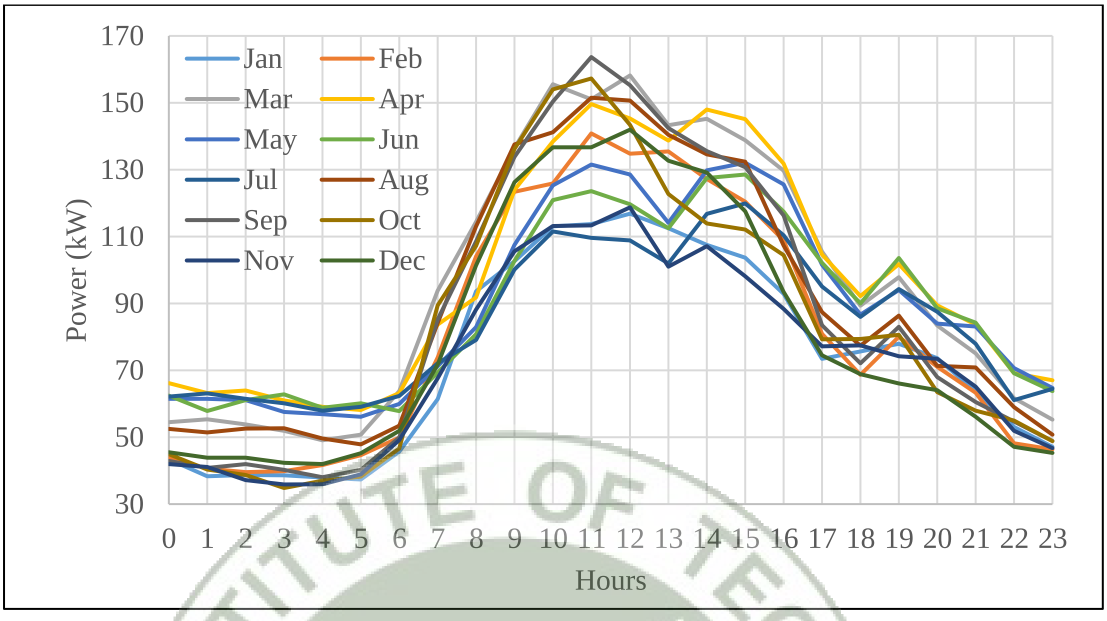
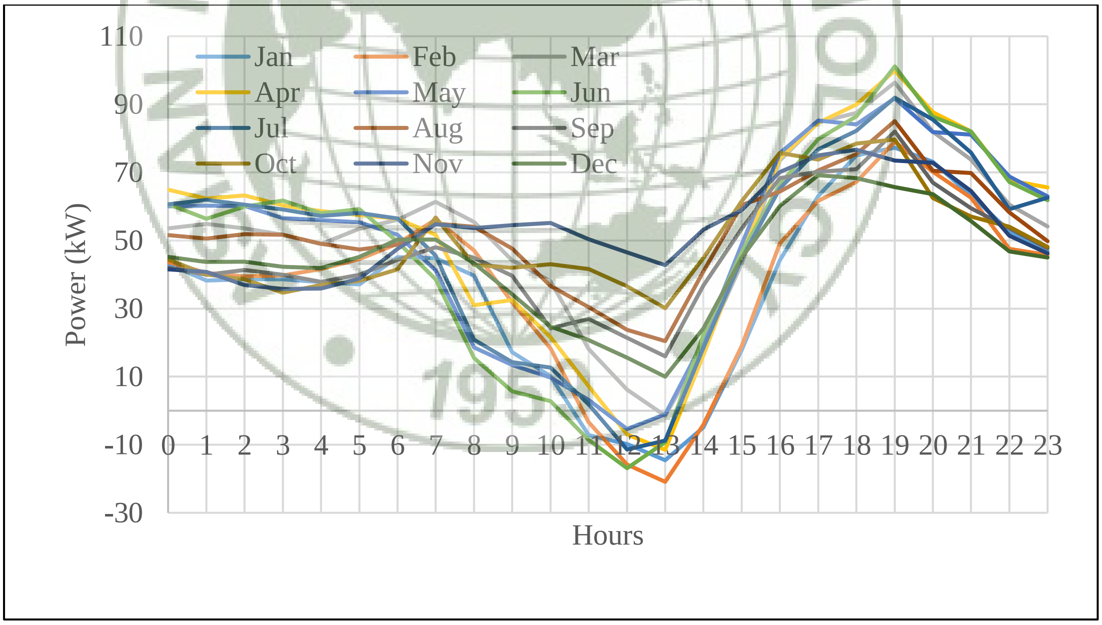


Figure 4.9:

Distritution transformer net load forecast for 2030



4.1.7 Discussion

The appliance-wise and DT load profiles were projected to 2030. This projection considered several factors, such as population growth, appliance ownership rates in the future, and appliance efficiency improvements. The responsibility factor was high for ACs, refrigerators and EVs, showing that these appliances' peaks coincide with the system's peak. Furthermore, the share of these appliances to the aggregated appliance-wise peak load (the flexible component of the DT demand) was around 45%, 19% and 21%, respectively. Thus, this indicates their potential for DR.

The residential sector has a second significant peak in the morning, with a share of around 75% of the aggregated appliance-wise peak load. Here, the electric water heaters' peak coincides with the morning peak, while refrigerators' and washing machines' peaks almost coincide. Thus, these appliances' DR potential was the most significant during the morning peak. However, since the DT doesn't have a significant second peak, their DR potential may not be utilized in this study as DR is applied only to peak periods of the DT demand.

The aggregated appliance-wise peak load was projected to increase from the current demand by almost 60%. Furthermore, the projections for 2030 were based on an important assumption that all new ACs to be bought by 2030 be energy-efficient. Without this assumption, the increase in demand from residential appliances would be even higher. Thus, a policy in the township that promotes only the purchase of energy-efficient ACs would be effective. Furthermore, the cooling demand changes due to climate change were not accounted for in this study. Thus, considering the past trends in rising temperatures in the region, this measure is even more attractive.

To summarize, this section provided the results of specific objective 1 – the DT and appliance-wise monthly average daily load profiles for 2030. These results are utilized in the next specific objective, which is discussed in the next section.

4.2 Modified Distribution Transformer Load Profiles with Demand Response

This section presents the results of specific objective 2 – modified DT load profiles with DR and the resulting technical DR potential. The appliance DR factors considered for the different DR scenarios are discussed in section 4.2.1, and section 4.2.2 provides the results of the modified DT load profiles with DR. The results of the different DR scenarios are compared by looking at the peak load reduction, load factor, and curtailed and shifted electricity consumption. The technical DR potential is the peak load reduction achieved.

4.2.1 Appliance Demand Response Factors for Different Demand Response Scenarios

This study developed different DR scenarios based on the customer participation factor and the appliance types selected for DR. The appliance DR factors for each DR scenario are given in Table 4.5. The appliance DR factor is the product of customer participation and appliance-specific technical factors. While the former factor was assumed to change in all DR scenarios, the latter factor was the same since it is unaffected by any scenario.

Table 4.5:

Appliance DR factors assumed for all appliances under all DR scenarios

Scenario Name	**DR maximum**	**DR medium**	**DR minimum**	**DR EV&AC**	**DR New App**
Appliances selected for DR	All	All	All	EV & AC	Only all new appliances by 2030
Customer participation factor:					
Air conditioner	1.00	0.75	0.50	0.75	0.40
Refrigerator	1.00	0.75	0.50	0.00	0.00
Washing machine	1.00	0.75	0.50	0.00	0.00
Electric storage water heater	0.54	0.41	0.27	0.00	0.18
Electric vehicle	1.00	0.90	0.80	0.90	0.31
Appliance-specific technical factor:					
Air conditioner	0.40				
Refrigerator	0.20				
Washing machine	1.00				
Electric storage water heater	1.00				
Electric vehicle	1.00				
Appliance DR factor:					
Air conditioner	0.40	0.30	0.20	0.30	0.16
Refrigerator	0.20	0.15	0.10	0.00	0.00
Washing machine	1.00	0.75	0.50	0.00	0.00
Electric storage water heater	0.54	0.41	0.27	0.00	0.18
Electric vehicle	1.00	0.90	0.80	0.90	0.31

It is not easy to estimate the share of customers participating in DR; therefore, a scenario-wise analysis was considered important. In DR Maximum, DR Medium and DR Minimum scenarios, all appliance types and existing and future appliance stock were assumed to participate in DR. Only the share of customers participating varied from 100%, 75% and 50%, respectively, for the maximum, medium and minimum DR scenarios for ACs, refrigerators and washing machines. Since it is not possible for instant water heaters to participate in DR without affecting customer comfort, only the storage water heater type was considered. In the study region, 54% of the electric water heater stock was from the electric storage water heater type. From the survey conducted in Auroville, more customers were interested in participating in EV DR programs. Thus, the EV customer participation factor varied from 100%, 90% and 80%, respectively, in the maximum, medium and minimum DR scenarios. In the DR_EV&AC scenario, only electric vehicles and air conditioners were assumed to participate in DR. In the last scenario, only the new appliances to be bought by 2030 were considered to participate in DR and their share was estimated from the survey results.

The appliance-specific technical factor ensured customer comfort during DR and was assumed the same in all DR scenarios. The rationale for the assumptions made for this factor is explained here. In a pilot of AC DR run in Auroville, the AC was curtailed for 12 minutes for a maximum of 2 times per hour. When the AC was curtailed 2 times in an hour, that AC was prohibited from participating in DR in the next hour. The room temperature was also monitored during this pilot and the results showed an increase of 1.1 °C during the hours when DR was implemented (AVC, 2021c), which would not affect the customer's comfort much. Thus, using the DR program and the results of this pilot, it was assumed in this study that the technical factor for AC is 24/60 = 0.4 (24 minutes per hour). Next, for refrigerators, Southern California Edison (2012) conducted a detailed study on the ability of refrigerators to participate in DR and found that the performance of the refrigerators was not affected much for curtailment of less than 10 minutes. Thus, the technical factor for refrigerators was assumed to be 10/60 = 16.7% and was rounded up to 20%. The customers are expected to completely shift the operation timings of washing machines, electric storage water heaters and electric vehicles from peak to off-peak hours since it is assumed that their usage cannot be stopped in the middle of their operation cycle and they don't operate in part-load conditions. Thus, the technical factor of these appliances was assumed to be 100%. However, the DR algorithm ensured that the shifted load was returned online within 24 hours for washing machines and EVs and within 4 hours for storage water heaters. Furthermore, the load of storage water heaters was only shifted before the usage time to ensure that the customers could use the appliance according to their normal operation time without losing comfort. To summarize, the appliance-specific technical factors ensured customer comfort by considering the duration of DR events and the shifting time of appliances.

4.2.2 Comparison of the Results of Different Demand Response Scenarios

Table 4.6 provides the results of different DR scenarios for the DT load profiles in 2030. The monthly average daily load profiles for each DR scenario are provided in Appendix G. DR was applied only from March to September. For each DR scenario, the peak load reduction from the scenario without DR, the load factor, curtailed energy in a day, shifted energy in a day, and the technical potential of each appliance selected for DR are given. The observations are as follows:

- The peak load reduction, also the overall technical potential of DR, in DR Maximum and DR New App scenarios are respectively 20.7% and 8.1%. Thus, even in the worst case where only all the new appliances to be purchased by 2030 participate in DR (thus, this scenario has the least customer participation factor), 8.1% of peak load reduction from the scenario without DR can be obtained. It is also interesting to note that the peak load reduction from the DR EV&AC scenario is higher than the DR Minimum scenario.
- The effects of DR are also shown on the average load factor of the DT. The load factor is the ratio of the average demand in a day to the peak demand in a day. It increases from 55.8% in the scenario without DR to 63% in the DR Maximum scenario.
- The average curtailed energy in a day ranges from 2.1 to 6.1 kWh. This is from the curtailment of a share of the AC and refrigerator loads during the peak hour of the day. In all scenarios where both appliances contribute to DR, around 86 to 87% of the curtailed energy is from ACs.
- The average shifted energy in a day ranges from 40 to 51.8 kWh, except in the DR New App scenario. More than 90% of this is from EVs. Less than 8% is from water heaters, while only a small fraction of around 2% is from washing machines.
- The technical DR potential of each appliance is the peak load reduction achieved from each appliance. This potential of ACs and EVs is the highest, with 11.9 and 7.8%, respectively, in the DR Maximum scenario. The technical DR potential from refrigerators, washing machines and electric water heaters is quite low even in the

DR Maximum scenario, with 1.4%, 0% and 2.4%, respectively. This emphasizes the attractiveness of the DR EV&AC scenario.

Table 4.6:

Comparison of the results of different DR scenarios of the DT load profile in 2030

Performance metrics		DR minimum	DR medium	DR maximum	DR EV&AC	DR New App	No DR
Peak load (kW)		86.9	82.8	80.2	85.7	93.0	101.1
Energy consumption (kWh/day)		1138.0	1136.7	1135.4	1136.6	1138.8	1140.5
Peak load reduction (%)		14.0%	18.1%	20.7%	15.2%	8.1%	-
Load factor (%)		60.6%	62.0%	63.0%	60.7%	58.2%	55.8%
Curtailed energy	Total (kWh/day)	3.1	4.6	6.1	4.0	2.1	-
	Fridge (%)	13.7%	13.7%	13.0%	0.0%	0.0%	-
	AC (%)	86.3%	86.3%	87.0%	100.0%	100.0%	-
Shifted energy	Total (kWh/day)	40.0	45.9	51.8	42.4	15.9	-
	EV (%)	94.1%	92.3%	90.9%	100.0%	91.9%	-
	WM (%)	1.1%	1.4%	1.7%	0.0%	0.0%	-
	WH (%)	4.8%	6.3%	7.4%	0.0%	8.1%	-
Technical potential	Fridge (%)	0.7%	1.1%	1.4%	0.0%	0.0%	-
	AC (%)	6.0%	8.9%	11.9%	8.9%	4.8%	-
	EV (%)	6.3%	7.1%	7.8%	7.1%	2.4%	-
	WM (%)	0.0%	0.0%	0.0%	0.0%	0.0%	-
	WH (%)	1.2%	1.8%	2.4%	0.0%	0.8%	-

4.2.3 Discussion

The technical potential of DR under DR_Minimum, DR_Medium, DR_Maximum, DR_EV&AC and DR_New App scenarios are respectively 14.0%, 18.1%, 20.7%, 15.2% and 8.1%. In terms of absolute values, they are 14.2 kW, 18.3 kW, 20.9 kW, 15.4 kW, and 8.2 kW, respectively. The DR potential ranges from 8.1 to 20.7% in these scenarios, indicating the importance of the share of customers participating in DR and the appliance types selected for DR in the estimation of DR potential. Importantly, even when only all the new appliances to be purchased by 2030 participate in DR, 8.1% of peak load reduction is achieved. This leads to the requirement of an important policy measure to ensure all new appliances are embedded with smart features enabling them to participate in DR programs.

The appliance-wise technical potential in the DR_Maximum scenario for ACs, EVs, refrigerators, washing machines and electric storage water heaters was 11.9%, 7.8%, 1.4%, 0.0% and 2.4%, respectively. This provides an insight into which appliances to target for DR among the appliances selected for DR. Washing machines barely contributed to DR since their operation didn't coincide with the system peak. The contribution of electric storage water heaters would be higher if most of the electric water heaters were of the storage type. Their technical potential was 2.4% despite the assumption that all new electric water heaters to be purchased by 2030 are of the storage type. Targeting ACs and EVs for DR would be recommended for financial and practical reasons as they have the highest DR potential. This is also represented by the DR_EV&AC scenario which has higher technical DR potential than the DR_Minimum scenario where all the appliances participate in DR although with a lower share of customer participation.

The approach for implementing EV DR is through behavioral changes. In the survey conducted in Auroville, when the respondents who currently used an EV were asked how likely they were to change their vehicle charging hours to sunshine hours so that they use more solar energy than grid electricity even without receiving any electricity credits from the electricity utility, more than 75% said they were very/extremely likely (almost 40% said they were extremely likely) to change their vehicle charging pattern to sunshine hours (Appendix D). Thus, if offices and other public areas are equipped to charge EVs during the sunshine hours, it would facilitate EV DR implementation. This would require policy changes to bring charging stations to the necessary areas as public demand is already there.

The approach for implementing AC DR is slightly different as it requires an automation system that can allow direct control of ACs. Firstly, this would require Wi-Fi as the communication technology and smart plugs for ACs not embedded with smart features to enable DR. In the survey conducted in Auroville, around 85% of the households are already equipped with wi-fi connection (Appendix D). The ACs are curtailed for at least 12 minutes and a maximum of 24 minutes a day during the summer months according to the technical factor considered in this study. According to the AC DR pilot conducted in Auroville, this would increase the temperature by around 1.1 °C (AVC, 2021c). Thus, as a real-time strategy to implement AC DR exists already, a business model to ensure high customer participation must be developed.

While the above analyses were made, it is important to understand that the study's results depend on the composition of the DT loads. The technical DR potential will be greater in a DT that is mainly dominated by residential loads. The appliance-wise DR potentials will also be higher. This emphasizes the need for policies to mandate the embedding of smart features enabling DR in appliances.

To summarize, this section presented the results of specific objective 2 – modified DT load profiles with DR and the resulting technical potential of DR. The appliance DR factors for each DR scenario were provided and the results of modifying the DT load profiles in 2030 with DR were discussed. The appliance-wise and aggregated technical DR potential, the average curtailed and shifted energy in a day, and the load factor were also provided for each DR scenario. DR EV&AC and DR New App scenarios are carried forward to the next specific objective to assess their financial feasibility. Among the DR scenarios where all appliances participate in DR, the DR Medium scenario is selected as it doesn’t assume a high or low customer participation factor. The results of microgrid sizing and the resulting financial analysis are discussed in the next section.

4.3 Microgrid Sizing and Financial Analysis of Demand Response Scenarios

This section presents the results of specific objective 3 – microgrid sizing of different DR scenarios and the resulting financial analysis. Firstly, the inputs required to size the microgrid for each DR scenario are provided. These include the description of the system configuration, project-specific and technology-specific inputs, and the capital costs of the different components in the system. Next, the outputs from the HOMER Pro software are presented. These include the analysis of the capacities of the different components in the system, the verification of the power balance in the microgrid, the analysis of the system's electricity generation and consumption, and the financial analysis to compare each DR scenario.

4.3.1 HOMER Pro Inputs

The various inputs required to design the microgrid are presented in this section.

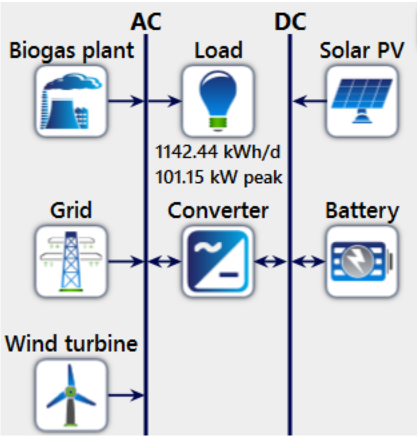
4.3.1.1 System configuration

The renewable energy resources considered in this study for achieving a 100% net renewable energy microgrid in Auroville for the scenario without DR are biomass, solar and wind. The biomass available in the region is the pressmud, a byproduct of making sugar. The pressmud is converted to biogas and a biogas power plant generates electricity in the model. Solar and wind resources are also available in the region and, thus, considered in the model.

Figure 4.10 shows the configuration of the microgrid. The biogas plant, grid and wind turbine are connected to the AC bus through which they supply to the load directly. Solar PV and battery are connected to the DC bus and supply to the load through the converter.

Figure 4.10:

System configuration



4.3.1.2 Project-specific inputs

The different project-specific inputs required to design the microgrid are provided in Table 4.7. The discount rate and project lifetime were obtained from the Tamil Nadu Electricity Regulatory Commission (TNERC) (TNERC, 2021). The inflation rate was the average inflation rate over the past five years in India (The World Bank, 2023). The current values of the grid energy and demand charges, network charges and feed-in tariff were escalated by 4% per annum by 2030 (TNERC, 2022). The maximum net grid purchases and minimum renewable energy fraction were set to 0 and 80%, respectively, according to the objective of this study.

Table 4.7:

Project-specific inputs for designing the microgrid in HOMER Pro software

Project-specific Inputs	Units	Value in 2030	Current value	Remarks	Reference
Discount rate	%	8.67	-		TNERC (2021)
Project lifetime	years	25	-		TNERC (2021)
Inflation rate	%	4.55	-	Average inflation rate of past 5 years in India	
Grid energy charges	₹/kWh	9.69	7.08	Current value: 6.75 ₹/kWh + 5% tax = 7.08 ₹/kWh Future value: 4% escalation rate per annum	TNERC (2022)
Grid demand charges	₹/kW/ month	878	642	Current value: 550 ₹/kVA or 611 ₹/kW (0.9 power factor) + 5% tax = 641.67 ₹/kW Future value: 4% escalation rate per annum	TNERC (2022)
Network charges	₹/kWh	1.31	0.96	Future value: 4% escalation rate per annum	TNERC (2021)
Feed-in tariff	₹/kWh	4.24	3.10	Future value: 4% escalation rate per annum	TNERC (2021)
Maximum net grid purchases	kWh/year	0	-	Study Objective	
Minimum renewable fraction	%	80		Study Objective	

Note: The current (April 2023) exchange rate for one Indian Rupee (₹) to US dollars is $ 0.012.

4.3.1.3 Component-specific inputs

The different component-specific inputs are provided in Table 4.8. The solar PV efficiency, derating factor, temperature coefficient and operating temperature were based on the generic solar PV module in HOMER Pro software and were compared with secondary data. The solar radiation data was obtained from the NASA database for Auroville (HOMER Pro, 2023). The lithium-ion battery storage nominal voltage, capacity, and roundtrip efficiency were also based on the generic lithium-ion battery in HOMER Pro software. The minimum battery state of charge was set to 20%, as is common for these batteries (Independent Power Systems, 2021). The wind turbine rating was 10 kW and the hub height was set to 20m. The wind speed data was also obtained from the NASA database for Auroville (HOMER Pro, 2023). The biomass pressmud available per day in the region is around 1.2 tons and costs around 3,644 ₹/ton, including transportation (AVC, 2022). These values were obtained from Auroville Consulting, which extensively reviewed the township's biomass feedstock for electricity generation. The gas yield from pressmud is 0.241 l/g (Agrawal et al., 2012). The lower heating value of biogas was assumed to be 20 MJ/m^3(Frazier & Ndegwa, 2019). The typical lifetime of all components was obtained from Auroville Consulting's 'Levelized Cost Calculator for Distributed Energy Resources' tool (AVC, 2021d).

Table 4.8:

Component-specific inputs for designing each component in the microgrid in HOMER Pro software

Component	Unit	Value
Solar PV		
Rated capacity	kW	1
Efficiency	%	13
Derating factor	%	80
Temperature coefficient	%/ °C	0.5
Operating temperature	°C	47
Lifetime	years	25
Lithium-Ion battery pack		
Nominal voltage	V	6

Component	Unit	Value
Nominal capacity	kWh	1
Nominal capacity	Ah	167
Roundtrip efficiency	%	90
Minimum state of charge	%	20
Lifetime	years	13
Converter		
Nominal power	kW	1
Efficiency	%	95
Lifetime	years	14
Wind turbine		
Rated capacity	kW	10
Hub height	m	20
Lifetime	years	25
Biogas plant		
Rated capacity	kW	50
Biomass availability (pressmud)	ton/day	1.2
Gas yield	L/g	0.241
LHV of biogas	MJ/m^3	20
Cost of biomass	₹/ton	3,644
Lifetime	years	25

4.3.1.4 System capital cost scenarios

In the previous section, the component-specific details were provided. Here, the components' capital cost and O&M costs are provided. A sensitivity analysis was done on the system capital costs (SCC) and two scenarios, SCC Min and SCC Max, were created as a fraction of the current technology costs. In the minimum scenario, the component capital cost for 2030 was considered 80% of the current costs. In the maximum scenario, the current values were also assumed to be used for 2030. Due to several reasons, such as the ongoing Russia-Ukraine war and Covid -19, the cost reductions by 2030 were not expected to be high. The current costs were obtained from the Central Electricity Regulatory Commission of India (CERC) and Auroville Consulting (AVC, 2021d; CERC, 2020) and provided in Table 4.9. In this study, smart plugs were considered the DR enabling technology for the existing residential appliances that don't have smart features. 16A smart plugs were considered for electric vehicles, air conditioners and electric water heaters, whereas 6A smart plugs were considered for refrigerators and washing machines. The current costs of the smart plugs were obtained from an online search.

Table 4.9:

Component capital cost in 2030 in minimum and maximum system capital cost scenarios

Technology	Units	Current (2020-21)	SCC Min	SCC Max
Solar PV	₹/kW	38,000	30,400	38,000
Battery pack	₹/kWh	22,171	17,737	22,171
Converter	₹/kW	35,700	28,560	35,700
Wind turbine	₹/kW	140,000	112,000	140,000
Biogas plant	₹/kW	142,320	113,856	142,320
Smart plug 16A	₹/unit	2,000	1,600	2,000
Smart plug 6A	₹/unit	1,000	800	1,000

The number of smart plugs to be purchased for 2030 is based on the number of customers participating in DR; hence, the capital cost of smart plugs is different under each DR scenario. Thus, Table 4.10 provides the cost of DR in each scenario as well as the breakdown of the share of each appliance type to the overall cost. In the DR New App scenario, since only the new appliances to be purchased by 2030, which are also enabled with smart features, are considered to participate in DR, the hardware cost of DR is assumed to be 0.

Table 4.10:

The breakdown of the DR capital cost for the different DR scenarios

Smart plug cost breakdown	DR medium	DR EV&AC	DR New App
Total capital cost of smart plugs under SCC Maximum (Million ₹)	0.315	0.096	0
Total capital cost of smart plugs under SCC Minimum (Million ₹)	0.252	0.077	0
Refrigerator (%)	30.0%	0.0%	-
Air conditioner (%)	10.8%	35.5%	-
Electric vehicle (%)	19.6%	64.5%	-
Washing machine (%)	7.4%	0.0%	-
Electric storage water heater (%)	32.2%	0.0%	-

Next, the O&M cost of each component is given in Table 4.11. The Central Electricity Regulatory Commission of India (CERC) used these values while determining tariffs for renewable energy sources (CERC, 2020). They assumed a cost escalation of 3.84% per annum, and this value was used to project the O&M costs for 2030 for the technologies considered in this study. However, for the biogas plant, a labour cost of 10,000 ₹/month was added to consider the human resources required to operate and maintain a biogas power plant.

Table 4.11:

O&M cost of each component in the microgrid

Technology	O&M Cost 2021 (₹/kW-year)	O&M Cost 2030 (₹/kW-year)
Solar PV	600	875
Battery pack	215	313
Converter	750	1093
Wind turbine	600	875
Biogas plant	126,131	183,852

4.3.2 HOMER Pro Outputs

This section presents the outcomes of designing the microgrid under various DR and system capital cost scenarios. There are 8 scenarios – DR_Medium, DR_EV&AC, DR_New App and No DR under maximum and minimum system capital cost scenarios. The system sizing, power balance verification, system electricity generation, and financial analysis of the different scenarios are described in the subsequent sections.

4.3.2.1 System sizing

Table 4.12 and Table 4.13 present the component capacities for all DR scenarios for SCC Maximum and SCC Minimum scenarios, respectively. Only the best case or the winning system architecture of each scenario is selected. For all scenarios, the winning system consists of battery, grid and solar PV since wind and biomass technologies are more expensive than solar PV in the region. DR has the most impact on battery sizing for both SCC scenarios, with 7.3% and 6.2% reduction for the maximum and minimum scenarios, respectively. DR_Medium has the highest DR potential, followed by DR_EV&AC and DR_New App scenarios. Thus, the battery sizing increases progressively with DR_EV&AC, DR_New App and No DR scenarios. This is according to expectations since DR curtails or shifts load from peak to off-peak periods, a service that storage also performs by discharging during peak hours and charging during off-peak hours. Thus, the higher the DR potential, the lower the need for storage. The battery autonomy ranges from 14 to 15 hours in all scenarios. DR doesn't affect the sizing of the other systems too much in both the SCC scenarios.

Table 4.12:

System sizing of the different DR scenarios under the System Capital Cost Maximum scenario

Component Capacity	DR_Medium	DR_EV&AC	DR_New App	No DR
Battery (kWh)	836	870	886	902
Converter (kW)	64	63	61	61
Grid (kW)	83	86	93	101
PV (kW)	338	329	335	338

Table 4.13:

System sizing of the different DR scenarios under the System Capital Cost Minimum scenario

Component Capacity	DR_Medium	DR_EV&AC	DR_New App	No DR
Battery (kWh)	844	868	888	900
Converter (kW)	62	62	62	59
Grid (kW)	83	86	93	101
PV (kW)	338	335	333	342

4.3.2.2 Power balance verification

Power balance verification checks whether the flow of electricity at each node or component of the microgrid is matched. This step is important to assess the truth of the results generated by the software. For each scenario, the software generated hourly values for grid purchases, grid sales, excess electricity, battery charging power, battery discharging power, solar generation and the load. This section explains the power balance verification step.

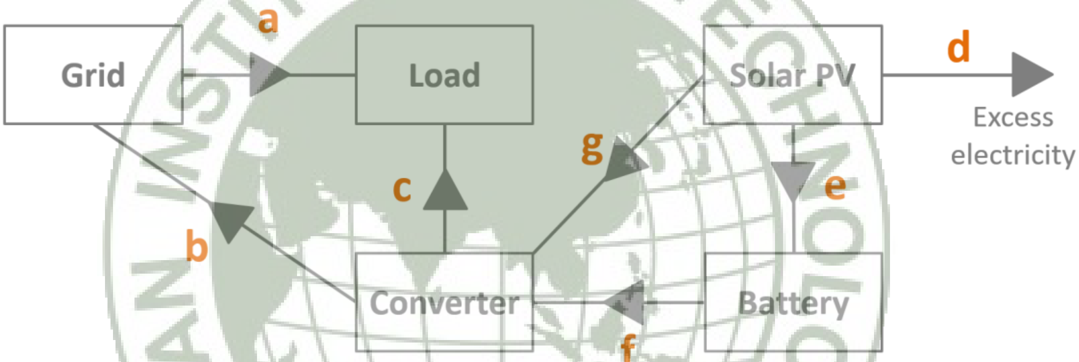
Figure 4.11 shows the schematic of the system configuration highlighting the different flows of electricity, where a = grid purchases or grid import, b = grid sales or grid export, c = converter to load, d = excess electricity or curtailed solar energy, e = battery charging power, f = battery discharging power, and g = solar to the converter. The power flow from the converter to the load is calculated from Equation 4.1, and the power flow from the solar panel to the converter is calculated from Equation 4.2:

c = Load – grid purchases Equation 4.1

g = Solar PV generation – e – d Equation 4.2

Figure 4.11:

Schematic of the system configuration for power balance verification



Note: The rectifier power input and output, representing AC to DC power conversion, was always zero for all scenarios. Thus, the grid charged the battery at no point and, therefore, was not indicated by the flow of arrows.

In this study, the power balance was verified for each timestep according to Equation 4.5, where the converter output power equals the product of the converter input power and converter efficiency.

Converter input = f + g Equation 4.3

Converter output = c + b Equation 4.4

c + b = (f + g) x converter efficiency Equation 4.5

4.3.2.3 System electricity generation

The two sources that supply the load in the microgrid are solar PV and the grid. Table 4.14 and Table 4.15 show the breakdown of this energy for SCC Maximum and Minimum scenarios, respectively. The microgrid design ensures that the load is supplied by 100% net-renewable energy. Thus, the annual grid purchases are less than the annual grid sales. Solar self-consumption is the electricity that is directly supplied to the load or through the battery. In all scenarios, this value is around 75% of the load. However, there is excess electricity production and system losses for all scenarios, and these values are around 10% of the solar PV generation. The energy balance was verified in all scenarios, i.e., the solar PV generation and grid purchases equal the solar self-consumption, grid sales, electricity excess and system losses.

Table 4.14:

The breakdown of annual electricity usage in the system under the System Capital Cost Maximum scenario

System electricity breakdown (kWh/year)	**DR_Medium**	**DR_EV&AC**	**DR_New App**	**No DR**
Solar PV generation	515,069	501,572	511,419	515,835
Grid purchases	104,322	103,101	102,821	103,922
Grid sales	106,628	103,434	103,168	106,537
Solar self-consumption	310,757	312,208	313,168	312,843
Excess electricity	55,140	43,090	51,510	52,395
Electricity losses	42,544	42,840	43,573	44,060
Electricity consumption	415,079	415,309	415,989	416,765

Table 4.15:

The breakdown of annual electricity usage in the system under the System Capital Cost Minimum scenario

System electricity breakdown (kWh/year)	**DR_Medium**	**DR_EV&AC**	**DR_New App**	**No DR**
Solar PV generation	515,226	510,792	507,976	521,805
Grid purchases	101,945	100,295	104,138	102,224
Grid sales	102,153	101,400	106,467	103,483
Solar self-consumption	313,134	315,014	311,851	314,541

System electricity breakdown (kWh/year)	DR_Medium	DR_EV&AC	DR_New App	No DR
Excess electricity	57,203	51,210	46,144	59,598
Electricity losses	42,736	43,168	43,514	44,183
Electricity consumption	415,079	415,309	415,989	416,765

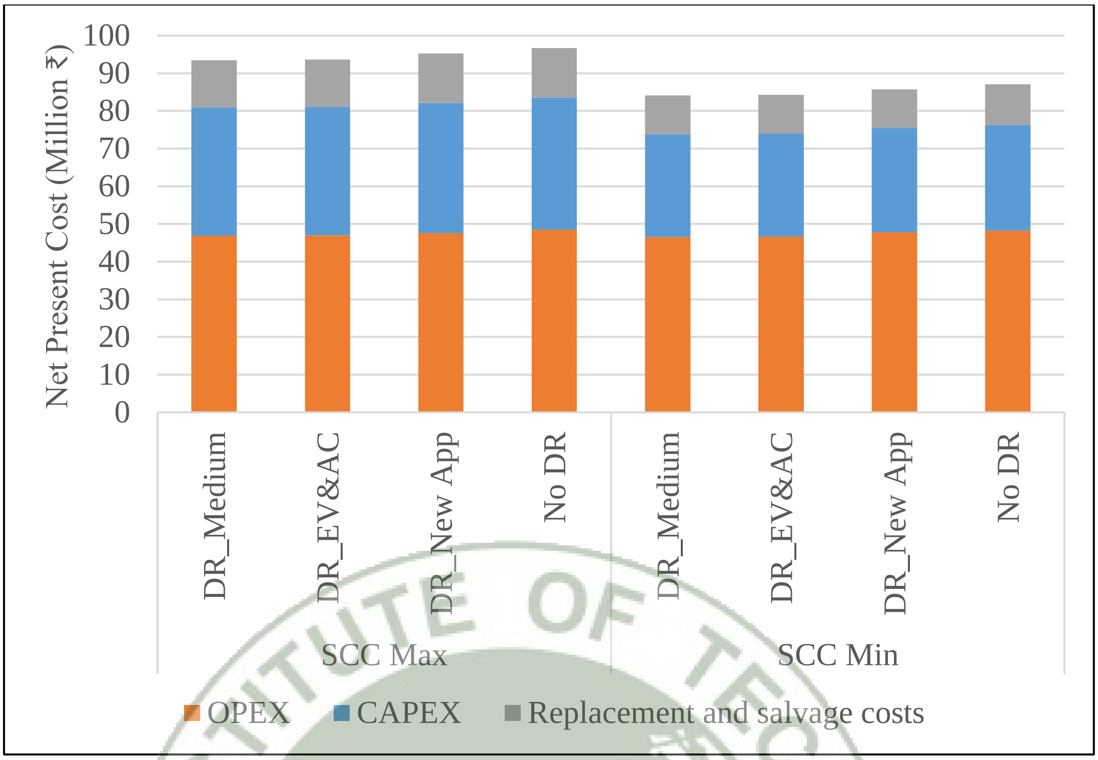
4.3.2.4 Financial Analysis of DR Scenarios

A financial analysis was done to assess the financial benefits of DR. The NPC, CAPEX and OPEX of the systems for each DR and SCC scenario are compared first. Then a summary table with all the financial analysis performance metrics, including LCOE, avoided costs and return on investment, is provided and discussed.

The NPC of the system for each DR scenario is shown in Figure 4.12. In SCC Maximum and Minimum scenarios, the NPC of the system increases as the DR potential of the scenario decreases. In SCC Maximum scenario, around 36%, 50% and 14% of the NPC are due to CAPEX, OPEX, and replacement and salvage costs, respectively. In SCC Minimum scenario, these values are around 33%, 55% and 12%, respectively. The absolute cost of OPEX remains the same, whereas NPC reduces owing to CAPEX, so the share of OPEX to the NPC reduces in the minimum cost scenario compared to the maximum scenario.

Figure 4.12:

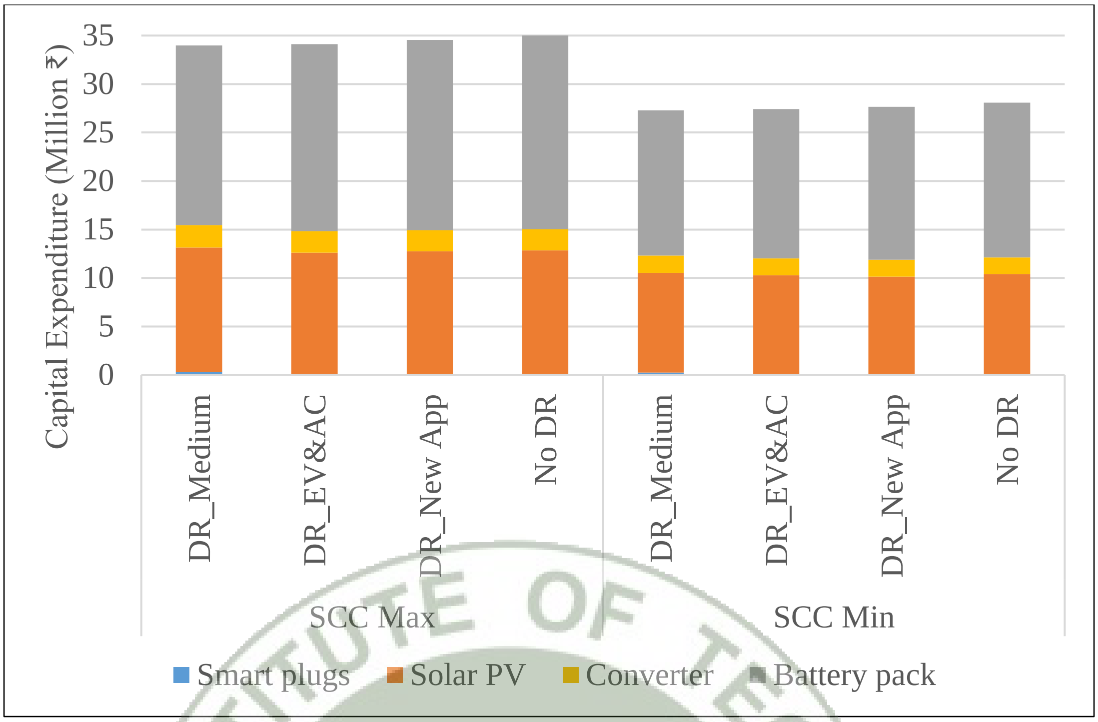
The net present cost of the system under all scenarios with a breakdown of the type of expenditure



The breakdown of CAPEX according to each component in the system is shown in Figure 4.13. The contribution of smart plugs to CAPEX is negligible even in the SCC Max with the highest DR potential scenario. Around 55 to 57% of CAPEX is due to the battery pack, 37 to 38% due to solar PV and a small share of 6 to 7% due to converter. The cost of solar and converter are almost the same in all DR scenarios within the same SCC scenario. The CAPEX of the battery increases as the technical potential of the DR scenario decreases.

Figure 4.13:

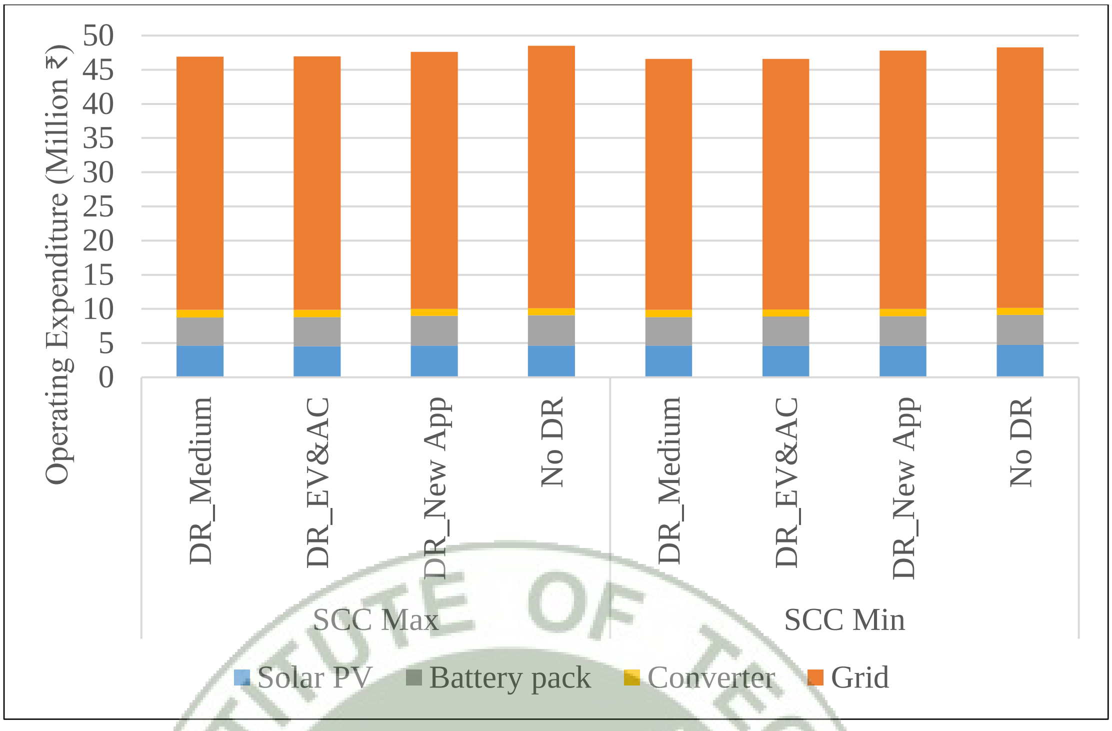
System CAPEX under all scenarios with the breakdown of the components in the system



The OPEX breakdown according to each system component is shown in Figure 4.14. As explained earlier, OPEX is unaffected by the SCC Maximum and Minimum scenarios. However, due to reductions in demand charges, OPEX reduces with higher DR potential scenarios. Around 80% of OPEX is due to grid charges. The remaining is due to the O&M costs of solar PV, converter and battery pack.

Figure 4.14:

System OPEX under all scenarios with the breakdown of the components in the system



The summary of all the performance metrics, including LCOE, avoided cost of energy and return on investment, for the financial analysis is provided in Table 4.16. The observations are as follows:

- Compared to the scenario without DR, DR_Medium achieved a 3.4% and 3.5% reduction in NPC in SCC Maximum and Minimum scenarios, respectively. Although less than DR_Medium scenarios, a comparable share of reduction was achieved by DR EV&AC scenarios. Annualized cost is the annualized value of NPC and another way to view the costs of the system. Thus, the percentage reductions in annualized costs remained the same as with the percentage reductions in NPC.
- Similarly, LCOE reduction was 3.1% and 2.9% in SCC Maximum and Minimum scenarios, respectively.
- The avoided energy cost ranges between 0.9 to 0.36 ₹/kWh and 0.21 to 0.31 ₹/kWh for the SCC Maximum and Minimum scenarios, respectively.
- The return on investment is the highest for the DR_EV&AC scenario as the initial investment for DR is only 0.096 MM ₹ and, whereas the returns are 3.06 MM ₹ for the high capital cost scenario.

Table 4.16:

Summary of the financial analysis of different DR scenarios

Scenario	SCC Max				SCC Min			
	DR_Medium	**DR_EV&AC**	**DR_New App**	**No DR**	**DR_Medium**	**DR_EV&AC**	**DR_New App**	**No DR**
Peak load (kW)	82.8	85.7	93.0	101.2	82.8	85.7	93.0	101.2
Electricity consumption (kWh/day)	1137.2	1137.8	1139.7	1141.8	1137.2	1137.8	1139.7	1141.8
NPC (Million ₹)	93.46	93.66	95.20	96.72	84.08	84.31	85.76	87.09
CAPEX (Million ₹)	33.97	34.11	34.55	35.01	27.27	27.42	27.64	28.06
OPEX (Million ₹)	46.91	46.97	47.61	48.50	46.56	46.61	47.81	48.27
NPC % reduction from No_DR	3.4%	3.2%	1.6%	-	3.5%	3.2%	1.5%	-
NPC savings from No_DR scenario (Million ₹)	3.26	3.06	1.52	-	3.00	2.78	1.32	-
Annualized cost (Million ₹)	5.95	5.96	6.06	6.15	5.35	5.36	5.46	5.54
LCOE (₹/kWh)	11.40	11.49	11.67	11.76	10.34	10.38	10.44	10.65
LCOE % reduction from No_DR Scenario	3.1%	2.3%	0.8%	-	2.9%	2.5%	1.9%	-
Avoided cost of energy (₹/kWh)	0.36	0.27	0.09	-	0.31	0.27	0.21	-
Smart plug cost (₹)	315000	95750	0	0	252000	76600	0	0
Return on Investment	9.33	30.93	-	-	10.92	35.26	-	-

4.3.3 Discussion

The microgrid was sized for each DR scenario, and a financial analysis was conducted to compare the scenarios with and without DR. According to the objectives of this study, the microgrid demand was designed to be sourced from 100% net renewable energy while limiting the share of grid imports/exports. This is important to ensure more renewable energy self-consumption rather than depending on the grid to highlight the effect of DR. The grid is only used as a balance so that there is a financial benefit as well as resources used efficiently.

The renewable resources considered in the study were solar, wind and biomass. Biomass available in the region was pressmud. The model estimated the biogas generation from pressmud and used a biogas plant to generate electricity. The region's cheapest resource was solar; thus, the winning system architecture excluded wind turbines and biogas plants.

The NPC of the system reduced from the scenario without DR according to the increasing potential of DR of the scenario. This is because of CAPEX reduction due to battery size reduction as well as OPEX reduction due to demand charges. As DR shifts the load from peak to off-peak hours, resembling the working of battery storage to discharge the battery during peak hours and charge the battery during off-peak hours, the decrease in battery capacity is according to expectations. Similarly, as DR reduces the peak load, the demand charges reduce proportionally.

DR programs have different types of costs involved. In this study, the only costs estimated for DR are the hardware or smart plug costs to retrofit existing appliances that don’t have smart features enabling DR. Another important cost of DR is the incentive amount to be paid to the customers enrolled in DR. This value was estimated based on the total savings in NPC from scenarios with and without DR and the savings were divided among the customers participating in DR according to each DR scenario (Appendix H). The incentive amount was the highest for the DR_EV&AC scenario since it has the least number of appliances and customer participation, while the savings from NPC were relatively high. The share of the monthly incentive amount to the average monthly electricity bill of the customer was found to be 22.3% and 20.3%, respectively, for maximum and minimum system capital cost scenarios (Appendix H). This is a good amount to attract customers to enroll in DR.

DR also has different types of benefits for different stakeholders. Firstly, in this study, the DT demand in 2030 didn't exceed its capacity (250kVA). Thus, the transmission and distribution capacity deferral benefits were not considered for the microgrid operators. Secondly, by reducing the peak demand from the grid, the grid operators save costs due to network congestion. Thirdly, the customers enrolled in DR profit from the incentive amounts paid to them by the microgrid operators.

To summarize, this section provided the results of specific objective 3 – microgrid sizing and financial analysis of scenarios with and without DR. The various project-specific and technology-specific inputs required to design the microgrid in the HOMER Pro software were provided. Different performance metrics such as NPC, CAPEX, OPEX, LCOE, avoided energy cost, and ROI were presented to compare all the scenarios with and without DR.

4.4 Summary

This chapter presented the results of each specific objective of this study. The DT and appliance-wise monthly average daily load profiles for 2030 were forecasted. Next, the DT load profiles were modified with DR based on different DR scenarios. Finally, the microgrid was sized and the results of the financial analysis were presented. The next chapter provides the conclusions and recommendations of this study.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

The concluding chapter presents the key findings according to the study's objectives. Finally, some recommendations for further study are also discussed.

5.1 Conclusion

The appliance-wise and DT monthly average daily load profiles were projected for 2030. The aggregated appliance-wise peak load increased from the current demand (2022) by almost 60%. The DT peak load in 2030 was 101.1 kW. The responsibility factor for ACs, refrigerators and EVs was 1.00, 0.98 and 0.86, indicating that their peaks coincide greatly with the system peak. Electric water heaters and washing machines had relatively low RF – 0.45 and 0.01, respectively, as their peaks occur during the mornings.

Next, the modified DT load profiles with DR were generated through a DR algorithm for several DR scenarios. These scenarios differed through the customer participation factor and the appliances considered for DR. The technical potential of DR under DR_Minimum, DR_Medium, DR_Maximum, DR_EV&AC and DR_New App scenarios was respectively 14.0%, 18.1%, 20.7%, 15.2% and 8.1%. And the appliance-wise technical potential in the DR_Maximum scenario for ACs, EVs, refrigerators, washing machines and electric storage water heaters was 11.9%, 7.8%, 1.4%, 0.0% and 2.4%, respectively. The highest DR potential was from AC and EVs.

Finally, the microgrid was designed for the modified DT load profiles with DR and a financial analysis was conducted to compare the benefits of DR from the scenario without DR. Here, a sensitivity analysis was performed on the system capital costs (SCC). For the SCC maximum scenario, the NPC for the scenario without DR was 96.72 MM ₹. The NPC reduction achieved by DR_Medium, DR_EV&AC and DR_New App was 3.4%, 3.2%, and 1.6%, respectively. The LCOE for the scenario without DR was 11.76 ₹/kWh. The avoided cost of energy for DR_Medium, DR_EV&AC and DR_New App was 0.36, 0.27 and 0.09 ₹/kWh. For the scenarios with DR, the CAPEX ranged between 33.97 and 34.55 MM ₹ and the OPEX ranged between 46.91 and 47.61 MM ₹. The CAPEX and OPEX for the scenario without DR were 35.01

and 48.50 MM ₹, respectively. ROI was the highest for DR_EV&AC, with 30.93. Supposing these benefits were translated into incentives that could be provided to the customers enrolled in DR programs, the share of the incentive to the average monthly bill in Auroville was estimated at 22.3%. Next, for the SCC minimum scenario, the NPC and LCOE for the scenario without DR were 87.09 MM ₹ and 10.65 ₹/kWh, respectively. The NPC and LCOE reductions achieved by the DR scenarios were similar to the SCC maximum scenario. Again, ROI was the highest for DR_EV&AC, with 35.26. The share of the incentive to the average monthly bill was estimated at 20.3%.

Overall, the DR_EV&AC scenario had the highest ROI and is the most financially attractive DR scenario. This study shows the potential and importance of residential DR, particularly in India. India is planning to power 50% of its electricity consumption in 2030 with renewable energies. Parallelly, the penetration rates of household appliances such as air conditioners and electric vehicles are growing rapidly, contributing to around 50% of the evening peak demand in 2030 (IEA, 2021). In this context, the outputs of this techno-economic study were able to help both network operators and residential customers see the financial viability of demand response programs in the residential sector which are currently in a nascent stage in India.

5.2 Recommendations

This section provides some recommendations to improve this study and further recommendations to go beyond the scope of this study. There are a couple of suggestions to improve the data used in this study. Firstly, water heaters were only monitored during the monsoon months due to limitations of the data collection period of this study. Thus, monitoring water heaters for a full year is recommended as their usage depends on temperature and season. Secondly, to facilitate the survey respondents, the options for typical usage hours of an appliance in a day were provided in large intervals, i.e., 9 am – 12 pm. It is recommended to provide all hours in a day as options in the survey questionnaire since the resolution of the resulting load profiles in this study is hourly. Further recommendations for future studies are the following:

- This study assessed the potential of DR to achieve a 100% net renewable energy microgrid. However, extending the scope to consider other demand side techniques could be more financially attractive – energy conservation measures from behavioural changes, energy efficiency measures and a shift of technology to provide the same services, i.e., solar water heaters, solar cookers, decentralized and small-scale ice storage systems for refrigeration needs, etc.

- For example, Appendix I provides the results of a scenario termed Solar_WH where along with DR, all the existing electric water heaters and those to be purchased by 2030 were assumed to be replaced with solar water heaters.
    - The results show a 5 to 6% reduction in NPC compared to the scenario without DR.
    - The LCOE in SCC maximum and minimum scenarios are 11.22 and 10.11 ₹/kWh, respectively.
    - The avoided cost of energy is 0.54 ₹/kWh.
    - ROI is 1.12 and 1.79 in SCC maximum and minimum scenarios, respectively.
    - Compared to the DR_Medium scenario, the reduction in NPC and LCOE from the scenario without DR is higher. However, ROI is 4 to 5 times lower. This is due to the high initial investment in solar water heaters. Thus, from an investor's perspective, the DR_Medium scenario is attractive due to higher returns from lower investments. However, from the user's perspective, Solar_WH is attractive due to the higher avoided cost of energy.
- The results of this study demonstrated the attractiveness of DR, especially DR_EV&AC, where ROI was above 30 for both SCC scenarios. It also provided the margin to pay incentives to the customers enrolled in DR, which amounted to around 20% of their average monthly electricity bill. Thus, a business model that benefits both the microgrid operators and customers is recommended to be developed. This model could target both ACs and EVs.
- A few policies are required to support the business model. The policy instruments for these changes, their barriers and challenges must be explored:
    - Only smart and energy-efficient appliances must be encouraged to be purchased. This is particularly important for ACs and EVs. Smart ACs are already available in the Indian market; however, this is not true with EVs. Furthermore, smart EVs must also have bidirectional inverters to enable vehicle-to-grid (V2G) discharging to support the grid during peak hours.

- For water heaters, either electric storage water heaters or solar water heaters must be encouraged to be purchased.
- Customers responded in the survey that they were very likely to shift their charging hours to sunshine hours if they could use more solar energy than grid energy. Thus, to complement EV DR, more public charging stations, especially in offices, are recommended to be built as the customer demand already exists.

- The results of this study are dependent on the case study region and the selected DT for DR. The selected DT demand didn’t cross its rated capacity even in 2030. So, if this research is applied to other DTs in India that are dominated by residential loads and have reached 60 - 80% of the rated capacity, the distribution capacity deferral benefit along with the other benefits of DR would be highlighted. It would also increase the incentive amount that could be paid to the customers enrolled in DR.
- According to the survey conducted in Auroville, customers were more likely to participate in incentive-based DR than price-based DR. Thus, a flat grid tariff was used in this study. However, since price-based DR has potential in other parts of India, performing a sensitivity analysis on the TOU grid tariff structure and conducting a financial analysis under those scenarios is recommended. This would also highlight the DR potential since the savings from the scenario without DR would be relatively higher due to the services provided by DR.

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APPENDICES

APPENDIX A

Pilots of Demand Response Programs in India

Very few DR pilot projects have been implemented in India to date. One project was run in Mumbai, India, by the Tata Power electric utility in 2014. It was for the commercial and industrial (C&I) sectors for customers connected to above 500 kW load. The program curtailed air-conditioning load and shifted the process-heating applications' electricity consumption using thermal storage. The peak load reduction potential was 18 MW (Hale et al., 2018). Another pilot project was conducted in Delhi, India, by the Tata Power Delhi Distribution Limited (TPDDL) in 2016. It was for C&I customers connected to above 300 kW load. The peak load reduction potential was 12 MW (Hale et al., 2018). One more pilot was implemented in Rajasthan, India, by the Jaipur Vidyut Vitran Nigam Limited. It was for 10 large industrial customers and the DR potential was found to be 22 MW (Sarkar & Mukhi, 2016). All these above pilots targeted the C&I sectors in India.

Very recently, the first-ever residential DR pilot was launched by TPDDL in India in 2021. The program's first phase, which lasted 3 months, involved 4,000 residential customers with smart meters (TPDDL, 2021). Only the distribution transformers (DT) whose maximum loading capacity reached 65 – 80% during the peak periods were selected. Forty-nine such DTs were selected for the program (TPDDL 2022). The information was communicated through SMS, emails and calls to interested customers a day in advance. They were given attractive incentives based on participation, ranging up to vouchers worth INR 4200. As many as 16 events ranging from 1 to 2 hours were called during this period, with 7.68 MW of DR potential (TPDDL 2022). The project was launched to understand the impact of customers' participation during peak demand and to assess the acceptability of customers towards such. Of course, this was also intended to reduce network management costs (TPDDL, 2021). This pilot was especially possible due to the smart meter infrastructure in TPDDL (TPDDL 2022).

APPENDIX B

Studies that Estimated Economic Demand Response Potentials

Advanced Energy Economy Institute (2017) assessed the economic potential of DR in the residential sector in Michigan, United States. Two types of DR programs were considered for the residential sector – critical peak pricing (CPP) and direct load control (DLC) for smart thermostats. The cost benefits of DR are in reducing the need for generation capacity and deferring updates to transmission and distribution networks. Since valuing these benefits is a complicated endeavor, three scenarios with high, medium and low values of generation, transmission and distribution capacity deferral benefits were created. On the other hand, participant incentives comprise most of the cost of DR programs, and for the three scenarios, different incentive costs were assumed. Their modelling approach maximized the net benefits and not the demand reduction potential. The economic potentials assessed for CPP and DLC in the residential sector were respectively 382 and 151 MW (AEE Institute, 2017).

One study assessed the economic potential of 5 households in India that are currently under the flat tariff scheme. Three different tariff structures – flat tariff, TOU, and RTP were studied to find the impact of dynamic pricing schemes on the load profiles of the customers. RTP was simulated using day-ahead electricity market price data obtained from the Indian Energy Exchange. This data was used to schedule residential appliances such as air conditioners, water boilers, EVs, washing machines, water pumps and vacuum cleaners, subject to some operating constraints such as user comfort levels, operating patterns of appliances, weather conditions, the priority of appliances, etc. The results showed a potential of around 2.8 kW during peak load periods from 11 pm to 3 pm and 6 pm to 9 pm. The study found that with TOU and RTP tariffs, the customer bill reduces respectively by 4.35% and 5.69% from flat tariff bills (Nair & Rajasekhar, 2014).

APPENDIX C

Studies that Estimated Achievable Demand Response Potentials

Smart Electric Power Alliance (SEPA) assessed the achievable potential in the residential sector in the United States. From survey data collected from around 190 electric utilities across the country, the study found that around 7.4 GW was enrolled in the residential sector in 2018. This is namely from AC, thermostat control, water heater and other behavioural DR. From 7.4 GW, the actual demand reduction achieved or the achievable potential was around 4.3 GW, with a majority from AC switch programs (Medha et al., 2019).

One pilot was conducted by TPDDL utility in Delhi, the capital of India, and found a potential of around 7.68 MW during 16 events called in a span of 3 months (TPDDL, 2022). This project is described in Appendix A.

APPENDIX D

Survey Questionnaire

The survey conducted in Auroville was divided into two parts. The first part consisted of the general household appliances such as air conditioners, electric water heaters, and washing machines, referred to as the ‘general survey’, while the second part consisted of only electric vehicles and is referred to as the ‘EV survey’. The survey questionnaires of both the general and EV survey are provided below. The answer options are provided in square brackets along with the questions. Figure D1 shows the Wi-fi usage patterns in Auroville. Figure D2 shows the likelihood of EV users shifting their vehicle charging hours to sunshine hours.

General survey:

1. Including you, how many people usually live in your household? [Single option: 1/2/3/4/More than 4]
2. Which of the following do you do with respect to wi-fi connection in your house? [Single option: I don’t have a wi-fi connection / Leave it on always/ Switch it off at night/ Switch it on only when needed]
3. Which of the following appliances are used in your residence? [Multiple choice: Air conditioner/ Washing Machine/ Electric water heater/ Electric Vehicle/ Refrigerator/ None of the above]
4. Are you likely to install an AC in the next 5 to 8 years if there is no policy on AC purchase? [Single option: Yes/ No/ Maybe]
5. Are you likely to buy any other appliance that provides cooling in the next 5 to 8 years? [Multiple choice: Fan/ Air cooler/ None/ Other]
6. Are you likely to install an electric water heater in the next 5 to 8 years? [Single option: Yes/ No/ Maybe]
7. If you are not using an electric vehicle currently, are you likely to get an electric vehicle in the next 5 to 8 years? [Single option: Yes/ No/ Maybe]
8. Changing your electricity consumption patterns can help the environment and can reduce costs. Suppose the electricity utility was to provide you with some electricity credits to operate some of your appliances at a different time of the day instead of your current usage. How likely would you be to participate in

such a program? [Single option: Not at all likely/ Slightly likely/ Moderately likely/ Very likely/ Extremely likely]

9. If the electricity prices are changed such that during the evening hours (5 pm to 9 pm), it is priced 20-30% higher than the normal periods and 15-20% lower during the afternoon hours (10 am – 4 pm), how likely are you to change the usage pattern of your appliances? [Single option: Not at all likely/ Slightly likely/ Moderately likely/ Very likely/ Extremely likely]
10. How many ACs do you use? [Single option: 1/2/3/More than 3]
11. What is the typical temperature setting you use? [Single option: Less than 18 °C/ 18 – 20 °C/ 20 – 22 °C/ 22 – 24 °C/ 24 – 26 °C/ 26 – 28 °C/ More than 28 °C]
12. What is the type of your water heater? [Electric water heater - instant (heats water instantaneously)/ Electric water heater - storage (requires longer time to heat water)/ Solar water heater/ Hybrid (solar & electric water heater)/ Not sure]
13. How frequently is hot water used in the monsoon season? [Single option: Almost every day/ Almost 3 to 4 days a week/ 2 days a week/ Less than once a week]
14. When is the washing machine usually used on a weekday?
15. When is the washing machine usually used on a weekend day?
16. How many rounds are done on a weekday?
17. How many rounds are done on a weekend day?

EV Survey:

1. Including you, how many people usually use your vehicle? [Single option: 1/2/3/More than 3]
2. Which of the following do you do with respect to wi-fi connection in your house? [Single option: I don’t have a wi-fi connection / Leave it on always/ Switch it off at night/ Switch it on only when needed]
3. For how many km (on average) does your vehicle run on a weekday?
4. For how many km (on average) does your vehicle run on a weekend day?
5. Where is your electric vehicle usually charged? [Single option: Home/ Office/ Home & Office/ Other]
6. When is your electric vehicle usually charged on a weekday?

7. When is your electric vehicle usually charged on a weekend day?
8. How often is your electric vehicle charged in a week? [Single option: Every day/ Once in two days/ Thrice a week/ Twice a week]
9. For how long is your electric vehicle usually charged? [Single option: Less than 3 hours/ 3 hours/ 4 hours/ More than 4 hours]
10. Suppose the electricity utility was to provide you with some electricity credits if you charged your electric vehicle at a different time of the day instead of your current charging hours. Are you likely to participate in such a program? [Single option: Not at all likely/ Slightly likely/ Moderately likely/ Very likely/ Extremely likely]
11. Suppose the electricity utility provides you with some electricity credits as an incentive to allow your vehicle's battery to power the grid during some period of a month. Are you likely to participate in such a program? [Single option: Not at all likely/ Slightly likely/ Moderately likely/ Very likely/ Extremely likely]
12. Suppose the electricity prices are changed such that during the evening hours (5 pm to 9 pm), it is priced 20-30% higher than the normal periods and 15-20% lower during the afternoon hours (10 am – 4 pm). How likely are you to change your current vehicle charging hours? [Single option: Not at all likely/ Slightly likely/ Moderately likely/ Very likely/ Extremely likely]
13. Would you change your vehicle charging hours to sunshine hours to use more solar energy than grid electricity (without receiving electricity credits from the electricity utility)? [Single option: Not at all likely/ Slightly likely/ Moderately likely/ Very likely/ Extremely likely]

Figure D1:

Wi-fi usage patterns in Auroville

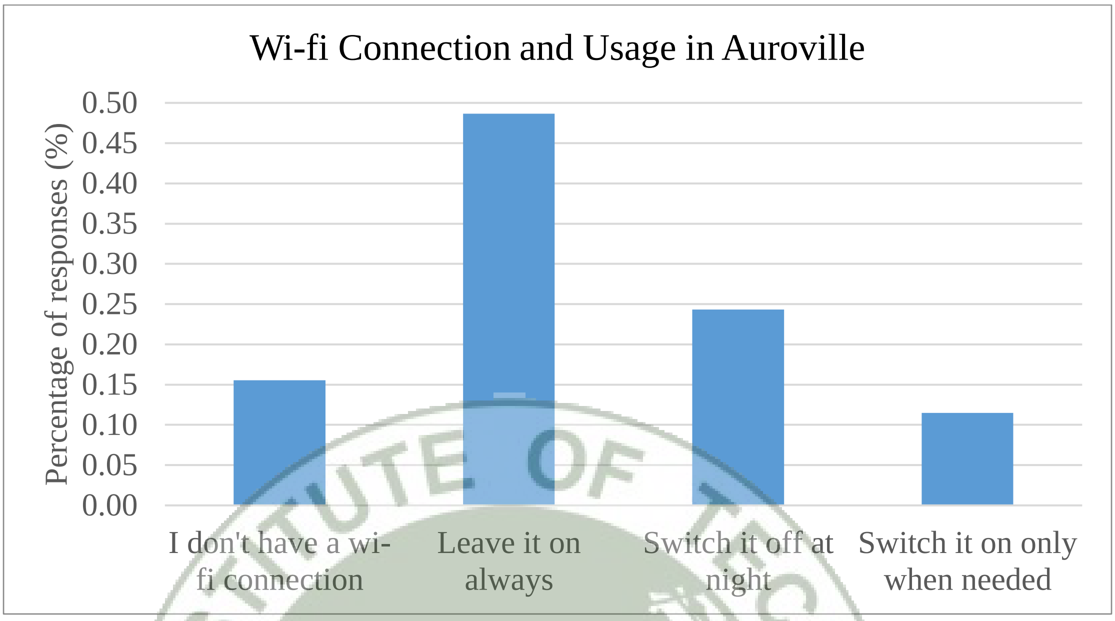
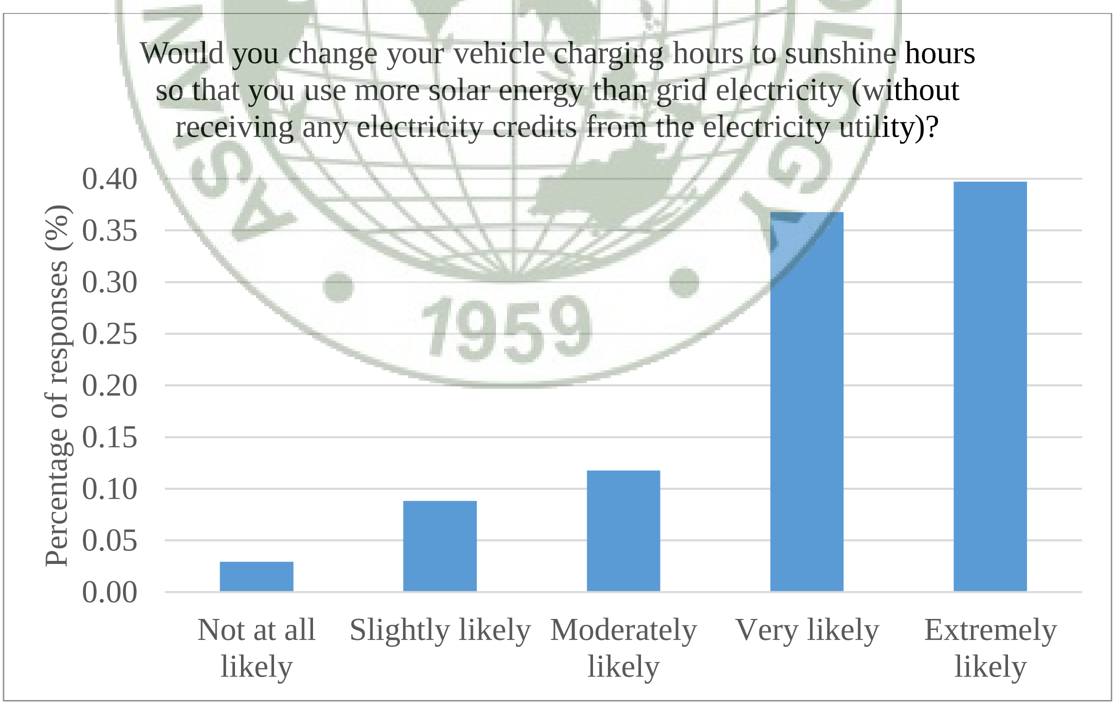


Figure D2:

Customer likelihood to change electric vehicle charging hours



APPENDIX E

AC and EV Stocks in 2030 in India from Secondary Data

AC stock in 2030 in India:

Room air conditioners (RAC) stock has grown massively in the past years in India, starting with 0.3 million in 2007 (Pandita et al., 2022) to 39 million units in 2017, equivalent to around 7% penetration in 2017 (AEEE, 2018). Projections from various sources such as the Ministry of Environment, Forest & Climate Change; the Ministry of Power (MoP); Indian think tanks (Council on Energy, Environment, and Water (CEEW) and Alliance for Energy Efficient Economy (AEEE)) and international think tanks (IEA and Lawrence Berkeley National Laboratory (LBNL)) show a significant increase in RAC stock and RAC penetration in India. Table E1 provides RAC stocks or RAC penetration projections in India by the above sources.

Table E1:

RAC stock or penetration rate projections in India in 2030

Projection for India	**Year**	**The methodology used for the projection**	**Reference**
60% ownership	2030	Not found	IEA, 2021
21% penetration (&1.2 RACs / household with AC)	2027-28	Expert surveys from building constructors and industry professionals and studying trends in other appliances	MEFCC, 2019
170 million units / CAGR 15%	2027	Bureau of Energy Efficiency (BEE) production data is used for RAC sales, which will grow at CAGR of 15%	MOP & AEEE, 2018

According to IEA (2021), by 2030, the AC ownership will be 60%, or in other words, there will be 60 units of ACs per 100 households. This value is significantly different from MEFCC (2019) estimates based on expert surveys from buildings constructors and industry professionals. The AC penetration is 21% and households that own an AC own, on average, 1.2 ACs, which results in a total of 21% x 1.2 x 100 households = 25 ACs per 100 households.

India is estimated to have 386 million households by 2030 (Confederation of Real Estate Developers' Associations of India, 2019). Using this figure, according to MOP & AEEE (2018), the appliance ownership with 170 million AC units is 170/386 = 44%. In this latter study, RAC stock is predicted using BEE production data.

EV stock in 2030 in India:

The adoption of EVs in India is also growing. There are favorable policies for EV growth, such as Faster Adoption & Manufacturing of (Hybrid &) Electric Vehicles (FAME) India Scheme, Production Linked Incentive for Advanced Chemistry Cell Battery Storage (PLI-ACC) Scheme, Battery Swapping Policy, etc. (IBEF, 2022). According to the Federation of Automobile Dealers Associations' (FADA) data, EV sales have risen 155% yearly since 2019, reaching around 430 thousand units now (Rudra, 2022). The growth of EV adoption is set to continue, as per the Government of India's policy think tank, Niti Aayog, and other institutions such as the Rocky Mountain Institute (RMI), JMK Research and Analytics, and IEA, and their projections are provided in Table E2.

Table E2:

EV stock or penetration rate projections in India in 2030

EV sales penetration/ stock projection for 2030 in India	The methodology used for the projection	Reference
92% of EV (sales) penetration according to 3 scenarios.	The projection is based on three scenarios with different demand incentive periods, battery cost and vehicle performance. A full constraint is imposed on the charging infrastructure and vehicle production.	Niti Aayog, 2022

EV sales penetration/ stock projection for 2030 in India	**The methodology used for the projection**	**Reference**
A cumulative value of 50 million EVs, 79% of which is 2Ws.	Electric 2Ws are assumed to have a CAGR of 57.86% from current growth rates.	JMK Research and Analytics, 2022
19% of the total stock of 2&3W is electric/total 55 million electric 2&3W stock.	The projection is for the stated policies scenario, which considers several government policies and incentives for EV purchase and charging infrastructure.	IEA, 2021
80% of 2&3 wheelers sales penetration is electric.	The projection is based on implementing Faster Adoption and Manufacturing of Electric Vehicles - 2 (FAME 2) & other stated policies and measures.	RMI & Niti Aayog 2019

In forecasting the penetration of electric two-wheelers (E2W) in India, Niti Aayog modeled 8 scenarios for E2W penetration, out of which in 3 scenarios, the penetration is around 92% by 2030 (Niti Aayog, 2022). According to the study by JMK Research and Analytics (2022), there will be 50 million EVs in 2030, out of which 79% is electric, resulting in 50 million x 79% = 39.5 million E2W. Assuming that the 2-wheeler stock in India in 2030 is 313 million (Singh et al., 2020), the ownership rate is estimated at 39.5 / 313 = 12.6%. This figure is comparable to IEA's (2021) projection which is 19% for E2W and E3Ws. If FAME 2 and other policies supporting EV adoption in India are implemented, RMI & Niti Aayog (2019) predict that the sales penetration of E2W and E3W in 2030 will be 80%.

APPENDIX F

Monthly Average Appliance-wise Daily Load Profiles in 2022 & 2030

Figure F1 shows the appliance-wise monthly average daily load profiles for the case study residential region in Auroville from July to November 2022. The simulated load profiles are compared with the aggregated residential smart meter data. Figure F2 shows the appliance-wise monthly average daily load profiles forecasted for 2030.

Figure F1:

Appliance-wise monthly average daily load profiles from July to November 2022 compared with smart meter aggregated residential data

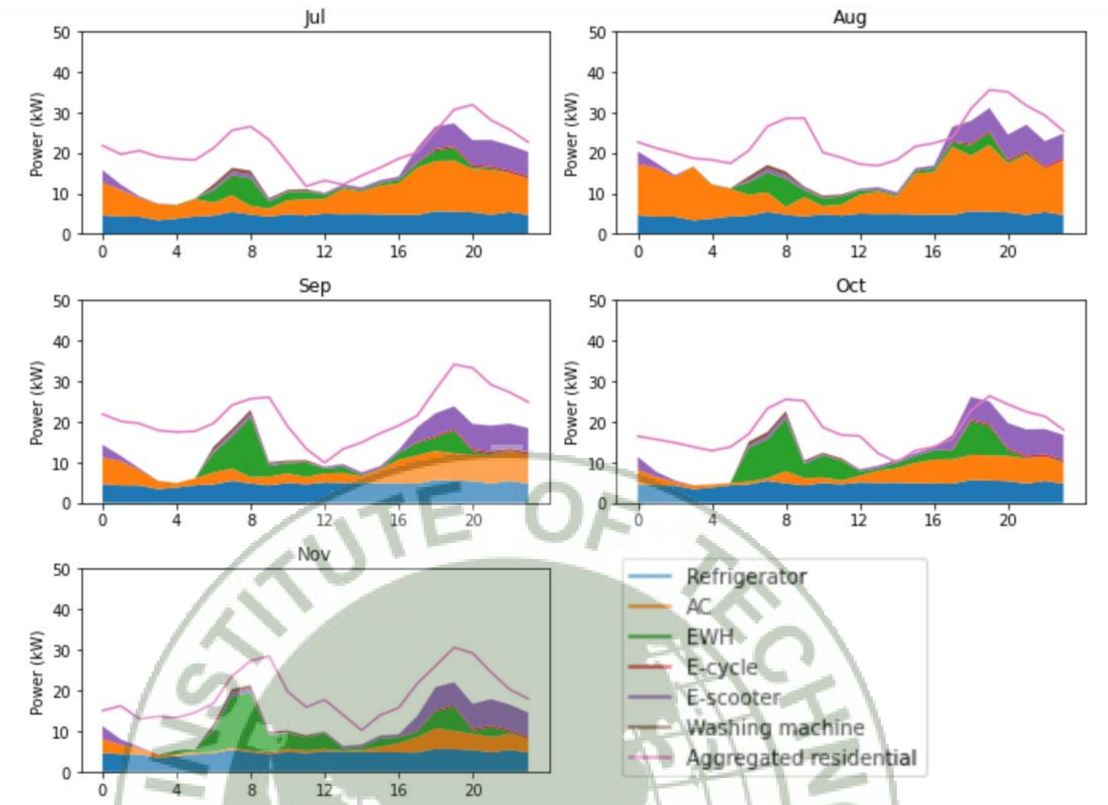
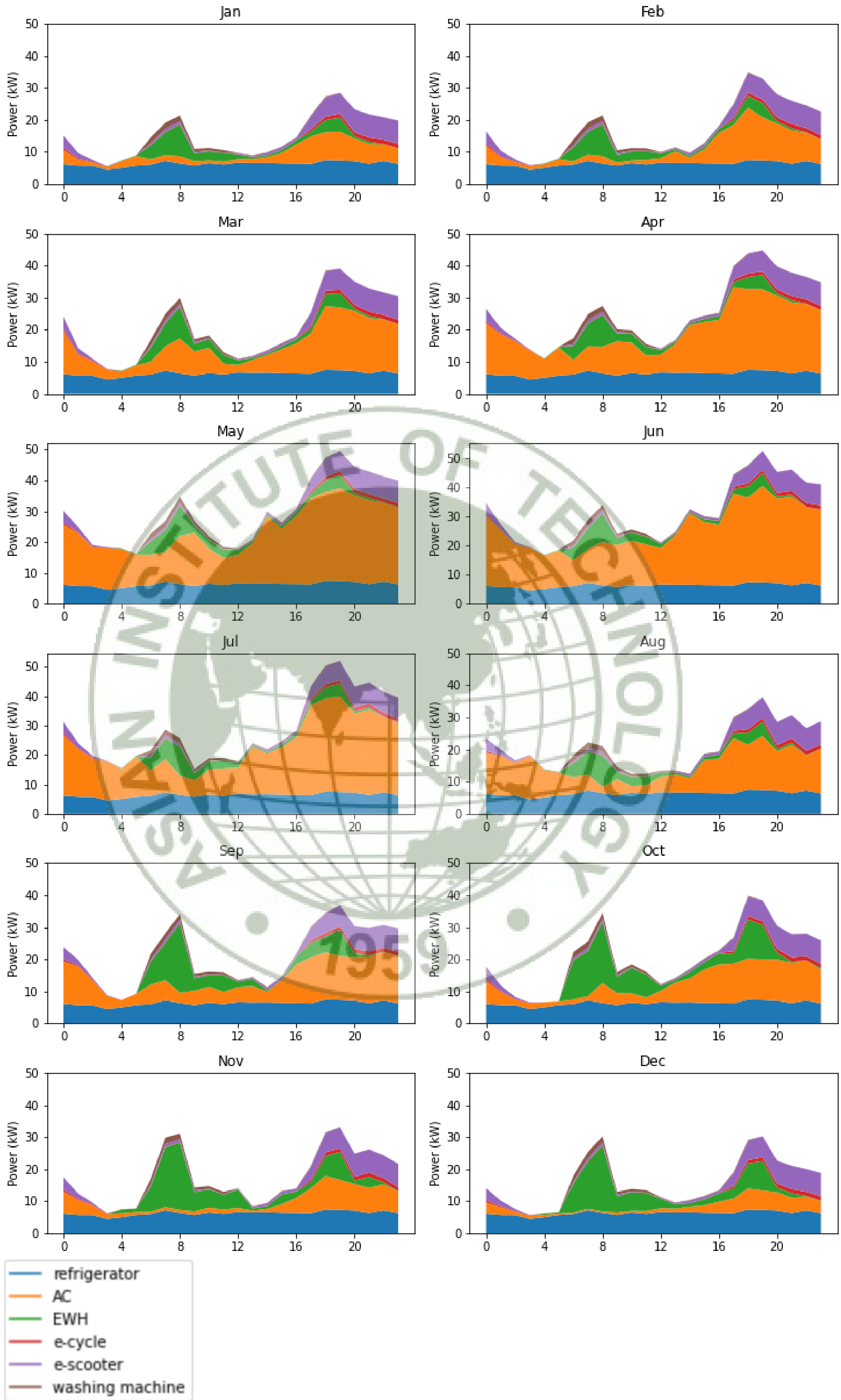


Figure F2:

Appliance wise monthly average daily load profiles forecasted for 2030



Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec
Power (kW)
refrigerator
AC
EWH
e-cycle
e-scooter
washing machine

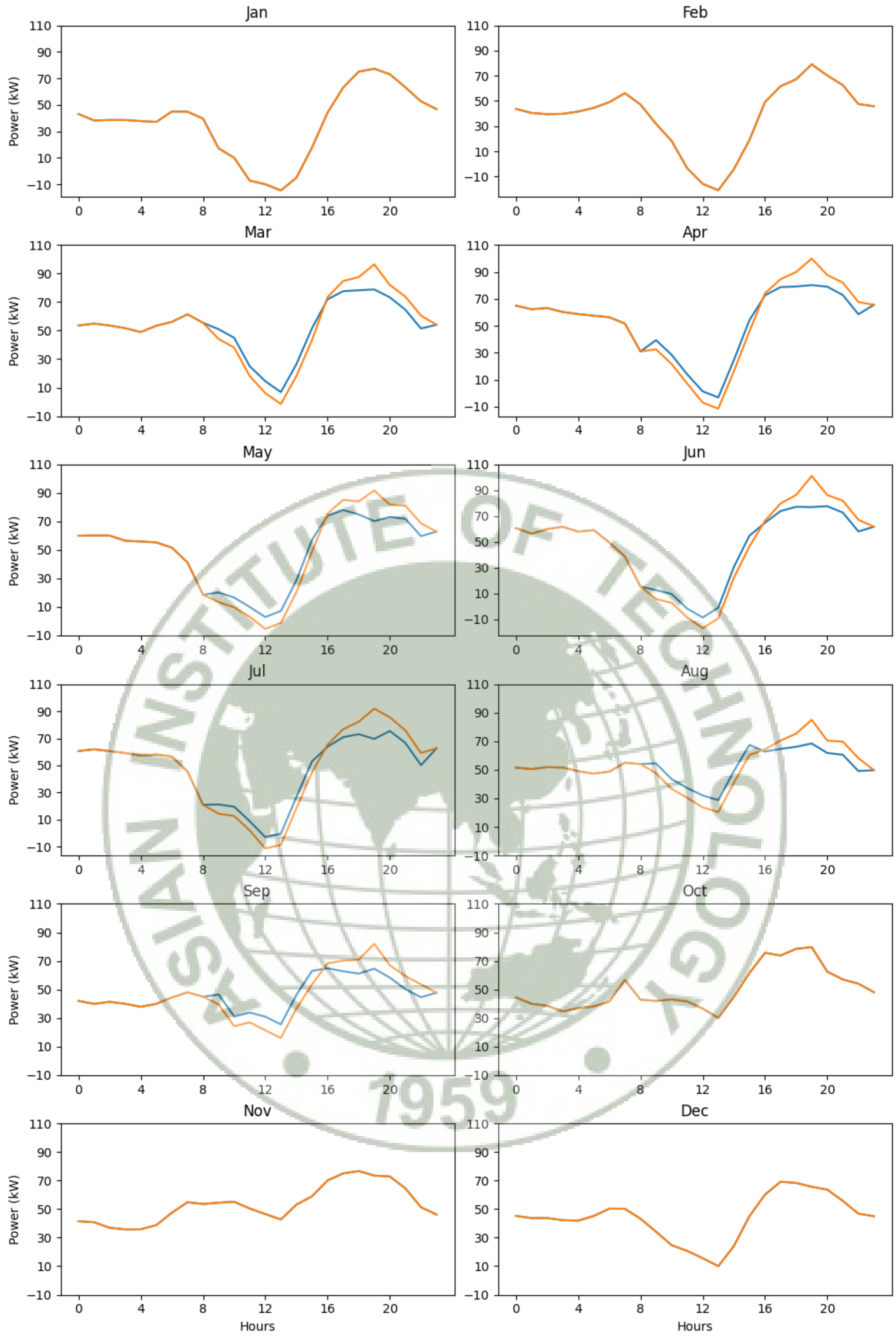
APPENDIX G

Modified Distribution Transformer Load Profiles in 2030 with Demand Response

The modified DT monthly average daily load profiles in 2030 with DR are presented in this section. Several DR scenarios were created in this study, among which the load profiles of the DR scenarios with the highest and lowest DR potential are illustrated in Figure G1 and Figure G2. The figures compare the DT load profiles with (blue line) and without (orange line) DR. It can be seen that DR is applied only from March to September, which also coincides with the hottest months of the year in Auroville.

Figure G1:

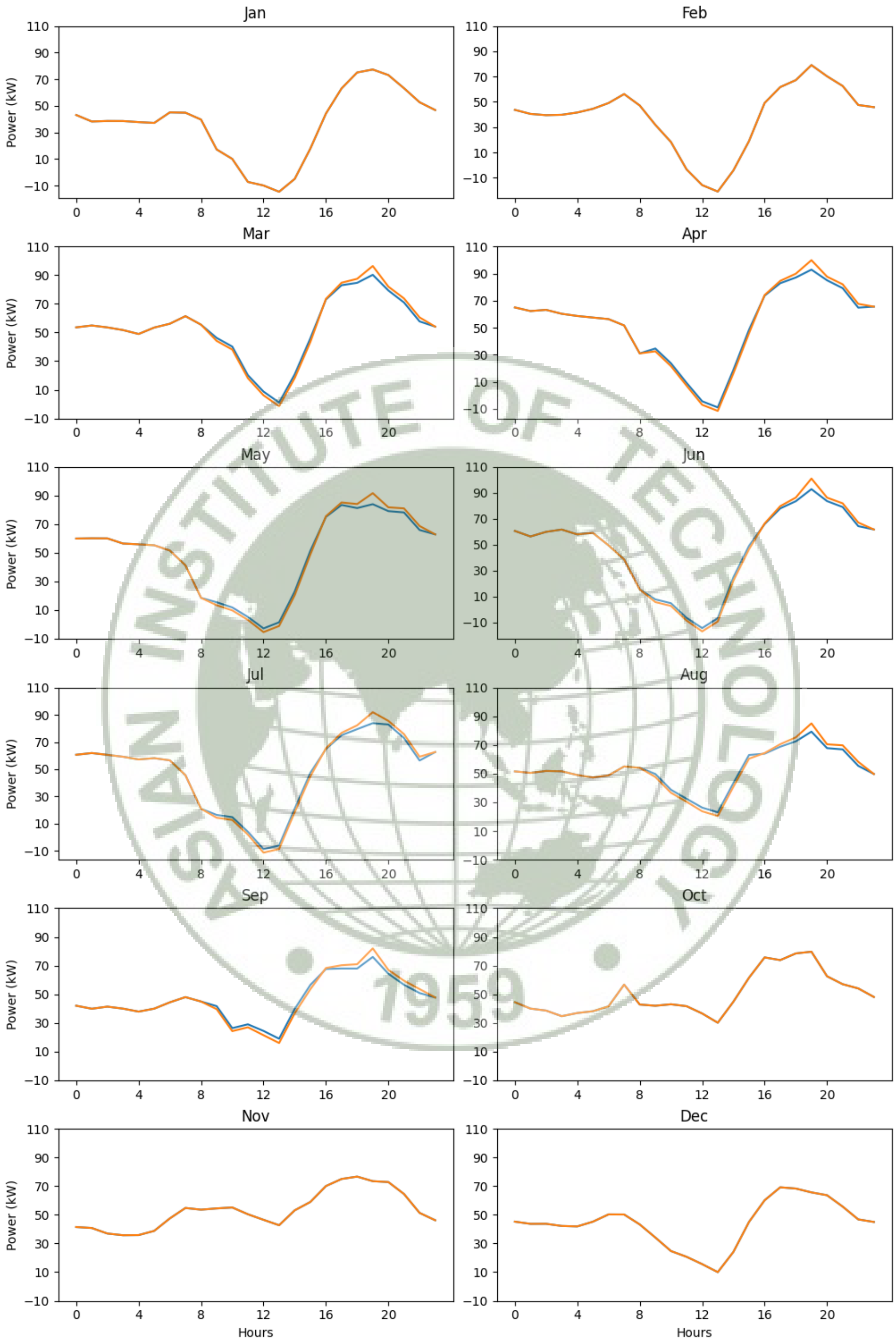
DT monthly average daily load profiles in 2030 with (DR_Maximum) and without DR



Note: Orange line represents load profiles without DR and blue line represents modified load profiles with DR

Figure G2:

DT monthly average daily load profiles in 2030 with (DR_New App) and without DR



Note: Orange line represents load profiles without DR and blue line represents modified load profiles with DR

APPENDIX H

Estimation of Incentive Amount for Implementation of the DR_EV&AC Scenario

Based on the average monthly electricity consumption in Auroville, and the number of customers participating in DR in the DR_EV&AC scenario, Table H1 provides the maximum monthly incentives that can be paid to the customers for enrolling in DR. Under both system capital cost scenarios, the share of the incentive to the monthly electricity bill is attractive, with 22.3% and 20.3% for maximum and minimum system capital cost scenarios, respectively.

Table H1:

Monthly incentive amounts to customers for implementing the DR_EV&AC scenario

Incentive amount estimation for DR EV&AC Scenario	**SCC Max**	**SCC Min**
Savings in annualized cost from No DR Scenario (₹)	194,487	176,685
The monthly incentive to customers (₹)	427	387
Share of incentive to the monthly bill	22.3%	20.3%

APPENDIX I

Technology Shift

Solar Water Heaters:

In this study, only the effect of DR to achieve a 100% net renewable energy microgrid was analyzed. However, there are other demand side techniques that could also be combined to achieve this target with low-cost options. One such option is the substitution of electric water heaters with solar water heaters, in addition to DR. Thus, a scenario termed Solar_WH was created, assuming that all the existing water heaters and those to be purchased by 2030 are replaced with solar water heaters. The assumptions/inputs used for this scenario are provided in Table I1, and Table I2 provides the financial analysis of this scenario.

Table I1:

Assumptions and inputs used for Solar_WH scenario

Assumption/input	Value	References
Electric storage water heater size for a 2-person household	15 liters	Racold (2021)
The typical cost of a 15l electric storage water heater	7900	Joy (2022)
Solar water heater size for 2 persons	100l	Unilet Solar (2023)
The typical cost of a 100l solar water heater	30000	Kenbrook Solar (2022)

Table I2:

Financial analysis of Solar WH scenario under System Capital Cost maximum and minimum scenarios

Performance metric	SCC Max			SCC Min		
	Solar WH	DR_Medium	No DR	Solar WH	DR_Medium	No DR
Peak load (kW)	79.2	82.8	101.2	79.2	82.8	101.2
Electricity consumption (kWh/day)	1075.6	1137.2	1141.8	1075.6	1137.2	1141.8

Performance metric	SCC Max			SCC Min		
	Solar WH	DR_Medium	No DR	Solar WH	DR_Medium	No DR
Cost of solar water heaters (Million ₹)	2.00	0.00	0.00	1.57	0.00	0.00
Cost of smart plugs (Million ₹)	0.21	0.32	0.00	0.17	0.25	0.00
Initial investment (Million ₹)	2.21	0.32	0.00	1.74	0.25	0.00
LCOE (₹/kWh)	11.22	11.40	11.76	10.11	10.34	10.65
NPC (Million ₹)	92.04	93.46	96.72	82.23	84.08	87.09
Avoided cost (₹/kWh)	0.54	0.36	-	0.54	0.31	-
NPC savings (Million ₹)	4.68	3.26	-	4.86	3.00	-
NPC savings (%)	0.05	0.03	-	0.06	0.03	-
ROI	1.12	9.33	-	1.79	10.92	-

Vapor Absorption Chiller Systems:

The study region also has cooling demand which is currently met by ACs. This section presents the preliminary analysis done to find the financial viability to meet this demand with vapor absorption chiller systems (VACS). The cooling demand in the case study region is roughly 40 TR. Table I3 presents the assumptions/inputs used for the estimations. The results show that VACS is not financially viable as ACs are cheaper in the case study region.

Table I3:

Assumptions and inputs used for VACS financial analysis

Parameter	Value	Unit	Reference
40 TR VACS capital cost	8.5	MM ₹	Online search
Average installation cost	0.28	MM ₹/TR	(U.S. Department of Energy, 2017)
Annual typical cooling demand met by ACs	1800	kWh/year	From study results

Parameter	Value	Unit	Reference
Annual cost of cooling demand met by ACs	697,680	₹/year	
Annualized cost of 40 TR VACS	1,253,144	₹/year	

VITA

Yogitha Miriyala

Education Background

- Master of Science in Sustainable Energy Transition; Asian Institute of Technology; Pathumthani, Thailand; May 2023.
- Bachelor of Science in Physics, Chemistry, Mathematics and Solar Science; Sri Aurobindo International Centre of Education; Puducherry, India; October 2020.

Work Experience

- External Consultant; Data Analytics with PYTHON; Indian Institute for Human Settlements; Bangalore, India; May 2022 to September 2022.
- Research Intern; Life Cycle Assessment of Innovative Wall Systems; Indian Institute for Human Settlements; Bangalore, India; January 2021 to July 2021.

Academic Conferences

Miriyala, Y., Thounaoujam, A., Vaidya, P., & Mangrulkar, A. (2022). Opportunities and challenges for LCA in India for innovative technologies. *Proceedings of the PLEA 36th Conference* (pp. 486 – 491). Passive and Low Energy Architecture. https://plea2022.org/wp-content/uploads/2023/03/PROCEEDING-ONLINE-FINAL-MARZO.pdf