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I, Lakshmi Palaparambil Dinesh, hereby submit this original work as part of the requirements for the degree of Doctor of Philosophy in Business Administration.

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Essays on Mathematical Optimization for Residential Demand Response in the Energy Sector

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Essays on Mathematical Optimization for Residential Demand Response in the Energy Sector

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Doctor of Philosophy

In the Department of Operations, Business Analytics & Information Systems
of the Carl H. Lindner College of Business

by

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Abstract

In the electric utility industry, it could be challenging to adjust supply to match demand due to large generator ramp up times, high generation costs and insufficient in-house generation capacity. Demand response (DR) is a technique for adjusting the demand for electric power instead of the supply. Direct Load Control (DLC) is one of the ways to implement DR. DLC program participants sign up for power interruption contracts and are given financial incentives for curtailing electricity usage during peak demand time periods. This dissertation studies a DLC program for residential air conditioners using mathematical optimization models. First, we develop a model that determines what contract parameters to use in designing contracts between the provider and residential customers, when to turn which power unit on or off and how much power to cut during peak demand hours. The model uses information on customer preferences for choice of contract parameters such as DLC financial incentives and energy usage curtailment. In numerical experiments, the proposed model leads to projected cost savings of the order of 20%, compared to a current benchmark model used in practice. We also quantify the impact of factors leading to cost savings and study characteristics of customers picked by different contracts. Second, we study a DLC program in a macro economic environment using a Computable General Equilibrium (CGE) model. A CGE model is used to study the impact of external factors such as policy and technology changes on different economic sectors. Here we differentiate customers based on their preference for DLC programs by using different values for price elasticity of demand for electricity commodity. Consequently, DLC program customers could substitute demand for electricity commodity with other commodities such as transportation sector. Price elasticity

of demand is calculated using a novel methodology that incorporates customer preferences for DLC contracts from the first model. The calculation of elasticity based on our methodology is useful since the prices of commodities are not only determined by aggregate demand and supply but also by customers' relative preferences for commodities. In addition to this we quantify the indirect substitution and rebound effects on sectoral activity levels, incomes and prices based on customer differences, when DLC is implemented.

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Dedication

This dissertation is dedicated to my dad.

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Chapter 1

Introduction

Electricity consumption is positively correlated with the GDP of the United States with a correlation value of ≈ 0.9 for the last 40 years (Outlook 2016). Although correlation does not imply causation, this strong correlation for several years suggests a direct relationship between electricity use and GDP. This relationship is represented in Figure 1.1. This confirms that electricity is both vital to the production of goods and services as well as a key contributor to aggregate economic output. These facts make electricity an interesting area of research. In this area, energy conservation via Demand Response (DR) has gained recent importance. DR is a technique for adjusting electricity usage during times of peak electricity demand. The light gray areas in Figure 1.2 show the states where DR implementation is relatively low, compared to the darker areas. The light areas are higher in number compared to the dark areas, and this shows DR implementation has immense potential. In the broad area of DR, this dissertation focuses on residential DR programs since 40-50% of the peak electricity demand comes from the residential sector in some parts of the US (Outlook 2016). There are two essays in this dissertation that explore how a residential DR program can affect a utility service provider as well as the entire society.

The first essay focuses on generation cost savings for a utility provider when a DR program is implemented using our novel Contract Design (CD) model. This essay shows that the cost savings of the CD model are sizable compared to a benchmark share-of-choice (SOC)

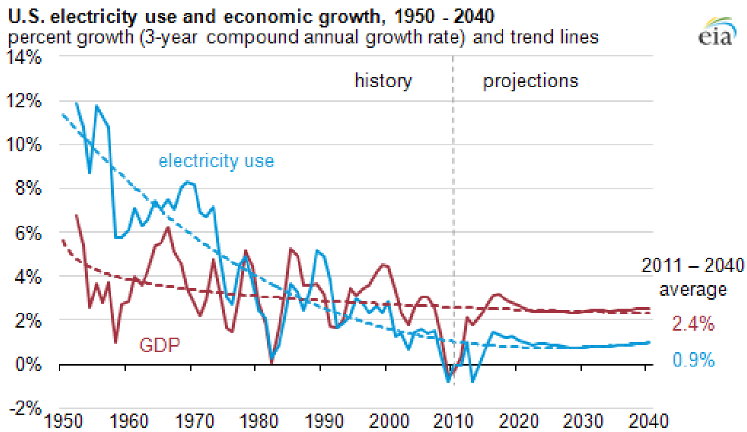


Figure 1.1: Electricity Use and Economic Growth, 1950-2040

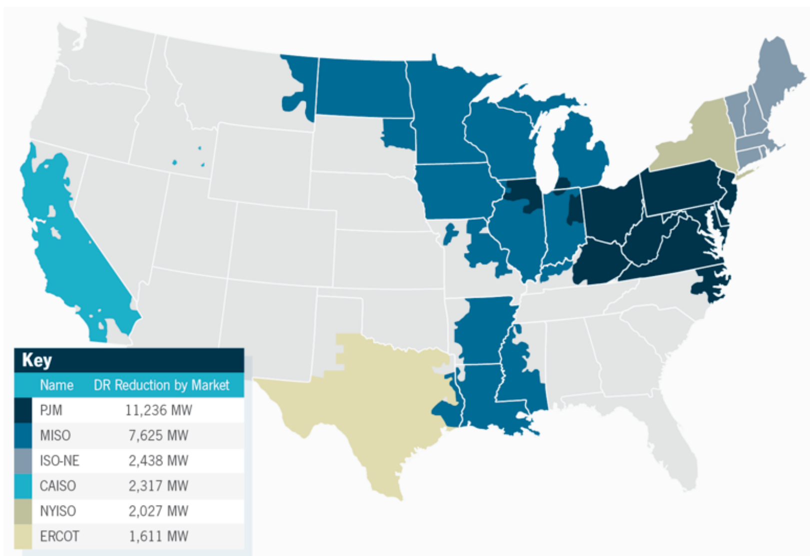


Figure 1.2: DR Peak Load Reduction in US Electricity Markets, 2014

model. The parameters leading to cost savings are identified and quantified. Customers are differentiated based on their preference for DR contracts and contract design parameters are identified.

Since electricity sector does not function in isolation, the impact of a residential DR program on the entire society is assessed using a Computable General Equilibrium (CGE) model in the second essay. A CGE model relies on the circular flow of economy as shown in Figure 1.3. An economic equilibrium model computes prices and activity levels when the total outflows are equal to the total inflows in an economy. In this essay, we develop a methodology to incorporate customer preferences into a macroeconomic model and quantify how the differences in customer preferences affect emission costs, factor costs, customer incomes and expenditures.

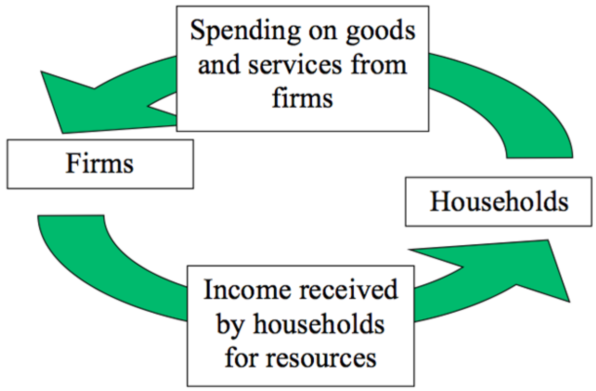


Figure 1.3: The Circular Flow of Economy

Chapter 2

A Contract Design (CD) Model for Power Interruption Contracts

2.1 Introduction

In today's world where both environmental and cost concerns are critical, Demand Response (DR) occupies an important place in the electric utility sector. There are two ways in which a demand response program operates: (i) The electricity provider can encourage customers to shift their usage from a period of peak demand to a period of low demand by reducing prices during the low demand period. This is called time-based rates. (ii) Alternatively, the electricity provider can enter into contracts with customers to externally control the customer's use of electricity for air conditioners and water heaters during periods of peak demand. This is called direct load-control. Here, providers offer customers financial incentives to participate in the DR program (Dem 2012a). We focus on direct load-control because it leads to higher peak load reduction and gives the provider more control over demand response, compared to time-based rates (Newsham & Bowker 2010).

The above DR programs are targeted at both industrial and residential consumers.

We focus on residential consumers because of the residential sector's market size, growth, share of peak load and potential for demand response. As per the US Energy Information Administration (EIA)'s 2016 Annual Energy Outlook (Outlook 2016): (i) The residential sector makes up 20% of total energy demand. (ii) This demand is expected to grow by 41% by 2040. (iii) In addition, the residential sector accounts for over 50% of the total peak load in certain parts of the country. These aspects make the residential sector an attractive area of DR study.

Motivated by residential demand response, we study Duke Energy's Power Manager Program (*PMCIES* 2006), where residential air conditioners are subject to direct load control. Customers sign up for the program through a power-interruption contract. The contract offered is based on a share-of-choice (SOC) model (Camm et al. 2006), which aims at maximizing customer participation and many utility providers are believed to use a share-of-choice based approach. This SOC model may not minimize total costs, another important objective. Many utility providers including Duke Energy use a separate unit commitment (UC) model, to reduce supply-side costs (Hobbs et al. 2006). A challenge in cost minimization is that costs depend on the interaction between supply (power generation) and demand (power consumption). Since the demand side comes from the residential customers, another challenge is to determine which potential customers to target and what power interruption contract to offer. Our novel Contract Design (CD) model addresses both these challenges by combining data on customer preferences and supply side UC. Using computational experiments, we study key factors that contribute to cost savings by the CD model. Finally, we compare customer selection and contract parameters for the CD model and the SOC approach. This model can be extended easily to include other areas such as appliance selection and scheduling based on utility rates and alternative sources of adjusting customer power usage including storage batteries and solar cells.

This paper's focus is on a tactical problem that helps to design a cost minimizing power interruption contract. The contract chosen by the CD model is assumed to be for all the summer months. Since choosing customers for DR contracts is an important problem faced by electricity service providers, this paper adds to their business insights by providing a new method to design contracts.

The rest of this paper is organized as follows: Section 2 summarizes relevant literature on both SOC and UC models and previous work on DR. Section 3 explains the benchmark model i.e. the UC model with SOC customers as an option. Section 4 describes the CD model. Section 5 focuses on data and results. Section 6 concludes with avenues for future research.

2.2 Literature Review

On the electricity supply side, the UC model is a well-studied mathematical model. According to Hobbs et al. (2006) the UC model schedules production of electric power by generating units over a daily to a weekly time horizon to accomplish some objective such as minimizing supply side generation cost. Padhy (2004) compiled 150 articles over 35 years on various methods used to solve UC problems and noted two popular ways of solving UC problems: Mixed Integer Linear Programming (MILP) and Lagrangian Relaxation. Johnson et al. (Johnson et al. 1997) solved a UC model using Lagrangian relaxation for a generator dataset based on the California Electric Company (CalECo) system. In this paper, we used the CalECo dataset, but adopted the MILP UC model of Hobbs et al. (2006), since our primary focus was on targeting customers for power interruption contracts and not on the comprehensive supply side UC constraints in Johnson et al. (1997).

Demand response has been a more recent interest in the literature compared to UC. Albadi & El-Saadany (2008) provided a comprehensive overview of demand response mechanisms in deregulated markets and their relative costs and benefits. Conejo et al. (2010) developed an optimization model in a time-based rate demand response environment that maximizes customer utility and reduces power consumption. On the demand side in our study, we have a power interruption contract offered to customers. A contract is a product in the conjoint optimization terminology of Camm et al. (2006). Product choice is guided by a statistical technique known as conjoint analysis and it is key to our model for contract design. The optimization framework for product choice is called the share-of-choice (SOC) methodology. We used the SOC integer programming model from Camm et al. (2006). We developed a CD model that combines the demand side SOC from Camm et al. (2006) with the supply side UC from Hobbs et al. (2006). This model provides an optimal solution to an electricity service provider's cost minimization problem.

In 2006, Duke Energy Indiana and Kentucky conducted the Power Manager Customer and Impact Evaluation study to understand which attributes (features) are valued the most by customers participating in a direct load control Power Manager Program (*PMCIES* 2006). A relevant subset of attributes and levels from this study are used in our model. To ensure that the data points are realistic, these attributes and levels are compared with a study conducted by Con Edison in 1988 (Kritler 1988) prior to introduction of their DR program, which is still offered today (Dem 2012*b*). In addition to the CalECo dataset, another dataset called DRPricer was supplied to us by Integral Analytics (Dem 2013). One of the streams of research in the area of demand response for electric utilities is appliance scheduling by customers. Zhu et al. (2012) minimized peak load by shifting the usage of both time-shiftable and power-shiftable appliances. Another stream of research by Yu et al. (2013) included alternative sources of power like batteries and solar cells into the model. The area of direct load management through power interruption contracts considered in this paper has not yet been well studied.

This paper expands the existing literature as below:

(i) Direct load-control programs in forward energy markets are modeled and applied for a dataset of electric vehicles (Negrete-Pincetic et al. 2016) . There are three limitations in the work of Negrete-Pincetic et al. (2016) that we address: (a) We use an SOC benchmark model for comparing CD model cost savings. (b) We identify customer differences that lead to differences in contract design. (c) We apply our model to two datasets containing residential direct load-control customers.

(ii) Although there is some existing literature focusing on cost minimizing power interruption contracts similar to Parvania et al. (2013), they do not focus on features other than the amount of power interruption. Our model already considers features such as fixed and variable payments to customers. According to *PMCIES* (2006) surveys, fixed payments to customers are highly valued by the customers. They also form part of the supplier's objective function, in addition to generation costs. Our objective function incorporates these costs and hence makes an incremental contribution to the contract design literature.

2.3 The UC-SOC Model

In this benchmark model, we seek to minimize total cost. The UC and SOC models that form this model are explained in detail in Appendix A.1. The UC model considers only the supply side costs. When power interruption contracts are used, the demand side costs including fixed and variable payments to customers also must be considered. Further, the set of customers to interrupt must be chosen. These factors are governed by the SOC model output. Several electricity service providers *PMCIES* (2006) currently use the optimal SOC contract and SOC customers in the UC model. Thus the approach in this section provides a practice-based benchmark for cost minimization when power interruption contracts are used. The parameters representing the attributes, and the variables representing the amount of interruption and the actual demand in this model are as below.

Parameters

$\mathbb{F}$ Fixed payment for contract (\$)

$\mathbb{V}$ Variable payment for contract (\$/MW/h)

$\mathbb{C}$ Interruption ceiling for contract (MW)

<u>*Continuous variables*</u>

D'_t Actual demand for period t (MW/h)

w_t^j Amount of power reduced for customer j, period t (MW/h)

An MILP formulation of the modified UC model with interruption and SOC customers as an option is given below.

$$\text{MILP} : Z_{\text{SOC}} = \text{Min} \sum_{s=1}^{S} \sum_{t=1}^{T} [C_s g_{st} + F_s z_{st} + S_s n_{st}]$$
$$+ \sum_{j \in SOC} [\mathbb{F} + \mathbb{V} \sum_{t=1}^{T} w_t^j], \tag{2.1}$$

subject to $(A.3)$-$(A.5)$

$$D'_t = D_t - \sum_{j \in SOC} w_t^j \qquad t \in \mathcal{T}, \tag{2.2}$$

$$D'_t \leq \sum_{s=1}^{S} g_{st} \qquad t \in \mathcal{T}, \tag{2.3}$$

$$w_t^j \leq \mathbb{C} \qquad t \in \mathcal{T},\ j \in \mathcal{J}, \tag{2.4}$$

$$g_{st} \geq 0, n_{st}, z_{st}, x_{k\ell}, y_j \in \{0, 1\}.$$

As stated earlier, $\mathbb{F}$, $\mathbb{V}$, and $\mathbb{C}$ are the attribute levels chosen by the SOC model and are fixed as parameters in the UC model. All the other notation pertaining to UC and SOC models are explained in Appendix A.1. The objective in (2.1) represents total supply-side + demand-side costs. Note that, since variable payments are calculated per MW of interruption, the amount of interruption w_t^j is multiplied by $\mathbb{V}$ to calculate the overall variable payments per customer j. UC Constraints (A.3)-(A.5) ensure that generated power, g_{st}, satisfies floor and ceiling limits and enforces startup-defining constraints on n_{st}. Constraint (2.2) calculates the net or actual demand after interruption. Constraint (2.3) ensures that the net demand should be satisfied by the power generated. Constraint (2.4) ensures that the amount of interruption does not exceed the interruption ceiling $\mathbb{C}$ chosen by the SOC model.

2.4 Proposed Contract Design (CD) Model

In the CD model, decisions on customer interruption contracts including attribute level choices such as amount of interruption, and use of the generators are made concurrently in one model. Constraints from both the UC and SOC models are included in addition to new constraints to ensure that the supply cost-minimizing contract is chosen. Supply side parameters and variables are identical to those in the UC model from Appendix A.1.1. The demand variables and parameters identical to the SOC model in Appendix A.1.2 are not repeated in this section. M is a large number (big "M").

Parameters

$\mathcal{F}_\ell^a$ Value of fixed payment for $k = 1$, level ℓ

$\mathcal{C}_\ell^a$ Value of interruption ceiling for $k = 2$, level ℓ

Continuous variables

D_t' Actual demand for period t (MW/h)

w_t^j Amount of power reduced for customer j, period t (MW/h)

$\mathcal{F}$ Fixed payment for chosen contract ($)

$\mathcal{F}_j^c$ Fixed payment if customer j joins the chosen contract ($)

$\mathcal{C}$ Interruption ceiling for chosen contract (MW)

Binary variables

y_j $= 1$, if the utility for the contract exceeds the hurdle utility for customer j, 0 otherwise

$O_j = 1$, if customer j signs up for the contract, 0 otherwise

Note that the CD model does not have a parameter for levels of the variable payment. This is because the variable payment is set to be constant at value $\mathbb{V}$ \$/MWh, based on information from the Power Manager Program (*PMCIES* 2006). We kept the variable payment fixed instead of having levels since the total variable payments calculated as the variable payment level in \$/MWh multiplied by the w_t^j, will be nonlinear if levels are present. While nonlinearity in the objective can be incorporated into a mathematical programming model, we preferred to work with a simpler linear model instead. The cost parameters such as $\mathcal{F}_l^a$ can be written in terms of the corresponding variable payment level, so that w.l.o.g. the variable payment can be treated as constant.

The MILP formulation of CD model is given below.

$$\text{MILP}: Z_{\text{CD}} = \text{Min} \sum_{s=1}^{S} \sum_{t=1}^{T} [C_s g_{st} + F_s z_{st} + S_s n_{st}] + \sum_{j=1}^{J} [\sum_{t=1}^{T} \mathbb{V} w_t^j + \mathcal{F}_j^c], \tag{2.5}$$

subject to $(A.3)$-$(A.5)$, $(A.7)$-$(A.8)$, (2.3)

$$D'_t = D_t - \sum_{j=1}^{J} w_t^j \qquad t \in \mathcal{T}, \tag{2.6}$$

$$w_t^j \leq \mathcal{C} \qquad t \in \mathcal{T},\ j \in \mathcal{J}, \tag{2.7}$$

$$w_t^j \leq MO_j \qquad t \in \mathcal{T},\ j \in \mathcal{J}, \tag{2.8}$$

$$\mathcal{F}_j^c \geq \mathcal{F} - M(1 - O_j) \qquad j \in \mathcal{J}, \tag{2.9}$$

$$\sum_{\ell=1}^{L_k} \mathcal{F}_\ell^a x_{k\ell} = \mathcal{F} \qquad k = 1, \qquad \sum_{\ell=1}^{L_k} C_\ell^a x_{k\ell} = \mathcal{C} \qquad k = 2, \tag{2.10}$$

$$O_j \leq y_j \qquad j \in \mathcal{J}. \tag{2.11}$$

The objective minimizes total costs for the electricity service provider as in Section 2.3. Constraints (2.3) and (2.6) ensure that the demand after interruption is met through the amount of power generated. In addition, constraints (A.3)-(A.5) in the UC model are required. Constraints (A.7)-(A.8) and (2.10) are derived from the SOC model and modified to suit our problem environment. Constraint (A.7) ensures that only one level is chosen per attribute for the contract. Constraint (A.8) ensures that y_j is 1 only if the contract provides a higher utility than the hurdle utility for customer j. Constraints (2.7) and (2.8) state that a customer can only be interrupted upto the ceiling $\mathcal{C}$ and if they join the contract. Constraint (2.9) ensures that a customer j is paid the fixed payment $\mathcal{F}$ only if they join the contract. Constraint (2.10) picks the value of fixed cost $\mathcal{F}$ and interruption ceiling $\mathcal{C}$ when $x_{k\ell}$ is 1 for $k = 1$ and $k = 2$ respectively. Constraint (2.11) ensures that a customer can sign up for a contract only if the utility of the contract exceeds the customer's hurdle. Non-negativity and binary restrictions are included but not listed. Note that Constraints (2.7)-(2.9) and (2.11) are novel and ensure that the CD model chooses the attribute levels and customers such that the cost minimizing contract results. Further, because attribute level choice is a variable in the CD model, its cost objective value will be no bigger than that in the UC-SOC model from Section 2.3.

Please note that the average variable payments of generation ($\approx$ \$30/MW) are much larger than the variable payments of interruption ($\approx$ \$5/MW) and hence the value of an interruption amount is positive, whenever interruption can lead to reduction in generation costs.

2.5 Data and Results

In this section, we study how solutions from the UC, UC-SOC, and CD models differ for various problem instances. We first describe our test datasets and then the results.

Table 2.1: Data requirements for the model

Supply Side	**Demand Side**
Generator Capacities Generation costs (fixed and variable)	Forecast Demand Levels of contract attributes (e.g.: contract payments and interruption amounts) Utilities for the levels of the contract attributes Hurdles

2.5.1 Data

Table 2.1 splits the data into supply side and demand side for the cost minimization model.The supply side generator capacities and generation costs as well as the forecast demand were taken without any modification from the datasets available to us. Two datasets were used for supplier prices and capacities: The CalECo system data used by Johnson et al. (1997) and the Demand Response (DR) Pricer software data from Integral Analytics (Dem 2013). The CalECo dataset is based on a fictitious California utility and the DRPricer dataset is based on Duke Energy. The generators in these datasets are a mix of coal, diesel and hydro. On the demand side, customer utilities were simulated based on an established technique outlined by Camm et al. (2006) . The relative values of utilities for the contract attributes were derived from two empirical studies on power interruption contracts by Lawton et al. (2003) and San Diego Gas & Electric (*SDGEDRPPE* 2016). The hurdle estimation technique is briefly described later.

The CalECo system dataset is widely cited in the literature as a representative dataset for unit commitment, MILP models. There are 16 generators out of which 9 have capacities and generation costs available. So we chose these 9 generators and also include a spot market. The demands in this dataset represent 7.5 million customers. There are 168 time periods, each time period representing an hour and 168 hours representing a week. The DRPricer dataset is supplied to us by Integral Analytics as a relevant dataset on which a demand response mechanism was implemented. This dataset has information on interruption duration, amount and generation costs. The DRPricer dataset has the generators commonly used by Duke Energy. We took a subset of 9 generators out of 20 generators from the DRPricer dataset so that the number of generators in each fuel type is the same as that of CalECo. For this dataset, the demand was chosen from the Pennsylvania-New Jersey-Maryland (PJM) Interconnection (Est 2012), for a summer week in 2014 with Duke Energy's demand response customers in Ohio and Kentucky. A week of data was chosen to be consistent with the time horizon in CalECo.

The overall demands from PJM demand data represent approximately 890,000 customers for Ohio and Kentucky. Our original datasets are large in terms of the demand size and off-the-shelf optimization software could not solve problems beyond 200 customers in 24 hours. So, we split the customers into segments instead of using individual customers. According to the information provided by Peak Load Management Alliance (DR 2012) there are 200,000 to 260,000 air conditioners participating in Power Manager Program designed by Duke Energy. 30% of the overall residential customer base considered in the Power Manager Customer and Impact Evaluation study are likely to participate in the Power Manager Program (*PMCIES* 2006). These statistics were compared with those available from Pacific Gas & Electric Company (Marshall 2014) to ensure that they are close to the numbers obtained from California residential demand response programs and hence can be used in the CalECo dataset.

We divided the customers in the CalECo and DRPricer dataset as follows: From the data, 30% of the market is open to interruption. So all the potential interruption segments together constitute 30% of the population. For instance, the CalECo dataset was split into 10 customer segments each with 225,000 customers. The total size of the 10 segments was 2.25 million customers (30% of 7.5 million). The 11^{th} customer segment had no interruption and constituted the rest of the customers not interested in the DR program.

Per the literature (Wang & Curry 2012), we used a multivariate normal distribution for utility estimation in our base set of utilities. A normal distribution assumes homogeneity between segments and provides a smaller range of utility values. When greater customer heterogeneity was required with more varied customer segments, we used a beta distribution per Camm et al. (2006). The relative values of the attributes fixed payment and interruption ceiling are multiples of the corresponding regression coefficients from the regression models in Lawton et al. (2003) and San Diego Gas & Electric (*SDGEDRPPE* 2016). Based on these models, the fixed payment utilities are $\approx$ 10 times higher than interruption ceiling utilities for all customers. These differences in utility estimation are important in contract design. Utilities are monotone increasing in fixed payments and monotone decreasing in interruption amounts as expected.

The hurdles were also simulated based on Camm et al. (2006). The overall product utilities were ranked for each customer segment in descending order and a segment's p^{th} percentile is used as the hurdle. If the hurdles are too low, an unrealistically large number of customers might sign up for the contract. Hence we chose the hurdle to be the 95^{th} percentile as suggested by Camm et al. (2006)

For conducting a sensitivity analysis on the CalECo dataset, we used two ratios: ratio of average demand to average capacity (D/C) and ratio of spot market price to average generation costs (S/G). The CalECo dataset had a ratio of 4:1 for both the ratios. We did a two-way sensitivity analysis by considering both DRPricer and CalECo datasets as well as a change in the above ratios by $\pm$ 0.5. We changed the ratios by only 0.5 because larger changes would result in an infeasible problem when capacity is too low.

In the contract design sub section a small dataset derived from CalECo is used to illustrate how a different contract design is chosen by the CD model compared to the UC-SOC model. This dataset had 10 customer segments each representing the demand of 22,500 customers. These 10 segments are derived from the interruption segment (customer segment participating in the contract) representing 225,000 customers in the original CalECo dataset. We chose 10 customer segments because with an increase in the number of customer segments the solution times increased significantly. For example, a problem with 200 customer segments did not solve in 24 hours. For the purpose of illustrating the differences in contract design, we could achieve the desired results with 10 customer segments. The contract design is dependent on the degree of customer heterogeneity, not necessarily the number of segments.

2.5.2 Results

In this section we discuss the results and insights from solving the mathematical models. All the models were run on an Intel Core i7-4790 CPU with 3.60 GHz processor and 32 GB RAM. The mathematical models were solved using AMPL with GUROBI Fourer et al. (1993), with solution times averaging 2 seconds.

2.5.2.1 Overall cost savings for the supplier from CD model

We use Z_{CD}, Z_{SOC}, and Z_{UC} to denote, respectively, the objective function of the CD model, the UC-SOC model and the UC model. Although we know that $Z_{\mathrm{SOC}} \geq Z_{\mathrm{CD}}$, computational experiments were used to study how the magnitude of cost savings, $Z_{\mathrm{SOC}} - Z_{\mathrm{CD}}$, differ and under what conditions. We used two ratios that contribute to change in cost savings, D/C and S/G, as explained in the Section 3.5. We also conducted preliminary experiments to understand the effects of utility values. Our results on cost savings for the two base datasets are presented in Table 2.2.

Table 2.2: Comparison of cost savings across datasets, measured in millions of dollars

Dataset	Z_{UC}	Z_{SOC}	Z_{CD}	$(Z_{\text{SOC}} - Z_{\text{CD}})/Z_{\text{SOC}}$	$(Z_{\text{UC}} - Z_{\text{CD}})/Z_{\text{UC}}$
CalECo	\$ 28.18	\$ 27.09	\$21.86	19.30%	22.42%
DRPricer	\$ 19.13	\$ 16.51	\$12.51	22.42%	34.57%

From Table 2.2 we see that the CD model generates significant savings compared to both the UC and UC-SOC alternatives:

(i) The UC costs are of the order of \$19-28 million, whereas the CD model costs range from \$12.5-\$21.9 million. This shows that the CD model can lead to overall cost savings relative to UC of $\approx 28.5\%$, calculated as $(22.42 + 34.57)/2$.

(ii) The UC-SOC costs are of the order of \$16.5-\$27 million. Thus the overall cost savings of the CD model relative to UC-SOC is $\approx$20%, calculated as $(19.30 + 22.42)/2$.

Although not presented in Table 2.2, we note that in the CalECo (DRPricer) dataset the reduction in demand by the CD model compared to the UC model is 600 MW (285 MW), which is 20% (19%) of the average demand. In the case of CD compared to UC-SOC, the corresponding demand reduction is 200 MW (120 MW), which is 6.7% (8%) of the average demand. Note that these demand reduction percentages are smaller than the overall cost savings percentages from the CD model. This is because, percent-wise, there can be significant generation cost savings from peak demand reduction, due to reduction in use of more expensive sources of power. In addition, we note that the generation cost savings are higher in DRPricer compared to CalECo because the DRPricer dataset has a more expensive set of generators. These results led us to further study whether the values of demand or the generation cost data have a higher effect on cost savings.

Effects of Demand and Spot Market Price: We identified two ratios for understanding whether the demands or the generation costs affect the cost savings more: ratio of average demand to average capacity (D/C) and ratio of spot market price to average generation costs (S/G). We considered these ratios because interruption is driven by two parameters: costs and amount of interruption. S/G captures the effect of costs and D/C captures the effect of amount of interruption. Since the datasets are very different from each other, we conducted a sensitivity analysis on CalECo dataset from Section 3.5 to study the relative contribution of these ratios on overall cost savings. We changed the values of D and S by keeping C and G constant. In the base case the ratio values for D/C and S/G were 4.0. Here we use a low ratio value of 3.5 and a high ratio value of 4.5. Table 2.3 presents results from a two-factor, two-level (2X2) experimental design. The main effects and interaction effects for the two factor two level (2X2) experimental design are interpreted based on the literature (Winer et al. 1971).

Table 2.3: Sensitivity Analysis of CalEco Dataset, measured in millions of dollars

Cost savings of the CD model compared to the UC model, $(Z_{\text{UC}} - Z_{\text{CD}})/Z_{\text{UC}}$				
D/C	S/G		Marginal Means D/C, (H+L)/2	Simple Effects S/G, (H- L)
	Low	High		
Low	15.30%	16.88%	16.09%	1.58%
High	21.71%	26.31%	24.01%	4.61%
Marginal Means S/G, (H+L)/2	18.51%	21.59%		
Simple Effects D/C, (H-L)	6.41%	9.43%		

From Table 2.3 we observe the following:

(i) The largest percentage cost savings in the table corresponds to 26.31% for the case of high D/C and high S/G. Thus the results support the intuition that the cost savings from CD relative to UC are higher in the high demand and high spot market price environments.

(ii) The difference between the marginal means is higher for D/C than S/G ($24 - 16 > 21.6 - 18.5$). This shows that D/C contributes more to cost savings than S/G.

(iii) In a low demand environment, the simple effect of S/G is 1.58%. This effect is illustrated in Figure 2.1 by the slope of the dashed low-demand line. In a high demand environment, the simple effect has a value of 4.61%, corresponding to the slope of the solid high-demand line in Figure 2.1. Since the simple effect of S/G is not the same in the low and high demand environments, i.e., $1.58\% \neq 4.61\%$, there is an interaction effect. Thus the magnitude of cost savings depends on the combination of D/C and S/G values. Nonetheless, the cost savings from the CD model still average about 20%, similar to the result for the original CalECo dataset in Table 2.2.

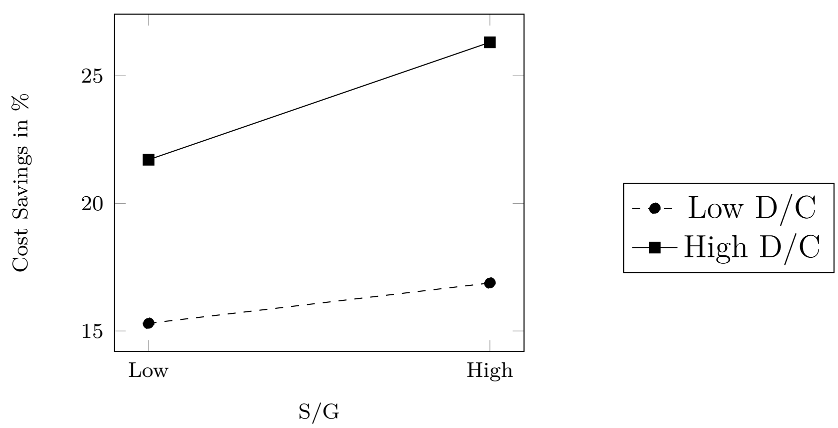


Figure 2.1: Interaction effect with D/C held at a fixed level

Note that we also conducted a CD vs. UC-SOC cost savings sensitivity analysis. We observed that D/C continued to contribute more than S/G to the CD vs. UC-SOC cost savings. We also noticed that CD has higher cost savings than UC-SOC in the low demand, low spot market price environments compared to high demand high spot market price environments. A plausible reason for this could be that the interruption ceiling restricts CD from taking more advantage of interruptions than SOC in the case of higher demands.

Another aspect in which problem instances differ is related to customer preferences for interruption payments and interruption amounts, which we studied next in terms of contract choice and cost savings.

2.5.2.2 Insights on contract design

We explored how customers chosen by UC-SOC and CD models are different from one another and how this influences contract design and cost savings. From the Power Manager Program we saw that there are different segments of customers based on wealth, types of home cooling systems and customer age (*PMCIES* 2006). The existence of different customer segments also was confirmed by the Con Edison study that classified customers as duration-sensitive, over-ride sensitive and frequency-sensitive (Kritler 1988). This affirms that the customers can be differentiated based on their preferences. The illustrative example below shows how customer differences influence contract design.

Each customer segment has a utility for each attribute and level combination. The contract chosen by the UC-SOC model has the highest payment per customer and the lowest interruption. But the CD model chooses a contract with a lower payment per customer and higher interruption. So the CD contract can exclude some customers but achieve a desired total interruption at lower cost by interrupting fewer customers in higher quantities. This is illustrated below using an example. Consider two customers, A and B, with utilities shown in Table 2.4. The hurdle at 95% is 13.3 for both customers. Suppose the UC-SOC model chooses the \$45, 1kW contract whereas the CD model chooses the \$35, 1.5 kW contract. Then the UC-SOC contract delivers total utility of 14 to each customer (A or B); the CD contract delivers total utility 13.4 to customer A and 12 to customer B. We see that both contracts exceed the customer A's hurdle utility of 13.3. However, only the UC-SOC contract exceeds customer B's hurdle. This simple example illustrates that an CD contract with lower payment and higher interruption can pick only a subset of customers picked by the UC-SOC contract.

Table 2.4: Comparison of utilities and hurdles for customers A and B

Customer	**Attribute**	**Level**	**Utility Score**
A	Fixed Payment	\$45	12
		35	11.5
		25	11
	Per event Interuption	1kW	2
		1.5 kW	1.9
		2kW	1.8
B	Fixed Payment	\$45	11
		35	10
		25	9
	Per event Interuption	1kW	3
		1.5 kW	2
		2kW	1
Hurdle at 95% of the highest utility = 0.95*(12+2) = 0.95*(11+3) = 13.3			

Motivated by the above illustrative example, we considered a smaller version of the CalECo dataset described in Section 3.5 with 10 customer segments and utilities derived from both the multivariate normal and beta distributions. Contract attributes and levels are the same as in the above illustrative example. By solving the corresponding UC-SOC and CD models, we noted the following:

(i) The idea in the illustrative example above holds in the smaller CalECo dataset with utilities derived from the beta distribution. In this case, the SOC model picks 6 customer segments for interruption. The CD model chooses a subset of 5 customer segments. One

SOC customer segment is not chosen by the CD model because it does not prefer a contract that pays \$10 more for a 0.5 kW increase in interruption.

(ii) We also saw that this utilities derived from the beta distribution, corresponding to more heterogeneous customers, had 5% (4%) larger cost savings relative to UC-SOC (UC) than for the case with multivariate normal utilities. This suggests that DR programs will result in greater cost savings when the customer segments are more heterogeneous.

Next, we studied if the contract and customer selection results from the illustrative example and small CalECo dataset could be generalized. This led to the following Definition and Proposition that characterizes the customers selected by CD relative to UC-SOC using a notion of customer "sensitivity" to changes in attribute levels. (Sensitivity is the range of utilities of the customers in each of the CD and UC-SOC models.)

Definition 1. *Sensitivity is defined mathematically using Equations (2.12)-(2.13).*

$$\sigma^m = \max_j u_j^m - \min_j u_j^m, \qquad m \in \{CD, SOC\}, \tag{2.12}$$

$$\textit{where,} \quad u_j^m = \sum_{k=1}^{K} \sum_{\ell=1}^{L_k} u_{k\ell}^j x_{k\ell}^m, \qquad j \in \mathcal{J}. \tag{2.13}$$

In order to state our key results (Lemma 1 and Proposition 1), we need to specify the following condition on the simulated utilities. Many methods to simulate utilities for our problem environment satisfy this condition.

Condition 1. Utility Simulation: $u_{kl}^j = \alpha_{k\ell}\gamma_{k\ell} + \beta_{k\ell} + \epsilon_j^h$.

Lemma 1. *(i) CD* $\subseteq$*SOC. (ii) For all* j*,* $u_j^{CD} = u_j^{SOC} + RHS$*, with* $RHS > 0$.

Proposition 1. *Under Condition 1, the sensitivity of CD model customers is less than or equal to that of SOC customers. With sensitivity denoted by* σ^m*, as defined by equation (2.12),* *we have* $\sigma^{CD} \leq \sigma^{SOC}$.

Details of the proofs of Lemma 1 and Proposition 1 are provided in A.2. Here we briefly discuss potential implications of our results. Not only is the cost from the CD model lower that the cost from the UC-SOC model, by Proposition 1, the CD model identifies less sensitive customers. This allows the CD model to reduce its peak load with lower customer contract payments while delivering higher utility to its customer base. In the CalECo dataset, the cost savings of CD model compared to UC-SOC model from reduction in fixed payments was $\approx$ \$5 million and for the DRPricer dataset it was $\approx$ \$2.5 million . The cost savings for CD model compared to UC-SOC model from reduction in generation was $\approx$ \$1 million for the CalECo dataset and $\approx$ \$1.5 million for the DRPricer dataset. In addition, characterization of CD and SOC customers can be useful in a macroscopic Generalized Equilibrium Model (Paltsev 2004) that seeks to identify how social welfare gets impacted by DR and the impact of policy choices including taxation.

2.6 Conclusions and Future Research

This paper provides two contributions: one in the domain of electricity provider cost savings and the latter in the domain of power interruption contract design. The CD model consistently leads to significant overall cost savings. The cost savings are higher when there is an increase in demand than an increase in spot market prices. Beta distributed utilities (for creating heterogeneous customer segments) generated cost savings of $\approx 5\%$ for CD vs. UC-SOC in the CalECo dataset, compared to multivariate normal distributed utilities (for creating homogeneous customer segments). The CD model helps to identify the customers who are less sensitive to interruption and payments and designs a more cost effective contract compared to the SOC model.

Avenues for future research include: 1. Incorporating power interruption contracts into customer centric models with objectives of customer load reduction and customer bill reduction. These models will have practical applications in the customer behavioral studies explored by electricity service provider companies. 2. Extending the results of the current model to an economy and understanding the long term cost savings and customer welfare is another possible avenue. 3. The size of problems solvable with off-the-shelf code is an open question. Hence larger problems for more customers using exact algorithms or heuristics is an area that needs further study. 4. Robustness of contracts to changes in demand and supply patterns could also be worthy of investigation. 5. Finally, this model could be extended to include other demand response mechanisms such as in-home batteries or solar cells.

Chapter 3

A Computable General Equilibrium (CGE) Model for Power Interruption Contracts

3.1 Introduction

Computable General Equilibrium (CGE) models (Paltsev 2004) are used to study economy wide effects of external factors such as policy and technology changes. Typically a CGE model output quantifies sectoral activity levels, commodity and primary factor prices, and customer incomes. An economic sector engages in production of raw materials, transformation of raw materials into goods or supply of services to end users. An example of a single sector in the CGE model would be electricity sector. In this sector, the commodity is electricity. Activity level is the amount of electricity produced. Primary factors are capital investments in power plants, labor supply used in operations and maintenance, fuel and natural resources used as inputs in the production of electricity. Customers derive income from this sector in the form of labor wages, investments in capital etc.

Macroeconomic policy makers find CGE models useful broadly in two aspects: (i) To quantify the impact of a policy change such as taxation on the economic variables. Although a directional change could be guessed by the policy makers, a model is required to quantify the magnitude of such a change. (ii) To understand the secondary economic effects of a policy change. For example, a demand reduction for electricity could lead to a demand reduction for sectors using electricity as an input to their production process. This can be studied only with a CGE model as opposed to a model with only one sector.

This research studies how differences in customer preferences for Demand Response (DR) contracts can affect various economic variables such as primary factor costs, emission levels, societal welfare, customer income and sectoral activity levels. Although existing literature has studied DR contracts in a CGE environment, there is little existing research on incorporating customer preferences into the CGE model. Our understanding of Direct Load Control (DLC) contracts for residential customers in the US in a CGE model is limited. Traditionally capital and labor were only considered as the primary factors. But currently in the US economy, energy is used as an input to many other sectors of production including transportation and manufacturing. The electricity sub-sector in the energy sector foresees further growth through the advent of electric vehicles and increase in residential square footage. Although an increase in activity level in the electricity sector could lead to higher GDP, there are societal costs such as emission costs that should not be ignored. An increase in activity levels in the electricity sector could also lead to depletion of fossil fuels. In this context, electricity saving mechanisms and their effects on sectoral prices and activity levels gain importance. Residential DLC contracts are one of the chief energy saving mechanisms in the DR domain. Hence we focus on DLC contracts in a CGE model.

This paper seeks to answer the following research questions: (i) How can customers be differentiated based on their preference for DLC contracts? (ii) What are the effects of such customer differentiation on sectoral activity levels, incomes and prices?

In response to the first question we develop a methodology to calculate price elasticity of demand. Elasticities are traditionally taken from literature with little room for customer preferences. We incorporate customer preferences into elasticity calculations by using a customer "sensitivity" metric from Dinesh et al. (2017). The "sensitivity" metric incorporates customer preferences for DR by using a range of customer utilities. The calculation of elasticity based on our methodology is useful since production and utility functions rely on the value of elasticity parameters. The estimation of elasticity parameters will affect the calculations of sectoral activity levels and prices. For example, in a Leontief production function primary factors are treated as complements, while in a Cobb-Douglas production function they are treated as substitutes. The prices of commodities are not only determined by the changes in demand and supply but also on how much the customers prefer certain commodities over others.

In response to the second question we quantify the indirect substitution and rebound effects on sectoral activity levels, incomes and prices based on customer differences, when DR is implemented. Our experiments show that an increase in price elasticity of demand for electricity leads to an increase in emission levels in sectors other than electricity since customers migrate to those sectors when there is no power. On an average, the increase in emissions with DR is $\approx 0.25\%$. There is a reduction in emissions in the electricity sector of $\approx 1.65\%$ due to DR. But there is an increase in emissions by $\approx 1.90\%$ in the other sectors. Further, the migration of DR customers causes a decrease in economy wide fuel prices and activity levels in the peak coal generation sector. Although the DR customers have some increase in societal welfare, they have an income reduction due to decrease in payments they receive from primary factors. These results are useful in implementing customer targeted DR policies. For example, a regulatory body can understand if there is a higher electricity bill reduction when customers have a higher preference for DR and how much of the generation cost savings are translated into these bill savings. Since in the US economy regulatory bodies such as Federal Energy Regulatory Commission (FERC) and North American Electric Regulatory Corporation (NERC) have a role in regulating wholesale electricity prices, they can compare generation cost savings and electricity bill savings due to DR and determine whether utility companies are overcharging their customers.

The rest of this paper is organized as follows: Section 2 summarizes relevant literature on CGE models and elasticity. Section 3 explains the methodology to calculate price elasticity of demand for electricity. Section 4 describes the CGE model. Section 5 focuses on data. Section 6 explains results. Section 7 concludes with avenues for future research.

3.2 Literature Review

A CGE model has core elements such as variables representing prices and activity levels, equilibrium equations and assumptions under which the equations hold. The Arrow-Debreu (AD) model (Geanakoplos 1989) is the most general model representing a competitive economy and the assumptions of the AD model (perfect competition, convex preferences and demand independence) were used in this paper. Under these assumptions the CGE model can generate a certain set of commodity prices for which aggregate supply will equal aggregate demand in the economy. Martin & Skinner (1998) developed a CGE model on resource taxation for the Czech Republic. The market equilibrium equations in our model were motivated by this work. Rutherford (1999) and Paltsev (2004) built and solved CGE models using

General Algebraic Modeling System (GAMS) and this approach was adopted in building and solving our model. Burfisher (2017) gave a comprehensive overview of CGE models. This work was used as a guideline for defining inputs and outputs and endogenous and exogenous variables and parameters. Whether a variable is treated as endogenous or exogenous will have have different implications from a modeling point of view. To give an example, if supply of capital for electricity sector is exogenous (fixed at its initial level) and the cost of capital is endogenous (solution to the equations of the model), the cost of capital adjusts till the supply and demand for capital are equal. If there is a reduction in demand for electricity, there will be less investment in the capital sector and economy wide cost of capital will continue to fall until capital investments equal to the initial decrease are deployed in other sectors. On the other hand, if cost of capital is exogenous, then the supply of capital adjusts till the demand and supply are equal. This would mean that the reduction in cost of capital due to decreased electricity demand would lead to a decrease in the supply of capital in the economy as a whole.

Since our CGE model uses data from a micro optimization model, it is worthwhile to discuss the literature pertaining to micro-macro integration models. Methods for micro-macro integration were described in detail by Baekgaard (1995). Davies et al. (2009) implemented a micro-macro CGE model in developing economies using a microsimulation of household data. Cockburn et al. (2010) implemented a micro simulation approach in a CGE model for households in Nepal and Philippines. We use some of the characteristics of these models for the micro-macro integration. For example, as Baekgaard (1995) mentioned that an elasticity parameter could be calculated from a micro model. We went a step further and calculated the price elasticity of demand using customer utilities from the micro model. Similar to Davies et al. (2009) we use the output from the micro optimization model in our macro CGE model. The challenges of collecting micro data and combining with a macro model are described by Kretschmer & Peterson (2010) in the domain of bio-fuels. Rodrigues & Linares (2015) addressed these challenges in a residential DR environment in Spain. We differ from this work in that instead of assuming a fixed amount of DR and then using that amount to reduce the peak load, we used realistic data from a micro optimization model. Moreover, we differentiate customers based on their price elasticity of demand for DR. The empirical literature on such customer differentiation is currently sparse.

Next we summarize some of the relevant literature pertaining to elasticity parameters. Robustness of CGE models to elasticity parameters had been studied by Harrison et al. (1993) in three application scenarios. Harrison & Vinod (1992) assumed the elasticity parameters are derived from three distributions: normal, t or uniform and then conducted a sensitivity analysis on them. Pagan & Shannon (1987) conducted a sensitivity analysis on elasticity of supply parameters. DeVuyst & Preckel (1997) compared the approaches of Pagan & Shannon (1987) and Harrison & Vinod (1992) to their novel approach using Gaussian quadrature. Epstein & Zin (1989) separated risk aversion of customers from the inter-temporal elasticity of substitution. In our study, we develop a methodology to incorporate customer preferences into the price elasticity of demand for electricity in a DR environment. This is our contribution to the body of literature.

Construction of a benchmark Social Accounting Matrix (SAM) is an important element in a CGE model (Burfisher 2017). Here we discuss the data sources we use for constructing this matrix. Wing (2006) compared top-down and bottom-up generation technologies and their welfare effects. The elasticity of substitution parameters, factor inputs, non-energy sector gross outputs and carbon costs per MWH of generation from this model were used in our model, with the gross outputs and inputs used in the SAM matrix scaled according to our data. The scaling procedure is described in detail in Section 3.5. The data was verified for correctness by comparison with the elasticity parameter values from EMPAX model

(Ross et al. 2005) and capital and labor costs from EIA (2013). For the micro optimization model, the supply-side is based on a unit commitment model by Hobbs et al. (2006) and the demand-side is based on a share-of-choice model by Camm et al. (2006). Types of demand response mechanisms were studied in detail by Albadi & El-Saadany (2008) and this work helped in incorporating a DLC mechanism in the CGE model. The data for the unit commitment side on the micro optimization model came from Johnson et al. (1997). The conjoint study data came from surveys by *PMCIES* (2006).

3.3 Methodology to Compute Price Elasticity of Demand for Electricity

Price elasticity of demand is defined as the rate of change of demand of a commodity with respect to price of that commodity(Burfisher 2017). In the context of electricity, it is the rate of change in electricity demanded, for a unit change in the price the customers have to pay for electricity. DR customers receive a subsidy for participating in DR. Customers who reduce their electricity usage more than others for the same amount of subsidy are deemed to have a higher price elasticity of demand. Epstein & Zin (1989) showed that customer preferences for consumption (risk aversion metric) is inversely proportional to substitution of consumption between goods for unit changes in real interest rates (intertemporal elasticity of substitution). Motivated by this, we develop a methodology to incorporate customer preferences for DR contracts in the calculation of price elasticity of demand for electricity. In this study the base price elasticity of demand for electricity is used from the literature (Ross et al. 2005). This value is multiplied by the reciprocal of "sensitivity' to calculate the customer preference adjusted price elasticity of demand. "Sensitivity" is defined as the range of customer preferences for DR contracts. A larger value for sensitivity denotes that customers have lower preference for DR and vice versa. In summary, a larger value for sensitivity denotes that a customer has lower price elasticity of demand for electricity and vice versa. The detailed structure of elasticities and how the customer preferences are incorporated in the elasticity calculations is described in the Appendix B.2.

3.4 Model

The micro optimization model is a Mixed Integer Linear Programming (MILP) model. This takes generation costs, demands and customer preferences as inputs. The outputs are amount of power reduction, total generation costs, potential customers participating in DR and the DR contract chosen by these customers. For the CGE model, the modeling approach in GAMS by Rutherford (1999) and Paltsev (2004) was used.

In the CGE model, the economy was divided into j production sectors. The electricity sector was divided into sub-sectors of coal, hydro and nuclear based generation. The generators were further divided into peak and non-peak generation sectors. The non-electricity sectors were transportation, emissions and all the rest of the economy. There were i factor inputs. The hydro and nuclear generation sectors used capital, labor and natural resource inputs. The coal sector used capital, labor and fuel inputs. The emissions sector had coal generation as an input from both transportation and electricity. In the electricity sector emissions sector takes inputs from the generation sub-sectors. There were H customers. The customers were DR participants and non-DR customers. They availed welfare W_H by consuming commodities at prices P_H.

There are two models used in this paper. One is a benchmark equilibrium model called

Base. We constructed a balanced SAM matrix with the inputs and outputs and simulate that equilibrium in this benchmark model. We introduce DR in the benchmark by reducing the electricity input in the welfare block of DR customers. Welfare block in the CGE model represents the share of different commodities in purchasing utility for customers. DR is introduced by subtracting both the emission costs and the DR payments from the electricity input in the welfare block and these subtractions are explained in (i) and (ii). The subtraction is made from the peak coal sector since the highest amount of generation cost savings are from the peak coal sector in the micro model.

(i) The benchmark model has 13% peak load reduction compared to base model in the micro optimization model. The emission reduction corresponding to peak load reduction is subtracted from the peak coal input in the welfare block, where the per unit cost of emissions is taken from the literature (Wing 2006).

(ii) From the micro model we use the variable and fixed payments to the customers participating in DR. These payments corresponding to DR peak load reduction are also subtracted from the peak coal input in the welfare block. We call this model the DR model and this is analogous to the DR micro model currently used in practice (Dinesh et al. 2017).

In order to incorporate the customer preferences for DR, we conduct a sensitivity analysis on this model in two ways. The micro model leads to a peak load reduction and reduction in the use of polluting fuels. This is represented by (i). We also see that customers differ in their preferences for DR contracts (denoted by “sensitivity”Dinesh et al. (2017)). This is represented by (ii).

(i) By reducing the payments to the customers and the carbon emissions by a further demand reduction (20% compared to Base). This percentage is used since the micro optimization model for DR leads to a 20% peak load reduction compared to base. This variant model is called DR with expenditure reduction.

(ii) By changing the price elasticity of demand (σ_H) for peak load sector. This is achieved by multiplying the elasticity of substitution between peak load and transportation in the welfare block by the reciprocal of the "sensitivity" metric described in Dinesh et al. (2017). The sensitivity metric captures a range of utilities for the DR customers. If the reciprocal of this metric is high, the price elasticity of demand for electricity will be high and vice versa. These sensitivity metrics make the DR model analogous to our novel Contract Design (CD) model mentioned in Dinesh et al. (2017). This variant model is called DR with elasticity increase.

Transportation sector is used as a substitute for electricity since transportation is the highest consumer of electricity, next to manufacturing. Manufacturing is a primary sector that produces goods. Transportation is a tertiary sector that provides a service. Residential customers are likely to use services such as entertainment and travel when they cannot avail electricity. Also as per the EMPAX model, transportation is the second largest source of Greenhouse Gas (GHG) emissions in the US, next to electricity. Since we are studying emission levels using our model, we studied the sectors that are more likely to contribute to emissions when DR is implemented.

We compare the performance of the base and DR models in terms of the economic variables such as input and output costs, activity levels and customer incomes. All the equations leading to the model as well as the diagram showing the elasticity structure for the peak demand sector and transportation are described in the detail in Appendix B.1.

In the next section, we describe the relevant data used in the model.

3.5 Data

The generation data is the output of the micro optimization model. The raw generation data comes from Johnson et al. (1997). This dataset is called CalECo data set and is widely cited in the literature. This model is for a peak demand week in California. We do not expand the time horizons since higher demands and lower demands might require different generation technologies that are not incorporated in this model. Moreover, to take advantage of DR during higher demand periods, the contract attributes like power interruption ceiling will have to be significantly altered based on customer preferences from an actual conjoint study. For incorporating the electricity sector in CGE, we divide the sector into three sub-sectors: coal, nuclear and hydro. The SAM matrix cells for these sub-sectors are populated using the generation data from micro model. For example, if the peak coal sector generation from the micro model is 0.5 million MWh, we use that data in the SAM matrix for peak coal. Peak load calculated as (Load in a time period)- (Average Generator Capacity). If this is a positive number, it is treated as peak. For example, if the average capacity of a generator is 100 MW and in a particular time period if the generation is 200 MW, the peak load is (200-100)=100 MW. The base load is 100 MW in this case. The data for the gross outputs of the sectors other than electricity are calculated based on Wing (2006). For example, if transportation covers 40% of the gross economic activity, transportation output is given the same weightage in our model. The factor inputs for all the sectors are calculated in a similar fashion. Different types of generators use different shares of capital and labor and these differences are incorporated by using weighted average values for factor inputs. For example, if 90% of the generation is from pulverized coal fired power plants and the capital investment in those types of generators is 0.5 million dollars, 0.5 million is multiplied by 90% in the overall capital investment calculation. Elasticity values are calculated based on Wing (2006) and sensitivity analysis is performed based on customer preferences from the micro model. The range of utilities for the different sets of customers vary by about 25% and this is used as a beginning range for sensitivity analysis. The SAM matrix constructed is given in Table 3.1 with all the gross outputs and inputs in millions of dollars.

3.6 Results

Our models were run in GAMS using the subsystem Mathematical Programming System for General Equilibrium Analysis (MPSGE) (Paltsev 2004). The Base model, the DR model and the changes in the DR model due to elasticity changes and expenditure reduction are considered in the Table 3.2.

Table 3.1: Base SAM Matrix for Replicating Benchmark Equilibrium

	Base Coal	**Peak Coal**	**Base Hydro**	**Peak Hydro**	**Base Nuclear**	**Peak Nuclear**	**Transportation**	**Emissions**	**Others**	**Welfare non-DR**	**Welfare DR**	**Customers non-DR**	**Customers DR**
Base Coal	2.6						-1.3	-0.3		0.9	0.1		
Peak Coal		2.5					-1.2	-0.3		0.9	0.1		
Base Hydro			3.38							3.042	0.338		
Peak Hydro				3.38						3.042	0.338		
Base Nuclear					2.9					2.61	0.29		
Peak Nuclear						1.5				1.35	0.15		
Transportation							45.5	-0.29		40.689	4.521		
Emissions								0.89		0.801	0.089		
Others									123.9	111.51	12.39		
Income non DR										164.844		164.844	
Income DR											18.316		18.316
Capital	1.5	1.4	1.89	1.89	1.77	0.92	27.1		41.2			69.903	7.767
Labor	0.4	0.4	0.81	0.81	0.37	0.19	15.9		82.7			91.422	10.158
Fuel	0.7	0.7										1.26	0.14
Natural Resources			0.68	0.68	0.76	0.39						2.259	0.251

Table 3.2: Comparison of Equilibrium Prices and Activities with and without DR

Model	Variable	Percentage Change compared to Base (DR-Base)/(Base)	Million Dollar Savings compared to Base
Base	Activity Level in Peak Coal		
DR		-1.04	0.0104
DR with elasticity increase of 25%		-1.04	0.0104
DR with elasticity increase of 200%		- 0.95	0.0095
DR with elasticity increase of 200% and expenditure reduction		-1.99	0.0199
Base	Activity Level in Emissions Sector		
DR		-0.20	0.0018
DR with elasticity increase of 25%		-0.20	0.0018
DR with elasticity increase of 200%		0.10	-0.0009
DR with elasticity increase of 200% and expenditure reduction		0.50	-0.0045
Base	Fuel Costs		
DR		-0.90	0.0113
DR with elasticity increase of 25%		-0.90	0.0113
DR with elasticity increase of 200%		-0.80	0.0101
DR with elasticity increase of 200% and expenditure reduction		-1.60	0.0202
Base	Welfare Costs of DR Customer		
DR		-0.20	0.0366
DR with elasticity increase of 25%		-0.20	0.0366
DR with elasticity increase of 200%		-0.20	0.0366
DR with elasticity increase of 200% and expenditure reduction		-0.41	0.0751
Base	Income of DR Customer		
DR		-1.94	-0.3553
DR with elasticity increase of 25%		-1.84	-0.3371
DR with elasticity increase of 200%		-1.35	-0.2472
DR with elasticity increase of 200% and expenditure reduction		-3.59	-0.6575

The results show the following:

Average Coal Emissions

DR leads to an increase in emission costs averaging $1800. This is calculated as $ (0.0018+0.0018-0.0009-0.0045)/(4) million from the 4th column of Table 3.2 under the Variable 'Activity Level in Emissions Sector.' The 4th column is calculated as Emission Sector Activity Level * Emission Sector Price from the CGE model output. Emissions are considered as a cost to the society as per Wing (2006) and EMPAX model. Hence we represent the increase in total emission output as an increase in emission costs.

The increase in emissions is due to two reasons. (i) As the price elasticity of demand for electricity peak load is increased, the customers migrate to other sectors such as transportation that consume more coal and this increases emissions. (ii). Since there is a decrease in peak coal use from DR as seen from the Table 3.2 , Variable 'Activity Level in Peak Coal', Column 3, the demand for the rest of the customers can be met through more base coal generation. Base coal is a larger constituent in generation compared to peak coal and hence leads to higher amount of emissions.

This result is non-intuitive if we consider the micro model output. In the micro model there is an activity shift from coal sector to nuclear sector. So it is plausible that DR could lead to emission cost savings in the CGE model as well. However, the customers are not just reducing their consumption due to DR. They are migrating to other sectors that have a bigger share in the total output compared to DR and this creates an increase in coal consumption in those sectors for generating electricity and subsequently an increase in emissions. The decrease in activity level due to DR is also compensated by an increase in activity levels for the non-DR customers. This implies that in a macro environment residential DR can lead to a reduction in carbon emissions only if more customers are willing to participate in DR from the non-DR customer sector.

Average Fuel Costs

As expected there is a decline in average fuel costs as a direct effect of the decline in the activity level in the peak coal sector. As per Table 3.2, Variable 'Activity Level in Peak Coal', Columns 3&4, the activity levels in Peak Coal sector decline when DR is implemented. Fuel is used as an input in coal based generation. In addition to this, there are non-intuitive indirect effects such as increase in activity levels of sectors such as hydro and nuclear that use DR. These effects can be studied only using a CGE model. Since hydro and nuclear sectors use more natural resources that are inexpensive compared to fuel, the cost of natural resources increases and that of fuel declines. The average fuel cost savings are \$13,230. This is calculated as \$ (0.0113+0.0113+0.0101+0.0202)/(4) million from the 4th column of Table 3.2 under the Variable 'Fuel Costs'. This implies that since fuel costs are reduced, there could be more consumption of coal in sectors that do not participate in DR, such as transportation. This is a potential opportunity for implementing DR in these sectors.

Comparison of Income Reduction and Welfare Costs

The average savings in welfare costs is \$46,247.90. This is calculated as the average of the 4th column under Variable Welfare Costs for DR Customer in Table 3.2. The average reduction in income on the other hand is ≈\$3.9 million. This is calculated as the average of the 4th column under Variable Income of DR Customer in Table 3.2. The welfare cost savings come from payments for participating in DR and for reducing emissions. The income reduction comes for decrease in fuel sector payments and decrease in capital sector payments. The results here show that the cost savings from DR are not fully reflected in customer electricity bill savings, at least in the short term. This also points to why DR leads to an increase in activity levels and emissions in non-DR sectors. Since the income reduction for

DR customers is larger than the expenditure reduction, this has to be compensated by higher incomes from other sectors. Short term is considered as 10 iterations of the CGE model on its path to convergence. 10 iterations correspond to 10 weeks, since the base SAM matrix has one week of data. The equilibrium values are unaffected by the starting “seed” as described in Appendix B.3.

Effect of Customer Differences

We see that as customers are more willing to participate in DR, they are more likely to migrate to other sectors that lead to an increase in emissions. But at the same time, this migration leads to a decrease in fuel costs since renewable fuels are used. A decrease in fuel costs further increases coal consumption if DR is not implemented in other sectors that use fossil fuels as an input to their production process.

These results together imply the following:

(i). Since non-DR sectors constitute a larger share in the total electricity output from coal generation compared to DR sector, implementing in DR in non-DR sectors could lead to a net reduction in carbon emissions. This points to using a conjoint study in the non-DR participants sector to understand how they can be motivated to participate in DR. Additionally, sectors such as transportation can use energy saving mechanisms like electric vehicles to compensate for the increase in emissions due to DR.

(ii). It is promising that DR leads to a shift in activity levels from coal sector to nuclear and hydro sectors. Currently the income increase due to the increase in activity in these sectors is not sufficient to compensate for the income reduction due to DR. As the activity level in hydro and nuclear sectors go on increasing due to DR, these sectors will be able to recover a larger portion of their initial investments and these could eventually translate to income for customers.

3.7 Conclusions and Future Research

From this study we conclude that DR leads to an increase in emission costs and a reduction in customer income. As the customers increase their preference for DR, the emission costs increase. This points to an area of opportunity for DR in sectors that use fossil fuels as an input to production. Implementation of DR in such sectors could lead to potential emission cost savings since these are larger sectors in terms of peak coal consumption and hence show a larger potential for peak load reduction. The reduction in customer income could be remedied by increasing payments to DR customers over time. Although DR leads to a decrease in fuel prices, it could further increase the use of polluting fuels if DR is not implemented in other sectors. Since the increase in price elasticity of demand lowers fuel costs and activity level in the peak coal generation, it is important to consider customer differences in DR contract design. Based on these conclusions a regulatory body can look into the current DR contract payments vs. the customer income from electricity and calculate the electricity end user payments to increase societal welfare. They can also utilize data on customer differences and understand how to increase the price elasticity of demand for DR across sectors. This paper points to the following future research avenues. 1. A conjoint study to collect empirical data and test and refine our results in support of price elasticity of demand changes. 2. Inclusion of DR in other sectors using pollutants and testing the model. 3. Using different production and utility functions other than standard CES functions, based on differences in generation technology. 4. Forming a "hard-link" between micro and macro models by re-framing the macro equations to incorporate micro model characteristics such as marginal changes in demand over time. 5. Quantifying changes in spot market prices for electricity with the implementation of DR.

Chapter 4

Overall Summary and Future Directions

In the first chapter of this dissertation, a novel Contract Design (CD) model has been formulated for electricity service providers. This model minimizes generation costs when Demand Response (DR) is implemented. The cost savings of the CD model are noticeably higher compared to a share-of-choice (SOC) benchmark. The model also identifies parameters for contract design and differentiates customers based on their contract preferences. Sensitivity analysis is performed on the model based on demand and spot market price changes and demand is seen to have a higher effect on cost savings than spot market price.

In the second chapter of this dissertation, a Computable General Equilibrium (CGE) model has been formulated. The effects of DR customer differences on macroeconomic variables such as emission costs, fuel costs and customer incomes and expenditures have been studied. It is seen that DR implemented in electric sector alone doesn't lead to as much cost savings as in the micro model due to an increase in societal costs.

In terms of future research, there are multiple avenues that can be explored. Some of them are as follows. 1. Implementation of a conjoint study to elicit customer preferences for DR contracts. 2. Inclusion of alternative sources of power such as batteries in the model. 3. Solving large scale problems. 4. Modification of the CGE model to incorporate carbon taxes in other sectors. 5. Technology calibration of production and utility functions based on micro model data. 6. Integration of DR into the first order cost minimization conditions and forming a “hard-link” (Burfisher 2017) between the micro and macro models using equations.

Bibliography

Albadi, M. H. & El-Saadany, E. (2008), 'A summary of demand response in electricity markets', *Electric power systems research* **78**(11), 1989–1996.

Baekgaard, H. (1995), Integrating micro and macro models: mutual benefits, *in* 'International Congress on Modelling and Simulation Proceedings', Vol. 4, pp. 253–8.

Burfisher, M. E. (2017), *Introduction to computable general equilibrium models*, Cambridge University Press.

Camm, J. D., Cochran, J. J., Curry, D. J. & Kannan, S. (2006), 'Conjoint optimization: An exact branch-and-bound algorithm for the share-of-choice problem', *Management Science* **52**(3), 435–447.

Cockburn, J., Corong, E., Cororaton, C. et al. (2010), 'Integrated computable general equilibrium (cge) micro-simulation approach', *International Journal of Microsimulation* **3**(1), 60–71.

Conejo, A. J., Morales, J. M. & Baringo, L. (2010), 'Real-time demand response model', *IEEE Transactions on Smart Grid* **1**(3), 236–242.

Crabbe, M., Jones, B. & Vandebroek, M. L. (2011), 'A comparison of two-stage segmentation methods for choice-based conjoint data: a simulation study'.

Davies, J. B. et al. (2009), 'Combining microsimulation with cge and macro modelling for distributional analysis in developing and transition countries', *International Journal of Microsimulation* **2**(1), 49–65.

Dem (2012*a*). Retreived 2016-01-23.
URL: *http://energy.gov/oe/technology-development/smart-grid/demand-response*

Dem (2012*b*). Retreived 2016-04-26.
URL: *http://www.coned.com/energyefficiency/demand_response_program_details.asp*

Dem (2013). Retreived 2016-03-21.
URL: *http://www.integralanalytics.com/products-and-services/dsm-planning-and-evaluation/drpricer.aspx*

DeVuyst, E. A. & Preckel, P. V. (1997), ‘Sensitivity analysis revisited: A quadrature-based approach’, *Journal of policy modeling* **19**(2), 175–185.

Dinesh, L., Camm, J., Skinner, K. & Rao, U. (2017), ‘A contract design (cd) model for power interruption contracts’, *Unpublished Manuscript* .

DR (2012). Retreived 2016-03-17.
URL: *http://www.peakload.org/events/EventDetails.aspx?id=459630&group=*

EIA, U. (2013), ‘Updated capital cost estimates for utility scale electricity generating plants’, *US Energy Inf. Adm* .

Epstein, L. G. & Zin, S. E. (1989), ‘Substitution, risk aversion, and the temporal behavior of consumption and asset returns: A theoretical framework’, *Econometrica: Journal of the Econometric Society* pp. 937–969.

Est (2012). Retreived 2016-03-21.
URL: *http://www.pjm.com/markets-and-operations/energy/real-time/loadhryr.aspx*

Fourer, R., Gay, D. M. & Kernighan, B. (1993), *Ampl*, Vol. 117, Boyd & Fraser Danvers, MA.

Geanakoplos, J. (1989), Arrow-debreu model of general equilibrium, *in* ‘General Equilibrium’, Springer, pp. 43–61.

Harrison, G. W., Jones, R., Kimbell, L. J. & Wigle, R. (1993), ‘How robust is applied general equilibrium analysis?’, *Journal of Policy Modeling* **15**(1), 99–115.

Harrison, G. W. & Vinod, H. D. (1992), ‘The sensitivity analysis of applied general equilibrium models: Completely randomized factorial sampling designs’, *The Review of Economics and Statistics* pp. 357–362.

Hobbs, B. F., Rothkopf, M. H., O’Neill, R. P. & Chao, H.-p. (2006), *The next generation of electric power unit commitment models*, Vol. 36, Springer Science & Business Media.

Johnson, R. B., Oren, S. S. & Svoboda, A. J. (1997), ‘Equity and efficiency of unit commitment in competitive electricity markets’, *Utilities Policy* **6**(1), 9–19.

Kehoe, T. J. (1985), ‘The comparative statics properties of tax models’, *Canadian Journal of Economics* pp. 314–334.

Kretschmer, B. & Peterson, S. (2010), ‘Integrating bioenergy into computable general equilibrium modelsâĂŤa survey’, *Energy Economics* **32**(3), 673–686.

Kritler, V. (1988), ‘Using conjoint analysis to evaluate variations in program design’.
URL: *http://aceee.org/files/proceedings/1988/data/papers/1988_V6_011.pdf*

Lawton, L., Sullivan, M., Van Liere, K., Katz, A. & Eto, J. (2003), 'A framework and review of customer outage costs: Integration and analysis of electric utility outage cost surveys', *Lawrence Berkeley National Laboratory* .

Marshall, J. (2014). Retreived 2016-10-21.
URL: *http://www.pgecurrents.com/2014/10/30/how-pge-is-using-demand-management-to-make-smarter-use-of-the-grid/*

Martin, W. E. & Skinner, R. K. (1998), 'Resource taxation and sustainability: A cge model of the czech republic', *Natural Resources Research* **7**(4), 287–300.

Negrete-Pincetic, M., Nayyar, A., Poolla, K., Salah, F. & Varaiya, P. (2016), 'Rate-constrained energy services in electricity', *IEEE Transactions on Smart Grid* **PP**. Retreived 2017-08-23.
URL: *http://ieeexplore.ieee.org/abstract/document/7725917/*

Newsham, G. R. & Bowker, B. G. (2010), 'The effect of utility time-varying pricing and load control strategies on residential summer peak electricity use: a review', *Energy policy* **38**(7), 3289–3296.

Outlook, A. E. (2016), 'US Energy Information Administration Washington'.
URL: *https://www.eia.gov/outlooks/aeo/pdf/0383(2016).pdf*

Padhy, N. P. (2004), 'Unit commitment-a bibliographical survey', *IEEE Transactions on power systems* **19**(2), 1196–1205.

Pagan, A. R. & Shannon, J. H. (1987), 'How reliable are orani conclusions?', *Economic Record* **63**(1), 33–45.

Paltsev, S. (2004), 'Moving from static to dynamic general equilibrium economic models', *Notes for a beginner in MPSGE. Technical Note* (4).

Parvania, M., Fotuhi-Firuzabad, M. & Shahidehpour, M. (2013), 'Optimal demand response aggregation in wholesale electricity markets', *IEEE Transactions on Smart Grid* **4**(4), 1957–1965.

PMCIES (2006). Duke Energy Power Manager Customer Impact Evaluation Study, Personal Communication from Dr. Tom Osterhus, Integral Analytics.

Ray, S. (2009), Mean value theorem, IIT.

Rodrigues, R. & Linares, P. (2015), 'Electricity load level detail in computational general equilibrium–part ii–welfare impacts of a demand response program', *Energy Economics* **47**, 52–67.

Ross, M., Beach, R., Depro, B. & Murray, B. (2005), 'Empax-cge model documentation'.

Rutherford, T. F. (1999), ‘Applied general equilibrium modeling with mpsge as a gams subsystem: An overview of the modeling framework and syntax’, *Computational economics* **14**(1), 1–46.

SDGEDRPPE (2016). San Diego Gas & Electric Demand Response Program Process Evaluation.
URL: *http://www.calmac.org/publications/SDG&E_Demand_Response_Process_Evaluation_Final_041316.pdf*

Wang, X. J. & Curry, D. J. (2012), ‘A robust approach to the share-of-choice product design problem’, *Omega* **40**(6), 818–826.

Winer, B. J., Brown, D. R. & Michels, K. M. (1971), *Statistical principles in experimental design*, Vol. 2, McGraw-Hill New York.

Wing, I. S. (2004), ‘Computable general equilibrium models and their use in economy-wide policy analysis’, *Technical Note, Joint Program on the Science and Policy of Global Change, MIT* .

Wing, I. S. (2006), ‘The synthesis of bottom-up and top-down approaches to climate policy modeling: electric power technologies and the cost of limiting us co 2 emissions’, *Energy Policy* **34**(18), 3847–3869.

Yu, T., Kim, D. S. & Son, S.-Y. (2013), ‘Optimization of scheduling for home appliances in conjunction with renewable and energy storage resources’, *International Journal of Smart Home* **7**(4), 261–272.

Zhu, Z., Tang, J., Lambotharan, S., Chin, W. H. & Fan, Z. (2012), An integer linear programming based optimization for home demand-side management in smart grid, *in* ‘2012 IEEE PES Innovative Smart Grid Technologies (ISGT)’, IEEE, pp. 1–5.

Appendix A
Appendix to Chapter 1

A.1 Previous Models

In this section we describe the two models: UC and SOC that are combined in our CD model and explain how they are currently used by several electricity service providers to reduce overall costs *PMCIES* (2006). We use a single contract model in this study.

A.1.1 The UC Model

The UC model Johnson et al. (1997) helps to decide which power generation units should be turned on or off and when, in order to meet the electricity demand while minimizing cost incurred by the service provider. There are suppliers (generators) indexed by s, where $s \in \mathcal{S}$ $= \{1, 2, ..., S\}$. Similarly there are time periods indexed by t, where $t \in \mathcal{T} = \{1, 2, ..., T\}$.

<u>*Parameters*</u>

D_t Forecast demand for period t (MW/h)

F_s Fixed cost incurred when supplier s is committed ($)

C_s Variable cost incurred for supplier s ($/MW/h)

S_s Start-up cost for supplier s ($/start-up)

$\mathcal{L}_s$ Minimum power supply threshold for supplier s (MW)

$\mathcal{U}_s$ Maximum power supply threshold for supplier s (MW)

<u>*Continuous Variable*</u>

g_{st} Amount of power generated (supplied) by supplier s in time period t (MW/h)

<u>*Binary Variables*</u>

$n_{st} = 1,$ if supplier s is started in period t, 0 otherwise

$z_{st} = 1,\quad$ if supplier s is committed or generates power in time period t, 0 otherwise

Expressions (A.1)-(A.5) below is a Mixed Integer Linear Programming (MILP) formulation of the UC problem.

$$\text{MILP} : Z_{\text{UC}} = \text{Min} \sum_{s=1}^{S} \sum_{t=1}^{T} [C_s g_{st} + F_s z_{st} + S_s n_{st}], \tag{A.1}$$

subject to

$$\sum_{s=1}^{S} g_{st} \geq \ D_t \qquad t \in \mathcal{T}, \tag{A.2}$$

$$g_{st} \geq z_{st} \mathcal{L}_s \qquad s \in \mathcal{S},\ t \in \mathcal{T}, \tag{A.3}$$

$$g_{st} \leq z_{st} \mathcal{U}_s \qquad s \in \mathcal{S},\ t \in \mathcal{T}, \tag{A.4}$$

$$z_{st} \leq z_{s(t-1)} + n_{st} \qquad s \in \mathcal{S},\ t \in \mathcal{T}, \tag{A.5}$$

$$g_{st} \geq 0, n_{st}, z_{st} \in \{0, 1\}.$$

The objective (A.1) minimizes the overall costs for the service provider, including fixed (F_s) and variable (C_s) costs of generation, and start-up costs (S_s) incurred each time a generator is started. Constraint (A.2) ensures that the amount of power generated (g_{st}) meets the demand (D_t). Constraints (A.3) and (A.4) represent the floor ($\mathcal{L}_s$) and ceiling ($\mathcal{U}_s$) values for the amount of power generated. Constraint (A.5) states that if a generator needs to be committed in period t and it was not committed in $t-1$, it has to be started in period t. The boundary condition is that no generator is committed at $t = 0$. i.e. $z_{s0} = 0$.

A.1.2 The SOC Model

In this section, we introduce the SOC model. The objective of the SOC model is to maximize the number of customers who sign up for a power interruption contract. We use the notation from Camm et al. Camm et al. (2006) in our paper. Each contract has attributes indexed by k, where $k \in \mathcal{K} = \{1, 2, ..., K\}$. Attributes are features of a contract. For example, a contract could have attributes like customer power interruption ceiling and compensation. Each attribute has levels. For example customer power interruption ceiling could have levels 1kW, 1.5kW and 2kW per hour. The levels on each attribute k are indexed by ℓ, where $\ell \in \mathcal{L}$ $= \{1, 2, ..., L_k\}$. The total number of customers or respondents are indexed by j , where $j \in \mathcal{J} = \{1, 2, ..., J\}$.

Parameters

$u^j_{k\ell}$ Part-worth utility of level ℓ on attribute k for customer j. The term part-worth is the preference score or utility of an attribute level combination.

h_j The hurdle utility for customer j, corresponding to the utility of their present plan without interruption)

Binary Variables

$x_{k\ell}$ $= 1$, if level ℓ is chosen for attribute k, 0 otherwise

y_j $= 1$, if the hurdle utility h_j is exceeded by the contract, 0 otherwise

An Integer Programming (IP) formulation for the SOC model is as follows:

$$\text{IP} : Z = \text{Max} \sum_{j=1}^{J} y_j, \tag{A.6}$$

subject to

$$\sum_{\ell=1}^{L_k} x_{k\ell} = 1 \qquad k \in \mathcal{K}, \tag{A.7}$$

$$\sum_{k=1}^{K} \sum_{\ell=1}^{L_k} u^j_{k\ell} x_{k\ell} \geq h_j y_j \qquad j \in \mathcal{J}, \tag{A.8}$$

$$x_{k\ell}, y_j \in \{0, 1\}.$$

The objective (A.6) maximizes the number of customers for whom the utility of a contract exceeds their hurdle. Constraint (A.7) ensures that only one level is chosen per attribute for each contract. Constraint (A.8) enforces that y_j is 1 only if a contract satisfies customer j's hurdle utility.

In this paper, motivated by the Power Manager Customer and Impact Evaluation study conducted by Duke Energy Indiana and Kentucky in 2006 *PMCIES* (2006), we focus on three key attributes: Fixed payment to customer (participation incentive), variable payment (per hour credit and interruption ceiling per customer per hour. Thus any solution to the SOC model provides a list of SOC customers (corresponding to $y_j = 1$) and a set of attribute levels chosen (corresponding to $x_{k\ell} = 1$. For increased clarity, we represent the values of chosen attribute levels as $\mathbb{F}$, $\mathbb{V}$, and $\mathbb{C}$, respectively representing the fixed, variable payment and the interruption ceiling. In Section 2.3 we explain how we use the customers from the SOC approach in the UC model.

A.2 Proof of Proposition 1

In order to prove Proposition 1, we introduce the following basic notation and methodology regarding utility values and their simulation. These simulated utilities satisfy the condition 1 specified in the Section 2.5.2.2.

1. **Additive Utility with Random Deviations:** For $m =$ SOC or CD, the utility for customer j is additive in the attributes and given by $u_j^m = \sum_{k=1}^{K} u_{k\ell^m}^j + \epsilon_j^h$ where ϵ_j^h is a suitably defined random variable. For instance, adapting the utility simulator from Crabbe et al. Crabbe et al. (2011), we could use $\epsilon_j^h = S_j n_h d_j$ with S_j denoting a randomly generated sign, $n_h = 1$ or 2 respectively for the case of homogeneous or heterogeneous customers, d_j is a random deviation specific to customer (or segment) j. Typically, $\sum_{j=1}^{J} S_j n_h d_j = 0$, so there are only $J - 1$ degrees of freedom.

2. **Attribute-specific Utility:** The utility from each attribute k at level ℓ is given by $u_{k\ell}^j = u_{k\ell}^{base} + \beta_{k\ell}$, per Camm et al. (2006). $u_{k\ell}^{base}$ is a random utility generated similar to utility for segment 1 in Crabbe et al. (2011) and $\beta_{k\ell}$ is random variable (that is beta distributed in Camm et al. (2006)). Typically, $\sum_{\ell=1}^{L_k} \beta_{k\ell} = 0$, $\forall\ k$ and this is achieved by generating $L_k - 1$ random variates and setting the L_k^{th} variate to $-\sum_{\ell=1}^{L_k-1} \beta_{k\ell}$.

3. **Mapping Between Utility and Attribute Value:** Motivated by the utility rank model in *SDGEDRPPE* (2016), $u_{k\ell}^{base} = \alpha_{k\ell}\gamma_{k\ell}$, where $\alpha_{k\ell}$ is a partworth coefficient from a statistical (regression) model for utility estimation from actual customer preference data and γ denotes the value of attribute k at level ℓ.

In this paper, we consider only two attributes $\mathcal{F}$ and $\mathcal{C}$. Further, based on *SDGEDRPPE* (2016), $|\alpha_{\mathcal{F}\ell}| >> |\alpha_{\mathcal{C}\ell}|$ with $\alpha_{\mathcal{F}\ell} > 0$ and $\alpha_{\mathcal{C}\ell} < 0$, since utilities are monotone increasing in fixed payments and montone decreasing in interruption ceilings. Thus, for our two-attribute case and $m \in \{\text{CD}, \text{SOC}\}$, $u_j^m = \alpha_{\mathcal{F}}^m \mathcal{F}^m + \alpha_{\mathcal{C}}^m \mathcal{C}^m + \beta^m + \epsilon_h^j$, where $\beta^m = \beta_{\mathcal{F}\ell^m} + \beta_{\mathcal{C}\ell^m}$, $\alpha_{\mathcal{F}}^m = \alpha_{\mathcal{F}\ell^m}$ and $\alpha_{\mathcal{C}}^m = \alpha_{\mathcal{C}\ell^m}$. So clearly

$$\begin{aligned} u_j^{\text{SOC}} - u_j^{\text{CD}} &= \alpha_{\mathcal{F}}^{SOC}\mathcal{F}^{SOC} - \alpha_{\mathcal{F}}^{CD}\mathcal{F}^{CD} + \alpha_{\mathcal{C}}^{SOC}\mathcal{C}^{SOC} - \alpha_{\mathcal{C}}^{CD}\mathcal{C}^{CD} + \\ &\quad \beta_{\mathcal{F}}^{SOC} - \beta_{\mathcal{F}}^{CD} + \beta_{\mathcal{C}}^{SOC} - \beta_{\mathcal{C}}^{CD} + \epsilon_j^h - \epsilon_j^h, \end{aligned} \tag{A.9}$$

which is independent of j.

Before we proceed to the proof, we note that SOC is the largest set of potential customers for the DR program. Hence, $|\text{SOC}| \geq |\text{CD}|$, where the vertical lines denote set cardinality. In the remainder of this section we only consider the non-trivial case when SOC contains a customer who is not in CD with $|\text{SOC}| > |\text{CD}|$.

Proof of Lemma 1. Since $|\text{SOC}| > |\text{CD}|$, there is at least one customer $j \in$ SOC, $j \notin$ CD. This j must have $u_j^{SOC} \geq h_j$ and $u_j^{CD} < h_j$. Hence, for this j, $u_j^{SOC} > u_j^{CD}$. Therefore the right-hand-side of (A.9), henceforth referred to as RHS, must be positive for this customer and hence positive for all customers. Consequently, $u_j^{SOC} > u_j^{CD}, \forall j$, since RHS independent of j. Hence, CD $\subseteq$ SOC, which proves Lemma 1. $\square$

Proof of Proposition 1. :

$$\begin{aligned}
\sigma^{SOC} &\overset{\text{Definition}(1)}{=} \max_{j \in SOC} u_j^{SOC} - \min_{j \in SOC} u_j^{SOC} \\
&\overset{\text{Lemma 1(ii)}}{=} \max_{j \in SOC} u_j^{CD} - \min_{j \in SOC} u_j^{CD} \\
&\overset{\text{Lemma 1(i)}}{\geq} \max_{j \in CD} u_j^{CD} - \min_{j \in CD} u_j^{CD} \\
&\overset{\text{Definition}(1)}{=} \sigma^{CD}. \quad \square
\end{aligned}$$

Appendix B
Appendix to Chapter 2

B.1 CGE Equation Set

A CGE model involves a two stage procedure of minimizing production costs at the customer end subject to Constant Elasticity of Substitution (CES) production function and minimizing expenditures at the customer end subject to a CES utility function. Using the first order cost and expenditure minimization conditions, we derive a cost function for each producer and an expenditure function for each customer. The cost and expenditure functions are then used to formulate the Mixed Complementarity (MCP) problem.

The CES production function is given as:

$$y_j = A_j[\sum_i \alpha_j^i {x_j^i}^{(\sigma_j-1)/(\sigma_j)}]^{(\sigma_j-1)/(\sigma_j)}, A > 0, 0 < \alpha_j^i < 1, \sum_i \alpha_j^i = 1, \forall j \tag{B.1}$$

The CES utility function is given as:

$$U_H = A_H[\sum_i \alpha_H^i {x_H^i}^{(\sigma_H-1)/(\sigma_H)}]^{(\sigma_H-1)/(\sigma_H)}, A > 0, 0 < \alpha_H^i < 1, \sum_i \alpha_H^i = 1, \forall H \tag{B.2}$$

Here, y_j denotes the output in each sector j and x_i denotes the inputs from each factor sector i. A is a technology parameter calculated from the SAM calibration. α^i represents the share of inputs in the production and expenditure. σ_j is the elasticity of substitution of supply and σ_H is the elasticity of substitution of demand. Elasticity values are externally supplied.

After solving for the first order cost minimization conditions as mentioned by Martin &

Skinner (1998), the cost function for each output sector j takes the form:

$$c_j = [\sum_i \alpha_j^i {p_j^i}^{(\sigma_j-1)/(\sigma_j)}]^{(\sigma_j-1)/(\sigma_j)}, 0 < \alpha_j^i < 1, \sum_i \alpha_j^i = 1, \forall j \tag{B.3}$$

and the expenditure function takes the form:

$$e_H = [\sum_i \alpha_H^i {p_H^i}^{(\sigma_H-1)/(\sigma_H)}]^{(\sigma_H-1)/(\sigma_H)}, 0 < \alpha_H^i < 1, \sum_i \alpha_H^i = 1, \forall H \tag{B.4}$$

.

Here p_j^i denotes the price of input i for sector j and p_H^i denotes the price of commodity i for customer H. These cost and expenditure functions are used to formulate the MCP problem. Martin & Skinner (1998) have used a two factor, two product , single household economy to facilitate the understanding of these equations. The economy has two commodities X and Y with unit price P_x and P_y. There are factor inputs L and K sold at w and r respectively.

There are unit cost function for the commodities X and Y ($c_x$and c_y) expressed as functions of factor inputs. These cost functions are the output of the first order cost minimizations at the producer level as mentioned earlier.

$$c_x = c_x(P_w, P_r), c_y = c_y(P_w, P_r) \tag{B.5}$$

There is an expenditure function for the customer expressed as a function of commodity prices. This expenditure function is an output of the first order expenditure minimization as mentioned earlier.

$$e_x = e_x(P_x, P_y) \tag{B.6}$$

The equations below are used to formulate the MCP problem based on the cost and expenditure functions.

Zero Profit for X

$$P_x = c_x(P_w, P_r) \tag{B.7}$$

Zero Profit for Y

$$P_y = c_y(P_w, P_r) \tag{B.8}$$

Zero Profit for W

$$P_w = e(P_x, P_y) \tag{B.9}$$

Market Clearance for X

$$X = e_{px}e(P_x, P_y)W \tag{B.10}$$

Market Clearance for Y

$$Y = e_{py}e(P_x, P_y)W \tag{B.11}$$

Market Clearance for L

$$L* = c_{xw}X + c_{xw}Y, L* = L_x + L_y \tag{B.12}$$

Market Clearance for K

$$K* = c_{xr}X + c_{xr}Y, K* = K_x + K_y \tag{B.13}$$

Market Clearance for W

$$W = I/P_w \tag{B.14}$$

Income Balance

$$M = WL * +rK* \tag{B.15}$$

These nine equations are solved to get nine unknowns X, Y, W, P_x, P_y, P_w, w, r and M. These equations are identical to the equations of the Base model in this paper.

In the DR model, a subsidy is given to DR customers. Once a subsidy is implemented, the equilibrium equations change to incorporate that subsidy. For example, if we consider a subsidy for sector X, the subsidy for sector X is represented as T_x. The equations are modified for sector X as below.

Price of X with a subsidy

$$P'_x = P_x(1 - T_x) \tag{B.16}$$

Zero Profit for X

$$P'_x = c'_x(P_w, P_r) \tag{B.17}$$

Market Clearance for X

$$X = e_{px'}e(P'_x, P_y)W \tag{B.18}$$

B.2 Nested Price Elasticity and Elasticity Structure of Peak Demand and Transportation Sectors

When there are multiple groups of commodities with differing elasticity of substitution between them a nesting structure is beneficial as per Martin & Skinner (1998). In our model, there is a nest of peak load and transportation and another nest of base load and all the other sectors.

A nested expenditure function can be represented as below. If prices for goods X and Y are P_x and P_y and these are arguments to the expenditure function $e(P_x, P_y)$. Then in a two level nest, we would have:

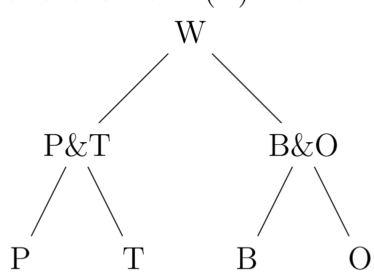
$$e(P_x, P_y) = (\sum_k \theta^k c^k(p)^{(1-\sigma_0)})^{(1/1-\sigma_0)}, \tag{B.19}$$

where θ is the share parameter and σ is the elasticity parameter

$$c^k(p) = (\sum_{k \in I_k} \alpha_{ik} p_i^{1-\sigma_k})^{(1/1-\sigma)}, \tag{B.20}$$

where I_k indicates the commodities entering nest k, α is the share parameter and σ is the elasticity parameter

This is illustrated for our specific example of welfare (W), peak load (P) and transportation (T) and base load (B) and the other sectors (O) as below:



Between P and T , there is the elasticity of substitution σ_{PT} and between B and O there is the elasticity of substitution σ_{BO}. In the Base model σ_{PT} is taken from the literature (Ross et al. 2005) and no changes are made. Our framework varies σ_{PT} and studies its effects on economic variables when DR is implemented in the Base model. Then the value of the new σ_{PT} is calculated as $\sigma_{PT'}$ = (1/Sensitivity) * σ_{PT} . The sensitivity values are lower for more elastic customers compared to less elastic customers. In other words, a customer with a higher preference for DR will have a higher elasticity compared to one who has a lower preference for DR.

B.3 CGE Solution Methodology

In a CGE model, the objective function is a joint minimization of excess demands. In other words, it is a joint minimization of equations B.7-B.15. The solution method is a Newton-type steepest-descent optimization algorithm as mentioned in Wing (2004). The algorithm is briefly described as follows. Consider a function $f(x)$ that has a root. In order to find this root, construct a tangent line through the point $(X_0, f(X_0))$, with a slope $f'(X_0)$. It is possible that this line intercepts the X-axis at a point X_1 which maybe a better approximation to the root than X_0. So we iterate according to the relation $X_{n+1} = X_n - f(X_n)/f'(X_n)$ until convergence occurs. In the case of a CGE model, x is replaced with the vector of prices and activity levels. $f(x)$ represents the equilibrium equations (excess demands). The derivative $f'(x)$ is replaced with its multivariate analogy called Jacobian matrix. If the Jacobian matrix is non-singular it can be inverted and the model can be solved to determine the relevant x values.

A non-singular Jacobian matrix implies that $f(x)$ is both continuous and differentiable in x. Newton's algorithm converges regardless of the starting "seed" if $f'(x) \neq 0$ in the interval where the solution is present. According to Ray (2009), if $f(x)$ is both continuous and differentiable, there exists at least one point c where $f'(x) \neq 0$. In the context of CGE models like ours with exogenous distortions (parametric changes in elasticities and subsidies), $f(x)$ is both continuous and differentiable in x, and hence the algorithm converges. In addition to that, in the presence of exogenous distortions there is a unique equilibrium as proven by Kehoe (1985). Additionally, as per Wing (2004) the conditions of existence and uniqueness of equilibrium are met by the excess demand equations in our model, since the production and utility function remain concave. In summary, since the algorithm converges to a unique equilibrium, the value of the starting "seed" doesn't change the equilibrium solution.