SOCIALLY-AND-ENVIRONMENTALLY-AWARE POWER MANAGEMENT IN RESIDENTIAL NEIGHBORHOODS EXPOSED TO HEAT WAVES CONSIDERING UNCERTAINTIES

by

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ABSTRACT

Natural disasters threaten efficient and normal operation of power grids all around the world. These natural events may negatively affect the capacity of power delivery to the consumers or may cause power outage in all or parts of a region. To make electric power grids more resilient against natural hazards, power grid operators have to adopt optimal strategies in order to mitigate the effects of natural disasters and make post-disaster power grid recovery faster, easier, and with less costs. Another important factor in developing strategies to cope with a natural disaster is the type of the natural disaster. For instance, a heat wave event only causes a reduction in the ampacity of power grid assets such as lines and transformers; on the other hand, a flood event might destroy parts of power grid and cause disconnection of some regions from the power grid depending on the intensity of the event.

In the course of extreme ambient temperatures that pushes various power grid components towards their operational limits, it is desired for the electric utility company to reduce the power consumption to alleviate the stress on assets. This can be achieved by implementing demand response targeting air conditioning units which typically account for the largest portion of residential demand during a heat wave. However, this is a delicate matter since excess indoor temperatures can affect the health of residents, especially children and the elderly. This places a limitation on how frequently and to what extent A/C demand response should be used. In addition to reducing demand, efficient asset utilization necessitates that impacts of temperature on capacity and lifetime of assets be considered. Therefore, the energy dispatch problem poses multiple objectives that need to be optimized simultaneously.To make matters more complicated, the problem is subject to uncertainties associated with parameters and input data, e.g. building occupancy levels, electric demand, and temperature-related correction factors for capacity of generation resources, to name a

few. To address these uncertainties, the energy dispatch model needs to be able to guarantee feasibility even under worst-case conditions. In this study, a robust optimization solution is introduced that tries to solve the above multi-objective optimization problem subject to uncertainties in model parameters and input data. It is shown through a case study that considering the uncertainties makes the dispatch more conservative. However, this is necessary since failing to include them can lead to mismatches between demand and generation, which could jeopardize the security of the grid.

The above-mentioned problem can be viewed from a customer's point of view as well. When equipped with a home energy management system (HEMS), residential customers can become important actors for enabling demand response. This can be done by changing the setpoint of the air-conditioning units or by shifting appliance loads from peak hours to off-peak hours. From the HEMS' standpoint, this can be modeled as an optimization problem where the goal is to reduce power consumption while maximizing financial DR incentives received. However, another equally important goal would be to make sure that the comfort level of the residents is not compromised. This is in particular crucial during periods of extreme temperatures where maintaining an acceptable indoor temperature has a direct impact on the residents' health, especially for children and the elderly. What makes this multi-objective optimization problem more challenging is the uncertain nature of some model parameters, e.g. electricity rates, building occupancy levels, etc. In this part of this study, a novel solution for energy management of a smart home using demand response by considering the above factors is presented. The problem is formulated as a robust multi-objective one and is solved for a given time horizon. Simulation results are provided to illustrate the impact of uncertainties on the final solution.

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index for loads (customers/buildings) connected to the service transformer(Chapter 2) . i

time index (Chapter 2 and 3) . . . . k

time index (Chapter 2 and 3) . . . . t

index for objective functions in the multi-objective framework (Chapter 2 and 3) . . . . . q

index used for uncertain parameters (Chapter 2) l

index used for demand shiftable appliances at the residential building (Chapter 3) . . . . s

set of customers connected to the service transformer . . . . N

set of all time indices (Chapter 2 and 3) . . . . T

set of objective functions in the multi-objective framework (Chapter 3) . . . . Q

set of demand shiftable appliances at the residential building (Chapter 3) . . . . S

uncertainty set (Chapter 2 and 3) . . . . Ψ

uncertainty parameter used in robust optimization (Chapter 2 and 3) . . . . ζ

total window frame area of building i (m^2)(Chapter 2) . . . . A_i^F

total transmission area of building i (m^2)(Chapter 2) . . . . A_i^W

age factor of residents at building i(Chapter 2) . . . . AF_i

price of using one deep discharge of the battery (\$)(Chapter 2) . . . . c^B

heat transfer constant ($\frac{W}{m^2K}$) (Chapter 2) . . . . h

PV temperature coefficient of power ($°C^{-1}$)(Chapter 2 and 3) . . . . k^{PV}

maximum available power from the battery (kW)(Chapter 2) . . . . $P^{B,max}$

active power generation of rooftop photovoltaic unit of customer i at time t (kW)(Chapter 2) . . . . $P_{i,t}^{d,PV}$

active power consumption for non-shiftable loads of customer i at time t (kW)(Chapter 2) . . . . $P_{i,t}^{d,NS0}$

active power for shiftable appliance of customer i at time k that can be shifted from time $k<t$ to a later time t (kW)(Chapter 2) . . . . $P_{i,k}^{d,SH}$

power provided by PV panel under standard test condition (STC) for customer i (kW) (Chapter 2) . . . . P_i^{STC}

maximum power that can be delivered by the utility through the PCC transformer at time t (kW) (Chapter 2) . . . . $P_t^{u,max}$

A/C solar load for customer i at time t (kW) (Chapter 2) . . . . $Q_{i,t}^S$

total solar radiated heat flux rate (elevation corrected) $(\frac{W}{m^2})$ (Chapter 2) . . . . Q^{se}

maximum allowable battery state-of-charge (%) (Chapter 2) . . . . $SOC^{B,max}$

minimum allowable battery state-of-charge (%) (Chapter 2) . . . . $SOC^{B,min}$

maximum allowable number of times a customer may experience demand shifting. Clearly: $TSH<T$ (Chapter 2) . . . . TSH

Occupancy at residence of customer i at time t (Chapter 2) . . . . $U_{i,t}^{Occ0}$

solar absorptivity (dimensionless) (Chapter 2) . . . . α^S

effective angle of incidence of the sun's rays at time t (degree); assumed to be the same for all customers (Chapter 2) . . . . β_t^S

budget of uncertainty for occupancy(Chapter 2) . . . . $\gamma^{U_{Occ}}$

budget of uncertainty for non-shiftable loads at time t (Chapter 2) . . . . $\gamma_t^{d,NS}$

self-discharge rate for battery $(p.u.)$(Chapter 2) . . . . γ^B

power correction factor for the battery power due to ambient temperature at time t (%)(Chapter 2) . . . . ΔP_θ^{B0}

power correction factor for the battery lifetime due to ambient temperature at time t (%)(Chapter 2) . . . . $\Delta P_\theta^{B,LF0}$

power correction factor for the service transformer due to ambient temperature at time t (%)(Chapter 2) . . . . ΔP_θ^{Xfmr0}

deviation of ΔP_{θ}^{B0} (Chapter 2) . . . . $d\Delta P_{\theta}^{B0}$

deviation of $\Delta P_{\theta}^{B,LF0}$ (Chapter 2) . . . . $d\Delta P_{\theta}^{B,LF0}$

deviation of $\Delta P_{\theta}^{Xfmr0}$ (Chapter 2) . . . . $d\Delta P_{\theta}^{Xfmr0}$

deviation of $U_{i,t}^{Occ0}$ (Chapter 2) . . . . $dU_{i,t}^{Occ}$

deviation of $P_{i,t}^{d,NS0}$ (kW)(Chapter 2) . . . . $dP_{i,t}^{d,NS}$

charge/discharge efficiency of the battery $(p.u.)$(Chapter 2) . . . . $\eta^{B,c}/\eta^{B,d}$

ambient temperature at time t ($^{\circ}C$), (Chapter 2 and 3) . . . . θ_t^a

desired A/C set-point ($^{\circ}C$), i.e. highest acceptable temperature to avoid health risks to residents(Chapter 2 and 3) . . . . θ^{des}

reference temperature ($^{\circ}C$), assumed to be $25^{\circ}C$(Chapter 2 and 3) . . . . θ^{ref}

incident solar irradiance at PV panel for customer at node i at time t ($\frac{W}{m^2}$)(Chapter 2) . . . . $\Phi_{i,t}$

incident solar irradiance at PV panel at time t ($\frac{W}{m^2}$)(Chapter 3) . . . . Φ_t

incident solar irradiance at STC ($\frac{W}{m^2}$) (Chapter 2 and 3) . . . . Φ^{STC}

goal value for objective function q in the multi-objective framework (Chapter 2 and 3) . b_q

a small positive number (Chapter 2 and 3) . . . . ϵ

rated power of PV panel at customer i building at STC condition (kW) (Chapter 2) . . . . P_i^{STC}

cost of energy at time t ($\frac{\$}{kWH}$) (Chapter 3) . . . . c_t^u

number of time periods needed for an appliance to complete its cycle (No. of hours, etc.) (Chapter 3) . . . . N_s

number of solar panels installed at the building (Chapter 3) . . . . N^{PV}

financial payment to the customer upon reducing its consumption beyond desired target ($\frac{\$}{kWH}$) (Chapter 3) . . . . p_t

desired active demand level for the customer at time t (kW) (Chapter 3) . . . . . . $P_t^{d,des}$

active power level for different sources or appliances at time t (kW), (.) could be A/C for air conditioning, PV for rooftop photovoltaics, SH for shiftable loads or MISC for miscellaneous loads (Chapter 3) . . . . $P_t^{d,(.)}$

rated active power related to shiftable appliance s (kW) (Chapter 3) . . . . $P_s^{d,SH,n}$

power provided by PV panel under standard test condition (STC) (kW) (Chapter 3) . . . . $P^{PV,STC}$

latest permissible end-time for the operation of appliance s (hour) (Chapter 3) . . . . T_s^{end}

earliest permissible end-time for the operation of appliance s (hour) (Chapter 3) . . T_s^{start}

occupancy level at the residential building at time t (Chapter 3) . . . . U_t^{Occ}

budget of uncertainty for the price of energy (Chapter 3) . . . . Γ^{c^u}

budget of uncertainty for the occupancy (Chapter 3) . . . . $\Gamma^{U_{Occ}}$

budget of uncertainty for miscellaneous loads at time t (Chapter 3) . . . . $\Gamma_t^{Pd,Misc}$

budget of uncertainty for occupancy at time t (Chapter 3) . . . . $\Gamma_t^{U_{Occ}}$

coefficient of A/C power consumption for the kth time lag (dimensionless) (Chapter 3) . α_k

coefficient of occupancy for the kth time lag (kW) (Chapter 3) . . . . β_k

coefficient of ambient temperature for the kth time lag ($\frac{kW}{^\circ C}$) (Chapter 3) . . . . γ_k

coefficient of A/C temperature setpoint for the kth time lag ($\frac{kW}{^\circ C}$) (Chapter 3) . . . . . η_k

active power consumption of customer i at time t (kW) (Chapter 2) . . . . $P_{i,t}^d$

active power for air conditioning of customer i at time t (kW) (Chapter 2) . . . . . $P_{i,t}^{d,A/C}$

power provided to charge the battery at time t (kW) (Chapter 2) . . . . $P_t^{B,c}$

power discharged by the battery at time t (kW) (Chapter 2) . . . . $P_t^{B,d}$

power delivered by (purchased from) the utility at time t (kW) (Chapter 2 and 3) . . . P_t^u

A/C transmission load for customer i at time t (kW) (Chapter 2) . . . . $Q_{i,t}^{Tr}$

state-of-charge of battery at time t (%) (Chapter 2) . . . . SOC_t^B

binary variable indicating if battery is charged at time t (= 1: charged, 0: not charged) (Chapter 2) . . . . $u_t^{B,c}$

binary variable indicating if battery is discharged at time t (= 1: discharged, 0: not discharged) (Chapter 2) . . . . $u_t^{B,d}$

binary variable indicating if the shiftable appliance load has been shifted from time $k<t$ to a later time t (= 1: shifted, 0: not shifted). (Chapter 2) . . . . $v_{i,k,t}$

temperature set-point for A/C unit of customer at node i at time t ($°C$) (Chapter 2) $\theta_{i,t}^{set}$

uncertain variable of power correction factor for the battery due to ambient temperature at time t (%) (Chapter 2) . . . . ΔP_θ^B

uncertain variable of power correction factor for the battery lifetime due to ambient temperature at time t (%) (Chapter 2) . . . . $\Delta P_\theta^{B,LF}$

uncertain variable of power correction factor for the transformer due to ambient temperature at time t (%) (Chapter 2) . . . . ΔP_θ^{Xfmr}

uncertain variable of occupancy at residence of customer i at time t (Chapter 2) . . . $U_{i,t}^{Occ}$

uncertain variable of active power for non-shiftable loads of customer i at time t (kW) (Chapter 2) . . . . $P_{i,t}^{d,NS}$

objective function q in the deterministic case (Chapter 2 and 3) . . . . O_q

objective function q in the non-deterministic case (Chapter 2) . . . . O_q^{RO}

total active demand for the customer at time t (kW) (Chapter 3) . . . . P_t^d

positive deficiency variable for the goal (target) of objective function q in the multi-objective setting (Chapter 2 and 3) . . . . s_q^+

positive deficiency variable for the goal (target) of objective function q in the non-deterministic multi-objective setting (Chapter 2) . . . . s_q^{RO+}

binary variable indicating if the shiftable load s is ON at time t (= 1: ON, 0: OFF) (Chapter 3) . . . . $u_{s,t}$

temperature set-point for A/C unit at time t ($°C$) (Chapter 3) . . . . θ_t^{set}

variable indicating maximum deviation from goals in the multi-objective optimization (Chapter 3) . . . . δ

variable indicating maximum deviation from goals in the deterministic multi-objective optimization (Chapter 2) . . . . λ

variable indicating maximum deviation from goals in the non-deterministic multi-objective optimization (Chapter 2) . . . . λ^{RO}

LIST OF ABBREVIATIONS

Demand Response . . . . DR

Community energy Storage . . . . CES

Chebyshev Goal Programming . . . . CGP

Robust Counterpart . . . . RC

Photovoltaic . . . . PV

State of Charge . . . . SOC

Existing Apartments . . . . EA

Existing Attached Houses . . . . EAT

Existing Detached Houses . . . . EDT

New Apartments . . . . NA

New Attached Houses . . . . NAT

New Detached Houses . . . . NDT

Single Objective Optimization . . . . SO

Multi-objective Optimization . . . . MO

Robust Multi-objective Optimization . . . . RMO

Home Energy Management System . . . . HEMS

Auto-regressive with Exogenous Input . . . . ARX

Air Conditioning . . . . A/C

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To Mom, Dad, and my beloved brothers and sister.

CHAPTER 1
INTRODUCTION

Natural disasters can cause significant damages to electric power grids and the amount of damage depends on the intensity and type of the disaster. Based on the report in [1], natural disasters have been identified as one of the two main reasons for large blackouts in North America (the other main reason being cascading failures). Since many critical infrastructures such as water sanitation and sewage systems, telecommunication networks, and hospitals and emergency services rely on the availability of power grid, the grid operators should have plans to optimally and with minimum cost recover the electric power network after occurrence of a natural disaster as fast as possible. It is also worthwhile to mention that each natural hazard affects the power grid in a different way. For instance, a heat wave event, depending on its intensity, might only push system assets towards their operational limits and limit the power delivery capacity to the consumers; on the other hand, a flood event or an earthquake might damage parts of power grid such as towers and generation units. Therefore, in devising strategies to cope with the effects of a natural hazard it is necessary to consider the type and intensity of the event.

1.1 Wildfires and Heat Waves

Wildfires occur all around the world every year and can be caused as a result of excessively high temperatures or spread of small man-made fires in grasslands and forests. A significant example of wildfires is the recent fires in Australia in 2020 which caused a considerable damage to the natural environment. Also, it is reported in [2] that an average number of 72000 wildfires have happened in the U.S. every year between 2000 and 2016 which have burnt nearly 6 million acres of land. These wildfires can adversely affect the power grid with the most effect on transmission lines since they pass through grasslands, forests, mountains, etc. Some of these effects are discussed in the literature and can be summarized as follows:

- Tower collapsing as a result of burnt wooden poles of the transmission lines
- A decrease in the thermal dynamic rating of conductors as a result of high temperatures caused by the fire [3]
- Conductor annealing [4]
- Tripping the transmission lines and possible chance of blackouts [4]

In addition to wildfires, many heat wave events with different intensities have occurred as a result of global climate change. Examples of heat events include but are not limited to the United States especially in 2006 and 2012 [5], [6], as well as the 2003 heat wave in Europe and some parts of Asia [7], [8] and the 2009 heat wave in Australia [9]. Heat waves are generally considered as a "prolonged period of excessive heat" [9]. Like wildfires, heat waves pose some adverse effects on the society which can be summarized as follows:

- Health-induced issues for individuals as a result of high temperatures [5, 8]
- Significant increases in power consumption especially as a result of over-utilization of A/C units [9, 10]
- Scarcity of water required for steam power plants during hot days [11]
- Various damages to electrical energy infrastructures [3]

In order for power grid operators to consider the effect of a wildfire or heat wave, they need to redispatch the network considering adequate provisions ahead of time in order to manage the energy resources in the most effective way. A key for ensuring safe and secure operation of the grid is to incorporate the effect of temperature into its operation planning.

1.2 Adverse Effects of Excess Temperatures on Power Grids

As it was mentioned in previous section, because of over-utilization of A/C units by the consumers, total power demand in distribution systems will increase during the periods of excess temperature [12]. For instance, it has been shown in [13] that the power consumption of Taipei city can increase by up to 22 percent when the temperature rises by 5°C. Moreover, generation capacity of most energy generation units is dependent on temperature. An increase in the ambient air temperature will decrease maximum power limit of synchronous generators and also causes a lower air density which limits the output power generation of diesel generators; so, these effects must be considered as a derating factor. On the other hand, battery energy storage systems capacity increases by an increase in the temperature because of the increased electro-chemical reactions speed in the battery [14, 15]. The battery capacity can be modeled considering a temperature correction coefficient. Photovoltaic (PV) panels are affected by the excess temperatures as well. By an increase in the temperature, the open circuit voltage of PV panels decrease while the short circuit current is almost constant [16]; therefore, the output power of PV panels decreases as the temperature increases. Finally, overhead lines are dramatically affected by excess heat. High temperatures increase the temperature around overhead lines and cause conductor sag that might lead to flashovers. Therefore, to avoid damages to the line and interruptions in power supply, decreasing the ampacity of lines during heat wave events is necessary.

1.3 Demand Response and Community Energy Storage

In this section, two options that electric power company can use to cope with the adverse effects of heat waves and wildfires are introduced. These two options, if utilized optimally, can reduce the adverse effects of natural hazards both economically and socially.

In a published report [17], US department of energy defines demand response (DR) as "Changes in electric usage by end-use customers 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." Implementation of various DR programs requires employing advanced metering infrastructure or smart meters. In the literature, DR programs are grouped into two main categories: incentive-based programs, and price-based programs. Incentive-based programs can be listed as follows:

- Emergency DR programs (EDRPs), in which during an emergency condition, defined by the system operator, participants are paid to reduce their power consumption [18]

- Direct load control (DLC), which is based on an agreement between the system operator takes the control of the electrical appliances of customers remotely inside a household [19]

- Interruptible/Curtailable (I/C) Programs, where customers have options to either curtail or completely interrupt their power consumption and be paid some incentives for lowering their power consumption to some pre-defined levels [18]

- Capacity Market Programs (CAPs), where customers commit to providing pre-specified load reductions when system contingencies arise, and are subject to penalties if they do not curtail when asked to do so [17]

- Demand Bidding, where participants can participate in the wholesale electricity markets and bid load reductions [18]

- Ancillary Services, which can be considered a virtual source for providing spinning reserve and other ancillary services with bidding for load reduction in spot markets [18]

On the other hand, price-based DR programs fall into the following categories:

- Time of Use (TOU) Programs, in which high prices are assigned to some hours like peak hours so consumers try to shift their loads to cheap hours as much as possible [17]

- Real-Time Pricing (RTP) Programs, which expose costumers to the variability of electricity prices in the wholesale market from one hour to 24 hours ahead of time and customer will decide upon load reduction based on this information [17]

- Critical Peak Pricing (CPP) Programs, in which some critical time intervals such as peak hours have electricity rates much higher than normal. This scheme results in participants to reduce their consumption and it can perform well with DLC scheme [17]

- Peak Time Rebate (PTR) Programs, which offer rebates to customers who reduce their consumption during critical peak hours [20]

In this thesis, two types of DR programs are modeled: a DLC program in which based on an agreement between the customers and the electric utility company, the utility controls the A/C units of participants via setting the temperature set-points. Also, an I/C program is considered in which customers will be paid an incentive if they reduce their power consumption below a desired value.

During the course of a heat wave event where the capacity of power delivery to the customers is significantly jeopardized and in the presence of intermittent renewable energy resources such as wind and PV generation units, utilization of DR along with a community energy storage (CES) seems inevitable. In fact, in a situation in which there are various sources of uncertainty including the intensity and future progression of the natural hazard, inherent intermittency in renewable energy resources' power generation, and uncertainty associated with the level of participation of customers in DR programs, utilization of a CES system can provide some flexibility for the power grid operator to dispatch its resources optimally.

In many studies in the literature utilization of CES systems in the grid operation is proposed. To solve the problem of neutral current and voltage rise in a power grid due to the unbalanced allocation of PV units, a power balancing algorithm by deploying CES systems has been proposed in [21].Authors of [22] used CES systems and capacitor banks to provide continuity of service, voltage support, and loss minimization. In [23], an optimal strategy for allocation of CES systems based on net present value which was obtained from peaking power generation, energy loss reduction, system expansion deferral, CO2 emission reduction, Var support, capital and maintenance costs was proposed. In the study in [24] the CES was able to perform both PV energy shift and demand load shifting simultaneously. There are also several examples of utilities employing CES systems in their network for improving the efficiency of the network. To name a few of these examples, Detroit Edison (DTE) project with 500 kW Li-ion batteries to couple with a 500 kW solar array [25], installation of a 500 kW/250 kWh Li-ion system in Ontario, Canada, a small 25 kW/25 kWh McAlpine CES system]. there are also other CES projects which use various technologies such as NaS batteries, lead-acid batteries, and hydrogen storage [26].

1.4 Multi-Objective and Robust Optimization

In many situations where the power grid operator is trying to find optimal energy dispatch strategy, there are multiple objectives that usually are contradictory. For instance, in the case of optimal power management in a residential neighborhood, reducing costs, maintaining an acceptable level of healthy condition for residents, and reducing the pressure on power grid assets are some objectives that might be taken into consideration. In the case of having a multi-objective problem to solve, there are various methods to adopt. The simplest method here would be to optimize a linear combination of all individual objective functions. However, this approach has some drawbacks, namely, the assignment of weights to each individual objective function is a subjective matter and also individual objective functions might not have the same units and levels of priority. Goal programming (GP) which was first introduced by [27, 28], is an appropriate approach which transforms the problem into one that seeks a solution whose value is as close to the utopian set as possible. In the study in [29] authors suggested Lexicographic GP and the weighted GP as two most well-known approaches to solve the GP. In [30], Chebyshev GP (CGP) was introduced for solving GPs. CGP tries to achieve an appropriate balance between individual objective functions, as opposed to the other two methods which prioritize some objective functions over the others. In addition, one important aspect of a solution to a multi-objective problem is Pareto optimality. A solution to a multi-objective problem is Pareto efficient if no other feasible solution exists that is at least as good with respect to all objectives and strictly better with respect to at least one objective [31]. If the solution is not Pareto optimal, it is subject to decision maker's choice of the goal values for individual objective functions.

Another thing that must be taken into consideration when planning ahead of time is the uncertainty associated with some parameters. To name some sources of uncertainty, one can mention intermittent nature of renewable energy resources, demand uncertainties, price variations, level of participation of customers in DR programs, modeling and forecast errors, etc. It is necessary for the power grid operator to consider the effect of uncertainties in making decisions ahead of time because otherwise, solutions based on deterministic assumptions might be infeasible when the parameters deviate from their nominal values. There are different methods for incorporating uncertainty into the decision making process. To name a few, stochastic optimization, sensitivity analysis, and robust optimization have been characterized as widely used methods in the literature. In this thesis, to accommodate uncertainty, a robust multi-objective optimization (RMO) will be performed based on the robust counterpart theory in [32]. Robust optimization techniques provide optimal decisions based on worst-case realization of uncertain parameters [32]. Therefore, in this thesis, robust optimization is employed for uncertainty consideration due to modeling and forecast errors to find optimal and feasible solutions even if the worst-case happens. This way one can assure that the decisions are not too optimistic and no infeasible decisions are made. Otherwise, it is possible that the system security is jeopardized and system operator might have to curtail some loads during hot hours in the course of a heat wave event.

CHAPTER 2

POWER MANAGEMENT IN A RESIDENTIAL NEIGHBORHOOD UNDER HEAT WAVE EVENTS

2.1 The Goal of Power Management

Heat waves are meteorological events with prolonged periods of excessive heat [9]. In addition to affecting the health of the residents who are exposed to excessive temperatures [33], heat waves can lead to increased demand due to over-utilization of A/C units [12, 13]. For instance, it has been shown in [13] that the power consumption of Taipei city can increase by up to 22% when the temperature rises by 5°C. Excess demand of A/C units can negatively affect the power grid by resulting in congestion in various circuits and additional operational stress on the assets. One way to combat this is by using the DR potential at the end user's level [34, 35]. To do this, the electric utility can remotely control the A/C units by temporarily turning them off or raising their temperature set-points. However, A/C-based DR during extreme temperature events is a delicate matter that needs to be handled carefully. This is because if used excessively or for long durations, it can negatively affect the health of the residents, especially children and the elderly who are more vulnerable. Hence, a socially-aware energy dispatch during a heat wave event necessitates balancing energy costs due to turning off A/C units with the impacts on residents' health.

At the same time, extreme temperatures have been shown to negatively affect the available capacity of most generation resources such as diesel generators and rooftop PV panels [16] (batteries are the only exception that may experience increase in available capacity [36]). Hence, increased demand can potentially coincide with periods of reduction in generation, which can be challenging for the grid operator. To make matters more complicated, the available capacity and lifetime of transformers and overhead lines can also be negatively affected by the heat [37–39]. This can result in additional stress on the components and potential reduction in their remaining lifetime, leading to premature failures and need for replacement, which can be harmful for the environment. It is therefore necessary to derate the assets by incorporating the effects of temperature into the energy dispatch model [40].

To be aware of the social and environmental consequences of heat waves, the energy dispatch problem must be modified to simultaneously consider all (at times contradictory) objectives, namely minimization of operational costs, minimization of loss of life of assets, and minimization of adverse health impacts on the residents. This problem should then be solved subject to various technical constraints, while incorporating the impact of ambient temperature whenever necessary [40]. However, deterministic approaches may fail to accurately portray the dynamics of the system when some model parameters or inputs are uncertain. One example of this would be the occupancy level of residential units, which often cannot be estimated with a high level of confidence [41, 42]. Other examples are the temperature-based models for lifetime of assets and their available capacity, which are typically empirical and subject to inaccuracies. Under these conditions, the optimization problem needs to be robust so as to ensure feasibility even under the worst-case scenarios. Developing such a solution is the main goal of the current chapter. An energy dispatch model is developed here for a distribution grid subject to a heat wave event. By considering the health of residents (through reasonable control of A/C temperatures) and lifetime of assets (through derating) within a multi-objective framework, the proposed problem ensures that social and environmental concerns are not sacrificed at the expense of technical ones.

2.2 Proposed Methodology

2.2.1 Assumptions

Although our problem formulation can be extended to any distribution grid, we limit our analysis to a neighborhood of residential units equipped with rooftop PV modules as well as a CES system, which is a battery. Residential loads are assumed to be demand responsive through direct load control of their A/C units as well as demand shifting for some appliances.

A conceptual diagram of the problem under consideration in this chapter is illustrated in Figure 2.1.

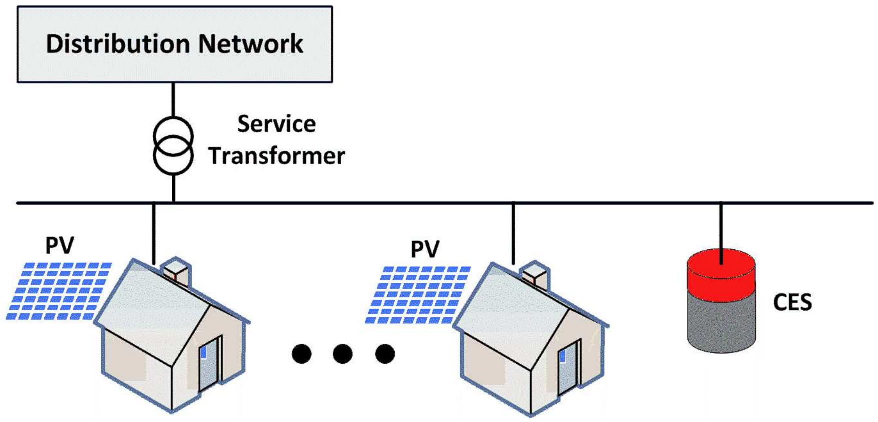

Figure 2.1: Conceptual diagram of the systems under study.

2.2.2 Deterministic Problem Formulation

The problem can be formulated as a multi-period one, where each day is divided into T time slots. Without loss of generality, each time step is assumed to be one hour long.

2.2.2.1 Objective Functions

During a heat wave event, it is envisioned here that the utility may wish to maintain the comfort level and health of residents, as well as the physical health of its own assets in order to ensure sustainability. In a sense, this can be thought of as a dispatch strategy that is socially and environmentally aware. To do this, four objective functions have been considered as described below.

The first two objective functions are related to management of assets. It is known that asset lifetime can be significantly affected under extreme ambient temperatures, and as such, it may sometimes become necessary to derate them to avoid heat-induced damages. Some assets that can be affected by extreme temperatures include generators, batteries, transformers and overhead lines. Objective 2.1 tries to minimize the loss-of-life of the CES by minimizing the cost of using the battery, which is modeled based on the total number of deep discharges over the entire lifetime of the battery. The cost function has been corrected for the impact of temperature on battery lifetime and its maximum power.

$$O_1 = \min_{P_t^{B,d}} \sum_{t \in T} [c^B \frac{P_t^{B,d}}{P^{B,max}.\Delta P_\theta^{B0}.\Delta P_\theta^{B,LF0}}] \tag{2.1}$$

The second objective tries to ensure that the transformer is loaded below its temperature-corrected capacity. While this can in theory be modeled as a hard constraint, achieving the feat may not be possible at times, e.g. during extreme weather events, utilities sometimes allow assets to be slightly overloaded in order to avoid load shedding. To reflect this, transformer loading has been modeled here as a soft constraint in the form of an objective function to be minimized (see Eq. 2.2), where function (.)+ returns its argument if it is positive, and zero otherwise.

$$O_2 = \min_{P_t^u} \sum_{t \in T} (P_t^u - P_t^{u,max}.\Delta P_\theta^{Xfmr0})_+ \tag{2.2}$$

The third objective function takes into account the health of residents by ensuring that indoor temperatures remain within an acceptable range to avoid any potential heat-induced health issues. The function is also penalized by the occupancy level of the building and the age of residents in order to give higher priority to units with higher number of elderly residents. Naturally, this objective function contradicts Objectives 2.1 and 2.2.

$$O_3 = \min_{P_t^u} \sum_{i \in N} \sum_{t \in T} |\theta_{i,t}^{set} - \theta^{des}|.U_{i,t}^{Occ0}.AF_i \tag{2.3}$$

Finally, the fourth objective function tries to maintain acceptable customer comfort levels by minimizing the instances of load shifting for customers, with higher penalties given to customers (buildings) with higher number of occupants.

$$O_4 = \min_{v_{i,t,k}} \sum_{i \in N} \sum_{t \in T} \sum_{k=t+1}^{K} U_{i,t}^{Occ0}.v_{i,t,k} \tag{2.4}$$

2.2.2.2 Constraints

The problem is solved subject to the following constraints. Equations 2.5 and 2.6 indicate the power balance at the service transformer as well as the customer load point. Overloading the service transformer more than 20% is not allowed, as indicated in 2.7. The two constraints in 2.8 ensure that the load is shifted to a point in time in future and that the instances of demand shifting are limited. Equations 2.9 and 2.10 provide limits on the temperature set-points of individual A/C units. Temperature corrected capacities of energy resources are given in 2.11, 2.12 based on 2.13- 2.15 (see [38, 40] for derivation of those equations). Battery constraints are listed in 2.16- 2.18. Equation 2.16 indicates that the battery can be charging or discharging at any point in time, but not both. Equation 2.17 represents a model for the SOC of the battery, along with its upper and lower limits in 2.18. Finally, set constraints appear in 2.19.

$$\forall t \in T : P_t^u + P_t^{B,d} - P_t^{B,c} = \sum_{i \in N} P_{i,t}^d \tag{2.5}$$

$$\forall i \in N, \forall t \in T : P_{i,t}^d = P_{i,t}^{d,A/C} + \sum_{k=1}^{t} v_{i,k,t} P_{i,k}^{d,SH} + P_{i,t}^{d,NS0} - P_{i,t}^{d,PV} \tag{2.6}$$

$$\forall t \in T : P_t^u \leq 1.2 \times P_t^{u,max} \tag{2.7}$$

$$\forall i \in N, \forall t \in T : \sum_{k=t}^{T} v_{i,t,k} = 1, \sum_{t=1}^{T} v_{i,t,t} \geq T - TSH \tag{2.8}$$

$$\forall i \in N, \forall t \in T : \theta_{i,t}^{set} \geq \theta^{des}, \theta_{i,t}^{set} - \theta^{des} \leq 4.44 \tag{2.9}$$

$$\forall i \in N : \sum_{t=1}^{T} |\theta^{des} - \theta_{i,t}^{set}| \leq 27.77 \tag{2.10}$$

$$\forall t \in T : \begin{cases} P_t^{B,d} \leq P^{B,max} u_t^{B,d} \Delta P_\theta^{B0} \\ P_t^{B,c} \leq P^{B,max} u_t^{B,c} \end{cases} \tag{2.11}$$

$$\forall i \in N, \forall t \in T : P_{i,t}^{d,PV} = P_i^{STC} \frac{\Phi_{i,t}}{\Phi^{STC}} [1 - k^{PV} (\theta_t^a - \theta^{ref})] \tag{2.12}$$

$$\Delta P_\theta^{B0} = -0.00016 (\theta_t^a)^2 + 0.0197.\theta_t^a + 0.6075 \tag{2.13}$$

$$\Delta P_\theta^{B,LF0} = -0.00768.\theta_t^a + 1.195 \tag{2.14}$$

$$\Delta P_\theta^{Xfmr0} = 0.996^{\theta_t^a - 30} \tag{2.15}$$

$$\forall t \in T : u_t^{B,c} + u_t^{B,d} \leq 1 \tag{2.16}$$

$$\forall t \in T : SOC_t^B = (1-\gamma^B)SOC_{t-1}^B + \frac{P_t^{B,c}\eta^{B,c}}{P^{B,max}} - \frac{P_t^{B,d}}{\eta^{B,d}P^{B,max}} \tag{2.17}$$

$$\forall t \in T : SOC^{B,min} \leq SOC_t^B \leq SOC^{B,max} \tag{2.18}$$

$$\forall t \in T : u_t^{B,d}, u_t^{B,c}, v_{i,\tau,t} \in \{0,1\}, P_t^{B,d}, P_t^{B,c}, P_t^u \geq 0 \tag{2.19}$$

2.2.3 Power Consumption of A/C Units

In this section, a mathematical function is presented based on the model in [43] for estimating A/C power consumption, where the cooling load for the A/C units consists of four terms, (a) transmission load which is the heat gain caused by the temperature difference between the building elements (e.g. walls and windows) and the outside, (b) infiltration load which is the heat gain due to the flow of outdoor air into the building, (c) solar load, i.e. heat gain due to direct solar irradiation, and (d) internal load which is the heat gain caused by the heat released into the building space by different equipment (such as lighting) or people. In this chapter, for simplicity and without loss of generality, we only consider the transmission load and the solar load, since the value of the other two terms can be assumed to be reasonably small. We assume that the A/C starts operating whenever the indoor temperature falls below the set-point value. This means that the indoor temperature can be assumed to be the same as the set-point. The transmission load is therefore calculated as follows:

$$\forall i \in N, \forall t \in T : Q_{i,t}^{Tr} = h.A_i^W(\theta_t^a - \theta_{i,t}^{set}) \tag{2.20}$$

calculate the solar heat gain, the model in [3] has been used here, as shown in 2.21.

$$\forall i \in N, \forall t \in T : Q_{i,t}^s = \alpha^s Q^{se} A_i^F sin(\beta_t^s) \tag{2.21}$$

Therefore, the total power consumption of the AC unit will be calculated as follows:

$$\forall i \in N, \forall t \in T : P_{i,t}^{d,A/C} = Q_{i,t}^s + Q_{i,t}^{Tr} \tag{2.22}$$

2.2.4 Solution Methodology

The formulated problem is a multi-objective problem with four linear objective functions and linear constraints (equation 2.2 can be easily linearized). In this section, Chebyshev Goal Programming (CGP) approach is adopted which provides a balance between goals without a need for considering priorities for objective functions [31]. The combined objective function to be minimized can be written as 2.23- 2.26. Note that $sq+$ and λ are auxiliary variables.

$$F = \min_{\lambda, O_q} \lambda + \sum_{q=1}^{4} \epsilon \frac{O_q}{b_q} \tag{2.23}$$

Subject to:

$$\forall q \in \{1..4\} : \frac{s_q^+}{b_q} \leq \lambda \tag{2.24}$$

$$\forall q \in \{1..4\} : O_q - s_q^+ \leq b_q \tag{2.25}$$

$$\forall q \in \{1..4\} : s_q^+ \geq 0 \tag{2.26}$$

In 2.23, a small percentage of each objective function (ϵ here is chosen to be 0.05) is added to the CGP objective function in order for the program to continue optimizing even if all the individual goals are achieved [31]. This pushes the solution towards Pareto optimality.

2.3 Robust Counterpart

The problem formulation presented in section 2.2 assumed all deterministic parameters. Naturally, this is usually not the case and there are many aspects of the model that are not known with certainty. Some examples include battery power correction factors ΔP_θ^B and $\Delta P_\theta^{B,LF}$, transformer temperature correction factor ΔP_θ^{Xfmr}, building occupancy level $U_{i,t}^{Occ}$, and the power of non-shiftable loads $P_{i,t}^{d,NS}$. These have been considered as uncertain parameters/input data in this chapter. One way to incorporate these uncertainties into the original optimization model is to develop its robust counterpart. The solution to the latter will guarantee feasibility even under worst-case scenarios.

2.3.1 Box Uncertainty

In the theory of robust counterpart (RC) [32], the uncertainty set is always assumed to be parametric in an affine fashion. For instance, if a vector c is uncertain, the uncertainty set is rewritten as in 2.27:

$$\Psi = \{\widetilde{c} = c^0 + \sum_{k \in K} \zeta_k . \widehat{c}_k : \zeta \in Z \subset \mathbf{R}^K\} \tag{2.27}$$

where Z denotes a closed and convex perturbation set. The term c^0 in 2.27 represents the nominal value of c and the hat-signed term denotes the basic shifts to the nominal value (these are scaled by the uncertainty parameter ζ_k). As an example, consider the trivial case of uncertain scalar parameter c that varies within $[0.95, 1.05]$. Using 2.27, this can be expressed as: $c = 1.0 + \zeta \times 0.05$, where $\zeta \in [-1, +1]$. The uncertainty set can further be defined based on the constraints on the uncertainty parameter ζ. For instance, if the L_∞ norm of ζ is limited, this is referred to as box uncertainty, e.g. $\|\zeta\|_\infty \leq 1$, which means: $\forall k \in K : \zeta_k \leq 1$. Box uncertainty is the most conservative perturbation set [19], and is considered in this section for ΔP_θ^B, $\Delta P_\theta^{B,LF}$, and ΔP_θ^{Xfmr} ($U_{i,t}^{Occ}$ and $P_{i,t}^{d,NS}$ are modeled as budgeted uncertainty as shown in the next section). Since ΔP_θ^B, $\Delta P_\theta^{B,LF}$, and c^B are always positive, they can be lumped together as one uncertain parameter. Considering the intervals 2.28- 2.29 for these uncertain parameters, the parameters are lumped together as in 2.30.

$$\forall t \in T : \Delta P_\theta^{B0} - d\Delta P_\theta^B \leq \Delta P_\theta^B \leq \Delta P_\theta^{B0} + d\Delta P_\theta^B \tag{2.28}$$

$$\forall t \in T : \Delta P_\theta^{B,LF0} - d\Delta P_\theta^{B,LF} \leq \Delta P_\theta^{B,LF} \leq \Delta P_\theta^{B,LF0} + d\Delta P_\theta^{B,LF} \tag{2.29}$$

Therefore:

$$\begin{aligned}\forall t \in T : &\Delta P_\theta^{B0} . \Delta P_\theta^{B,LF0} - \Delta P_\theta^{B0} . \Delta P_\theta^{B,LF} - \Delta P_\theta^{B,LF0} . d\Delta P_\theta^B + d\Delta P_\theta^B . d\Delta P_\theta^{B,LF} \leq \Delta P_\theta^B . \Delta P_\theta^{B,LF} \\ &\leq \Delta P_\theta^{B0} . \Delta P_\theta^{B,LF0} + \Delta P_\theta^{B0} . \Delta P_\theta^{B,LF} + \Delta P_\theta^{B,LF0} . d\Delta P_\theta^B + d\Delta P_\theta^B . d\Delta P_\theta^{B,LF}\end{aligned} \tag{2.30}$$

Defining a new uncertain cost parameter as in 2.31, the objective function in 2.1 is rewritten as in 2.32. In this model, the optimization model considers the worst-case scenario as denoted by the internal maximization function. Naturally, the maximum value of the uncertain cost function in 2.31 equals the parameter c^B divided by the left-hand side of 2.30 and can be inserted into 2.32.

$$\forall t \in T : \widetilde{c}_t^B = \frac{c^B}{\Delta P_\theta^B . \Delta P_\theta^{B,LF}} \tag{2.31}$$

$$O_1^{RO} = \min_{P_t^{B,d}} \max_{\widetilde{c}_t^B} \sum_{t \in T} [\widetilde{c}_t^B \frac{P_t^{B,d}}{P^{B,max}}] = \min_{P_t^{B,d}} \sum_{t \in T} [\widetilde{c}_t^{B,max} \frac{P_t^{B,d}}{P^{B,max}}] \tag{2.32}$$

Objective function O_2 remains the same, although uncertain parameter ΔP_θ^{Xfmr} is represented as:

$$\forall t \in T : \begin{cases} \Delta P_\theta^{Xfmr} = \Delta P_\theta^{Xfmr0} + \zeta_t^{Xfmr} . d\Delta P_\theta^{Xfmr} \\ \zeta_t^{Xfmr} \in Z_t^{Xfmr} \equiv \{z \in \mathbf{R}^T : \|z\|_\infty \leq 1\} \end{cases} \tag{2.33}$$

Since O_2 is a minimization problem, the worst-case realization occurs when ζ equals –1. Finally, constraint 2.11 is affected by an uncertain parameter with a box uncertainty set. Since O_1^{RO} tries to minimize the cost of battery discharge and power discharge of battery is limited by ΔP_θ^B, the worst-case realization of ΔP_θ^B for this constraint is its maximum value which is $\Delta P_\theta^{B0} + d\Delta P_\theta^B$. Therefore, the robust counterpart of 2.11 can be formulated as:

$$\forall t \in T : \begin{cases} P_t^{B,d} \leq P^{B,max} u_t^{B,d} (\Delta P_\theta^{B0} + d\Delta P_\theta^B) \\ P_t^{B,c} \leq P^{B,max} u_t^{B,c} \end{cases} \tag{2.34}$$

2.3.2 Budgeted Uncertainty

Uncertainties associated with $U_{i,t}^{Occ}$ and $P_{i,t}^{d,NS}$ of customers are modelled here using the budgeted uncertainty, because all worst-case scenarios are unlikely to occur at the same time. First, since $U_{i,t}^{Occ}$ is a parameter included in objective functions O_3 and O_4, they should be written in their epigraph forms to derive the corresponding robust counterpart (using auxiliary variables μ^{O_3} and μ^{O_4}). Using 2.9, O_3^{RO} can be written as in 2.35:

$$O_3^{RO} = \min_{\mu^{O_3}} \mu^{O_3} \tag{2.35}$$

$$\mu^{O_3} \geq \sum_{i\in N}\sum_{t\in T}(\theta_{i,t}^{set} - \theta^{des}).U_{i,t}^{Occ}.AF_i \tag{2.36}$$

Similarly, O_4^{RO} can be written as:

$$O_4^{RO} = \min_{\mu^{O_4}} \mu^{O_4} \tag{2.37}$$

$$\mu^{O_4} \geq \sum_{i\in N}\sum_{t\in T}\sum_{k=t+1}^{T} U_{i,t}^{Occ}.v_{i,t,k} \tag{2.38}$$

For the budgeted uncertainty model, the perturbation set is defined as follows [32]:

$$Z \equiv \{\zeta \in \mathbf{R}^L : \|\zeta\|_\infty \leq 1, \|\zeta\|_1 \leq \gamma\} \tag{2.39}$$

where $\gamma \in [1, L]$ is a given uncertainty budget, with L indicating the number of uncertain parameters, which sets an upper limit on total uncertainty. In total, there exist $T \times N$ uncertain parameters for $U_{i,t}^{Occ}$ and $P_{i,t}^{d,NS}$. The perturbation sets for $U_{i,t}^{Occ}$ and $P_{i,t}^{d,NS}$ can be considered as follows:

$$Z^{U^{Occ}} \equiv \{\zeta^{U^{Occ}} \in \mathbf{R}^{N\times T} : \|\zeta^{U^{Occ}}\|_\infty \leq 1, \|\zeta^{U^{Occ}}\|_1 \leq \gamma^{U^{Occ}}\} \tag{2.40}$$

$$Z^{P^{d,NS}} \equiv \{\zeta^{P^{d,NS}} \in \mathbf{R}^{N\times T} : \|\zeta^{P^{d,NS}}\|_\infty \leq 1, \|\zeta^{P^{d,NS}}\|_1 \leq \gamma^{P^{d,NS}}\} \tag{2.41}$$

According to [32], the robust counterpart of 2.36 and 2.38 with the uncertainty set described in 2.40 can be derived as follows (using auxiliary variables $z_{i,t}^{Occ(1)}$, $z_{i,t}^{Occ(2)}$, $w_{i,t}^{Occ(1)}$ and $w_{i,t}^{Occ(2)}$):

$$\sum_{i\in N}\sum_{t\in T} U_{i,t}^{Occ0}.AF_i.(\theta_{i,t}^{set} - \theta^{des}) + \gamma^{U^{Occ}}.\max_{i,t}(|w_{i,t}^{Occ(1)}|) + \sum_{i\in N}\sum_{t\in T}|z_{i,t}^{Occ(1)}| \leq \mu^{O_3} \tag{2.42}$$

$$\sum_{i\in N}\sum_{t\in T}\sum_{k=t+1}^{T} U_{i,t}^{Occ0}.v_{i,t,k} + \gamma^{U^{Occ}}.\max_{i,t}(|w_{i,t}^{Occ(2)}|) + \sum_{i\in N}\sum_{t\in T}|z_{i,t}^{Occ(2)}| \leq \mu^{O_4} \tag{2.43}$$

$$\forall i \in N, \forall t \in T : z_{i,t}^{Occ(1)} + w_{i,t}^{Occ(1)} = -dU_{i,t}^{Occ}.AF_i.(\theta_{i,t}^{set} - \theta^{des}) \tag{2.44}$$

$$\forall i \in N, \forall t \in T : z_{i,t}^{Occ(2)} + w_{i,t}^{Occ(2)} = -dU_{i,t}^{Occ}.(\sum_{k=t+1}^{T} v_{i,t,k}) \tag{2.45}$$

Equations 2.42 and 2.43 are nonlinear due to the presence of the absolute value term; however, they can be easily linearized using auxiliary variables, for instance:

$$\max_{i,t}(|w_{i,t}^{Occ(1)}|) \equiv \chi\ s.t. \forall i \in N, \forall t \in T : |w_{i,t}^{Occ(1)}| \leq \chi \equiv \chi\ s.t. \forall i \in N, \forall t \in T : -\chi \leq w_{i,t}^{Occ(1)} \leq \chi \tag{2.46}$$

The last uncertain parameter that affects constraints in 2.5 and 2.6 is $P_{i,t}^{d,NS}$. In the presence of uncertainties, it is often recommended to convert equalities to inequalities [32]. In the context of power systems, this is equivalent to considering a certain amount of reserve margin for load-generation balance. Hence, constraints 2.5 and 2.6 are rewritten as:

$$\forall t \in T : P_t^u + P_t^{B,d} - P_t^{B,c} \geq \sum_{i \in N}(P_{i,t}^{d,A/C} + P_{i,t}^{d,NS} - P_{i,t}^{d,PV} + \sum_{k=1}^{t} v_{i,k,t}.P_{i,k}^{d,SH}) \tag{2.47}$$

Using the same approach as for $U_{i,t}^{Occ}$, the following robust counterpart can be derived, with $z_{i,t}^{d,NS}$ and $w_{i,t}^{d,NS}$ as auxiliary variables:

$$\begin{aligned} \forall t \in T : \sum_{i \in N} |z_{i,t}^{d,NS}| + \gamma_t^{d,NS}. \max_i |w_{i,t}^{d,NS}| - P_t^u - P_t^{B,d} + P_t^{B,c} \leq \\ \sum_{i \in N}(P_{i,t}^{d,PV} - P_{i,t}^{d,A/C} - P_{i,t}^{d,NS0} - \sum_{k=1}^{t} v_{i,k,t}.P_{i,k}^{d,SH}) \end{aligned} \tag{2.48}$$

$$\forall i \in N : \forall t \in T : z_{i,t}^{d,NS} + w_{i,t}^{d,NS} = -dP_{i,t}^{d,NS} \tag{2.49}$$

Finally, the CGP objective function in 2.23 and the corresponding constraints in 2.24- 2.26 must be modified for the robust case (s_q^{RO+} and λ^{RO} are auxiliary variables).

$$F^{RO} = \min_{\lambda^{RO}, O_q^{RO}} \lambda^{RO} + \sum_{q=1}^{4} \epsilon \frac{O_q^{RO}}{b_q} \tag{2.50}$$

$$\forall q \in \{1..4\} : \frac{s_q^{RO+}}{b_q} \leq \lambda^{RO} \tag{2.51}$$

$$\forall q \in \{1..4\} : O_q^{RO} - s_q^{RO+} \leq b_q \tag{2.52}$$

$$\forall q \in \{1..4\} : s_q^{RO+} \geq 0 \tag{2.53}$$

Having the robust counterpart of all objective functions and constraints, the mixed-integer multi-objective robust problem is therefore defined as minimize F^{RO} subject to 2.7- 2.10, 2.12- 2.22, 2.28- 2.38, 2.42- 2.49, and 2.51- 2.53.

2.4 Case Study

2.4.1 System Data

We assume a neighborhood with six types of buildings: existing apartments (EA), existing attached houses (EAT), existing detached houses (EDT), new apartments (NA), new attached houses (NAT), and new detached houses (NDT). For demonstration purposes, it is assumed that three customers exist for each building type, making a total of 18 customers, with the age factors as listed in Table 2.1. Note that in Table 2.1 value of 1 indicates a building with young residents, 3 is for middle-aged residents, and 5 is for at least one elderly resident. Weights are arbitrary. Ambient temperature data for this case study has been obtained from the heat wave event that happened in Sacramento, CA on July 23, 2006.

Table 2.1: Age factors for each customer.

Building type	Age Factor		
	C1	C2	C3
EA	1	3	5
EAT	3	3	5
EDT	3	3	3
NA	1	3	1
NAT	3	3	1
NDT	3	5	5

Nominal capacity of the distribution transformer and the desired A/C temperature set-point are assumed to be $80kW$ and $23.33°C(74°F)$, respectively. Figure 2.2 illustrates the average occupancy profile used for different types of buildings. These values are used for the deterministic optimization case and are considered to be the nominal values $U_{i,t}^{Occ0}$ for the robust case. Moreover, characteristics of the PV panels as well as the battery as the CES are provided in Table 2.2 and Table 2.3, respectively.

Table 2.2: Characteristics of the PV panels.

No. of Panels	Panel Size (kW)	$P^{STC}(kW)$	$\Phi^{STC}(W/m2)$	k^{PV} ($°C^{-1}$)
36	200	200	1,000	0.004

Table 2.3: Characteristics of battery

$P^{B,max}$	$I^{max}(A)$	SOC^{min}	SOC^{max}	$\eta^{B,c}, \eta^{B,d}$	γ^B	$c^B(\$)$
40	0.25	10%	100%	0.8	0.0025	20.5

Other data used in this chapter are provided in [44].

2.4.2 Simulation Results

To find the goal (target) values for the objective functions, each objective function is first independently minimized subject to its corresponding constraints. Then, goal values are set by adding a small error margin (here 15%) to each single objective optimum. In addition, the box uncertainty set for each uncertain parameter is considered to be between 0.9 and 1.1 times its nominal value, i.e. representing a ±10% deviation. Furthermore, the budget of uncertainty for non-shiftable loads ($P_{i,t}^{d,NS}$) at each hour and for occupancy ($U_{i,t}^{Occ}$) over the entire dispatch period are considered to be 9 and 108, respectively. Finally, the optimization is carried out over a 12-hour period from 9:00am to 8:00pm. Both the deterministic and robust problems are solved using the GAMS/BDMLP solver using a computer with Intel®

CoreTM i7-4790 with 3.6 GHz CPU and 16 GB RAM. The multi-objective deterministic and robust problems solve in 10 and 17 seconds, respectively. Table 2.4 lists the optima associated with the various objective functions for different models.

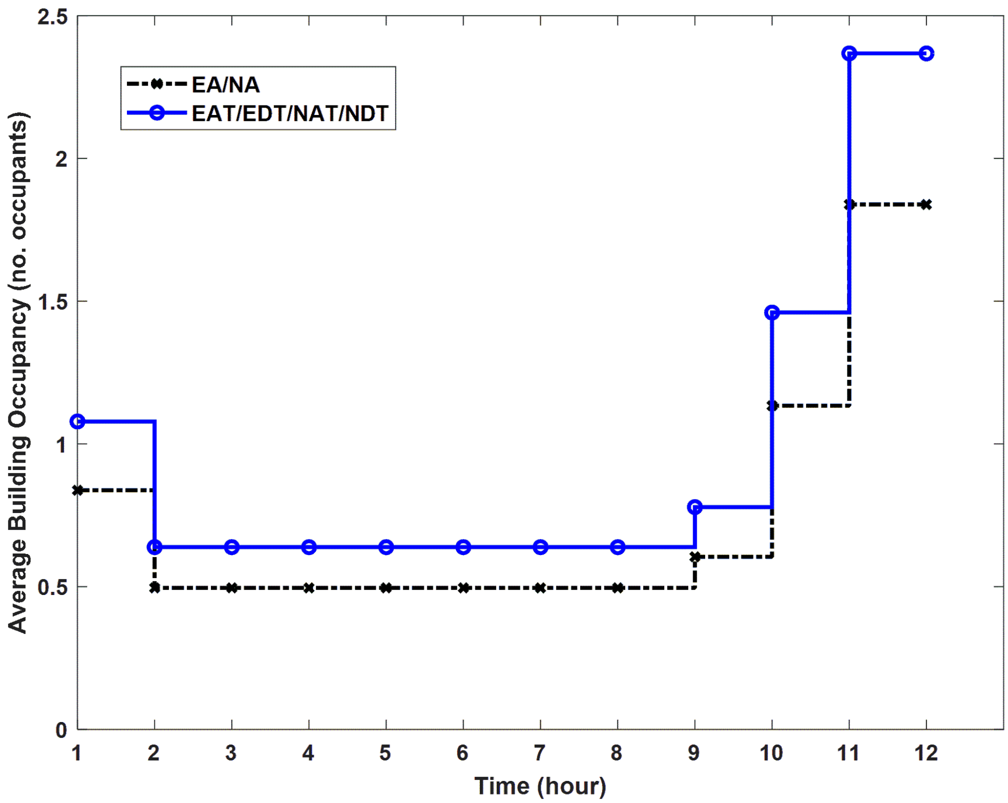

Figure 2.2: Occupancy profile (average values) for each type of building.

Note in Table 2.4 that SO means single objective optimization, MO refers to multi-objective optimization, and RMO stands for robust multi-objective optimization.

The data in Table 2.4 shows that in all cases, the MO problem manages to meet the goal (target) values. In some cases, it is also able to improve upon them, which indicates the problem reaches the Pareto optimal solution. Comparing the two cases shows that incorporating the uncertainties discussed in the previous section can significantly affect the optimal operation of the system. In the robust case, the four objective functions (O_1, O_2, O_3, and O_4) are deteriorated by 29.25%, 46.77%, 13.91%, and 95.68% compared to the deterministic

Table 2.4: Optimal values and assigned goals.

Optimal Values	Objective Functions			
	O1 ($)	O2 (kW)	O3 ($^{\circ}C$)	O4
SO	12.33	188.76	831.89	8.5
Goal (Target) Values	14.18	217.07	956.67	9.78
MO	14.19	190.67	931.1	9.5
RMO	18.34	279.85	1,060.64	18.59

case, respectively. Therefore, it can be concluded that relying only on deterministic parameters will not lead to a reliable and trustworthy solution where in reality some parameters are subject to forecast or modeling errors. Not considering the uncertainties can cause the load-generation balance to be violated (infeasible solution), which forces the utility to tap into the more expensive reserves or to exercise load shedding, which would be highly undesirable. Figure 2.3 shows the average A/C temperature set-points of all customers, while power discharge levels of the battery and the power received from the service transformer are illustrated in Figure 2.4 and Figure 2.5, respectively. In addition, Table 2.5 lists the total demand shifting under both deterministic and robust scenarios.

In Table 2.5, for instance $2.2kW(2 \rightarrow 12)$ means that a total of $2.2kW$ demand is shifted from hour 2 to hour 12. The results demonstrate an interesting pattern. As evident in Figure 2.3, temperature set-points in the deterministic and non-deterministic cases are not very different, and at some time instances, the average A/C set-point in the deterministic case is even higher than the non-deterministic case, which sounds counter-intuitive. This happens due to the fact that objective O_2 is being heavily penalized by considering worst-case realization of the occupancy levels. Hence, to balance the objectives, the CGP technique tries to use more load shifting instead of raising the temperature set-points (as seen in Table 2.5).

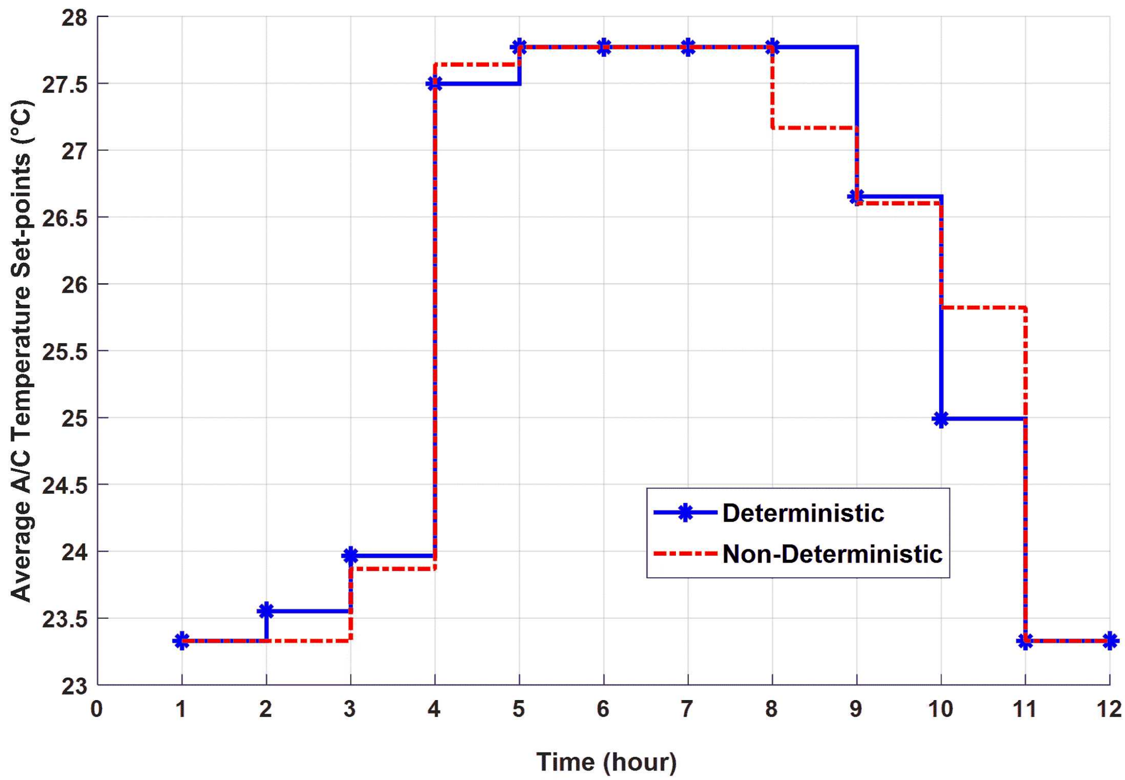

Figure 2.3: Average A/C temperature set-points in the neighborhood.

Table 2.5: Load shifting decisions for the two cases.

Deterministic	Non-deterministic
$2.2kW(2 \rightarrow 12)$	$3.7kW(2 \rightarrow 11)$
$3.15kW(3 \rightarrow 12)$	$3.65kW(3 \rightarrow 11)$
$3.65kW(4 \rightarrow 12)$	$0.5kW(3 \rightarrow 12)$
$0.5kW(5 \rightarrow 11)$	$2.2kW(4 \rightarrow 11)$
$0.5kW(5 \rightarrow 12)$	$1.45kW(4 \rightarrow 12)$
$1.4kW(6 \rightarrow 12)$	$1kW(5 \rightarrow 11)$
$3.15kW(7 \rightarrow 12)$	$1.65kW(6 \rightarrow 11)$
$1kW(8 \rightarrow 12)$	$1kW(7 \rightarrow 11)$
$3.15kW(7 \rightarrow 12)$	$1.65kW(6 \rightarrow 11)$
....	$2.15kW(7 \rightarrow 12)$
....	$1kW(8 \rightarrow 11)$
....	$0.5kW(9 \rightarrow 11)$
....	$0.75kW(9 \rightarrow 12)$
....	$0.5kW(10 \rightarrow 11)$

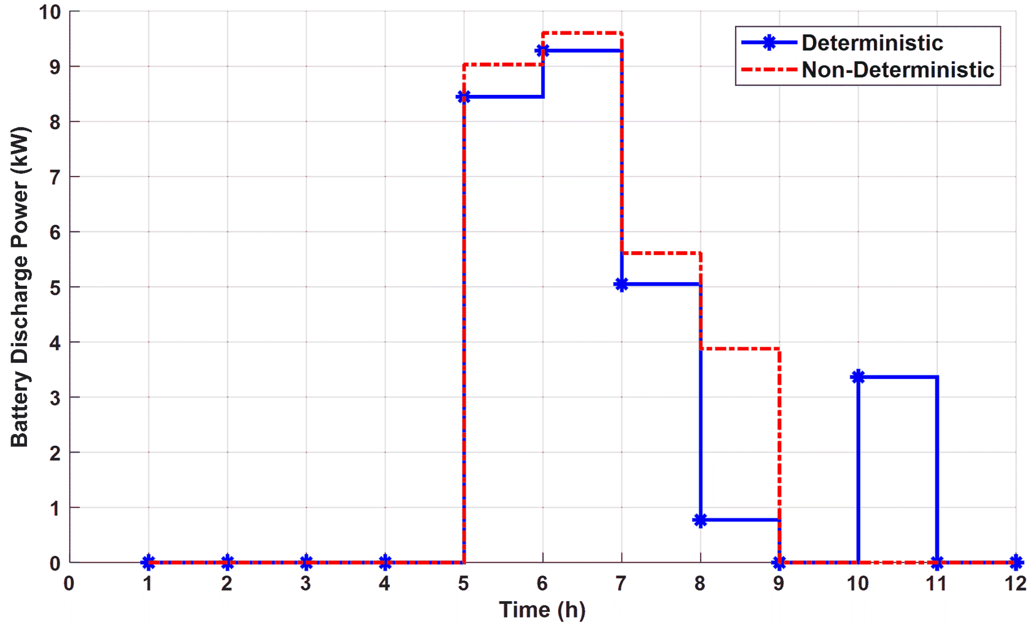

Figure 2.4: Power discharge levels of the battery.

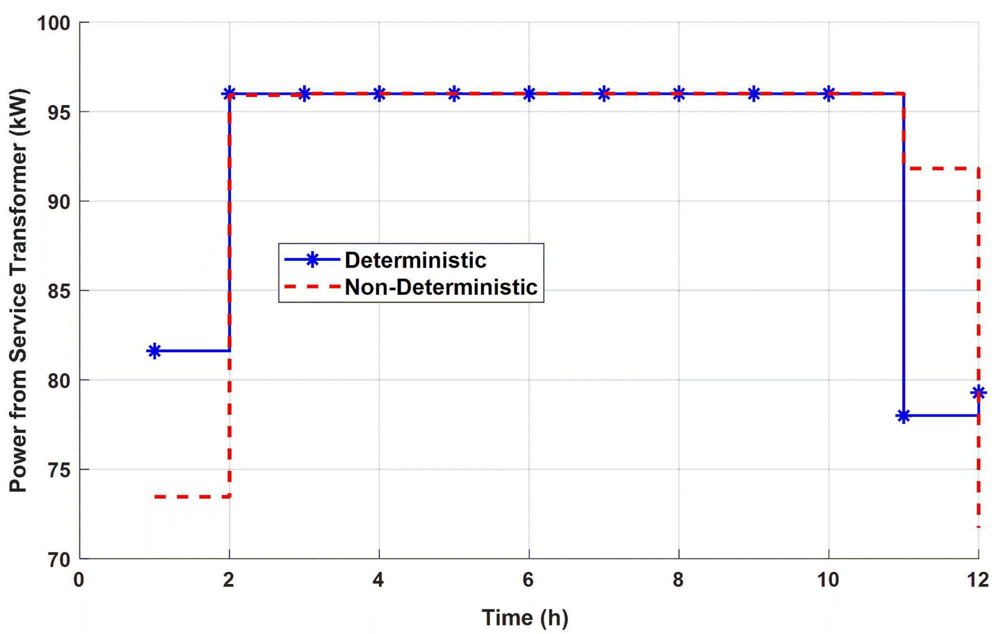

Figure 2.5: Power delivered through the service transformer.

Moreover, the total power delivered through the service transformer for the deterministic and non-deterministic cases are $1,102.9kW$ and $1,100.9kW$, respectively. This indicates that the problem tries to reduce P_t^u to help reduce the overall value of objective O_2. Finally, to show the effect of different levels of uncertainty, a sensitivity analysis is carried out. Figure 2.6 illustrates the effect of the budget of uncertainty on the values of the objective functions. As expected, increasing the budget of uncertainty, i.e., allowing uncertain parameters to deviate further from their nominal values, deteriorates the optimal values of all objective functions, with the exception of O1 whose value may at times be improved instead. This happens because objective O1 is not directly related to the parameters for which budgeted uncertainty is considered.

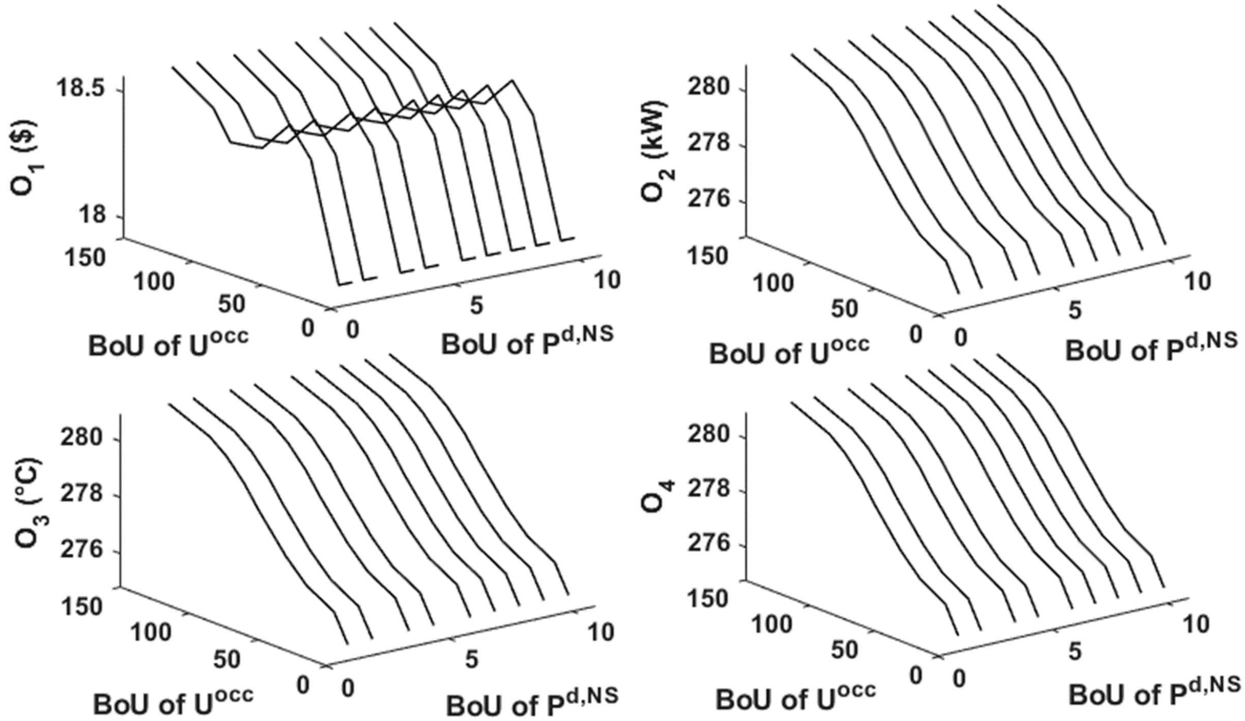

Figure 2.6: Objective functions for different values of budget of uncertainty.

2.5 Conclusion

A robust mixed-integer multi-objective optimization problem was proposed in this chapter to address energy dispatch in a power distribution grid exposed to extreme temperatures. Multiple objective functions were considered, with the goal of ensuring the health of the residents as well as the physical health of assets during the heat wave event. The former was achieved by ensuring reasonable A/C temperature set-points for residential units to avoid any adverse health effects on the residents. To model the latter, impact of ambient temperatures on the available capacity and lifetime of assets was incorporated into the problem formulation. To account for the non-deterministic nature of the problem, building occupancy levels, non-shiftable demand, and the temperature-related power correction factors for the battery and the transformer were assumed to be uncertain. Then, models based on box uncertainty and budgeted uncertainty were proposed in order to reflect those uncertainties. A robust counterpart of the deterministic multi-objective optimization problem was then developed to provide comparison with the deterministic case. It was observed that considering uncertainty in problem parameters can noticeably change the dispatch strategy and value of the objective functions, which means a fully deterministic model is likely to be overly-optimistic and may not be able to reflect the true nature of the problem, potentially leading to infeasibility. Under worst-case conditions, this could mean the violation of load-generation balance, which can jeopardize the security of the system.

CHAPTER 3

SMART ENERGY MANAGEMENT IN A HOUSE CONSIDERING UNCERTAINTY

3.1 An Introduction to the Problem

DR is one of the pillars of the Smart Grid paradigm, where end-use consumers are encouraged to voluntarily reduce their electricity consumption levels in response to financial incentives or variable electricity rates [45]. At the residential level, DR can be deployed in the form of direct load control (DLC) or demand shifting. Through the DLC program, the utility may temporarily turn off or change the set-point of one or more appliances, usually the air-conditioning (A/C) unit, in exchange for a certain amount of credit being applied to the customer's bill. On the other hand, demand shifting is a form of interruptible DR program in which certain loads may be shifted to a future time step to take advantage of more favorable electricity prices. Many savvy customers can manually arrange the operation schedule of their shiftable appliances such as the washer, dryer, dishwasher, or perhaps the electric vehicle (EV) charger; however, as some utilities are trying to move towards the more granular real-time pricing (RTP) scheme, there is a need for automated home energy management systems (HEMS) that can optimize power consumption through a human-out-of-the-loop approach. Proposing one such system is the objective of the current chapter. This will enable interfacing the HEMS with the utility's DR platform and can convert residential DR to a more dynamic resource for energy management.

The concept of automated HEMS is not new. During the past decade, many researchers have tried to address this issue by designing various solutions to optimize the power consumption of a smart home that consists of various loads. For instance, authors in [46] proposed a decision-support tool to co-optimize utilization schedule of appliances and generation schedule of distributed energy resources with the goal of maximizing net benefits. In [47], an algorithm was proposed to minimize the amount of power drawn from the utility and replace it with onsite PV power while also considering power quality issues. Authors in [34] proposed an algorithm to dynamically prioritize household appliances while taking into account the availability of onsite renewable energy and battery power. A similar method was proposed in [35] where appliances were modeled based on their start time, operation length and the acceptable delay in their operation. Other solutions have been proposed for coordinated control of home energy resources such as appliances, EV, battery and/or PV panels [48], [49].

Often, residential load management is tied in with control of A/C units. Since indoor temperature is directly related to the comfort level of residents, some authors have incorporated customer convenience into their optimization models, e.g. by defining cost of discomfort (assumed to be a linear function of temperature deviation from the desired temperature range) [50], hard constraints on upper and lower temperatures [51], [52], or heuristic models to determine thermal comfort as a function of indoor temperature, relative humidity and air motion [53], [48]. Naturally, an important aspect of A/C-centered DR solutions is to be able to predict the A/C unit consumption based on ambient temperature and other parameters. Various models have been used for this purpose, e.g. simplified state space models [48], [50], reduced-order heat transfer models [53], [43], and artificial neural networks [52].

The goal of this chapter is to devise a solution for residential DR that is aware of building occupancy. Building occupancy level is used for two purposes: estimating the A/C consumption as well as ensuring the convenience and health of residents when using demand response. To do this, a multi-objective optimization framework is proposed here that concurrently considers cost minimization, demand reduction and the residents' comfort. A goal programming approach will be used to ensure that no individual objective function will dominate the others. In addition, this approach allows us to ensure the Pareto optimality of the solution. To address the uncertainty in parameters such as the occupancy level or demand patterns, we employ a robust optimization model that safeguards the solution against deviations from nominal values. The proposed robust multi-objective (RMO) problem formulation can be applied to any smart home with any given set of controllable loads and onsite energy resources.

3.2 Proposed Methodology

3.2.1 Assumptions

It is assumed here that the customer has two options for demand response: reducing the A/C unit power consumption and/or shifting the demand of one or more smart appliances from peak hours to off-peak hours. Further, DR contract between the utility and the customer is assumed to present two financial mechanisms. First, once the power utility sends a demand reduction request, the customer is expected to limit its power consumption at the level requested by the utility. Failure to do so may for instance lead to financial "cost," e.g. either penalties or disqualifying the customer from receiving financial incentives per the DR contract. Second, reduction beyond what requested by the utility can entitle the customer to additional financial reward (on top of the incentives per the DR contract). For simplicity, and without loss of generality, each time step is considered here to be 1 hour, which means the power levels in (kW) would be equivalent in value to the energy levels in (kWh).

3.2.2 Problem Formulation

3.2.2.1 Objective Functions

The following objective functions are considered:

Demand Minimization: Suppose that the DR program has set a desired demand level $P_t^{d,des}$ for the customer at time t. Robust Demand Response (RDR) would then try to minimize the surplus consumption beyond the target value. This objective function does not consider the financial incentives and/or the penalties associated with complying or failure to comply with the target demand reduction.

$$O_1 = \min_{P_t^d} \sum_{t \in T} (P_t^d - P_t^{d,des})_+ \tag{3.1}$$

where the $(\Delta)_+$ function is defined as follows:

$$(v)_+ = \begin{cases} v & for\ v > 0 \\ 0 & otherwise \end{cases} \tag{3.2}$$

Cost Minimization: reducing demand must be achieved in a way that maximizes the financial gains by the customer and minimizes costs. As such, the customer would prefer to avoid penalties or missed financial payments (by meeting the desired demand reduction as in Eq. 3.1). In addition, whenever possible, it would prefer to reduce its consumption beyond the desired amount to qualify for additional payments. This has been expressed as in 3.3.

$$O_2 = \min_{P_t^d, P_t^u} \sum_{t \in T} \{c_t^u P_t^u - p_t.(P_t^{d,des} - P_t^d)_+\} \tag{3.3}$$

A/C Temperature Control: although demand reduction by turning off the A/C or increasing its temperature setpoint is an effective way to reduce consumption, one must ensure that indoor temperatures at the residential building are within an acceptable range in order to maintain healthy conditions for the residents, in particular children and the elderly. Hence, RDR would try to minimize the function in 3.4, where the objective function is penalized by the building's occupancy level.

$$O_3 = \min_{\theta_t^{set}} \sum_{t \in T} |\theta^{des} - \theta_t^{set}|.U_t^{Occ} \tag{3.4}$$

3.2.2.2 Constraints

The problem is solved subject to the following constraints:

Power Balance: this constraint models the total consumption at the residential unit. Simple power balance equation is used here since it provides adequate level of accuracy for one customer. To estimate demand for A/C, an auto-regressive with exogenous input (ARX) model has been developed that estimates the A/C power consumption at time t based on its previous values as well as the current and previous values of three exogenous inputs, i.e. ambient temperature, occupancy level, and A/C temperature set-point (see 3.7, where α, β,

γ and η are the coefficients of the ARX model). More details can be found in [40].

$$\forall t \in T : P_t^u = P_t^d \tag{3.5}$$

$$\forall t \in T : P_t^d = P_t^{d,A/C} + \sum_{s \in S} u_{s,t}.P_s^{d,SH} + P_t^{d,Misc} - P_t^{d,PV} \tag{3.6}$$

$$\forall t \in T : P_t^{d,A/C} = \sum_{k=1}^{K} \alpha_k P_{t-k}^{d,A/C} + \beta_k U_{t-k+1}^{Occ} + \gamma_k \theta_{t-k+1}^{a} + \eta_k \theta_{t-k+1}^{set} \tag{3.7}$$

$$\forall t \in T : P_t^{d,PV} = N^{PV} P^{PV,STC} \frac{\Phi_t}{\Phi^{STC}} [1 - k^{PV} (\theta_t^a - \theta^R)] \tag{3.8}$$

Demand Shiftable Loads: if shiftable appliance s is turned on at time t then (a) it must be off during the previous time steps, (b) it needs to remain on for the duration of time it needs to complete its cycle, and (c) it must turn off after the completion of the cycle. These constraints are modeled as in 3.9-3.10. Equation 3.9 ensures that demand can be shifted to a future time step only if enough time remains in the dispatch period to complete the cycle. Appliance s cannot start earlier than the predetermined start time (see 3.11) and should finish its cycle prior to the predetermined end time (see 3.12). Also, demand shifting is not performed partially here and if scheduled, the entire load will be shifted to a future time step.

$$\forall s \in S : \sum_{t \in T} u_{s,t} = N_s \tag{3.9}$$

$$\forall s \in S, \forall t \in T : u_{s,t+1} \geq \frac{u_{s,t}}{N_s} (N_s - \sum_{\tau=1}^{t} u_{s,\tau}) \tag{3.10}$$

$$\forall s \in S : \sum_{t=1}^{T_s^{start}-1} u_{s,t} = 0 \tag{3.11}$$

$$\forall s \in S : \sum_{t=T_s^{end}+1}^{T} u_{s,t} = 0 \tag{3.12}$$

A/C Temperature Limits: For health reasons, it is desired that the set-point temperature of the A/C unit does not exceed a certain predetermined threshold. In this chapter, we have considered the desired A/C set-point to be 23.88°C (75°F), and that the set-point may not exceed $25.55°C$ ($78°F$) at any point in time.

$$\forall t \in T : |\theta_t^{set} - \theta^{des}| \leq 1.67 \tag{3.13}$$

In addition, we wish to place a limit on the overall variations of set-point temperature from the desired set-point. This is intended to reduce the inconvenience on the end user; otherwise, the optimization problem will force the set-point to be at the upper limit at all times. This is expressed as below:

$$\sum_{t=1}^{T} |\theta^{des} - \theta_t^{set}| \leq 19.44 \tag{3.14}$$

Moreover, to eliminate the possibility of more consumption due to overcooling of the house by the A/C unit, the following constraint is considered.

$$\forall t \in T : \theta_t^{set} \geq \theta^{des} \tag{3.15}$$

Integrality Constraints:

$$\forall s \in S, \forall t \in T : u_{s,t} \in \{0, 1\} \tag{3.16}$$

3.2.3 Robust Counterpart

The formulation presented in the previous section is based on the assumption that all the parameters are deterministic. However, in reality this is not always the case and some parameters cannot be assumed to be with 100% certainty. In this chapter, occupancy level for the first time interval is assumed to be deterministic and known, but after that it is assumed to be uncertain. In addition, miscellaneous loads ($P_t^{d,Misc}$) and electricity rates (c_t^u) for the planning horizon are other uncertain parameters in the formulation. To guarantee the feasibility and optimality of the solution under worst-case scenarios, budgeted RC, which is less conservative than the box RC and more conservative than the ball RC, of the formulation is developed. As it was discussed in chapter 2, in theory of RC, if a vector c is uncertain, the uncertainty set can be written as [32]:

$$\Psi = \{\widetilde{c} = c^0 + \sum_{k \in K} \zeta_k \widehat{c}_k : \zeta \in Z \subset \Re^K\} \tag{3.17}$$

Where Z is perturbation set and is assumed to be closed and convex. The term c^0 in 3.17 is the nominal value of c and $\widehat{c}_k$ denotes the basic shifts to the nominal value which is scaled by ζ_k which is the uncertainty parameter and belongs to Z. For the budgeted uncertainty model, Z is defined as follows [32]:

$$Z \equiv \{\zeta \in \Re^L : \|\zeta\|_\infty \leq 1, \|\zeta\|_1 \leq \gamma\} \tag{3.18}$$

where $\gamma \in [1, L]$ is a given uncertainty budget, with L indicating the number of uncertain parameters.

In this study, RC of all the constraints that include uncertain parameters need to be derived. First of all, 3.1 and 3.3 are linearized using auxiliary variable W_t as:

$$O_1 = \min_{W_t} \sum_{t \in T} W_t \tag{3.19}$$

$$O_2 = \min_{P_t^u, W_t} \sum_{t \in T} (c_t^u P_t^u + p_t.W_t) \tag{3.20}$$

$$\forall t \in T : W_t \geq P_t^d - P_t^{d,des} \tag{3.21}$$

$$\forall t \in T : W_t \geq 0 \tag{3.22}$$

In addition, since O_2 and O_3 include uncertain parameters, they need to be written in their epigraph form so to derive their RC. Note that μ^{O_2} and μ^{O_3} are auxiliary variables.

$$O_2 = \min_{\mu^{O_2}} \mu^{O_2} s.t. \mu^{O_2} \geq \sum_{t \in T} (c_t^u P_t^u + p_t.W_t) \tag{3.23}$$

$$O_3 = \min_{\mu^{O_3}} \mu^{O_3} s.t. \mu^{O_3} \geq \sum_{t \in T} (\theta_t^{set} - \theta^{des}).U_t^{Occ} \tag{3.24}$$

In presence of uncertainty, it is often recommended to have a reserve margin for the generation-consumption balance. Therefore, constraints 3.5, 3.6, and 3.7 are rewritten as:

$$\forall t \in T : P_t^u \geq \sum_{s \in S} u_{s,t} P_s^{d,SH,n} + P_t^{d,Misc} - P_t^{d,PV} + \sum_{k=1}^{K} \alpha_k P_{t-k}^{d,A/C} + \beta_k U_{t-k+1}^{Occ} + \gamma_k \theta_{t-k+1}^{a} + \eta_k \theta_{t-k+1}^{set} \tag{3.25}$$

Considering $\Gamma_t^{U_{Occ}}$ as the budget of uncertainty for occupancy in each time interval, the robust counterpart of 3.21 can be written as [32]:

$$\begin{aligned}\forall t \in T : W_t \geq & \sum_{s \in S} u_{s,t} P_s^{d,SH} + P_t^{d,Misc,n} - P_t^{d,PV} + \sum_{k=1}^{K} \alpha_k P_{t-k}^{d,A/C} + \beta_k U_{t-k+1}^{Occ,n} + \gamma_k \theta_{t-k+1}^{a} + \eta_k \theta_{t-k+1}^{set} \\ & + \Gamma_t^{U_{Occ}}.\max(|w_t^{Occ(1)}|) + |z_t^{Occ(1)}| + \Gamma_t^{Pd,Misc}.\max(|w_t^{Pd,Misc}|) + |z_t^{Pd,Misc}| - P_t^{d,des}\end{aligned} \tag{3.26}$$

$$\forall t \in T : w_t^{Occ(1)} + z_t^{Occ(1)} = \sum_{k \in K, k<t} \beta_k dU_{t-k+1}^{Occ} \tag{3.27}$$

$$\forall t \in T : w_t^{Pd,Misc} + z_t^{Pd,Misc} = dP_t^{d,Misc} \tag{3.28}$$

By introducing some auxiliary variables,3.26 can be linearized. For instance:

$$\max(|w_t^{Occ(1)}|) \equiv \chi \ s.t. \forall t \in T : |w_t^{Occ(1)}| \leq \chi \equiv \chi \ s.t. \forall t \in T : -\chi \leq w_t^{Occ(1)} \leq \chi \tag{3.29}$$

$$|z_t^{Occ(1)}| \equiv \gamma_t \ s.t. \forall t \in T : |z_t^{Occ(1)}| \leq \gamma_t \equiv \gamma_t \ s.t. \forall t \in T : -\gamma_t \leq z_t^{Occ(1)} \leq \gamma_t \tag{3.30}$$

Note that $0 \leq \Gamma_t^{U_{Occ}} \leq t-1$ because there are $t-1$ uncertain parameters in each time interval; also, $\Gamma_t^{U_{Occ}} < \Gamma^{U_{Occ}}$. Using the same technique, RC of 3.23, 3.24, and 3.25 can be derived as follows.

$$\mu^{O_2} \geq \sum_{t \in T} (c_t^{u,n} P_t^u + p_t.W_t) + \Gamma^{c^u}.\max(|w_t^{c^u}|) + \sum_{t \in T} |z_t^{c^u}| \tag{3.31}$$

$$\forall t \in T : w_t^{c^u} + z_t^{c^u} = dc_t^u P_t^u \tag{3.32}$$

$$\mu^{O_3} \geq \sum_{t \in T} (\theta_t^{set} - \theta^{des}).U_t^{Occ,n} + \Gamma^{U_{Occ}}.\max(|w_t^{Occ(2)}|) + \sum_{t \in T} |z_t^{Occ(2)}| \tag{3.33}$$

$$\forall t \in T : w_t^{Occ(2)} + z_t^{Occ(2)} = (\theta_t^{set} - \theta^{des}).dU_t^{Occ} \tag{3.34}$$

$$\forall t \in T : P_t^u \geq \sum_{s \in S} u_{s,t} P_s^{d,SH} + P_t^{d,Misc,n} - P_t^{d,PV} + \sum_{k=1}^{K} \alpha_k P_{t-k}^{d,A/C} + \beta_k U_{t-k+1}^{Occ,n} + \gamma_k \theta_{t-k+1}^{a} + \eta_k \theta_{t-k+1}^{set} + \Gamma_t^{U_{Occ}}. \max(|w_t^{Occ(1)}|) + |z_t^{Occ(1)}| + \Gamma_t^{Pd,Misc}. \max(|w_t^{Pd,Misc}|) + |z_t^{Pd,Misc}| \tag{3.35}$$

3.2.4 Solution Methodology

The problem to be solved can be described as minimizing O_1–O_3 subject to 3.8-3.16, 3.22, 3.26-3.28, and 3.31-3.35. This is a multi-objective nonlinear problem, and is solved here using Chebyshev goal programming (CGP), because it provides a balance between goals, as opposed to other GP techniques that suffer from the incommensurability problem or require prioritizing the goal values [31]. CGP uses the Chebyshev L_∞ norm for measuring the distances of the objective functions to their corresponding targets (goals). It then tries to minimize the maximum deviation from any goal. This way, all objective functions are given equal priority and a balance is maintained between the goals without making the problem subjective. To ensure Pareto optimality, we adopt the methodology proposed in [54], where we add a small percentage of each original objective function to the CGP function (the ϵ value has been chosen as 0.05 in this chapter). This way, even if the specified goal is achieved, the problem continues to improve the solution further by minimizing the overall objective function. The multi-objective problem has been formulated as below:

$$\min F = \delta + \sum_{q \in Q} \epsilon O_q \tag{3.36}$$

$$\forall q \in Q : \frac{s_q^+}{b_q} \leq \delta \tag{3.37}$$

$$\forall q \in Q : O_q - s_q^+ \leq b_q \tag{3.38}$$

$$\forall q \in Q : s_q^+ \geq 0 \tag{3.39}$$

In the above equations, 3.36 is the multi-objective function that should be minimized. The last term in this equation, i.e. a percentage of each objective function, is intended to ensure Pareto optimality. Equation 3.37 tries to minimize the distance of each objective function from their corresponding target (goal) values (set by the user). Constraint 3.38 indicates our desire for the individual objective functions to be less than their specified targets (goals). The associated deficiency variables s^+ convert these requirements into soft constraints.

3.3 Case Study

3.3.1 Data

In this chapter, a particular house in Tennessee is analyzed for implementing the proposed methodology. The data is measured for this house in August 7^{th}, 2019 and used in this study for showing the effectiveness of the proposed methodology. The data for ambient temperature when a heat wave happens is obtained from the heat wave event that happened in Sacramento, CA on July 23, 2006. Also, the data for occupancy is normalized to be between zero and one. The desired indoor temperature is chosen to be 23.88$°C$ (75$°F$). The power generated by PV units located on the roof of the house with characteristics shown in Table 3.1, is shown in Figure 3.1. Moreover, Table 3.2 shows the characteristics of the shiftable loads which consist of two loads (e.g., washing machine and dryer and dish washer) with 0.5kW and 1.5kW of nominal (rated) power. The start and end time of dishwasher is considered to be 11:00 AM and 4:00 PM, respectively. Also, for the washing machine and dryer the start and end time are 3:00 PM and 6:00 PM, respectively. These two loads can be controlled by the HEMS to optimize the objective function within the specified time span. Other data used in this study are provided in [55].

3.3.2 Simulation Results

After setting the goal values (set by the user), the simulation is carried out over a 12-hour time period between 9:00AM to 8:00PM considering 8 previous time intervals for modeling

Table 3.1: Characteristics of the PV panels.

No. of Panels	Panel Size (kW)	$P^{STC}(kW)$	$\Phi^{STC}(W/m2)$	k^{PV} $(°C^{-1})$
2	200	200	1,000	0.004

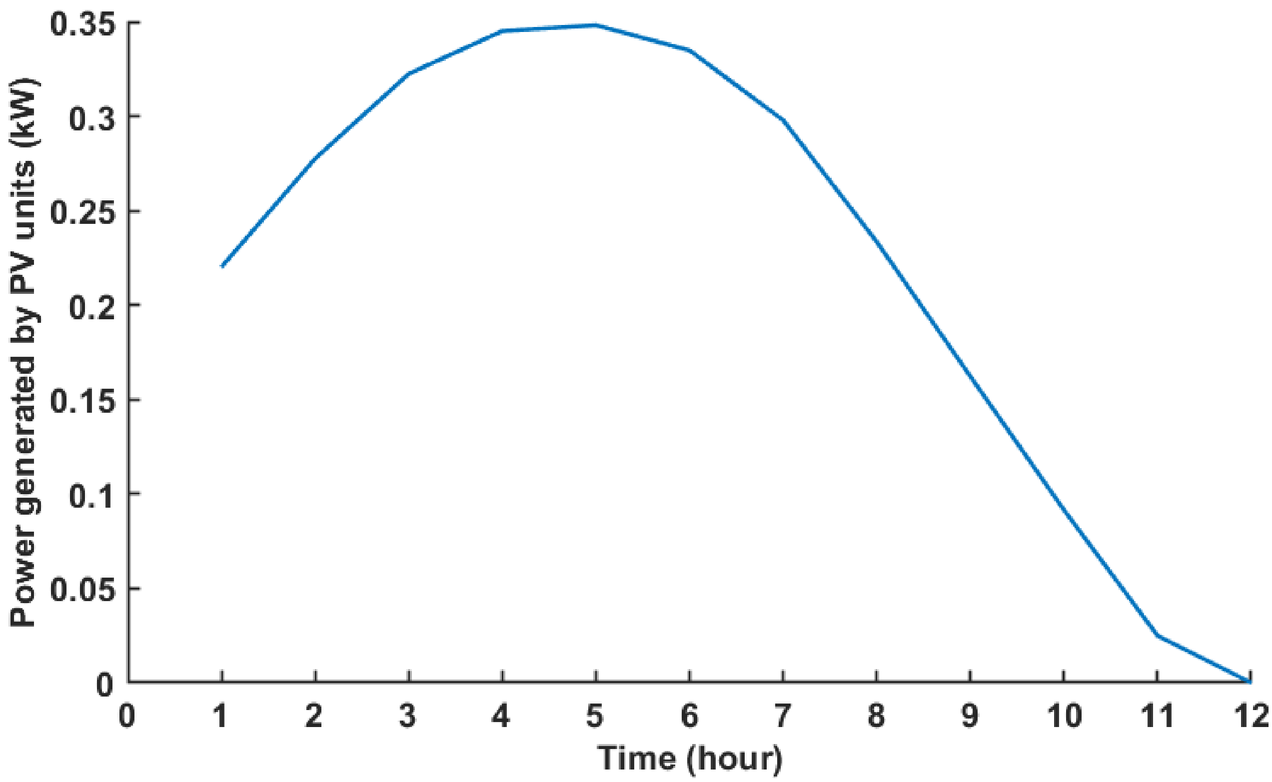

Figure 3.1: Power generated by rooftop PV units.

Table 3.2: Characteristics of shiftable loads

Appliance	Tstart	Tend	Rated Power (kW)	Ns
S1 (Dish-washer)	11	16	0.5	1
S2 (Washing Machine and Dryer)	15	18	1.5	2

A/C power consumption ($K = 8$). Moreover, the budget of uncertainty for occupancy at each time ($\Gamma_t^{U_{Occ}}$) is set to let 50% deviation for all uncertain parameters at that time interval ($\Gamma_t^{U_{Occ}} = 0.5 \times (t-1)$); also, the budget of uncertainty for the miscellaneous loads at each time interval ($\Gamma_t^{Pd,Misc}$), the occupancy ($\Gamma^{U_{Occ}}$), and electricity price (Γ^{c^u}) are set to be 0.5, 5.5, and 3.5, respectively. For the deterministic case, all the budgets of uncertainty are set to zero which means no deviations from the nominal values for the uncertain parameters is allowed. Furthermore, the multi-objective non-linear deterministic and robust problems solve in 0.362 and 0.565 seconds, respectively using GAMS/LINDOGLOBAL solver on a computer with Intel® Core™i7-9750H with 2.60 GHz CPU and 16 GB RAM. Optimal values for various objective functions for different models are listed in Table 3.3. It is worthwhile to mention that since there are more variables in the non-deterministic problem, it takes more time for the solver to solve the non-deterministic problem than the deterministic one. Also, note in Table 3.3 that MO means multi-objective optimization and RMO stands for robust multi-objective optimization. In this chapter, values of goals are chosen arbitrarily and without optimizing each individual objective function like what was done in chapter 2. Based on the results of Table 3.3, goal values for O1 and O2 are set optimistically and O3 very pessimistically. Also, the effect of uncertainty in objective functions values can be seen

Table 3.3: Optimal values and assigned goals.

Optimal Values	Objective Functions		
	O1 (kW)	O2 ($)	O3 ($^\circ C$)
Goal (Target) Values	12	7.8	6
MO	22.73	11.52	0.31
RMO	23.58	14.95	0.54

in Table 3.3 where O_1, O_2, O_3 are deteriorated by 3.7%, 29.8%, and 74.2% compared to the deterministic case, respectively. Therefore, for a HEMS to give more realistic power management schemes in a house, uncertainty needs to be taken into account since some parameters are subject to modeling or forecast errors. Not considering uncertainty may cause some of the load to shift to time intervals with high electricity rates or it may cause the load-generation balance to be violated.

Figure 2 shows the A/C temperature setpoints in both deterministic and non-deterministic cases. As it can be seen, the temperature setpoints in the two cases are exactly the same and introducing uncertainty does not affect this variable in the multi-objective optimization problem proposed in this chapter. The reason for this is that since O_3 is being penalized by the normalized occupancy and the deviation of occupancy is not large enough compared to the other objective functions and also the goal for this objective function is set very pessimistically, the robust multi-objective problem tries to achieve the goal values for the other two objective functions with optimistic goal values. Therefore, the multi-objective problem in both deterministic and non-deterministic suggests the same setpoints for the A/C load in the house. Power purchased from the utility grid and also total and A/C power consumption in both deterministic and non-deterministic cases are depicted in Figs. 3 and 4. It is observed that the purchased power in all time intervals except two is higher in the non-deterministic case which shows the effect of uncertainty in making decisions on how much power to buy from the utility grid. Total energy purchased from the utility grid in deterministic and non-deterministic cases are $59.73kWH$ and $60.69kWH$. Moreover, total and A/C power consumptions are higher in the non-deterministic case which is due the nature of robust optimization where the worst-case realization of uncertainty is considered for obtaining the optimal decisions. Total A/C consumption in deterministic and non-deterministic cases are $54.41kWH$ and $55.08kWH$, respectively.

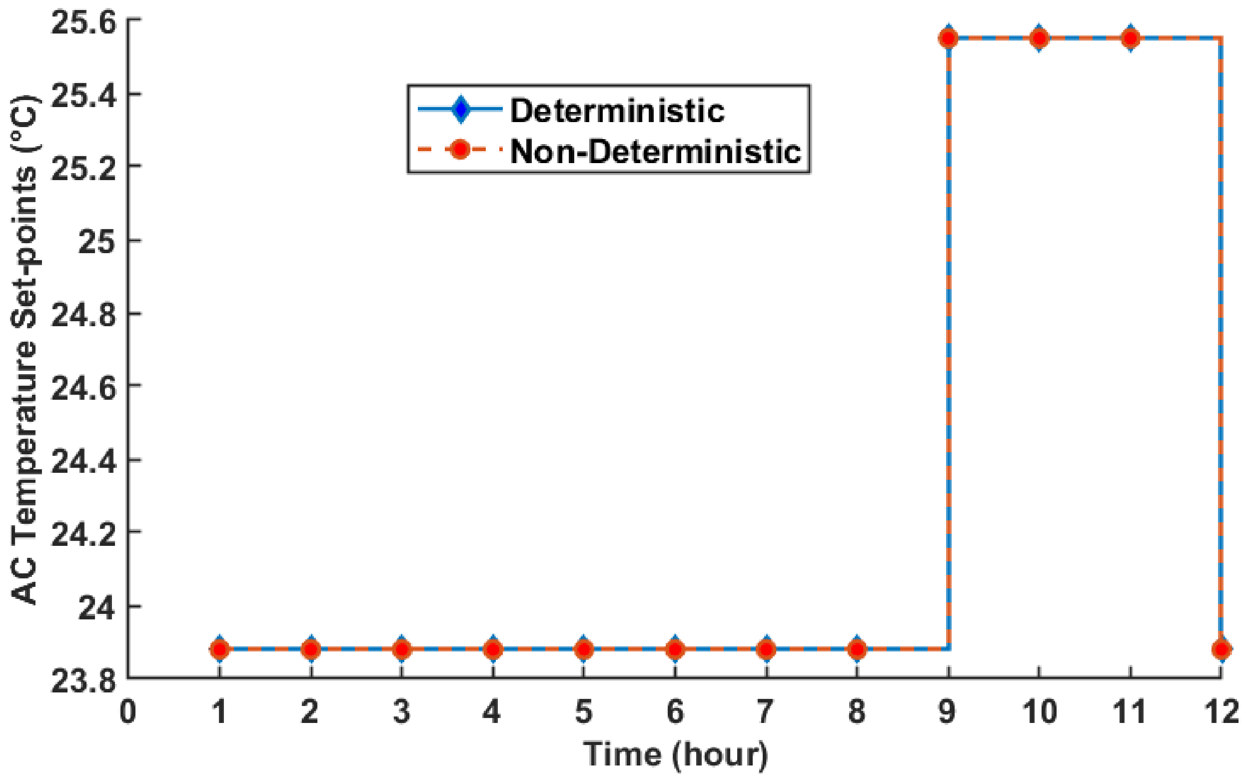

Figure 3.2: A/C temperature setpoints.

In Table 3.4, the dispatch of shiftable loads in both deterministic and non-deterministic cases is shown. It is observed that the dishwasher is dispatched the same in both cases. However, washing machine and dryer have different scheduled working cycles. This is a result of introduction of the uncertainty in the problem which changes the optimal decisions of the HEMS. This is because of a higher deviation in the electricity price at hour 7 and 8 which caused the optimiziation problem to push the loads from hour 7 and 8 to 9 and 10 to

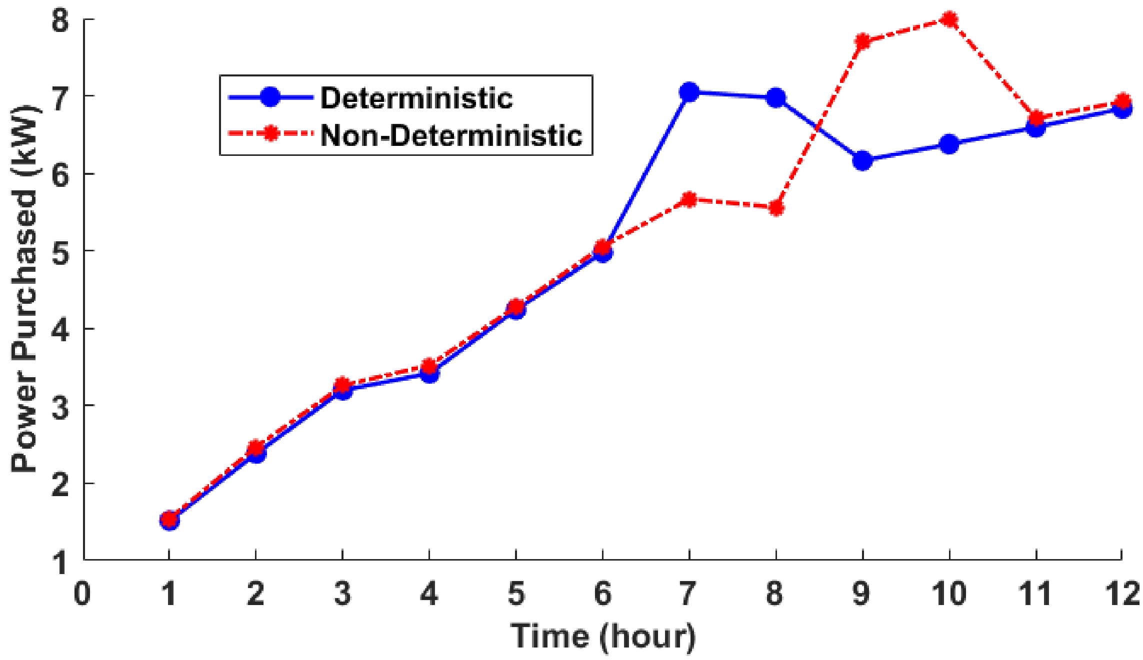

Figure 3.3: Power purchased from utility.

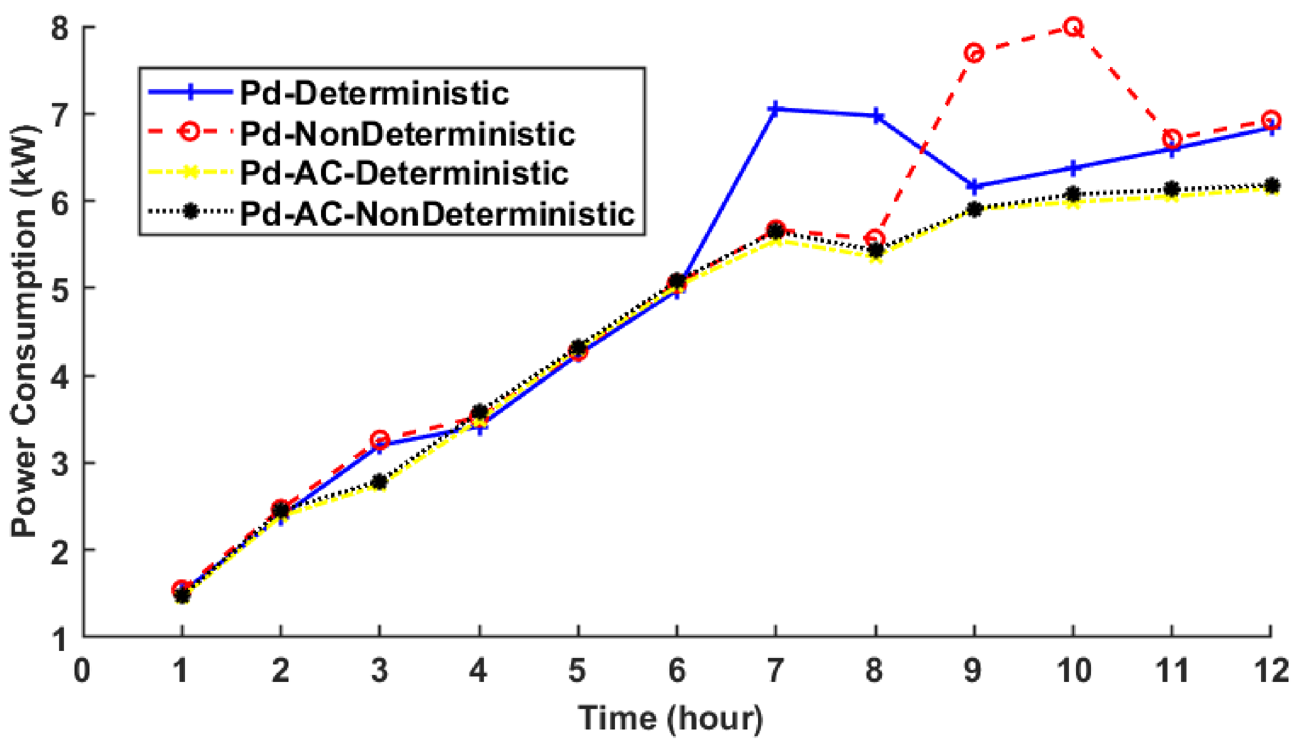

Figure 3.4: Total and A/C power consumption for the planning period.

Table 3.4: Decisions made for working cycles of shiftable loads.

Appliance Hour	u(s1,t)-Deter.	u(s1,t)-Nondeter.	u(s2,t)-Deter.	u(s2,t)-Nondeter
1	0	0	0	0
2	0	0	0	0
3	1	1	0	0
4	0	0	0	0
5	0	0	0	0
6	0	0	0	0
7	0	0	1	0
8	0	0	1	0
9	0	0	0	1
10	0	0	0	1
11	0	0	0	0
12	0	0	0	0

furhter minimize O_2 and make this objective functioins closer to its predefined goal.

Finally, Fig. 5 shows a sensitivity analysis on the effect of the amount of uncertainty on the values of objective functions. To perform this sensitivity analysis, the values of budgets of uncertainty are increased from low to high. In Fig. 5 only budgets of uncertainty for occupancy and electricity price are shown. However, the budgets of uncertainty for occupancy and miscellaneous loads at each time interval are also changed from low to high. As it is shown in Fig. 5, in a more uncertain environment objective functions take higher values which in a minimization problem means worse solutions. It is worthwhile to mention that by letting uncertain parameters to deviate more from their nominal values, O_3 first is deteriorated and after some point it stays constant which indicates that the uncertain parameter which affects O_3 (U_t^{Occ}) is at its maximum deviation from tits nominal value and this point is the worst value for O_3. As it can be observed, the relation between the objective functions and budgets of uncertainty is not linear and depends on the type of the problem and dependency of the objective function on the uncertain parameter. This dependency can be direct or indirect which means the uncertain parameter can be in the objective function expression or it can be in some constraints that affect that objective function. Therefore, it is difficult to find any linear or clear relationship between an objective function and an uncertain parameter. However, in general, the more the input data, modeling, and forecasts are accurate, the less conservative and more beneficial decisions can be made for future operation of systems.

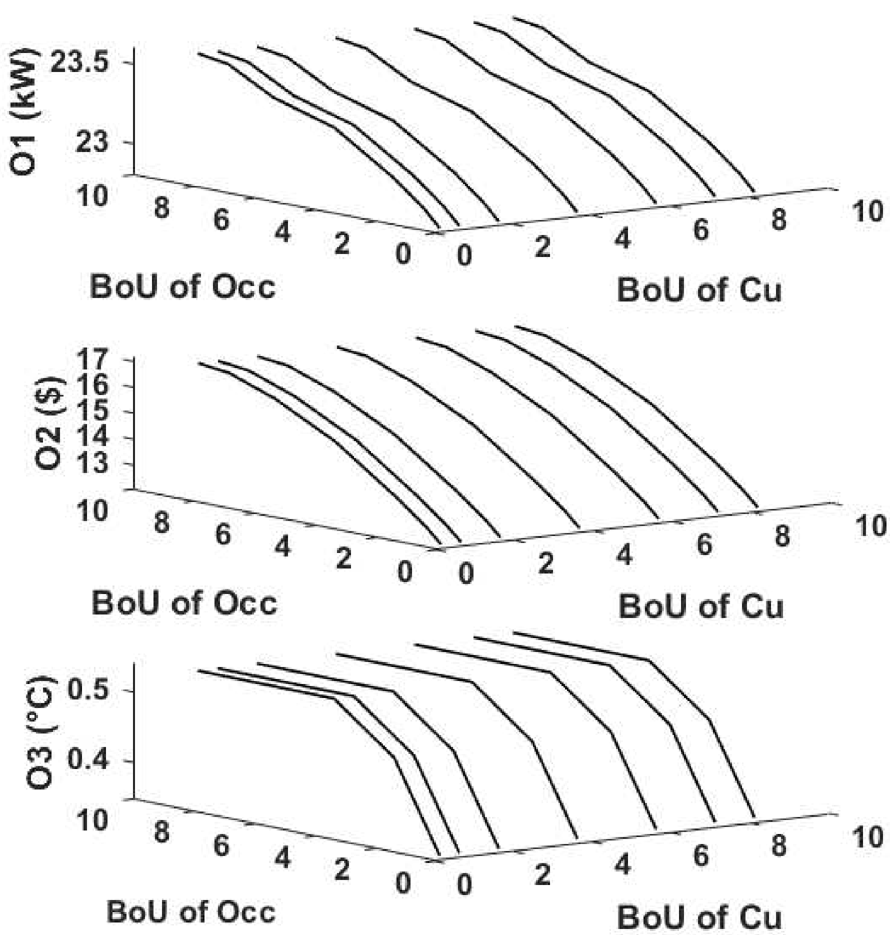

Figure 3.5: Objective functions for different values of budgets of uncertainty.

3.4 Conclusion

Power utilities issue demand response during the hours of peak load in order to reduce the demand on the network and provide congestion relief to overloaded circuits. When equipped with an HEMS, residential customers can become important actors for enabling demand response. This can be done by changing the setpoint of the air-conditioning units or by shifting appliance loads from peak hours to off-peak hours. From the HEMS' standpoint, this can be viewed as an optimization problem where the goal is to reduce power consumption while maximizing financial DR incentives received. However, another equally important goal would be to make sure that the comfort level of the residents is not compromised. This is in particular crucial during periods of extreme temperatures where maintaining an acceptable indoor temperature has a direct impact on the residents' health, especially for children and the elderly. What makes this multi-objective optimization problem more challenging is the uncertain nature of some model parameters, e.g. electricity rates, building occupancy levels, etc. This chapter presented a novel solution for energy management of a smart home using demand response by considering the above factors. The problem was formulated as a robust multi-objective one and is solved for a given time horizon. Simulation results are provided to illustrate the impact of uncertainties on the final solution.

CHAPTER 4

CONCLUSIONS AND FUTURE WORK SUGGESTIONS

4.1 Conclusions

In this thesis, the problem of optimal energy management in residential neighborhoods affected by heat waves has been studied, while also considering the uncertainties associated with parameters such as buildings occupancy, miscellaneous load consumption, and electricity price. In chapter 2, the problem was formulated as a robust multi-objective optimization problem considering cost of battery as the CES, deviation of power delivery of the main transformer from its temperature-corrected capacity, total deviation of A/C temperature setpoints from the desired indoor temperature, and instances of load shifting as individual objective functions. Effect of heat waves was modeled as high temperatures that cause the capacity and lifetime of the battery and also the capacity of the main transformer to change. Also, the problem was solved considering worst-case realization of uncertain parameters through developing the robust counterpart of constraints affected by uncertainties. The results of chapter 2 indicated that introducing uncertainty to the problem deteriorates the value of objective functions and leads to taking more conservative decisions. Moreover, more uncertainty in the problem results in more severe deterioration of objective functions; however, this relationship is not linear and increasing uncertainty has different effects on different objective functions in a multi-objective problem.

In chapter 3, the problem is viewed from an individual customer's point of view. In this chapter, it was taken into account that an individual customer, using an HEMS, can take advantage of the opportunities provided by the utility company through DR programs to minimize his or her costs of energy. Three potential objective functions including demand minimization, cost minimization, and A/C temperature control were considered for an individual customer. The problem was formulated as a robust multi-objective problem considering the uncertainties in occupancy in the house, electricity price, and miscellaneous loads. Based on the obtained results, introducing uncertainty in the problem caused the value of all individual objective functions to deteriorate (increase). Also, a sensitivity analysis was performed on the effect of the amount of deviation of uncertain parameters from their nominal values. The results showed that in a more uncertain environment, due to more conservative decisions, worse values for individual objective functions are achieved.

To recapitulate, it can be concluded that if a utility company utilizes various resources available in the distribution system, the best decisions can be made through implementing an optimal energy management in the system considering adverse effects of heat waves on the system. As it was shown in this thesis, such an approach will lead to optimal decisions that can not only meet the demand, but also can minimize costs, protect the assets from degradation, and protect people and especially the elderly from health issues. Moreover, if the utility company tries to obtain more accurate data of the system parameters, they can make less conservative decisions that lead to better values for the objectives that they have. In such an environment, each individual customer can also benefit from various DR programs provided by the utility company in order to minimize their cost of energy and maintain an acceptable indoor temperature during hot days using the methodology proposed in this thesis.

4.2 Contributions

In this thesis, power management in a residential neighborhood affected by heat waves was formulated as a robust multi-objective problem in chapter 2. This problem was an extension of the work in [40]. However, in this problem formulation, different objective functions and modeling of A/C power consumption units is considered. The main difference however is that in this thesis, uncertainty associated with modeling and forecast errors are taken into consideration through developing robust counterpart of the original multi-objective problem. Moreover, in chapter 3 of this thesis a new methodology for an individual house in a distribution exposed to extreme temperature where there are DR options available is proposed considering uncertainty associated with some problem parameters. The main findings from this work underline the importance of modeling uncertainties in the power system during instances of extreme ambient temperature. It was shown through simulation results that, if not properly taken into account, uncertainties can force the system operating conditions that are infeasible. This is because the energy dispatch solution will be overly optimistic and not equipped with dealing with the worst case conditions.

The work done in chapter 2 of this thesis was accepted for publication in the IEEE IAS annual meeting [56]. The work in chapter 3 is under preparation to be submitted to a journal in the field.

4.3 Future Work Suggestions

The proposed topic in this thesis is a broad research area that can be further developed to devise new solutions for better operation of the electric power grid. Below are some suggestions for future work on this topic.

- Integrating more components in the grid operation such as electric vehicles, wind turbines, and diesel generators.
- Study of the effect of various types and intensities of natural disasters such as floods, and hurricanes on the optimal operation of the grid.
- Considering different methods for uncertainty consideration in the problems such as stochastic optimization, sensitivity analysis or a combination of these methods.
- Devising a method for occupancy detection in the houses based on their power consumption in a non-intrusive way.
- Considering the option of load shedding and its cost based on the importance of the loads in each feeder of the grid.
- Considering power flow constraints within the grid and effect of power losses on conductors temperature.

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