Model development for the comprehensive analysis of demand response programs in the Japan Electric Power Exchange (JEPX) day-ahead wholesale market

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Model development for the comprehensive analysis of demand response programs in the Japan Electric Power Exchange (JEPX) day-ahead wholesale market

Doctor of Engineering Thesis

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ABSTRACT

Among all countermeasures recommended by the Japanese government, Demand Response Programs (DRPs) is a voluntary program that allows end-user customers (CUs) to reduce their electricity usage during higher electricity prices and achieve specific outcomes on the electrical grid at varying levels. However, there has been little success in adopting DPRs in the smart electricity market due to insufficient integration between major market players, which is affected not only by technical and financial issues, but also by the social acceptance of DPRs. The purpose of this study is to investigate the main drivers of the successful application of DRPs in the Japan Electric Power Exchange (JEPX) wholesale market, through the development of a robust mathematical modeling framework that can be used to formulate both Price-Based Demand Response Programs (PBDRPs) and Incentive-Based Demand Response Programs (IBDRPs). The modeling approach is founded on the concept of social welfare maximization of market actors, considering both service providers (SPs) and CUs profitabilities from trading electricity, while addressing the aversion of the CUs to the risk of choosing PBDRPs and their satisfaction with participation in IBDRPs.

The modeling framework developed in this research is divided into three main models. The first model focuses on developing an analytical approach grounded in customer theory in microeconomics, using the concept of the expected utility function to model the behavior of the risk-averse CUs in response to different PBDRPs. An hourly-based model for short-term price elasticity of demand is introduced, considering the day-ahead price mechanism in the Japan Electric Power Exchange (JEPX) market. The estimated price elasticities are utilized in a price elasticity matrix of demand (PEMD) to accurately reflect various response strategies such as flexible, in-flexible forward-shifting, backward shifting, and optimizing responses. Accurate day-ahead hourly load forecasting using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is performed. The developed model is then employed to analyze the behavior of CUs with different response strategies in the JEPX market. The results indicate that, applying the Time-of-Use (TOU) and Real-Time-Pricing (RTP) programs suggests a peak reduction potential of 10.7% and 7.3%, respectively, for the flexible CUs. Applying the RTP program to the curtailable loads can achieve a 7.7% reduction in daily peak demand and a 1.6% reduction in daily electricity consumption.

The second model is developed to investigate the potential of Real-Time Pricing Demand Response Programs (RTP-DRPs) in adjusting the microeconomic equilibrium of the wholesale electricity market. A region-wise modeling approach is proposed to maximize end-users' social welfare by considering regions with varying supply-demand dynamics, including excess supply, high demand burden, and inter-regional connections. The results revealed that, the RTP-DRPs could potentially reduce the peak demand of the residential sector in Chubu, Chugoku, Kansai, Kyushu, Tokyo, and Tohoku by 1.91% to 7.81%. Meanwhile, in Hokkaido, Hokuriku, and Shikoku by 16.13% to 22.9%. The avoided

greenhouse emission (GHG) in Tokyo is estimated to be 82.6 and 192.2 tons in summer and winter, respectively.

The third model focuses on IBDRPs, which aim to encourage customers to reduce electricity consumption during peak periods in exchange for incentives. A multi-objective modeling approach is employed to maximize the social welfare of both SPs and CUs participating in IBDRPs. The Long–Short Term Memory (LSTM) artificial neural networks approach is used to forecast an accurate day-ahead hourly load on four years of Tokyo Electric Power Company (TEPCO) hourly power demand data from 2016 to 2020. The Kano model for customer satisfaction is utilized to assess CUs' satisfaction with participation, considering attributes such as comfort, flexibility, energy security, and environmental protection. A questionnaire survey is carried out to collect 330 responses to a pair of functional and dysfunctional questions on the four attributes mentioned above, which helps identify the explicit formulation of the CUs' satisfaction function. The analysis of the proposed IBDRP in the JEPX market using real-time wholesale electricity prices and demand loads in Tokyo's residential areas reveals that the environmental protection attribute positively impacts CUs' satisfaction and welfare, leading to greater reductions in electricity consumption and increased incentive incomes.

Overall, this research contributes to the development of mathematical models for evaluating demand response programs in Japan's wholesale electricity market. The findings demonstrate the potential of different strategies to maximize welfare, reduce peak demand, mitigate greenhouse gas emissions, and enhance customer satisfaction, ultimately leading to a more sustainable and efficient electricity system.

Keywords: Demand response programs (DRPs), Price elasticity matrix (PEM), Time series forecasting, Optimization modeling, Wholesale electricity market, multi-objective optimization modeling.

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RESEARCH ACHIEVEMENTS

This dissertation resulted in the following journal papers and conference proceedings, which were all part of the thesis, in which I am leading the first and second authors.

Journal papers:

1. Malehmirchegini,L., Suliman M., Farzaneh H. (2023). Region-wise evaluation of energy saving and greenhouse emissions reduction from the implementation of the price-based demand response programs in Japan's wholesale electricity market, *iScience* (in press). https://doi.org/10.1016/j.isci.2023.106978
2. Malehmirchegini,L., Farzaneh, H.(2023). Incentive-based demand response modeling in a day-ahead wholesale electricity market in Japan, considering the impact of customer satisfaction on social welfare and profitability. *Sustainable Energy, Grids and Networks*,101044
https://doi.org/10.1016/j.segan.2023.101044
3. Malehmirchegini,L., Farzaneh, H.(2022). Demand response modeling in a day-ahead wholesale electricity market in Japan, considering the impact of customer risk aversion and dynamic price elasticity of demand, *Energy Reports*, 8, 11910-11926
https://doi.org/10.1016/j.egyr.2022.09.027
4. Farzaneh, H., Malehmirchegini, L., Bejan, A., Afolabi, T., Mulumba, A., Daka, P.P. (2021). Artificial Intelligence Evolution in Smart Buildings for Energy Efficiency. *Applied Sciences*, 11, 763.
https://doi.org/10.3390/app11020763

Conference Proceedings:

1. Malehmirchegini, L., Farzaneh, H.(2022). Modeling and prioritizing price -based demand response programs in the wholesale market in japan," in 7th International Exchange and Innovation Conference on Engineering and Sciences(IEICES 2021), Fukuoka, Japan, 2021.

2. Malehmirchegini, L., Farzaneh, H.(2021). Price–based demand response programs considering fixed and dynamic price elasticity matrix (PEM) of demand in the wholesale market in Japan, EcoDesign for Sustainable Products, Services and Social Systems, Nara, Japan

Chapter 1
Introduction and Motivation

1.1. Electricity sector liberalization and wholesale electricity market development in Japan

The historical progress of the liberalization of the electric market in Japan is shown in Figure 1.1. The electricity market in Japan was liberalized before World War II, then nationalized during the war, and finally reprivatized after the war. Liberalization cannot be achieved without reconciling the need for greater efficiency and protecting the public interest. The first stage of liberalization occurred in 1995 when independent power producers (IPPs) and competitive bidding systems were introduced to create General Electric Utilities (GEUs) and incorporate the price-taker customers into the market. Then, in 1999, the market was liberalized for special high-voltage customers with a usage of over 2000 kW, such as factories, hospitals, and even shopping malls (Exchange TC, 2019). In the third stage of the liberalization in 2004 and 2005, high-voltage customers with a usage of over 50 kW, such as small or medium-sized buildings and factories, were also included in the deregulation programs. In addition, the wholesale market was established: for example, the Japan Electric Power Exchange (JEPX) and the Electricity System Commercial Operator (ESCJ) were put into place. The fourth stage took place in 2008 with the introduction of the hourly wholesale market and the inventory method for transmission tariffs. The Great East Japan Earthquake and the Fukushima incident in 2011 and its aftermath led to many changes that resulted in the reform of Japan's electricity market and the complete deregulation of the electricity market. In April 2016, full market liberalization was achieved, encompassing households and small businesses, and provided for legal unbundling (Shinkawa, 2018) and (JEPIC,2020).

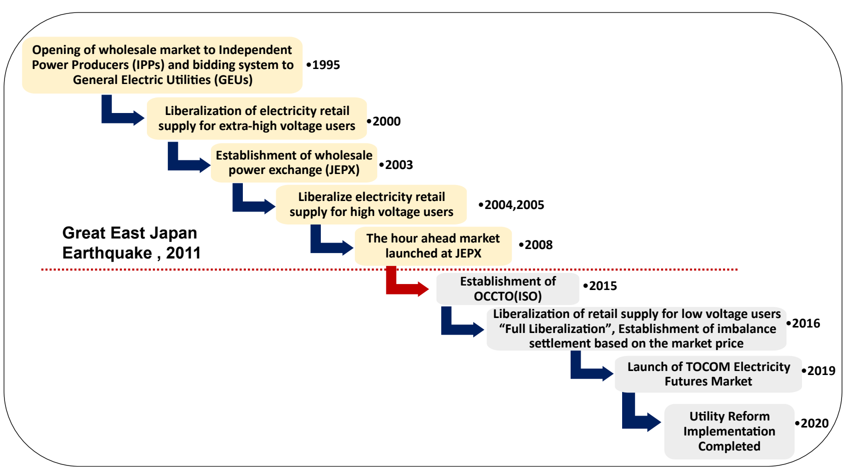

Figure 1.1 Historical progress of the liberalization of the electric market in Japan (Adapted from Shinkawa, 2018)

In Japan, electricity sector liberalization is one of the measures toward climate change and maximizing social welfare. This introduced several forms of electricity markets where the price varies based on the offered supply and demand biddings per time intervals. The dominant electricity price over other electricity markets is the wholesale Market Clearing Price (MCP), which is the unique product of a double-blind auction between independent power producers, retailers, and demand aggregators. The wholesale biddings and Market Clearing Mechanisms (MCM) are operated based on the microeconomic balance of the offered supply and demand patterns organized by the Japan Electric Power eXchange (JEPX) market.

The JEPX participants include the nine General Electric Utilities (GEUs) (except Okinawa, which is not connected to the main grid), J- POWER, power producers and suppliers (PPSs), and captive generators. The JEPX offers "spot market" products for trading electricity to be delivered on the next day at 30-minute intervals, "forward market (firm form)" products for trading electricity at 1-month and 1-week intervals, and "forward market (bulletin board)" products for freely trading electricity for future delivery (Electric T, 2004). In Addition, the JEPX began trading "carbon-free electricity" and Kyoto mechanism credits in November 2008 and an "hours-ahead" (intraday) market in September 2009 (Japanese electricity market, 2021). Figure 1.2 shows the basic structure of the JEPX.

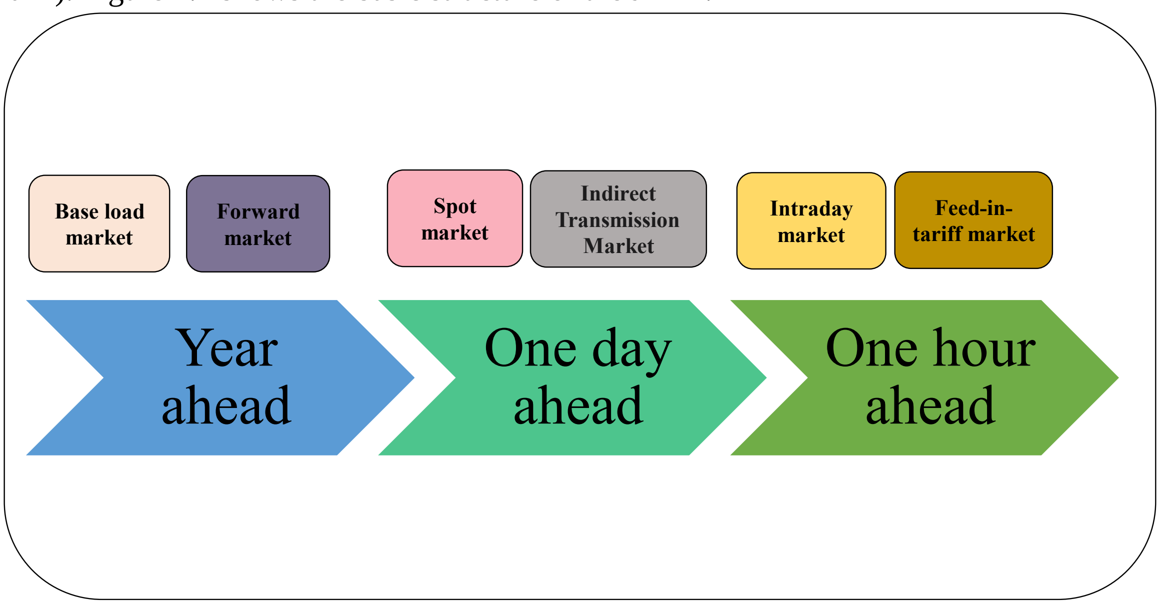

Figure 1.2 The basic structure of the JEPX (Asano, 2013)

The JEPX arranges the offered supply bidding curve based on the price-quantity bids of the energy in ascending order, while the demand aggregators' price-quantity bids curve is arranged in descending order (Samin and Kanamura, 2023).
Sequentially, the market clearing mechanism finds the cross-section between the two curves to be the market clearing price (MCP) for the particular hour, as demonstrated in Figure 1.3.

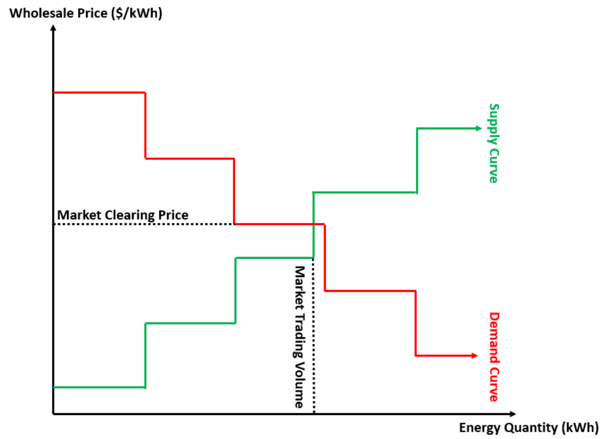

Figure 1.3 Conceptualization of the microeconomic MCM

On the other hand, the interconnected national grid is fragmented into nine regional grids, which are Chubu, Chugoku, Hokkaido, Hokuriku, Kansai, Kyushu, Shikoku, Tokyo, and Tohoku, as depicted in Figure 1.4. Each regional grid has an independent electric power utility, whereas it operates its own regional supply and demand resources (Japan Electric Power Information Center (JPIC), 2019). This produces nine regional MCPs as well as a nationwide MCP. Although the nationwide MCP applies to all energy transactions nationwide, the regional MCPs override it when the regional interconnections are employed to balance other regional supply and demand patterns. This can be justified due to the absence of a real-time frequency balancing market. Sequentially, using regional interconnections is a costly solution that produces numerous regional supply and demand equilibriums that fragment the MCM, which causes spatiotemporal price volatility (Suliman and Farzaneh, 2022).

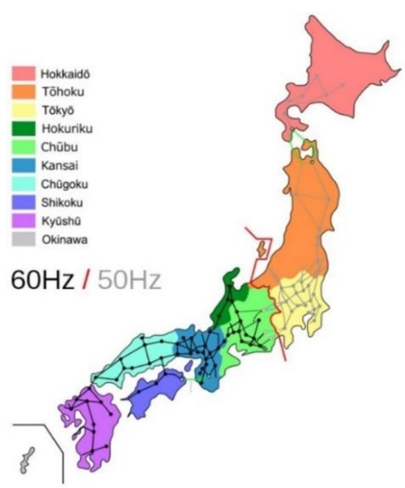

Figure 1.4 National topology of the electricity grid

Alternatively, Demand Response (DR) can tackle the regional microeconomic supply-demand imbalance without the need for inter-regional connections in a cost-effective manner. The DR is the management measures to control the electricity demand during peaks, enhance energy efficiency, and reduce greenhouse gas emissions (GHG). Responding to the shortage of supply, electricity end-users can be motivated to adjust their consumption, which can be reflected in the overall regional supply and demand equilibrium (Farzaneh H et al., 2021).

1.2. Demand response programs, classifications, and definitions

The worldwide inventory of adaptable energy-saving techniques, such as DPRs in the residential, commercial, and industrial sectors must increase tenfold from its current level by 2030 (IEA, 2019). With an annual energy consumption of 0.93 trillion kWh, Japan is one of the world's largest users and importers of energy. It ranks fifth in terms of electricity consumption globally (Renewables, 2020). In the traditional electricity market, the stability of power systems is seriously affected by increasing power demand, especially during peak times. However, in recent years, developments in the smart electricity market and the implementation of demand response programs (DRPs) have resulted in electricity price reduction, improved loads with demand flexibility, and enhanced stability by interactions between customers and the market (Malehmirchegini and Farzaneh, 2022). DRP, one of the measures suggested by the Japanese government, is a voluntary program that allows end-user customers to cut their electricity use during periods of increased power costs while also achieving particular objectives on the electrical grid at varied levels (Batchu and Pindoriya, 2015). After the Great East Japan Earthquake, solutions such as demand response have been suggested to tackle the issues in Japan's State of Supply and Demand Balance (The federation of electric power companies of Japan, 2016). In Japan, Demand response has been utilized to increase demand by 2030, based on the advancement of supply-demand balancing and grid stabilization technology, as the plans for establishing next-generation electric power networks to achieve carbon neutrality in 2050 intensify (JEPIC, 2020). DRPs are implemented in Japan by electric utilities, demand aggregators, retailers, and governmental agencies (JEPIC,2020). Currently, residential customers are billed with regulated prices (i.e., flat-rate tariffs) for their electricity consumption. Meanwhile, the government plans to install digital smart meters for countrywide households and apply the deregulated electricity prices to the residential sector are scheduled to be implemented by 2024 (JEPIC, 2022). The viability of DRPs was validated by Tokyo Electric Power Company (TEPCO) in the Tokyo power grid region for a few days in January 2018. The outcomes reported that DR has supported in critical management of supply-demand imbalance by preserving a capacity equivalent to a medium-sized thermal power plant, which demonstrates the potential capability of DRPs (Yorita, 2018).

DRPs, which play an increasingly important role in energy markets, can be considered an effective measure to reduce energy demand by changing energy consumption due to changes in tariffs or incentive rates. These programs are designed to increase power reliability and prevent price spikes that, by applying their network, market, and customers can benefit from in the short term. These programs can be generally classified into two categories: Incentive-based (IB) and Time-based (TB) programs (price-based), each having different types of programs (Malehmirchegini and Farzaneh, 2021). Figure 1.5 demonstrates the classification of different types of DRPs. The voluntary contribution of customers is required in the IBP programs to participate in a program in which the system operator immediately turns off some appliances to lower the consumer's energy use during peak time (Vardakas et al., 2015). The TBR program, on the other hand, seeks to balance the electricity load by altering consumer electricity rates during specific periods. This program primarily depends on dynamic pricing and intends to motivate consumers to respond swiftly by decreasing their electricity usage during specific times of the day (Farzaneh et al., 2021).

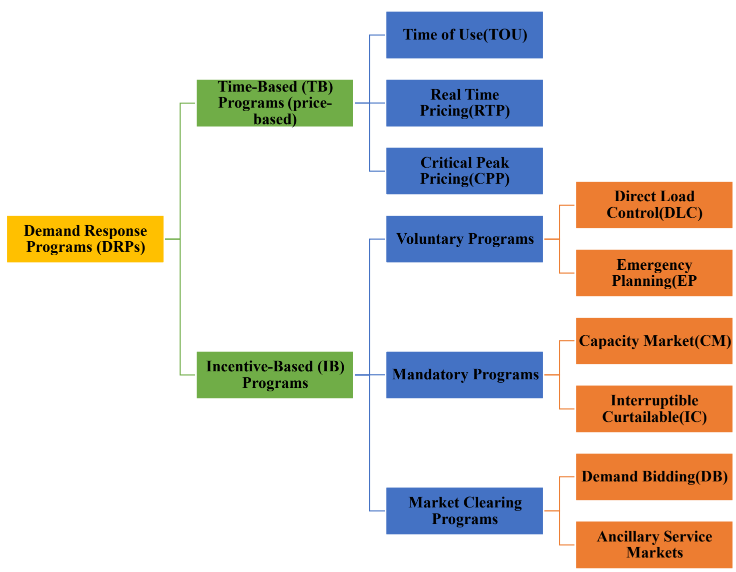

Figure 1.5 Classification of DPRs (Aalami HA et al. 2019)

1.2.1. Price-based demand response programs (PBDRPs)

Time of use (TOU): Electricity costs in a TOU pricing scheme are determined by distinct pricing intervals. By splitting a day into three parts, including peak, mid-peak (daytime), and off-peak (nighttime) times, the electricity tariffs may be computed for these intervals. These tariffs may be estimated at various times of day, days of the week, or even days of the year. Depending on the tariff, loads can be transferred from peak hours to off-peak times (Malehmirchegini and Farzaneh, 2021).

Critical peak pricing (CPP): It is an electricity pricing strategy that involves charging consumers higher rates during peak demand periods, generally a few hours per day on the warmest or coldest days of the year or when the power reliability of the market is under threat. CPP is intended to assist utilities in managing peak load by lowering electricity consumption during key peak hours and minimizing the need to construct additional power units to fulfill demand (Kato et al., 2016).

Real-time pricing (RTP): In the electricity markets, RTP refers to a pricing mechanism that determines electricity prices based on real-time supply and demand conditions. This means that the price of electricity can change rapidly, depending on factors such as weather, power plant outages, and changes in consumer demand. In this plan, the electricity tariffs are calculated, modified, and announced to the market on an hour-ahead or a day-ahead basis before starting each period (Yu et al. 2016).

1.2.2. Incentive-based demand response programs (IBDRPs)

The IBDRPs may be classified into three sub-groups based on how penalties or incentives are implemented: mandatory, voluntary, and market clearing programs. DLC and EDRP are voluntary programs in which participating consumers are not penalized if they do not reduce their use. Furthermore, the CAP and I/C are classified as mandatory programs, with enrolled consumers susceptible to fines if they do not reduce their use as recommended. A/S and DB are market-clearing programs designed to incentivize large customers to offer or provide consumption reductions at a favorable price or to identify a favorable load to curtail at the posted prices. Lastly, A/S programs allow customers to bid their consumption curtailments in the electricity markets as operating reserves (Aalami et al. 2019).

1.3. Potential of demand response programs in Japan

The Japanese electricity sector has multiple initiatives to promote and investigate the viability of DRPs. The smart community program, launched in 2012, aims to encourage smart grid technologies adoption with the implementation of DRPs (Electricity Review Japan, 2016). Furthermore, the Japan Smart Community Alliance established in 2010, promotes energy-saving technology by optimizing energy consumption through DRPs and energy management systems (JSCA, 2015). On the wholesale electricity market scale, since 2017, demand aggregators have normally been bidding for negawatts contracts based on their customized DRPs (JEPIC, 2022).

On the other hand, several contributions have developed various DRP modeling approaches oriented to the Japanese electricity market to evaluate the effectiveness of different DRPs and their policy implications. (Rohman and Kobayashi, 2014), have investigated the potential of DRP for peak reduction, considering outage scenarios in Japanese rural residential customers. To determine actual demand, the study applied load measurements on 18 households in Tsuru and 8 houses in Izu for a week in winter, spring, and summer. The results indicated that this scheme has the potential to decrease peak demand by 5.2 to 10.2%. (Mizutani et. al., 2018), have explored the impact of DR on household behavior using the influence of a reference price effect, considering peak and off-peak periods. The findings revealed that households tend to decrease their consumption when the current price is higher than the previous, and vice versa. Furthermore, based on various DRPs, residential customers can reduce their consumption by an average of 4.7 to 14% based on the implemented DRP. In addition, (Li, Y et al., 2018) have assessed the economic viability and technological benefits of demand-side management in residential buildings, focusing on analyzing CPP impact on electricity conservation and distribution patterns among different types of end-users in the Kitakyushu Smart Community Project. (Malehmirchegini and Farzaneh, 2022) have developed a mathematical modeling technique to maximize the welfare of residential end-users in Japan's wholesale market, considering a price-based DR mechanism. The model was applied to JEPX wholesale market, which found the potential reduction in peak demand for flexible customers in Tokyo using TOU and RTP pricing schemes are 7.3% and 10.7%, respectively. Furthermore, the RTP for curtailable loads can reduce the daily peak demand by 7.7% with a daily electricity consumption reduction of 1.6%. (Yunqin Lu et al., 2022) have developed a dynamic price DRP targeting the residential sector in Japan. The study collected consumption patterns of smart community and household surveys, whereas the obtained results have revealed that the air conditioner number, household income, family members number, and floor area are the major parameters affecting the DRP program. The developed DRP has the potential to reduce the residential demand by 7.8% to 16.2% in the winter and 11.3% to 13% in the summer.

However, based on the earlier contributions that have applied the DRPs in JEPX, it is observed that, although the conducted studies have reported a high potential of DRPs to decrease the peak demand in the residential sector, it lacks correlating the amount of energy saved and peak demand reduction of end-users considering the regions of the wholesale market.

1.4. Literature survey on modeling approaches used in DRPs

The DRPs in this study can be quantified into two main categories: price- or incentive-based programs. The price-based programs incentivize the end-users to adjust their electricity usage by sending price signals, which include time-of-use (TOU), critical peak pricing (CPP), and real-time pricing (RTP) (IDA et al. 2016). The incentive-based programs are based on sending quantity signals to the end-users to adjust their electricity usage of pre-identified load types based on time variation in return for incentives paid by the service provider (SP). The former notifies the price signal to the end-users to avoid consuming electricity at peak prices, while the latter incentives the end-users to shift the consumptions out of peak time (Dranka GG et al., 2019). This can further classify the methodological modeling approaches of DR applications into end-user scope and electricity market scope. Particularly, in the wholesale electricity market, the market participants of demand aggregation submit demand quantity-price bids in the form of negawatt contracts, which the market operator further employs to adjust the microeconomic equilibrium of the supply and demand quantities (Azim MI et al., 2022). In this context, (Jing Z et al., 2019) have proposed the conceptual architecture of a blockchain-based negawatt trading platform to discuss two trading scenarios, involving negawatt trading between a demand response aggregator and buildings. The study highlighted the potential of building energy management units while maintaining occupant comfort requirements by considering double auction and game theory to calculate market clearing prices. Furthermore, (Tushar et al., 2020) have comprehensively reviewed the prospects and challenges of negawatt trading considering the recent technological advancements. However, the earlier contributions either limit their investigation on the microeconomic equilibrium to formulate the biddings considering various market participants or explore the potential of a specific market form such as wholesale and real-time prices.

On the other hand, DRPs can participate in the real-time balancing market, in which the price of power is decided depending on the instantaneous balance between demand and supply patterns. In this context, several contributions have investigated the end-user's behavior toward considering real-time market prices (Xu B et al.,2021). Furthermore, customer behavior toward the real-time retailer's pricing scheme can be explored versus TOU (Kamyab F and Bahrami S , 2016), CPP(Chen W et al., 2021), and RTP (Yang J et al., 2014). (Zhu H et al., 2018) have applied the alternating direction method of multipliers (ADMM) algorithm with Gaussian back substitution (GBS) to develop a RTP method in guiding customers' consumption behavior and cutting peaks, as well as the rationality and validity of the proposed algorithm. (Hafeez G et al., 2020) have proposed an optimization approach to manage the energy consumption in residential buildings using day-ahead demand response. The approach aimed to reduce consumer electricity bills by 23.90% and the peak-to-average ratio by 47.05% compared to the benchmark strategies. In (Hu M et al., 2018), a real-time pricing DRP was utilized to schedule energy consumption and balance the rising demand for energy with the available power supply. The primary objectives were to effectively manage the demand for energy in relation to power supply, leading to increased social welfare and decreased energy bills. Furthermore, (Tostado-v M et al., 2022) have proposed a day-ahead scheduling model for prosumers in energy communities, which takes into account energy transactions with different entities. The model addressed uncertainties using a stochastic-robust approach, considering both predictable and volatile parameters. The case study results have shown that storage assets play a vital role in reducing electricity bills by 86%, while the impact of uncertainties leads to an increase in monetary cost. The RTP-DRPs were further explored by (Jordehi AR et al., 2022), considering the operation of microgrids with dispatchable generators and wind turbines under uncertain demands and renewable power. The study modeled a two-stage stochastic optimization problem to minimize the expected operation cost considering the day-ahead and real-time decision variables. Table 1-1 presents an overview of demand response models developed in earlier contributions considering different scopes.

Table 1-1 Summary of Demand response models developed in the previous studies

Category	**Type**	**Domain**	**Scope**	**Ref**
Price based	RTP	Wholesale and retail electricity markets	Profit and social welfare of the distribution company	(Moghimi FH et al.,2020)
Price based	Load curtailment (LC) Load shifting (LS) Onsite generation (OG) Energy storage (ES)	Wholesale energy markets	Aggregator benefit	(Parvania M et al.,2013)
Price based	RTP CPP TOU	Wholesale electricity market	End-user welfare	(Malehmirchegini and Farzaneh, 2022)
Hybrid DR mechanism (PB – IBDRPs)	Real-time pricing Real-time incentive	Retailer market	User welfare Retailers’ profits	(Xu B et al.,2021)
Price based	RTP	Retailer market	Retailer’s profit	(Wei W et al., 2015)

Category	Type	Domain	Scope	Ref
Price based	RTP	Wholesale market	End user’s cost of electricity and dissatisfaction	(Cortés-Arcos T et al.,2017)
Price based	CPP RTP	Wholesale market	Utility of End-user and power company	(Hafeez G et al., 2019)
Price based	TOU RTP day-ahead pricing scheme (DAPS)	Wholesale market	End user comfort	(Hafeez G et al.,2020)
Price based	TOU	Retailer market	Social welfare of the distribution company	(Fan S et al.,2018)
Price based	TOU RTP	Wholesale market	End users’ discomfort	(Javadi MS et al.,2021)
Price based Incentive based	TOU IBDRP	Wholesale market	Aggregator profit	(Vahid-Ghavidel M et al.,2021)
Price based	RTP	Regionally fragmented wholesale market	End user welfare using region-wise price elasticity matrix of demand	This study

In order to assess the impact of the CUs' participation in the different DRPs on load management in a wholesale electricity market, the development of computational modeling approaches is necessary (Patnam and Pindoriya, 2021). Previous studies have addressed the different modeling approaches which can be used in both price-based (Shaqour and Farzaneh, 2021; Torriti, 2012; Simkhada et al., 2022) and intensive-based (Yu and Hong, 2017; Lu and Hong, 2019) demand response markets considering different levels of implementation at the individual household level, the aggregate household level, the grid level, and the market level. CUs are the main actors in the wholesale electricity market. The CUs' behavior in terms of load profile and patterns are reflected in the utility function, which measures the satisfaction level of the CUs from using electricity. (Conejo et al., 2010) presented an optimization model for adjusting consumer load levels based on hourly electricity prices. The model maximized consumer utility while considering energy consumption, load limits, and price uncertainty. Numerical simulations showcased the effectiveness of the proposed model in maximizing the utility or reducing the electricity bill. Using smart metering and pricing based on hourly spot prices, a 1 kWh/h demand response was observed for customers with standard electrical water heaters (Saele and Grande, 2011). Extrapolating this response to 50% of Norwegian households, the potential demand response is estimated at 1000 MWh/h, equivalent to 4.2% of registered peak load demand in Norway.

Therefore, a respective customer-based demand response model seeks the optimal utility, maximizing the CUs' profit/welfare from consuming electricity (Niromandfam et al., 2020; Yu et al., 2020; Heydarian-Forushani et al., 2020). The CU's behavior models are widely used to analyze the impact of the optimal price on peak demand reduction (Simkhada et al., 2022; Aalami et al., 2008; Moghaddam et al., 2011) and consumption scheduling in the demand response market (Derakhshan et al., 2016; Yan et al., 2022). The rapid development of the smart energy system encourages the modeling and scheduling of integrated demand response aggregators.

The effect of demand response on power system reliability was investigated by proposing a two-stage stochastic security constraint unit commitment that considers both wind volatility and line interruptions (Mansourshoar et al., 2022). Furthermore, Dadkhah et al. designed a scheduling framework, using the reliability-constrained unit commitment program to reduce power system operation costs through identifying optimal electricity prices and incentives while ensuring system reliability during contingencies. In the emergency case, the suggested method assists system operators and customers in reliably scheduling generation and consumption units and selecting the appropriate DR program based on stated prices and incentives (Dadkhah et al., 2022).

A summary of Demand response models developed in the past investigation and previous studies taking into account to price-based demand response model is presented in Table 1-2.

Table 1-2 Summary of Price-Based Demand response models developed in the past investigation and previous studies

Purpose	Objective	Method	Results	Dynamic elasticity	Risk aversion coefficient
Applying different types of prices based DRPs for four types of residential consumers (Derakhshan et al., 2016)	Customer cost	Optimization using Teaching & Learning Based Optimization (TLBO) and Shuffled Frog Leaping (SFL) algorithms	Lower electricity cost Lower electricity consumption	*	*
Developing a dynamic electricity pricing system based on linear regression to maximize the profit of load consumers (changeable and unchangeable) in an integrated DR- renewable microgrid (Hassan et al., 2022)	Customer profit	Optimization using Particle swarm optimization (PSO) technique	Improved customer profit through adopting a price based DPR.		*
Developing a dynamic price elastic DRP scheme, taking into account the uncertainty in the load demand of a single residential customer due to behavioral factors (Sharma et al., 2022).	Customer load	Statistical analysis	Lower energy cost Lower electricity consumption		*
Optimal designing of energy hub systems, considering a price-based DPR (Asgarian and Mahmoudi, 2022).	Customer cost	Optimization using mixed-integer linear programming (MILP) problem, CPLEX solver in GAMS software.	Improved demand curve Reduced investment operating costs Reduced excess capacity of the electrical storage system	*	*

Purpose	Objective	Method	Results	Dynamic elasticity	Risk aversion coefficient
Developing a price-based self-scheduling approach for a DR aggregator to maximize the aggregator's reward for involvement in day-ahead energy markets (Parvania et al., 2013).	Aggregator’s payoff	Optimization using mixed-integer linear programming (MILP) formulation	Optimized electricity supply scheduling	*	*

To achieve the full potential of IBDRPs, it is necessary to develop an ideal DR scheme that balances the social welfare of both SPs and CUs (Haider HT et al.,2016). Although in a proposed IBDRP, the welfare of CUs is directly affected by the incentive income obtained from reducing their energy consumption, it is also affected by other factors that influence their satisfaction/dissatisfaction with participating in DRPs. For example, discomfort caused by the curtailed electricity during peak hours may cause CUs to be dissatisfied with a proposed IBDRP. This can be further expressed as a dissatisfaction penalty or cost (Yu M and Hong SH, 2017). Conversely, environmentally conscious CUs might be more satisfied with a proposed IBDRP, even if the curtailed electricity during peak hours causes discomfort. Therefore, to implement a successful IBDRP, in addition to financial incentives and drivers, it is vital to assess other relevant social factors that influence CUs' satisfaction with participating in that program. This would require developing a robust methodological approach that takes into account both the economic aspects, such as the impact of fluctuation of spot market prices and incentive rates, and the social aspects, such as the impact of CUs’ preferences in choosing the proposed IBDRP. Previous studies on IBDRPs have basically employed different modeling approaches to maximize the welfare function of the wholesale electricity market, considering the main market actors such as generators, SPs, and CUs. However, in most of these studies, the welfare function is defined as a general expression of the economic benefits of both SPs and CUs from participating in the IBDRPs, without taking the social factors influencing CUs’ preferences into account (Chai Y et al.,2019), (Heydarian-Forushani E et al., 2020) and (Yu D et al., 2019). There are good examples of this range of studies. For instance, Takano H et al. provided a modeling approach based on maximizing social welfare function, taking into account the utility and cost functions of both SPs and CUs (Lu R et al. 2018). CHAI et al. developed an IBDRP model that takes into consideration CU's utility and fixed elasticity values for residential, commercial, and industrial consumers, during valley periods to maximize retailer benefits (Chai Y et al.,2019). Yu et al. developed an IBDRP model, considering customer benefit and flexible demand elasticity, including both the penalty and incentive factors in the CUs’ benefit function (Yu D et al., 2019). As one of the comprehensive studies, Yu et al. developed a novel IBDRP model based on a combination of the two-loop Stackelberg game theory with the multi-objective optimization method in which the wholesale market welfare function is optimized through a simultaneous optimization of the procurement cost of Grid Operator (GOs), the revenue from the wholesale market trading with the GOs while decreasing incentive payments to enrolled customers for the SPs, and the utility function for the CUs (Yu M and Hong SH, 2017). The social aspect of the CUs' preferences in participating in the IBDRPs has been addressed in a few studies, by quantifying CUs' dissatisfaction with curtailed electricity during the implementation of the programs. Three are a few examples here. Lu et al. proposed an IBDRP modeling approach that maximizes the CUs' profit from participating in the IBDRPs, as a function of both incentive income and dissatisfaction cost caused by the curtailed electricity (Yu M and Hong SH, 2019). Takano H et al. suggested a method that calculates the appropriate incentive payment as the degradation of the CUs' comfort caused by the curtailed electricity, using sigmoid functions, which are frequently employed to express the link between human senses and external stimuli (Takano H et al.,2018). Using game theory, Lu et al. (Lu Q and Zhang Y, 2021) developed a multi-objective optimization model adjusting the dynamic electricity price mechanism to assess customer satisfaction with the electricity consumption mode. In another effort, Lu et al. (Lu R et al., 2018) proposed the dynamic pricing DR algorithm for energy management in a hierarchical electricity market to optimize the profit of the service provider and the costs of the customers using the Reinforcement learning (RL) technique while also taking into account the convex CU satisfaction function and the varying CU preference values. Renzhi Lu et al. also proposed an hour-ahead demand response strategy for home energy management systems (HEMS), which uses artificial intelligence (AI) to lower the user's energy costs and level of discomfort, considering the quadratic dissatisfaction cost (Lu R et al., 2019).

1.5. What will be elucidated in this research

Due to the lack of sufficient integration among main market actors, only little success in the adoption of DPRs in the smart electricity market has been achieved, which is influenced not only by the technical and financial problems but also by the social acceptance of the DPRs. Therefore, for enhanced diffusion and further development of DPRs in the future electricity market in Japan, this research addresses a new interdisciplinary approach that includes both technical and social diffusion barriers faced by the commercialization process of the DPRs in the future electricity market in Japan.

1.6. Research Methodology

Following the previous studies, the study examines the best way to establish DRPs in the wholesale electricity market in Japan, considering the market actors' profitabilities from trading electricity in the market, taking into account the aversion of the CUs to the risk of choosing PBDRPs and their satisfaction with participation in IBDRPs. The modeling framework developed in this research has the following three main parts:

1) **PBDRP-based modeling approach, considering the impact of customer risk aversion and the dynamic price elasticity of demand:** This includes a mathematical modeling approach to maximize the welfare of the price-responsive customers in a wholesale electricity market in Tokyo, Japan. Based on the research methodology, the hourly demand is forecasted using the time series technique, considering four years of hourly electricity demand data collected from TEPCO. Next, the dynamic price elasticity of demand is estimated using day-ahead electricity demand and price in the JEPX. An accurate day-ahead hourly load forecasting is performed, using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The price elasticity matrix of demand is then established by defining the self and cross-elasticity coefficients. Elasticity values are used to estimate the risk aversion coefficients needed for calculating the expected utility function. Finally, taking into account different DRPs and CU's response strategies, including flexible, in-flexible forward-shifting, backward-shifting, and optimizing responses, the welfare of the price-responsive customers is maximized and evaluated.

2) **Region-wise PBDRP-based modeling approach, considering microeconomic equilibrium in the wholesale electricity market:** This explores the application of the developed PBDRP-based model to the nationwide scale, considering the regions of the wholesale electricity market to investigate the regional-wise potential of energy savings, peak shaving, and avoided greenhouse gas (GHG) emissions. To this aim, an integrated modeling approach is developed based on applying customer welfare maximization in regionally fragmented wholesale electricity markets, by formulating the PEMD for a regionally fragmented wholesale electricity market by estimating the self- and cross-price elasticity matrix of demand, considering spatial-temporal wholesale electricity prices and demand profiles

3) **IBDRP-based modeling approach, considering the impact of customer satisfaction on social welfare and profitability:** This includes the development of a comprehensive multi-objective mathematical modeling approach, based on maximizing the social welfare function of both SPs and CUs involved in the IBDRPs in order to find the optimal incentive rates paid to the CUs for decreasing their electricity consumption, taking into account the impact of price elasticity of demand and day-ahead wholesale electricity market price. The Long–Short Term Memory (LSTM) artificial neural networks approach is used to forecast an accurate day-ahead hourly load on four years of Tokyo

Electric Power Company (TEPCO) hourly power demand data from 2016 to 2020. Second, the social aspect of IBDRP participation is further addressed by introducing a satisfaction function, which estimates the level of CUs' satisfaction from participation in the proposed IBDRP, taking into account the impact of the four IBDRP attributes of comfort, flexibility, energy security, and environmental protection, using the Kano model. Third, a questionnaire survey is carried out to collect responses to a pair of functional and dysfunctional questions on the four attributes mentioned above, which helps identify the explicit formulation of the CUs' satisfaction function. The elasticity of CUs' satisfaction with their social welfare is estimated, reflecting how the CUs' welfare might be affected by the changes in the level of fulfillment of different IBDRP attributes.

1.7. Thesis organization

Chapter 2: The contributions made by this chapter in the quest to determine the role of CUs in a demand response market are twofold. First, the aversion of the CUs to the risk of choosing the PBDPRs is taken into account by considering their expected utility from consuming electricity. Second, it introduces an hourly-based model for the short-term price elasticity of demand, considering the day-ahead price mechanism defined in the Japan Electric Power Exchange (JEPX) market.

Chapter 3: This chapter proposes integrating the customer profitability of the residential sector with the utility scale using a single price-based RTP-DRP optimization model for all the regions, while considering the microeconomic equilibrium of the regional wholesale prices through estimating the PEMD for each region dedicatedly. Moreover, the region-wise potential benefits (peak reduction, energy savings, and avoided emissions) of implementing the DRP in Japan's wholesale electricity market are investigated, considering the wholesale market's regions and prices.

Chapter 4: This chapter introduces the welfare maximization problem in the IBDRPs. The social aspect of the CUs' participation in the IBDRPs is evaluated with respect to their satisfaction with the intangible benefits, which cannot be measured in monetary terms. To this aim, a Kano model for customer satisfaction is developed to estimate the level of CUs' satisfaction with participation in the IBDRPs. The chapter then discussed the results of the proposed IBDRP implemented in the JEPX market, using real-time wholesale electricity prices and demand loads in the Tokyo residential areas.

Chapter 5: The last chapter summarizes the major findings of the research, and the study limitations and future work will be further elaborated in this chapter.

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Chapter 2
Price-based demand response modeling in a day-ahead wholesale electricity market in Japan, considering the impact of customer risk aversion and dynamic price elasticity of demand

Abstract: This chapter aims to develop a mathematical modeling approach to maximize the welfare of the price-responsive customers (CUs) in a wholesale electricity market in Tokyo, Japan. The contributions made by this chapter in the quest to determine the role of CUs in a demand response market are twofold. First, the aversion of the CUs to the risk of choosing the Demand Response Programs (DPRs) is taken into account by considering their expected utility from consuming electricity. The proposed model is founded on the customer theory in microeconomics, using the concept of the expected utility function to model the behavior of the risk-averse CUs in response to different DPRs. Second, it introduces an hourly-based model for the short-term price elasticity of demand, considering the day-ahead price mechanism defined in the Japan Electric Power Exchange (JEPX) market. The estimated price elasticities are used in a price elasticity matrix of demand (PEMD) to precisely reflect the different response strategies, including flexible, in-flexible forward-shifting, backward shifting, and optimizing responses. An accurate day-ahead hourly load forecasting is performed, using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, which is trained on four years of data provided by the Tokyo Electric Power Company (TEPCO), with a mean absolute percentage error (MAPE) of 0.94%. The developed model is used to analyze the CUs' behaviors with different response strategies in the JEPX market in Tokyo. Applying the Time-of-Use (TOU) and Real-Time-Pricing (RTP) programs reveals a peak reduction potential of 10.7% and 7.3%, respectively, for the flexible CUs. Applying the RTP program to the curtailable loads can achieve a 7.7% reduction in daily peak demand and a 1.6% reduction in daily electricity consumption.

2.1. Introduction

The CU's welfare is a complex function of its utility as a central function that is affected by electricity usage at different hours of the day and the cost of electricity. Most previous studies focused on optimal CU's utility obtained under certainty, revealing little about the CU's behavior toward risk (Lu and Hong, 2019; Samadi et al., 2012; Niromandfam and Choboghloo, 2020). However, in a demand-responsive market, CUs' preference for participating in the DPRs and their responses to the price changes are made under a given probability of risk with uncertain payoff and satisfaction. Price elasticity is essential in modeling the CUs' behavior in the demand response models. Previous models are mainly based on given fixed values for the long-term price elasticities of demand for the incentive-based programs (Yu et al., 2020; Moghaddam et al., 2011), for time-based DRPs (Aalami et al., 2015) and for both time-based and incentive-based programs (Aalami et al., 2010). However, in a day-ahead price-responsive demand market, the value of the price elasticity changes with respect to the hourly pattern of electricity demand and should not be considered a fixed value for the whole period. Besides considering the different DRPs, including TOU, RTP, and CPP, which were addressed in the previous studies on residential load scheduling (Roh et al., 2016; Bahrami et al., 2018), home energy management systems (Lu et al., 2019), smart residential community (Nan et al., 2018), the impact of different response strategies such as flexible, in-flexible, forward-shifting and backward shifting should comprehensively be taken into account in evaluating the CUs' participation in the demand response market.

To fill the above gaps, this chapter proposes a customer-based demand response model, which can be used in a price-responsive wholesale electricity market in Tokyo, considering the following main contributions:

- The concept of the expected utility function taken from the cardinal utility theory will be further emphasized and used to address the risk-averse customers more precisely, with the risk appetite and preferences of the CUs in choosing the desired DPRs taken into account.
- An hourly-based model for the short-term price elasticity of demand is developed, considering the impact of the hourly price of electricity and also climate conditions (Heating and cooling degree days) on electricity demand. Furthermore, a precise PEMD was developed, using day-ahead hourly electricity prices in the JEPX to model the CUs' behavior in response to the DPRs implemented in Tokyo.
- An accurate day-ahead hourly load forecasting is performed, using the SARIMA time series method on four years of Tokyo Electric Power Company (TEPCO) hourly electricity demand data from 2016 to 2020.

The overall research study in this chapter is represented in Figure 2.1. Based on the research methodology, the hourly demand is forecasted using the time series technique, considering four years of hourly electricity demand data collected from TEPCO. Next, the dynamic price elasticity of demand is estimated using day-ahead electricity demand and price in the JEPX. The price elasticity matrix of demand is then established by defining the self and cross-elasticity coefficients. Elasticity values are used to estimate the risk aversion coefficients needed for calculating the expected utility function. Finally, taking into account different DRPs and CU's response strategies, the welfare of the price-responsive customers, is maximized and evaluated, which will be explained in the following sections.

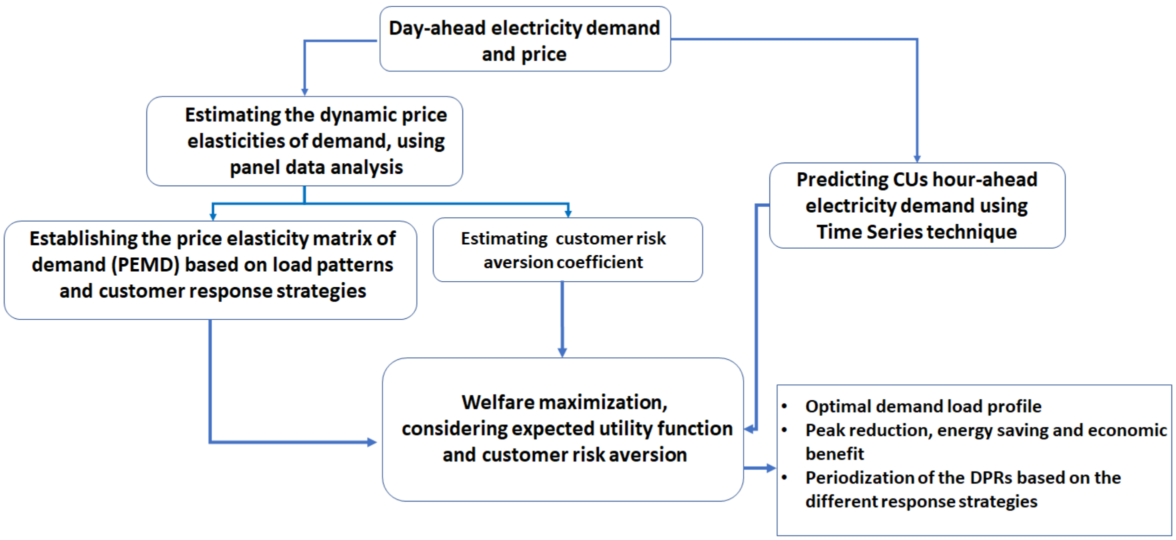

Figure 2.1 Research methodology used in this chapter

2.2.Problem formulation

2.2.1. Welfare maximization of the risk-averse customer in the price-based demand response market

The welfare-seeking optimization model of the customer in a day-ahead electricity wholesale market can be expressed as follows (Niromandfam et al., 2020; Aalami et al., 2008) :

$$\text{Maximize: } W_{CU} = \sum_{h=1}^{H} \lambda_h U(E_h) - E_h p_h \tag{2-1}$$

Subject to:

$$E_h = E_h^0 \left[1 + \varepsilon_{i,i} \frac{p_h - p_h^0}{p_h^0} + \sum_{h=1,}^{24} \varepsilon_{i,j} \frac{p_h - p_h^0}{p_h^0} \right] \tag{2-2}$$

$$p_{h_{Min}} \leq p_h \leq p_{h_{Max}} \tag{2-3}$$

Where, U refers to the customer utility, which measures the level of satisfaction from using electricity, and its unit is Utils. E_h is the CU's electricity demand after taking part in the DRPs. E_h^0 refers to the CU's hour-ahead electricity demand before taking part in the DPRs. p_h and p_h^0 denote new (based on the selected DPR) and initial electricity prices, respectively. λ_h is a multiplier used to calibrate the estimated value of the utility with the cost term in the objective function, and its value can be defined when the welfare (W_{CU}) is maximized, as follows(Niromandfam et al., 2020):

$$\lambda_h = {p_h^0}\Big/{\frac{\partial U}{\partial E_h^0}} \tag{2-4}$$

Constraint 2-2 represents the electricity demand as a combination of the single period that can be moved from peak time to off-peak time or turned ON or OFF in the multi-period loads. In a wholesale market, the price elasticity of demand is used to measure the change in electricity consumption with respect to the change in electricity price as follows(Men et al., 2019):

$$\varepsilon = {\frac{\Delta E}{E_0}}\Big/{\frac{\Delta p}{p_0}} \tag{2-5}$$

The CUs response to the price change in a selected DRP can be expressed by the price elasticity matrix of demand (PEMD) in a 24-hour interval, as follows (Matsukawa et al., 1993; Men et al., 2019):

$$\begin{bmatrix} \Delta E_h/E_h^0 \\ \vdots \\ \Delta E_{h,i}/E_{h,i}^0 \\ \vdots \\ \Delta E_{h,24}/E_{h,24}^0 \end{bmatrix} = \begin{bmatrix} \varepsilon_{1,1} & \cdots & \varepsilon_{1,j} & \cdots & \varepsilon_{1,24} \\ \vdots & & & & \vdots \\ \varepsilon_{i,1} & \ldots & \varepsilon_{i,i} & \cdots & \varepsilon_{i,j24} \\ \vdots & & & & \vdots \\ \varepsilon_{24,1} & \cdots & \varepsilon_{24,j} & \cdots & \varepsilon_{24,24} \end{bmatrix} * \begin{bmatrix} \Delta p_h/p_h^0 \\ \vdots \\ \Delta p_{h,i}/p_{h,i}^0 \\ \vdots \\ \Delta p_{h,24}/p_{h,24}^0 \end{bmatrix} \tag{2-6}$$

In the above PEMD, the self-elasticity coefficient, $\varepsilon_{i,i}$ represents the effect of the price varying in a time interval (i) on the electricity consumption for the same interval (i). The cross-elasticity, $\varepsilon_{i,j}$ captures the demand response for a time interval (i) to the price change in another interval (j).

The utility function is used to determine the CUs' satisfaction with using electricity in different DRPs. As an independent decision-maker, the electricity demand of a CU varies due to the selection of the different DRPs. In a day-ahead wholesale electricity market, the CUs' expected level of satisfaction from consuming electricity can be considered as a function of their aversion to the risk of choosing the different DPRs, which can be expressed by the "risk aversion" factor (R). As shown in Figure 2.2, the risk attitude of CUs is directly related to the curvature of their utility functions, which can be represented with an exponential form of the utility function (Johnstone and Lindley, 2013):

$$U(E) = 1 - e^{-RE} \quad ,R > 0 \tag{2-7}$$

And:

$$U'(E) = Re^{-RE} \quad > 0 \tag{2-8}$$

$$U''(E) = -R^2e^{-RE} \quad < 0 \tag{2-9}$$

Therefore, the risk aversion factor can be estimated as follows(Thompson, 1993):

$$\mathrm{R} = -\frac{\mathrm{U''(E)}}{\mathrm{U'(E)}} \tag{2-10}$$

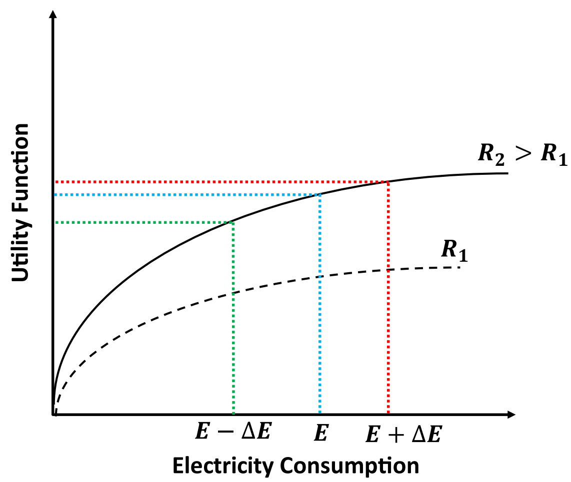

Figure 2.2 Utility function of a risk-averse customer

As an extension of the customer theory, the CUs will decide to maximize the expected value of their utilities, in uncertain circumstances, over risky choices(Roxburgh et al., 2010). The utility function is concave if the expected utility maximizer is risk-averse. This can further be explained using a Mean-Variance analysis to consider a normally distributed electricity demand ($E = E_h + \epsilon$) function with its mean and variance (Buccola, 1982). The probability density function (PDF) of E can be presented as follows:

$$f(E) = \frac{e^{\frac{-(E-\mu)^2}{2\sigma^2}}}{\sigma\sqrt{2\pi}} \tag{2-11}$$

Assume utility is exponential, the expected utility function can be expressed by using the following formula (Spiegel, 2013):

$$EU(E) = \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty} -e^{-RE}e^{\frac{-(E-\mu)^2}{2\sigma^2}}dE \tag{2-12}$$

Therefore, the CU's expected utility can be estimated as follows, keeping the range of the function between 0 and 1 over the domain of non-negative values for R (Buccola and French, 1978) :

$$EU(E) = 1 - e^{-RE}e^{-R\mu+\frac{R^2\sigma^2}{2}} \tag{2-13}$$

Hence, in a wholesale electricity market, the CUs' expected utility is higher with the mean of their electricity consumption and lower with the variance. Larger values of R are associated with more risk-averse behavior from the CUs. This satisfies the decisions of CUs that maximize their expected utility, by maximizing the probability that the consequences of the decision are preferable to other DPRs. Equation (2-13) can be replaced in the objective function of the model (Equation (2-1)), indicating that, under uncertainty, the expected utility best represents the utility at any given point in time. So, the risk-averse CUs will change their load pattern after participating in the desired DPR, which results in the highest expected utility from electricity consumption in a given period

As explained in Equation (2-2), E_h reflects the hourly CU's demand after implementing the desired DRP, which can be estimated with respect to the value of three main parameters: 1) the new electricity price decided by the market operator based on the desired DPR, 2) the hourly price elasticity of demand and 3) the CU's hour-ahead electricity demand which can be predicted, using the forecasting method explained in the following section.

2.2.2. Time series forecasting of the day ahead hourly electricity demand

In this chapter, a day-ahead hourly load forecasting model was performed, using the time-series decomposition technique. The application of the time series technique in estimating the energy demand has been addressed by scholars worldwide(Victor Gil, 2016; Shah et al., 2019; Chujai et al., 2013). The proposed forecasting model is based on the multi-seasonal time series Auto-Regressive Integrated Moving Average (ARIMA) method to predict the electricity consumption of the CUs, with the effects of seasonality taken into consideration. Compared to the classical ARIMA model, the Seasonal ARIMA model (SARIMA) used in this study has additional seasonal terms and relies on differences and seasonal lags to fit the seasonal patterns. It can be written using the following operator polynomials (Zemkoho, 2018) :

$$\begin{aligned}&\left(1-\phi_1 B-\cdots-\phi_p B^p\right)\left(1-\Phi_1 B^s-\cdots-\Phi_P B^{sP}\right)(1-B)^d\left(1-B^s\right)^D E_t^0 \\ &=\left(1-\theta_1 B-\cdots-\theta_q B^q\right)\left(1-\Theta_1 B^s-\cdots-\Theta_Q B^{sQ}\right) e_t\end{aligned} \qquad \text{2-14}$$

Here, E_t^0 denotes the observed value of CU's electricity demand (before taking part in the DPRs) at time t. The non-seasonal autoregressive and moving average elements are represented by polynomials $\phi_p(B)$ and $\theta_q(B)$ of trend orders p and q. $\Phi_P(B)$ and $\Theta_Q(B)$ refer to seasonal autoregressive and moving average elements of trend orders P and Q, respectively. d and D represent the non-seasonal and seasonal difference components, respectively. B is the backward shift operator ($BE_t^0 = E_{t-1}^0$). e_t refers to the error term, normally distributed with mean 0 and variance 1. s is the number of periods per season. ϕ , Φ, and Θ are the model coefficients.

The detailed steps of the time series forecasting with the SARMIA model used in this study are explained in Figure 2.3.

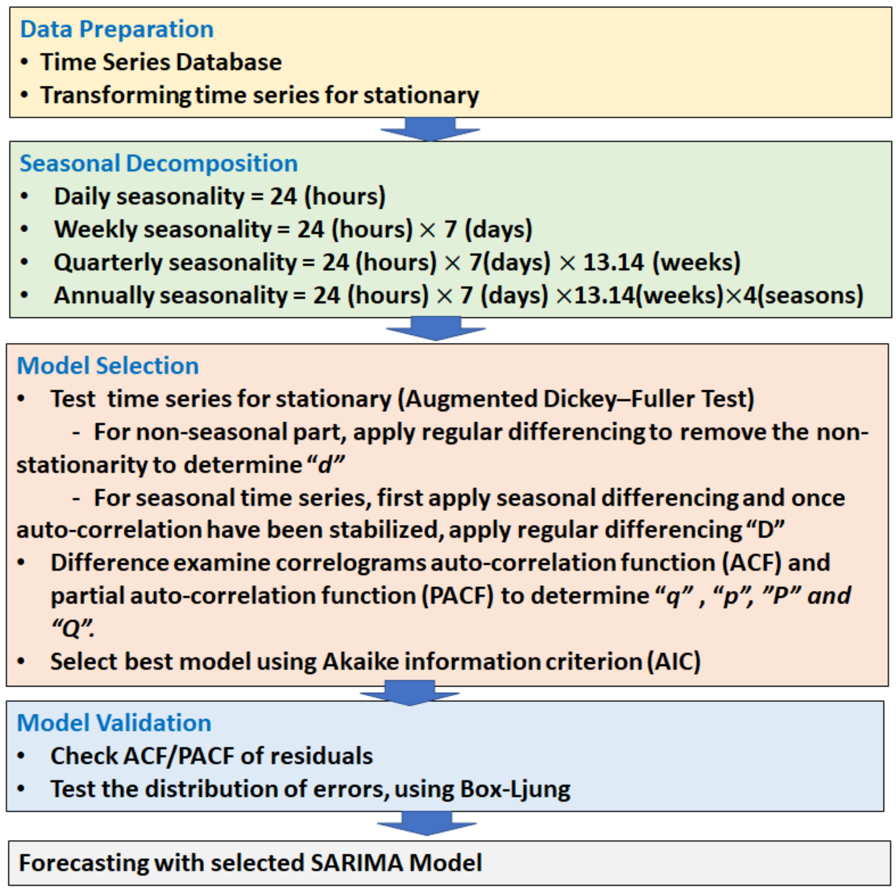

Figure 2.3. Structure of the time series forecasting model in this study

According to the forecasting model structure, the model selection and forecasting process can be separated into three stages: model identification, model estimation and testing, and model application for forecasting the future. The Dicky fuller test can be performed in the first stage of data preparation to check whether the data is stationary. Seasonal decomposition of the data is performed to decompose a time series into trend, seasonal, cyclical, and irregular components. Because hourly demand data is employed, the time series is decomposed into daily, weekly, quarterly, and yearly seasonality. Following that, data time plots are examined using the autocorrelation function (ACF) and the partial autocorrelation function (PACF) to identify potential models. Then, the parameters (p, d, q) and (P, D, Q) are estimated in potential models, and the best model is selected using Akaike's information criterion (AIC). Finally, the residual portmanteau test is used to validate the model. The selected model is then utilized to forecast the electricity demand.

2.2.3. Panel data analysis of the dynamic price elasticity of the electricity demand

Extensive empirical studies have been conducted to estimate the long and short-run price elasticities of electricity demand, using different modeling approaches, such as dynamic random variable models, log-linear fixed effects, generalized Leontief, and general equilibrium analysis. Shigeharu et al. estimated the fixed price long-run and short-run elasticities of residential electricity demand at -0.48 and -0.39, considering areas clustered by income stages and weather patterns in Japan (Okajima and Okajima, 2013). Hosoe and Akiyama, used the ordinal least squares (OLS) method to quantify the short-run and long-run price elasticities for nine regions in Japan and reported them to be -0.09 to -0.3 and -0.12 to -0.56, respectively(Hosoe N, 2008.). Matsukawa estimated the price elasticity of residential Japanese electricity demand at -0.37, using the data of the General Electric Utilities in Japan from 1980 to 1988 (Matsukawa et al., 1993). Nakajima estimated the elasticity of the (long-run) electricity price of residential demand in Japan to be -1.12, using empirical panel analysis techniques for the data from 1975 to 2005(Nakajima, 2010).

However, in a day-ahead electricity demand-responsive market, the value of the price elasticity changes with respect to the hourly pattern of electricity demand. Therefore, the degree of demand flexibility and its utility within this market differ depending on the time of the day. This highlights the necessity of estimating a time-varying price elasticity to reflect the dynamic interaction between the CUs and the SPs in a day-ahead wholesale electricity market. As a novel contribution, in this study, a dynamic form of the self-elasticity of demand in Japan's day-ahead wholesale electricity market was formulated, using a panel data analysis technique based on the least-squares dummy variable regression to consider the effect of the hourly price of electricity and the impact of climatic conditions on electricity consumption (Torres-reyna, 2007). This can be expressed as follows:

$$E_h^0 = \alpha_h + \varepsilon_h p_{h,D} + \gamma_h \mathrm{HDD}_{h,D} + \rho_h \mathrm{CDD}_{h,D} + U_{h,D} \qquad \text{2-15}$$

The panel dataset has 24 hours as cross-section (entity or subject) variables and days of the year as time-series variables. h and D are indices for hour and day. α_h is the unknown intercept. β, γ, ρ are coefficients of the independent variables whose values need to be estimated using the regression method. ε_h is here the hourly price elasticity of electricity demand. HDD and CDD refer to the Heating Degree and Cooling Degree Days, respectively. $p_{h,D}$ is the hourly price of electricity each day. U is the error term.

The following formula describes the relationship between the price elasticity of demand and the risk aversion coefficient (R_h), under the exponential utility function(Niromandfam and Choboghloo, 2020.):

$$\varepsilon_h = -{}^{1}\!/_{R_h E_h^0} \qquad \text{2-16}$$

2.2.4. Customer behavior modeling

In order to reflect the CUs' behavior in responding to the DPRS, the PEMD was formed using the values of self and cross elasticities. The self-elasticity includes the estimated values of the hourly electricity price of demand explained in the previous section. The value of the cross-elasticities is defined based on how the CUs reschedule their demands due to responding to the different DRPs (Kirtley et al., 2008). Figure 2.4. shows the definition and classification of the CUs' behavior and the load characteristics in the PEMD. Considering price-based DRPs (TOU, CPP, and RTP), three different load types are introduced based on the flexibility to reduce or transfer the consumption in specified time intervals known as shiftable, curtailable, and fixed load types.

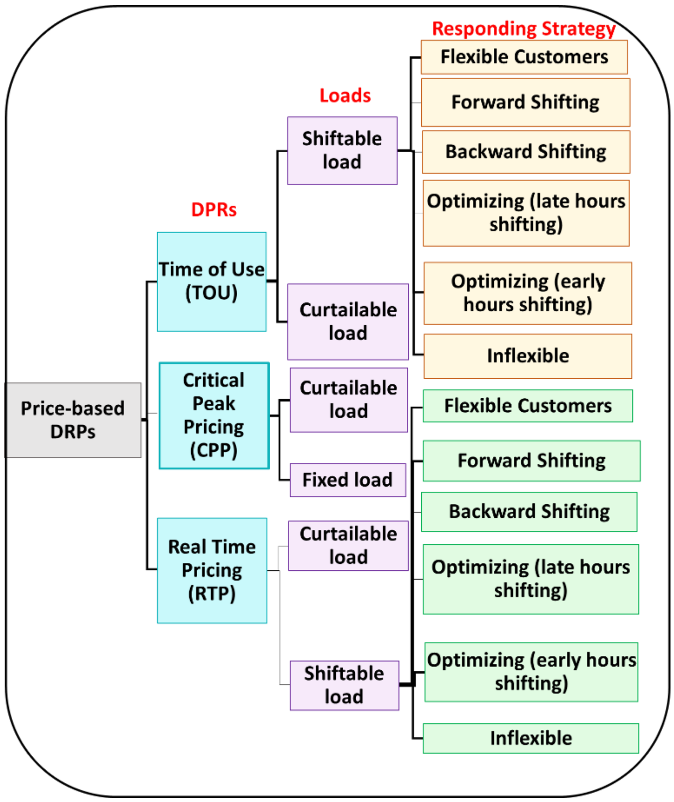

Figure 2.4 Definition and classification of the different DRPs, loads, and CUs behavior in PEMD used in this study

The PEMD structure based on the different load types and CUs behaviors is depicted in Figure 2.5. The load pattern of single or multiple CUs is classified into fixed, curtailable, and shiftable. Fixed loads are considered to be either "ON" or "OFF" during the specified periods, and they are price inelastic. Therefore, all elements in the PEMD are equal to zero (see Figure 2.5.). Curtailable loads represent insubstantial loads that can be reduced (but not shifted) when high prices are announced. The PEMD of the curtailable and fixed loads includes non-zero elements only during peak hours (self-elasticity) since loads can be reduced or disconnected during peak hours but not shifted to other hours. Shiftable loads may be moved to different periods of the day in a lossless PEMD with negative values along the diagonal and zero values for off-diagonal elements (Kirtley et al., 2008).

The CU's behavior with different responding strategies is reflected in the PEMD by introducing flexible, in-flexible, forward shifting, backward shifting, and optimized CUs, as shown in Figure 2.5. The backward shifting and forward shifting CUs react to high prices by shifting their consumption earlier or postponing it until after the high price period, respectively. Flexible CUs can reschedule their electricity consumption over a long period throughout the day. However, because the inflexible CUs are limited to shifting their loads, the non-zero elements are distributed around the diagonal of the PEMD before and after peak hours. Finally, the optimizing CUs take advantage of the hours with the lowest prices; therefore, they prefer to shift their consumption to early morning or late night.

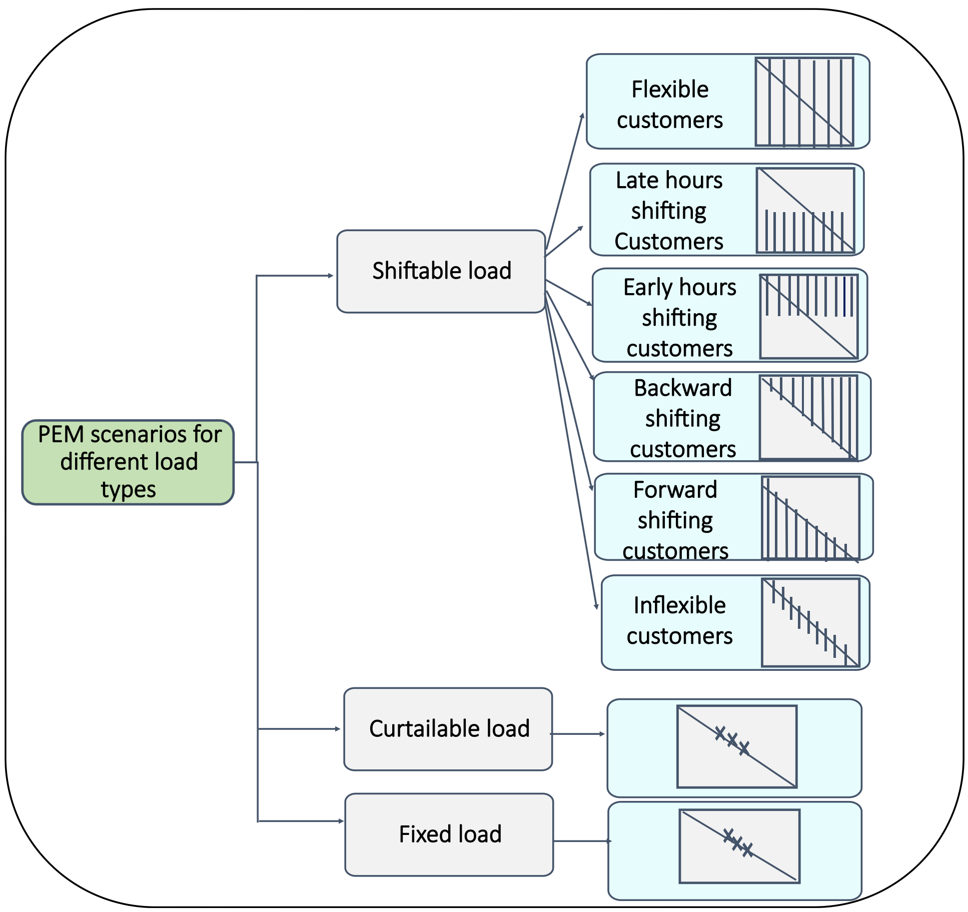

Figure 2.5 PEMD structure for different loads and CUs

2.3.Results and Discussion

The developed model was applied to the JEPX as the current existing hour-ahead wholesale electricity market in Japan in order to analyze the behavior of the risk-averse CUs in response to different DPRs, as shown in Figure 2.6. The model was performed, utilizing the General Algebraic Modeling System (GAMS) software, using the constrained optimization (CONOPT) method, which is a solver for large-scale nonlinear programming (NLP) optimization problems.

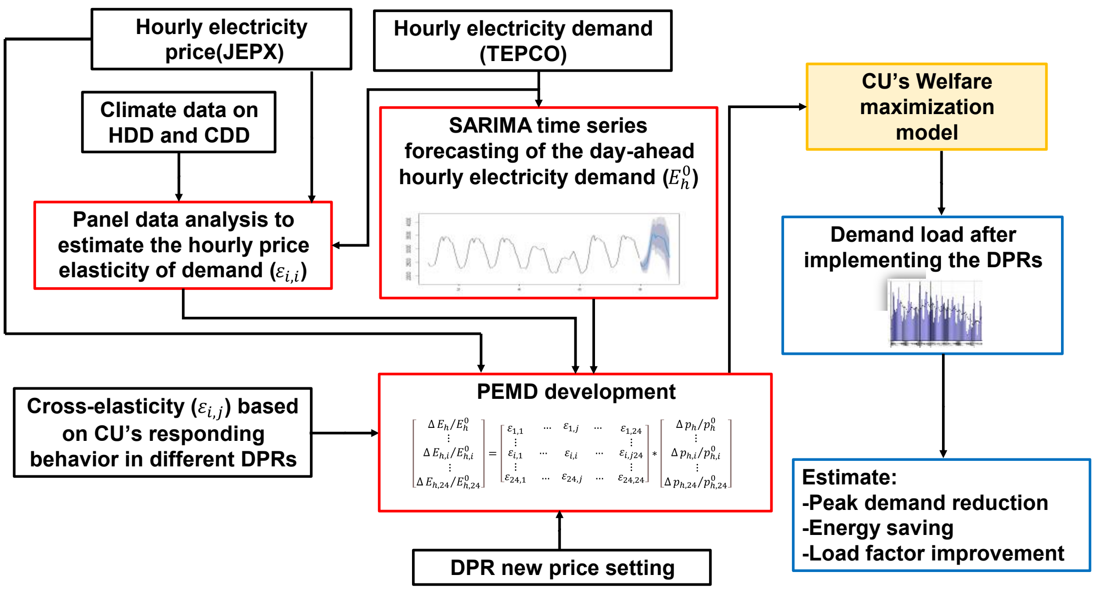

Figure 2.6 Application of the developed model to the JEPX hour-ahead wholesale electricity market in Japan

2.3.1. Day-ahead hourly electricity demand prediction in Tokyo

The time series dataset includes four years of hourly electricity demand data collected from TEPCO between 2016 and 2020 (TEPCO,2021). Figure 2.7shows the time series decomposition.

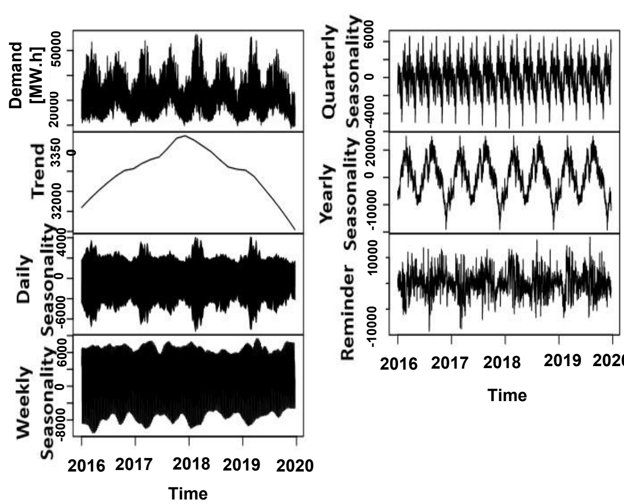

Figure 2.7 TEPCO electricity demand time series decomposition (2016-2020)

The four-year hourly demand data was split into 80% training data to train the model, and 20% for testing validation of the predicted data. By applying the calculation steps explained in Figure 2.3 to the collected time series dataset, the best SARIMA model to predict the day-ahead hourly electricity demand in Tokyo can be formulated as follows:

$$SARIMA : ARIMA \ (4,0,4)\ (2,1,0)_{24} \tag{2-17}$$

The estimated values of the model coefficients are given in Table 2-1.

Table 2-1 Estimated values of the SARIMA model coefficients

Seasonal and non-seasonal autoregressive and moving average elements	Coefficient
ϕ_1	-0.04
ϕ_2	1.05
ϕ_3	0.11
ϕ_4	-0.23
θ_1	1.58
θ_2	0.88
θ_3	0.39
θ_4	0.14
Φ_1	-0.32
Φ_2	-0.29

The mathematical expression of this model in terms of the backshift notation and with respect to the estimated coefficients can be written as:

$$\begin{aligned} E_t^0 = C + [-0.04E_{t-1}^0 + 1.05E_{t-2}^0 + 0.11E_{t-3}^0 - 0.23E_{t-4}^0 - 0.32E_{t-24}^0 \\ - 0.29E_{t-24-1}^0] + (E_{t-1}^0 - E_{t-24-1}^0) + [-1.58e_{t-1} - 0.88e_{t-2} \\ - 0.39e_{t-3} - 0.14e_{t-4}] \end{aligned} \tag{2-18}$$

$$C = \mu \times (1 - \sum \phi_i)(1 - \sum \Phi_i) \tag{2-19}$$

Where C is the ARIMA constant (Oracle,2021), $\phi_i$are nonseasonal AR coefficients, Φ_i are seasonal AR coefficients, and μ is the mean of the series which is about 32556.8. Therefore, the value of C is estimated at 1396.6.

The distribution of the residuals in the selected SARIMA model was checked, using the Box-Ljung test to reject a null hypothesis on the independent distribution of errors, where the p-value was reported to be greater than 0.05 (p-value= 0.9). Furthermore, the mean absolute percentage error (MAPE) for the test data achieved a 0.94%, with an R^2 at 0.99, indicating the high accuracy of the predicted model. Figure 2.8 represents a comparison between actual and predicted demand in 2020.

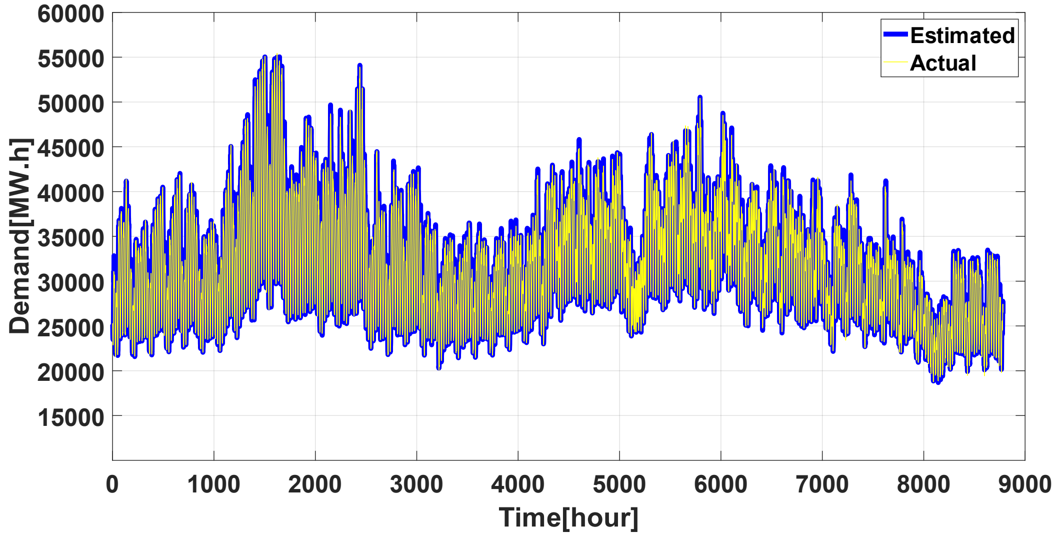

Figure 2.8 Comparison between actual and estimated data in 2020

The result of the day-ahead hourly load prediction for a selected day (the first day of June 2020), as an example, is represented in Figure 2.9.

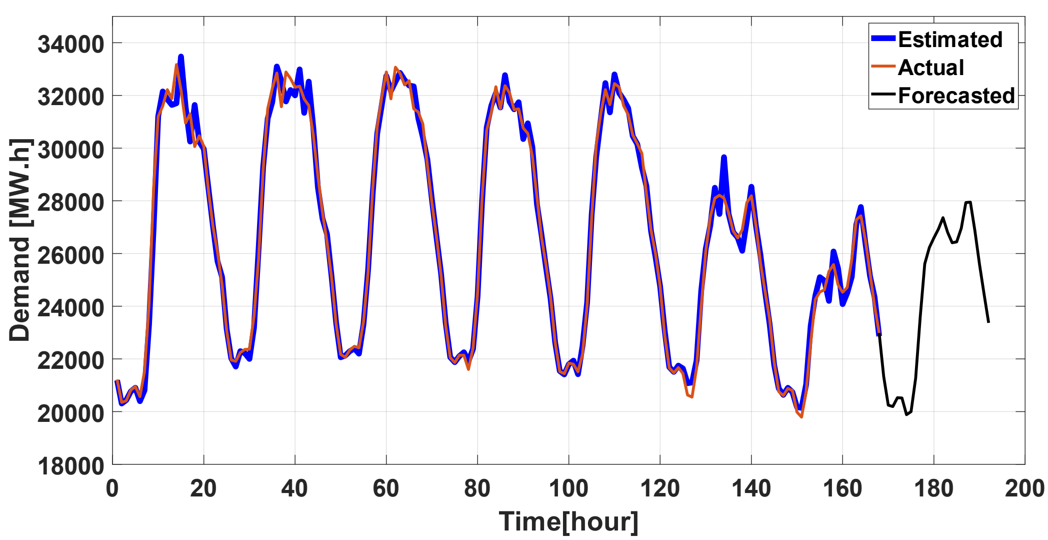

Figure 2.9 Day-ahead hourly load prediction in Tokyo for a selected day (June 1st, 2020)

2.3.2. Hourly estimation of price elasticity of demand in the JEPX market

The dataset used in the panel data analysis consists of hourly load and day-ahead prices collected from the JEPX covering the period of 2016 to 2020(JEPX,2021). The values of HDD and CDD were estimated, using hourly temperature data in Tokyo collected from Japan Meteorological Agency (JMA)(JMA, 2021) and compared with the values given in (Degree Days, 2021). Table 2-2 provides a summary of the statistics used in the panel data analysis.

Table 2-2 Dataset used in the panel data analysis

Variable	Mean	Std. Dev.	Min	Max
Load (MWh)*	21.78	2.98	13.55	31.75
Price (JPY/kWh)	6.85	6.71	0.01	75.10
HDD	2.83	3.80	0.00	16.20
CDD	4.35	4.82	0.00	13.20

*The JEPX market provides 40% of the total electricity demand in Tokyo

The least-squares dummy variable model was applied to the panel dataset, using the fixed-effect technique. The fixed effect only analyzes the impact of variables that vary over time. Therefore, the Hausman test was carried out to test the null hypothesis that the error term of the entity is not correlated with the regressors. The test results indicated a significant p-value (p-value<0.001): this rejects the null hypothesis and validates the results from the fixed effect panel data analysis.

The result of the panel data analysis for the price elasticity of demand for Tokyo on a 24-hour interval is given in Table 2-3. Figure 2.10 shows the hourly variation of the price elasticity in Tokyo. The elasticity peaks in the morning as the working hours start. Therefore, some industrial and service processes can start operation earlier when the prices are low during the early morning (5:00 am to 7:00 am). On the other hand, the following peaks form when the residents return home from work in the evening. Therefore, the DRPs for shifting or delaying electricity consumption can be effectively implemented during these periods, when elasticities are higher in absolute values. In addition, hot and cold climates positively affect electricity consumption, since the heating and cooling loads are provided using air conditioning systems in Tokyo. This may explain the lower values of elasticity observed in the evening compared to in the morning.

Figure 2.10 shows the variation of the hourly price elasticity of demand and the risk aversion coefficient with hourly average electricity demand in the JEPX market. In an elastic demand market, electricity consumption decreases further by the price increments at the higher values of the risk aversion coefficient.

Table 2-3 Results of the panel data analysis

Hour	$\boldsymbol{\varepsilon}$ Price elasticity	$\boldsymbol{\gamma}$ HDD coefficient	$\boldsymbol{\rho}$ CDD coefficient
0	-0.072	0.058	0.055
1	-0.082	0.043	0.041
2	-0.077	0.040	0.041

Hour	ε Price elasticity	γ HDD coefficient	ρ CDD coefficient
3	-0.086	0.046	0.050
4	-0.126	0.060	0.060
5	-0.119	0.057	0.054
6	-0.097	0.046	0.042
7	-0.083	0.033	0.031
8	-0.085	0.027	0.027
9	-0.091	0.027	0.026
10	-0.085	0.018	0.015
11	-0.071	0.013	0.013
12	-0.066	0.013	0.014
13	-0.079	0.020	0.022
14	-0.089	0.024	0.024
15	-0.074	0.026	0.025
16	-0.056	0.023	0.024
17	-0.058	0.029	0.031
18	-0.061	0.037	0.039
19	-0.072	0.046	0.047
20	-0.078	0.046	0.045
21	-0.079	0.042	0.041
22	-0.073	0.036	0.035
23	-0.071	0.038	0.040
Mean	-0.080	0.035	0.033
R^2 =0.99 p-value < 0.001 Residuals test: Min =-0.450 Max=0.386 Median= 0.006			

2.3.3. Customer behavior analysis based on the application of the different DRPs in Tokyo

The following assumptions were considered in developing the PEMD in Tokyo:

- The JEPX wholesale market can provide about 40% of the total electricity demand of Tokyo in 2020.
- The curtailable loads cover 27.16% and 10% of the total electricity demand in the residential and industrial sectors, respectively, consisting of lighting, heating, cooling, and ventilation(Ikeda, 2019) (METI, 2021).
- The share of fixed, shiftable, and curtailable loads in the residential sector are assumed at 36.57%, 9.16%, and 54.27%, respectively(Matsumoto, 2016).
- In developing the PEMD for the flexible end-user, it is assumed that only 5% of self-elasticity in each column is assigned to the peak times and the rest to the off-peak periods.
- The share of the residential sector in total electricity demand is assumed to be 27.16% (Statistics bureau of Japan, 2021).

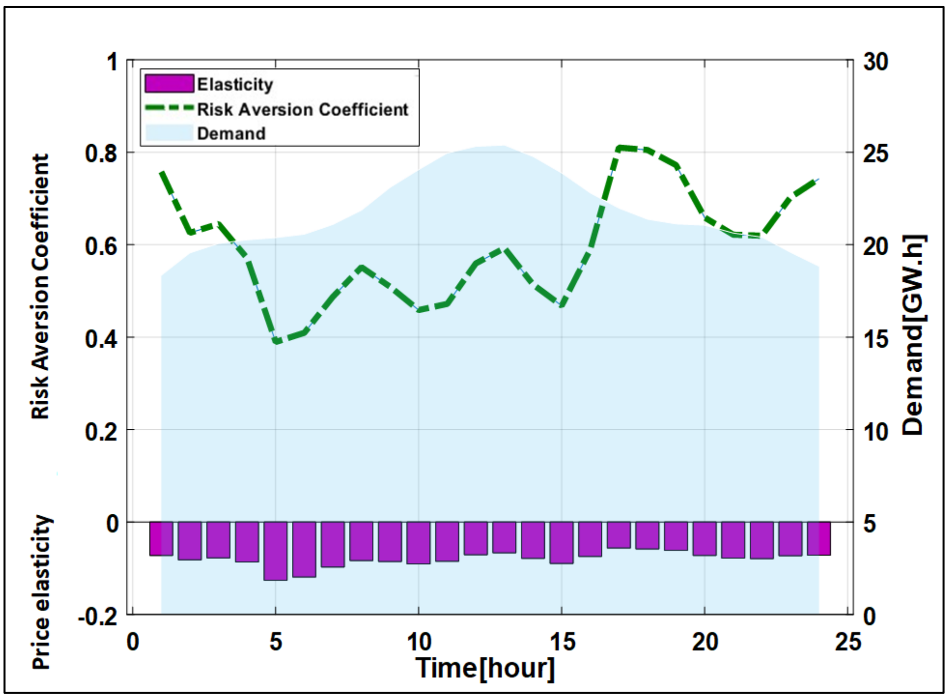

Figure 2.10 Variation of the price elasticity of demand and the risk aversion coefficient with hourly electricity demand in 2020

The electricity load profile in the summer season differs from the Tokyo winter season. The summer load profile includes only one peak from 1 pm to 4 pm, while the winter load profile includes two prominent peaks, one in the morning (8 am to 11 am) and another in the evening (5 pm to 7 pm) as shown in Figure 2.11 represents the electricity load profile in Tokyo.

The TOU program covers three different tariffs, including Peak tariff, Off-peak, and Valley tariff, considering the tariff mechanism introduced by TEPCO (Electric and Company, 2014). The CPP tariffs are added to the TOU tariffs and are applied to the market in order to reduce demand during critical hours when electricity consumption is high. The RTP tariffs are the dynamic hour-ahead prices that are announced to the CUs in advance. The initial price for RTP, TOU, and CPP were based on the spot dynamic prices of the JEPX. Figure 2.12 shows the tariff scheme applied to the different DRPs in this study.

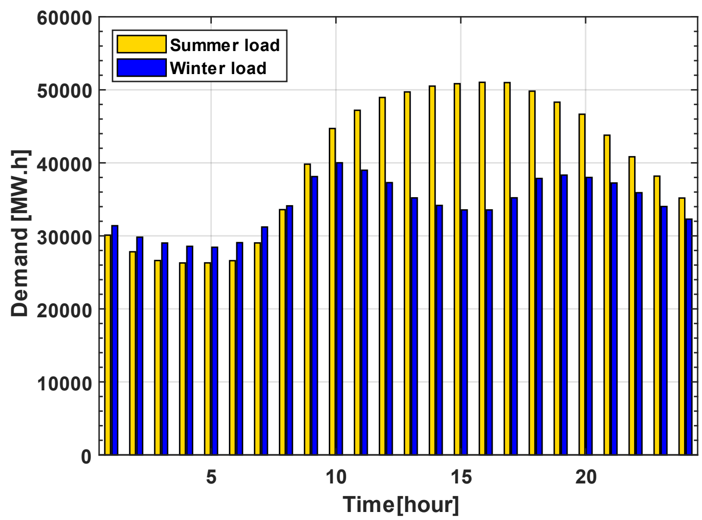

Figure 2.11 Electricity load profiles in Tokyo

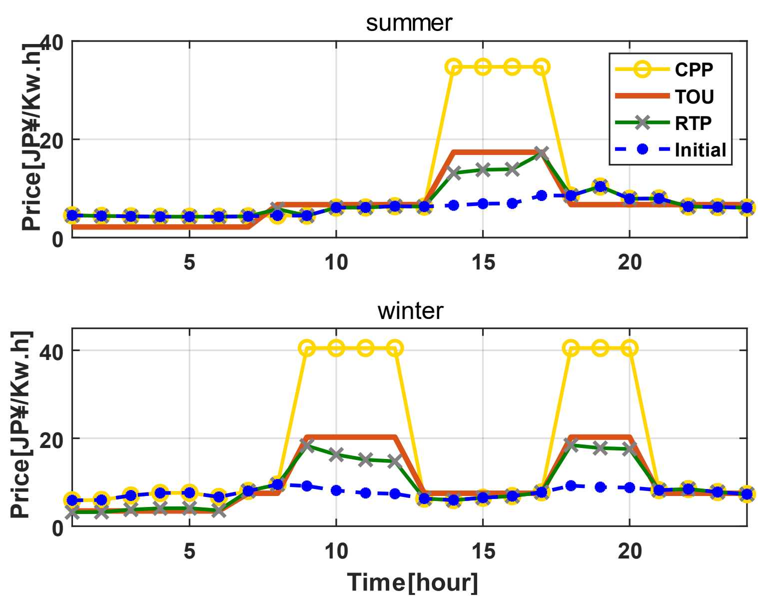

Figure 2.12 Tariff scheme for DRPs in this study

The details of the tariff calculation, which is based on the TEPCO pattern (Electric and Company, 2014) for the DRPs during the different time intervals in a 24 hr period, are given in
Table 2-4.

Table 2-4 DRPs pricing mechanism in this study

Program	**Time**	**Electricity price (¥/kWh)**
TOU	Peak Time	(JEPX prices in peak time ×2.4)
	Off-peak	(Average JEPX prices in the daytime)
	Valley	(Average JEPX at nighttime ×0.5)
CPP	Peak Time	P(TOU) ×2
	Off-peak and Valley	JEPX Prices
RTP	Peak Time, Off-peak and Valley	JEPX dynamic hour-ahead prices

Details of the calculations for the cross-elasticity values of different customers are provided in Table 2-5.

The results of applying TOU and RTP to the shiftable loads for a selected day in August 2020 are shown in Figure 2.13 and Figure 2.14. It can be observed that the flexible CUs reschedule their demand throughout the day by shifting demand from peak to off-peak hours. Compared with the flexible CUs, the forward-shifting and backward-shifting behavior led to new peaks just before or after the peak time. The backward-shifting CUs are able to shift their demand from peak to pre-peak times, which can widely be spread during the daytime, without predominant newly formed peaks. However, the forward-shifting CUs are limited to the remaining short period after the peak time to shift their loads. Therefore, higher consumption is observed around 7:00 pm, immediately after peak time. The shifting mode for the optimizing CUs is the same as the forward or backward shifting CUs, with limited shifts in the early morning and late night and without the significant newly formed peaks. The inflexible CUs are limited to shifting periods, leading to the form of new high peaks after and before the peak time.

Table 2-5 Calculation of the cross elasticities

End-User Type	Time	Cross Elasticity
Flexible	Summer: - Off-peak (hours 7-12 and 17-23) - Peak Time (hours 13-16) - Valley (hours 0 -6)	-(β×γ×$\varepsilon_{i,i}$)/13 -(α×$\varepsilon_{i,i}$)/4 -(β× (1-γ)×$\varepsilon_{i,i}$)/7
	Winter: - Off-peak (hours 6-7, 12-16, and 20-23) - Peak Time (hours 8-11 and 17-19) - Valley (hours 0-5)	-(β×γ×$\varepsilon_{i,i}$)/11 -(α×$\varepsilon_{i,i}$)/7 -(β× (1-γ)×$\varepsilon_{i,i}$)/6
Forward shifting	The same as the flexible PEM, considering only the area above the diagonal	The calculation scheme is the same as the flexible
Backward shifting	The same as the flexible PEM, considering only the area below the diagonal	The calculation scheme is the same as the flexible
Late hours shifting	(Hours 17-23)	-($\varepsilon_{i,i}$)/7
Early hours shifting	(Hours 0-6)	-($\varepsilon_{i,i}$)/7
Inflexible	2 hours above and below the diagonal, excluding peak times	-($\varepsilon_{i,i}$)/4

α: share of the shifted demand in peak period (5%); β: share of the shifted demand in off-peak period (95%); γ: share of β in off-peak period (30%); $\varepsilon_{i,i}$: self-elasticity

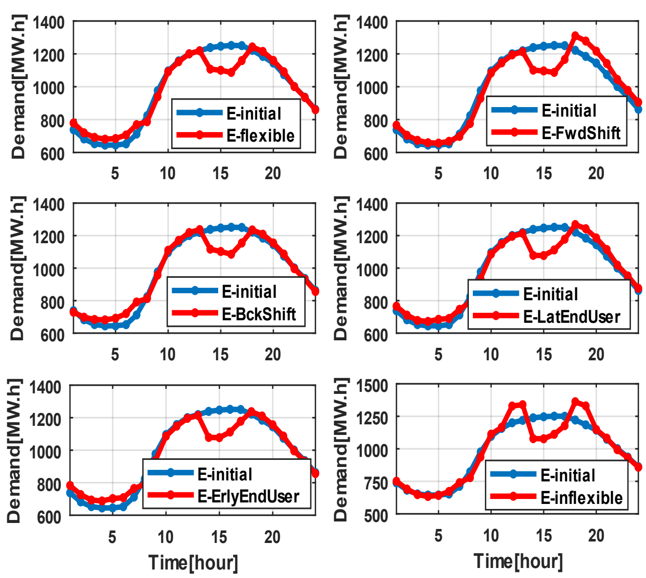

Figure 2.13 Implementation of the TOU with the shiftable loads (11th August 2020)

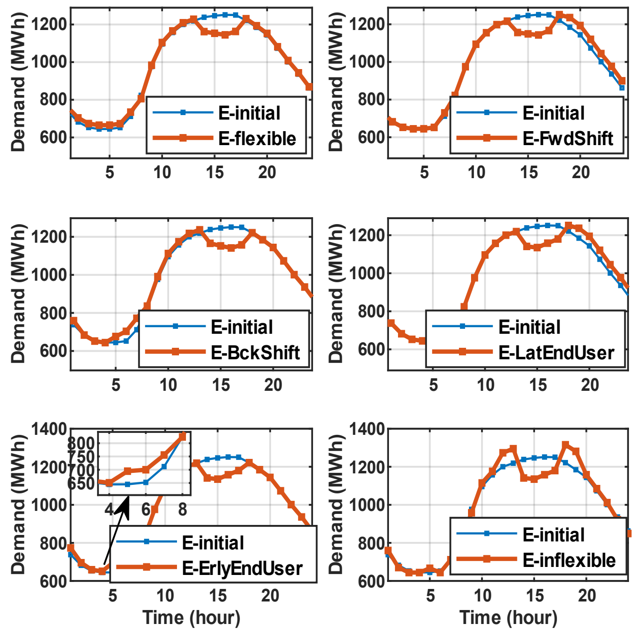

Figure 2.14 Implementation of the RTP with the shiftable loads (11th August 2020)

The impact of the RTP program on load reduction is smaller than the TOU. This is because the RTP-based CUs follow a real-time pricing scheme offered by the JEPX, which is cheaper than the peak time tariff for the TOU-based CUs. The comparison between the TOU, CPP, and RTP programs applied to the curtailable load is represented in Figure 2.15. It is noted that, in the curtailable load, the non-zero elements (those with self-elasticity) are only in the diagonal of the PEMD, which means that the demand for electricity decreases only during the peak periods throughout the day.

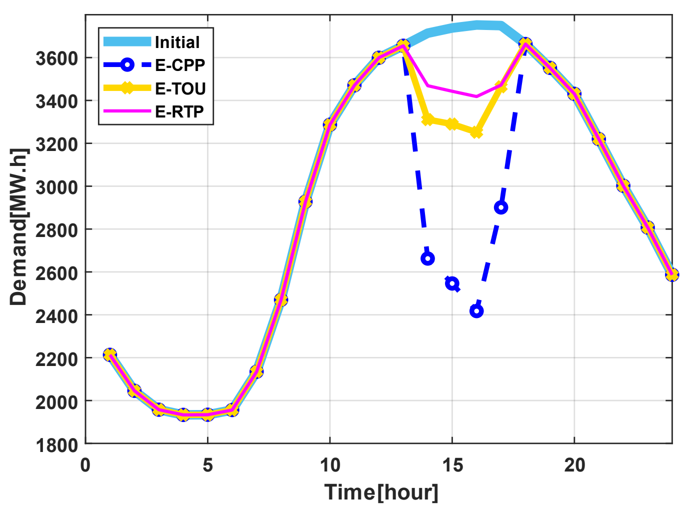

Figure 2.15 Implementation of the different DRPs with the curtailable loads (11th August 2020)

2.3.4. DPRs prioritization based on different response strategies

Figure 2.16 and Figure 2.17 represent each program's peak reduction, energy-saving, and load factor estimations. For the TOU program, the flexible, inflexible, and optimizing CUs (both early and late end-users) perform better in peak reduction, while the flexible and early CUs gain higher reduction rates in energy consumption. For the RTP, flexible, forward shifting, and optimizing CUs achieve higher peak reduction, while the flexible and optimizing CUs (both early and late end-users) perform better in energy consumption. This is because, in the PEMD of the optimizing and inflexible CUs, there is no demand shift in the peak hours, meaning the elements of the matrix are zero. However, for the flexible CUs, it was assumed that there is a small proportion of cross-elasticities in all peak hours (5% of the self-elasticities, since the proportion of demand shift, should be distributed throughout the day, even in the peak hours). The results indicate the improvement of the load factor in early, backward shifting, and flexible CUs in both DPRs. Also, the flexible CUs perform well in a combined assessment of the peak reduction, energy-saving, and load factor.

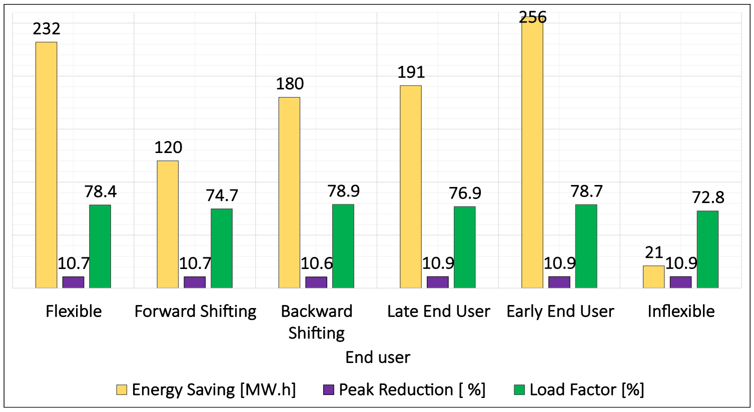

Figure 2.16 Technical performance analysis for the TOU program

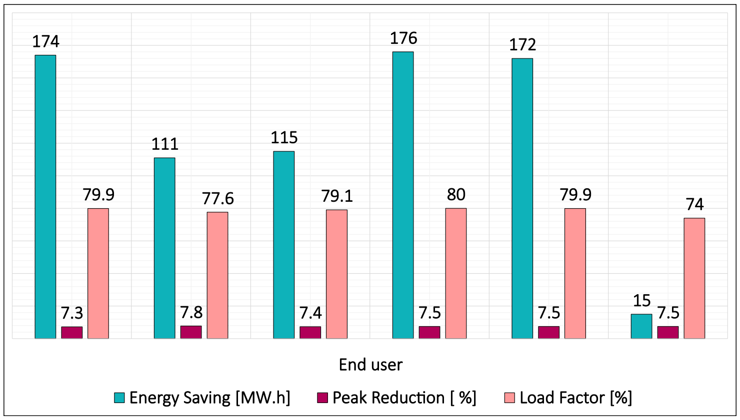

Figure 2.17 Technical performance analysis for the RTP program

For the CCP program with higher cross-elasticity, a higher peak price leads to a higher peak reduction and consequently a higher energy consumption reduction for the whole day. In contrast, in the RTP program, the price increase leads to a slight decrease in the demand peak. As a result, the CPP-based CUs suffer a lower load factor since the average daily demand is lower in this program. This indicates the remarkable impact of the duration of the peak period and the price difference between peak and off-peak periods in the CPP program, shown in Figure 2.18.

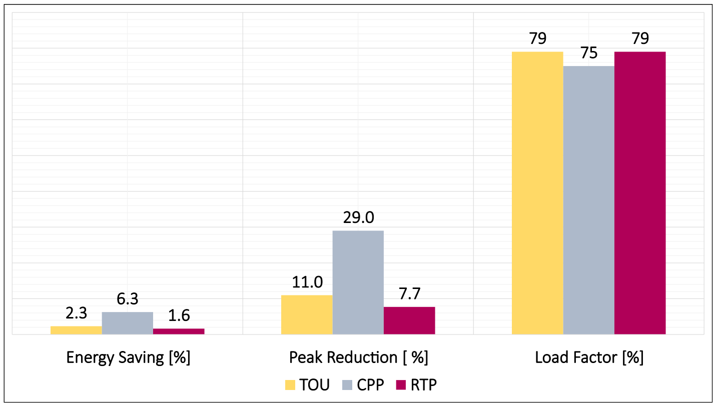

Figure 2.18 Technical performance analysis of the DRPs applied to the curtailable loads

2.3.5. Impact of the weather condition

Tokyo has a humid subtropical climate with hot and humid summers and mild winters. The coldest month is January, with an average temperature of 5°C and the hottest month is August, with 31°C. Figure 2.19shows the peak load reduction during the winter season for the RTP, TOU, and CPP programs applied to the shiftable and curtailable loads of the flexible CUs, considering two peak periods during morning and evening times in the day. The results reveal a peak reduction potential of 10.4% and 7.1%, respectively, from applying TOU and RTP programs for the flexible CUs in the winter. Applying the CPP, TOU, and RTP programs to the curtailable loads can achieve a 9.4%,3.5%, and 2.45% reduction in daily electricity consumption, respectively. The effect of the outdoor temperature on the outcomes of the DRPs is represented in Figure 2.20. The DRPs perform more impactful in the summer. This is mainly due to the high average daily temperature, leading to a significant increase in electricity consumption in air conditioning and cooling systems in Tokyo.

2.3.6. Impact of the dynamic price elasticity of demand on peak reduction

Figure 2.21 represents the impact of the fixed and dynamic self-elasticities on the peak reduction of an RTP-based CU with a shiftable load. The fixed value of the short-run self-elasticity in Japan was considered at -0.3 (Okajima and Okajima, 2013). Compared with the dynamic self-elasticity estimated in this study, the application of fixed self-elasticity results in unrealistic anticipation of peak reduction. This further emphasizes the significance of using dynamic self-elasticity to precisely estimate the demand profile in a real-time electricity spot market.

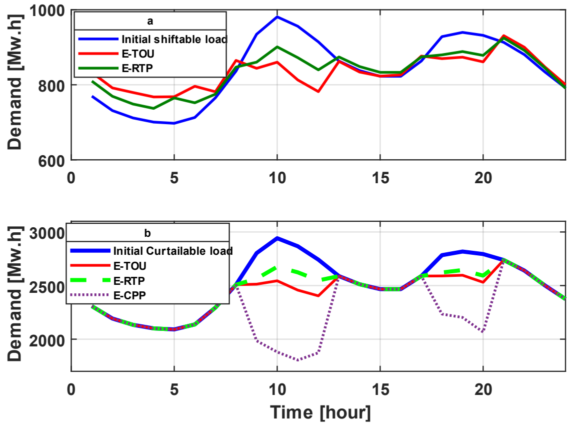

Figure 2.19 Comparison between the flexible CUs, using (a) shiftable loads in the TOU and RPT programs and (b) curtailable loads in the RTP and TOU and CPP program in winter

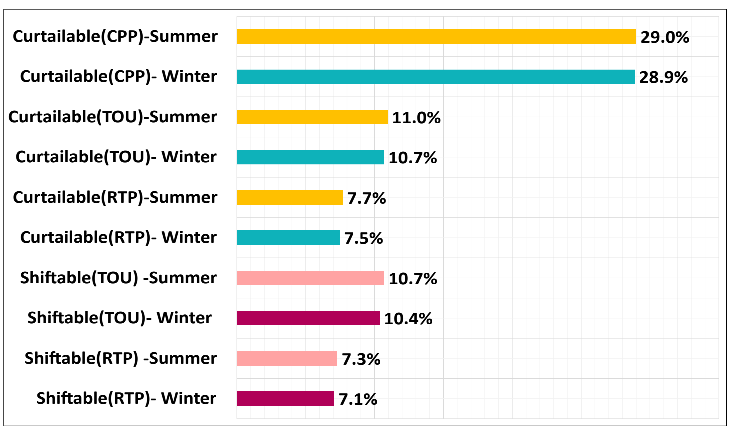

Figure 2.20 The peak load reduction potential in summer and winter

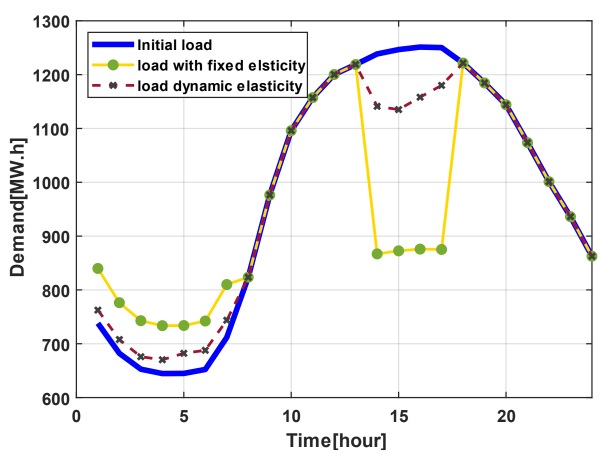

Figure 2.21 Implementation of the RTP with the shiftable loads (11th August 2020) using both fixed and dynamic elasticities

2.3.7. Impact of risk aversion coefficient on expected utility and customer preference

The comparison between the expected utility of two different customers, including a risk-averse CU in this study and a risk-neutral CU (with a constant value of risk aversion coefficient), is represented in Figure 2.22. It can be observed from this figure that, the risk-averse CU performs better in receiving higher values of the expected utility compared with the risk-neutral CU. Thus, although the reduction in consumption results in lower utility, the risk-averse CUs decide to decrease electricity consumption more rapidly with the price increment during the period when the absolute values of the elasticity are higher.

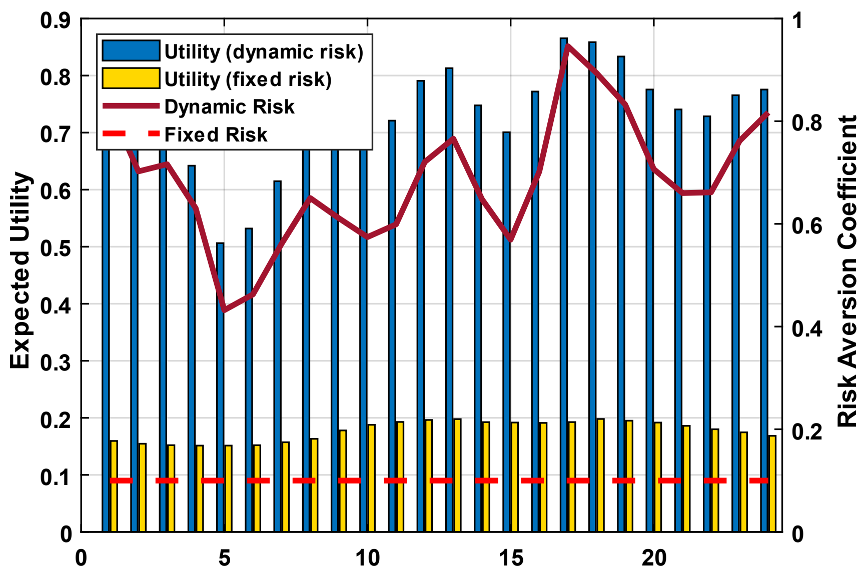

Figure 2.22 The impact of the risk aversion coefficient on expected utility

Figure 2.23 and Figure 2.24 illustrate the change in the risk-averse CU's expected utility due to different consumption levels. From an economic viewpoint, the TOU is the best DPR, as the risk-averse CU can save more electricity with the TOU program. However, from the customer's view, the risk-averse CU is more satisfied with the price change in the RTP program as its expected utility is affected less by the price changes.

The maximum welfare per each MWh of electricity consumption, based on different CUs response strategies in TOU and RTP to the shiftable load, is reported in Table 2-6 . According to the results, the welfare of CUs is maximized in RTP compared with TOU, in all response strategies, particularly in flexible mode, indicating the higher satisfaction of the CUs due to the consistency of their expected utility from electricity consumption with the price change scheme in this program.

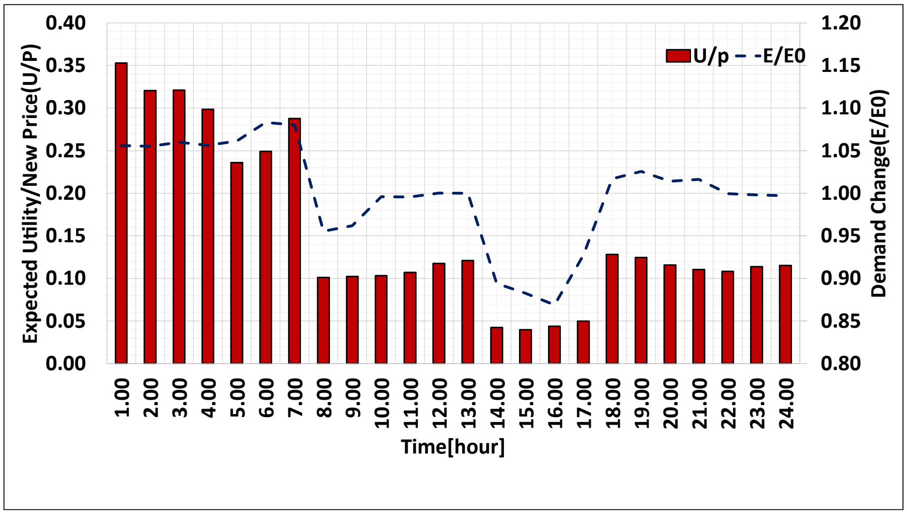

Figure 2.23 Expected utility change with price and demand changes in the TOU program

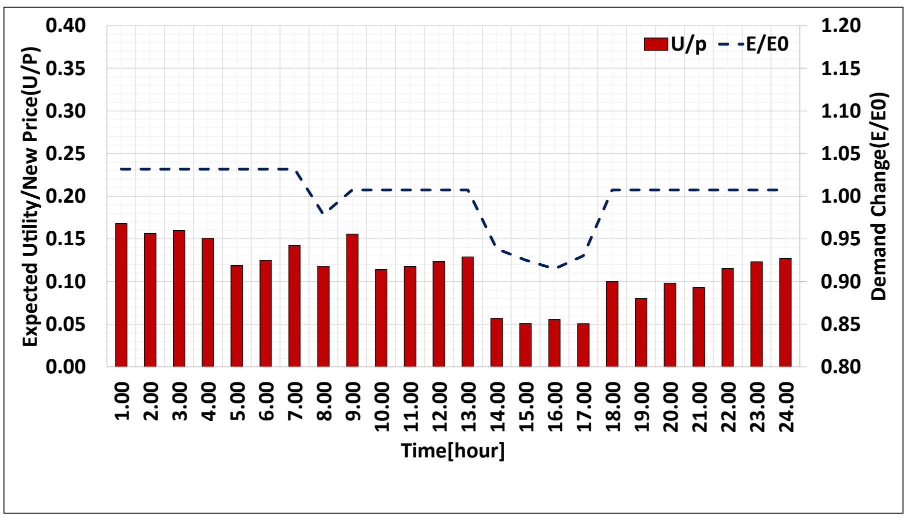

Figure 2.24 Expected utility change with price and demand changes in the RTP program

Table 2-6 Maximum welfare per MWh electricity consumption for different DRPs to the shiftable load

		Responding strategy					
Welfare [¥/MWh]	**DRPs**	**Flexible**	**Forward Shifting**	**Backward Shifting**	**Early End-User**	**Late End-User**	**Inflexible**
	RTP	6830	6780	6800	6820	6830	6660
	TOU	6480	6410	6450	6500	6460	6360

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Chapter 3
Region-Wise Evaluation of Price-Based Demand Response Programs in Japan's Wholesale Electricity Market Considering Microeconomic Equilibrium

Abstract: Real-time pricing demand response programs (RTP-DRPs) are practical measures that ensure the end user's profitability from using electricity by adjusting the supply and demand equilibrium without activating costly solutions. This study explores the potential of RTP-DRPs by developing and applying a region-wise modeling approach based on maximizing the end-user's social welfare in the wholesale electricity market in Japan. The regions of the wholesale market are classified based on their response into; regions with excess supply, regions with high demand burden, and regular suppliers of inter-regional connections. The results revealed that, the RTP-DRPs could potentially reduce the peak demand of the residential sector in Chubu, Chugoku, Kansai, Kyushu, Tokyo, and Tohoku by 1.91% to 7.81%. Meanwhile, in Hokkaido, Hokuriku, and Shikoku by 16.13% to 22.9%. The avoided greenhouse emission (GHG) in Tokyo is estimated to be 82.6 and 192.2 tons in summer and winter, respectively.

3.1.Introduction

Based on the literature survey explained in Chapter 1, several contributions have reported the significance of DRP in reducing the residential sector demand, which reflects the customer's profitability from regulating their electricity demand. However, these contributions are either related to the negawatt microeconomic bidding mechanism or lack of correlation between the amount of energy saved and peak demand reduction of end-users considering the regions of the wholesale market. On the other hand, although the earlier contributions have developed a sophisticated modeling approach to demonstrate the potential of DRPs considering multi-layer wholesale and real-time market forms, it lacks a fundamental exploration of determining the potential of fragmented regional wholesale markets. This can be explored through the region-wise evaluation, which estimates the PEMD of each regional market considering the microeconomic price driving parameters of each region. Therefore, this study aims to investigate the potential of DRPs in the fragmented wholesale electricity market concerning the achieved peak reduction, energy saving, and greenhouse gas emission avoidance for each region. To achieve this, the study applies a single price-based RTP-DRP optimization model on various fragmented markets in different regions, considering the regional wholesale prices and using dedicatedly estimated PEMD for each market's region.

Furthermore, in Japan, due to the absence of a real-time balancing market, the use of regional interconnections fragments the national supply and demand equilibrium, which causes region-wise MCMs and, consequently, regional MCPs. The study aims to explore DRPs' potential to adjust the microeconomic balance by estimating the capability of each region to adjust the supply and demand equilibrium. The microeconomic equilibrium is considered in this study using the wholesale MCP for all the regions, along with estimating the region-wise PEMD. The outcome is expected to demonstrate the capability of each region to reduce its peak or maximize energy savings. To this aim, the study proposes integrating the customer profitability of the residential sector with the utility scale using a single price-based RTP-DRP optimization model for all the regions, while considering the microeconomic equilibrium of the regional wholesale prices through estimating the PEMD for each region dedicatedly. Therefore, this study investigates the region-wise potential of energy savings, peak shaving, and avoided greenhouse gas (GHG) emissions from implementing a DRP on a region-wise scale considering the regions of the wholesale electricity market. Thus, the contribution of this study is three-fold:

- Formulating the PEMD for a regionally fragmented wholesale electricity market by estimating the self- and cross-price elasticity matrix of demand, considering spatial-temporal wholesale electricity prices and demand profiles.
- Development of integrated region-wise and price-based demand response modeling approach based on applying customer welfare maximization in regionally fragmented wholesale electricity markets.
- Investigating the region-wise potential benefits of peak reduction, energy savings, and avoided emissions from implementing the DRP in Japan's wholesale electricity market.

The rest of the chapter is organized as follows: Section 3.2 explains the data acquisition and model development, where the regional hourly price elasticity of demand is estimated, the DRP of customer's welfare maximization is modeled, and avoided emissions are calculated. Section 3.3 shows the results and discussion.

3.2.Methodological Approach

The developed methodological approach is divided into three parts: 1) data acquisition, 2) modeling of price elasticity of demand, and 3) designing the price-based demand response program. The data is collected nationwide, covering all the regions of the wholesale market of Japan. The data includes electricity demand, wholesale prices, temperatures, regional emission factors, and penetration of Variable Renewable Energy (VRE). The price elasticity of demand is modeled in two milestones. Firstly, estimating the hourly self-elasticity for each region. Then, formulating the self- and cross-price elasticity matrix of demand. Eventually, the RTP-DRP to maximize the customer's welfare is formulated, and avoided emissions are calculated. The overall research methodology in this study is presented in Figure 3.1.

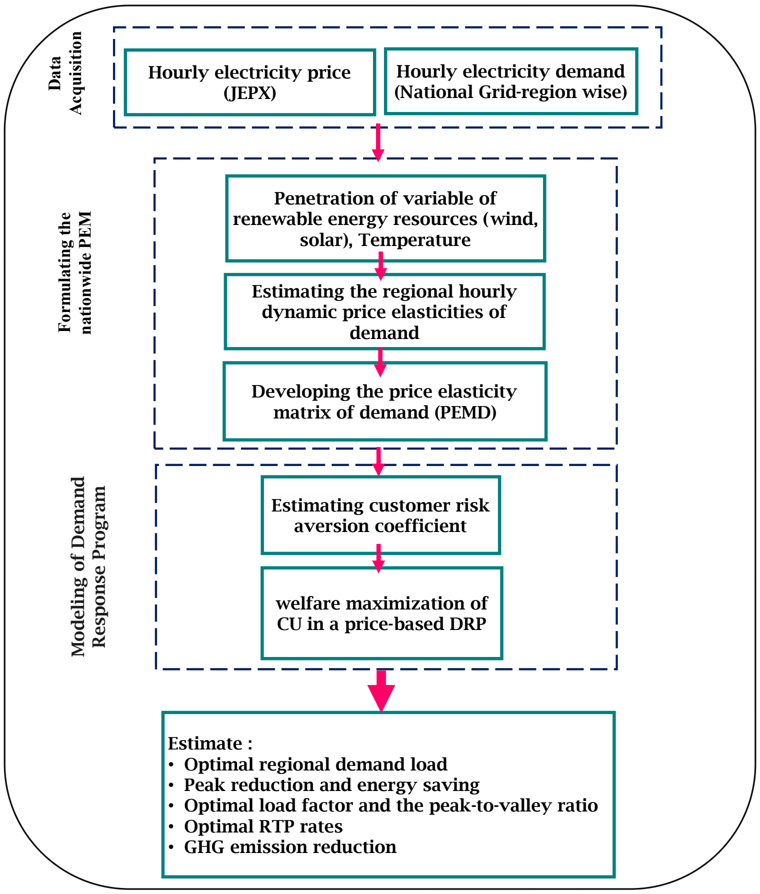

Figure 3.1 Overall methodological approach

3.2.1. Data Acquisition

The hourly electricity prices from the period of 2016 to 2022 are collected for all regions in half-hourly intervals (JEPX, 2022). The hourly electricity demand for all the regions participating in JEPX is collected from all the regional utilities*, whereas the collected demand capacity is lumped in regional demand. The share of the residential sector from the regional demand is assumed to be 27% (JEPX, 2022). In addition, the amount of VRE (i.e., the sum of solar PV and wind power) are collected regionally for the same period. To align

* **1-**(Chubu electric power grid, 2022); **2-**(Chugoku electric power transmission and distribution company, 2022); **3-**(Hokkaido electric power network,2022); **4-**(Hokuriku electric power transmission and distribution company, 2022); **5-**(Kansai transmission and distribution, 2022); **6-**(Kyushu electric power transmission and distribution, 2022); **7-**(Shikoku electric power transmission and distribution company, 2022); **8-**(TEPCO power grid, 2022); **9-**(Tohoku electric power network, 2022).

the half-hourly time intervals of prices with the demand and VRE quantities, the price intervals were converted using the weighted average and the market contracted volume. On the other hand, the CO_2 emissions factors (i.e., for thermal electricity generation including coal, crude oil, liquified natural gas, and biomass) per kWh for all the regions are collected from the electricity utilities, as shown in Table 3-1. The hourly temperatures of the major cities in the regions (i.e., Hiroshima, Matsuyama, Sapporo, Nagano, Fukuoka, Nîgata, Osaka, Yamagata, and Tokyo) were acquired for the same period from (Japan Metrological Agency, 2022).

Table 3-1 Regional and national emission factors collected from electric utilities

Region	Emissions Factor[1] ($Kg\text{-}CO_2/kWh$)	Region	Emissions Factor ($Kg\text{-}CO_2/kWh$)
Chubu	0.382	Kyushu	0.365
Chugoku	0.521	Shikoku	0.525
Hokkaido	0.549	Tokyo	0.452
Hokuriku	0.465	Tohoku	0.457
Kansai	0.266	National	0.439

[1]Annual average emission factor for the fossil-based powerplants, including waste-to-electricity and biomass power

3.2.2. Formulating the nationwide price elasticity matrix of demand

The price elasticity of demand is a crucial parameter for formulating DRP, which measures the degree of demand quantity response to the price change. The direct impact of changing the pricing on the demand quantity at the same hour is named self-elasticity, while the reflection resulting from the price change of this hour to the other hours is named cross-elasticity. This study estimates the national self-elasticity coefficient indicating the direct impact of price changes by one ¥/kWh on the quantity of demand. Sequentially, the price elasticity matrix of demand is formulated based on the obtained self-elasticity and calculating the cross elasticity. The study applies linear panel regression using Fixed Effect (FE) and Two Stage Least Squares (2SLS) to model the effect of regional cross-section dimension against the time (Wooldridge, 2010). The price is estimated in the first stage of the 2SLS based on the VRE penetration to the demand, while the PED is estimated in the second stage (Suliman and Farzaneh, 2023). The first stage is expressed in equation 3-1:

$$\hat{P}_{i,t} = \beta_o + \beta_1 Solar_{i,t} + \beta_2 Wind_{i,t} + \beta_3 Daytime_{d,t} + \beta_4 Year_{d,t} + \beta_5 Peak_{d,t} + \mathrm{c_i} + \mathrm{u_{i,t}} \qquad 3\text{-}1$$

$$d_{i,t} = \alpha_o + \alpha_1 \hat{P}_{i,t} + \alpha_2 T_{i,t} + \alpha_3 \dot{D}_{i,t} + \alpha_4 W_{D,t} + \alpha_5 H_{D,t} + \alpha_6 Spring_{D,t} + \alpha_7 Summer_{D,t} + \alpha_8 Autumn_{D,t} + \alpha_9 Winter_{D,t} + \delta_1 Solar_{i,t} + \delta_2 Wind_{i,t} + \delta_3 Daytime_{d,t} + \delta_4 Year_{d,t} + \delta_5 Peak_{d,t} + \gamma_i + \epsilon_{i,t} \qquad 3\text{-}2$$

Where $\hat{P}_{i,t}$ is the dependent variable of regional wholesale price in a vector of $T \times 1$. i, d, and t denote the regional cross-section panels (i.e., the nationwide wholesale regions depicted in (Figure 1.4), timing dummy variables, and hourly intervals, respectively. T is the panel's vertical time intervals from 2016 to 2022, which forms 52,560 observations for one panel of i. For all the regions, the total observations number N = 525,600 records of data. $PV_{i,t}$ and $Wind_{i,t}$ are the VRE electricity capacities assigned as independent variables.
$daytime_{d,t}$, $Year_{d,t}$, and $Peak_{d,t}$ are the timing dummy variables. β are the first stage estimates coefficients. c_i is the error value of the first stage, which captures the unobserved effect of the regional cross-sections i. $u_{i,t}$ is the idiosyncratic error, which captures the variation across i and t. The first-stage consistency is validated orthogonally versus the second-stage equation's idiosyncratic error based on strict exogeneity conditions. The estimated price, $\hat{P}_{i,t}$, based on VRE contribution, is then substituted into the second stage equation of estimating the self-PED as expressed in equation 3-2.

Where $\mathrm{d}_{\mathrm{i,t}}$ is the dependent variable of regional demand quantity in a vector of $T \times 1$. $\mathrm{T}_{\mathrm{i,t}}$, and $\dot{\mathrm{D}}_{\mathrm{i,t}}$ are the temperature and lagged demand values assigned as the second-stage independent variable. $\mathrm{W}_{\mathrm{D,t}}$, $\mathrm{H}_{\mathrm{D,t}}$, $\mathrm{Spring}_{\mathrm{D,t}}$, $\mathrm{Summer}_{\mathrm{D,t}}$, $\mathrm{Autumn}_{\mathrm{D,t}}$, and $\mathrm{Winter}_{\mathrm{D,t}}$ are the timing dummy variables indicating weekend, hour of the day, and seasonality, respectively. α denotes the second stage estimates coefficients. γ_i is the second stage error value, which captures the unobserved effect of the regional cross-sections i. $\epsilon_{i,t}$ is the idiosyncratic error, which captures the variation across i and t. Sequentially, the hourly self-elasticity in percent is calculated for each region using the estimated PED coefficient, α_1, as expressed using equation 3-3 (Holmes and Illowsky, 2017):

$$\varepsilon s_{i,t} = \alpha_1 \frac{\overline{\mathrm{P}}_{\mathrm{i,t}}}{\bar{\mathrm{d}}_{\mathrm{i,t}}} \qquad \text{3-3}$$

Where $\varepsilon s_{i,t}$ is the self PED for region i at hour t. $\overline{\mathrm{P}}_{\mathrm{i,t}}$ is the average hourly wholesale price for each region. $\bar{\mathrm{d}}_{\mathrm{i,t}}$ is the average regional demanded quantity per hour.

Figure 3.2 demonstrates the formulated matrix based on self and cross-elasticity dimensions to formulate the demand elasticity matrix for the flexible end-users. In the Figure, the vertical and horizontal axis represent the hourly time intervals, while the diagonal axis presents the self-elasticity values. The values upper and lower regions of the diagonal axis are the cross-elasticity values, which indicate how much one variable is affected by changes in other variables. Furthermore, it is assumed only 5% of self-elasticity in each column is assigned to peak hours, and the share of the shifted demand in off-peak and valley periods accounts for 95%.

$$\begin{bmatrix} \varepsilon s_{0,0} & \varepsilon c_{0,1} & \cdots & \varepsilon c_{0,23} \\ \varepsilon c_{1,0} & \varepsilon s_{1,1} & \cdots & \varepsilon c_{1,23} \\ \vdots & \vdots & \cdots & \\ \vdots & \vdots & & \\ \varepsilon c_{23,0} & \varepsilon c_{23,1} & \cdots & \varepsilon s_{23,23} \end{bmatrix}$$

Figure 3.2 Time schedules of the price elasticity matrix of demand

(Off-peak (hours 8-12 and 17-22) : $\varepsilon c = -(A \times \mathrm{B} \times \varepsilon s)/11$; Peak Time (hours 13-16) : $\varepsilon c = -(\mathrm{C} \times \varepsilon s)/4$; Valley (hours 23 – 7) : $\varepsilon c = -(\mathrm{A} \times (1-\mathrm{B}) \times \varepsilon s)/9$; C: share of the shifted demand in peak period (5%); A: share of the shifted demand in off-peak period (95%); B: share of A in off-peak period (30%); εs : Self-elasticity ; εc: Cross-elasticity)

3.2.3. Modeling of Demand Response Program

The DRPs are classified into incentive-based and Price-based programs. The price-based program seeks to flatten the load by varying consumer electricity costs at specific periods. This study applies a price-based RTP-DRP that relies on dynamic pricing to encourage end-users to respond promptly by reducing their power consumption at specific periods of the day (Farzaneh et al., 2021). The prime aspect of designing nation-scale RTP-DRP is ensuring equal benefits for the utility sector as a service provider and customers as end-users. Therefore, it is crucial to determine the end-user's willingness based on their behavior patterns toward the RTP-DRP; meanwhile, maximizing the service provider profits. This can be done by identifying the price-responsive customers for the RTP-DRP to estimate the cost savings on electricity and energy quantity reduced during high-demand periods. This study explores the customer's welfare function as a combination of the customer's expected utility function and the cost of electricity. The customer's economic consumption model is formulated by subtracting the cost of electricity from their utility function to determine changes in their demand based on their participation in the RTP-DRP. The maximization of customer's welfare in regional wholesale electricity may be formulated as follows (Malehmirchegini and Farzaneh, 2022; Yu et al., 2020):

$$Max \quad W\left(d_{i,t}\right) = \sum_{t=0}^{23} Ca_{i,t} \times U\left(d_{i,t}\right) - d_{i,t} \times P_{i,t} \qquad 3\text{-}4$$

Where $W\left(d_{i,t}\right)$ is the customer's welfare resulting from the adjusted demand, $d_{i,t}$, after implementing the proposed DRP. This is divided into the expected utility and cost incurred by consuming electricity. $U\left(d_{i,t}\right)$ is the expected utility function, and $P_{i,t}$ is the suggested new price in the RTP scheme implemented by the proposed DRP. $Ca_{i,t}$ is the calibration coefficient that aligns the utility function unit from "Utils" to the monetary unit (Niromandfam et al., 2020). t denotes daily time intervals in hours, and i denotes the regional indices.

The welfare's function is maximized considering the constraints of the customer's demand changes as expressed in equation 3-5:

$$d_{i,t} = d0_{i,t}\left\{1 + \frac{\varepsilon s_{i,t}\left[P_{i,t} - P0_{i,t}\right]}{P0_{i,t}} + \sum\nolimits_{t=0}^{23} \frac{\varepsilon c_{i,t}\left[P_{i,t} - P0_{i,t}\right]}{P0_{i,t}}\right\} \quad \text{3-5}$$

Where $d0_{t,i}$ is the initial demand before participation in the RTP-DRP. $\varepsilon s_{i,t}$and $\varepsilon c_{i,t}$ are self and cross PED coefficients, respectively. $\varepsilon s_{i,t}$ and $\varepsilon c_{i,t}$ are employed to calculate the change in electricity use in relation to the change in electricity price before and after RTP-DRP, as denoted by $P0_{i,t}$ and $P_{i,t}$, respectively.

The utility function, $U\left(d_{i,t}\right)$, models the satisfaction of the end-user from utilizing electricity, which is influenced by consumption patterns at various times of the day. This is formulated in an exponential form as expressed in 3-6 (Johnstone and Lindley, 2013) and (Buccola and French, 1978).

$$U\left(d_{i,t}\right) = 1 - e^{-r(d_{i,t})}e^{-r\mu+\frac{r^2\sigma^2}{2}} \quad \text{3-6}$$

Where r is the risk aversion parameter that evaluates the end-user's willingness to engage in the proposed RTP-DRP. The risk attitude of the end-user is intimately connected to the exponential curvature of the utility function, as explained in (Niromandfam and Choboghloo, 2020). μ and σ^2 are the mean and variance of electricity consumption (Buccola, 2013). The RTP scheme constraints is conditioned as expressed in 3-7:

$$P_{\min i,t} \le P_{i,t} \le P_{\max i,t} \quad \text{3-7}$$

Where $P_{i,t}$ is the optimal RTP. $P_{\min i,t}$ and $P_{\max i,t}$ are the minimum and maximum RTP boundaries, respectively. The price-changing mechanism for the RTP scheme in this study is formulated based on the peak hours as expressed in condition 3-8, off-peak hours as expressed in 3-9, and valley as expressed in 3-10:

$$2.5P_{JEPX} \le P_{RTP} \le 3P_{JEPX} \quad \text{3-8}$$

$$1.1P_{JEPX} \le P_{RTP} \le 1.5P_{JEPX} \quad \text{3-9}$$

$$0.5P_{JEPX} \le P_{RTP} \le P_{JEPX} \quad \text{3-10}$$

Where P_{JEPX} and P_{RTP} are the wholesale price and RTP, respectively. The model was performed, utilizing the MINOS solver of GAMS (General Algebraic Modeling System) software, which uses the Lagrangian project algorithm by solving subproblems, involving linear versions of the nonlinear constraints, as well as the original linear constraints and bounds to satisfy the optimality criterion of the developed model in this research (Murtagh et al., 1983).

3.2.4. GHG Emissions Reduction

The electricity market in Japan is a significant source of GHG emissions, whereby the power sector accounts for about a third of total national GHG emissions (Energy Policy Review, 2021). In this study, the potential of avoided emissions stems from the demand reduced by the implemented RTP-DRP. The mathematical formulation of the avoided GHG emissions considering the dedicated regional emission factor is expressed in equation 3-11.

$$AE_i = \gamma_{EF_i} \times \sum_{t=0}^{23} \Delta d_i \qquad \text{3-11}$$

Where AE_i is the avoided CO_2 emission for region i. γ_{EF_i} is the CO_2 emission factor. Δd is the total daily demand reduced after implementing the proposed DRP in each region.

3.3. Results and Discussion

3.3.1. Price elasticity of demand estimation

The estimated PED values and the risk aversion coefficients for all the regions depicted in Figure 3.3 can be elaborated based on three major parameters: hourly regional prices, supply and demand equilibrium, and penetration of the VRE. In addition, Figure 3.4 and Figure 3.5 show the average regional prices and regional electricity patterns, respectively. Although the PED of all the regions, including the national dimension, varies hourly between -0.005 to -0.09, the PED of Hokkaido, Hokuriku, and Shikoku varies between -0.09 to -0.21. Meanwhile, the estimated risk aversion coefficients that evaluate end-users' willingness to engage in RTP-DRP vary in all the ranges and nationally in a similar range of 0.001 to 0.003. This means that, the PED variation is not caused by the end-user side, but rather by the price-driving parameters of inter-regional connections, penetration of VRE, and the supply and demand equilibrium. For Hokkaido, the low electricity demand, the highest regional price, and the topology of the national grid that connects Hokkaido from the side of Tohoku only, drive the elasticity to the high ranges. For Hokuriku and Shikoku, although the supply patterns are higher than their demand patterns, their price is interdependent to Kansai reported by (Suliman and Farzaneh, 2022), driving the PED to high levels. This is demonstrated by the negative patterns of the inter-regional connections between Hokuriku and Shikoku, which meets a positive pattern in Kansai, as depicted in Figure 3.5 Region-wise and National Electricity Patterns from 2016-2022. This implies that Kansai imports electricity from these regions, whereby the demand is ranked the highest after Tokyo. Furthermore, the quantity produced of VRE in Hokkaido, Hokuriku, and Shikoku is the least among all the regions, whereas the estimated elasticities drop to the least between hours 11:00 to 14:00 when the penetration of the VRE at the peak.

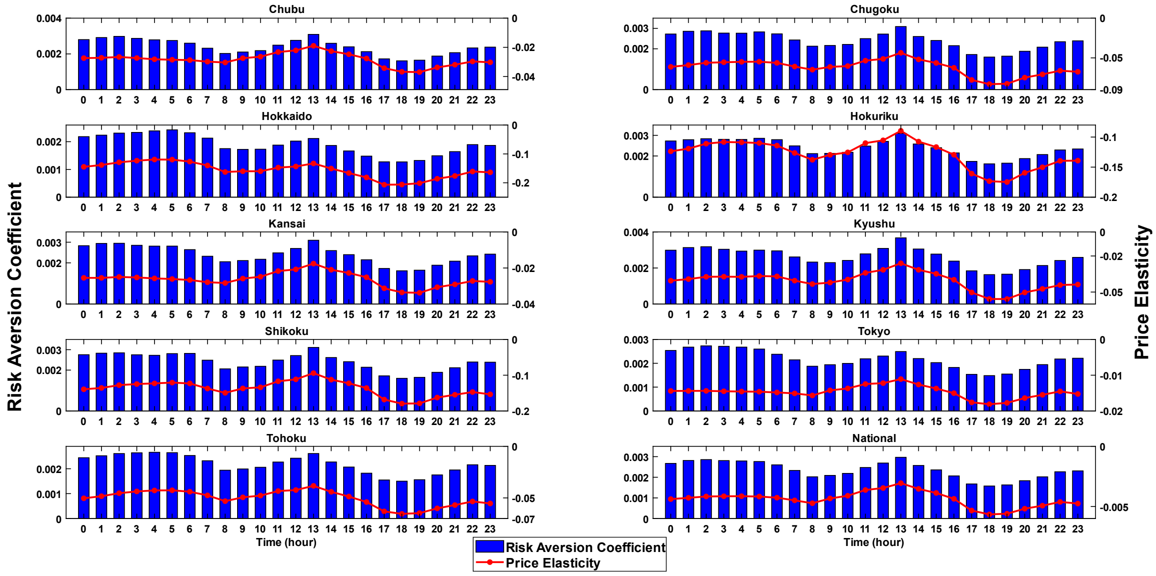

Figure 3.3 Estimated Hourly Region-wise and National PED and Risk Aversion Coefficient

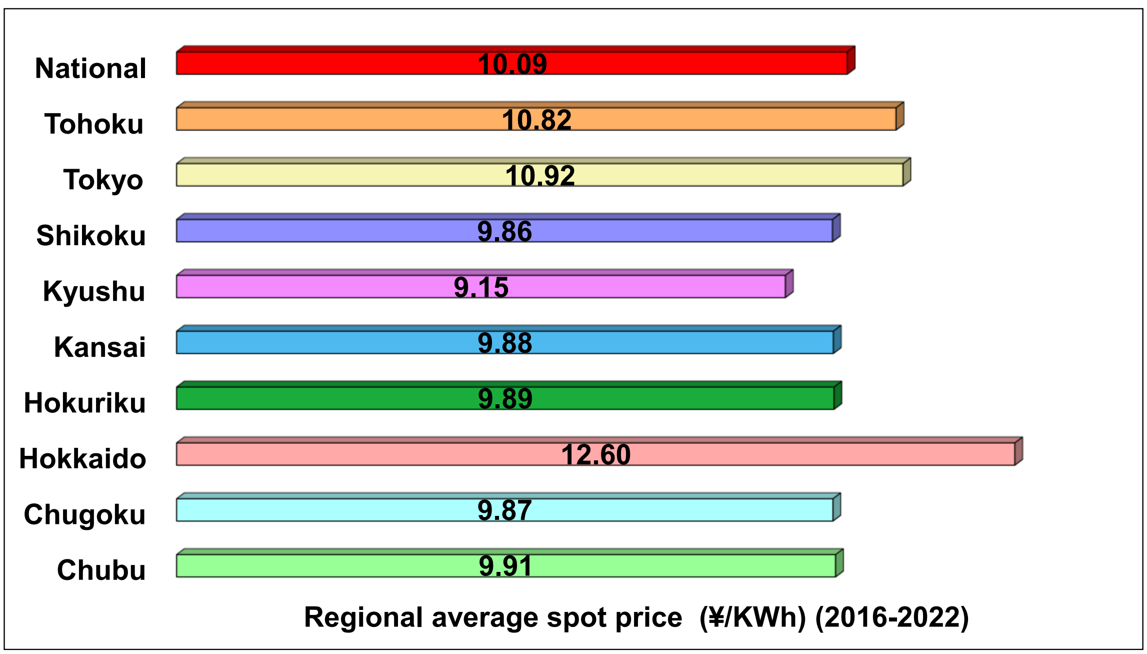

Figure 3.4 Region-wise hourly day-ahead market prices on an average basis (2016–2022)

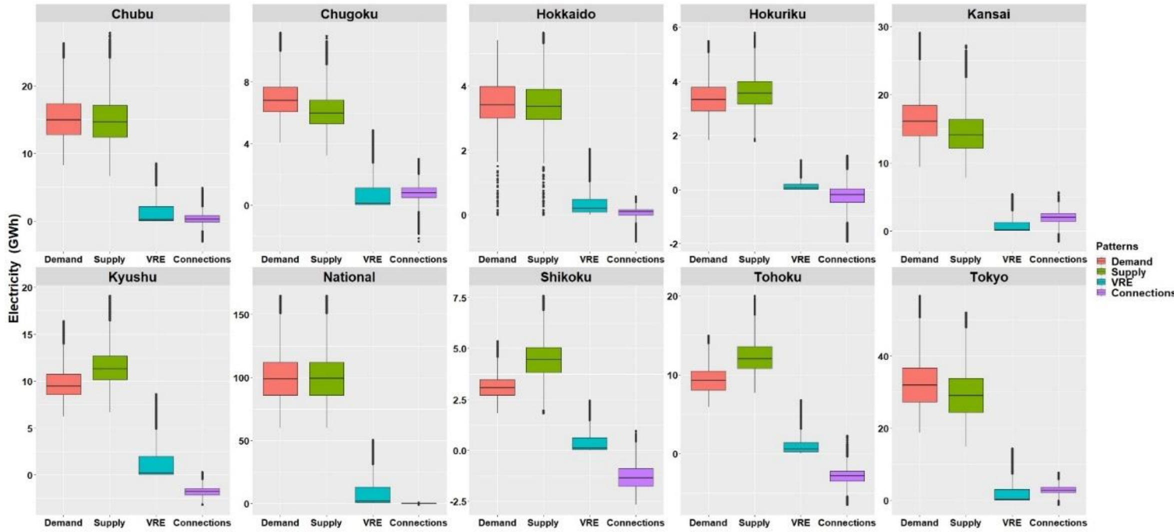

Figure 3.5 Region-wise and National Electricity Patterns from 2016-2022

3.3.2. Regional implementation of the demand response program

The resulting hourly demand loads after the RTP implementation on the shiftable residential loads are plotted for August 11th, 2021, and December 1st, 2021, in Figure 3.6 and Figure 3.7, respectively. It can be observed that the price drops during valleys up to half of the initial price and increases during off-peaks and peaks to up to half and triple folds, respectively. This incentivizes the residential end-users to shift their flexible loads to the valley period.

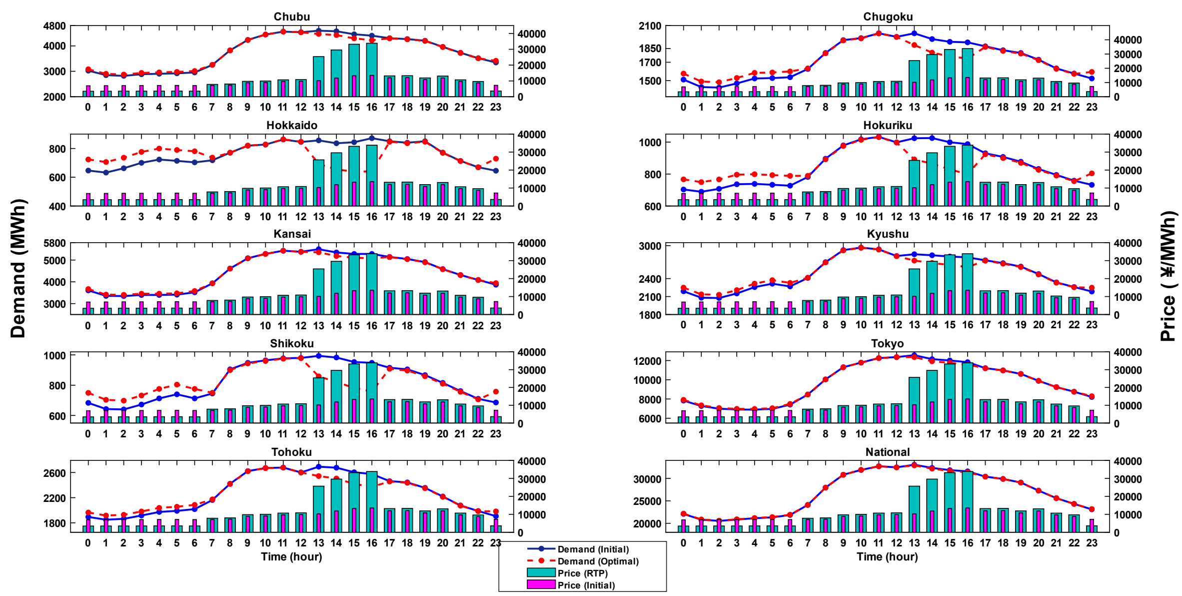

Figure 3.6 Implementation of the RTP with the shiftable loads (11th August 2021)

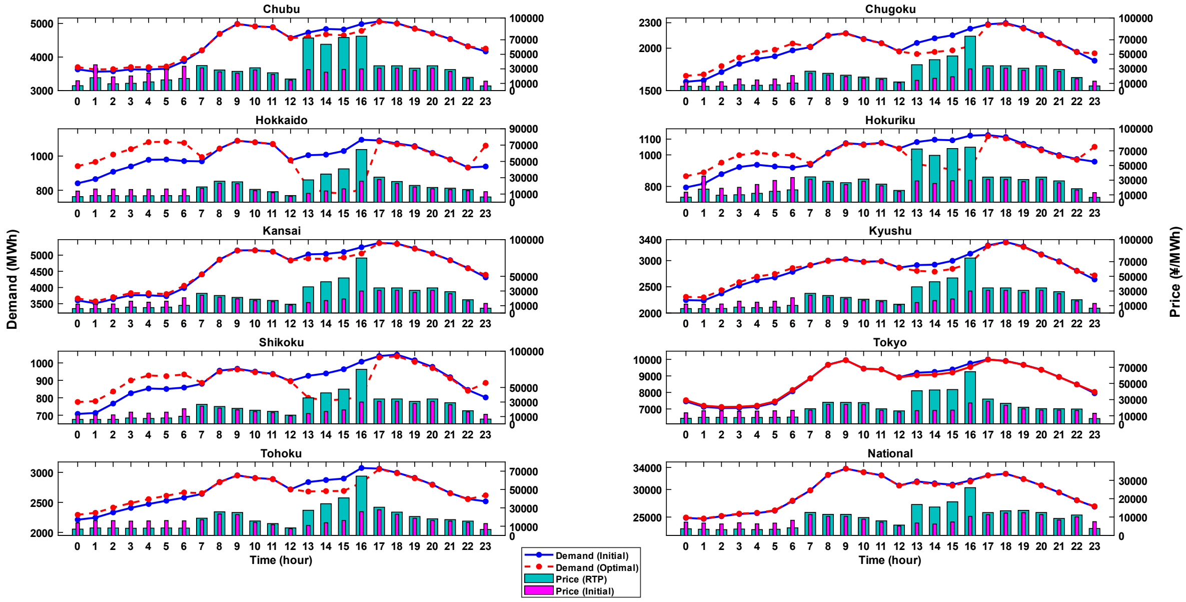

Figure 3.7 Implementation of the RTP with the shiftable loads (1st December 2021)

The results of the RTP-DRP implementation on the residential sector's shiftable loads for the selected days in summer and winter for all the regions of Japan are shown in Table 3-2. For the selected summer and winter days, the implemented RTP-DRP can shave the peak of national demand of the residential sector by 0.54% during both seasons. Meanwhile, it can reduce the national energy consumption in the selected summer and winter days by 0.03% and 0.02%, respectively. On the other hand, implementing the developed RTP-DRP in different regions individually have the potential for reducing the peak demand of the residential sector ranging from 1.91% to 7.81% in winter and summer. Meanwhile, the peak reduction for the residential sector of Hokkaido, Hokuriku, and Shikoku varies between 16.13% to 22.9%. The obtained daily energy saving varies regionally between 0.16% to 1.02%.

The findings indicate that the load factor has been enhanced in all the regions, emphasizing a lower performance for Chugoku, Hokuriku, Kyushu, and Kansai during summer. This can be attributed to the daily load profile of these regions, which peaks between 10:00 to 12:00, as depicted in Figure 3.8.

Table 3-2 Optimization results of the RTP-DRP

Season	Region	Initial Electricity Consumption (MWh/day)	Optimized Electricity Consumption (MWh/day)	Electricity Saving (%)	Peak Reduction (%)	Load Factor Enhancement	Avoided GHG emission ($kgCO_2$ /kWh)
Summer	Chubu	90,588	90,361	0.25	3.43	0.5	86,767
	Chugoku	41,524	41,374	0.36	7.81	-0.23	77,973
	Hokkaido	18,372	18,210	0.88	22.93	0.03	89,051
	Hokuriku	20,605	20,412	0.94	16.13	-0.66	89,825
	Kansai	107,126	106,874	0.24	3.16	0.88	67,208
	Kyushu	60,212	60,090	0.20	4.83	-0.05	44,720
	Shikoku	19,859	19,656	1.02	16.96	0.44	106,477
	Tokyo	233,920	233,534	0.16	1.91	1.13	174,332
	Tohoku	54,662	54,466	0.36	6.73	0.16	89,732
	National	646,870	646,624	0.04	0.54	0.34	107,998
Winter	Chubu	105,834	105,662	0.16	3.45	0.01	65,460
	Chugoku	48,406	48,286	0.25	7.86	0.13	62,525
	Hokkaido	23,940	23,836	0.43	22.99	0.09	56,982
	Hokuriku	24,068	23,926	0.59	16.19	0.07	65,802
	Kansai	110,663	110,479	0.17	3.17	-0.01	49,037
	Kyushu	68,671	68,563	0.16	4.86	0.13	39,310
	Shikoku	21,643	21,518	0.58	17.07	0.28	65,640
	Tokyo	209,458	209,292	0.08	1.92	-0.002	74,951
	Tohoku	64,889	64,743	0.23	6.77	0.33	67,056
	National	710,448	710,319	0.02	0.54	-0.002	56,719

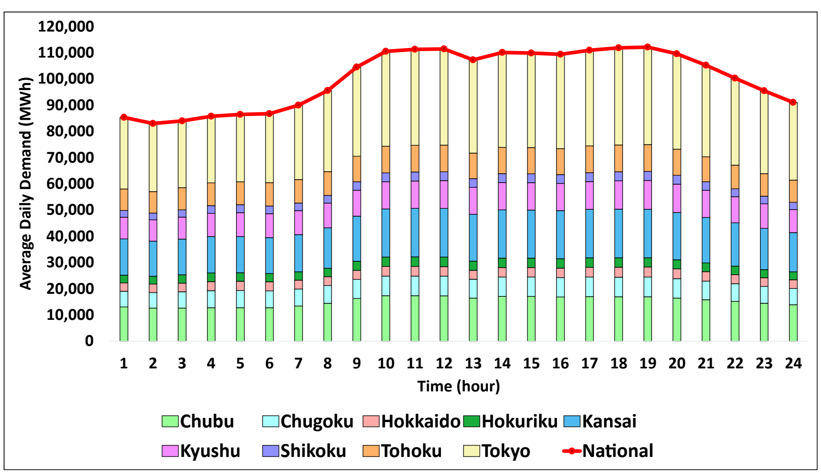

Figure 3.8 Hourly Load profiles for each region on an average basis (2016-2022)

Figure 3.9 shows the peak-to-valley ratio that measures the demand peak to the valley in summer and winter for all the regions. All the regions have shown remarkable peak-to-valley improvements, yet Hokkaido, during the winter, have shown lower performance in the peak-to-valley metric. This can be justified by the nature of the RTP-DRP, which is formulated to reduce the national peak demand by shifting it to the valley period. However, due to the unique climate nature of Hokkaido, where the temperature during the winter decreases to -8, shifting the peak demand to the valley has shown an extra burden to the existing loading of heating appliances. In other words, the fact that more demand reduction occurs during the designated peak periods, resulting in a lower minimum demand than the initial demand, leads to a higher peak-to-valley ratio compared to the initial ratio. On the other hand, Tokyo has shown substantial improvement in the peak-to-valley ratio during winter, demonstrating the efficiency of the developed RTP-DRP since Tokyo dominates around 32% of the national demand.

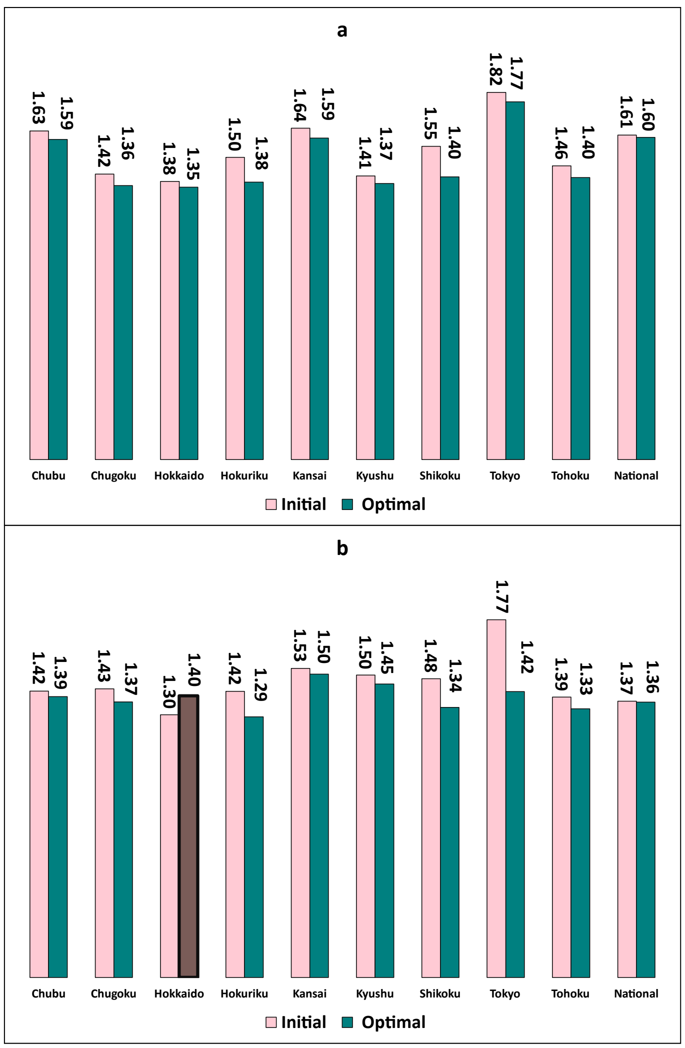

Figure 3.9 Region-wise peak-to-valley ratio improvement; a: summer; b: winter

3.3.3. Estimating the regional avoided GHG emission

The avoided emissions of each region are calculated based on the regional energy saved from the implementation of the RTP-DRP. Figure 3.10 shows the region-wise avoided emissions in summer and winter. During summer, Tokyo has avoided emissions of 82.6 and 192.2 (TonCO2e) in summer and winter, respectively, which is the highest compared to the rest of the regions. This is justified due to the highest demand in Tokyo, which is the highest demand reduction consequently. In the winter, even though Chubu and Kansai have the highest demand reduction, Tokyo is still considered the region with the highest avoided emissions resulting from the demand amount and the emissions factors.

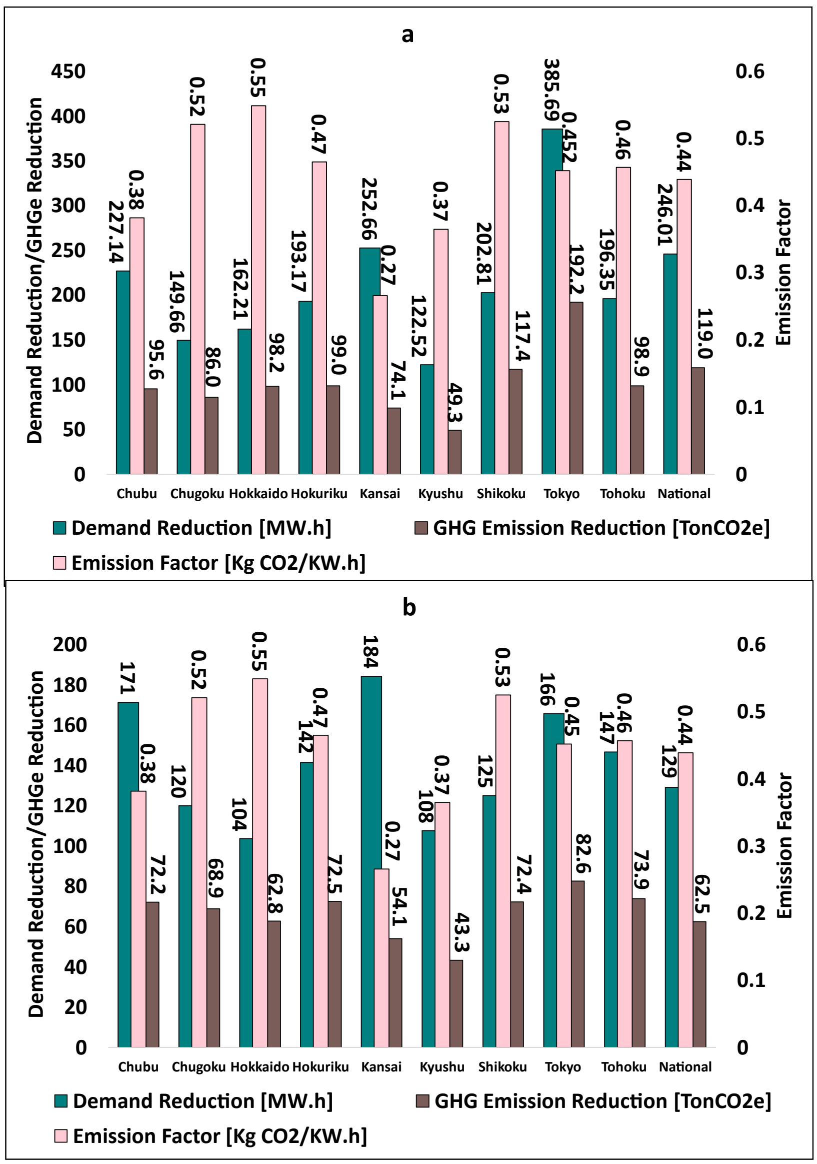

Figure 3.10 Region-wise GHG emission reduction; a: summer, b: winter

3.3.4. Region-wise evaluation of price-based demand response program

Figure 3.11 shows the major output indices of the implemented RTP-DRP along with the topological connections of the national electricity grid. This can be classified based on the supply and demand equilibrium, VRE penetration, and regional prices into three categories; regions with excess supply; regions with high demand burden; and regular suppliers of inter-regional connections. Kyushu is a region with excess supply that is the richest VRE region with 15.52% penetration to the local demand of 9.79 GWh in the period of 2016-2022, whereby this implies that Kyushu, on average, produces 1.52 GWh per hour. In addition, the price in Kyushu is the least among the other regions. Given this, its response to the energy savings and peak reduction of the RTP-DRP is the least. On the other hand, Tokyo and Kansai are regions with a high demand burden and low supply resources, whereby their response to the developed RTP-DRP is high. This implies that their local utilities can avoid importing around 0.82 GWh and 0.66 GWh during the peaks from the inter-regional connections, respectively. Chugoku, Hokuriku, and Shikoku are regular suppliers of inter-regional connections for Kansai, which have a moderate response to energy savings and peak reduction of the RTP-DRP. It can be further elaborated that Chugoku, Hokuriku, and Shikoku utilities can take advantage of the end-user response to maximize their profits by trading in Kansai, where the price is higher during the supply shortage periods. However, although Tohoku can be classified as a region with excess supply, yet it has a high response to RTP-DRP. This is due to the high demand burden of its neighboring regions, whereas during the peaks, its response to the RTP-DRP is very high, considering the local demand and the price interdependency between Tohoku and Tokyo. Similarly, Hokkaido is a region with high demand burden (i.e., resulting in low supply capacity), the highest average price, low VRE penetration, and positive inter-regional connection patterns influencing the estimated PED to be the highest. Consequently, it has high energy saving and peak reduction response, considering the small amount of demand.

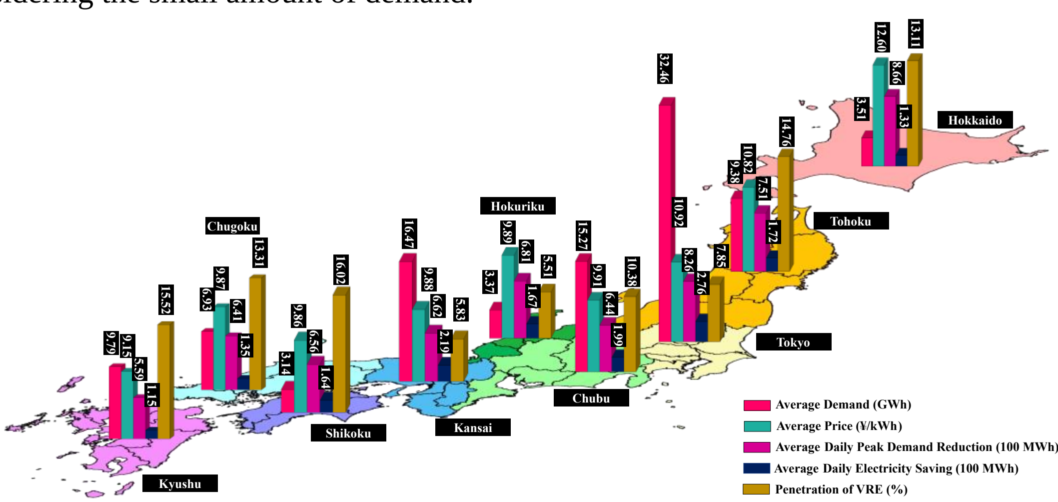

Figure 3.11 Region-wise performance map of the RTP-DRP

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Chapter 4
Incentive-based demand response modeling in a day-ahead wholesale electricity market in Japan, considering the impact of customer satisfaction on social welfare and profitability

Abstract: Incentive-based demand response programs (IBDRPs) are voluntary programs that encourage customers (CUs) to cut their electricity usage during peak periods, in return for receiving incentives from the service provider (SP). This research addresses a comprehensive multi-objective modeling approach, based on maximizing the social welfare function of both SPs and CUs involved in the IBDRPs, considering both the economic drivers and the social factors affecting the market actors. The social aspect of the CUs' participation in the IBDRPs is evaluated with respect to their satisfaction with the intangible benefits, which cannot be measured in monetary terms. To this aim, a Kano model for customer satisfaction is developed to estimate the level of CUs' satisfaction with participation in the IBDRPs, taking into account the impact of the four attributes of comfort, flexibility, energy security, and environmental protection. The model then analyzes the proposed IBDRP implemented in the Japan Electric Power Exchange (JEPX) market, using real-time wholesale electricity prices and demand loads in the Tokyo residential areas. The results revealed that, the environmental protection attribute could more positively impact the CUs' satisfaction level; consequently, their welfare is higher with more reduction in electricity from incentive incomes.

4.1.Introduction

As explained in chapter 1, most studies focused on seeking an optimal interaction between SPs and CUs, maximizing their welfare functions, revealing little about the CU's preference in participating in the IBDRPs. Although, few attempts have been made to formulate CUs' dissatisfaction with the curtailed electricity caused in IBDRPs, participation in such programs may bring additional discomfort to CUs, due to the extra burden of time and costs. On the other hand, other positive drivers, such as energy security and environmental protection, might help motivate CUs to participate in the IBDRPs. Therefore, more comprehensive research should be conducted to identify fundamental factors affecting the CU's satisfaction or dissatisfaction with IBDRPs.

To address the above gap, this research first develops a comprehensive multi-objective mathematical modeling approach, based on maximizing the social welfare function of both SPs and CUs involved in the IBDRPs in order to find the optimal incentive rates paid to the CUs for decreasing their electricity consumption, taking into account the impact of price elasticity of demand and day-ahead wholesale electricity market price. Second, the social aspect of IBDRP participation is further addressed by estimating the level of satisfaction that CUs may experience from participation in the proposed IBDRP, taking into account the impact of the four IBDRP attributes of comfort, flexibility, energy security, and environmental protection, using the Kano model. Third, a questionnaire survey is carried out in order to collect responses to a pair of functional and dysfunctional questions on the four attributes mentioned above, which helps in identifying the explicit formulation of the CUs' satisfaction function. The developed satisfaction function is then used to estimate the subjective benefits attributable to the IBDRPs that cannot be quantified in monetary terms, as the novelty of this research. The elasticity of CUs' satisfaction with their social welfare is estimated, reflecting how the CUs' welfare might be affected by the changes in the level of fulfillment of different IBDRP attributes. Finally, the developed model is used to analyze a proposed IBDRP, which can be implemented in the Japan Electric Power Exchange (JEPX) market, using real-time wholesale electricity prices and demand loads in the Tokyo residential areas. The Long Short-Term Memory (LSTM) artificial neural networks approach is used to forecast an accurate day-ahead hourly load on four years of Tokyo Electric Power Company (TEPCO) hourly power demand data from 2016 to 2020. The overall methodological approach used in this research is represented in Figure 4.1.

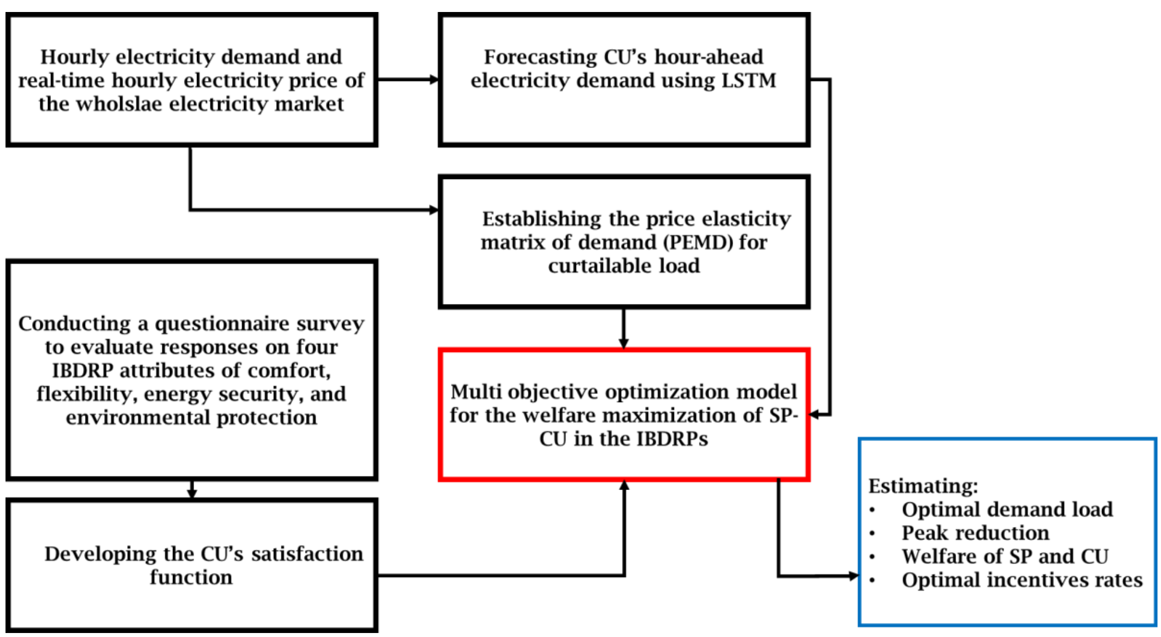

Figure 4.1 Overall methodological approach used in this research

The rest of the chapter is structured as follows. The framework of the proposed model is presented in Section 4-2, and the main terms of the model are discussed in the subsections of this part, which include the welfare maximization problem in the IBDRPs, the prediction of day-ahead hourly load, and the CUs' satisfaction model. Section 4-3 presents the results and discussions, and Section 4-4 concludes with the main findings of the research.

4.2.Model development

4.2.1. Welfare maximization problem in the IBDRPs

The welfare-seeking multi-objective optimization model developed in this study focuses on optimal interaction between the SPs and CUs by maximizing their welfare functions from trading electricity in a day-ahead wholesale electricity market, which can be expressed as follows:

$$\max\ (f_{SP}, f_{CU}) \quad 4\text{-}1$$

$$f_{SP} = \sum_{t=1}^{24}\left[(E_t \times P_{CU,t}) - (E_t \times P_{M,t}) + (\Delta E_t \times P_{M,t}) - (\Delta E_t \times inc_t)\right] \quad 4\text{-}2$$

$$f_{CU} = \sum_{t=1}^{24}\left[(CA \times U(E)_t) - (E_t \times P_{CU,t}) + \phi(inc_t \times \Delta E_t) + (1 - \phi)(S \times \Delta E_t \times inc_t)\right] \quad 4\text{-}3$$

Subject to:

$$E_t = E_t^0\left[1 + \varepsilon_t \times \frac{P_{CU,t} - P_{CU,t}^0 + inc_t}{P_{CU,t}^0} + \sum_{t=1}^{24} \varepsilon_t^* \times \frac{P_{CU,t} - P_{CU,t}^0 + inc_t}{P_{CU,t}^0}\right] \quad 4\text{-}4$$

$$U(E)_t = 1 - e^{-RE_t} e^{-R\mu + \frac{R^2\sigma^2}{2}} \quad 4\text{-}5$$

$$E_{t,min} \leq \Delta E_t \leq E_{t,max} \quad 4\text{-}6$$

$$inc_{t,min} \leq inc_t \leq inc_{t,max} \quad 4\text{-}7$$

Where, f_{SP} and f_{CU} are the welfare functions of the SP and CU, respectively. E_t^0 and E_t refer to the electricity demand before and after implementing the proposed IBDRP, respectively. ΔE_t is the demand reduction. $P_{CU,t}$, $P_{M,t}$ and inc_t are the CU's electricity price, the wholesale market prices, and the incentives rates. ε_t and ε_t^* denote the self and cross price elasticities of demand. $U(E)_t$ and CA indicate the CU's utility function and the calibration coefficient. *R* is the risk aversion factor, which measures CU's tendency to participate in the proposed IBDRP. μ and σ^2 are the mean and variance of electricity demand. S represents the CU's satisfaction, and ϕ is a weighting factor. *t* denotes daily hours in a 24 hrs period. The multi-objective function, represented in Equation 4-1 , includes both SP's and CU's welfare functions (f_{SP}, f_{CU}). On the service provider side, the SP welfare maximization problem covers two types of profits for the SP: 1) profit from selling electricity to CUs, which is defined as the difference between the expected income from selling electricity to CUs (at $P_{CU,t}$) and the cost of purchasing electricity from the wholesale market (at $P_{M,t}$), 2) Profit from the electricity reduction offered during the curtailment hours, which is defined as the difference between the expected income from the CU's electricity reduction during peak hours (at $P_{M,t}$), and the incentive payment to the CUs in return for demand reduction (at inc_t). The SP will provide different incentive rates to encourage CUs to reduce their consumption, considering the hour-ahead electricity price announced by the wholesale electricity market.

The second part of the objective function explains the welfare maximization of the CUs from participating in the proposed IBDRP, covering four main parts: 1) CU's satisfaction from using electricity, considering its utility function that is affected by electricity usage at different hours of the day, 2) CU's payment for electricity usage (at $P_{CU,t}$), during the non-curtailment hours, 3) tangible benefit resulting from the income obtained at the incentive rates offered by the SP during the curtailment hours, and 4) intangible benefits resulting from participating in the proposed DRP, which are basically the subjective benefits ascribable to the proposed IBDRP that cannot be quantified in monetary forms.

In order to quantify the intangible benefits, a CU's satisfaction function *"S"* is introduced in the model, which models the level of CU's satisfaction from participating in the proposed IBDRP, taking into account the impact of the four IBDRP's attributes of comfort, flexibility, energy security, and environmental protection. *S* has negative values if the IBDRP's attribute does not meet the CU's expectations. For example, some customers may feel discomfort from their load interruption during the curtailment hours. This can be explained as an adverse benefit or, more precisely, the discomfort cost. On the other hand, an environmentally conscious CU may be satisfied with the environmental protection attribute of the proposed IBDRP. Therefore, *S* has a positive value representing the intangible benefit gained by this satisfied CU. The calculated value of *S* is then multiplied by the amount of demand reduction and the offered incentive rates to monetize the respective intangible benefits of the proposed IBDRP. The relative importance between the tangible and intangible benefits can be explained in the model, by introducing a weighting factor of $\phi \epsilon [0,1]$.

Constraint 4-4 shows the electricity demand as a function of off-peak electricity tariff, offered incentive rates, CU's hour-ahead electricity demand before taking part in the DRP, and, more importantly, the price elasticity of demand. Constraint 4-5 represents the utility function of the CU. In this equation, the risk aversion factor measures the tendency of CUs to participate in the proposed IBDRP. The risk attitude of CUs is directly related to the curvature of their utility functions which was comprehensively discussed in (Malehmirchegini L, Farzaneh H ,2022). *CA* is used to calibrate the CU's utility function, since the unit of the utility function is "Utils" and it should be expressed with a monetary unit (Niromandfam A et al., 2020):

$$CA = \frac{P_{CU,t}}{R}\ e^{RE_t^0} \tag{4-8}$$

Finally, constraints 4-6 and 4-7 represent the upper and lower bounds on the curtailed electricity and offered incentives during the curtailment hours.

In a multi-objective optimization problem, the "most preferred solutions" should be found within the Pareto optimal set, known as the non-dominated set of the global feasible decision space (Cortez P.,2014). In this study, the ε-constraint method is used to solve the abovementioned problem, which optimizes one of the objective functions while adding the other objective function to the constraints of the model as follows (Mavrotas G.,2006):

$$\max f_1(x) \tag{4-9}$$

Subject to:

$$f_2(x) \geq e_2\ , f_2(x) \geq e_2\ , \dots f_p(x) \geq e_p\,, x \in R \tag{4-10}$$

Where $f_1(x), \dots f_p(x)$ are the p objective functions, and R is the feasible region. In this study, f_{SP} and f_{CU} are defined as $f_1(x)$, and $f_2(x)$, and Equation 4-4 to 4-7 are used as constraints. x is a decision variable vector, which includes $[E_t, P_{CU,t}, P_{M,t}, \Delta E_t, inc_t, S, CA, U(E)_t]$.

4.2.2. Day-ahead hourly electricity demand prediction model

The proposed forecasting model in this study is based on the Recurrent Neural Networks (RNNs) model, using the Long-Short-Term-Memory (LSTM) technique, which represents long-term correlations in time series for a limited range of statistical data, to predict the electricity consumption of the CUs. LSTM has already been used to forecast electricity demand in previous studies (Mahjoub S et al.,2022) (Torres JF et al.,2022) and (Manowska A, 2020). It is worth noting that, unlike other classical time series prediction models such as Autoregressive Integrated Moving Average (ARIMA), recurrent neural networks may work with any type of sequential data. Furthermore, LSTM does not rely on data assumptions such as time series stationarity or the presence of a data field (Narayan A and Hipely KW, 2017). Figure 4.2 represents the structure of the LSTM model used in this study. First, data is divided into train and test using four years of Tokyo hourly demand. Then, the training set is fed into the network to predict the price of one hour ahead, as tested by the testing sets. The input gate (i_t) proceeds with the learning process to determine whether the new sample that entered the network has useful information or not. The forget gate (f_t) manage the retaining of useful information.

The useful information of the new sample is added to the previous one. The output gate(O_t) obtains the output information from the current cell state and propagates it to the hidden layers. The time step index, t, ranges from 1 to T. C_{t-1} and C_t reflect the cell state for the previous and current timestamps, respectively. To begin with the prediction process, a vector is created by applying a hyperbolic tangent function (indicated with "tanh" in Figure 4.2) in the cell. The information is then regulated using the "sigmoid function (σ) " and filtered, utilizing inputs to recall the values.

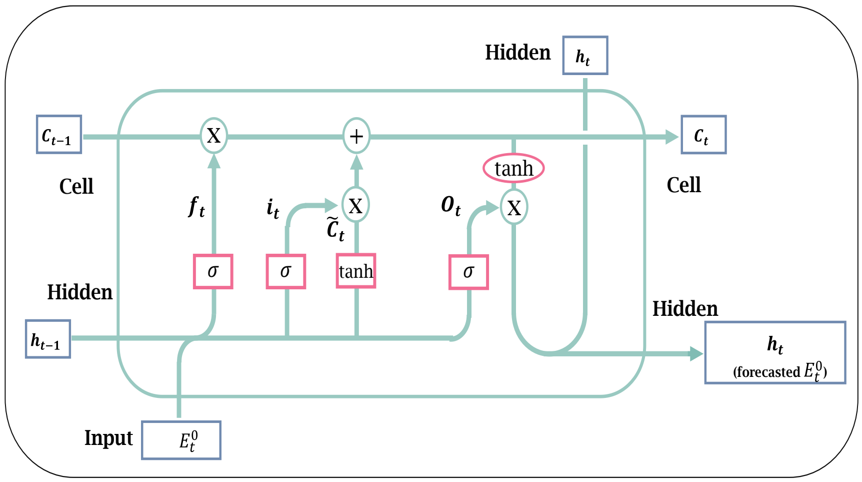

Figure 4.2 LSTM structure (adapted from (Zhang C et al., 2020))

The detailed formulation used in the above LSTM architecture is expressed as follows (Manowska A , 2020) , (Zhang C et al., 2020) and (Shohan MJA, 2022); equations 4-11to 4-16 contain the equations that explain the gate layer:

$$f_t = \sigma(X_t \times U_f + h_{t-1} \times W_f) \quad 4\text{-}11$$

X_t is the current timestamp's input, the weight matrix U connects the input layer to the hidden layer, and the weight matrix W connects the previous and current hidden layers. h_{t-1} is the previous timestamp's hidden state. After applying the Sigmoid function, it will make f_t a number between 0 and 1. If f_t equals to 0, then $C_{t-1} \times f_t = 0$ means forget everything. If f_t equals to 1 then $C_{t-1} \times f_t = C_{t-1}$ means forget nothing.

- Input Gate:

$$i_t = \sigma(X_t \times U_i + h_{t-1} \times W_i) \quad 4\text{-}12$$

- New information

$$\tilde{C}_t = \tanh\,(X_t \times U_c + h_{t-1} \times W_c) \quad 4\text{-}13$$

tanh is the activation function in this case. The tanh function causes the value of new information to range between -1 and 1.

- Updating Cell State

$$C_t = \sigma(f_t \times C_{t-1} + i_t \times \tilde{C}_t) \quad 4\text{-}14$$

- Output Gate

$$O_t = \sigma(X_t \times U_O + h_{t-1} \times W_O) \quad 4\text{-}15$$

Its value will also be between 0 and 1 due to the sigmoid function. We will now use O_t and tanh of the updated cell state to determine the current hidden state. As illustrated below.

$$h_t = O_t \times \tanh(C_t) \tag{4-16}$$

The LSTM hyper-parameters are optimized by searching the grid for all potential combinations in the searching space, as shown in Table 4-1.

Table 4-1 Hyper-parameters searching space and the selected values

Input sequence size	24
Output sequence size	1
Training batch size	32
Hidden Units	120,80,40
Number of hidden layers	384000
Epochs	25
Validation split	0.1
Optimizer	Adam Optimizer
Loss	Mean squared error

The test outcome is evaluated using three performance indicators. The mean average percentage error (MAPE), the root mean square error (RMSE), and the coefficient of determination (R^2) are the variables to consider. The performance metrics are calculated using Equations 4-17 to 4-19, where N is the number of data points.

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\left|\frac{Actual\ value - Forecasted\ value}{Actual\ value}\right| \tag{4-17}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{t=1}^{N}(\text{Actual value} - \text{Forecasted value})^2} \tag{4-18}$$

$$R^2 = 1 - \frac{\text{sum of squared residuals}}{\text{total sum of squares}} \tag{4-19}$$

4.2.3. CUs' satisfaction model

As explained above, the CU's welfare is not only affected by the incentive incomes during the curtailment hours, but also strongly influenced by other intangible benefits or costs caused by the implementation of the IBDRP during those periods. To this end, this study employs a satisfaction function that measures the CU's satisfaction level from participating in the IBDRPs, ranging from the proportion of possible satisfaction to probable dissatisfaction, using Kano's model. Even though Kano's model has widely been employed within academic research (He L et al., 2017), (Madzík P et al.,2019) and (Mkpojiogu EOC and Hashim NL,2016), its potential in the domain of demand response has not been completely realized. However, Kano's model is extremely effective for better understanding and prioritizing customer preferences and expectations from participating in demand responsive electricity market. Kano's model, unlike other models, does not assume a linear relationship between service quality and CUs satisfaction (Wang T and Ji P, 2010). According to this model, the level of CUs' satisfaction varies with respect to the attributes of the service delivered to them (Lin FH et al.,2017). In other words, CU's satisfaction from participating in a proposed IBDRP may vary depending on their expectations from the program, which cannot be explained with the incentive income, alone. To this end, this study considers four main attributes of comfort, flexibility, energy security, and environmental protection, which can influence the CU's satisfaction from participating in a proposed IBDRP. The CU's satisfaction can be further examined, taking into account both functional (having the attribute) and dysfunctional (not having the attribute) perspectives on each of the aforementioned IBDRP's attributes, as explained below:

Comfort: CU's preference for earning incentive income, even if it causes discomfort during the curtailment hours, or contrarily, the desire to have comfort, even if there is no incentive income.

Flexibility: CU's preference for earning incentive income, even if it requires spending time learning how to work complex software (reporting and monitoring programs) and hardware (measurement and control devices) or, contrarily, not spending time on the proposed program, even if there is no incentive income.

Energy security: CU's preference for participating in the IBDRP and reducing electricity consumption which ensures access to reliable electricity during critical periods throughout the year, or, contrarily, not to participate in the proposed program, even if it limits access to reliable electricity in the future.

Environmental protection: CU's preference for participating in the IBDRP in order to support climate change mitigation and air pollution reduction policies or, conversely, not to participate in the proposed program, even if it worsens climate change and air pollution issues in the future.

As shown in Figure 4.3, by applying the Kano original questionnaire survey consisting of functional and dysfunctional questions and evaluating the frequency of the responses to both questions, each of the four attributes mentioned above can be finally assigned to one of the six following groups (Wang T and Ji P, 2010):

1. One-dimensional (O): CU's satisfaction and the fulfillment level of attribute have a positive and linear correlation.

2. Must-Be (M): This attribute does not affect the satisfaction of CU, but if this criterion is not considered, CU will be very dissatisfied.
3. Attractive (A): This attribute indicates the satisfaction of CU, while its absence does not imply dissatisfaction.
4. Indifferent (I): Whether this attribute is satisfied will not affect CU's satisfaction.
5. Reverse (R): Higher score of this attribute lowers CU's satisfaction and vice versa
6. Questionable (Q): There is a contradiction in the CU's responses to the questions.

The most common observations of the sample set of responses are used to determine the final Kano category for that attribute.

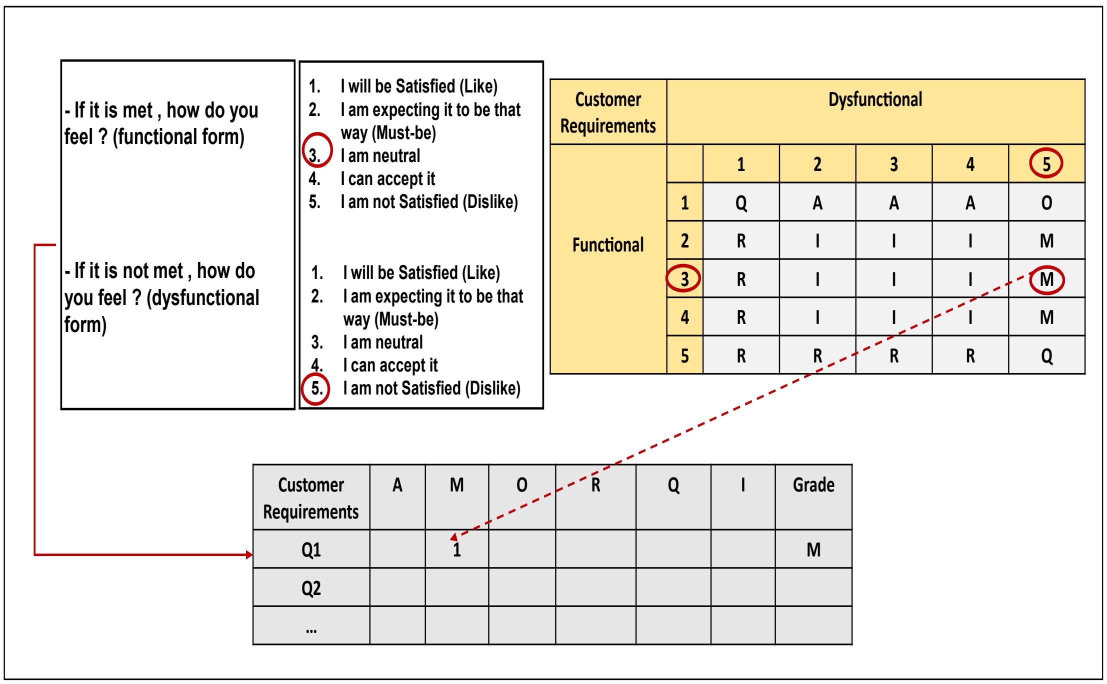

Figure 4.3 Schematic of the questionnaire of the Kano model (Madzík P et al., 2019)

Analysis of the Kano questionnaire results in estimating the customer satisfaction (CS) and customer dissatisfaction (DS) coefficients, which are explained as follows (Wang T and Ji P, 2010):

$$CS_i = \frac{f_A + f_O}{f_A + f_O + f_M + f_I} \tag{4-20}$$

$$DS_i = -\frac{f_M + f_O}{f_A + f_O + f_M + f_I} \tag{4-21}$$

Where, f_A, f_O, f_M and f_I are the total number of attractive, one-dimensional, must-be, and indifferent responses. CS_i ranges from 0 to 1, while the value of DS_i varies between -1 and 0. The degree of customer satisfaction from the participation in the proposed IBDRP can be estimated by $S = f(x, a, b)$, whereas x is the fulfillment level of the selected attribute (i.e., comfort, etc.), a and b are the adjustment factors for different feature categories (Mikulić J ,2007):

❖ One-dimensional attributes, considering $a = (CS_i - DS_i)$ and $b = DS_i$:

$$S_i = ax_i + b \quad (4\text{-}22)$$

❖ Attractive attributes, considering $a = \frac{(CS_i - DS_i)}{1.72}$ and $b = \frac{-(CS_i - eDS_i)}{1.72}$:

$$S_i = ae^{x_i} + b \quad (4\text{-}23)$$

❖ Must-be attributes, considering $a = \frac{e(CS_i - DS_i)}{1.72}$ and $b = \frac{eCS_i - DS_i}{1.72}$:

$$S_i = a(-e^{-x_i}) + b \quad (4\text{-}24)$$

Figure 4.4illustrates the S function curves, where the x-axis represents the level of fulfillment of a particular attribute (from Insufficient to Sufficient), and the y-axis represents the level of CU’s satisfaction or dissatisfaction with that attribute **(**Madzík P et al., 2019) and (Wang T and Ji P, 2010).

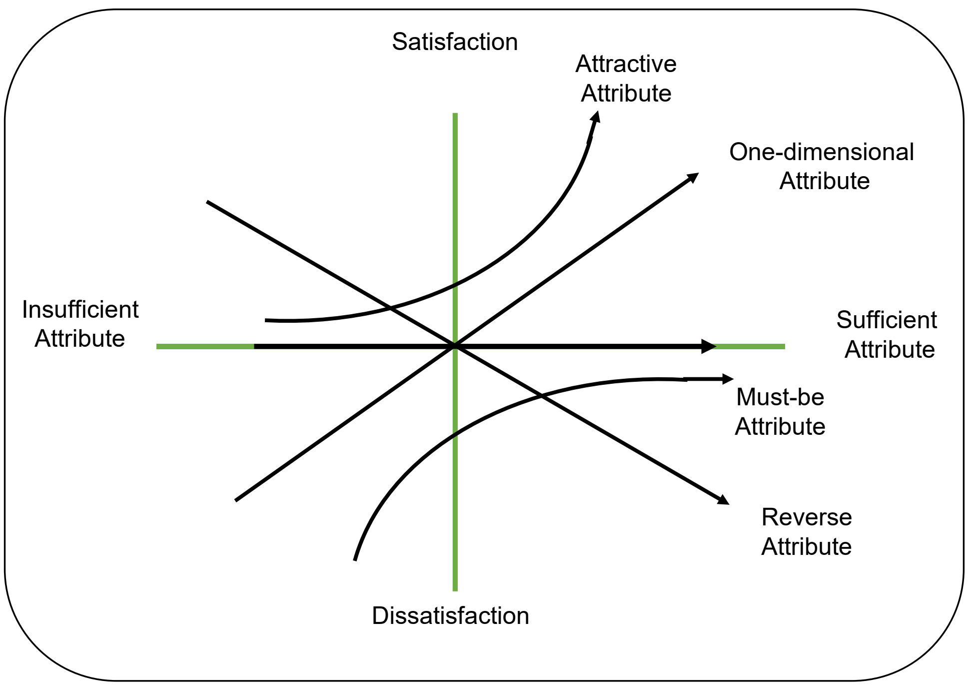

Figure 4.4 Demonstration of the S function curves (adapted from (Huang J, 2017))

Based on the above discussion, the overall methodological approach used in this research, including both quantification and qualification assessment frameworks, is represented in Figure 4.5.

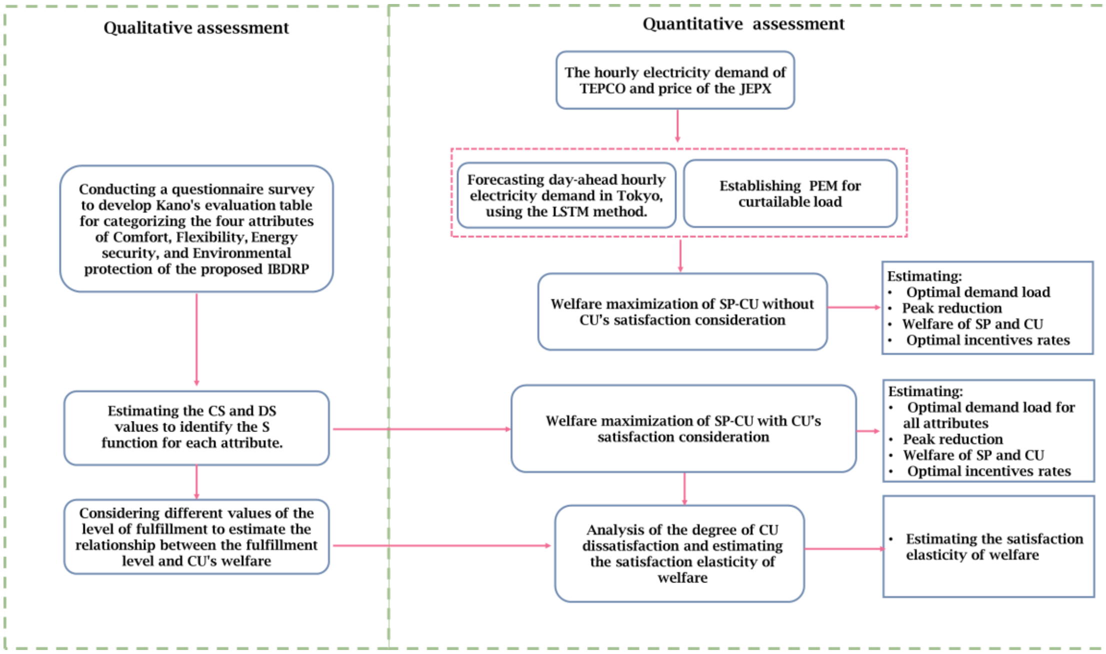

Figure 4.5 Overall methodological approach used in developing the model

4.3. Results and discussions

4.3.1. Day ahead hourly electricity demand prediction

The time series dataset, containing four years of hourly electricity demand data collected from Tokyo Electric Power Company between 2016 and 2020 (Huang J, 2017) is demonstrated in Figure 4.6 and Figure 4.7. This was split into 80% for training the model and 20% for testing validation of forecast data, as shown in Figure 4.6.

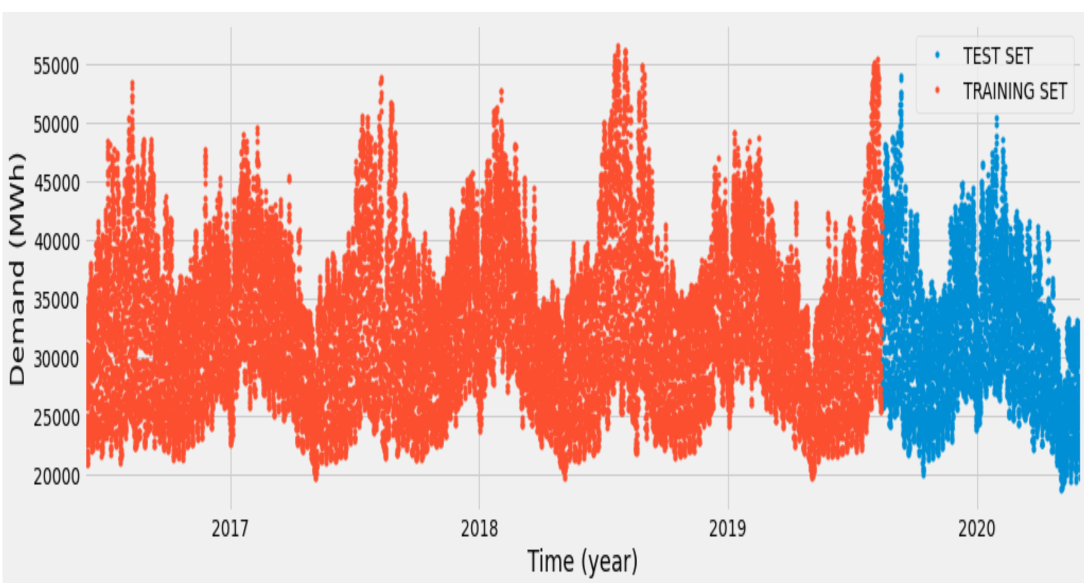

Figure 4.6 Hourly electricity demand data (2016-2020)

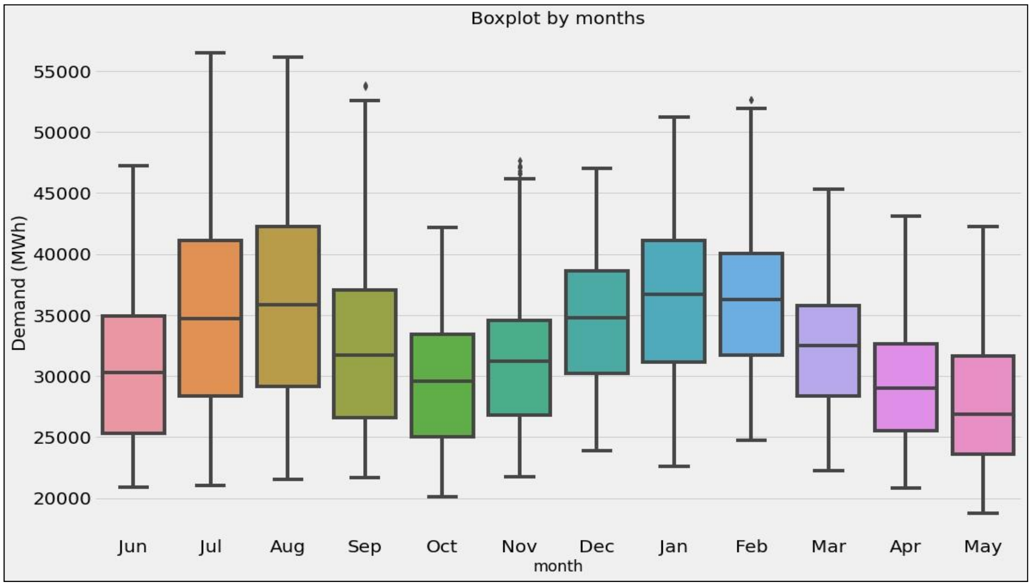

Figure 4.7 Demand visualization by months (2016-2020)

The predicted electricity demand by the model was tested using three performance metrics. The mean average percentage error (MAPE), the root mean square error (RMSE), and the coefficient of determination (R^2), which are reported at 0.91, 399, and 0.99, respectively, indicating the high accuracy of the predicted model. The comparison between the estimated and actual demand (the test part) is shown in Figure 4.8.

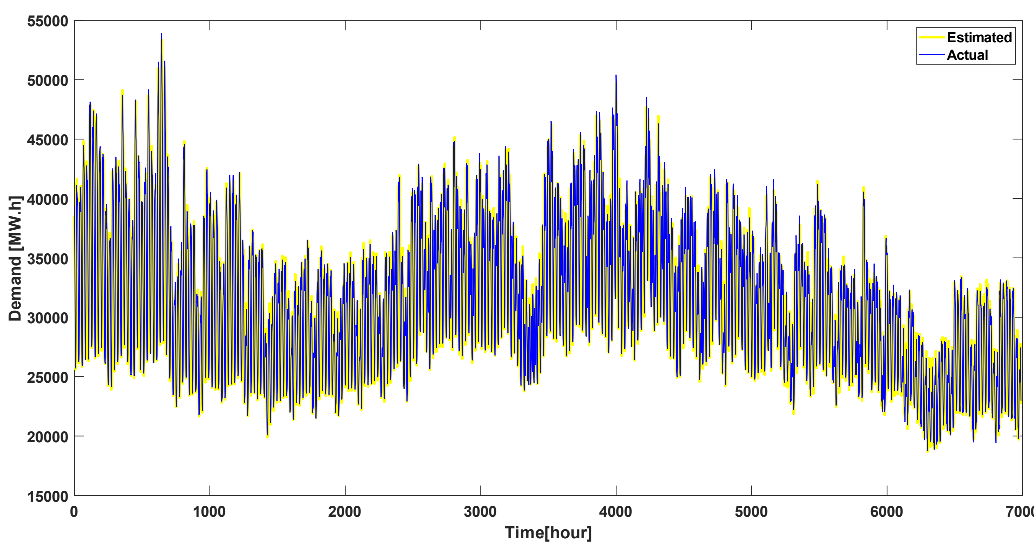

Figure 4.8 Comparison between actual and estimated data in 2020

Figure 4.9 shows the day-ahead hourly load prediction result for the selected day (June 1, 2020, as an example), which is denoted as E_t^0 in (Equation 4-4).

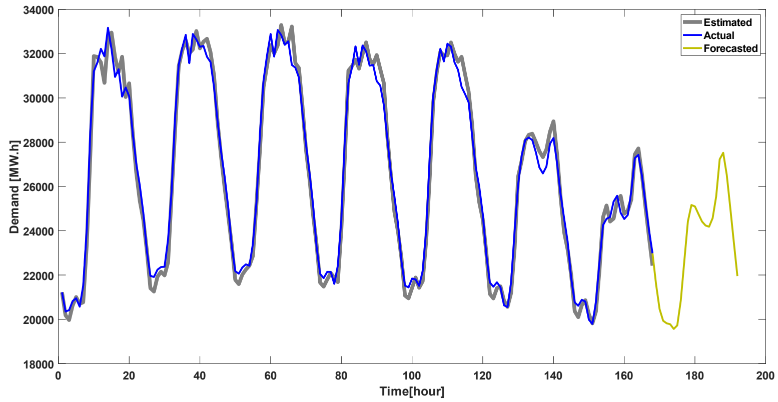

Figure 4.9 Day-ahead hourly load prediction in Tokyo

4.3.2. Customer satisfaction function

A questionnaire survey was carried out in this research to derive CU satisfaction functions, which can be further used to estimate the intangible benefits of CU from participating in the proposed IBDRP. To this end, an online questionnaire was formed to collect responses to a pair of functional and dysfunctional CU's questions on the four attributes of comfort, flexibility, energy security, and environmental protection. The details of the questionnaire are given in Appendix 1. The 130 respondents who participated in the survey were categorized, considering their age, gender, education, and occupation, as shown in Table 4-2. In order to avoid non-responses or incorrect answers, this survey focused on a limited respondent community, consisting of approximately 70% of graduates and 60% of employed individuals. Prior to the survey, the selected 130 respondents were provided with a brief overview of DRPs; after that, they were asked to answer the questions.

Table 4-2 Classification of the respondents involved in the survey

Item	Category	Respondents	Percentage [%]
Age	21 to 30 years old	23	17.7
	31 to 40 years old	62	47.7
	41 to 60 years old	40	30.8
	61 or more	5	3.8
Gender	Female	42	32.3
	Male	88	67.7
Education	Bachelor's degree	26	20
	Master's degree	71	54.6
	Doctorate degree	30	23.1
	Professional Certification	3	2.3
Occupation	Employed full-time	71	54.6
	Employed part-time	9	6.9
	Not currently employed	10	7.7
	Retired	7	5.4
	Student	31	23.8
	Homemaking	1	0.8
	Other	1	0.8

After analysis of the responses to the functional and dysfunctional questions, the values of CS and DS for the attributes were calculated, and their Kano classification was identified, as shown in Table 4-3.

Table 4-3 Kano response evaluation table

DRP's attributes	A*	O	M	I	R	Q	Total	Kano Category	CS value	DS value
Comfort	13	50	10	40	14	3	130	O	0.56	-0.53
Flexibility	8	11	54	28	22	7	130	M	0.18	-0.65
Energy security	19	74	11	22	3	1	130	O	0.74	-0.67
Environmental protection	64	41	9	13	0	3	130	A	0.83	-0.39

*Data in columns depict the total number of individual responses corresponding to a particular category.

The results in Table 4-3 show to what extent an IBDRP's attribute can affect the CUs' preference to participate in the program. The survey results revealed that, the two attributes of "Comfort" and "Energy security" belong to the one-dimensional Kano category, indicating satisfaction and fulfillment levels of these features have a positive correlation. However, "Environmental protection" and" Flexibility" attributes belong to the attractive and must-be categories, respectively. Based on this classification, the suitable "S" function for each attribute was extracted, as reported in Table 4-4.

Table 4-4 S functions for different IBDRP's attributes in this study

Attribute	$\boldsymbol{S = af(x) + b}$
Comfort	$S = 1.09x - 0.53$
Flexibility	$S = -1.32e^{-x} + 0.67$
Energy security	$S = 1.41x - 0.67$
Environmental protection	$S = 0.71e^{x} - 1.10$

Figure 4.10 shows the extracted *S* function curves. The y-axis represents the degree of CU's satisfaction ranging from -1 (fully dissatisfied) to 1 (fully satisfied). The x-axis represents the fulfillment level of the selected IBDRP's attribute, ranging from 0 (non-fulfillment) to 1 (fully fulfilled).

According to Figure 4.10, the CU's satisfaction (*S*) with the "comfort" and "energy security" attributes (as one-dimensional attributes) is directly proportional to the fulfillment level (*x*). So, the CU is more satisfied at higher fulfillment levels of these two attributes and vice-versa.

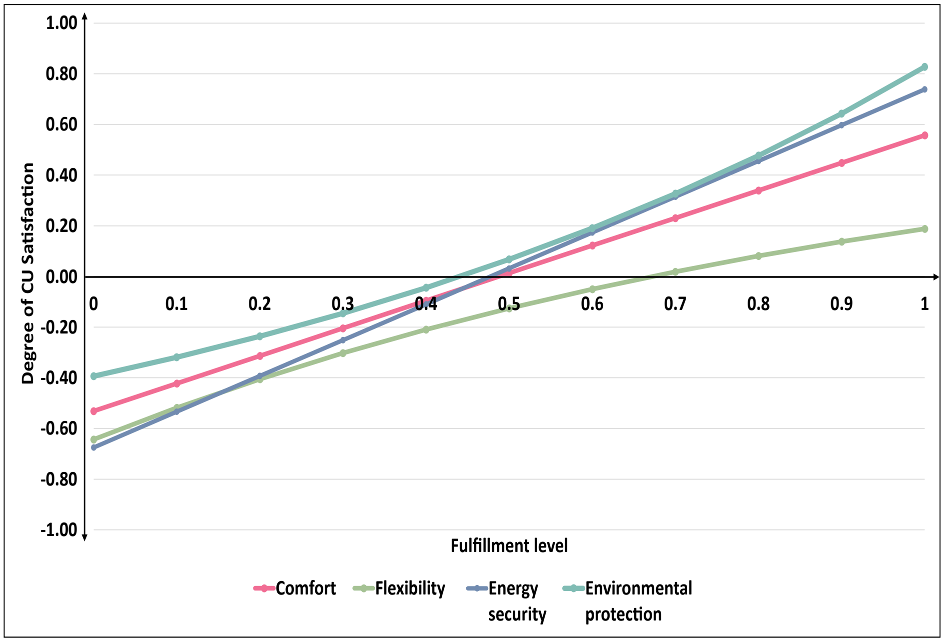

Figure 4.10 Satisfaction-fulfillment level (*S*-*x*) relationship curves based on the conducted survey in this study

On the other hand, for the "flexibility" attribute, the values of *S* decrease sharply at the lower values of *x*. Therefore, at the lower fulfillment levels, the CU is more dissatisfied with this attribute; however, the higher levels have no significant impact on the CU's satisfaction level. The CU is more satisfied with the higher fulfillment levels of the "environmental protection" attribute and less dissatisfied with the lower levels.

4.3.3. Estimation of the optimal load reduction and incentive rates

The developed model was used to find the optimal incentive rates offered by the SP (TEPCO) to induce the CUs (Tokyo residents) in order to reduce their electricity loads during peak hours, through participating in an IBDRP, which is to be implemented in the JEPX wholesale electricity market. The summer's electricity load profile differs from the other seasons in Tokyo. The summer load profile includes only one peak from 1 pm to 4 pm, while the other seasons' load profiles include one in the morning (8 am to 11 am) and another in the evening (5 pm to 7 pm) (Tariff of Electricity Rates, 2014). The IBDRP's pricing mechanism used in this study is explained in Table 4-5.

Figure 4.11represents an example of the tariff scheme and price elasticities (Malehmirchegini L, Farzaneh H,2022) and (Suliman MS and Farzaneh H, 2022) in the selected winter and summer days used in this study.

Table 4-5 The IBDRP's pricing mechanism used in this study

Price	Tariffs	
Wholesale market prices ($P_{M,t}$)	The spot dynamic prices of the JEPX[1]	
Customer price ($P_{CU,t}$)	$P_{CU,t} = P_{M,t} \times (\frac{\text{Flat rate price of TEPCO}}{\text{LCOE}})$ [2,3]	
Incentive payment (inc_t)	Peak: $0 \leq inc_t \leq 0.9P_{M,t}$	Off-peak: $inc_t = 0$

1. Ref (JEPX, 2021)

2. Flat rate price of TEPCO is assumed to be $22[\frac{¥}{KW.h}]$ (Tariff of Electricity Rates, 2014)

3. Levelized Cost of Electricity (LCOE) of the fossil-based power plant in Japan is assumed to be $13.06[\frac{¥}{KW.h}]$ (levelised-cost-of-electricity-calculator, 2020)

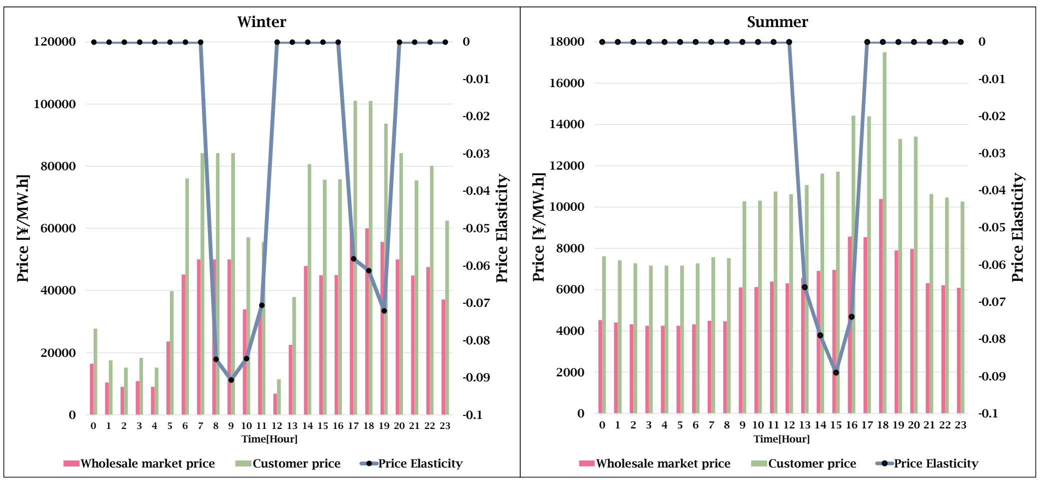

Figure 4.11 The dynamic elasticity and prices for winter (17th December 2020) and summer (11th August 2020)

Figure 4.12shows the price elasticity matrix of demand (PEMD) used to depict the CUs' behavior in responding to the proposed IBDRP. CUs start to reduce the curtailable loads, when the SP announces the high prices. The PEMD has non-zero elements only during peak hours (self-elasticity), since the curtailable loads can be reduced only during peak hours and cannot be shifted to other hours.

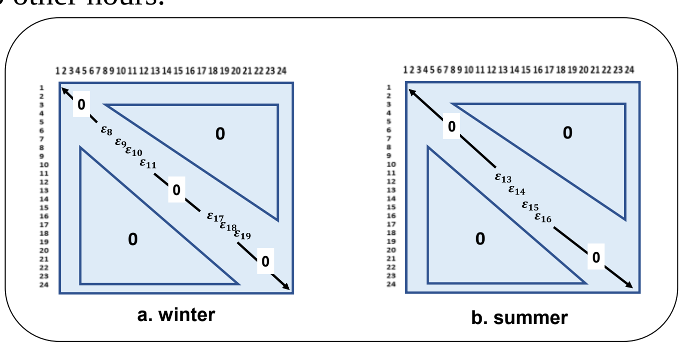

Figure 4.12 The PEMD structure of the curtailable loads in the proposed IBDRP

4.3.3.1. Scenario I; IBDRP analysis without CU's satisfaction consideration

Figure 4.13 and Figure 4.14 represent the CU's load profiles after implementing the IBDRP, based on the optimal incentive rates by the SP, without considering CU's satisfaction (ϕ =1 in Eq. 3) for a selected day in winter and summer, respectively. In general, the amount of the demand reduction is proportional to the incentive rates, so, the higher the incentive rates, the larger the demand reductions. From this Figure, it can be observed that, the incentive rates follow the same trend as the wholesale electricity market, which means that, during periods of high wholesale market prices, SP should offer higher incentive rates to the CUs to induce them to save more electricity. It is also noted that, although the SP offers lower incentive rates during the first peak hours (8:00 to 11:00), the electricity reduction in this period is larger compared to the second peak hours (17:00-19:00). This is because, during the first peak hours period, the value of the price elasticity of demand is larger and the electricity demand is more elastic. The same pattern was observed in the summer load, indicating that, despite the significant incentive, the amount of the demand reduction is smaller in hour 16 than in hour 15 due to their price elasticities. Table 4-6 shows the optimal demand reduction, incentive payment, and welfare of both CUs and SP. Since, there is only one peak period in the summer, the quantity of demand reduction is less than in the winter. However, the peak reduction compared to the initial demand is more significant in summer.

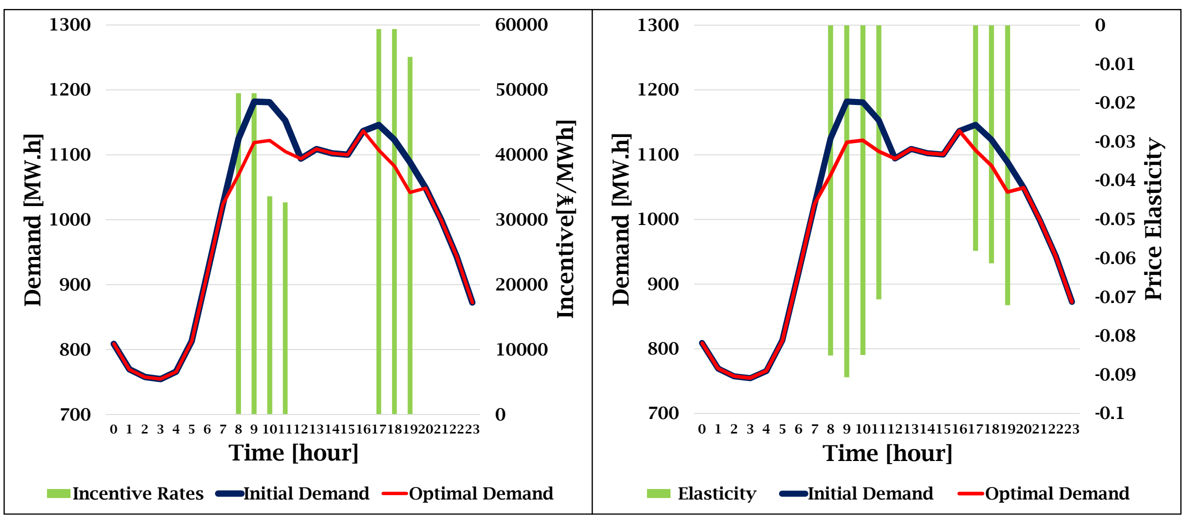

Figure 4.13 Optimal load reduction and incentive rates (17th December 2020)

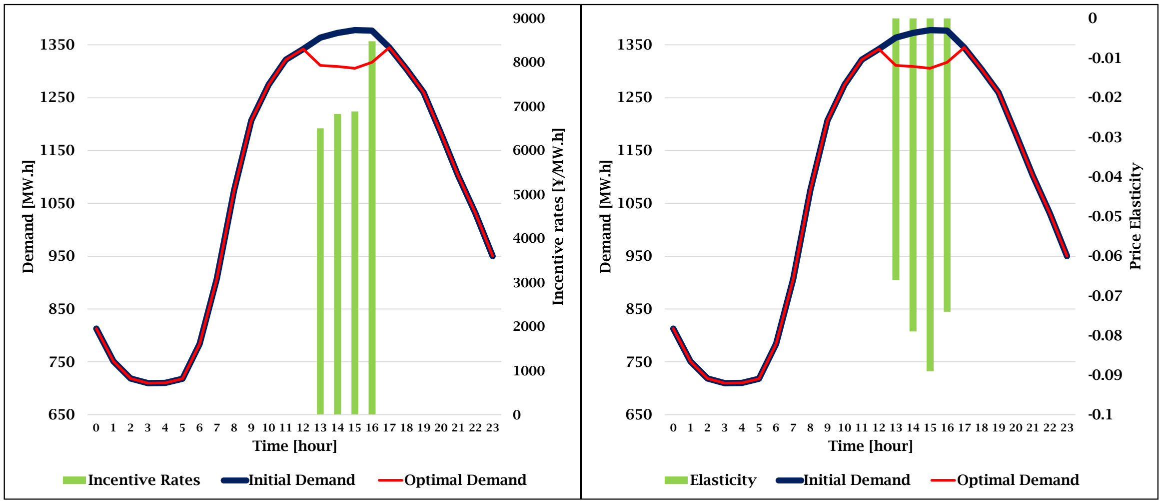

Figure 4.14 Optimal load reduction and incentive rates (11th August 2020)

Table 4-6 Optimal results in scenario I

Season	Peak Reduction	Incentive Payment [million ¥/day]	Demand Reduction [MW.h/day]	SP' Welfare [¥/MW.h]	CU' Welfare [¥/MW.h]
Winter	4%	6.4	277.1	12,928	36,257
Summer	5%	1.7	248.6	4,386	13,841

4.3.3.2. Scenario II; IBDRP analysis with CU's satisfaction consideration

In order to reflect the impact of the CU's satisfaction on optimal incentive rates and electricity reduction in the proposed IBDRP, in this scenario, it is assumed that a SP will interact with two groups (dissatisfied and satisfied) of CUs explained in Table 4-7 . The lower values assigned to ϕindicate the greater importance of the intangible benefits (CU's satisfaction) compared with the tangible benefits (incentive income), while the lowest values of x indicate less satisfaction with a selected IBDRP attribute. Therefore, as shown in Table 4-7, a satisfied CU (ϕ =0.9 and x=1) is more interested in obtaining incentive incomes from the SP and is always satisfied with all IBDRP attributes.

Table 4-7 CUs in scenario II

	Status	ϕ	x
CU1	dissatisfied	0.3	0
CU2	satisfied	0.9	1

Figure 4.15 shows the demand loads before and after the implementation of the proposed IBDRP for two groups of CUs, taking into account the level of satisfaction with the different

attributes. The findings from this Figure are three folds. First, the dissatisfied customer (CU1) is less inclined to reduce electricity consumption as expected. Therefore, CU1 receives less incentive payment from the SP. Second, the time scheduling of incentive payments from SP differs for CU1 and CU2. Compared to CU2, the incentive payment for CU1 starts later and ends earlier. Third, the amount of load reduction is also affected by the degree of CU's satisfaction with the IBDRP attributes. In general, CU1 is dissatisfied with the attributes of comfort, flexibility, and energy security, but it reduces electricity load in almost the same way as CU2 is satisfied with the environmental protection attribute of the IBDRP, indicating the role of the attractive attributes of the IBDRP in demand reduction, even for a dissatisfied customer.

The daily cumulative electricity consumption before and after the implementation of the proposed IBDRP for two groups of CUs is shown in Figure 4.16 . The daily cumulative load reduction of CU 1 ranges from 64 MWh with the energy security attribute to 186.2 MWh with the environmental protection attribute. Both CUs are more inclined to reduce their loads with the environmental protection attribute compared with other attributes of the proposed IBDRP. This can be explained with respect to the developed Kano categories. Compared with flexibility, which is a "must be" attribute of the program, an attractive attribute like environmental protection plays a more significant role in encouraging dissatisfied customers to participate in the IBDRPs and reduce their loads. In addition, as explained earlier, CU1, with a lower value of ϕ will be more conservative in reducing the load to avoid any dissatisfaction caused by the program. In contrast, the higher value of ϕ for CU2 implies that, incentive payments are more important than dissatisfaction cost, resulting in maximum demand reduction across all four attributes.

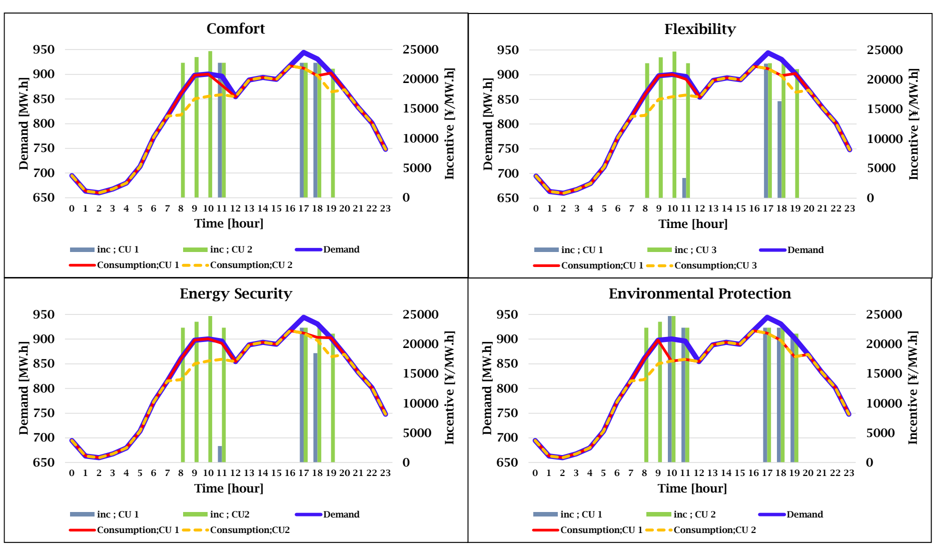

Figure 4.15 Optimal demand reduction and incentive rates for CU1 and CU2

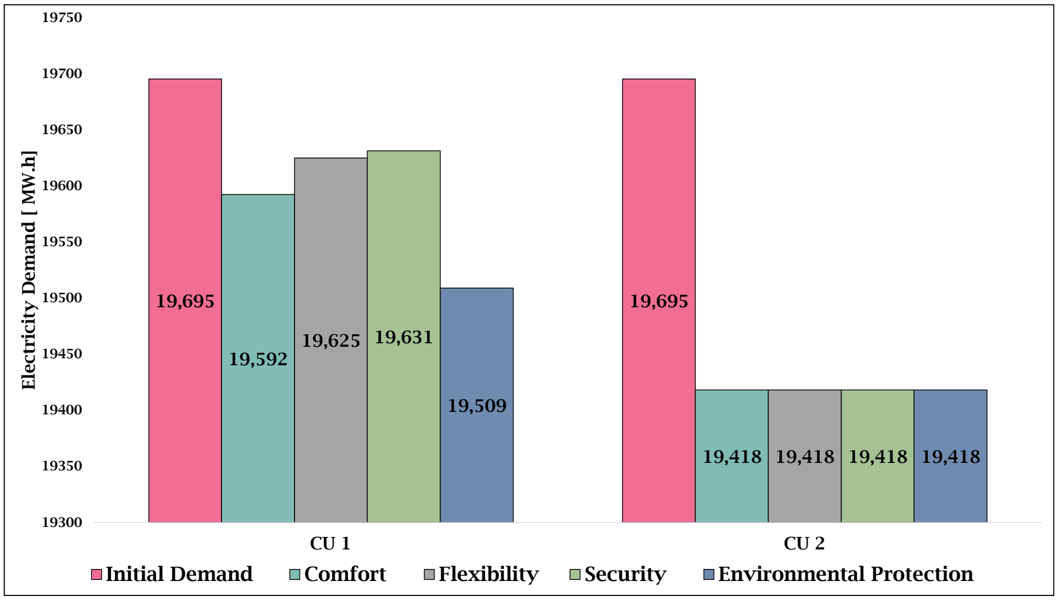

Figure 4.16 CUs' electricity demand under satisfaction with the different IBDRP's attributes

Table 4-8 shows the optimal welfare of both CUs, considering CU's satisfaction with the different IBDRP's attributes. The proposed IBDRP leads to lower welfare for CU1, which indicates that a dissatisfied customer is less willing to reduce electricity in exchange for receiving incentives from the SP. Among all attributes, the environmental protection attribute positively impacts the CU1's satisfaction level. Therefore, CU welfare with this attribute is higher for both customers due to a greater reduction in electricity from incentive incomes. On the other hand, the flexibility attribute makes CU1 more dissatisfied. So, CU1's welfare has the lowest value with this IBDRP's attribute.

Table 4-8 Optimal welfare of CUs [¥/MW.h]

	Comfort	Flexibility	Energy Security	Environmental Protection
CU1	35,595	35,563	35,551	35,800
CU2	36,256	36,255	36,256	36,257

Although the reduction of electricity demand for both CUs is directly proportional to the incentive payments offered by SP, if public awareness of climate change issues rises, the perceived value of CUs with environmental protection will increase; therefore, they will participate in the proposed DRP, even if they receive a less monetary incentive. A comparison of the two attributes of comfort and environmental protection is presented in Figure 4.17, which indicates that, for a given load reduction, the excess incentive payment needed to increase the satisfaction level of the CU (from CU1 to CU2) is lower with the environmental protection attribute.

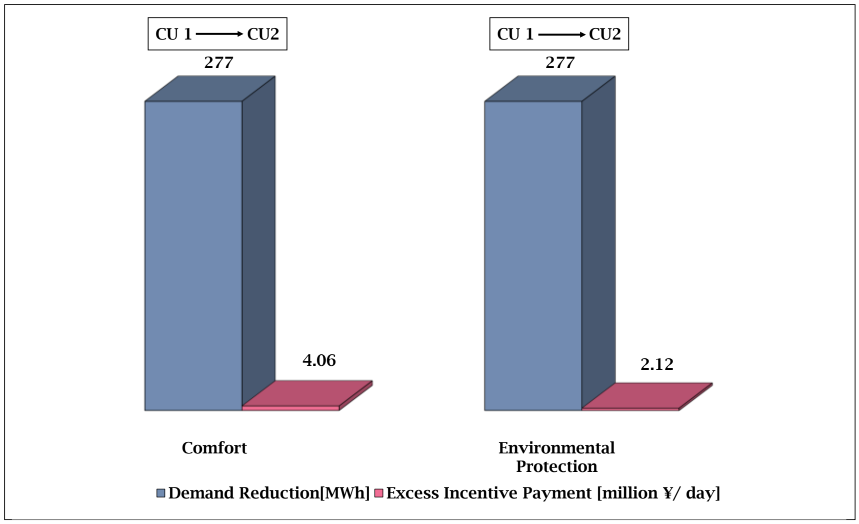

Figure 4.17 Excess incentive payments for shifting from CU1 to CU2

Figure 4.18 represents the variation of the welfare values with ϕ and x for a wide range of customers, from very dissatisfied ($\phi = 0.1$ and x= 0) to fully satisfied CUs ($\phi = 1$ and x= 1). As the welfare of CUs increases, the welfare of SP decreases to an extent due to the increase in costs imposed by incentive payments. However, after that, the savings from peak reduction can offset the costs of the incentive payment. Therefore, the welfare of SP remains constant.

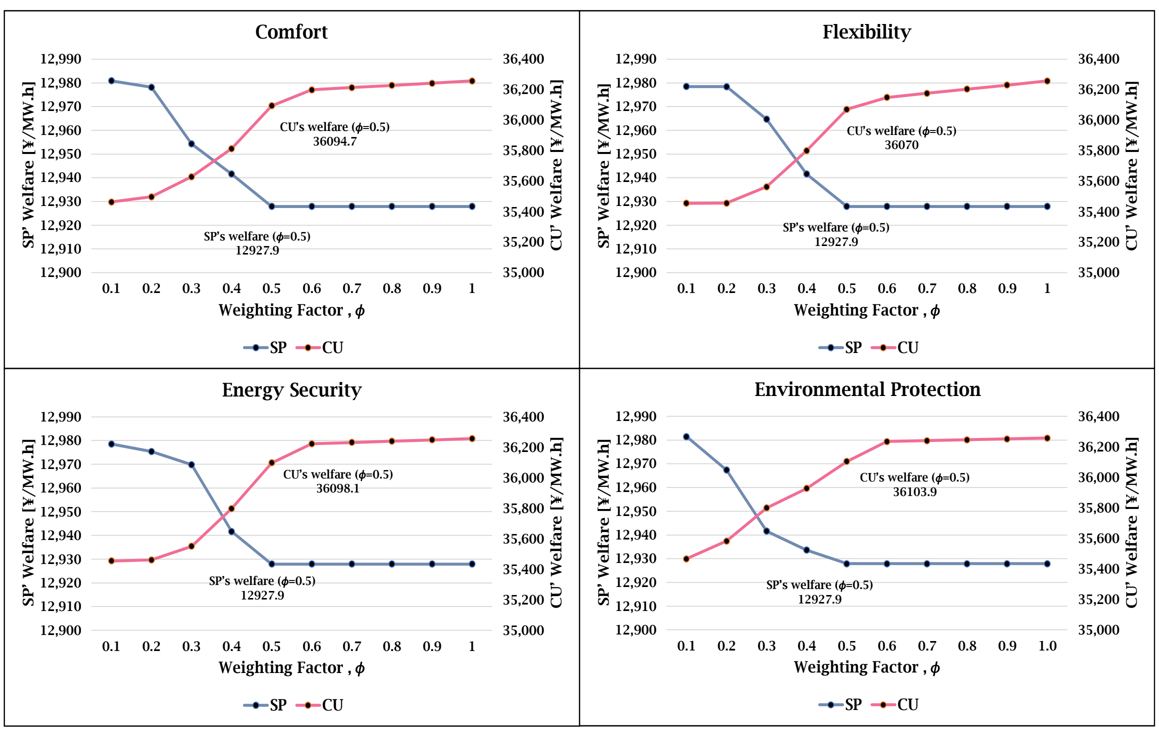

Figure 4.18 Variation of the welfare values with ϕ and x

To further evaluate the relationship between the CUs' welfare with their satisfaction with the different IBDRP's attributes, the satisfaction elasticity of welfare is calculated, as follows:

$$\varepsilon_W = \frac{\Delta W/W}{\Delta S/S} = \frac{(W_2 - W_1)/W_1}{(S_2 - S_1)/S_1} \quad \text{4-25}$$

Where, W represents consumer welfare, and S is a function of fulfillment level (x) value. Figure 4.19 illustrates the variation in ε_W with the fulfillment level of each attribute. According to the discussed Kano model, the attributes of "comfort" and "energy security" perform a linear trend, "flexibility" has a concave downward trend, and "environment protection" has a concave upwards trend.

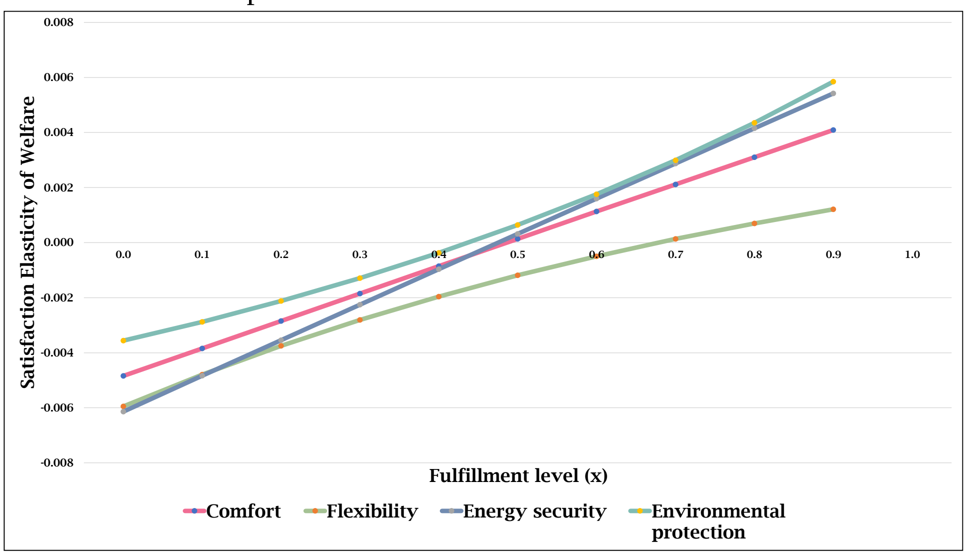

Figure 4.19 Kano curves of customer welfare

Looking at the elasticity values of comfort and energy saving as the "one-dimensional attributes" in Figure 4.20 , it can be noted that, when the *x* values are low, a unit change in the CUs' satisfaction can more significantly reduce their welfare. However, the higher *x* (satisfied) values positively influence welfare in these two groups. For the case of flexibility as a "must be" attributed, welfare does not increase significantly with increasing *x* values. As an attractive attribute, environmental protection significantly affects the CU's welfare at the higher values of x. Furthermore, in the categories of "comfort" and "energy security", ε_W improves positively with increasing x, while it decreases with the lower values of x. The environmental protection attribute is the least elastic attribute at x=0, indicating that a unit change in the CUs' satisfaction has less impact on CU's dissatisfaction. All of these suggest that welfare elasticity is more negative in the "flexibility" attribute and more positive in the "environmental protection" attribute.

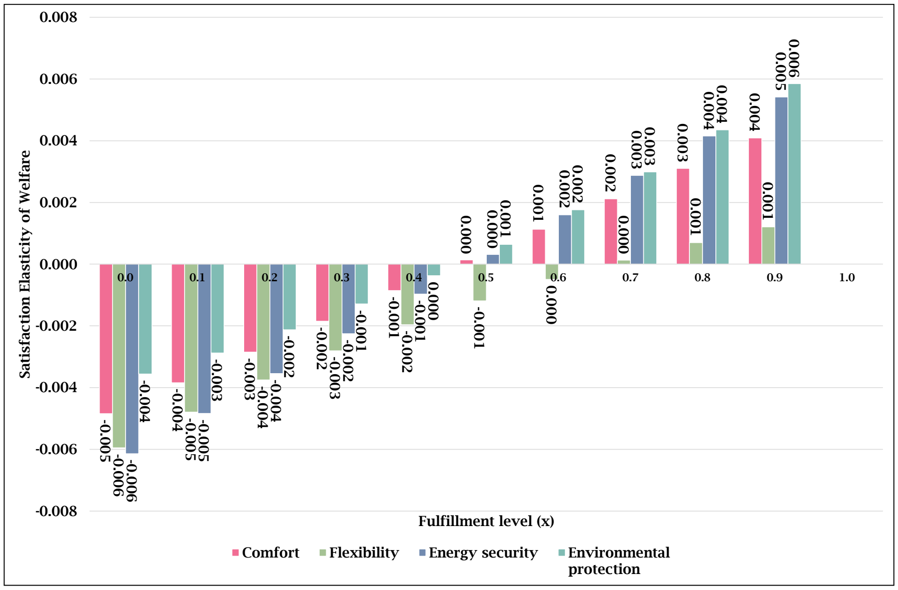

Figure 4.20 Satisfaction elasticity of welfare

4.3.4. Second stage of the assessment

It is noteworthy that demand response programs are new ideas, and even in developed countries such as Japan, these programs have not been widely implemented. It should be emphasized that during the second stage of the assessment, a survey was conducted among non-specialists to assess the potential impact of the energy management program on customer satisfaction. The findings are presented below and can be compared between experts and non-experts to illustrate the impact of increasing awareness and acceptance of such programs in society. The survey was limited to a sample size of 219 non-expert Japanese individuals. Details regarding the participants will be presented as follows:

Table 4-9 Classification of the respondents involved in the second stage of the assessment

Item	Category	Respondents	Percentage [%]
Age	21 to 30 years old	27	12.3
	31 to 40 years old	43	19.6
	41 to 50 years old	56	25.6
	41 to 50 years old	60	27.4
	61 or more	33	15.1
Gender	Female	115	52.5
	Male	104	47.5
Education	Less than high school	9	4.1
	High school	66	30.1
	Professional certification	38	17.4
	Bachelor's degree	96	43.8
	Master's degree	5	2.3
	Other	5	2.3

Item	Category	Respondents	Percentage [%]
Occupation	Employed full-time	114	52.1
	Employed part-time	47	21.5
	Not currently employed	38	17.4
	Student	3	1.4
	Homemaking	17	7.8
Current residence	Hokkaido area	10	4.6
	Tohoku area	11	5
	Kanto area	86	39.3
	Chubu area	34	15.5
	Chugoku area	11	5
	Kyushu area	23	10.5
	Shikoku area	4	1.8
	Kinki area	40	18.3

After analysis of the responses to the functional and dysfunctional questions, the values of CS and DS for the attributes were calculated, and their Kano classification was identified, as shown in Table 4-10.

Table 4-10 Kano response evaluation table for the second stage of the assessment

DRP's attributes	A	O	M	I	R	Q	Total	Kano Category	CS value	DS value
Comfort	3	5	7	166	20	18	219	I	0.04	-0.07
Flexibility	19	3	3	166	6	22	219	I	0.12	-0.03
Energy security	2	1	0	159	36	21	219	I	0.02	-0.01
Environmental protection	1	2	2	168	23	23	219	I	0.02	-0.02

It is evident that a significant proportion of the responses fall under the “Indifference” category, rendering them unsuitable for calculating the S-function. Nonetheless, the survey results indicate that among the three primary Kano categories, the "Flexibility" and "Energy security" attributes fall under the attractive category. Conversely, the "Environmental protection" attribute belongs to the one-dimensional category, indicating a positive correlation between satisfaction and fulfillment levels for this feature. The "Comfort" attribute is categorized as a must-be requirement. Using this classification, the appropriate "S" function was derived for each attribute, as outlined in Table 4-11.

Table 4-11 Satisfaction functions for different IBDRP's attributes in this study(non-expert Japanese individuals)

Attribute	$\boldsymbol{S = af(x) + b}$
Comfort	$S = -0.17e^{-x} + 0.11$
Flexibility	$S = 0.09e^{x} - 0.12$
Energy security	$S = 0.01e^{x} - 0.02$
Environmental protection	$S = 0.04x - 0.02$

To assess the influence of customer satisfaction and awareness on effective participation in Demand Response Programs (DRPs) and its impact on peak reduction, electricity-saving, and the welfare of both customers (CU) and service providers (SP), a comparison will be made between the results of the first phase of the survey (involving expert participants) and the second phase of the survey conducted among non-expert Japanese individuals. This comparison is conducted within the context of the proposed IBDRP. To achieve this objective, the interaction between the SP and two groups of CUs (dissatisfied and satisfied) is examined based on the framework presented in Table 4-7. By analyzing the data and outcomes from both phases of the survey; the aim is to gain insights into the relationship between CU satisfaction, awareness, and their willingness to actively participate in DRPs. Furthermore, the comparison will provide an understanding of the impact of these factors on peak reduction, electricity-saving, and the overall welfare of both CUs and SPs. The result of the comparison is presented in Table 4-12.

The new survey stage (non-expert) results indicate some changes in the attributes compared to the expert survey. For instance, in the expert survey, comfort was considered as a "one-dimensional" attribute based on the Kano categories. However, in the non-expert survey, it is now classified as a "Must be" category, suggesting that it is an essential requirement for non-expert individuals. When examining CU1, it is observed that although the CUs are unsatisfied, they exhibit the same level of demand reduction as satisfied CUs (CU2) in almost all attributes. This finding suggests that when CUs lack knowledge about the program, they tend to be neutral about participating, and there is no discernible difference in their consumption behavior.

By examining the differences between the expert and non-expert groups, valuable insights can be obtained regarding the effectiveness of raising awareness and increasing acceptance of DRPs among the general population. This analysis will contribute to the ongoing development and refinement of the IBDRP and help shape strategies to enhance customer engagement and satisfaction, while maximizing the benefits for all stakeholders involved.

Table 4-12 the results of the comparison between the first phase of the survey (involving expert participants) and the second phase of the survey conducted among non-expert Japanese individuals

Status	Attribute	Kano Category	$S = af(x) + b$	S	Peak reduction	Electricity saving
CU1	Comfort	O-Expert	$S = 1.09X - 0.53$	-0.53	1.6%	0.5%
		M- Non-expert	$S = -0.17e^{-x} + 0.11$	-0.06	4.4%	1.4%
	Flexibility	M-Expert	$S = -1.32e^{-x} + 0.67$	-0.65	1.1%	0.4%
		A-Non-expert	$S = 0.09e^{x} - 0.12$	-0.03	4.4%	1.4%
	Energy security	O-Expert	$S = 1.41X - 0.67$	-0.67	1.0%	0.3%
		A-Non-expert	$S = 0.01e^{x} - 0.02$	-0.01	3.7%	1.2%
	Environmental protection	A-Expert	$S = 0.71e^{x} - 1.10$	-0.39	2.9%	0.9%
		O-Non-expert	$S = 0.04X - 0.02$	-0.02	4.4%	1.4%
CU2	Comfort	O-Expert	$S = 1.09X - 0.53$	0.56	4.4%	1.4%
		M-Non-expert	$S = -0.17e^{-x} + 0.11$	0.04	4.4%	1.4%
	Flexibility	M-Expert	$S = -1.32e^{-x} + 0.67$	0.18	4.4%	1.4%
		A-Non-expert	$S = 0.09e^{x} - 0.12$	0.12	4.4%	1.4%
	Energy security	O-Expert	$S = 1.41X - 0.67$	0.74	4.4%	1.4%
		A-Non-expert	$S = 0.01e^{x} - 0.02$	0.01	4.4%	1.4%
	Environmental protection	A-Expert	$S = 0.71e^{x} - 1.10$	0.83	4.4%	1.4%
		O-Non-expert	$S = 0.04X - 0.02$	0.02	4.4%	1.4%

The findings indicate that among non-expert CUs who lack awareness about the program, even though they express dissatisfaction (CU1), they exhibit the highest level of potential savings, comparable to fully satisfied CUs. This observation aligns with the main output of the survey results, which revealed that the particular group of individuals exhibits indifference towards the DRPs.

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Chapter 5
Finding and Conclusion

This chapter presents the conclusions of the major findings of this work. Also, it provides the suggested recommendation that may help to achieve a more precise perception of customer satisfaction with the IBDRP, allowing for better implementation of the program in a large-scale society. This thesis included three main parts. The first part discussed how DPRs could improve market efficiency through maximizing the social welfare of the wholesale market actors, considering the impact of customer risk aversion and dynamic price elasticity of demand. The second part proposed a region-wise modeling approach based on maximizing end-users' social welfare in the wholesale electricity market. Finally, the third part examined the impact of customer satisfaction on the social welfare and profitability of the market actors.

The main finding of the thesis is that customers with high-risk aversion can benefit from effectively participating in demand response programs (DRPs) by obtaining higher expected utility. Thus, although the reduction in consumption results in lower utility, the risk-averse CUs decide to decrease electricity consumption more rapidly with the price increment during the period when the absolute values of the elasticity are higher. Additionally, the research highlights that real-time pricing (RTP) performs better in satisfying customers' electricity consumption needs compared to other DRP options. This is because RTP provides customers with greater flexibility and responsiveness, leading to higher expected utility values.

Furthermore, in a customer-oriented demand response market, customers' preferences regarding DRP choices are influenced by their satisfaction levels based on their consumption patterns. This satisfaction can be reflected in their expected utility function. Therefore, by considering customer satisfaction during the implementation of DRPs, the social welfare of customers can be maximized, and these programs can be implemented more efficiently.

Moreover, the research emphasizes the importance of understanding regional characteristics in implementing DRPs. Each region has unique aspects, such as supply-demand equilibrium, wholesale prices, variable renewable energy (VRE) penetration, and load profiles. These regional characteristics influence the response and effectiveness of implemented RTP-DRPs, which can be classified into three categories: regions with excess supply, regions with high demand burden, and regular suppliers to inter-regional connections.

Considering these findings, the study contributes to a better understanding of how DRPs can be operated in Japan's wholesale electricity spot market. It highlights the benefits of implementing DRPs, such as improving resource efficiency, decreasing electricity prices, enhancing load flexibility, and increasing security through customer and market engagement.

5.1.Summary and major findings

Price-based demand response modeling in a day-ahead wholesale electricity market in Japan, considering the impact of customer risk aversion and dynamic price elasticity of demand: A mathematical modeling approach was developed based on maximizing the CU's welfare by considering a price-responsive demand response system in the wholesale market in Japan. The proposed model is founded on the customer theory in microeconomics, using the concept of the expected utility function to model the behavior of the risk-averse CUs in responding to different DPRs. In order to precisely reflect the CUs' behavior in responding to the DRPs, the PEMD was developed based on identifying the hourly self-and cross-price elasticities of demand, considering different responding strategies: flexible, in-flexible, forward-shifting, backward-shifting, and optimizing responses. An hourly day-ahead electricity demand model was developed using the time series forecasting method to predict an hour-ahead demand with a MAPE of 0.94% and R^2 of 0.99. The results of applying the proposed model to the JEPX day-ahead spot price market revealed a peak reduction potential of 10.7% and 7.3%, respectively, from applying TOU and RTP programs to the flexible CUs. By applying the RTP program to the curtailable loads, a 7.7% reduction in the daily peak demand and a 1.6% reduction in daily electricity consumption can be achieved. The effect of risk aversion on expected utility was determined in this study, with results indicating that customers with high-risk aversion can obtain more expected utility by effectively participating in DRPs. Although the TOU and CPP programs show better results in savings, RTP performs better in satisfying the CUs from electricity consumption, providing higher expected utility values. Thus, although the wholesale market operators prefer to implement DRPs that guarantee more cost and energy savings, in a customer-oriented demand response market, the CUs' preference concerning the DPR choices is a function of their satisfaction due to their consumption levels, which can be reflected in their expected utility function.

Region-Wise Evaluation of Price-Based Demand Response Programs in Japan's Wholesale Electricity Market Considering Microeconomic Equilibrium: A mathematical modeling technique focused on maximizing the customer's welfare was implemented, taking into account an RTP scheme in Japan's wholesale market. The region-wise impact of the wholesale electricity market was explored by formulating the price elasticity matrix of demand for each region dedicatedly, while applying a single mathematical modeling technique of the customer's welfare to all the regions similarly. The region-wise price elasticity matrix of demand was formulated by estimating the hourly self and cross-price elasticities, considering the flexibility of consumers. Furthermore, the region-wise self-elasticity was calculated using two stages of econometrics, which estimate the regional wholesale price based on the VRE penetration and then evaluate the self-PED. The developed model was then applied to investigate the region-wise potential benefits (peak reduction, energy savings, and avoided emissions) of implementing the RTP-DRP in Japan's wholesale electricity market. The obtained results indicate a wide variation range of the hourly estimated region-wise PED of -0.005 to -0.21. Meanwhile, the estimated risk aversion coefficients that evaluate end-user's willingness to engage in RTP-DRP vary in all the ranges in a similar range of 0.001 to 0.003. This implies that, the PED variation is not caused by the end-user side, but rather by the price-driving parameters of supply and demand microeconomic equilibrium. In addition, given the application of similar RTP-DRP to all the regions, the potential for daily peak reduction of the residential sector considering flexible customers and shiftable load various between 1.91% to 22.9%. The energy saved from the developed RTP-DRP for all regions varies between 0.16% to 1.02%. On the other hand, the potential avoided GHG emissions resulting from the proposed program in the Tokyo region are remarkable, with values of 82.6 and 192.2 (TonCO_2e) in the summer and winter, respectively. The estimated PEMD has shown high elasticity indices for Hokkaido, Hokuriku, and Shikoku, which have been justified by the increased wholesale price considering their VRE penetration and the dependency on the inter-regional connections.

Incentive-based demand response modeling in a day-ahead wholesale electricity market in Japan, considering the impact of customer satisfaction on social welfare and profitability: A multi-objective mathematical model was developed that maximizes the social welfare function of both SPs and CUs to find the optimal incentive rates paid to the CUs for decreasing their electricity consumption, taking into account the impact of the CU's satisfaction with the different IBDRP attributes of comfort, flexibility, energy security, and environmental protection. The results revealed that the CUs' satisfaction with comfort and energy security has a linear relationship with their welfare. Furthermore, the satisfaction elasticity of welfare is more negative with the flexibility attribute and more positive with the environmental protection attribute. The findings highlighted the significance of the environmental protection attribute of the IBDRP in motivating the CUs to active participation in the program. The model was used to estimate the optimal demand load, peak reduction, optimal incentive rates, and welfare of CU and SP for two scenarios, including with and without CU's satisfaction. Based on the two scenarios considered in this study, the optimal load reduction of a dissatisfied customer was estimated at 186,103,70 and 64 MWh with environmental protection, comfort, flexibility, and energy security attributes, respectively. Despite that, the daily electricity reduction after implementing the proposed IBDRP was estimated at 277 MWh with all IBDRP attributes for a satisfied CU. The insights from this research may help the Japanese local government achieve a more precise perception of customer satisfaction with the IBDRP, allowing for better implementation of the program in a large-scale society.

To validate the results of this study, a comprehensive comparison has been conducted between various relevant studies and the findings of this research. The comparative analysis is presented in the table below, highlighting the key similarities and differences between the studies.

Table 5-1 A comprehensive comparison between the output results and other studies.

Program	Remarks	Demand peak reduction %	Electricity saving %	Reference
Combined PB and IB	-	9.7	6.4	(Yu et al.,2020)
IBDRP	Satisfied CU	-	8.2	(Lu et al., 2018)
	Dissatisfied CU	-	8.3	
PBDRP	TOU, CPP, RTP	7.6,4.6,7.4	0.3,0.1,0.1	(Aalami, H.A.,et al,2010)
IBDRP	DCL	7.2	1.3	
PBDRP	TOU, CPP, RTP	5.02,2.17,3.32	0.22, 0.1, 0.99	(Moghaddam, M.P.,et al.2011)
IBDRP	DCL	6.04	0.32	
DRP	Japanese rural residential customers	5.2 to 10.2	-	(Rohman and Kobayashi, 2014)
DRP	Residential customers	-	4.7 to 14	(Mizutani et al., 2018)
DRP	Winter	7.8 to 16.2	-	(Yunqin Lu et al., 2022)
	Summer	11.3 to 13	-	
PBDRP	TOU, RTP (shiftable load)	10.7, 7.3	1, 0.7	This study
	TOU, CPP, RTP (curtailable loads)	11, 29, 7.7	2.3, 6.3, 1.6	
IBDRP (DCL)	Satisfied CU	4.3	1.4	This study
	Dissatisfied CU	2.9	0.9	

5.2. Study limitation

Despite the significant contributions, some limitations of the study should be mentioned.

1- CUs preference is assumed to be unchanged and stable across participation in DRPs. However, it is possible that CUs that were motivated by a value, e.g., environmental protection, before participating in the DRP, may change their preferences during the program and begin to find value in economic incentives.

2- Only four features of comfort, flexibility, energy security, and environmental protection were considered in this study. However, other functional, epistemic, and social values may help people perceive the main benefits of DRP, which were not addressed in this study.

3- This modeling bears potential limitations in using similar relationships among service providers and end-users in the demand-responsive market of various regions. However, emphasizing the potential of adjusting the supply and demand imbalance cost-effectively in the different areas proposed in this study leads to a new formulation to target each region, with specific consideration for the regional supply-demand equilibrium, wholesale prices, VRE penetration, and load profiles.

5.3. Policy implications

Based on the conclusions of the study, the following policy implications can be drawn:

- Customer-Centric Approach: Policymakers should adopt a customer-centric approach when designing demand response programs. Understanding customer behavior, preferences, and risk aversion levels is crucial for the success of these programs. Consideration should be given to developing and implementing programs tailored to the needs and preferences of different customer groups
- Environmental protection awareness: The study highlights the importance of incorporating environmental protection awareness into demand response programs. Policymakers should emphasize the potential benefits of reduced greenhouse gas emissions and incentivize customers to actively participate in programs that contribute to environmental sustainability. Additionally, the remarkable potential for avoiding GHG emissions in Tokyo emphasizes the importance of tailoring strategies to address specific regional challenges and goals.
- Continuous monitoring and Improvement: Policymakers should establish mechanisms to continuously monitor and improve the implemented demand response programs. Monitoring the impact of programs, customer satisfaction levels, and cost-effectiveness will help identify areas for enhancement and optimize the overall performance of demand response initiatives.
- Collaboration with Wholesale Market Operators: Policymakers should collaborate closely with wholesale market operators to align the implementation of demand response programs with cost and energy-saving objectives. Balancing the preferences and welfare of customers with the goals of the wholesale market is essential for the success and acceptance of demand response initiatives.

The abovementioned policy implications empower policymakers to foster a customer-oriented demand response market in Japan. By considering customer preferences, regional variations, environmental concerns, and long-term goals, policymakers can design effective and sustainable demand response programs that optimize customer welfare, reduce peak demand, promote energy efficiency, and contribute to a more resilient and sustainable electricity system.

5.4. Future work

In the future, this project will investigate the interaction between Virtual Power Plants (VPPs) and Demand Response Programs (DRPs) in the Day-Ahead Market. It focuses on how VPPs might collect and manage distributed energy resources (DERs) in order to improve energy supply and market participation. It evaluates VPPs' ability to provide their aggregated capacity and flexibility in the day ahead market, hence contributing to the efficient operation of the energy system. The study explores the influence of integrating flexible loads into VPPs for demand-side activities in DRPs on market dynamics, revenue generation, and sustainability. It provides insights for policymakers, grid operators, and market participants to shape effective strategies for future energy markets and support the transition towards a more flexible, efficient, and resilient electricity system.

Furthermore, a detailed analysis of the climate co-benefits obtained from applying demand response programs and energy management actions in climate change mitigation should be carried out, in order to evaluate and quantify the additional benefits, such as local air quality and public health improvement or green job creation.

In addition, in evaluating the satisfaction function in IBDRPs, further justification should be provided for the selection of the four values: comfort, flexibility, energy security, and environmental protection. While these values have been identified as important considerations in the analysis, it is necessary to explore and justify their inclusion based on additional dimensions of value. Specifically, the study will delve into the various forms of value, including functional, epistemic, and social, to assess their relevance to the model. It will investigate whether these forms of value align with the identified values or if there are other dimensions that should be considered.

APPENDICES

Appendix 1: Examining the Customer satisfaction from participating in demand response programs (DRPs).

This questionnaire examines the electricity customer's satisfaction from participating in different Demand Response Programs (DRP). DRP allows electricity customers to maximize their bill savings and earn bounces from supporting the grid efficiency and security by cutting/shifting their electricity usage from peak hours (3:00 pm to 7:00 pm) to off-peak hours. Therefore, customers are asked to change their consumption patterns by cutting/shifting the electricity-drawing appliances (such as washing machines, vacuum cleaners, iron, etc.) from costly peak times to times when costs are less, and demand is down. This questionnaire proposes some key questions to explore the customer preference to subscribe to DRP, and the main factors influencing customer satisfaction.

The key terms considered in this questionnaire are as follows:

1. **Demand Response Programs (DRP):** Cutting/shifting some electricity usage from peak hours (3:00 pm to 7:00 pm) to off-peak hours.

2. **Comfort:** using electric appliances whenever a customer desires at any time (peak hours or off-peak hours)
3. **Peak hours:** The times of day when electric consumption is highest (e.g., 3:00 pm to 7:00 pm)
4. **Savings:** Earning money from reducing electricity consumption and bill payment or receiving credit or monetary incentives from the electricity supplier
5. **Stable and secure electricity supply:** ensuring that electricity is always available to meet the demand requirements, including peak times.
6. **Environmental protection:** climate change mitigation and air pollution reduction

- Basic information

Age	Less than 20 years 20	21 to 30 years old 21 30	31 to 40 years old	41 to 60 years old	61 or more	
Gender	Female	Male	Prefer not to say			
Education	Less than high school	High school	Professional certification	Bachelor’s degree	Master’s degree	Doctorate degree
Occupation	Employed full time	Employed part time	Not currently employed	Retired	Student	Homemaking /other
Current residence						

- Start main questions about DRPs
  Preference from 5 (high) to 1(low)

Effect	Question	Response				
		-I will be Satisfied (Like) (5)	I am expecting it to be that way (Must-be) (4)	I am neutral (3)	I can accept it (2)	I am not Satisfied (Dislike) (1)
Comfort	If participating in DRP improves your savings but decreases your comfort from electricity usage during peak hours, how do you feel? (Prefer to pay less for electricity bill but have less comfort)					
	If Not participating in DRP doesn't affect your comfort from using electricity during peak hours, while it doesn't provide any savings for you, how do you feel? (Prefer to pay more for electricity bill but have enough comfort)					
Flexibility	If participating in DRP offers lots of savings and pays less for electricity bills, but takes your time and effort in order to work with some data monitoring and reporting programs, how do you feel?					
	If the DRP is simple to follow, but offers few savings, how do you feel?					
	If participating in DRP offers lots of savings, but needs additional investment, such as installing smart metering, remote or online control systems, cables, applications, etc., how do you feel?					

	If participating in DRP is not costly and doesn't need too much investment, but offers few savings, how do you feel?					
Energy security	If participating in DRP grants you a stable and secure electricity supply, how do you feel?					
	If NOT participating in DRP doesn't grant you a stable and secure electricity supply, how do you feel?					
Environmental protection	If participating in DRP improves your savings. In addition, it protects the environment, how do you feel?					
	If participating in DRP improves your savings. But it doesn't protect the environment, how do you feel?					