MODELING OF CONSUMER RESPONSES TO DYNAMIC PRICING IN A SMART GRID

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ABSTRACT

This paper models the responses of three different types of consumers based on their sensitivity to dynamic price. Simulated household demand data is used to model the dynamic price of electricity. These prices are then used to experiment responses of consumers in a centralized dynamically priced power market. It is taken into consideration that some consumers will only have access to imperfect information but they can still alter their usage and benefit from the associated cost savings. Analysis based on a developed software system found that sensitive consumers, given full information and control with tools such as a Home Area Network and an Advanced Metering Infrastructure, could gain significant cost savings. Due to the reduction of the overall peak load caused by the shift in consumer demand, the electricity generation and distribution infrastructure could see significant savings as well.

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CHAPTER 1. INTRODUCTION

A smart grid is a digitally enabled electrical grid that gathers, distributes, and acts on real-time information in order to improve the efficiency, reliability and sustainability of the electric grid system (Ketter, Collins and Block, 2008). Dynamic pricing is an integral part of a smart grid. The dynamic price of electricity determines the price of electricity for a time period based on the demand in that given time period. The dynamic pricing of a smart grid could mitigate the effect of uncertainties in the electric grid system (Roozbehani, Dahleh and Mitter, 2010).

Dynamic price gives financial incentive to a consumer to lower his/her consumption or change the time of consumption from peak hours to off –peak hours. Across the range of experiments studied, dynamic price could reduce the peak demand that ranges between 3 and 6% and critical-peak pricing (CPP) tariffs could induce a drop in the peak demand which range between 13 and 20% (Faruqui and Sergici, 2010). It is assumed that the real time price declared by the utility company will be processed by a smart device that will control the appliances in a household (Mohsenian-Rad and Leon-Garcia, 2010). Consumers need to have a smart home to reap the benefits of dynamic pricing.

The objective of this paper is to model consumer responses when consumers do not have a smart home or a smart device to process the real-time price information. The consumers respond based on imperfect information about real-time price. With imperfect information, a consumer predicts the price of electricity based on an assumed pattern of price. Based on the estimated pattern of price, a consumer makes decisions to reduce consumption and/or shift a load.

Different forecasting methods have been applied to forecast the demand of electricity for the purpose of determining the real-time price, including the weighted average price prediction filter (Mohsenian-Rad and Leon-Garcia, 2010), the artificial neural network (Shakiba, Ghaderi and Amalnik, 2011), the regression model (Aggarwal, Saini and Kumar, 2008), etc. In this paper, a statistical time series forecasting technique, the Winters Method for Seasonality is applied for forecasting the demand of electricity. This forecasting method has the capability to capture trends from previous hours, recent days and seasons.

Two different cost functions are applied to calculate the dynamic price of electricity to model the variations in consumer responses. Three types of consumers are considered: moderate price sensitive, very price sensitive and not price sensitive. Different levels of sensitivity to price help to capture responses to price in a wider range of consumers. This makes the experiment more practical and applicable. The sensitivity to price rewards the consumers and the suppliers but adds a penalty for a consumer who is not sensitive to price. A scalable software is developed to demonstrate the developed model and calculate empirical benefits of applying dynamic pricing.

In the simulated analysis, it is established that a consumer could reduce up to $15.49 (14.1%) from his/her monthly electricity bill. This paper considers that a consumer might not be able to access or process the price of electricity every hour. With imperfect information, a consumer would be able to benefit from dynamic pricing. Thus, without having a smart home, the concept of dynamic pricing could be applied. This paper assumes that consumer will have smart meters so that the utility suppliers could have hourly consumption data. A consumer with perfect information processed by a smart device could save as high as 21.87% of monthly electricity bill. It is assumed that for a smart house, all appliances are controlled by an intelligent smart device that takes decisions based on the price sensitivity of the consumer and historical consumption data.

The structure of this paper is as follows. Chapter 2 describes the related literature in smart grid and dynamic pricing. In chapter 3, the electricity market, the current trends of consumption, the challenges for electricity market and source of data for this experiment are described. In chapter 4, the Winters Method for Seasonality is applied on test data to analyze its performance. In chapter 5, two cost functions are applied to calculate the dynamic price of electricity. In chapter 6, different categories of consumers and the utility function are presented. In chapter 7, structure, components and user interfaces in the simulated software are discussed. In chapter 8, experimental results are analyzed and benefits for consumers and suppliers are analyzed. Finally, in the last chapter, future research is presented.

CHAPTER 2. BACKGROUND AND LITERATURE REVIEW

The concept of smart grid enhances every corner of the electricity delivery system, which includes generation, distribution, transmission and consumption. It has the power to take new utility initiatives and influence or encourage consumers to react by modifying patterns of consumption. The Smart Grid provides an extraordinary prospect to upgrade the electricity industry with a new era of efficiency, availability, and reliability. In recent years, the smart grid has been studied to make the electric grid sustainable and effective.

2.1. The Smart Grid

The smart grid is a modernization of electric grid technologies. Smart grid provides an opportunity to dynamically optimize grid resources and incorporates consumers in an information infrastructure. The smart grid not only supplies electricity but also monitors the performance of distributed control. It makes real time decisions and implements them in the physical grid system (Hatami and Pedram, 2010). The smart grid provides a better sense of the status of equipments and options for robust control along the transmission lines by using the internet, a transmission control device, computer data processing, etc. The demand side management with smart appliances (automated control of equipments), scheduling loads like electric vehicle chargers (during off peak hours) are done by a smart device in a smart home (Kamilaris and Pitsillides, 2011). The smart grid requires improvement in transformations and upgrades in the infrastructures to support the digital layer of information processing.

More and more electronic devices are being added to households and utilized in the modern life style. The price of electricity is increasing every year (Figure 1) based on the data published by the Energy Information Administration (EIA, Factors Affecting Electricity Prices, 2010). To modernize the electric grid system, the smart grid will be adopted to make the grid system robust. The benefits from a Smart Grid include:

- Self-healing to reallocate power in near real time by quickly diagnosing problems and taking corrective actions after power cut-off (Nygard, Bou Ghosn, Chowdhury, Loegering, McCulloch and Ranganathan, 2011)
- Real time monitoring of equipment, control and sensor of distributed resources
- Two-way exchange of information
- Lower management and operation costs for the utility supplier and reduced price of electricity for consumers
- Lower peak demand
- Allow the integration of customer-owned small power generation systems to the grid
- Improved security against malicious attacks

Technology and modern data processing engines to process data and make decisions would make the smart grid possible. Wireless sensors could be networked with a secure time synchronization that is scalable, fast convergent, less latent, energy efficient, topology independent and less application dependent (Ranganathan and Nygard, Time Synchronization in Wireless Sensor Network: A Survey, 2010). The internet, remote device control and powerful computers provide the infrastructure to make the electric grid intelligent (Ranganathan and Nygard, An Optimal Resource Assignment Problem in Smart Grid, 2010).

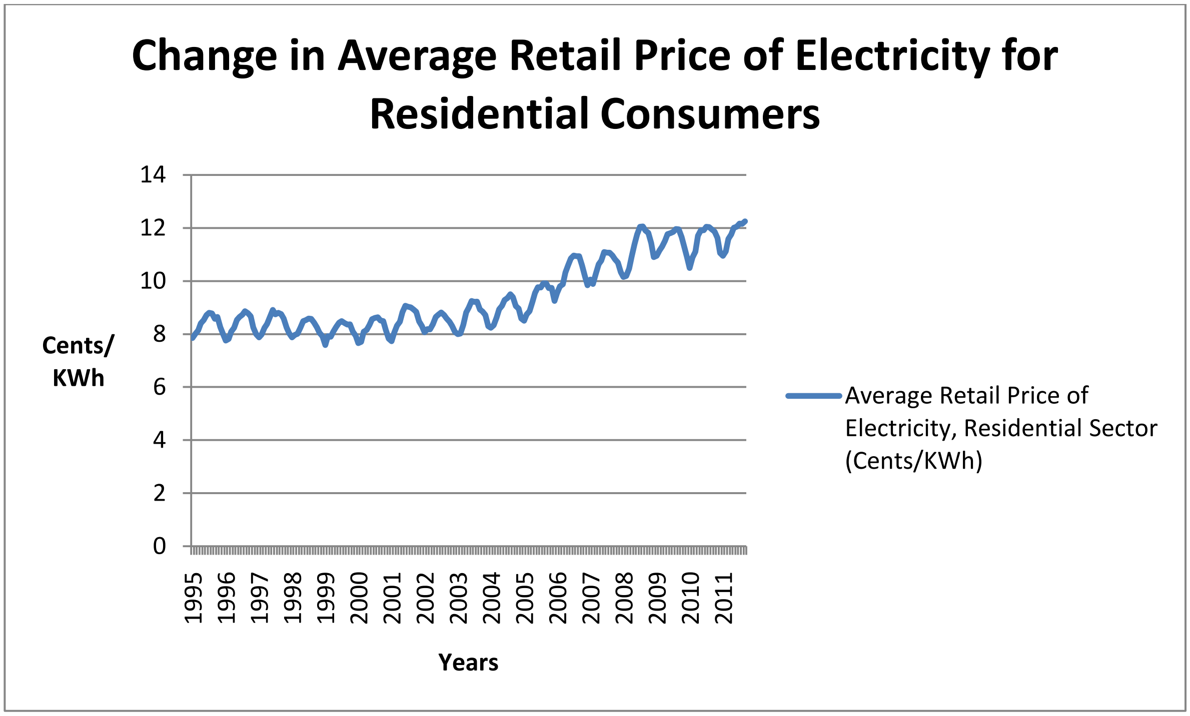


Figure 1. Average Retail Price of Electricity for Residential Consumers (Cents/KWh)

2.2. Dynamic Pricing

Dynamic pricing is studied and being applied for consumer goods. Dynamic pricing is effective in maximizing profit for a multi-item supply chain experimented by applying linear programming models (Nahapetyan and Pardalos, 2006). The US retail consumers pay a fixed price for electricity declared for all periods. This existing price model for electricity hides the temporal deviation in the demand of electricity. The institutions that govern the price of electricity vary across the nation. In the USA, the demand of electricity varies by region and season (Paul, Myers and Palmer, 2009). Electricity demand is higher during the afternoon and lower during the night time hours. The consumption of electricity in a household depends on several factors like household income, weather, number of rooms, price of electricity, etc

(Khattak, Tariq and Khan, 2010). The price not being elastic to demand creates an inefficient electricity market (Allcott, 2011).

In dynamic pricing, the intended cycle is divided into periods and the price for a period is declared at the beginning of the period of operation. Dynamic Pricing has been studied and potential benefits have been calculated for consumers and utility suppliers by lowering the consumption, in response to variable price (Faruqui, Hledik and Tsoukalis, 2009). To secure market stability and uninterrupted supply, contract-based baseline through demand subscription is studied to ensure that consumers will receive the minimum amount of electricity (Chao, 2010). In (Samadi, Mohesnian-Rad, Wong and Jatskevich, 2010), the authors considered a smart power infrastructure with the smart meter and a two-way communication for utility maximization for real time processing of price information by the consumers.

Real-time pricing of electricity based on grid load helps to lower peak electricity demand with respect to a given load profile (Oldequrtel, Ulbig, Parisio, Andersson and Morari, 2010). The grid load is comprised of all types of consumers, including household and industrial consumers. Using the grid load for the dynamic price of electricity for household consumers is not truly dynamic for them. This paper uses simulated data of a household consumer for modeling the consumer response. In another study with published articles regarding the dynamic price of electricity, the authors found that dynamic price for a consumer empowered by enabling technologies will reduce peak demand 27-44% (Faruqui and Segici, Household Response To Dynamic Pricing Of Electricity—A Survey of the Experimental Evidance, 2009).

Most of the published articles assumed smart device processing of real-time price of electricity (Bapat, Sengupta, Ghai, Arya, Shrinivasan and Seetharam, 2011) with the availability of perfect information (Samadi, Mohesnian-Rad, Wong and Jatskevich, 2010). In (Du and Lu, 2011), appliance scheduling is experimented to respond with dynamic price of electricity. This means consumers who do not have a smart device at home will not benefit from dynamic pricing. It is not certain when a significant number of households in the USA would have enabling technology to deal with real-time price of electricity. There would be a significant number of consumers who will be using traditional appliances (no connectivity with wireless network) and will keep consuming electricity without changing consumption pattern. This would be financially shocking as dynamic price of electricity will increase the monthly bill rather than decreasing it.

The aim of this paper is to model benefits for consumers who only have a smart meter but do not have a smart device/controller to make decisions based on the real-time price of electricity. The consumers are further categorized based on their level of sensitivity to price. The penalty for consumers not being price sensitive is also calculated based on simulated demand. Finally, typical load profile and load profile under dynamic pricing are simulated to experiment benefits under different level of sensitivity for a smart device in a smart home.

CHAPTER 3. ELECTRICITY MARKET AND CONSUMER BEHAVIOR

Surprisingly, the current grid system being used today in power grids were modeled and published in late 19th century. This grid system uses obsolete power grid features and assumptions like demand driven generation, unidirectional and centralized vision of the 19th century. During the period of designing of the electric grid, home demand was a few lights and maybe a radio. Modern houses consume electricity for various purposes like heating, air-condition, dish washers, computers and various other appliances. It becomes more challenging and less economic to deal with one directional centralized control of electricity supply. The major reason of holding a 120 year old technology is to avoid the huge infrastructural cost of adopting new techniques and to avoid the interruption of supply.

The electricity being used at any given time is generated less than a second ago many miles away by power grid system. The power being generated at any given time by the generator has to be equal to the demand of that point of time. Power plants need to keep running or add extra sources of power generation to meet the demands during peak load times. This adds higher overhead cost and eventually increases the price of electricity and the entire system becomes inefficient.

3.1. The Electricity Market in the USA

The electricity market is one of the key players in the US Economy. In 2009, the electric power market accounted for 2.6 percent of the US GDP and the net power generation was 3,950 million Megawatt hours (Hunt, 2010). In a survey conducted by the Energy

Information Administration (EIA), the total consumption of electricity in the USA from January to October 2011was 3,153,689 Million KWh (Electric Power Monthly, 2012). Residential consumers consumed 1,214,487 Million KWh (38.51%), commercial consumers consumed 1,115,476 Million KWh (35.37%) and industrial consumers consumed 817,354 Million KWh (25.92%) (Figure 2). The total revenue in the electricity market was 316,798 million dollars in the year 2011 from January to October. This revenue is 1.4% higher than the revenue during the year 2010 from January to October.

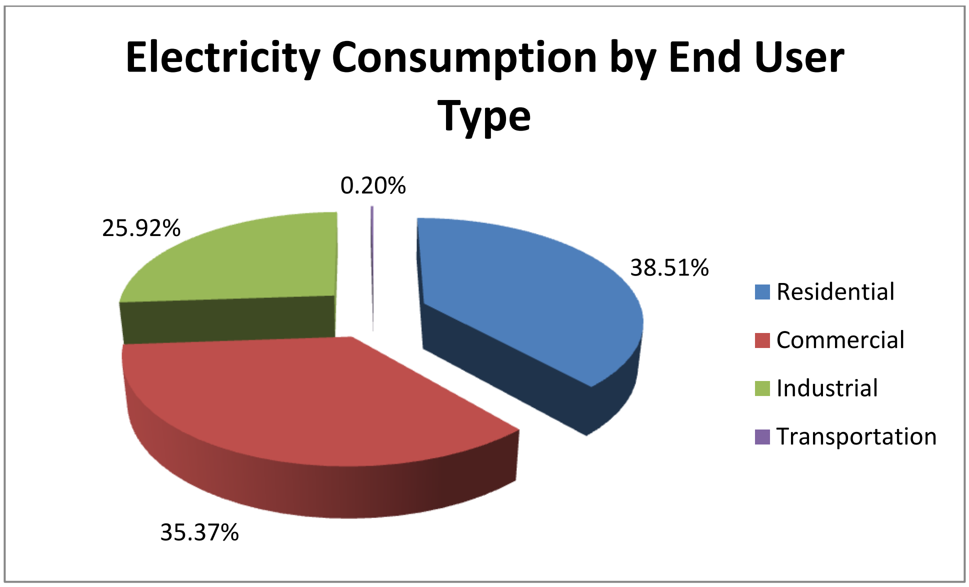


Figure 2. Total Electricity Consumption in the USA in 2011 from January to October

The highest amount of electricity is generated by using fossil fuels. In 2010, 45% of electricity was generated by using coal and 24% was generated by using natural gas. Nearly 20% of the consumed electricity was generated by nuclear power plants. The renewable source of electricity was about 6% from hydropower, about 1% from biomass, about 1% from wind power, about 1% from geothermal power and less than 1% from solar power (EIA, 2011).

The maximum demand of electricity occurs during the summer time due to the high power consumption of electricity by air-conditioners. In 2011, the peak demand for the Independent Service Provider (ISO)-New England occurred on June 22 at 2.00pm (DOE, 2011). This peak demand for one hour in a year decides the investment decision for electricity.

3.2. Electricity Demand

Consumption of electricity has some natural variation based on the type of consumers. The overall demand for electricity in a day increases during the day time and reaches its highest point in the afternoon or evening and then decreases at midnight (Figure 3). The horizontal axis of the figure shows the hours of the day starting from midnight (0…24). Figure 3, shows the total demand of electricity in the USA. One interesting point is that the required maximum power is nearly twice as high as the lowest amount of power consumption. In much of North America, the problem is especially pronounced during the top 60 to 100 hours of the year, which may account for as much as 10–18 percent of the system peak load (Faruqui, Hledik and Tsoukalis, 2009).

3.2.1. Household Consumer

For a household consumer, consumption increases during the evening time and decreases after midnight. The consumption is highly dependent on the weather. The simulated consumption pattern of an average household consumer is shown in figure (Figure 4). For a typical household consumer in San Diego, California, the electricity consumption increases in the summer time due to excessive use of air conditioning in a hot summer day. In the summer time, the power requirement doubles for only a few days (Bartley, T., 2009).

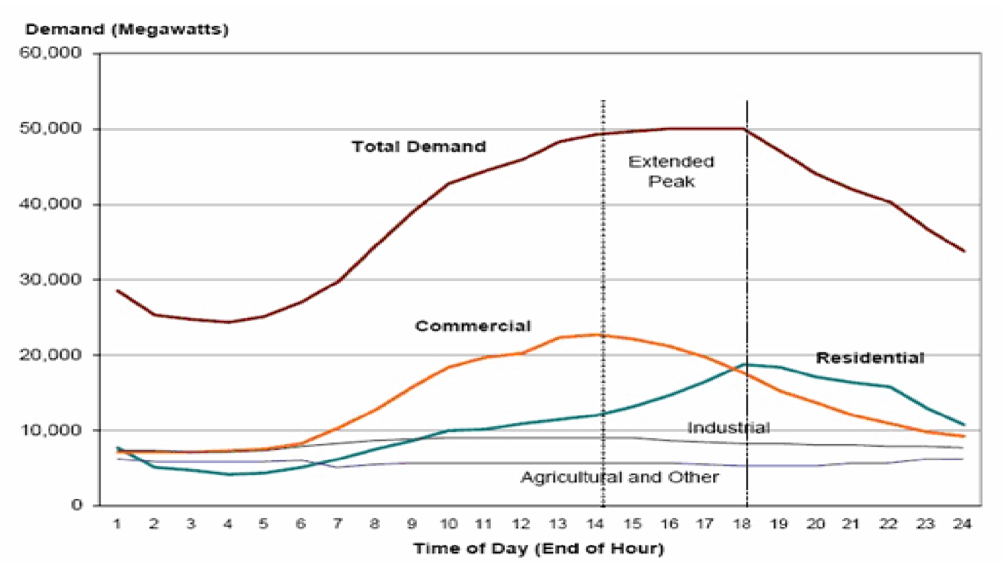


Figure 3. Variation in Total Consumption of Electricity and Type of Consumer (Electropaedia, 2006)

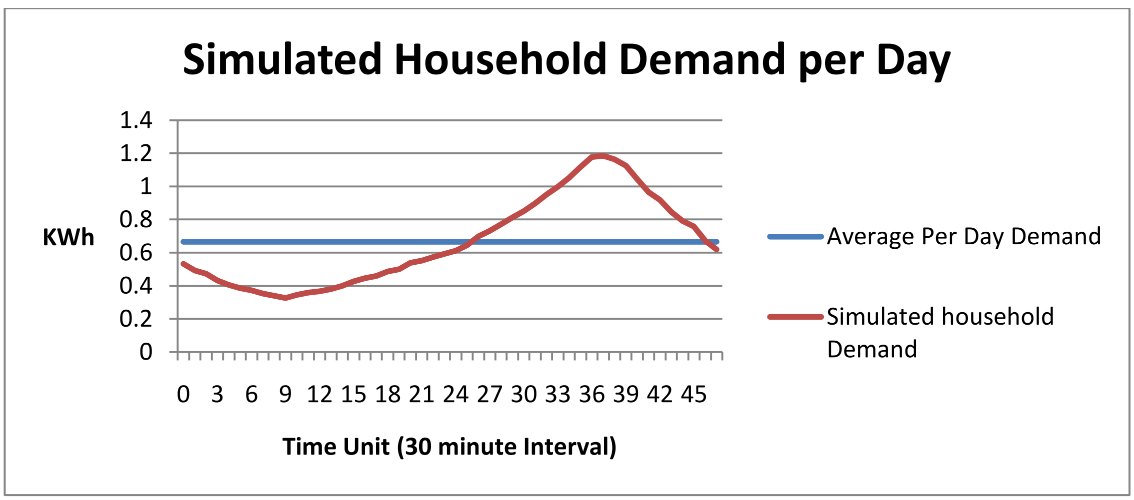


Figure 4. Simulated Household Demand per Day

A published report by the EIA (EIA, Residentail Energy Consumptionn Survery 2001, 2005) depicts the purpose of electricity consumption by household consumers. The highest amount of electricity is consumed by kitchen appliances and air-conditioning. Other major uses of electricity are for space heating, water heating, lighting, etc. By combining air-conditioning, space heating and other Heating Ventilation and Air Conditioning (HVAC) appliance consumption is total 31% (EIA, Electric Power Monthly, 2011).

3.2.2. Price and Usage of Household Electricity

Usually household consumers pay a different price per KWh than commercial consumers or industrial consumers. Table 1 shows the detailed price of electricity for household consumers in different states in the year 2011. On average, a household pays $110.55 per month as electricity bill. The average rate of electricity is 11.54 cents/KWh. A average a household consumes 958KWh per month.

Table 1. Price and Electricity Consumption by Residential Consumer in the USA in 2011

Census Division by State	Number of Consumers	Average Monthly Consumption (KWh)	Average Retail Price(Cents per KWh)	Average Monthly Bill (Dollar and cents)
New England	6,162,023	657	16.24	$106.66
Middle Atlantic	15,654,034	727	15.81	$114.91
East North Central	19,529,930	832	11.41	$94.96
West North Central	9,035,108	994	9.64	$95.87
South Atlantic	25,809,130	1,212	10.96	$132.94
East South Central	8,023,780	1,350	9.58	$129.32
West South Central	14,493,438	1,223	10.67	$130.57
Mountain	8,921,694	872	10.49	$91.49
Pacific Contiguous	17,402,274	675	12.31	$83.09
Pacific Noncontiguous	686,524	617	23.22	$143.28
U.S. Total	125,717,935	958	11.54	$110.55

3.2.3. Commercial Consumer

Commercial consumers consume 35.37% of the total electricity (Figure 2). The consumption of electricity for commercial consumers is during the day time (office hours).

The highest amount is consumed during the afternoon. In evening and nighttime, electricity is consumed mostly for space heating or small lighting and water heating purpose.

3.2.4. Industrial Consumer

There is less variation in the consumption habits of industrial consumers. This might be due to running nearly same amount of machines and equipment to keep production running 24 hours a day and 7 days a week. Due to less variation, there is a low chance to improvement by imposing variable price to become price sensitive and lower the consumption during peak hours or more consumption during off peak hours.

3.3. The Challenge of Electricity Storage

One solution to the variable demand could be storing electricity during the off peak hours and serve it during peak hours. The large scale storage of electricity is very expensive. There are different technologies like batteries, electric vehicles, compressed air, flywheels, hydrogen cells, pump water, etc. These storage facilities require huge infrastructure developments. In the case of a fuel based power development like coal, gas or oil storage needs to be held for a duration of 12 hours to store during the off peak hours in order to supply during the peak hours. If the price of electricity is flat, suppliers do not benefits from a variation in price. In the case of a variable price based on demand (higher price during peak hours and lower price during off peak hours), suppliers will have a higher incentive to store during low price electricity demand and supply it during high price demand. The greatest benefit from a variable price of electricity will be lower demand due to high price at peak hours. This will minimize the peak demand during peak hours which will reduce the necessity of storing electricity.

3.4. Electricity Demand Data

The New York Independent System Operator (NYISO) is a not-for-profit organization based on the New York's Capital Region to govern New York's electricity market to increase reliability. It administers and monitors the wholesale electricity market, conducts planning, assesses long term projects and develops or deploys state-of-the-art technology for a sustainable and efficient power grid in the state of New York. This model applies the Location Based Marginal Price (LBMP) which determines the cost of electricity based on production cost plus the transportation cost which includes losses in the transmission line (NYISO, 2011). The NYISO publishes the wholesale price of consumed electricity everyday on NYISO website.

The National Grid is a unified utility service provider, one of the largest international electricity and gas companies in the world. It supplies energy to millions of customers in Great Britain and the Northeast US. The National grid published half hourly data from April, 2001- December, 2011 (National Grid, 2012). The website also publishes live demand data for the last seven days of demand. One important note about this demand data is that it comprises all kinds of consumers (commercial, household, industrial, etc.). This data is very good for the general analysis of consumers. However, the behavior or load pattern for household consumers is different from the overall demand data. In this paper, both the general consumer data and household the consumer data is applied for analysis.

CHAPTER 4. DEMAND FORECASTING

For setting the dynamic price of electricity, utility suppliers need to predict demand. The demand of electricity is likely to vary based on the type of consumer (household, commercial or industrial) and other factors like weather, time of the day, day of the week, etc. The demand is usually estimated by using historical data of demand. This chapter applies a statistical time series forecasting model, the Winters Method for Seasonality for forecasting the demand of electricity. For the analysis purpose, demand data published on the National Grid website is used (National Grid, 2012).

4.1. Time Series Forecasting

Electricity consumption is very much time dependent. Demand that varies based on the time of consumption could be considered under the category of statistical time series forecasting to estimate future demand. For example, a household consumer consumes the highest amount of electricity in the evening while turning on many lights, watching TV or using computers whereas some loads are basic necessities like refrigerators, heating (during winter), air-conditioning (during summer), etc. A commercial consumer consumes mostly in the day time for space heating, running computers and other office appliances and consumes very little at night for keeping the place warm in the winter or comfortable during the summer (Figure 3).

For the purpose of analysis, in this paper, a demand is forecasted every half an hour. Let, $k \epsilon K$ (0…..47) be the time slots taken into consideration for analysis in a day.

4.2. The Winters Method for Seasonality

The demand for electricity is dependent on the time of the day as well as the weather. Consumers in the northern part of the USA consume more electricity in the winter season for heating purposes and consumers in the southern part of the USA consume more electricity during summer for air-conditioning purposes. The trends in electricity is divided into three parts-

1. Trends in the last couple of hours due to certain changes or malfunctions in the power grid. This captures uncertainties happening in real time.
2. Trend in recent days. For example, the last couple of days were really warm and household consumers were turning on their air-conditioners. The demand forecasting method should capture this trend.
3. The trend in the season to consider last year’s consumption on the same day.

The Winters Method for Seasonality considers all three kinds of trends to forecast demand (Hopp, 2005). The following equations are used to predict demand by applying the Winters Method for Seasonality-

$$F(k) = \alpha \frac{A(k)}{c(k-N)} + (1-\alpha)[F(k-1) + T(k-1)] \ldots \ldots \ldots (1)$$

$$T(k) = \beta[F(k) - F(k-1)] + (1-\beta)T(K-1) \ \ldots \ldots \ldots (2)$$

$$c(k) = \delta \frac{A(k)}{F(k)} + (1-\delta)c(k-N) \ldots \ldots \ldots (3)$$

$$f(k+\tau) = [F(k) + \tau T(k)]c(k+\tau-N) \ \ldots \ldots \ldots (4)$$

This method updates a smoothed estimate *F(k),* a smoothed trend *T(k),* a seasonal factor *c(k)* and compares with actual demand *A(k)*. The forecast period, τ is used to forecast more than one period in the future. Equation 1 and equation 2 calculate the smoothed estimate and the smoothed trend respectably by using exponential smoothing with a linear trend. These two equations capture the linear trend over recent days and the trend during the last couple of hours in consideration. The factor of seasonality is incorporated in equation 1 to get the data about last year's demand as *c(k-N)*. In this paper, *K =48* (48 time units in a day with half an hour interval) and N=12 (12 months in a year). $\alpha,\ \beta$ and δ are smoothing constants between 0 and 1 to be chosen by the utility suppers (estimate demand) determined by the lowest root mean square (RMS) deviation for the best performance in historical data. Equation 4 uses a seasonality factor as exponential smoothing to update season's ratio *A(k)/F(k)*. The RMS value is calculated by using the following equation-

$$RMS = \sqrt{\frac{\sum_1^n [f(k) - A(k)]^2}{K}} \dots\dots\dots (5)$$

4.3. Application of Winters Method for Seasonality

The Winters Method for Seasonality is applied with optimum smoothing constant $\alpha = 0.10, \beta = 0.10, \gamma = 0.10$ (Table 3). The demand of electricity is forecasted by using test data. The forecasted demand is compared with the actual demand in Table 2. For this analysis of the forecasting method, demand data from the National Grid (Grid, 2012) on July 27, 2011 is used. The second and third columns in Table 2 show the demand of the previous day and the same date in the previous year respectively. The fourth and fifth columns show the forecasted demand by applying the Winters Method for Seasonality and the actual demand respectively.

Table 2. Forecasting Total Demand of Electricity by Applying Winters Method of Seasonality in a Test Data Set

Time period	**Previous Day Load (MW)**	**Last Year Load (MW)**	**Forecasted Load (MW)**	**Actual Load (MW)**	**Deviation (MW)**	**Percentage Deviation**
0	27032	27729	26052	27125	1073	4%
1	28898	29710	27589.62	29010	1420.38	5%
2	31106	31856	29474.45	31184	1709.55	5%
3	33158	33868	31544.46	33114	1569.54	5%
4	34275	34910	33481.63	34039	557.37	2%
5	34325	34874	34468.49	33948	-520.49	-2%
6	34267	34510	34400.49	33788	-612.49	-2%
7	34870	35123	34064.22	34283	218.78	1%
8	35382	35543	34663.62	34991	327.38	1%
9	36159	36474	35094.55	35630	535.45	2%
10	36961	37458	35993.21	36560	566.79	2%
11	37567	38292	36926.06	37240	313.94	1%
12	38112	39071	37686.01	37887	200.99	1%
13	38573	39625	38370.43	38330	-40.43	0%
14	38337	39537	38840.92	38202	-638.92	-2%
15	37928	39267	38662.98	37876	-786.98	-2%
16	37603	38952	38297.77	37613	-684.77	-2%
17	37497	38877	37905.52	37576	-329.52	-1%
18	37491	38920	37748.29	37621	-127.29	0%
19	37758	39284	37705.15	37817	111.85	0%
20	37937	39496	37966.1	38066	99.9	0%
21	38247	39953	38088.54	38308	219.46	1%
22	38447	40009	38429.14	38443	13.86	0%
23	38619	40276	38431.8	38664	232.2	1%
41	22620	23159	22414.88	22660	245.12	1%
42	22787	23256	22449.29	22834	384.71	2%
43	23120	23676	22586.36	23143	556.64	2%
44	23568	24131	23013.42	23547	533.58	2%
45	23838	24519	23482.28	23937	454.72	2%
46	24277	25022	23862.91	24492	629.09	3%
47	25220	26052	24355.01	25494	1138.99	4%
Average			32424.45	32398.39	-26.06	0%

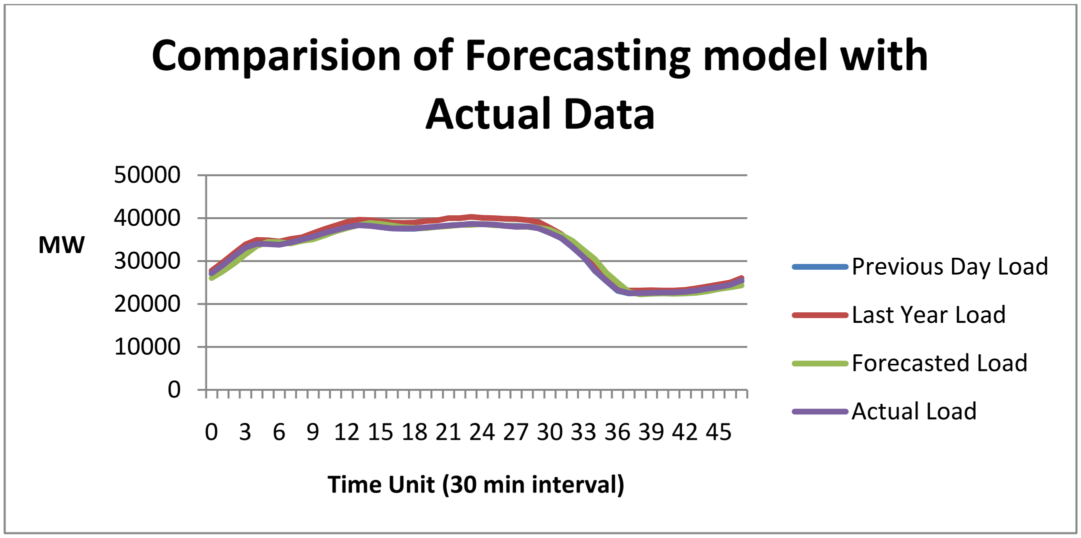


Figure 5. Comparing Variation in Total Demand Data Input and Output for a Forecasting Demand

In Figure 5, the previous day's demand, the last year's demand, the forecasted demand and the actual data is plotted. The figure shows that the forecasted demand is very close to the actual demand. There is some variation from the actual demand which is considered as an unavoidable error of forecasting.

4.4. Determination of the Seasonal Factors

In this paper different set of values of smoothing constants are applied to find the set of values that provides the lowest RMS value. The approach to find the optimum value of three variables is to fix two variables first and observe effect of one variable. This process is repeated until a satisfied local minimum RMS value is found. In Table 3, different set of smoothing constants is shown applied for the test data of July 27, 2011. From the analysis, it is established that the set of factors (0.1, 0.1, 0.1) provides the lowest RMS. Hence, this set of smoothing constant is applied for forecasting demand in this paper.

Table 3. Factors Sensitivity Analysis for Winters Method for Seasonality

No	α	β	δ	RMS	Decision
2	0.2	0.2	0.2	969	
3	0.1	0.1	0.1	847	Lowest
4	0.2	0.1	0.1	917	
5	0.3	0.1	0.1	967	
6	0.1	0.2	0.1	850	
7	0.1	0.3	0.1	883	
8	0.1	0.1	0.2	864	
9	0.1	0.1	0.3	889	
11	0.05	0.1	0.1	884	
12	0.1	0.05	0.1	881	
16	0.1	0.05	0.05	875	

In the following Table 4, the Winters Method for Seasonality is applied on more test data to evaluate performance. The average RMS value is 965 which is only 3.3% of the actual average demand.

Table 4. Application of Winters Method for Seasonality for Different Test Data Set

Date	Demand	0	1	2	3	4	46	47	RMS
8/17/2011	Forecasted	25806	27128	29064	31319	33447	24313	24869	950
	Actual	27404	29140	31235	33336	34935	24646	25685	
7/13/2011	Forecasted	26471	27600	29599	31914	33767	24354	24833	936
	Actual	27383	29409	31586	33287	33616	24786	25787	
7/27/2011	Forecasted	26052	27589	29474	31544	33481	23862	24355	847
	Actual	27125	29010	31184	33114	34039	24492	25494	
8/12/2011	Forecasted	25334	27179	29241	31371	33360	23460	23996	1085
	Actual	26530	28283	30082	31731	33325	25079	26102	
Average	25836	27315	29278	31447	33441	23807	24362	25836	965
	26949	28801	30876	32719	33908	24755	25752	26949	

CHAPTER 5. DYNAMIC PRICING AND COST FUCTIONS

Dynamic pricing changes the price of electricity based on the variation in the electricity demand. Dynamic pricing opens the window for the consumer to respond according to the price and play a significant role in determining the overall operation of the electric grid system. The main motivation for dynamic pricing is to decrease monthly electricity bill and annual peak load. The dynamic pricing model for electricity is the mechanism that minimizes the uncertainties in the electric grid by reacting to the real-time fluctuation of price. A sustainable dynamic pricing model should reflect consumer preferences, behavior and responses and reduce supply side uncertainties. This chapter presents two different cost functions for dynamic pricing.

5.1. Cost Functions for Dynamic Pricing

Dynamic pricing can lower the electricity price in the wholesale market and could save billion dollars investment for a new power plants or energy storing equipments. In this paper, two types of dynamic pricing based on demand are proposed which are generated from two different cost functions.

5.1.1. The Linear Cost Function

The Linear cost function takes the demand for a certain period of time and linearly sets the price of electricity. Let, K is the set of time periods and $k \varepsilon K$ and i is a consumer in the set of consumers in I and $i \varepsilon I$. Then, x_{ik} is the amount of electricity consumed by consumer i at the time period k and X_k is the total amount of electricity consumed by the set of consumers I at the time period k. Then the cost of electricity would be,

$$C_{xik} = \beta(X_{ik}) + \gamma \dots \dots \dots (6)$$

Here, β $(0 < \beta < 1)$ is the linear demand response factor which is set by the negotiation between the consumers and the utility company. The government agency could also play a role. When β =0, the price becomes constant which is equal to a flat rate factor, γ $(0 \leq \gamma < 1)$ that represents the lowest amount a utility supplier should charge to recover the minimum fraction of the cost for power production.

Factors in the linear cost function are very important. The sensitiveness of the price to demand depends on the factors. For example, for similar amount of flat rate factor, price of electricity will vary significantly for two different linear demand response factors. In the experimental result analysis chapter, factor sensitiveness of the linear cost functions is discussed with simulated household demand.

5.1.2. The Quadratic Cost Function

The quadratic function takes the variation of demand and provides a response that is quadratic in nature. For X_k, the total amount of electricity consumed by the set of consumers I at time period k. Then the cost of electricity would be,

$$C_{x_{ik}} = \alpha(X_{ik})^2 + \beta(X_{ik}) + \gamma \dots \dots \dots (7)$$

Here, α $(0 < \alpha < 1)$ is the quadratic demand response factor which is set by the negotiation between the consumers, the utility company and the government agency. When α =0, price becomes linearly demand sensitive like a linear cost function. There are a linear demand response factor, β $(0 \leq \beta < 1)$ and a constant flat rate, $\gamma(0 \leq \gamma < 1)$.

The price determined by quadratic cost function is highly dependent on the factors in the quadratic cost function. The quadratic demand response factor has the highest sensitiveness to the price. Experiment should be conducted to determine the factors in the cost function. The final selection of the factors should create a win-win situation for the consumer and utility supplier. A win-win situation means that the monthly bill for a price sensitive consumer would be lower and cost of operation for the utility supplier would also be lower.

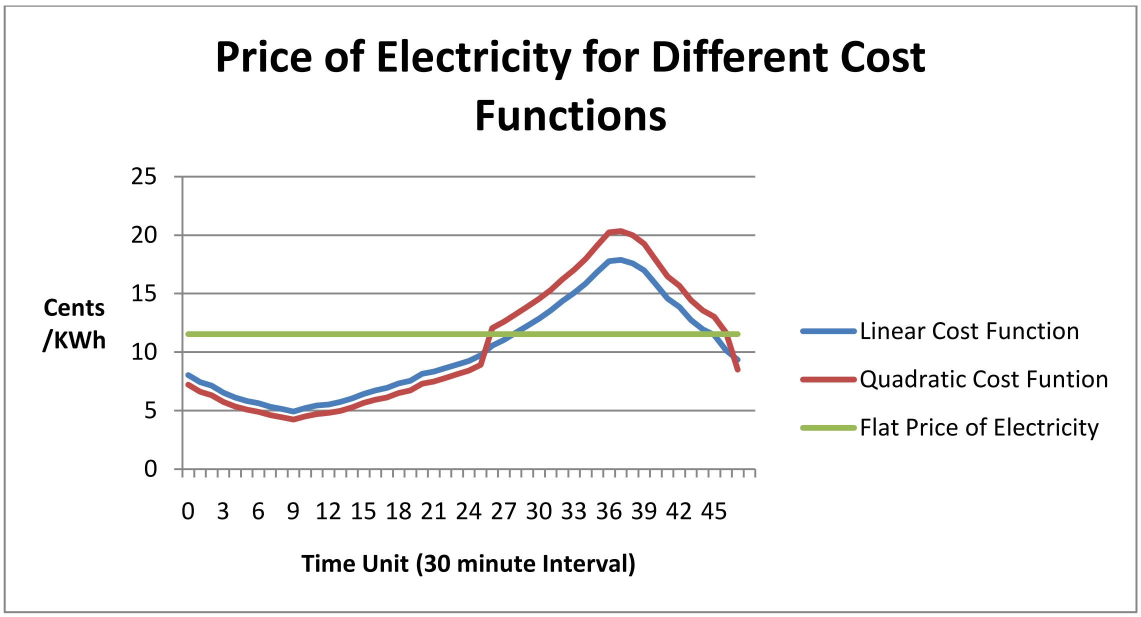


Figure 6. Dynamic Price of Electricity for Different Cost Functions

The household demand is simulated based on the (Figure 3). The demand of household is higher in the evening time and very low in the morning. The dynamic price of electricity will be proportional to the demand. In Figure 6, the dynamic price of electricity is shown. The linear cost function provides prices of electricity that are linearly proportional to the demand.

The prices derived by using quadratic cost function have a quadratic relation with the variation in demand. The quadratic cost function has higher degree of sensitiveness (Figure 6). When demand is higher the price of the quadratic cost function is higher than the price of the linear function. On the other hand, during the time of lower demand, price by quadratic cost function is lower than the price by using linear cost function.

5.2. Selection of a Cost Function

The selection of a cost function is very crucial. The stability of the electricity market will depend on the cost function and factors in the cost function. At the initial stage of implementation, linear cost function could be applied to observe the sensitivity of different categories of consumers. The selection of cost function should be public. This will allow consumer to know the process of determining cost function and will make the business in the electricity market transparent and trust worthy. After a successful implementation of linear cost function, quadratic cost function could be applied to make consumers more sensitive to the prices. The both cost functions should create a win-win situation for the consumers and the utility suppliers.

CHAPTER 6. CONSUMER PREFERENCES

Every consumer is different based on electricity consumption. The consumption of electricity varies time to time day to day. Though each consumer acts independently, the response of consumers is grouped into different categories based on their price sensitivity. In this chapter, behaviors of each group of consumers are modeled by adopting the concept of the utility function applied in microeconomics. Each consumer has a utility function depending on his willingness to consume a commodity. The utility function used in this paper represents the level of satisfaction of a consumer for consuming electricity.

6.1. Advanced Metering Infrastructure

Smart meters, also known as Advanced Metering Infrastructure (AMI) have the capability of two way communication among consumers and electricity suppliers. A smart meter is connected with the utility supplier's central communication system. The utility supplier's central communication system monitors electricity consumption and report remotely. It also keeps records of electricity consumption every hour or less. The information of consumption is used for billing purposes. Even though there is a privacy concern of exposing electricity consumption patterns, more and more households in the USA are accepting to install smart meters. At the end of 2010 about 15% of household consumers are using smart meters. The percentage of installed smart meters was only 7% in the year of (Figure 7). This indicates that within a couple of years there would be significant number of consumers that will be using smart meters for a better monitoring of energy consumption.

Based on the collected data utility suppliers could analyze consumption and take cost effective energy production decisions.

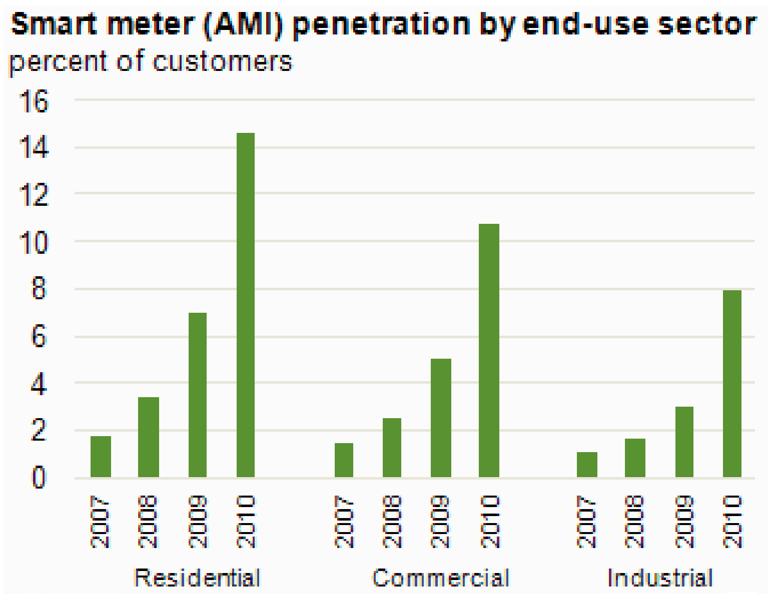


Figure 7. Smart Meter (AMI) Penetration and Growth by End Use Sector (EIA, Electricity Monthly Update, 2011)

6.2. Utility Functions and User Preferences

The consumption of electricity by a consumer based on the declared dynamic price of electricity is captured in a smart meter. The utility function of a consumer is private. The utility supplier knows the level of consumption and based on the level of consumption, utility supplier could estimate utility function for a consumer. Let, x_{ik} is the amount of electricity consumed by consumer i at the time period k and ω is a parameter that varies among users. It could vary based on the factors like weather, days in the week, household income, number of rooms, etc. that influence the consumption of electricity. Then, the utility function is represented by $U(x_{ik}, \omega)$. The utility function used in this paper (Equation 8) also uses a price factor α, ratio of estimated price by a consumer and estimated average price of the day.

The utility function for a consumer represents the level of consumer satisfaction after consuming electricity. Consumer satisfaction, frequently used in microeconomics and operations research for decision making under uncertainty, is a measure of satisfaction of a consumer from consuming a product or service. Change in utility is used to explain economic behavior of a consumer. As utility function measures the happiness or satisfaction gained by a consumer, it is used to analyze consumer behavior under the scenario of dynamic pricing. The utility function of household consumers is most likely to be different from that of a commercial consumer. This paper assumes the following properties of a utility function of a household consumer-

The utility function used in this paper has two parts. It is assumed that a rational consumer will compare the dynamic price of a time period with flat price or marginal cost price to make decisions. In the first part of a utility function is convex when the price of electricity is lower than the estimated average cost price of the consumer. The convex nature of the curve represents higher willingness of a consumer to consume more electricity in lower price. The utility of a price sensitive consumer increases in an increasing rate. The other part of the utility function is concave when the price of electricity is higher than the estimated average cost price of electricity for a consumer. In the concave section of the utility function, the utility of a consumer increases in a decreasing rate when the amount of consumption increases. A consumer wants to consume lowest possible amount of electricity at the point of highest price of electricity. However, due to habitual life-styles, a consumer cannot shift every load of higher price consumption to the lower price consumption.

$$U(x_{ik},\omega) = \begin{cases} c + \omega x_{ik} - \frac{\alpha}{2} x_{ik}^2 & if \;\; 0 \leq x_{ik} \leq \frac{\omega}{\alpha} \\ \frac{\omega}{2} x_{ik} + \frac{\alpha}{2} x_{ik}^2 & if \; x_{ik} \geq \frac{\omega}{\alpha} \end{cases} \quad \ldots\ldots\ldots\ldots..(8)$$

Utility functions are assumed to be non-decreasing, which means users are willing to purchase more until they reach the maximum point of satisfaction. Mathematically,

$$\frac{dU(x_{ik},\omega)}{dx_{ik}} \geq 0 \quad \ldots\ldots\ldots(9)$$

For simplicity let's define-

$$V(x_{ik},\omega) = \frac{dU(x_{ik},\omega)}{dx_{ik}} \quad \ldots\ldots\ldots\ldots..(10)$$

The utility function is a combination of one convex and one concave curve. At the initial part of the curve, when the ratio of price to average price is lower, the consumer is expected to consume more and more electricity with a small change (Figure 8) in the curve. As the price of electricity is becomes higher than the average price of the electricity the consumer becomes less interested to consume electricity. The curve starts convex and becomes concave. To maintain a life-style, a consumer consumes more electricity during peak hours with a higher price but gain a small level of satisfaction by comparing it with the level of satisfaction of consuming electricity at lower price.

Every consumer has their own utility function. A consumer with a higher level of ω will result in a higher level of satisfaction with the same level of consumption. For example, if two consumers consume the same level of consumption of electricity x_{ik}, a higher value of ω will provide a higher value of $U(x_{ik},\omega)$ and this is expressed by,

$$\frac{dU(x_{ik},\omega)}{d\omega} \geq 0 \quad \ldots\ldots\ldots\ldots(11)$$

The level of satisfaction starts when a consumer starts consuming electricity. If there s no electricity consumption, there is no benefit or no level of satisfaction. Hence,

$$U(0, \omega) = 0, \qquad \forall \omega > 0 \qquad \dots \dots \dots (12)$$

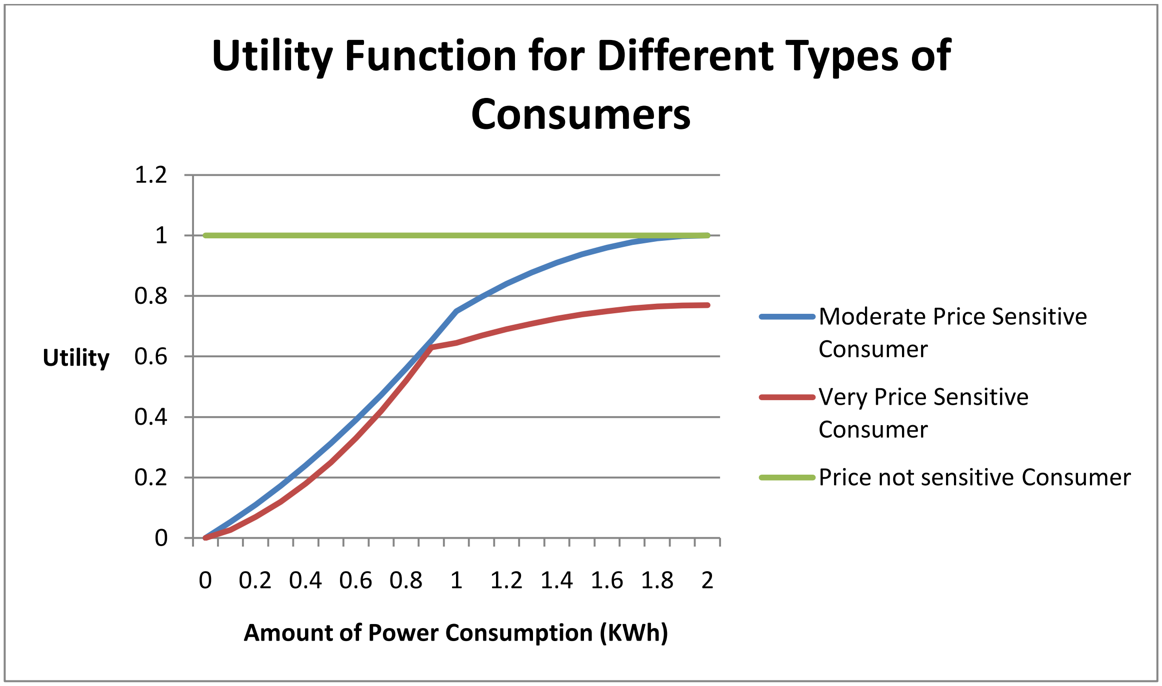


Figure 8. Utility Function for Different Types of Consumers

Three utility functions are developed for three different categories of consumers (Figure 8). The price of electricity is related to the consumption of electricity (Figure 6). Figure 8 shows consumption of electricity in the horizontal axis which is related to the price of electricity as consumption increase price of the electricity increases and price decrease when consumption decrease. The very price sensitive consumer will try to purchase more electricity while the price of electricity is lower. This type of consumer will try to have a consumption pattern very close to straight line of consumption. The goal of this type of consumer is to reverse the pattern of consumption. However, this is not possible to reverse the consumption pattern due to life style. This means it is not possible to consume maximum amount of electricity while price is the lowest.

6.3. Consumer with Imperfect Information

In this paper, two broad category of consumer is considered: Consumer with imperfect information and consumer with perfect information. Consumer with imperfect information knows about the dynamic pricing methodology. This consumer knows that due to dynamic pricing, the price of electricity is higher during the peak hours and price is lower during off peak hour. However, he or she does not know what the exact price is on a particular hour. This is due to not having perfect interface to get the updated information every hour, or do not have that much interest of being updated every hour. In addition, for a human being it is not practical to know the price of electricity every hour. A consumer with imperfect information takes necessary steps based on an assumed pattern of the dynamic price. The assumed pattern/price could be higher or lower but very close to the actual pattern. There are three sub categories of consumers with imperfect information.

6.3.1. The Moderate Price Sensitive Consumer

The Moderate Price sensitive consumer is careful about monthly electricity bill and interested to save little from electricity bill. This category of consumer knows about dynamic pricing and variation in the price due to change in demand but do not know the exact price. Hence, they try to avoid using those appliances that is used other times. For example, this category of consumers is interested to run the dishwasher at the 4.00am in the morning when price of electricity would be lower. This category of consumers will shift a small portion of daily load form the pick hours to off peak hours. However, the pattern of consumption would be very similar and life style will not be affected. Moderate price consumer will have a two distinct pattern in the utility function. The level of satisfaction will increase as they will consume more and more electricity at lower price. When price become higher, the change in level of satisfaction do not increase as the same rate before (Figure 8). Price below average will have a convex curve in nature and price after average will have concave in nature. The highest level of satisfaction would be 1.

6.3.2. The Very Price Sensitive Consumer

The very price sensitive consumer becomes very careful about dynamic pricing though do not have the exact information about the price in every hour. The very price sensitive consumer also schedule consumption based on estimated price pattern. This category of consumers lower the consumption by turning off the extra light or changing regular light bulb by energy saving bulb or lowering heater when not in home. This type of consumers also shift load like dishwasher, laundry to off peak hour. Due to extra sensitiveness than moderate sensitive consumer, this type of consumers is expected to save more money than moderate sensitive consumers. The nature of the utility function for very price sensitive consumer would be same as the moderate price sensitive consumer. The very price sensitive consumer will not be able to be completely satisfied (Figure 8) as they have to shift load and need to be aware of extra saving. The very price sensitive consumers are the household facing economic hardship or very concerned about electricity and/or environment.

6.3.3. Not Price Sensitive Consumer

This category of consumers is not price sensitive. Since this category of consumers is rich, the savings from being price sensitive are not significant for them. This category of consumers is in the higher income group with a higher standard of living and do not care about saving 10 - 20% of the electricity bill every month. Besides, they have more appliances and waste electricity. This category of consumers does not keep the track of price and do not care whether it is flat or dynamic. If the monthly electricity bill is not too high like two or three times of the usual monthly electricity bill, then this category of consumers do not care. They even do not mind to pay little more. This type of consumer is considered to be always satisfied with the utility service (Figure 8) and will have a horizontal line in the utility function. The level of satisfaction does not change in relation with the change in the price of electricity.

6.4. Consumers with Perfect Information

When a consumer keeps track of every hour price of electricity published by utility supplier, the consumer is called consumer with perfect information. The perfect information is collected and processed by a device (not a human being) to make necessary decisions and execute them. This is an ideal situation with smart grid whether every home would be smart home. In a smart home, all devices/ appliances would be connected by Home Area Network (HAN). There would be a centralized control device that would have the authorization to turn on or off any appliance at home. The centralized control device will have the intelligence to observe the consumption pattern of user and a certain level of autonomy to decide based on the price of electricity. The centralized control device or the scheduler will collect the price information from the utility supplier. This device will also keep track of previous consumption and price data. Based on historical data and provided user preferences, the device will schedule utilization of home appliances. For example, it will turn on charger of a hybrid/electric car so that the charging is done before 7.00am at the lowest priced rate.

CHAPTER 7. SOFTWARE SIMULATION

The developed methodology of dynamic pricing is simulated to model consumer responses. The simulation facilitates a good understanding of the proposed methods and consumer responses. The application models different consumers with different utility functions. The goal of the simulation is to establish savings for a consumer based on his level of price sensitivity.

7.1. The Development Environment

The simulation is developed by using C# (C-Sharp) as a programming language. The reason for choosing C# as a programming language is to benefit from powerful .NET framework. The Visual Studio 2010 makes it simple and quick to develop and deploy a software project. Two Graphical User Interfaces (GUI) are used in this software. The Window Forms Designer provides the flexibility to control the layout that houses controls (textbox, label, list box, etc.). The Windows Presentation Foundation (WPF) helps to control the GUI by event driven programming and the Extensible Application Markup Language (XAML) file. For simplicity and better visualization, Microsoft Excel 2010 is used to hold the raw data. This provides quicker processing of data as the National Grid demand data is published in Microsoft Excel format.

7.2. Class Diagram

The design pattern used to implement the dynamic pricing model is a façade design pattern. The dynamicPriceManager is the façade in the class diagram (Figure 9). The home area network for consumer with perfect information is not included in figure 9 to keep it simple.

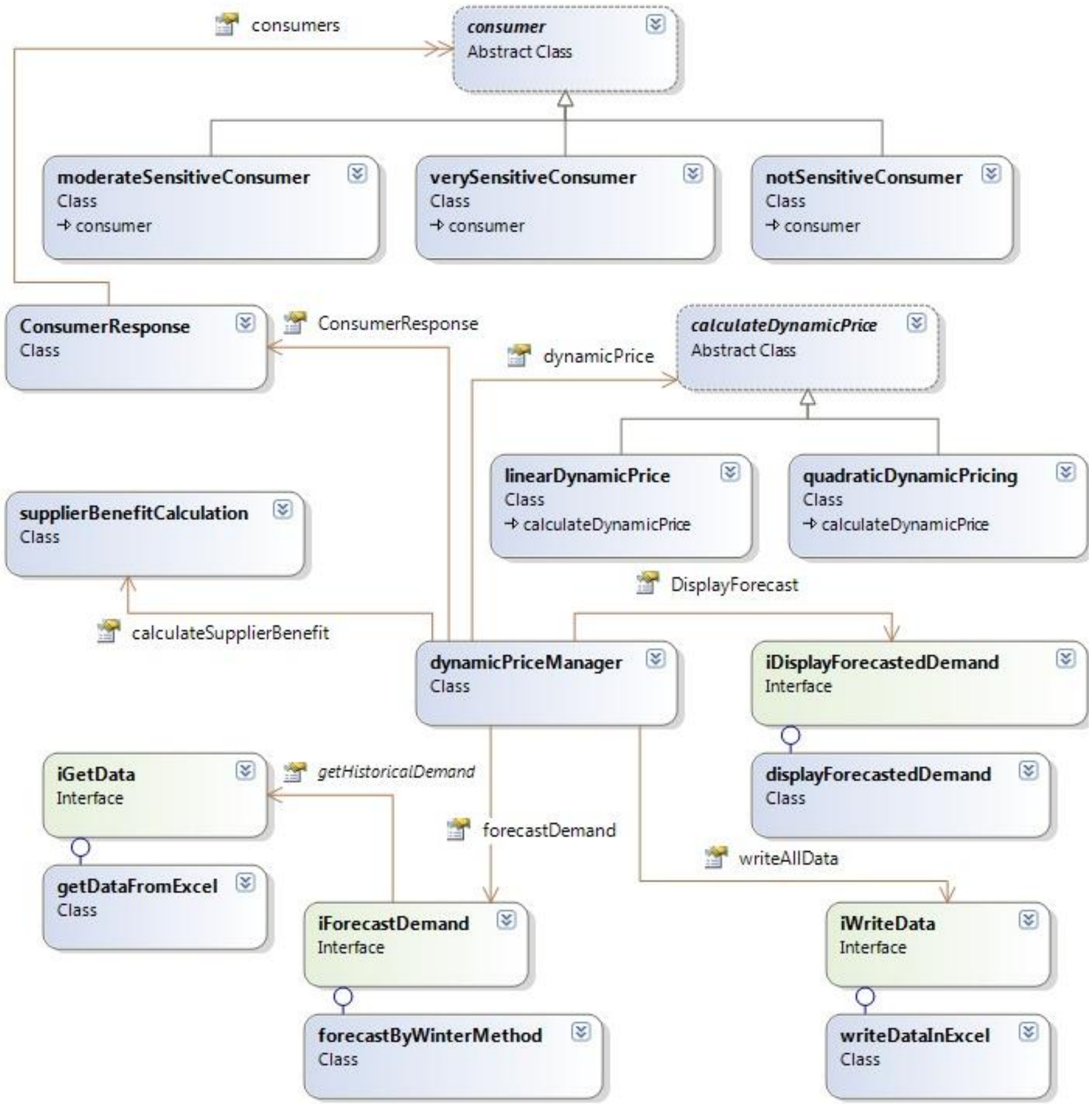


Figure 9. The Class Diagram for the Dynamic Pricing Model

The dynamicPriceManager is associated with interfaces like igetData, iWriteData, iForeccastDemand, etc. The dynamicPriceManager is associated with the calculateDynamicPrice abstract class which is inherited by linearDynamicPrice and quadraticDynamicPrice. The dynamicPriceManager is associated to the consumerResponse class.

7.3. Classes in Dynamic Pricing Model

The Dynamic Pricing model implements classes like getData, consumerResponse, forecastByWinterMethod, etc. There are abstract classes like consumer, calculateDynamicPrice.

7.3.1. The dynamicPriceManager Class

The dynamicPricingManager class is the heart of the architecture of the developed dynamic pricing model.

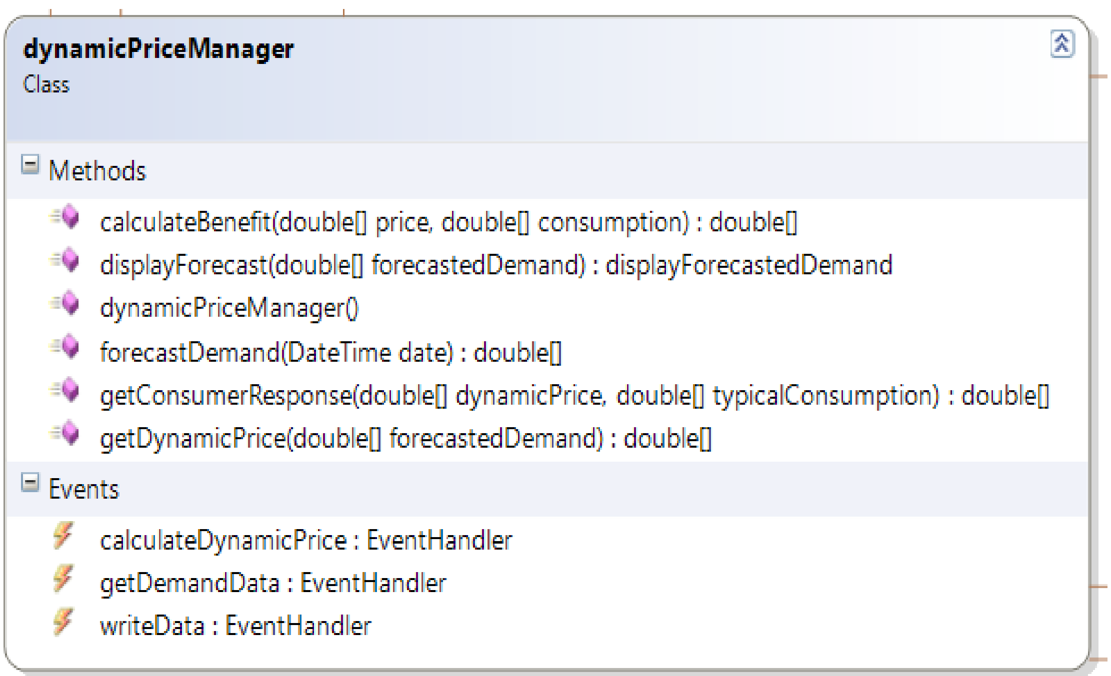


Figure 10. Class Members in the dynamicPriceManager Class

This class is considered as the façade in a façade design pattern. This class interacts with all of the interfaces and subsystems. This class knows which subsystem needs to be called to perform a task. Through this class all of the subsystems and functions of major classes are performed. This class consists of multiple methods and events (

Figure 10).

7.3.2. The iForecastDemand Interface and the forecastByWinterMethod Class

The iForecastDemand interface provides the flexibility to plug in any type of demand forecasting technique to the dynamic pricing model. In this paper, the Winters Method for Seasonality is applied to implement the interface.

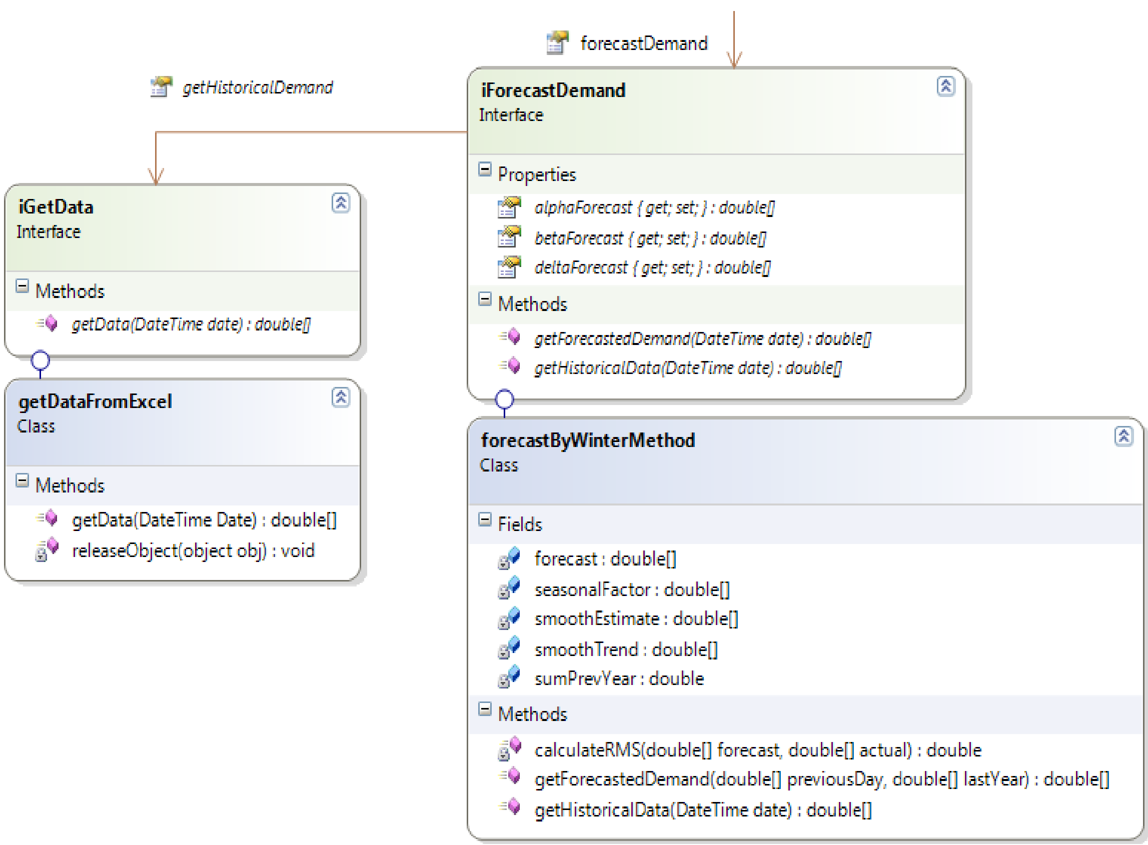


Figure 11. Members in the iForecasDemand Interface, the iGetData Interface, the getDataFromExcel Class and the forecastByWinterMethod Class

The interface has three properties of alphaForecast, betaForecast and deltaForecast applied in the forecasting method. These properties are declared in the interface so that these factors could be changed during the analysis of factors. The analysis of factors is important to minimize errors in the forecasting method. The forecastByWinterMethod class has five fields to facilitate algorithms in the class (

Figure 11). This class has three methods: two of them are public and one is private. The getForecastedDemand and the getHistoricalData implement the corresponding virtual method in the interface. The calculateRMS is a private method that calculates deviation of the forecasted demand from the actual demand for analysis or testing.

7.3.3. The iGetData Interface and the getDataFromExcel Class

The iGetData interface is used to provide the flexibility to collect data from any source. In this project, iGetData is implemented by getDataFromExcel class. The getDataFromExcel class takes an input of a date and searches for the demand data stored in a Microsoft Excel file (Figure 12). The getData method in the getDataFromExcel class returns an array of double type data. This class also has a private method to release connections and resources after getting data.

7.3.4. The calculateDynamicPrice Abstract Class and Implementation

The calculateDynamicPrice class is inherited by the linearDynamicPrice class and the quadraticDynamicPrice class. The parent class consists of two properties: the linearCostFactor and the constantCostFactor of double data type. Both of the child classes have these two properties and the quadraticDynamicPricing has an extra property named as the quadraticFactor.

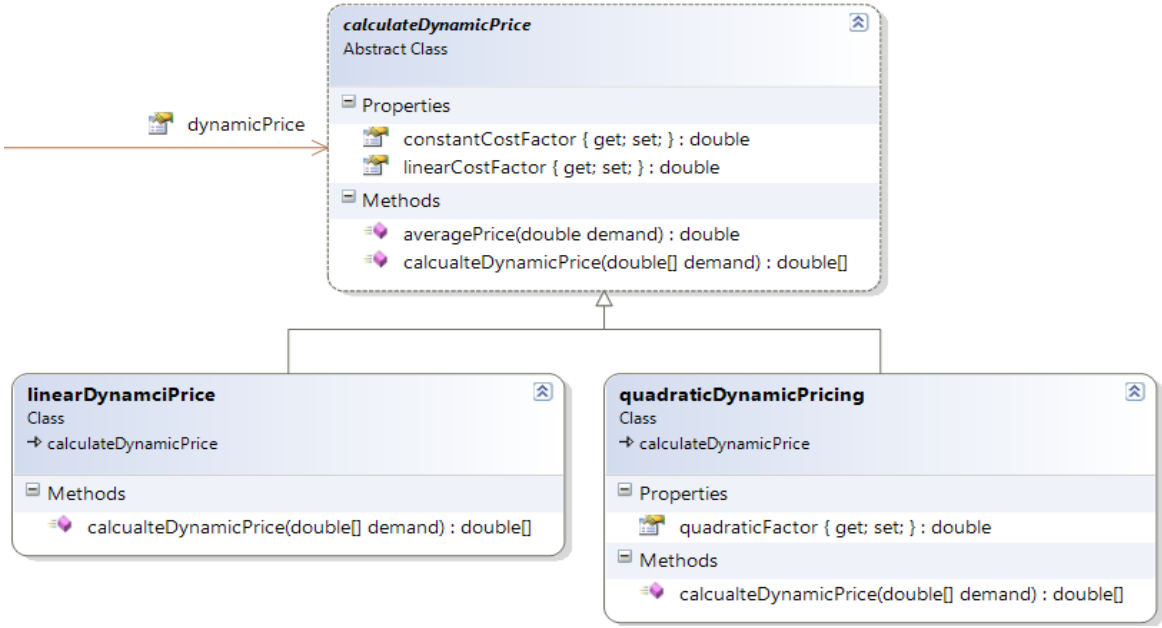


Figure 12. The calculateDynamicPrice Abstract Class and Inherited Objects

The linearDynamicPrice provides an array of price that is sensitive to the variation in demand of electricity (Figure 13). The quadraticDynamicPrice object also gives an array of price that contains prices of electricity generated by the quadratic cost function.

7.3.5. The consumerResponse Class

The consumerResponse class is associated with the dynamicPriceManager class to provide the response of consumers based on the dynamic price of electricity. This class has a collection of association with the consumer class (Figure 13). This class creates objects of consumers with categories of consumers. This class has properties to create a group of consumers from a similar category.

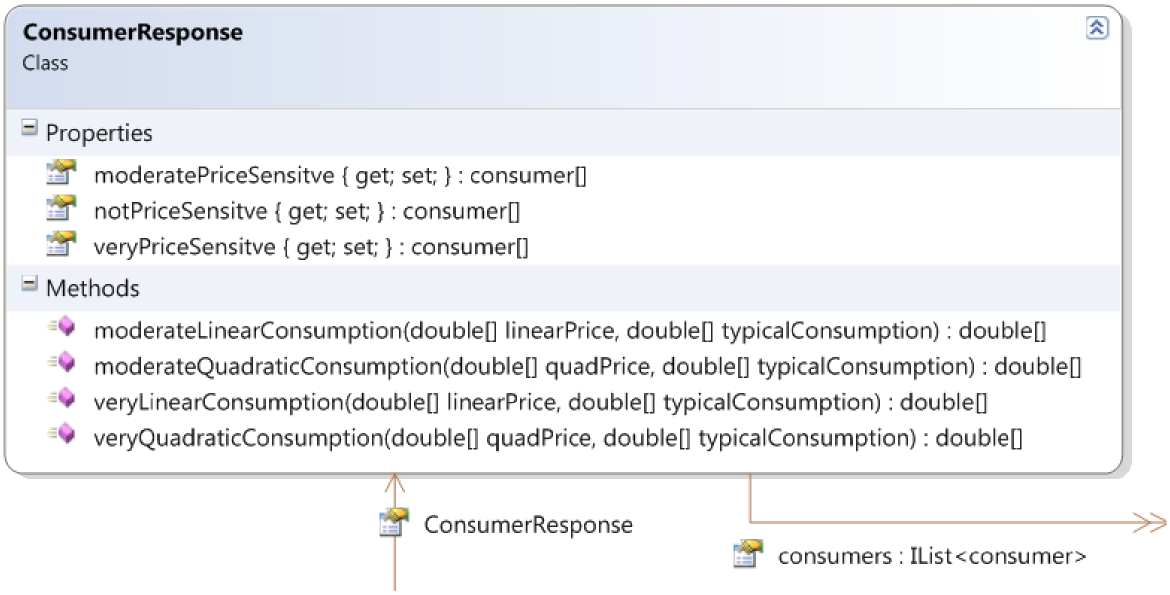


Figure 13. Members in the consumerResponse Class

7.3.6. The consumer Class

The consumer class is a parent class which has three children named as the moderateSensitiveConsumer, the verySensitiveConsumer and the notSensitiveConsumer. The parent class has four methods of getAverage, priceSensitiveConsumption, getMaximum and arrayToSortedDictionary. The getAverage and the getMaximum methods are internal and return a double value. The priceSensitiveConsumption is overridden by the implemented class where the load profile of the consumer is returned (Figure 14). The load profile is calculated by an algorithm that considers factors like dynamic price, existing load profile and consumer life-style, etc.

The consumer abstract class has properties like categoryOfConsumer, loadProfile, monthlyBill, savingMonthly, etc. The moderateSensitiveConsumer and the verySensitiveConsumer classes have properties like loadShiftPercent, loadShiftAmount, consumptionReductionAmount, etc.

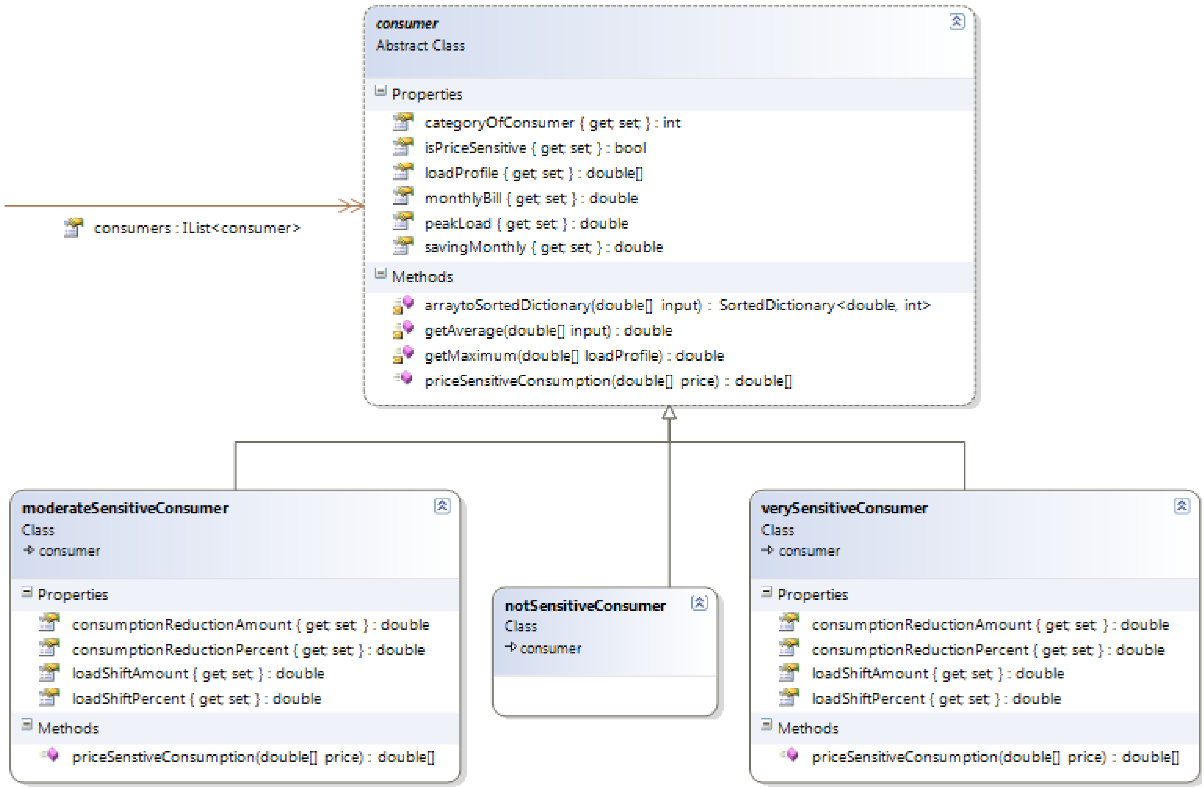


Figure 14. The consumer Class and Inherited Classes

7.3.7. The supplierBenefitCalculation Class

The supplierBenefitClaculation class is associated with dynamicPricemanager class. This class provides the getPeakLoadPerConsumer and the getPeakLoadTotal methods. The getPeakLoadPerConsumer method gives a Dictionary<int, double> of peak load for a consumer. The key of the Dictionary is the categoryOfConsumer defined in the consumer abstract class. The value of the Dictionary is the peak load for the respective category of consumer. All of the three properties in the supplierBenefitCalculation class use the data type of Dictionary<int, double> to have the key value pair of category of consumers and corresponding values (Figure 15).

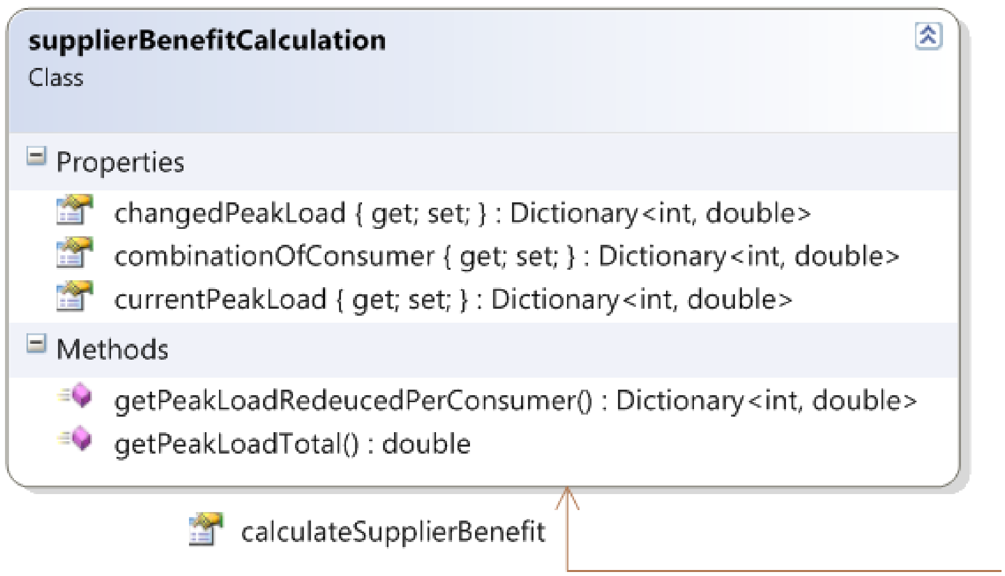


Figure 15. Members of the supplierBenefitCalculation Class

7.3.8. The iWriteData Interface and the writeDataInExcel class

The iWriteData interface provides a flexibility to choose a suitable type of database to store the calculated data for record and future analysis purposes. In this paper, iWriteData interface is implemented by the writeDataInExcel class. The writeDataInExcel class has a method called writeData that writes data in an MS Excel document (Figure 16). If data is written correctly, the method returns a boolean type value. The releaseObject method is used to release the resources used to write data. The writeData interface is associated with the dynamicPriceManager class. The dynamicPricemanager calls the iWriteData after getting the forecasted demand, consumer responses and supplier side benefits.

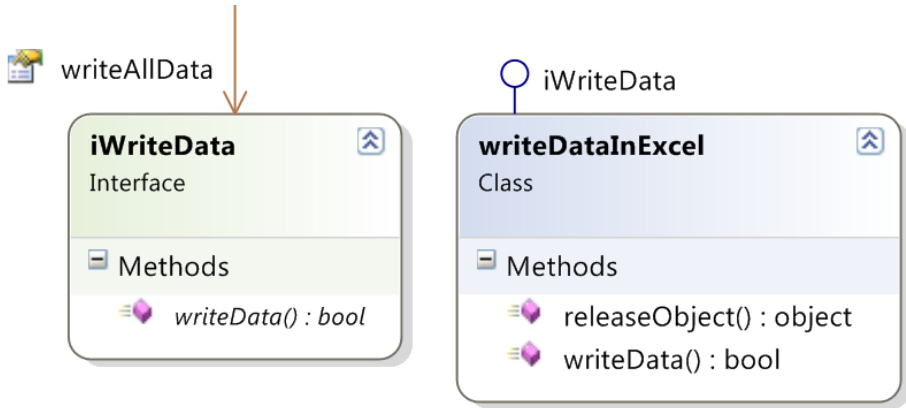


Figure 16. The iWriteData Interface and the writeDataInExcel Class

7.3.9. The consumerWithPerfectInformation and appliance Class

The consumerWithPerfectInformaton and appliance class are not shown in Figure 9. The consumerWithPerfectInformation class gives load profiles of a consumer with a smart device for weekdays, weekends. A load profile shows the amount of consumption throughout the day every 30 minutes. The consumerWithPerfectInformation class has properties like typicalMonthlyBill, typicalPeak, smartDeviceMonthlyBill, smartDevicePeak, etc. These properties are used to create load profiles for a consumer.

The appliance class creates appliance objects. Every appliance has properties like the AverageDailyUse, the EstimatedMonthlyUse, FlexibilityToShift, etc. These properties are set based on the preferences given by a consumer, the historical consumption data and the artificial intelligence of a smart device. The appliance class is associated with the consumerWithPerfectInformation class (Figure 17). Properties in an appliance are used by a smart device to schedule the appliance run time.

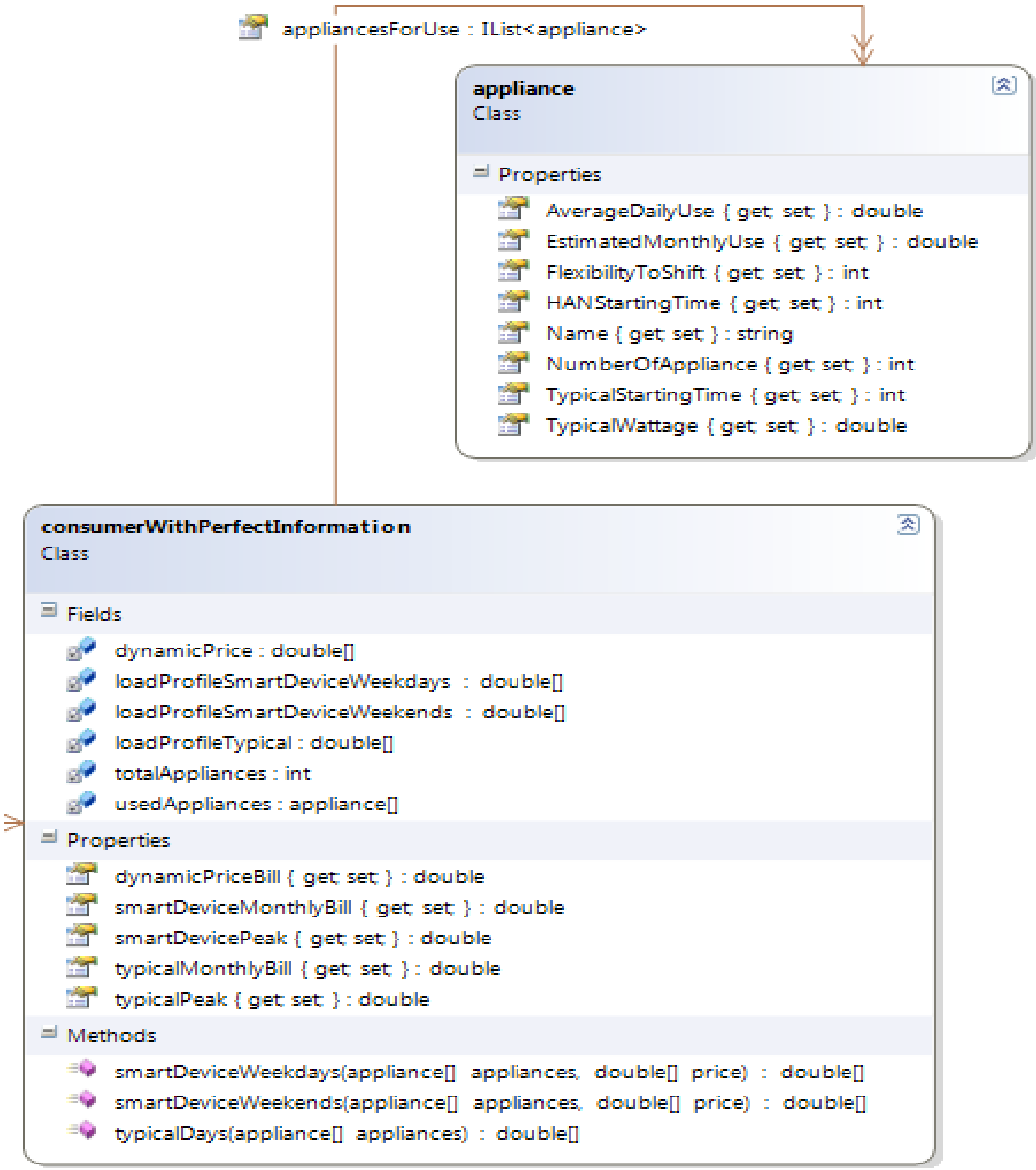


Figure 17. Members in the consumerWithPerfectInformation and appliance Class

7.4. The User Interface

The User Interface (UI) for the dynamic pricing model is developed by using Windows Form and Windows Presentation Foundation (WPF). These two user interfaces are selected for a higher level of compatiblity with .NET Framework.

7.4.1. The Welcome Screen

The welcome screen provides an option for viewing historical data of demand, dynamic price, consumer benefit, supplier benefit, etc. The welcome screen also provides an option to select a date to start calculating the dynamic price of electricity (Figure 18). This UI is developed by using WPF and using Extensible Application Markup Language (XAML).

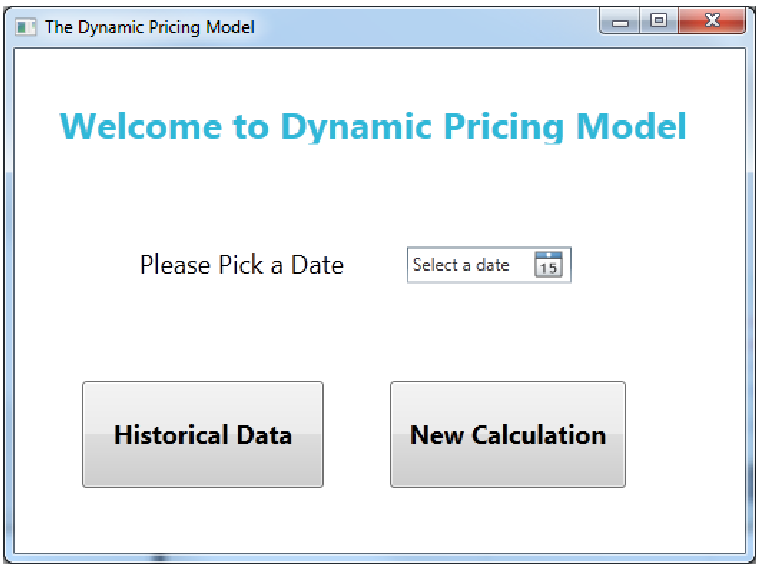


Figure 18. The Welcome Screen of Dynamic Pricing Model

7.4.2. The Forecast Demand User Interface

The Forecast Demand UI is also developed by using WPF and XAML. This UI has controls to retrieve data from the databases for the date which is selected on the welcome screen. After successfully retrieving the required data, a confirmation message is displayed. This UI has controls like Forecast Demand, Display Forecasted Demand, Forecasting Error, Write Excel File and Open Excel (Figure 19). The Forecast Demand is implemented to forecast demand by applying the Winters Method for Seasonality. The Display Forecasted Demand control opens a new user interface. The Forecasting Error control gives RMS value of the error while running this model for test data. The Write Excel File control saves the forecasted demand in an MS Excel File. Finally, the Open Excel control opens the file where the data is saved.

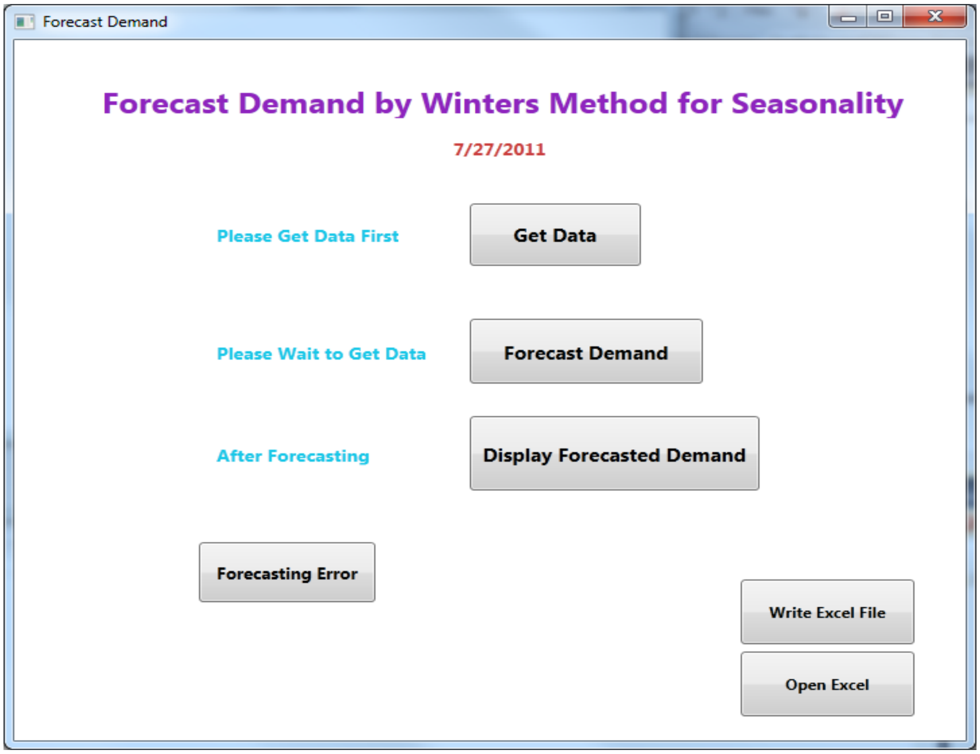


Figure 19. Controls in the Forecast Demand User Interface

7.4.3. The Display Forecasted Demand User Interface

The Display Forecasted Demand UI has a dataGridView control which displays a table of data. The table of data contains Time Period, Previous Day Demand, Last Year Demand, Forecasted Demand and Actual Demand (for test purposes). This UI also provides controls to take different values of alpha, beta and delta and the displays corresponding RMS value. This UI could take different values to analyze consumer response based on the simulated household demand. This UI also has controls to analyze the linear cost function or the quadratic cost function (Figure 20).

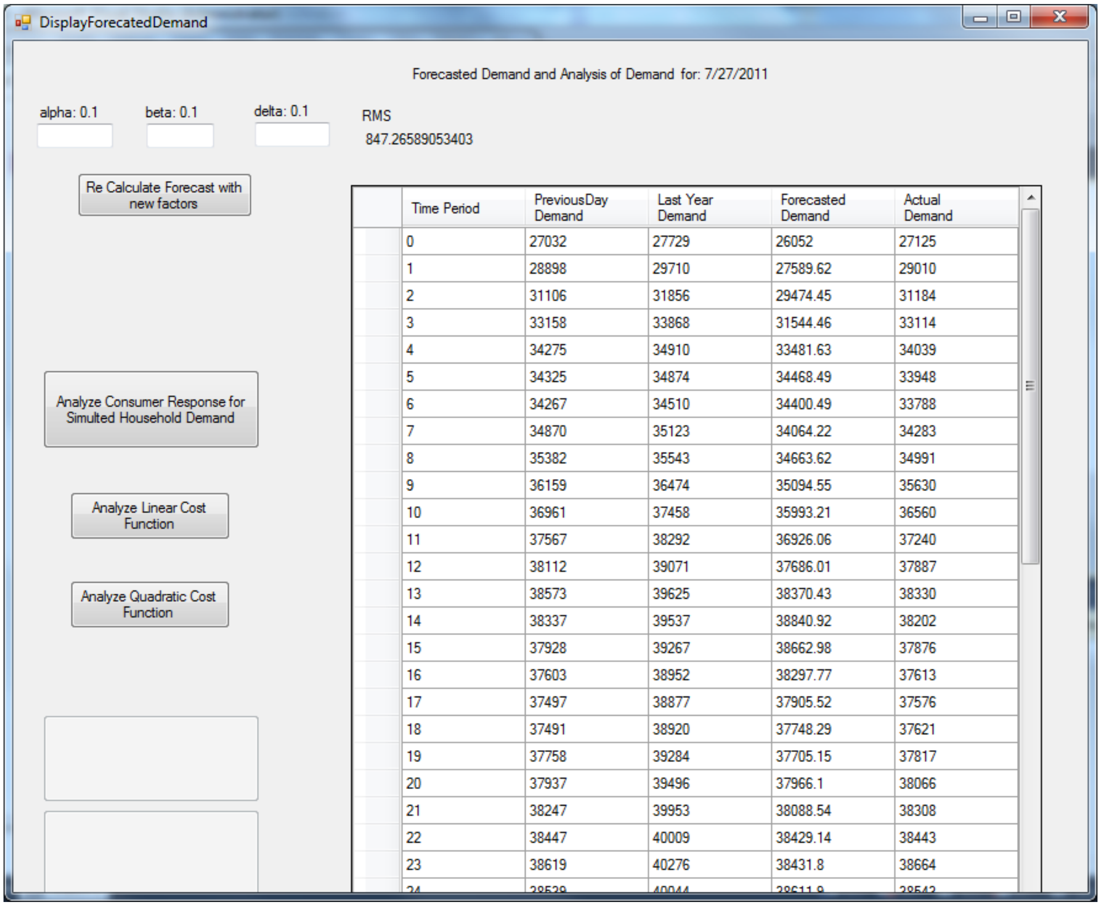


Figure 20. Controls in the Display Forecasted Demand User Interface

7.4.4. The Display Dynamic Price User Interface

The Display Dynamic Price User Interface also has a dataGridView that displays forecasted demand, dynamic price by using the linear cost function, consumption of moderate price sensitive consumers in response to the linear cost function and consumption of very price sensitive consumer in response to the linear cost function.

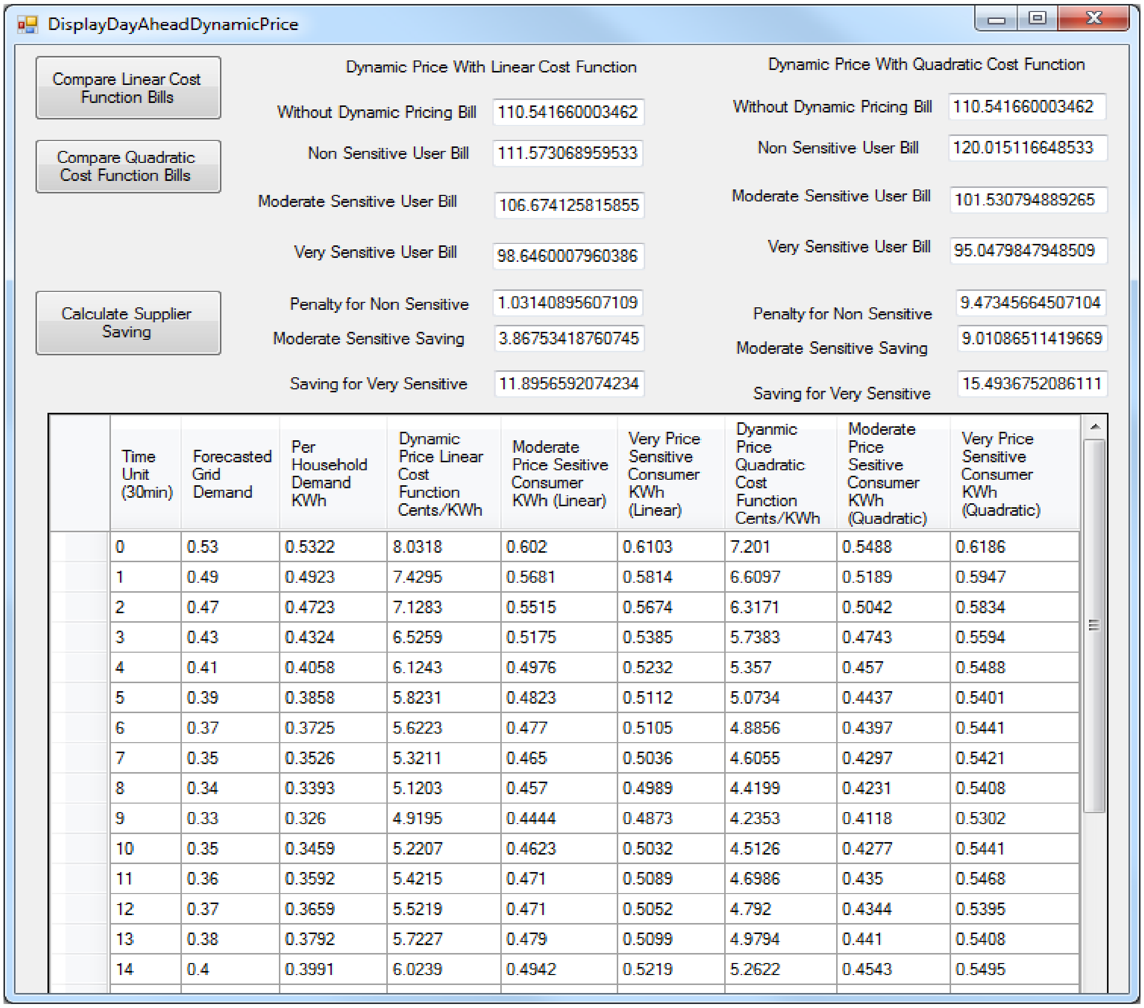


Figure 21. Controls in the Display Dynamic Price User Interface

This dataGridView displays dynamic price by using the quadratic cost function. It shows the consumption of moderate price sensitive consumer in response to the quadratic cost function and the consumption of very price sensitive consumer in response to the quadratic cost function (Figure 21). The benefits of adopting the linear cost function and the quadratic cost function are displayed in this user interface. This UI could also leads to supplier benefit user interface.

7.4.5. The Supplier Side Benefit User Interface

The supplier side benefit user interface displays the variation in peak load for a consumer and all consumers. This UI displays the overall benefit in a mixed scenario where 20% of consumers are not price sensitive, 30% of consumers are very price sensitive and 50% of consumers are moderate price sensitive (Figure 22).

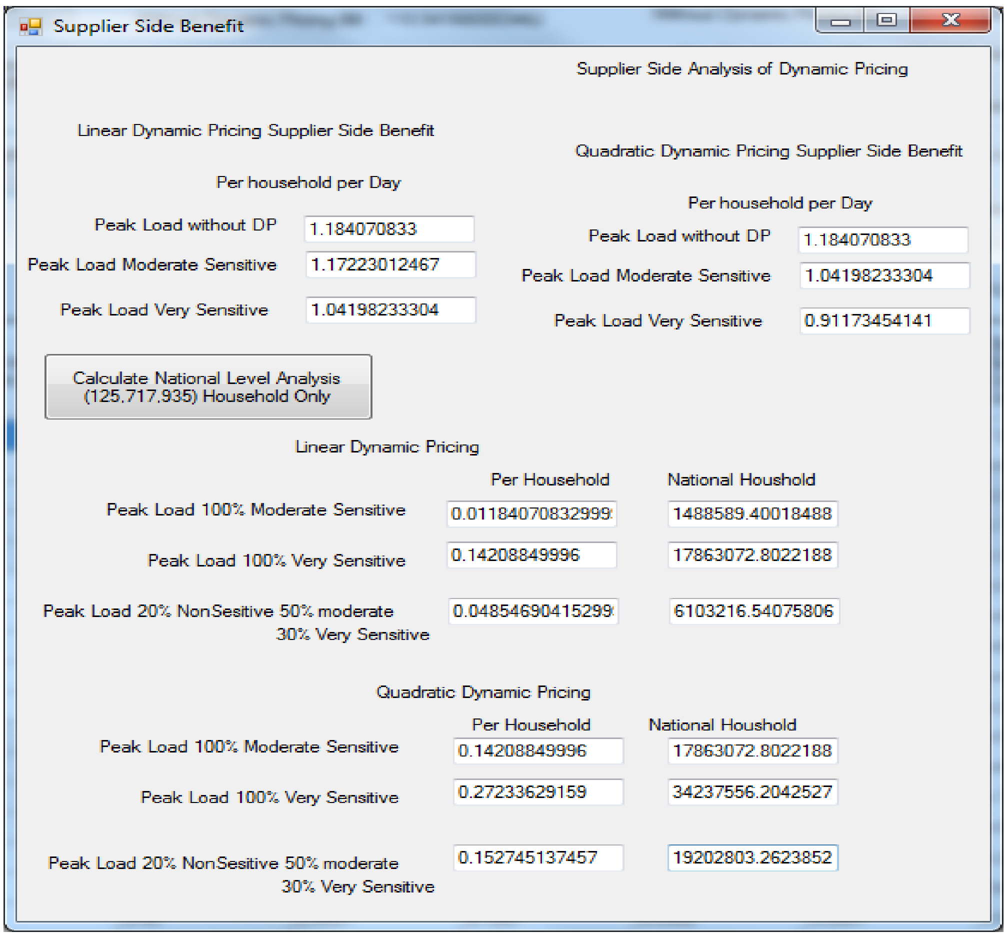


Figure 22. Controls in Supplier Side Benefit User Interface

7.4.6. The Analyze Cost Function User Interface

The analyze cost function UI is used for the linear cost function and the quadratic cost function. For the linear cost function, the linear factor and constant factor are displayed to calculate the dynamic price and benefits for different categories of consumers and suppliers (Figure 23).

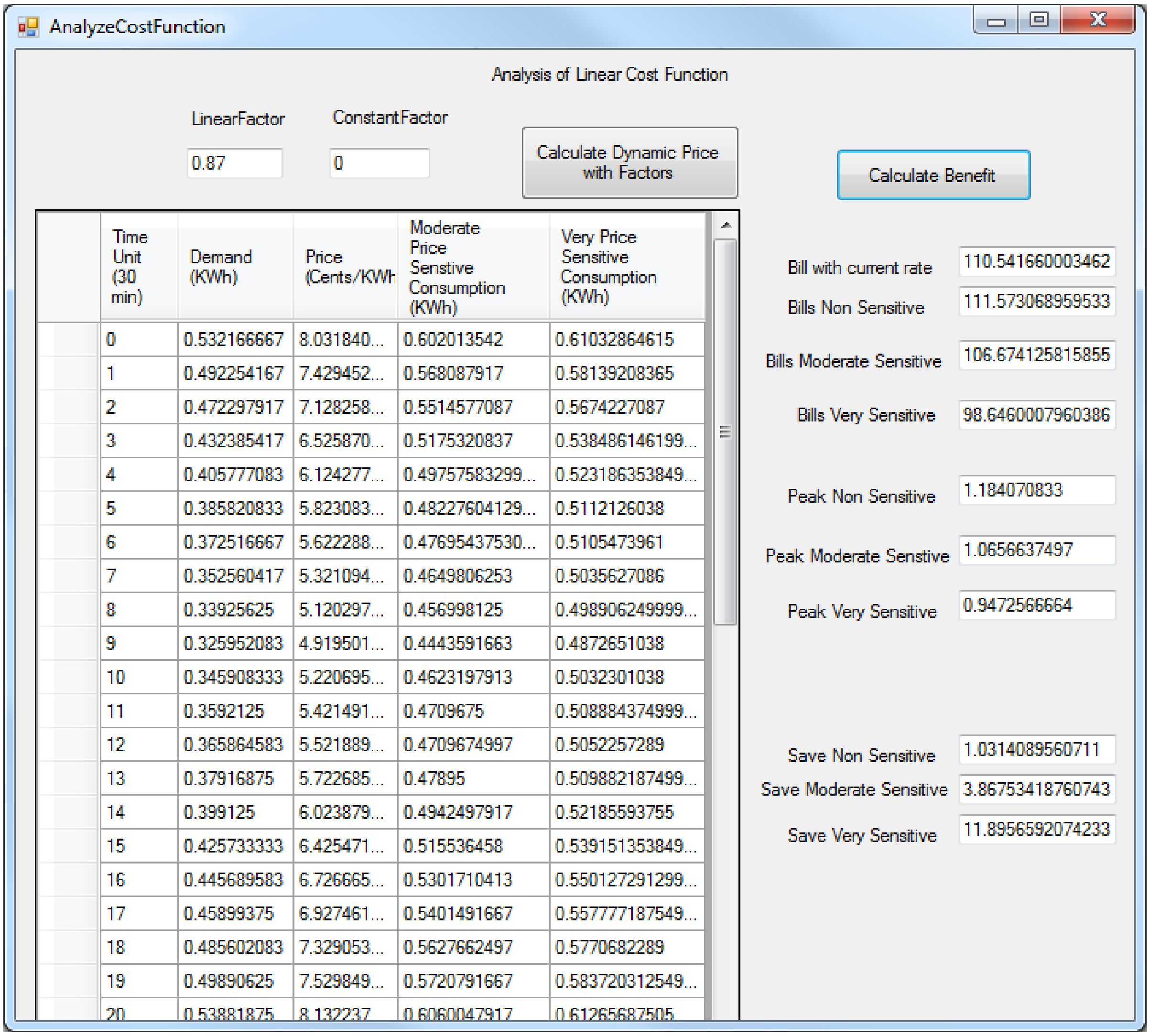


Figure 23. Controls in the Analyze Cost Function for a Linear Cost Function

The analyze cost function UI is also used for a quadratic cost function. In the case of a quadratic cost function, three controls are displayed to take various values of the quadratic factor, the linear factor and the constant factor. This UI also displays benefits for different types of consumers and suppliers (Figure 24).

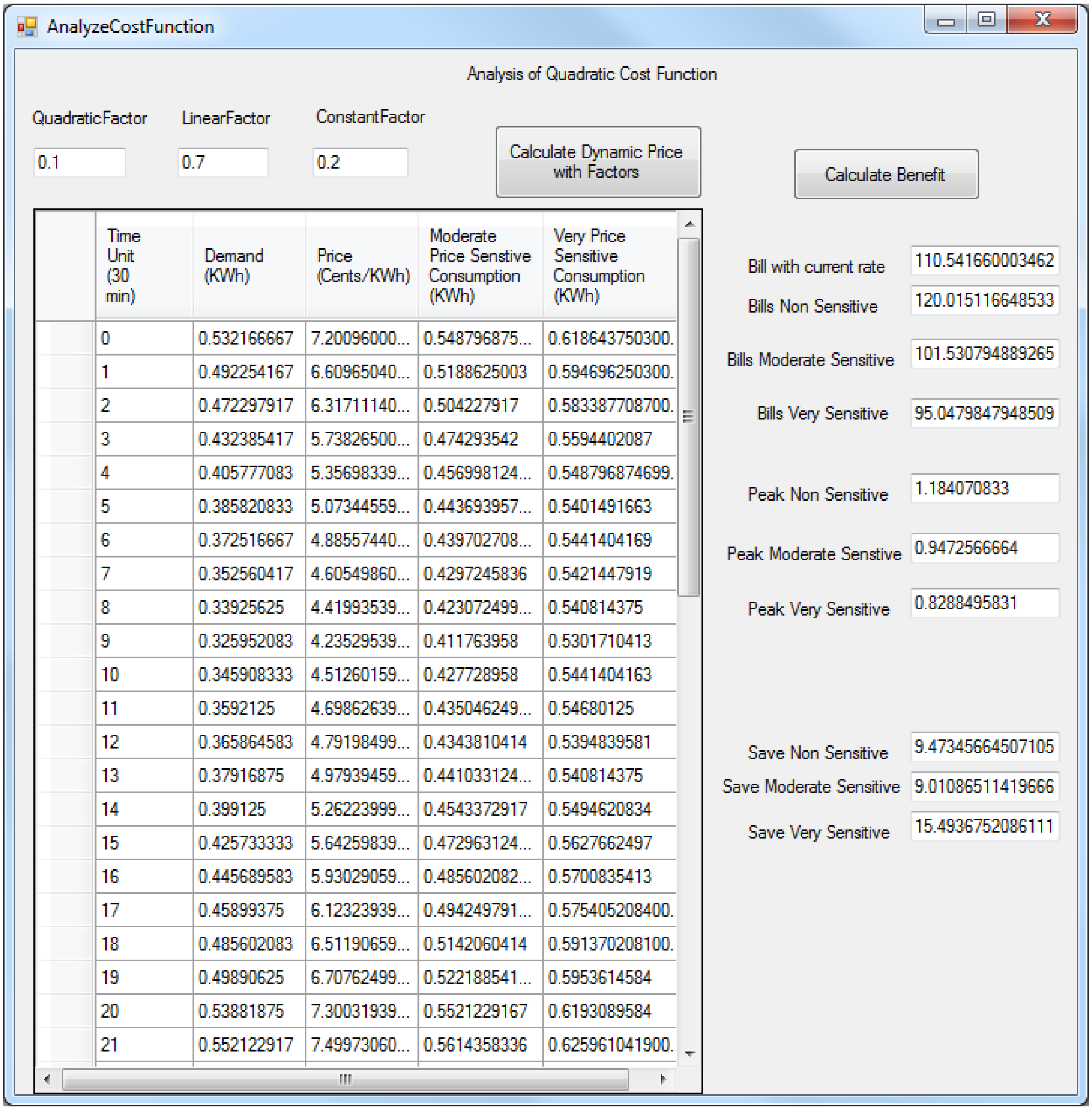
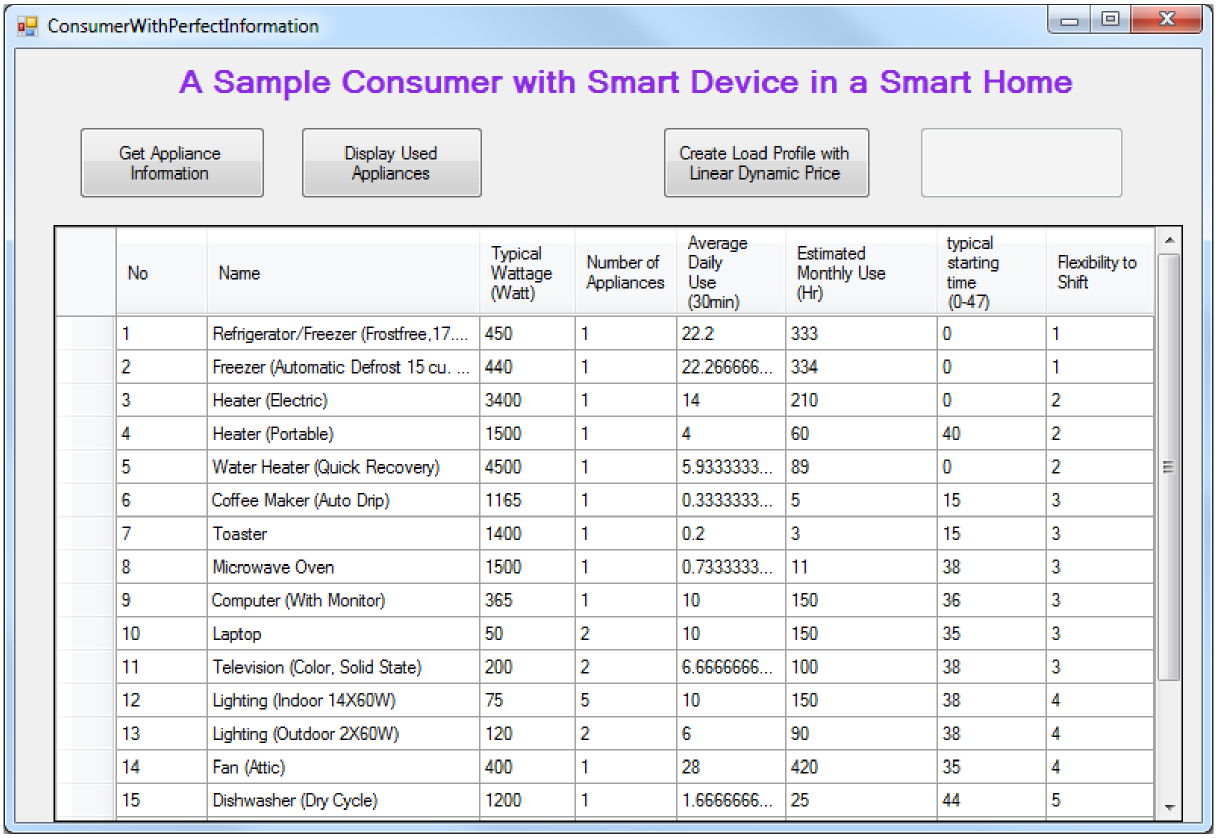


Figure 24. Controls in the Analyze Cost Function for a Quadratic Cost Function

7.4.7. The ConsumerWithPerfectInformation User Interface

The consumer with Perfect Information user interface provides a list of appliances considered for creating a load profile of a sample consumer. It displays all of the properties of each appliance used in this experiement, but not every appliance used in a typical household.

This user interface gets appliance information from an MS Excel file. The Create Load Profile with Linear Dynamic Price leads to the Home Area Network Load Analysis User Interface (Figure 25).



No	Name	Typical Wattage (Watt)	Number of Appliances	Average Daily Use (30min)	Estimated Monthly Use (Hr)	typical starting time (0-47)	Flexibility to Shift
1	Refrigerator/Freezer (Frostfree,17....	450	1	22.2	333	0	1
2	Freezer (Automatic Defrost 15 cu. ...	440	1	22.266666...	334	0	1
3	Heater (Electric)	3400	1	14	210	0	2
4	Heater (Portable)	1500	1	4	60	40	2
5	Water Heater (Quick Recovery)	4500	1	5.9333333...	89	0	2
6	Coffee Maker (Auto Drip)	1165	1	0.3333333...	5	15	3
7	Toaster	1400	1	0.2	3	15	3
8	Microwave Oven	1500	1	0.7333333...	11	38	3
9	Computer (With Monitor)	365	1	10	150	36	3
10	Laptop	50	2	10	150	35	3
11	Television (Color, Solid State)	200	2	6.6666666...	100	38	3
12	Lighting (Indoor 14X60W)	75	5	10	150	38	4
13	Lighting (Outdoor 2X60W)	120	2	6	90	38	4
14	Fan (Attic)	400	1	28	420	35	4
15	Dishwasher (Dry Cycle)	1200	1	1.6666666...	25	44	5

Figure 25. Controls in the ConsumerWIthPerfectInformation

7.4.8. The Home Area Network Load Analysis User Interface

The Home Area Network Load Analysis User Interface displays load profiles for a consumer. This user interface has a bar chart to display the load profile for a typical consumption with the appliances shown in Figure 25. The Load Profile Weekdays adds a weekday load profile to the typical load profile in the chart. The Load Profile Weekends adds another load profile in the bar chart. This UI has controls to take different levels of price sensitivity for a consumer as power should be lowered by the smart device when at least one person is in the home or when no one is in the home. Finally, the Calculate Monthly Bill control calculates daily peak load, monthly bills, savings, etc.

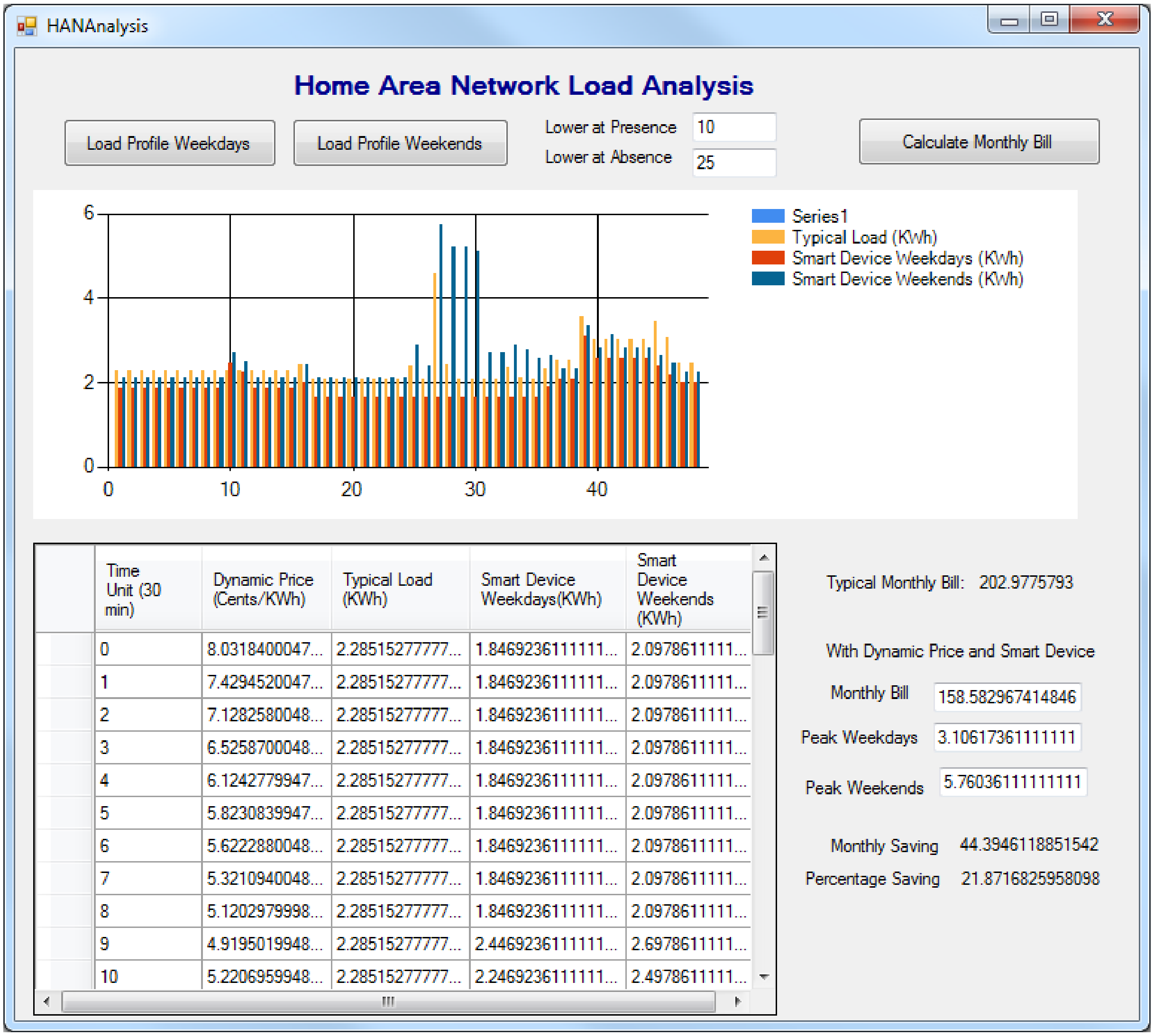


Figure 26. Controls in the Home Area Network Load Analysis User Interface

CHAPTER 8. EXPERIMENTAL RESULT ANALYSIS

The results based on the simulated demand for household consumers are discussed in this chapter. In the software all of the concepts and methodology discussed in the earlier chapters are applied. The consumer behavior and savings based on the levels of sensitivity to price. The analysis shows that all of the categories of consumers and utility suppliers will benefit from adopting dynamic pricing.

8.1. Household Consumer with Imperfect Information

Household consumers with imperfect information do not have the exact price information. Hence their response will not be based on the price of electricity at any particular time. The response of the consumer depends on his/her sensitivity to the monthly bill and his/her fear about penalty. Price sensitivity comes due to three reasons: do not want to pay more on monthly bills, want to save money or both.

8.1.1. The Linear Cost Function

The Linear cost function defines the price of electricity by keeping a linear relation to the variation in the demand of electricity (Figure 6). In Table 5, the responses of moderate price sensitive consumers and very price sensitive consumers are analyzed. The forecasted demand and the dynamic price are listed in the 2nd and 3rd columns. It is apparent that the consumption with higher price decreases when the price is higher than the average price and consumption increases when the price is lower than the average price. However, the lifestyles of both categories of consumers do not change. In Figure 27, the consumer still consumes more electricity during the evening hours. This is because the lifestyle of a typical consumer does not change. For example, a consumer may want to watch TV or play video games, etc. in the evening time when he or she returns home from work. The evening time period will remain as the peak of his or her consumption (Figure 27). To calculate the dynamic price in Table 5, the linear cost function uses the linear factor β=0.87, and the constant value γ =0.

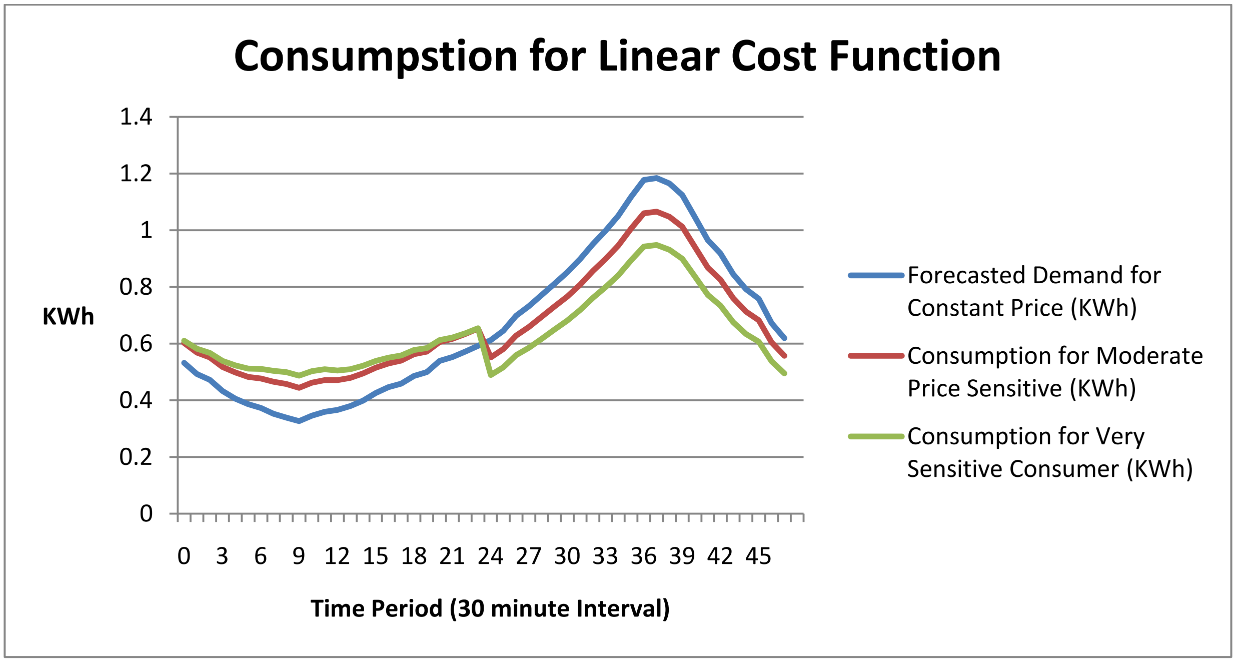


Figure 27. Expected Consumption Pattern of Electricity for Different Categories of Consumers for a Linear Cost Function

For the consumer response it is considered that the moderate price sensitive consumer will shift 10% of his or her peak hour consumption to off peak hour in order to have the benefit of a lower price. The very price sensitive consumer is assumed to lower overall consumption by 5% by turning off extra light bulbs and lowering the heater temperature in the room that is not being used. Besides this, very price sensitive consumer will also shift 10% of his/her load from peak hour consumption to off peak hour consumption.

Table 5. Half Hourly Simulated Demand, Dynamic Price by Using a Linear Cost Function and Consumption for Price Sensitive Consumer

Time Period	Forecasted Demand for Current Price(KWh)	Dynamic Price Linear Cost Function (Cents/KWh)	Consumption for Moderate Price Sensitive (KWh)	Consumption for Very Sensitive Consumer (KWh)	Change in Load Moderate Sensitive Consumer (KWh)	Change in Load Very Sensitive Consumer (KWh)
0	0.5322	8.0318	0.602	0.6103	-0.0698	-0.0781
1	0.4923	7.4295	0.5681	0.5814	-0.0758	-0.0891
2	0.4723	7.1283	0.5515	0.5674	-0.0792	-0.0951
3	0.4324	6.5259	0.5175	0.5385	-0.0851	-0.1061
4	0.4058	6.1243	0.4976	0.5232	-0.0918	-0.1174
5	0.3858	5.8231	0.4823	0.5112	-0.0965	-0.1254
6	0.3725	5.6223	0.477	0.5105	-0.1045	-0.138
7	0.3526	5.3211	0.465	0.5036	-0.1124	-0.151
8	0.3393	5.1203	0.457	0.4989	-0.1177	-0.1596
9	0.326	4.9195	0.4444	0.4873	-0.1184	-0.1613
10	0.3459	5.2207	0.4623	0.5032	-0.1164	-0.1573
11	0.3592	5.4215	0.471	0.5089	-0.1118	-0.1497
12	0.3659	5.5219	0.471	0.5052	-0.1051	-0.1393
13	0.3792	5.7227	0.479	0.5099	-0.0998	-0.1307
14	0.3991	6.0239	0.4942	0.5219	-0.0951	-0.1228
15	0.4257	6.4255	0.5155	0.5392	-0.0898	-0.1135
16	0.4457	6.7267	0.5302	0.5501	-0.0845	-0.1044
17	0.459	6.9275	0.5401	0.5578	-0.0811	-0.0988
18	0.4856	7.3291	0.5628	0.5771	-0.0772	-0.0915
19	0.4989	7.5298	0.5721	0.5837	-0.0732	-0.0848
20	0.5388	8.1322	0.606	0.6127	-0.0672	-0.0739
41	0.9646	14.5577	0.8681	0.7716	0.0965	0.193
42	0.918	13.8549	0.8262	0.7344	0.0918	0.1836
43	0.8448	12.7505	0.7603	0.6759	0.0845	0.1689
44	0.7916	11.9474	0.7124	0.6333	0.0792	0.1583
45	0.7583	11.4454	0.6825	0.6067	0.0758	0.1516
46	0.6719	10.1402	0.6047	0.5375	0.0672	0.1344
47	0.6186	9.337	0.5568	0.4949	0.0618	0.1237
Total	31.93		31.93	30.33		

In Table 6, benefits of adopting dynamic pricing are analyzed. The analysis depicts that the moderate sensitive consumer will have a benefit of $3.86 per month and the very price sensitive consumer will save $11.89 per month. In addition, the person who is not price sensitive will pay $1.03 more per month. Hence, the penalty for not being price sensitive is about 1% on the average monthly bill. It is assumed that not 100% of consumers will be moderate price sensitive or very price sensitive or not price sensitive. The total set of consumers are assumed to be 20% not price sensitive, 50% moderate price sensitive and 30% very price sensitive. For a combination of different categories of consumers the saving would be $5.27 per month which is about 4.8% of the average monthly electricity bill.

Table 6. Consumer and Supplier Benefit Analysis for Adopting the Linear Cost Function of Dynamic Pricing

	Not Price Sensitive Consumer	**Moderate Sensitive Consumer**	**Very Sensitive Consumer**	**Mixed Scenario (50% Moderate Price Sensitive, 30% very Price Sensitive, 20% not Price Sensitive)**
Constant Price Monthly Bill ($/month)	110.55	110.55	110.55	110.55
Price With Dynamic Pricing Model ($/month)	111.67	106.67	98.64	105.26
Benefit from Dynamic Pricing ($/month)	-1.03	3.86	11.89	5.27
Peak Load without Dynamic Pricing (KWh)	1.184	1.184	1.184	1.184
Peak load with Dynamic Pricing (KWh)	1.184	1.172	1.041	1.136
Saving in Peak Load for Supplier (per consumer) (KWh)	0	0.0118	0.142	0.048
Saving in Peak Load for all household in the USA (125,717,935 households) (KWh)	0	1,483,471	17,851,946	6,034,460

For the utility suppliers, dynamic pricing would be very beneficial. Both the moderate price sensitive consumer and the very price sensitive consumer are expected to shift consumption from peak hour to off peak hours. This will result in less aggregated peak load during peak hours. For flat pricing policy, the daily peak load per household is 1.184 KWh. For moderate price sensitive consumers, the daily peak load is 1.172KWh. Hence, utility suppliers need to supply 1.172KWh instead of 1.184KWh and this will save 0.0118KWh per household. There are 125,717,935 houses (Table 1) in the USA and the total saved in the USA would be 1,483,471KWh if 100% of consumers are moderate price sensitive. The total saved would be 17,851,946 KWh and 6,034,460 KWh for 100% very sensitive consumers and mixed scenario respectively.

8.1.2. Factors Sensitivity Analysis of Linear Cost Function

In Table 7, the sensitivity of factors in the linear cost function is evaluated. Different values of β and γ are applied. The optimal values of the factors are calculated so that bill becomes closer to the current monthly bills with flat rate electricity. The current monthly the bill for electricity is $110.55. It is also considered that the not price sensitive consumer will pay more than the current bill. A lower value of β gives a very low monthly bill. This will create a situation where utility suppliers would not be able to recover their cost. On the other hand, if the value of β is higher than 1, the bills for all categories of consumers become more than the average price. In such situation, all categories of consumers will have to pay more than a fair amount of the monthly bill and the utility company will earn more than the current revenue. In this simulation, the optimal value of β is 0.87 and γ is 0. For a real world application these values are negotiated between consumers and utility suppliers in the presence of a government agency.

Table 7. Factors Sensitivity Analysis for a Linear Cost Function of Dynamic Pricing

No	**Input**		**Monthly Bill**			**Saving per month**		
	β	γ	Price non Sensitive Consumer	Moderate Price Sensitive Consumer	Very Price Sensitive Consumer	Price non Sensitive Consumer	Moderate Price Sensitive Consumer	Very Price Sensitive Consumer
1	1	0	128.24	122.61	113.38	-17.70	-12.07	-2.84
2	1	1	137.82	132.48	122.48	-27.28	-21.64	-11.94
3	0.1	0.1	13.21	13.21	12.24	96.79	97.32	98.29
4	0.2	0.1	26.6	25.48	23.58	83.93	85.06	86.95
5	0.5	0.1	65.08	62.26	57.60	45.46	48.93	52.93
6	0.8	0.1	103.55	99.05	91.61	6.98	11.49	18.92
7	0.9	0.1	116.37	111.13	102.95	-5.83	-0.76	7.58
8	0.85	0.1	109.96	105.17	97.28	0.57	5.36	13.25
9	0.87	0	111.57	106.67	98.64	-1.03	3.86	11.89
10	0.87	0.1	112.53	107.63	99.55	-1.98	2.90	10.98

8.1.3. The Quadratic Cost Function

The quadratic cost function has a higher sensitivity to change in demand. By applying the quadratic cost function, the price would be higher than the price determined by the linear cost function at the peak demand. The price determined by a quadratic price would be lower than the price by using the linear cost function at the off peak demand. In Table 8, dynamic prices for the quadratic cost function are listed based on the forecasted demand for household demand. In the 4^{th} and 5^{th} columns consumption of moderate price sensitive and very price sensitive consumers are listed. The last two columns show the change in consumption in comparison to the usual consumption with flat price of electricity. For the calculation of quadratic dynamic price the quadratic factor $\alpha = 0.1$, the linear factor $\beta = 0.7$ and the constant factor γ=0.2 are employed.

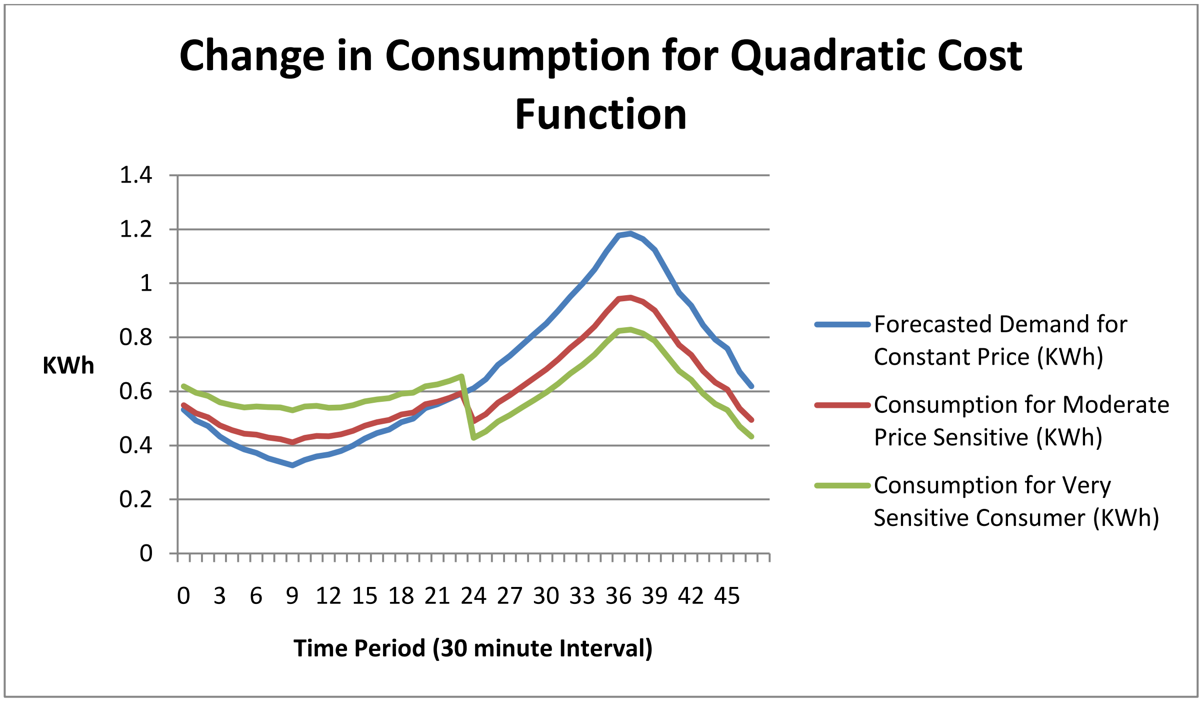


Figure 28. Expected Consumption Pattern of Electricity for Different Categories of Consumers with the Quadratic Cost Function

In Figure 28, the response of the customer to the quadratic price is illustrated. It shows a higher change in shift load. It is assumed that due to higher variation in price, moderate price sensitive consumers will turn off extra lights and will lower their consumption by 10%. Moderate price sensitive consumers will also shift 10% of the higher price load to the lower price load. The very sensitive consumer will lower the consumption by 10% and shift 20% of the demand to off peak hours. The consumer who is not sensitive to price will consume the same amount of electricity.

Table 8. Half Hourly Simulated Demand, Dynamic Price by Using a Quadratic Cost Function and Consumption for Price Sensitive Consumers

Time Period	**Forecasted Demand for Constant Price (KWh)**	**Dynamic Price Quadratic Cost Function (Cents/KWh)**	**Consumption for Moderate Price Sensitive (KWh)**	**Consumption for Very Sensitive Consumer (KWh)**	**Change in Consumption Moderate Sensitive Consumer (KWh)**	**Change in Consumption Very Sensitive Consumer (KWh)**
0	0.5322	7.201	0.5488	0.6186	-0.0166	-0.0864
1	0.4923	6.6097	0.5189	0.5947	-0.0266	-0.1024
2	0.4723	6.3171	0.5042	0.5834	-0.0319	-0.1111
3	0.4324	5.7383	0.4743	0.5594	-0.0419	-0.127
4	0.4058	5.357	0.457	0.5488	-0.0512	-0.143
5	0.3858	5.0734	0.4437	0.5401	-0.0579	-0.1543
6	0.3725	4.8856	0.4397	0.5441	-0.0672	-0.1716
7	0.3526	4.6055	0.4297	0.5421	-0.0771	-0.1895
8	0.3393	4.4199	0.4231	0.5408	-0.0838	-0.2015
9	0.326	4.2353	0.4118	0.5302	-0.0858	-0.2042
10	0.3459	4.5126	0.4277	0.5441	-0.0818	-0.1982
11	0.3592	4.6986	0.435	0.5468	-0.0758	-0.1876
12	0.3659	4.792	0.4344	0.5395	-0.0685	-0.1736
13	0.3792	4.9794	0.441	0.5408	-0.0618	-0.1616
14	0.3991	5.2622	0.4543	0.5495	-0.0552	-0.1504
15	0.4257	5.6426	0.473	0.5628	-0.0473	-0.1371
16	0.4457	5.9303	0.4856	0.5701	-0.0399	-0.1244
17	0.459	6.1232	0.4942	0.5754	-0.0352	-0.1164
18	0.4856	6.5119	0.5142	0.5914	-0.0286	-0.1058
19	0.4989	6.7076	0.5222	0.5954	-0.0233	-0.0965
20	0.5388	7.3003	0.5521	0.6193	-0.0133	-0.0805
41	0.9646	16.4474	0.7716	0.6752	0.193	0.2894
42	0.918	15.6533	0.7344	0.6426	0.1836	0.2754
43	0.8448	14.4283	0.6759	0.5914	0.1689	0.2534
44	0.7916	13.555	0.6333	0.5541	0.1583	0.2375
45	0.7583	13.0167	0.6067	0.5308	0.1516	0.2275
46	0.6719	11.644	0.5375	0.4703	0.1344	0.2016
47	0.6186	8.5106	0.4949	0.4331	0.1237	0.1855
Total	31.93		28.74	28.74		

In Table 9, the benefits of adopting quadratic dynamic pricing are analyzed. The analysis depicts that the moderate price sensitive consumer will have a benefit of $9.01 per month, which is equivalent to 8.1% of the average monthly electricity bill in the USA for household consumers. The very price sensitive consumer will save $15.49 per month which is equivalent to 14.1% of the average monthly electricity bill. In addition, the person who is not price sensitive will pay $9.47 more per month. Hence, the penalty for not being price sensitive is about 8.6% of the average monthly bill. For the mixed scenario a consumer will save $7.25 per month which is about 6.6% of the average monthly electricity bill.

Table 9. Consumer and Supplier Benefit Analysis for Adopting the Quadratic Cost Function of Dynamic Pricing

	Not Price Sensitive Consumer ($/month)	**Moderate Price Sensitive Consumer ($/month)**	**Very Price Sensitive Consumer ($/month)**	**Mixed Scenario (50% Moderate Price Sensitive, 20% very Price Sensitive, 20% not Price Sensitive)**
Constant Price Monthly Bill	110.55	110.55	110.55	110.55
Price With Dynamic Pricing Model	120.01	101.53	95.05	103.29
Benefit from Dynamic Pricing	-9.47	9.01	15.49	7.25
Peak Load without Dynamic Pricing (KWh)	1.184	1.184	1.184	1.184
Peak load with Dynamic Pricing (KWh)	1.184	1.041	0.911	0.9587
Saving in Peak Load for Supplier per household (KWh)	0	0.142	0.272	0.2253
Saving in Peak Load for all household in USA (125,717,935 households) (KWh)	0	17,863,072	34,237,556	19,200,803

The daily peak load per household is 1.184 KWh. For moderate price sensitive consumers, the daily peak load is 0.947KWh. Hence, utility suppliers need to supply 0.947KWh instead of 1.184KWh and this will save 0.236KWh per household. The total saved in the USA for household consumers would be 17,863,072 KWh if 100% consumers are moderate price sensitive. The total saved would be 34,237,556 KWh and 19,200,803 KWh for 100% very price sensitive consumers and mixed scenario respectively.

8.1.4. Factors Sensitivity Analysis of Quadratic Cost Function

The price set by the quadratic cost function in response to the change in demand highly depends on the factors in the cost function. In the quadratic function, there are three factors: quadratic factors (α), linear factors (β) and constant factors (γ). These factors contribute in determining the dynamic price. In Table 10, different sets of factors are considered to find the optimal set of factors. The final selection of factors should provide a win-win situation where price sensitive consumers will save on the monthly electricity bill. The utility supplier will gain if the peak load of the day reduces. In such case, utility suppliers do not have to invest in more generators to serve peak load for a couple of days in the summer time. Moreover, a consumer who is not sensitive to price will pay a little more than average on his/her monthly bill. This will motivate a consumer to lower electricity consumption. The optimal set of factors comprises α = 0.1, β = 0.7 and γ = 0.2. This provides a monthly saving of $9.01 for the moderate price sensitive consumers and $15.49 saving for the very price sensitive consumers. There would be a penalty of $9.47 per month if a consumer is not sensitive to price.

Table 10. Factors Sensitivity Analysis for a Quadratic Cost Function of Dynamic Pricing

No	Factor			Monthly Bill			Saving Per Month		
	α	β	γ	Price Non Sensitive Consumer	Moderate Price Sensitive Consumer	Very Price Sensitive Consumer	Price Non Sensitive Consumer	Moderate Price Sensitive Consumer	Very Price Sensitive Consumer
1	1	1	1	363.09	302.49	278.21	-252.54	-191.95	-167.67
2	.5	.5	.5	181.54	151.24	139.10	-71.00	-40.70	-28.56
3	.2	.2	.2	72.61	60.49	55.64	37.92	50.04	54.89
4	.3	.3	.3	108.92	90.74	83.46	1.61	19.79	27.07
5	.2	.5	.2	111.09	93.43	86.89	-0.54	17.10	23.65
6	.2	.7	.2	136.74	115.39	107.72	-26.19	-4.85	2.81
7	.2	.7	.3	143.49	120.80	112.45	-32.95	-10.25	-1.91
8	.1	.7	.2	120.01	101.53	95.04	-9.47	9.01	15.49
9	.1	.9	.2	145.66	123.48	115.87	-35.12	-12.94	-5.33
10	.1	.7	0	106.49	90.71	85.58	4.04	19.82	24.95

8.2. Household Consumer with Perfect Information

A household consumer with perfect information has a smart device to receive dynamic price information published by the utility suppliers and make decisions based on the price. For this experiment, a household of 3 persons is considered and appliances listed in Table 11 are used (Electropaedia, Domestic Electrica Energy Usage, 2009). All the properties in Table 11 are assumed to be used in a duplex house in the USA (Cornhusker-Power, 2009). The following flexibility factors are assumed for the appliances used in this experiment-

1. Always on and can’t lower consumption (T-1)
2. Always on but could lower consumption (T-2)
3. Usage on demand and can’t lower consumption (T-3)
4. Usage on demand but could lower consumption (T-4)
5. Allowed to change the time of consumption to midnight (T-5)

6. Allowed to change the time of consumption to weekend (T-6)

Table 11. Appliances Used for the Analysis of Household Consumption with Perfect Information

	Name of the Appliance	Typical Wattage (Watt)	Number of appliances	Average Daily Use (30 min)	Estimated Use Per Month (Hr)	Typical starting time (0-47)	Flexibility Factor
1	Refrigerator/Freezer (17.5cu.ft.)	450	1	22.20	333	0	1
2	Freezer (Defrost 15 cu. ft.)	440	1	22.27	334	0	1
3	Heater	3400	1	14.00	210	0	2
4	Heater (Portable)	1500	1	4.00	60	40	2
5	Water Heater (Quick Recovery)	4500	1	5.93	89	0	2
6	Coffee Maker (Auto Drip)	1165	1	0.33	5	15	3
7	Toaster	1400	1	0.20	3	15	3
8	Microwave	1500	1	0.73	11	38	3
9	Computer	365	1	10.00	150	36	3
10	Laptop	50	2	10.00	150	35	3
11	Television	200	2	6.67	100	38	3
12	Lighting (Indoor 14X60W)	75	5	10.00	150	38	4
13	Lighting (Outdoor 2X60W)	120	2	6.00	90	38	4
14	Fan (Attic)	400	1	28.00	420	35	4
15	Dishwasher	1200	1	1.67	25	44	5
16	Washer	512	1	1.13	17	32	6
17	Clothes Dryer	5000	1	1.13	17	26	6
18	Vacuum Cleaner	1560	1	0.40	6	24	6

Load profiles for a household are created for a typical consumption without a smart device for using appliances listed in Table 11. The days in a week are divided into weekdays and weekends.

Decision rules are set by consumers for the smart scheduler to make decisions. It is assumed that a smart device will lower the power consumption of T-2 and T- 4. It is also assumed that everyone will not be in the house during weekdays from 8.30am to 5.30pm. At that time, the smart device will lower the room heater, water heater, etc. of the entire house by assuming no one would be in the house. It is also assumed that consumers will be at home during weekends and the consumption of electricity would be doubled for using appliances of T-3 and T-4. Consumption of electricity by lights (T-4) will not be changed as they would be used only in the evening. However, consumption of electricity by fan (T-4) will be doubled. It is assumed that the appliances of T-6 are not used during the weekdays but are used in the weekends. The appliances of T-5 are assumed to be used at the time when the price of electricity is the lowest. Users may provide a percentage or number to lower consumption by T-2 and T-4 when no one is in the house (percent lower at absence) and one or all users are at home (percent lower at presence). If no such information is provided, the smart device uses the lowest default value of lower at presence 10% and lower at absence 25%. A smart device can detect the position of the consumers when they are not in the home by detecting the location of the smart phones used by the household member under a privacy agreement. It turns on the heater 5 minutes before the first person enters into the house. Values of lower at presence and lower at absence reflect the level of price sensitivity of the consumer. In Table 12, load profile for a consumer with smart device in a smart home is presented for a consumer with lower at presence 10% and lower at absence at 20%.

Table 12. Load Profile of a Consumer with a Smart Device with Home Area Network

Time Unit (30 min)	**Dynamic Price (Cents/KWh)**	**Typical Load (KWh)**	**Weekdays Load (KWh)**	**Weekends Load (KWh)**
0	8.03	2.29	1.85	2.10
1	7.43	2.29	1.85	2.10
2	7.13	2.29	1.85	2.10
3	6.53	2.29	1.85	2.10
4	6.12	2.29	1.85	2.10
5	5.82	2.29	1.85	2.10
6	5.62	2.29	1.85	2.10
7	5.32	2.29	1.85	2.10
8	5.12	2.29	1.85	2.10
9	4.92	2.29	2.45	2.70
10	5.22	2.29	2.25	2.50
11	5.42	2.29	1.85	2.10
12	5.52	2.29	1.85	2.10
13	5.72	2.29	1.85	2.10
14	6.02	2.29	1.85	2.10
15	6.43	2.42	2.00	2.43
16	6.73	2.09	1.67	2.10
17	6.93	2.09	1.67	2.10
18	7.33	2.09	1.67	2.10
19	7.53	2.09	1.67	2.10
20	8.13	2.09	1.67	2.10
41	14.56	3.03	2.56	2.81
42	13.85	3.03	2.56	2.81
43	12.75	3.03	2.56	2.81
44	11.95	3.44	2.38	2.63
45	11.45	3.06	2.20	2.45
46	10.14	2.47	2.02	2.27
47	9.34	2.47	2.02	2.27
	Total	117,26	92.93	126.58

In Figure 29, Load profiles for a household on a typical day, weekdays and weekends are displayed. It shows that at the time of office hours (8.30 am to 5.30pm) consumption lowers for assuming no one would be at home. The weekends have the highest load of the week for using washers and dryers.

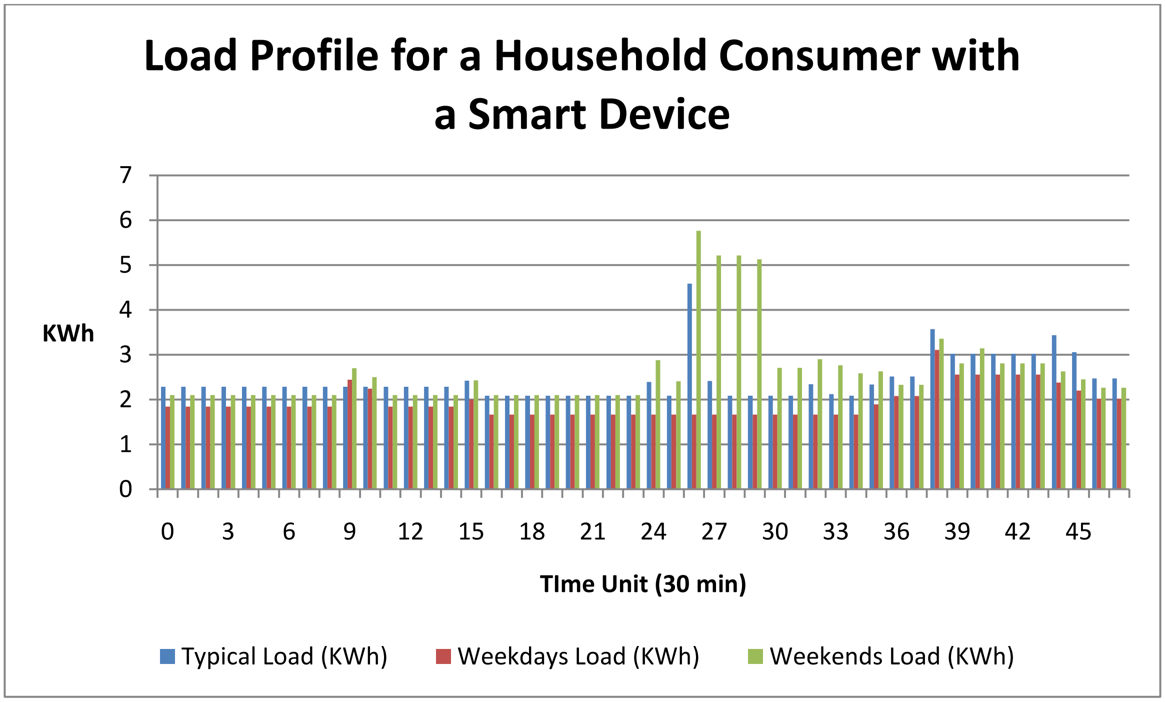


Figure 29. Load Profile for a Household with a Smart Device in a Smart Home.

The best way to save bills would be using both the washer and dryer at the time of lowest price of electricity. However, this could bring a little inconvenience for consumers as the complete cycle for washing and drying could take two days. To get the complete benefit of lowest price of electricity, a consumer will load the washer and the smart device will run it at the time of the lowest price of electricity (assumed to be at midnight). On the next day, the consumer unloads the washer and loads the dryer and it runs at the time of the lowest price of electricity (midnight). The final cycle of washing and drying would take two days. For simplicity, this paper assumes that consumers will do it at the afternoon during weekends for the convenience to get clean clothes immediately.

The benefits of a smart device will depend on the level of sensitivity of the consumer. It is also assumed that there will be 22 workdays and 8 weekends in a month. In Table 13, benefits for different values of lower at presence and lower at absence are presented. The monthly electricity bill without a smart device is $202.9 for the appliances considered in this experiment.

Table 13. Benefits from a Smart Device in a Home Area Network

No	**Lower at Presence (percent)**	**Lower at Absence (percent)**	**Peak at Weekdays (KWh)**	**Peak at Weekends (KWh)**	**Monthly bills ($)**	**Saving per month ($)**	**Percent Saving (%)**
1	0	0	3.58	5.96	185.60	17.38	8.56
2	0	5	3.49	5.96	181.16	21.81	10.74
3	0	10	3.40	5.96	176.72	26.24	12.93
4	0	15	3.32	5.96	172.29	30.68	15.11
5	0	20	3.24	5.96	167.85	35.11	17.30
6	0	25	3.15	5.96	163.42	39.55	19.48
7	5	0	3.54	5.86	183.17	19.80	9.75
8	5	5	3.47	5.86	178.74	24.23	11.94
9	5	10	3.38	5.86	174.31	28.67	14.12
10	5	15	3.29	5.86	169.87	33.10	16.31
11	5	20	3.21	5.86	165.44	37.54	18.49
12	5	25	3.13	5.86	161.00	41.97	20.68
13	10	0	3.52	5.76	180.75	22.22	10.95
14	10	5	3.44	5.76	176.32	26.65	13.13
15	10	10	3.35	5.76	171.88	31.09	15.31
16	10	15	3.27	5.76	167.45	35.52	17.50
17	10	20	3.18	5.76	163.01	39.90	19.68
18	10	25	3.10	5.76	158.58	44.39	21.87
Average			3.34	5.86	172.09	30.88	15.21

In Table 13, benefits for a linear cost function are presented. It is apparent that benefits are directly proportional to the percent lower at presence and percent lower at absence. The benefit for a consumer is 21.87%. Another important output is that if any consumption is lowered, there would be a minimum benefit of 8.56% for having a smart device.

CHAPTER 9. CONCLUSION AND FUTURE WORK

This paper discusses the concept of developing, implementing and analyzing consumer responses, as well as calculates benefits for consumers and utility suppliers. This paper considers that some consumers will not have access to perfect information about real-time market information. Based on the developed dynamic pricing model, the consumer responses could show benefit every month. This brings more practicality to implement the dynamic pricing in a smart grid.

The experimental result shows a promising outcome of dynamic pricing for a price sensitive consumer to be 10-15% of his monthly electricity bill. The suppliers will benefit by implementing the dynamic pricing model. The concept of dynamic pricing with perfect information (information processed at real time) is implemented by a smart controller in a home area network (HAN). In the HAN, appliances are connected by wireless/wired controllers which make decisions to run appliances during low price hours.

The simulation is implemented by keeping scalability in mind. Future research would be to run dynamic pricing for a longer period of time in a simulated environment and model the consumer responses. When the price of electricity is higher, a consumer lowers his/her consumption. For a lower demand, the price of electricity would be lower the next day. After running the model for a longer period of time, the price and the demand are expected to be close to the mean time with a lower fluctuation. However, due to lifestyle and weather factors a consumer might not be able to change the time of peak load. This effect of time of the peak load is considered in this paper. The combined effect of weather in a smart grid could be of interest for future research. Appliances are getting smarter and new appliances are being added to households. This could be considered for analyzing consumer response.

The Home Area Network is an interesting area for future work. The integration of existing appliances which are not smart and optimizing the overall price consumption could be examined. The artificial intelligence applied to make the scheduler/ controller smart in HAN could be another research interest. Finally, creating a smart phone interface and remote control of HAN could also be researched.

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