博士論文

ELECTRICITY DEMAND FORECAST

AND

DISAGGREGATION USING A SMART METER BASED ON

FOG COMPUTING SCHEME

（フォグコンピューティングスキームに基づく電力需要予測と機器分離に関する研究）

陳　浩

The University of Tokyo

Department of Technology Management for Innovation,

The University of Tokyo

This dissertation is submitted for the degree of Doctor of Philosophy

January 2017

研究概要

スマートメータの本格導入が、世界各国または日本の各電力会社により開始されている。その背景に、電力自由化などの市場の変化、ビッグデータ解析の発達、自然エネルギーの普及、蓄電池の性能向上と価格低下などの環境要因が存在する。スマートメータ導入の最大のメリットは、自動検針だと言える。現在日本で採用されているスマートメータは三十分刻みの計測値であり、従来の月一回の訪問検針と比べて、約千五百倍の細かさで電力需要を把握できる。そのデータを活用して、省エネを促進し、電力提供者と電力需要家に対して価値を高めていくサービスは社会への貢献が大きいと考える。個別需要家の電力需要データの収集はまだ開始したばかりであり、電力データの活用に関する研究が求められている。一方で、現状のスマートメータシステムは現状の電力のニーズに合わせて作られたので、処理能力や機能の限界があり、簡単なデータ解析や見える化など限られた目的にしか対応できない。特に、莫大な量の電力関連データをローカルから回収する場合、通信情報量、通信速度などがボトルネックである。

その解決策として、データをクラウドで処理するクラウドコンピューティングではなく、ローカルにデータをある程度計算処理、蓄積可能な計算機を取り付け、データ処理を行い、クラウドへの通信量を削減するフォグコンピューティングをベースとしたスマートメータシステムが既存研究で提案され始めている。しかしながら、既存研究は大きな枠組みでの考え方を示すに留まり、電力データの活用方法と必要条件を踏まえて十分な研究がなされていない。

この点を踏まえ、本研究では、電力データ活用の観点からさらにフォグコンピューティングに基づくスマートメータの概念を具体化させた。

フォグコンピューティングをベースとしたスマートメータでは、取得パラメータの制御が自由であり、計算能力があり、様々な通信方法も制御可能であることを提案した。需要家の特徴に応じて取得パラメータを自由に選定することができるため、さまざまな機能を有するソフトウェアが開発されうる。また、必要な計算結果のみを通信手段を選択肢し、送信することで送信データ量を削減することが可能であることから CPU やメモリを実装したハードウェア構成が必要となる。本研究ではソフトウェアとハードウェアの両方について研究を行なった。

ハードウェアの観点では、需要予測と機器分離における必要なデータを踏まえ、取得パラメータの自由度と計算能力があり、リアルタイムに通信可能なスマートメータの構成に

ついて提案し、その実装例を示した。これにより、電力データに対する分析のニーズに合わせて、電力データを活用することが可能となり、クラウドのみに頼ることなくローカルから電力データの解析が可能になった。

ソフトウェアの研究例として本論文では、提案したフォグコンピューティングをベースとしたスマートメータに実装されることを目的として、電力提供者向けに「電力需要予測」と電力需給者向けに「電力需要時系列の分離」について研究した。

「電力需要予測」については、第一に、機械学習及び深層学習を用いた需要カーブ予測に関する研究をし、ｎ個の需要家と需要予測誤差の関係を示した。過去、機械学習をベースとした様々な方法が実用化されている一方で，近年，ディープラーニングとグラディエントブースティングにより，多くの分野で予測精度が大きく改善可能であるという報告があるが、小規模の需要家群の需要カーブの予測を行った研究は無かった．これらを踏まえ，ディープラーニングとグラディエントブースティングを小規模需要家群の翌日の需要カーブの予測に適用し、良い結果を得た。また、需要予測の誤差を分析することでｎ個の需要家の間に存在する共分散が需要予測誤差に与える影響を示した。

第二に、ローカルのデータ（気温、需要家のスケジュール）等のローカルの情報を予測の特徴に追加することで、ボトムアップの手法を行うことが予測精度において優位性をもつことを示した。需要予測において個々の家庭の電力需要を予測し、その予測結果を足し合わせて予測をする方法をボトムアップ手法とし、逆に、個々の需要家の需要足しあわせてから予測をする方法をトップダウン手法とした。本研究では、この 二つの方法の比較、検討を行った。その結果、両者に大きな差は認められなかったことを確認した。その上で、ボトムアップ手法においてローカルな追加情報を加味すると精度が向上することを示した。

「電力需要時系列の分離」においては、第一に、低頻度電力需要データの応用に関しての研究を行い、教師なし学習による電力需要分離の方法を示し、その検証を行った。スマートメータのための３０分値電気需要データ分析方法は、既存研究において低頻度の需要データに対して、教師無し学習により推定し、検証した研究がなかった。そのため、住民の在不在を隠れマルコフ手法により推定する方法を提案し、教師なし学習でも十分精度ある電力需要分離が可能であることを示した。また、温度関連因子の需要分離は過去の研究においては、ステップごとに温度関連需要を抜きだす方法が提案されていないのに対して、本研究においては教師無し学習により抜き出す方法を示した。

第二に、スマートメータのみのデータを活用し家電機器のオン・オフ推定の研究を行い、データアーギュメンテーションを活用することで個別の家電の需要を直接測ることなく、合成された電力需要のみから機器分離することに成功した。過去の研究では教師あり学習を活用した手法が提案されているが、教師あり学習では常に多くの教師データを用意する

必要があることが問題であった。本研究では機器の稼働時のデータを活用して教師データを生成し、教師あり学習を行うことで機器分離が可能であることを示した。

本研究を通じて、現在のスマートメータシステムにおけるハードウェアとソフトウェアの問題点を浮き彫りにし、その解決策として、電力データの活用の観点からフォグコンピューティングをベースとしたスマートメータを提案し、ハードウェアの実装例を示した。次に、提案したスマートメータに実装されることを目的とした、電力需要予測と電力需要の分離という二つのキーとなる技術を取り上げ、それぞれにおいて新規性のある研究を行った。最終的に、提案されているフォグコンピューティングに基づくスマートメータの考えを具体化させ、ローカルにある電力データをさらに取得し、高度な分析を行うことが今後スマートメータシステムにおいて重要であることを示した。

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1 INTRODUCTION

1.1 Trends of smart grid

Electric power generation from renewable energy resources such as wind and solar has recently increased in many countries. Europe has set a target for 27% of final energy consumption to be produced by renewable resources by 2030 [EU 2015]. The United States and Japan are also actively debating whether to set ambitious goals to enhance the introduction of renewable energy [METI 2014][IEA 2014]. As indicated in Fig 1.1, Germany declared in the RES Act 2014 that it aims to achieve 80% of its power generation from renewables by 2050 [FMEAE 2014].

The generated energy and power demand from wind and solar vary unpredictably; however, the demand and supply should match at every moment. Therefore, there is a necessity to introduce the capacity of power generation for accepting large installations of renewable energy. The introduction of renewable energy makes it increasingly difficult to manage the power flows throughout the grid and to meet the demand and supply balance.

Under such circumstances, efficient energy use should be promoted by the optimal control of the power system using IT. Interest in the "Smart Grid" will be one critical factor to be overcome [FERC 2008]. One of the fundamental concepts of the smart grid is to measure, record ,and control the demand site activity. Moreover, the IT technology has just started to allow the great idea to work in the practical world.

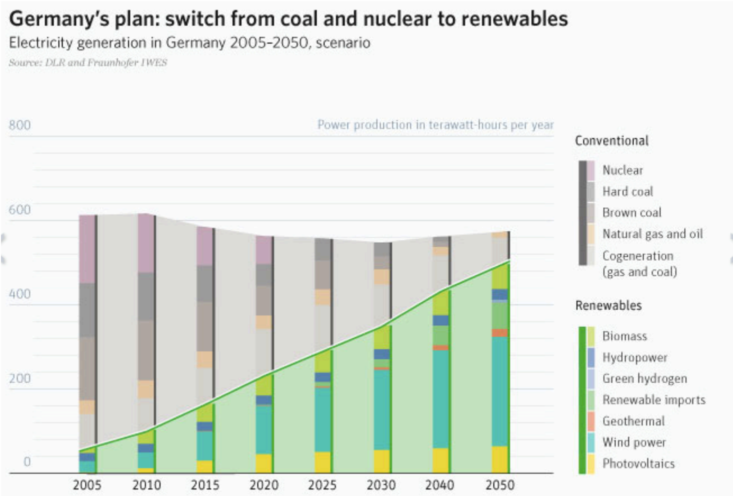


Fig 1.1 Germany plan: Switch from coal and nuclear to renewables [**Heinrich** 2016]

1.2 Key factors for the electricity grid management

Despite this difficulty, Spain has one of the most advanced electricity systems that allow more than 40% of renewable energy as a power generation source [REE 2015]. The main renewable energy compositions are solar 5.1%, hydro 15.4%, and wind 20.4%.

One of the essential points for this success is the advanced demand forecast and renewable power generation forecast system. Another key point is that European countries could develop a network between them, which allows balancing supply-demand by interchanging electricity between districts and countries. Fig 1.2 shows the balancing of supply- demand and the electricity demand from Red Electrica Espana. Fig 1.3 shows the distribution of forecasted error in the Spanish Grid [Chin 2015].

We understand from the Fig.s, Demand forecast 30 minutes away is about 0.083% on a MAPE basis. This error rate is considered to be a low number because TEPCO's daily demand forecast ability published in other papers is a 1.2% to 1.8% error rate, but the prediction error is not eliminated before. Conversely, this value is equivalent to 4 million kilowatts of the electricity imbalance in the electricity grid, and we believe that if the international, interconnected transmission line is not prepared for the capacity imbalance,

Spain's demand-supply balance cannot be kept. If the prediction goes even a bit worse than 0.08%, 4 million kilowatts of transmission lines will be blocked by capacity, and Spain will fall into a major blackout. Therefore, the electricity grid interconnection serves a key role for the electricity grid.
Spain has many interconnections between France, Northern Africa, and Portugal that allows Spain to manage the unpredictable demand and sudden change of renewable energy output. Furthermore, the grid management system control connects with the CCRE (Control Center for Renewable Energies), which [REE 2015] has an essential role in covering the imbalance of power supply-demand and reducing the cost of the international power interchange by backup-supports from the combined cycle, hydro, and coal power generation. Accurate demand forecast and the international interchange serve a critical role in supporting the renewable energy in the Spanish grid system. To perform higher forecasts in the electrical grid, the understanding of the demander's electricity usage pattern is a key part of the concept of the smart grid.

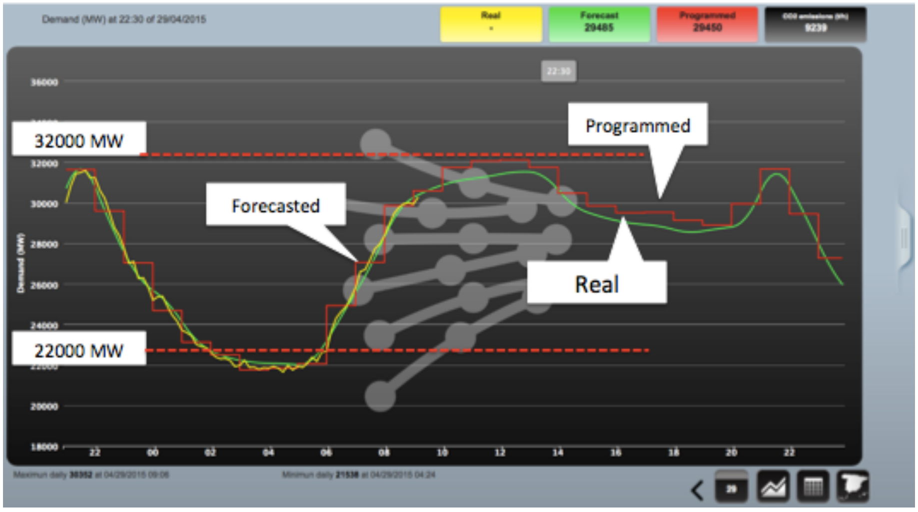


Fig 1.2 The electricity demand and forecast from Red Electrica Espana [REE 2015]

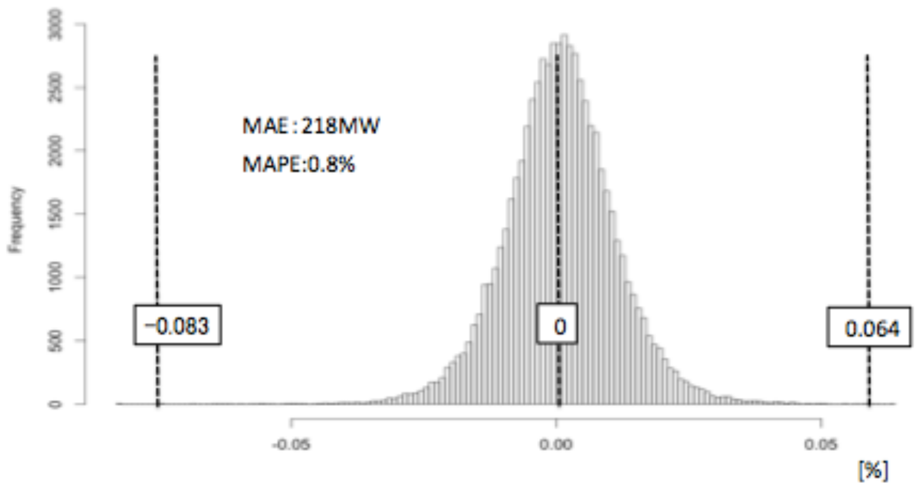


Fig 1.3 The distribution of Forecasted Error in Spanish Grid [Chin 2015]

The demand side management is another critical part of further introducing the renewable energy. We find that the average interchange and forecasted error is low, but the histograms are widely distributed, indicating that it is critical to provide additional backups. The backup system mainly consists of combined cycle, hydro, and coal to help balance the supply-demand. Once an unbalance of supply-demand occurs, the system will rely on the international power interchange to absorb it. Therefore, power interchange is inevitable when a high percentage of demand is met by unstable and unpredictable renewable sources. However, power interchange is not a general solution for introducing renewables due to the grid capacity, the management problem, and geographic conditions.

As an alternative solution, demand side management has been suggested and tested. Demand side management is a way to modify consumer demand balancing through various methods such as providing various incentives and suggestions [Ofgem 2016]. By demand side management, 1) the customer can improve their energy efficiency by using load-intensive appliances such as refrigerators, air conditioners or washing machines with more efficiency, 2) demand can be flattened or shifted by demand response to help the integration of variable renewable energy.

Therefore, data accumulation is necessary for both the supplier side and demand side. As indicated, to balance the electricity demand and supply in the grid, the demand forecast, and demand disaggregation are two key strategies.

1.3 Necessity for the smart meter and the general definition

Electronic meters having bidirectional communication is an important element of the smart grid. The introduction of so-called 'Smart Meters' has been studied in various countries [FERC 2008; METI 2011]. In Japan, April 2010, the next generation power transmission and distribution networks study group pointed out that further research is needed [METI 2010] during a series of discussions about the smart grid. Also, the cabinet determined Energy Master Plan in June 2010 showed the necessity of the construction of two-way communication with next generation power transmission and distribution networks, and the introduction of cost-effective smart meters should be introduced as early as the 2020s.

Also, the introduction of smart meters is expected to improve the quality of people's lives through the creation of new services that utilize energy usage information as well as further activating the economy through the creation of related industries (Green Innovation). To realize an energy-saving and low-carbon society in Japan, it is important to encourage behavioral changes such as increasing energy conservation awareness.

From the current situation, Kansai Electric Power Company has been promoting the research and introduction of smart meters. 2014 was also the start of the full-scale introduction of the smart meter for Tokyo, Tohoku, and Shikoku electric power companies. By the end of 2020, Tokyo electric power company (TEPCO) plans to schedule and complete the introduction of smart meters to the low voltage sector of households by the end of 2024 [TEPCO 2016]. The picture of a smart meter in Japanese smart meter transition is indicated in Fig. 1.4.

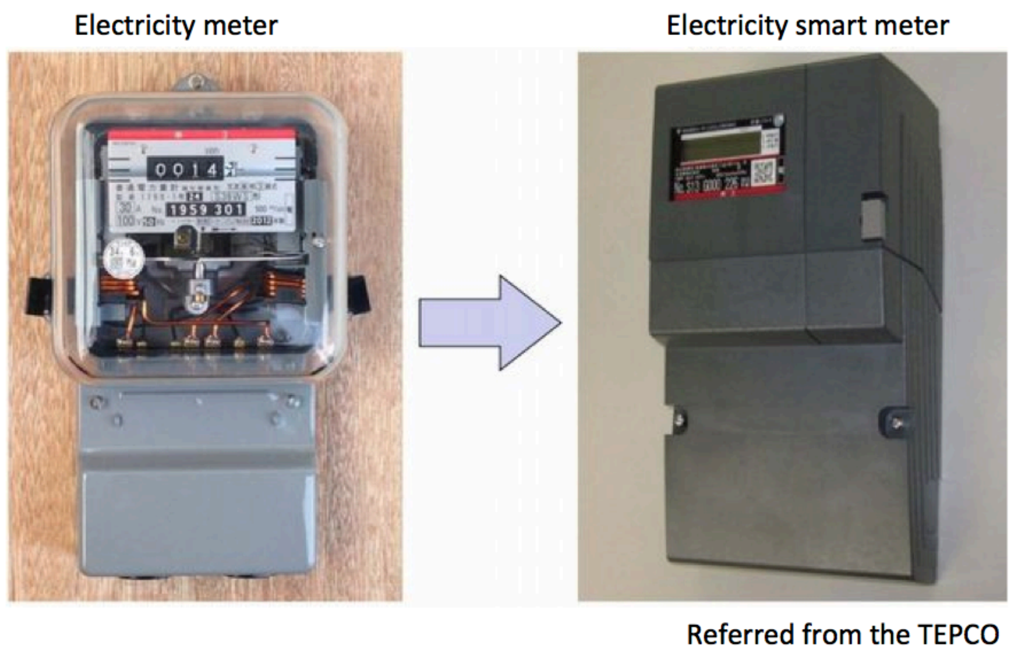


Fig 1.4 ***Transition of the smart meter in Japan [TEPCO 2016].***

The concept of smart meters has also been discussed in other countries [METI 2011] [OFGEM 2010]. Fig. 1.5 shows the definition of a smart meter. AMR, which stands for remote automated reading, is a smart meter that only has the remote automated reading. AMM is an electricity meter, which has a two-way communication with remote shutdown functions, remote meter reading, and electricity fee collection (so-called "narrow sense of smart meters"). The narrow-sensed smart meter is the smart meter that has been adopted in Europe. In the future, the connection and device control, HAN (Home Area Network), could be an option for the future (the so-called "broad sense of smart meter"). There are different images and different expectations for the smart meter. However, the broad sense of the smart meter seems the general expectation and image of a smarter meter.

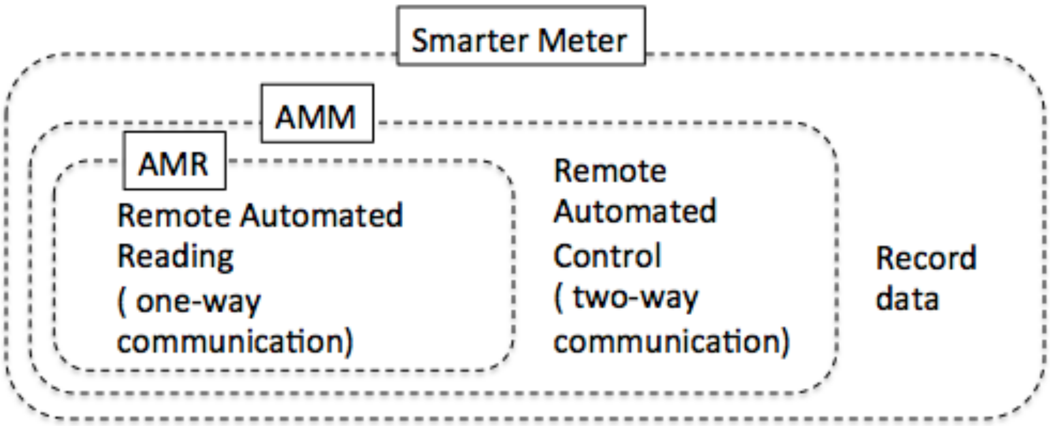


Fig 1.5 ***The definition of smart meter*** **[OFGEM 2010]**

1.4 Current smart meter specifications in Japan

As indicated in Table 1-1, the current smart meter in Japan is designed to measure only the power demand and reverse current. The time resolution (measurement interval) is 30 minutes [TEPCO 2016]. However, electricity values such as voltage and frequency are neglected. That is because initially, the Japanese government considered that the voltage and frequency are well controlled by the electricity company so that there is no need to record that information.

For data communication, the current smart meter provides three kinds of measurements. The current specification of the gateway to acquire the smart meter data is indicated in Table 1-1:

A route provides the data for the power company (transmission and distribution);
B route provides the data for household equipment (such as Home Energy Management System (HEMS)), 1~10 seconds' data are planned to be acquired;
C route provides the data for third party private businesses, retail power businesses, etc.

Table 1-1 Specifications of gateway to acquire the smart meter data[METI 2014]

Route	A	B	C
Explanation	For the electricity company through web	Directly from the meter	For third parties through web
Data contents	Time, Power, Reverse power flow	Time, Power	Time, Power, Reverse power flow
The necessary term to obtain the data	1 day	Real-time	2 hours to half day (planned)
Data span	30 min	1 second to 10 seconds (unstable)	30 min

Of these, B and C route are still not able to be carried out to their full-scale provision of services in April 2016, as problems with information infrastructure and transmission have caused significant delays in their installation. A, B, and C route data acquisition plans are indicated in Fig 1.5.

There is a big debate on the current smart meter design. Depending on the use case of the demanders, there are many demanders who need high-resolution data that can be supplied in real time. For example, demanders need to perform smart battery or demand control based on the electricity power. The need for the resolution of the data varies from 10MHz to 1 hour. We have summarized the current smart meter design and the possible design for the smart meter in Table 1-2.

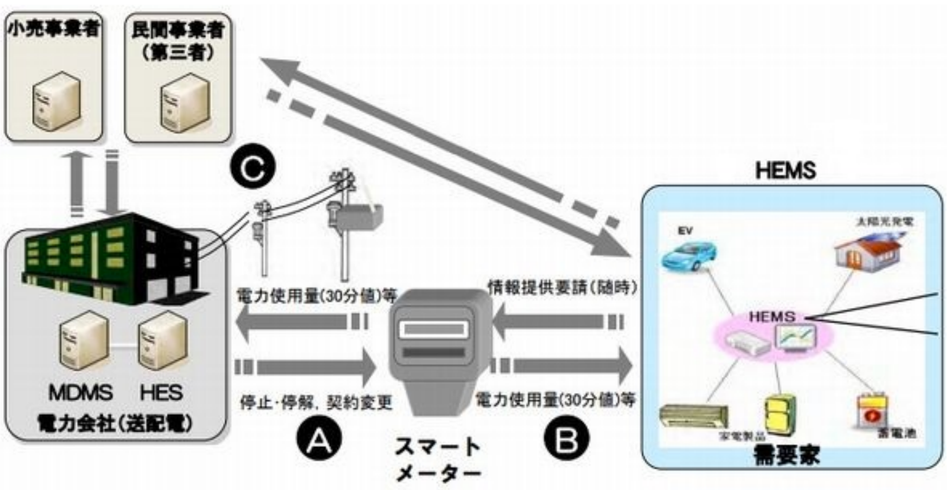


Fig 1.5 ***Smart meter data acquisition plans*** **[METI 2014].**

Table 1-2 Current smart meter design and possible design (Made by Author)

Items	Possible choice		Current situation	
Input data (measurement)	Voltage Current Frequency Effective power Ineffective power Power factor Reverse current Other data (Temperature, GPS, Time)	From 30 min to MHz	Power Reverse current	30 min only
Processing data (Calculation)	Buffering Processing Programing (forecast, disaggregation)		None	
Output data (Communication)	Can communication With Server and local Machines from every party	From 30 min to Seconds	Can retrieve data from Three ways (Need approval)	Half day

The wave of Internet of Things (IoT) or Machine to Machine (M2M) communication will generate much more needs for the electricity data. For example, to provide much more allowance of the renewable energy in the electricity grid, it is claimed that voltage or frequency cannot control only by the central control system. The smart meter is the key device to monitor the electricity quality on the edges of the grid.

There are several types of research showing the necessity of the edge controls and monitoring of the electricity voltage. Divan from Georgia Institute of Technology claims that, from AMI meters, significant gaps are visible regarding the ability of existing utility models [Divan 2016]. The existing voltage control model causes voltage limit violations and limits the level of demand control and PV hosting on distribution feeders. He also indicates that centralized control is too slow and cannot present the distributed nature of the observed voltage volatility. Varentec, Inc points out that the existence of greater volatility at the grid edge creates a set of problems that require the use of decentralized, dynamic controllers that monitor, and act at the point of the problem [Varentec 2014]. The impact of grid edge control illustrated by Varentec, Inc is indicated in Fig 1.7. As a matter of fact, more than ten commercial-scale projects across the United States have started to measure the edge voltage data as indicated in Fig. 1.8. Other than the voltage control, the data of harmonics and Impulse also provides special meaning for the grid from the perspective of electricity quality [Suslov 2011].

However, new trends such as distributed generation, electric vehicles, and unprecedented voltage visibility were not designed to be handled in the previous AMI.

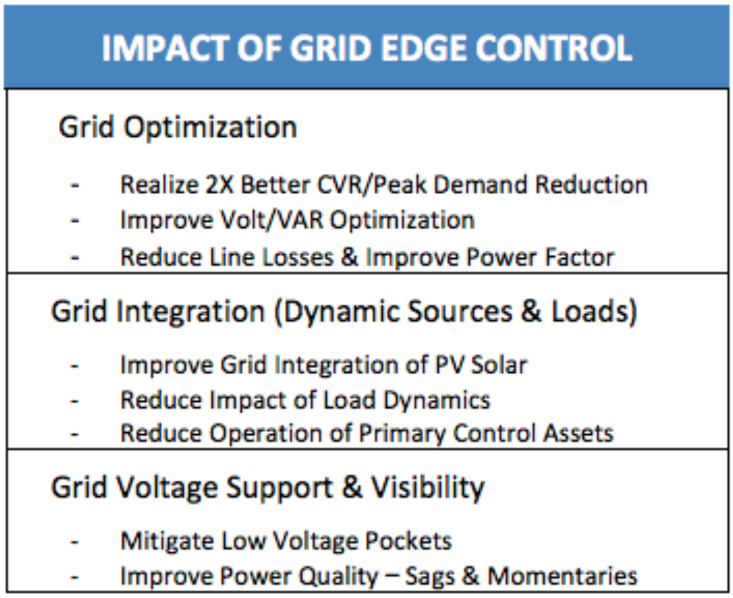


Fig 1.6 Impacts of grid edge control [VARENTEC 2014]

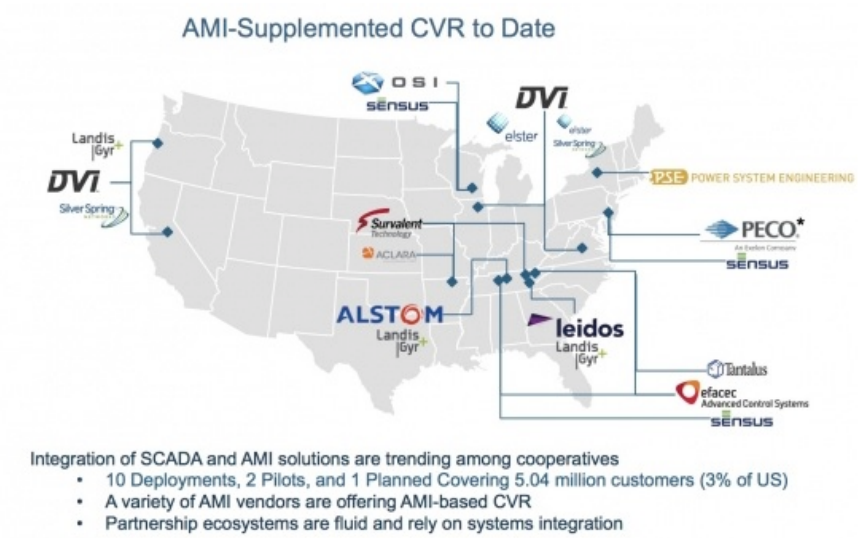


Fig 1.7 Automated metering infrastructure (AMI)-based voltage management projects in the US [John 2014]

From the data sensing point of view, the data for the local behavior might be able to provide much insight for electricity management. For instance, the local temperature and humidity differ based on the geological location, and human activities might be able to be sensed by the human activity sensor. In addition, to capture the detailed local behavior, the latency of the data acquisition is also varied dynamically depending on the necessity of the data.

From the data processing point of view, the amount, method, and span change depending on the information processing ability of the server, communication traffic, meter capacity and the manufacturing cost. Right now the smart meter can only meet the needs to provide simple visualization analytics in the cloud server. Therefore, the smart meter should have an allowance for future usage: if not, the current electricity will be obsolete and a headache for the smart grid.

From the communication point of view, the real time communication is required for the DR or services that utilize the electricity data. Furthermore, the difference in the communication method between the companies increases the maintenance fee and makes the data format different. Security problems such as the prevention of hacker attack is also a significant problem that has been apprehended. As a matter of fact, the problem of less mobile commutation ability depending on the areas and its cost benefit has been pointed out.

It is necessary to reconsider in term of the feasibility of various use cases from sensing, processing and communicating points of view based on various results of experiments and service ideas, as it is very difficult to change the power meter once installed, and the hardware limitation will become the barrier for further utilization of the electricity data.

1.5 Expected services based on the electricity demand data

It is important for customers to understand and utilize their energy usage information to raise energy-saving awareness and stimulate behavioral changes. Also, by the installation of the electricity smart meter, it is expected that the quality of life of citizens will be increased due to the increased operational efficiency of energy companies and the creation of new services through the use of the energy usage demand data. In this way, the use of energy usage information has societal merits for both energy companies and customers, and it is expected that a large amount of data can be fully utilized to provide valuable and unique services. The example usage and application of the electricity data and smart meter is highlighted in the Table 1-3.

There are three kinds of stakeholders, suppliers, demanders, and society. It is that it is possible to provide merits for each of them. The examples for each stakeholder are addressed as below.

For the suppliers, With smart meter data accumulated and grasping the actual demand situation, it is possible to streamline the formation of power distribution facilities such as transformers, lead-in wires, and meters [Zhou 2013].

For the demanders, There is also a movement to utilize smart meter data not only for energy saving and cost saving but also for services useful for daily living. For example, watching the elderly, It is expected to be applied to crime prevention, health care (health care), marketing of products and services [Chubu　2016]。

For the society, in demand responding program, there is a possibility that the program efficiency can be improved by appealing to households who frequently stay at home during the peak period and households that frequently use air conditioners [Kwac 2013].

However, as stated before there are many diverse and broad ways to apply power data, regarding types of information and the extendibility of measuring resolution sizes used from smart meters, it is necessary to appropriately re-examine the diverse possibilities of implementing use cases including factors such as the spread of HEMS and correspondence with other equipment.

Table 1-3 Expected services for Smart Meters (Made by Author)

Sectors	Merits	Previous Research
Demanders	Electricity saving analytics and advice	[Armel 2012]
	Demand shift for the cheaper electricity bill	[Kwac 2013]
	Electricity bill comparison service	[PG&E, 2016]
	The control used for the HEMS	[Hayashi 2014]
	Elderly monitoring system	[Chubu 2016]
Suppliers	Electricity procurement	[JPEX 2016]
	The acknowledge of the demand pattern for the individuals	[Kwac 2013]
	New electricity billing menu based on the ways data	[Flath 2012]
	Provide the customer beneficial service for better customer satisfaction	[Dromacque 2013]
	Understanding the appliance usage based on the electricity current information	[Kolter 2010]
	Efficient electricity devices planning	[KEPCO 2014]
	The recognition of the electricity quality	[Zhou 2013]
	Countermeasure for the electricity theft	[Zhou 2013]
	Targeting Strategy for marketing	[Allcott 2011]
	Efficient electricity charging system	[Flath 2012]
Society	Creation of new industry based	[METI 2014]
	The planned outage	[Nomura 2013]
	Delivery service optimization	[METI 2014]

1.6 Required technologies of the electricity demands data analysis

Despite the increasing demands of the electricity data utilization. The research on the data analysis, algorithms are few in our country. The data generated from the smart meter is enormous and advanced processing is required. Also, human activities, weather activities have a major impact on the use of electricity. A method of automatically creating a model by a computer by processing a large amount of data by Machine Learning rather than a method of determining a model by a conventional human and analyzing a pattern in a constraint condition of the model is sought.

Especially, as indicated in section 1.2, the research based on the state of art Machine Learning algorithm like the electricity demand forecast and electricity demand disaggregation are two key fields for the data utilization and seems to have much potential for innovations.

1.6.1 Demand forecast

In Japan, the household power market is going to be liberalized in 2016. As business change increases, many small-size power aggregation companies are expected to appear. As a result, the needs of demand and supply adjustment by demand sides is rising after the liberalization. For newly established power companies it is obligatory to equally balance the amount of power of supply and demand 30 minutes in advance [JPEX 2016]. A precise demand forecast can help the energy company to prevent a soaring buying power of consumers or running short of power, and control of the balance between supply and demand through the electric power system can be established. Also, as the power management generation resource has to be managed in one day the advance, to predict the electric demand curve of the following day is a prerequisite for the detailed scheduling.

The fundamental architectures of electricity markets are relatively similar between different countries. The general function of electricity markets is a non-discriminatory and transparent transaction platform for electricity commodities such as energy, various ancillary services [Wang 2015]. The wholesale electricity market comprises three marketplaces according to different time scales. The basic market architecture in modern power systems and the purpose of the markets is indicated in Table 1.4

Table 1-4 Basic market architectures in modern power systems [Wang 2015]

No.	Market Name	The purpose of the Markets
1	Day-ahead market (DAM)	For the settlement in a given hour of operation for the following day.
2	Intraday market (IDM)	For the settlement hour-ahead before the operation.
3	Real Time Market (RTM)	For the system balance during the operational hour, in some places, e.g., the Nord Pool, called Regulating Market.

The fundamental market architecture in modern power systems is illustrated in Fig 1.8. Note that, besides conventional large generating units with high ramping rates, e.g., hydro-power units, the Real Time Market (RTM) in modern power systems is also focusing on providing balancing services via the aggregations of small distributed generators and flexible demands.

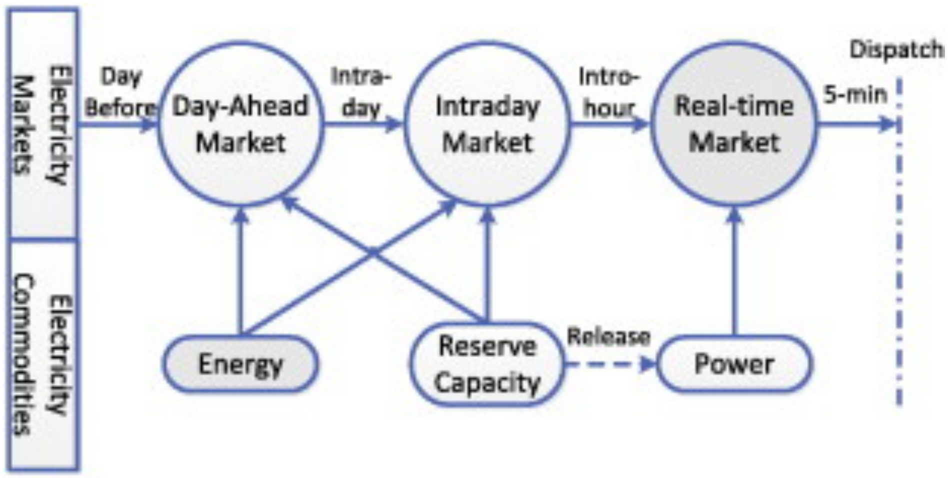


Fig 1.8 Basic market architectures in modern power systems [Wang 2015]

Ancillary Services is the services that kept the quality of electricity such as the voltage and frequency. Ancillary Services are critical for maintaining power systems' security and reliability during operation. Large system imbalance between demand and generation can cause high-frequency deviations and might cause system collapse. Minor imbalances can also provide negative effect the system's secure operation. The separation of electrical power production from power distribution and transmission has proceeded in the United States and some countries in Europe so that the ancillary service based on the market trade was developed. According to the definitions of the FERC (United States Federal Energy Regulatory Commission) and the general ancillary services are classified into six groups (Fig 1.10)[FERC 1995][Hirst 1996]. There is not an ancillary market for trading in Japan. The reason is that the general electric utility is obligated to provide the ancillary service, and the fee for the service is collected from the normal demanders as the electricity bill or electricity transportation fee. However, as the increasing demand for the renewable energy sources from the society, there is much possibility for Japan to start the ancillary service trading market.

Especially, the ancillary service relying on only the general electricity company is providing the limitation of the renewable energy in the society. Also, it might push the cost of the power generation and result in the extra facility. The creation of ancillary market can be a valid solution to solve this problem. In particular, the second level time series data of the voltage and frequency data are impossible to be measured just based on the smart meter for the low voltage market under the current situation.

In the future, it can be estimated the increasing demand for the balancing of the power generated by renewables will push the demand for data measured less than 30 min. As a matter of fact, in the previous days, the JPEX only have the market of 4-hours before but it creates 1-hour market [JPEX 2016].

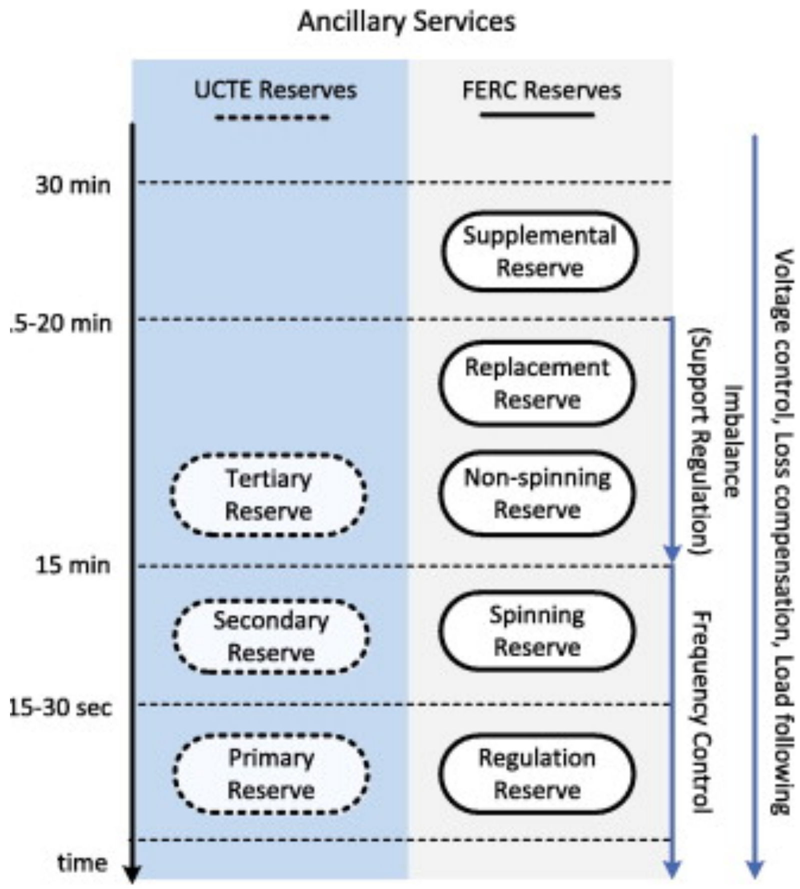


Fig 1.9 General ancillary services in modern power systems [Wang 2015]

1.6.2 Electricity demand disaggregation

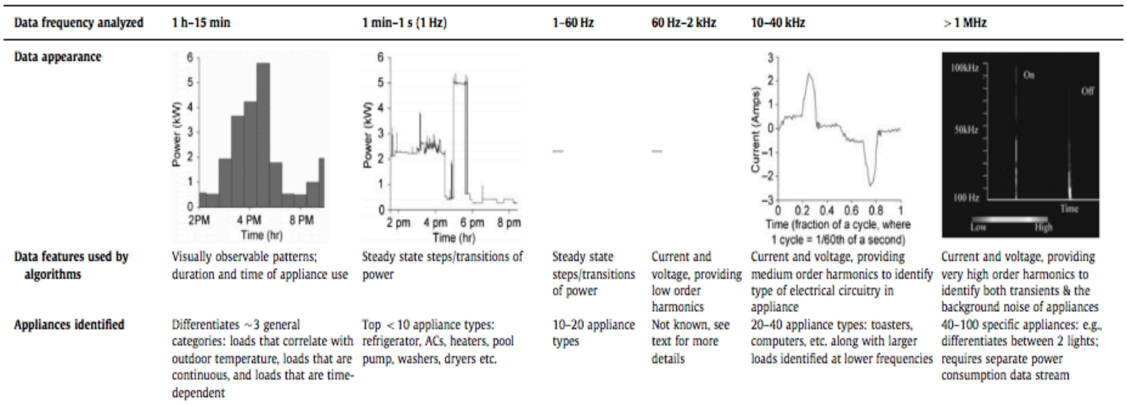
When it comes to making an energy-saving and low-carbon society a reality, it is important for customers to understand and utilize their energy usage information to raise energy-saving awareness and stimulate behavioral changes. Also, the quality of life of citizens can be increased due to the increased operational efficiency of energy companies and the creation of new services through the use of the energy usage information.

A technique for estimating the power usage of connected electrical devices through smart meter data without entering the home, called Non-Intrusive Load Monitoring (NILM) [Hart 1992], Power Fingerprint Authentication Technology, Equipment Separation technology, and demand disaggregation had been researched since the 1980s [Hart 1988].

The main advantage of NILM is that it allows the current condition of all attached electrical equipment to be understood from measurements taken from only one location, without necessitating the attachment of a measurement device to each piece of electronic equipment [Armel 2012]. There variety of disaggregation method depending on the resolution of the measurement, and it tends to have better disaggregation ability due to the signature of the each appliance from the pattern of the usage, the machine configuration, and the parts configuration. Fig. 1.10 shows the summary of patterns across existing electricity disaggregation work [Armel 2012].

As the matter of fact、there more and more start-up start to notice the very field of the electricity data analysis and provide the disaggregation service. In the recent years, energy disaggregation technologies from start-ups such as Bidgely and PlotWatt have shifted from lab level demonstrations to the real-world test, seeking to prove their idea in providing home electricity data into itemized receipt [Bidgely 2016][PlotWatt 2016]. Smappee is an advanced company putting its confidence in its accuracy. Unlike most energy disaggregation systems, which only can disaggregate the largest loads in the home. Smappee's newest app is aiming the disaggregation of devices such as Air conditioner. Laptops, microwaves, coffeemakers and low power load devices(Lumps) from different rooms in the house. However, the ultimate algorithm is still an on-going research for those start-ups and whole academia.

Existing research shows that if the electricity can provide finer resolution data for further disaggregation accurate of disaggregation because the parts configuration in each appliance create special features for their own[Armel 2012]. Also, those disaggregations can provide much insight into the electricity usage for the electricity supplier, demander and third party point of view. Furthermore, another service such abnormality detection and elderly monitoring service also can be performed from different level based on different level of electricity data [Tamura 2013].



Data frequency analyzed	1 h–15 min	1 min–1 s (1 Hz)	1–60 Hz	60 Hz–2 kHz	10–40 kHz	> 1 MHz
Data appearance			–	–		
Data features used by algorithms	Visually observable patterns; duration and time of appliance use	Steady state steps/transitions of power	Steady state steps/transitions of power	Current and voltage, providing low order harmonics	Current and voltage, providing medium order harmonics to identify type of electrical circuitry in appliance	Current and voltage, providing very high order harmonics to identify both transients & the background noise of appliances
Appliances identified	Differentiates ~3 general categories: loads that correlate with outdoor temperature, loads that are continuous, and loads that are time-dependent	Top < 10 appliance types: refrigerator, ACs, heaters, pool pump, washers, dryers etc.	10–20 appliance types	Not known, see text for more details	20–40 appliance types: toasters, computers, etc. along with larger loads identified at lower frequencies	40–100 specific appliances: e.g., differentiates between 2 lights; requires separate power consumption data stream

Fig 1.10 Summary of patterns across existing electricity disaggregation works [Armel 2012]

1.7 Gaps between expectation and the reality

As explained in the previous sections, there is a growing momentum to utilize electricity consumption data to enhance the energy conversion and renewable energy. The introduction of smart meters allow demanders and suppliers to identify patterns in demand has been promoted all over the world. Despite the high expectation of the expected capacity of the smart meters, it looks the problem of the hardware limitation and capacity of the current smart meter design is not suitable to perform all the expected service. Thus, The very function could become the precise electricity-bill-charging machine for the electricity company as before. Fig 1.11 shows the gap between the ideal merits that electricity data (light gray) and the actual merits in Japan that electricity data can provide (dark gray). The horizontal axis stands for the latency of the electricity power data; the vertical axis shows the computation power for the specific service. The services like demand repose, abnormality detection and electricity disaggregation are hard to be achieved effectively under the current architecture of the smart meter system. In another word, the current smart meter infrastructure has less computation and sensing power to analyze the local behavior. If the local behavior can be observed well, more valuable information can be provided to both demander side and supplier side.

In that sense, the effect for the society and demander is very questionable and unachievable goal. With the current smart meter, there are limitations in term of communication, the flexibility of measured parameter and the flexibility of calculation. The fixed hardware specification results in the possibility of achieved service being different from initial goal. As a result, the smart meter will be the role of a machine that can effectively collect energy charge without providing various services to customers. It might drastically lose initial social role. To prevent such a situation, it is necessary to implement new architecture for the smart meter.

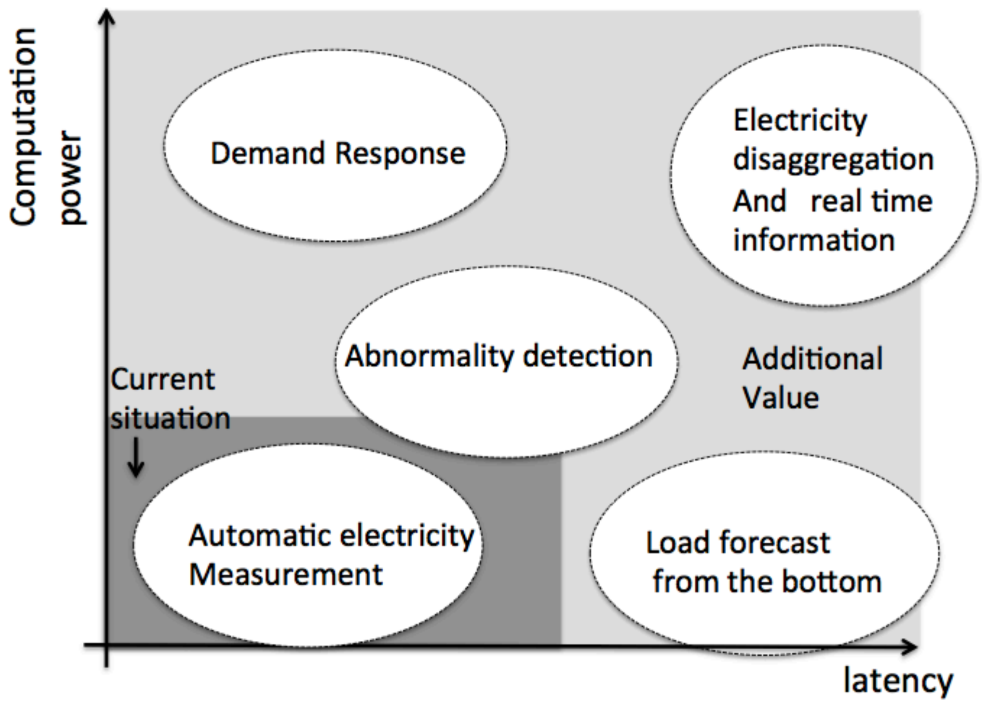


Fig 1.11 Position map of the smart meter service (Made by Author)

1.8 Purpose of this research

It seems that there is no infrastructure around us as popular and accessible as that of electricity in the world. For that reason, the sensing of electricity has many benefits for electricity demanders, suppliers, and society. The electricity smart meter seems like one of the most critical devices in the Internet of Things (IoT) system and the first IoT device that prevails widely in society. Thus, data utilization is a key matter for the successful implementation of the smart meter to achieve the so-called "Green Innovation."

However, as mentioned in previous sections, the recent smart meter is designed for the currently limited requirement of electricity usage, and the solutions provided by the smart metering system are just specific ones. From the hardware aspect, although there are many benefits and usages that can be considered and realized from the electricity data provided by the current smart meter, it is not enough to realize all the ideas based on the current smart metering system that has been introduced by the electricity companies in Japan. From the algorithm point of view, the necessity for the high-accuracy demand forecast and life-pattern recognition based on the electricity data is highly expected.

In this thesis, we show how to improve the smart-meter system from a hardware and software point of view. Based on this point, we further embody the concept of smart meters based on fog computing from the viewpoint of utilizing electric power data. Specifically, we approach from the viewpoint of hardware and software and propose a smart meter capable of communicating in real time in multiple communication ways with freedom of acquisition parameters and computational ability.

From the hardware point of view, it is necessary to recover a huge amount of power-related data from the local area, and the amount of calculation, communication volume, communication speed, etc. necessary are bottlenecks. As a solution to this problem, existing research has begun to propose smart-meter systems based on fog computing that installs data-processing computers that calculate data to some extent rather than cloud computing that processes data in the cloud. However, the existing research is limited to showing a concept of a smart-meter system based on fog computing in a large framework, studied based on the method of utilizing electric power data and necessary conditions, and has not been realized.

From the software point of view, we discuss the specific software application problems related to the data utilization based on state-of-the-art Machine Learning. From the increasing demand and technology innovation aspect, we focus on two key technologies for smart-meter data utilization: the electricity demand forecast and electricity demand disaggregation. Ultimately, we discuss the necessary smart-meter design based on the research result of the demand forecast and demand disaggregation.

1.9 Structure of this thesis

In chapter 2, we proposed our idea to overcome the difficulties addressed in chapter 1 of the current smart meter based on the emerging idea of the computing architecture idea – Fog Computing. Also, indicated the advantages of this suggestion and the practical possibilities of the proposal.

In chapter 3, 4, I have focused the demand forecast.

In chapter 3, we demonstrated a short-term power demand curve forecast based on Gradient Boosting machine and Deep Learning. Demand and supply balancing is the key technology for power management and high-efficiency planning. We have attempted to adapt the state of art Machine Learning method – Deep Learning – to check the forecast capacity. Also, we examine the relationship between individual demand and the total demand for the forecasts improvement.

In chapter 4, we have analyzed the problem between Top-Down and Bottom-Up method. Forecast based on the Top-Down versus Bottom-Up method was a constant discussion for various fields. We performed a short-term power demand curve forecast based on Gradient Boosting machine to compare the two methods. Then, we showed the advantages of the bottom-up forecast based on local data.

In chapter 5, 6, we have focused electricity data disaggregation.

In chapter 5, it shows an analysis method and validation of electricity disaggregation on low-resolution smart meter data to reveal the advantages for the residents. We provided that two kinds of disaggregation methods for the disaggregation of Low-resolution data. 1) Two-states-disaggregation, which can separate the active and the inactive state. 2) Temperature-sensitive demand disaggregation that can separate the total demand and temperature-sensitive demand.

In Chapter 6, we indicate the disaggregation based on the data of electricity current to disaggregate the appliance usage. In previous research, there were many types of research focused on the supervised learning algorithm for the disaggregation work. However, the disaggregation is not achievable based on supervised learning because it is almost impossible to measure the electricity usage of each appliance for individual homes. We could create the supervising data by taking advantage of the difference of electricity current of each appliance. After that, we used the supervised learning method to estimate the on/off status for each appliance.

In chapter 7, to realize the algorithms and ideas indicated in chapter 3,4,5,6 and the concept of Fog Computing based the electricity Smart Meter. We showed the implementation of a prototype version Fog Computing based the electricity Smart Meter-Home Master.

In chapter 8, we summarized this thesis and showed the future works and the idea that we could not achieve.

2 PROPOSAL OF THE SMART METER BASED ON FOG COMPUTING SCHEME

2.1 Background and purpose of this chapter

There is a growing momentum to the energy conversion and power liberalization of the natural energy. The introduction of smart meters that allow demanders and suppliers to identify patterns in demand has been promoted all over the world. Despite the high expectation of the smart meter, it looks the problem of the hardware limitation and capacity of the current smart meter design might only be able to provide limited functions the expected service and analytics.

In this chapter, we proposed our idea to overcome the difficulties address in chapter 1 of the current smart meter following emerging idea of the Fog Computing architecture. Also, indicated the advantages of this proposal and the practical possibilities of the proposal.

2.2 Deficiencies of IoT System

Recently, Internet of Things (IoT) [Cisco 2011] is becoming increasingly popular around the world. For example, power meter inspection staff can be replaced by a smart meter, which can notify the power company of the usage of the customer. However, IoT starts to have its problems as illustrated in Section 1.4, Big Data that is transferred from devices such as a sensor is concentrated on a cloud computer, which may struggle to process the data, results to high server maintaining cost. Furthermore, the amount of data that billion of devices produce can be enormous, and it could cause a network traffic explosion regardless of the method used. We can assume that millions of smart meters from individuals could have this same problem. We address the problems as below [Cisco 2015].

1) Minimize latency:

Milliseconds matter when trying to M2M commutations, outage prevention or accurate electricity disaggregation. Analysing data close to the device that collected the data is critical for elect city control.

2) Processing close to the data:
The place where is best to process depending on how quickly a decision is needed. Extremely time-sensitive communications should be made closer to the things producing and acting on the data such as battery control or HMES control. On the contrary, big data analytics on historical data is better to compute and storage resources of the cloud

3) Conserve network bandwidth:
In the real world, the tremendous amount of data is generated every second. For example, to make MHz level of data for electricity disaggregation. It is hard to transport vast amounts of data from thousands of edge devices to the cloud.

2.3 Fog Computing

To overcome the problem that addressed in the previous section, a new scheme called Fog Computing had been proposed. Fog Computing, suggested by Cisco Systems [Cisco 2015], is a distributed computing environment which sets up the data processing equipment closer to the device from the cloud, and the network structure is designed with a unified internet protocol. It is called Fog Computing as it is closer to the device than cloud and is more widely distributed like fog. Using Fog Computing, Machine Learning can be distributed using network devices and edge devices equipped with advanced Machine Learning algorithms. Therefore, without being bound to the bandwidth of the backbone of the network, it is possible to process massive amounts of data and pass the data only necessary ones to the cloud. With Fog Computing, it can reduce the latency (delay time) of the processing, and it makes it possible to coordinate between devices in real time. The image of Fog computing is indicated in Fig 2.1.

Processing data in local and where it is needed can provide a solution the bottleneck of exploding data volume, variety, and velocity. Fog Computing makes better awareness and response to machine events by avoiding a round trip to the cloud server. It eliminates the need for much bandwidth by offloading gigabytes of network traffic from the communication between the network. It also provides security for IoT data by analyzing it inside of the edge. As a result, Fog Computing can lead to increased communication agility, lower costs, and improved security.

Historically, the computing cycle between the concentration and distribution is periodically repeated. The Mainframe computer station was used when the computer invented. Gradually, the mainframe computing architecture was replaced by the individual smaller workstation for each organization, then as the prevailing of the personal computer, finally the computer is distributed to each user as the mobile device. After data, due to a large amount of communication between computer node and the server has increased, the cloud computing became a hot one as the centralized. Moreover, now, as the prevailing of IoT device, the Fog Computing might be next computing architecture for the IoT devices as the distribution system.

Benefits of Fog Computing is to extend the cloud closer to where the data generate and provide the following benefit in the following ways [Cisco 2015]:

- Greater business possibility:

Developers can implement fog applications based on the data provided by fog device and deploy in local through the application API.

- Privacy and security:

Analyze sensitive private data locally instead of directly sending it to the cloud for analysis can provide the much security

- Lower communication handle:

Conserve network bandwidth in communication process by processing selected data locally instead of using more bandwidth in the communication process.

- Amount of data and calculation:

The rapid spread of IoT will result in an explosive generation of data and cost of computation in the cloud; edge computing can reduce the burden caused by it.

- Time lag problem:

Avoid the response delay caused by the distance between the device to the cloud; Communication delay can create a bottleneck with services which require an immediate response.

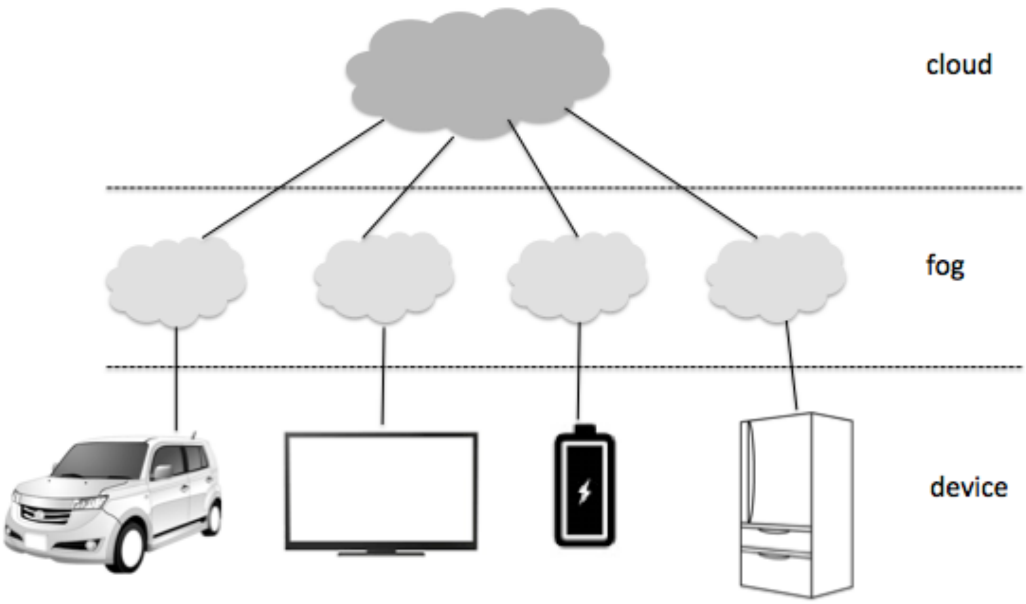


Fig 2.1 Image of Fog Computing (Made by Author)

2.4 Embedded OS to General purpose OS

Operating system (OS) is " the gathered necessary function for computer software."

The difference of the particularly embedded OS and the general-purpose OS is whether the system is having a function available universally various purposes or having a function of limiting to a certain purpose. While the specially embedded OS is constituted with the limited fundamental functions and limited minimum capacity of the hardware, the general purpose OS has more capacity than the required power to embarrass in a variety of usage. The difference between the General Purpose OS and specially embed OS is indicated in Fig 2.2.

Windows or MACOS are the examples of general purpose OS, and the OS developed by each main iTRON manufacturer are the examples of the embedded OS, For instance, no matter you are a game developer or the business application developer, there are both of DirectX. The general purpose OS will be used in a variety of environment without any customization. On the other hand, the specially embed OS will be used in the particularly fitting environment.

In the previous days, the high spec hardware could not be made. Moreover, Real-time OS which has simple functions was utilized with the Low functional parts. However, as the prevailing of the IoT device and smart device, besides the very basic functions, the functions such as data communication based on the Internet were required increasingly. The general purpose OS is getting popular gradually. Even the functional Linux OS can work efficiently as the Real Time OS. The difference between the general purpose OS and specially embedded OS is indicated in Fig 2.2.

Therefore, the battle of the General Purpose OS was initiated between the companies, As the practical trend, Google has started to create a new type of General Purpose for IoT that called Fuchsia. Also, Japanese government started to pay attentions to the movement of the industry. OPTiM Cloud IoT OS is the one of the OS that is implemented for the IoT devices [OPTIM 2016].

General-purpose OS based Micro computer device such as Intel Edison or Arduino have come out the market. They are not only providing price merit for the manufacturer to take advantage of the general-purpose OS to build their products but also giving a little threshold to develop multifunctional devices, and reduce the production cost.

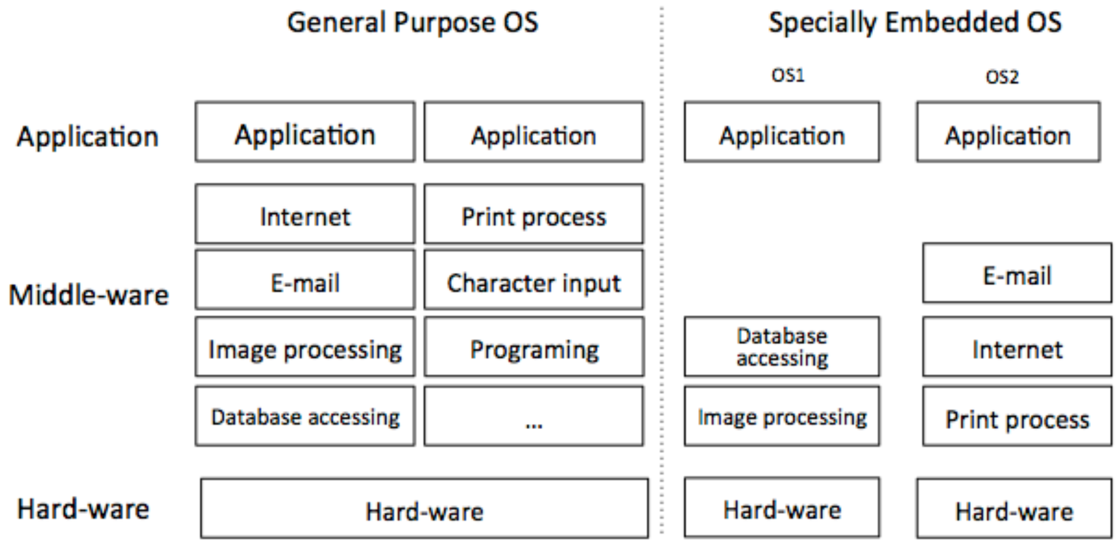


Fig 2.2 Difference between the General Purpose OS and specially embedded OS (Made by Author)

2.5 Problems of HEMS

Recently, the Internet of Things (IoT) and the sensor system are prevailing and extending [Monnier 2013]. There is attention to the automation and monitoring of energy providers and energy users because management systems for in-home and in-building electricity usage will support consumers monitor, analyze, and even forecast their usage pattern and behaviors. In the energy management system, the data communication among the grids, smart meters, solar/wind generators, power storages, sensor networks, and home appliances is critical. Suppose that this concept is realized the total system of the data management and computations will serve as another fundamental infrastructure at home that will dramatically change our way of life. However, until now, the "killer app and device" of HEMS has yet to appear. There might be some reasons for that.

- Hardware aspect

The energy device's specifications and the purposes of use change from time to time, depending on the owner's intention and combination with other energy devices. For instance, in measuring electricity consumption, various types of smart meters can be used. The specifications differ, such as measuring the duration of usage. It is hard to keep up with the changing demands of consumers. Technological innovations cannot be implemented by only modifying the hardware specification. This situation can be changed by considering the updates of specifications.

- Software aspect

The usual demand repose or power-saving application provided by the vendors is not enough to motivate individuals and realize the potential demand. One of the most popular success stories for this problem is the iPhone. The iPhone provided a new platform to the developer to develop the software for each customer, and now, the application on the iPhone brought our cell phone beyond the traditional product value and gained much more additional values. Therefore, to provide a platform that every developer can take advantage of electricity data is necessary. Also, the algorithms regarding the electricity data were not enough developed.

The treatment of personal information is a controversial point in the development of the HMES system because data and the electricity usage patterns will totally reveal personal life patterns and, thus, risk the privacy of the users. Therefore, some details should be kept confidential.

2.6 Existing researches on Fog Computing based smart meter

The necessity of Fog Computing based smart meter can be derived easily, from the data amount aspect if there is a need to record 10Hz power data for 1 million people, there is a necessity to prepare 100 peta byte storage. From the communication aspect, the cloud-based the communication system is redundant for the local demand control and communication between the machines. The individual Machine Learning calculation will provide substantial burdens to the cloud server and lead to high cost.

Smart meter system concept have been discussed for the decades, and the commercially-based system has been developed around the world. As for the smart meter system based on Fog Computing, there are several types of research. The concept of the Fog Computing based smart meter has been proposed by several groups around the world but still not clearly defined.

Bonomi who is one of the initial presenter of Fog Computing system in Cisco systems, who mentioned the importance of the Fog Computing as the real-time M2M solution is hard to be achieved by current cloud-based smart grid system [Bonami 2015].

Vinuea has demonstrated the whole idea of Fog Computing on the smart grid from technical support, security, Data Base analysis and utilization issues, and pointed out the difference between the former the cloud-based smart grid system [Vinuea 2016]. They stressed the general benefits of using Big Data to design and support SmartGrid applications on Fog Computing Platforms. Fig. 2.3 shows the classification of the application technologies in Fog Computing introduced by Vinueza. The ideas described in the Vinueza's paper are described in the Table 2-1.

Table 2-1 Classifications of the application technologies in Fog Computing smart grid[Vinueza 2016].

Technology	Applications	Fog Computing Applications
Energy Management	·Micro grid Management, · Dynamic demand response operated within the micro grid, · Real-time monitoring on application for Smart grid G.	· Datametric communication with the implementation of private Fog for small size network, · Fog Application dynamically increase bandwidth capacity to avoid congestion, · Micro grid to micro grid interaction through Fog, · Define demand response model in the into the internal micro grid operation.
Information Management	· Smart meter data streams in Cloud, · Dynamic data center operation,	·Guaranteed workflow latency and processing rates with the help of Fog data optimization, ·Dynamic pricing model in Smart grid architecture according to load on Fog Data Service, ·Adequate data transfer framework from users to Fog and, vice versa.
Security	· Security and protection system for electric power information, · Privacy preserving over encrypted metering data for SmartGrid,	·Fog as "Software as a Service" for data privacy issues in large scale deployment of Smart grid, · Define security mechanism for Smart grid while using public Fog Computing applications, · Effective and efficient security and privacy policies to support increasing data from smart meters.

Yan and his group have proposed an implantable data storage and processing solution for improving the existing smart meter infrastructure based on the Fog Computing concept (Referring to Fig 2.3). The practicality of the proposed solution is validated on a proof-of-concept testbed [Yan 2016].

Fig 2.3 Cloud and Fog Computing in Advanced Metering Infrastructure (AMI) [Yu 2016]

From the vendor side, Itron has announced its new Open-Way Riva communications platform to deliver distributed smart meter intelligence over Cisco networks [Itron 2015]. Itron claims that distributed smart meter intelligence provides adaptive and continuous selection of the best communications method and a preferable communication frequency to guarantee the communication speed and robustness communication path back to the utility. The picture of the intelligent edge smart meter proposed by Itron is shown in Fig 2.4.

Fig 2.4 Intelligent edge smart meter proposed by Itron [Itron 2015]

However, the fog based smart metering system is still a merging concept.; Still many types of research have to be done. Especially. The researches based on the actual possible application and data utilization point of view has not been studied. There is not a clear definition and clear picture for the Fog Computing based on the smart meter. In this thesis, we provide much insight for future the smart meter design and application, and clearly define the Fog Computing based on smart meter should have communicating in real time in multiple communication ways, with freedom of acquisition parameters, and computational ability.

2.7 Proposal of Smart Meter based on Fog Computing scheme

The goal of this project is to show the concrete concept of a fog computing-based smart meter. Despite the great attentions, we have discussed that there are several deficiencies of the current smart metering system.

The current smart meter provides less flexibility of the functions after the installation. As the smart meter is the very basic infrastructure of the society, a high amount of cost is invested in the installation process. Once it is installed in every demanders' place, it is quite hard to reinstall it or put some additional functions. However, due to the variety of the needs for the electricity data and increasing demand for the finer data of electricity resolution, the current design of the smart meter can result in significant problems. For example, the current smart meter can only measure the power data every 30 minutes, and it is impossible to do any calculation of the data. The rapid spread of the smart meter in every household results in an explosive generation of data and cost of calculation in the cloud server; fog computing can reduce the burden caused by it. Also, other kinds of local data such as temperature or human activity seem to provide much insight for the energy analytics. All of these should be analyzed locally rather than globally.

Locally analyzed data also provides less of a time lag problem, and avoids the response delay caused by the distance between the device to the cloud; communication delay can create a bottleneck with services that require an immediate response. Furthermore, from the privacy and security aspect, analyze sensitive private data locally instead of directly; sending it to the cloud can provide the most security of data. In this thesis, we propose a new type of smart meter that can overcome the drawbacks we have pointed out. Specifically, the idea is inspired by Fog computing and general purpose OS, which has started to prevail in the IoT world. A model of this idea was successfully implemented in the iPhone. We consider there is enough capacity for the smart meter to possess the ability of general purpose OS for the storage of the data, processing, running basic applications, and collaboration with other machines. Further, it can extend the cloud closer to the things, process the high-frequency data, then request the machines to perform necessary actions for the ancillary or other services for the demander. The image is indicated in Fig 2. 5 .

We define three main factions for the Fog Computing-based smart meter: 1) freedom of acquisition parameters; 2) computational ability; and 3) communicating in multiple communication ways. The freedom of acquisition parameters means that it is possible to measure the necessary latency of the electrical data from 30 min level to kHz or MHz level. Also, the data obtained is not limited to electrical power data, but it includes the voltage, ampere, frequency, effective power, ineffective power, room temperature, GPS, time, and other data that can represent human life activities. Computing power means that the smart meter can also process, analyze, communicate, and react to grid conditions for DR, demand forecast, HMES appliance control, optimal communication line detection, optimal electricity detection in the dynamic pricing condition, and so on. For example, it is possible to store data to build the abnormality detection model to detect the abnormality for the edge electricity quality and provide the necessary signal when the abnormality is found. Also, it is possible to access it from the outside to update the software condition. Communicating in real time in multiple communication ways means that it can serve as an API server to provide the information and control signals. Moreover, it is possible to provide information through several communication ways like WiFi, 3G, and PLS. For the implementation of this idea, we proposed a project to manufacture a new type of integrated HEMS control platform, which is called the Home Master. This device can modify the specifications of the software from driver API level and network API level and can be managed externally through private 3G communication lines.

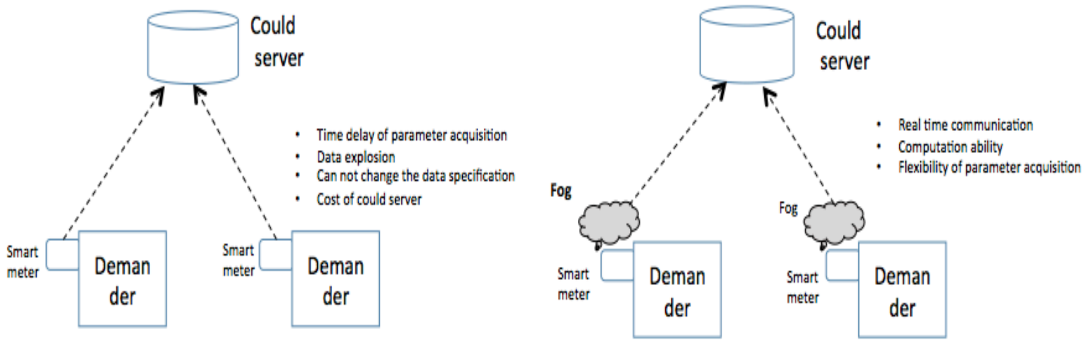


Fig 2.5 Comparison between cloud computing smart meter system and Fog Computing based smart meter (Made by Author)

2.8 Proto type of smart meter based on Fog Computing scheme

Home Master is the prototype for the idea of Fog Computing based smart meter.

The Home Master is a power measurement device utilizing the Intel Edison Compute Module and power measurement IC. This device can be used to estimate power demand as it measures power parameters including voltage, current, and electricity consumption and can be set to take measurements in short time intervals through the smart meter. Also, it has a high-speed electrical current waveform acquisition function.
Here we defined the Home Master as below.

a) Home Master is a stationary computer that can be installed at a terminal point between the home and outside (usually, the point of the switching board or breaker and smart meters are installed). It functions as a digital breaker, data server, smart meter, appliance manager, and communication device.

b) Home Master can measure power parameters such as electric power, voltage, and current,etc.. Furthermore, it possesses sensors for other parameters concerning with electricity such as atmospheric pressure, humidity, and temperature. It acts as a data server and collects the data located in the home and performs calculations on them.

c) The heart of Home Master is a high-performance CPU, such as an Intel Edison module, which allows the Home Master to function as a central control center of the home. It performs calculations using algorithms such as demand forecasts, power generation forecast demands, and disaggregation [Armel 2012]. The calculation results will be provided for better energy storage management, electricity purchases, appliance management, and home appliance control.

d) Energy management is based on a power line communication, and Wi-Fi, 3G, and PLC are available through the Home Master API. Some hardware specifications of the Home Master can be modified and controlled by the cloud management system.

e) Home Master is fixed in place of the switchboard in the home and will calculate the important personal information within the home, and only required information will be transmitted to the outside.

f) Home Master has its communication line from the cloud control center, accessed through such methods as 3G communication lines.

2.9 Demand forecast and disaggregation

Based on the proposed Smart meter, we focused on the electricity demand forecast and electricity demand disaggregation to find the characteristics of the electricity demand time series data, and the examine the new application and methodology of the smart meter data utilization.

The smart meter can provide the electricity forecast result based on the daily data to the minute data. Those results can be utilized for the management of battery and appliances for the demand shift and response problem. Also, the various scale of the electricity disaggregation algorithm can provide finer breakdown of electricity usage.

2.10 Summary

In chapter 2, we proposed our idea to overcome the difficulties addressed in chapter 1 of the current smart meter based on the emerging idea of the computing architecture idea – Fog Computing. Also, indicated the advantages of this proposal and the practical possibilities of the proposal. This device can be used to estimate power demand as it measures power parameters including voltage, current, and electricity consumption and can be set to take measurements in short time intervals through the smart meter. Also, it helps the data of smart meter to compute in the local directly.

3 ELECTRICITY DEMAND FORECAST BASED ON GRADIENT BOOSTING MACHINE AND DEEP LEARNING

3.1 Background and purpose of this chapter

In Japan, the household power market has been liberalized in 2016. As business change increases, many small-size power aggregation companies are expected to appear. As a result, the needs of demand and supply adjustment by demand sides will rise after the liberalization. For newly established power companies it is obligatory to equally balance the amount of power of supply and demand 30 minutes in advance. A precise demand forecast can help the energy company to prevent a soaring buying power of consumers or running short of power. Also, as the power management generation resource have to be managed in one day the advance, to predict the electric demand curve of the following day is necessary for the detailed scheduling.

In this chapter, to have an accurate forecast of one-day demand curve forecast (30 minutes per step) for newly emerged power companies; we used Gradient Boosting machines to confirm the forecast capacity for the demand curve for one day. Furthermore, we applied Deep Learning to check the capacity and overcome the problem of feature value selection. As the increase of the demanders, it is known that the forecasted error will be decreased. However, there is still a certain number of error left even though we have a large number of demanders in the demander portfolio. For this issue, we analyzed the relationship between individuals demand forecast and total demand forecast. We could explain the reason of limitation of the forecast is caused by non-independent covariance between the demanders.

3.2 Existing researches

There are two aspects of power demand forecast: The forecast target and the forecast model. There is few pre-existing research on short-term demand curve forecast, as the data is relatively hard to obtain compared to the mid- and long-term consumption with out smart meter. On the other hand, few studies using regression models predict the demand of the whole step in a day. For instance, Hatita [Hatita 1996] only predicts maximum demand in a day. Recently, Kobayashi [Kobayashi 2014] challenged this problem based on multi-regression analysis and could make a forecast model successfully. From the point of view of forecast methods, as a preceding study, there are predicting methods using multiple regression analysis, artificial intelligence like neural network or Support Vector Machine (SVM), and time series analysis like the MA method or ARIMA method. [Reccali 2004][Fan 2006][Tayler 2006][Hisatomo 2014][Haida 2009]. Non-linear Regression Analysis Models such as neural network or SVM could achieve high accuracy. However, for the Non-linear Regression Analysis model, the adequate model selection, and feature value selection were bottleneck problem of this Machine Learning effort.

In recent year, Deep Learning and Gradient Boosting based demand forecast have been proposed. Wan has compared the performances of different neural network models and show the advantages of the proposed methods for demand forecast[Wan 2014]. Her forecast target 24 hours ahead hourly demand in a northern city in China (9000 MW).The method is based on RBM pre-trained DNN with three layers and 100 hidden neurons. She could achieve around 2 % accuracy based on MAPE. Mocanu also FCRBM outperforms the benchmark Machine Learning approach like Support Vector Machine [Mocanu 2016]. His target was 1900 customer (2000KW) from the Eco Grid EU dataset collected from the Danish island for seven months to forecast, and it targets to forecast 6 hours ahead. Bansal showed the demand forecast based on Gradient Boosting machine [Bansal 2015][Hyndman 2015]. However, the time series relationship of the electricity demand was not considered.

Also, by examining the relationship of errors that stem from the individual forecasts, we found that there is a big gap in forecasting accuracy depending on the scale of demanders. While the forecasted errors at the individual level are quite high, around 20% ~ 40% (absolute mean error), after the aggregation of about 100 demanders, the forecasted error decreases dramatically. Despite the abundance of forecasting methodologies, few research studies have tackled this problem. In the study conducted by

Sevilan [Sevlian 2014], this phenomenon was referred to as the effect of load aggregation; however, the author could not adequately describe the principles of the phenomenon or the reason for the generation of the forecasted error. The relationship between the amount of demand and forecast accuracy is noteworthy because more and more small electricity companies are appearing in Japan as a result of the electricity delegation, and they have to follow the obligatory demand and supply balance. To overcome the problem of imbalance in the electricity supply, some electricity companies are gathering other companies as a balancing group to reduce the forecasted error for the individual company because of the strong relationships that influence the effects of demand aggregation. Also, the relationship between the number of demanders and forecast error having a relationship was not analyzed.

In this research, we performed a series of electricity demand foresting and could find that the error mainly occurs based on the non-independent case of the law of large numbers.

3.3 Method

3.3.1 Forecast process

We predict an electric demand curve of a day in one day ahead based on the non-linear regression instead of multivariate analysis. The purpose of regression analysis is to use the explanatory variable to forecast predictor variable. The better the fit, the more accurately the function describes the data. There are many kinds of the non-linear regression model. GBM and Deep Learning are the non-linear regression models with the highest forecast capacity.

We conducted the forecast for the electric demand curve of a day. Gradient Boosting Machine (GBM) and Deep Learning. The relationship between the predictor variable and explanatory variable is illustrated in the Table 3-1.

3.3.2 Deep Learning

Deep Learning [Bengio 2013] is a Machine Learning algorithm that attempts to acquire high-level abstractions in training data by using architectures composed of multiple Non-linear transformations based on neuron model. There were some drawbacks for the traditional Machine Learning methods. The recent breakthrough of Deep Learning idea indicated the possibility to overcome the drawbacks of the Machine Learning. Deep Learning has been applied various fields where they have been shown to produce the highest results on various tasks. The detail of the Gradient Boosting Machine is indicated in Appendix 1.

3.3.3 Gradient Boosting Machine

Gradient Boosting works in a way where they connect two powerful tools, and these powerful tools are well-known as boosting and gradient-based optimization. Boosting is used for gathering a band of frail models for the purpose to make a reliable learning system for the analytical task[Friedman 1999]. The detail of the Gradient Boosting Machine is indicated in Appendix 2.

3.3.4 Feature Engineering

The training parameter used in training is indicated in the Table 3-1. The minimum span of the data is 30min (48 steps per day). More than 90 feature quantities were tested, such as the amount of demand in the same time zone last week / last week as a feature value. The details are illustrated in Appendix 4.

There are two kinds of the relationships; the first one is the future forecastable information such as weekdays and temperatures. The second one is the fast information that will periodically occur, such as electricity demand.

The relationship between each feature and the electricity demand was checked. The plot diagram is indicated in Fig 3.1 and Fig 3.2 Demand curve pattern is different depending on the weekdays. Temperature has a strong relationship with demand.

The way to forecast the future from the past is still a debatable issue, however, as the previous research indicates, to use the value in one period before is a suitable choice. Fig 3.3 shows the feature for the time series with periodicity. The bold line at t - 1 shows the data necessary for prediction, the point ahead of it is the point to be predicted. In order to predict this point, we need to see points in the same period in the past. Looking at the past data of that same point, the future can be predicted by periodicity.

Prediction accuracy is greatly influenced by the feature quantity used for prediction. For this reason, it is desirable to extract feature quantities strongly correlated with the electricity demand amount and use it for learning. In general, it is greatly affected by the temperature. In addition, even if considering periodic fluctuations such as humidity and day of the week, there are many features with a strong correlation. Also, it is reported that feature quantities such as combinations of exponentiation, logarithms, arithmetic operations, etc. of them are effective for improving prediction accuracy.

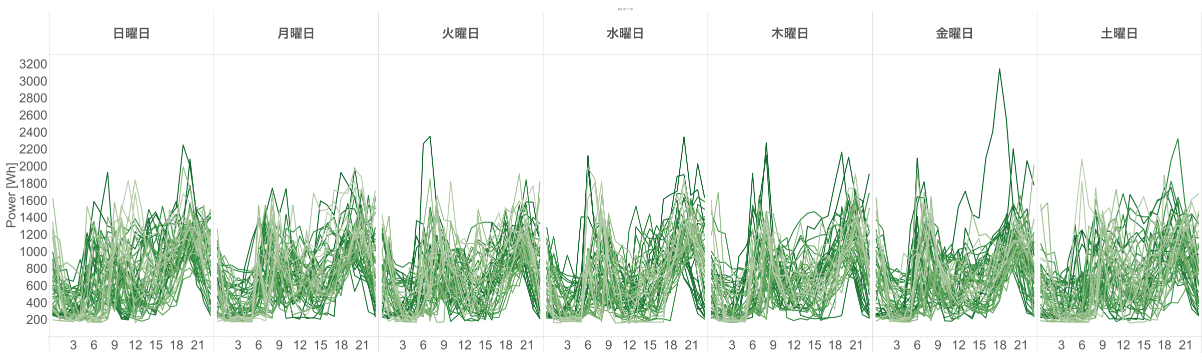


Fig 3.1 Relationship between weekdays and electricity demand (Made by Author)

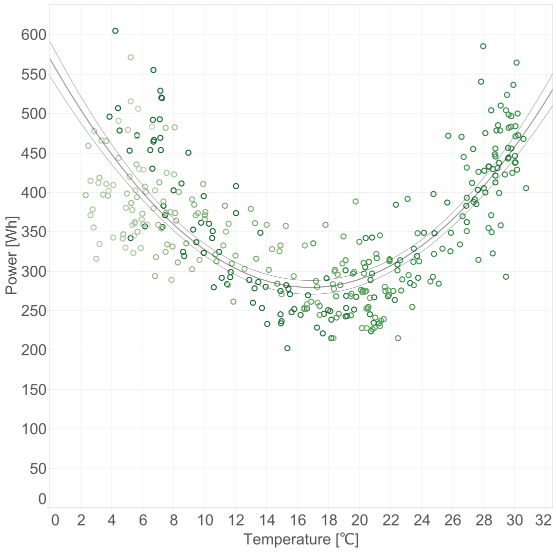


Fig 3.2 Relationship between temperature and electricity demand (Made by Author)

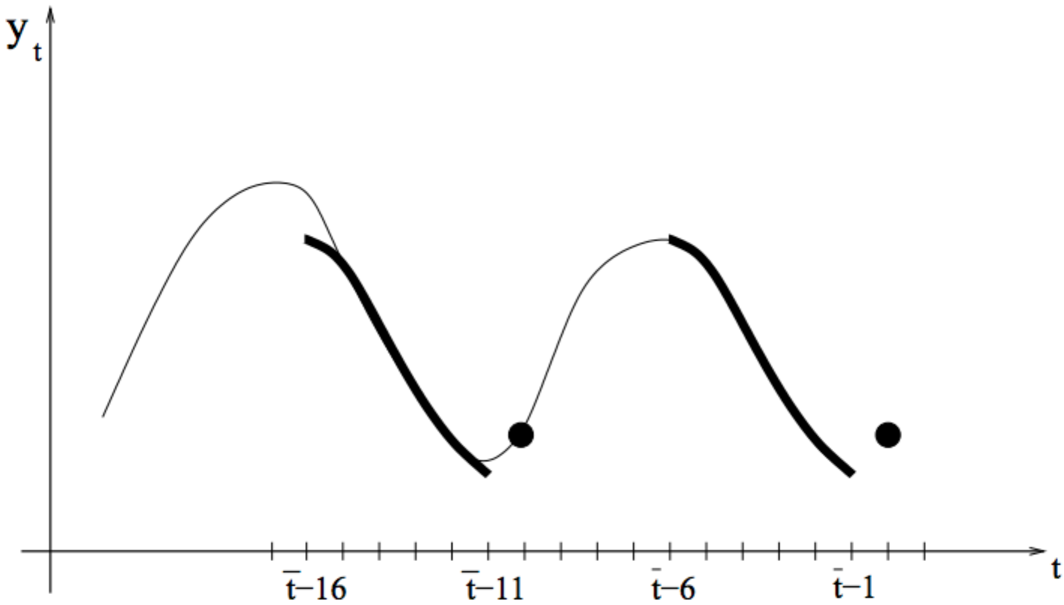


Fig 3.3 Feature for the time series with periodicity[Bontempi 2013]

3.4 Case study

3.4.1 Data and conditions

- Training data

We did case studies to test the effectiveness of this method using the real demand data.

1. The demand data came from an apartment located in Tokyo area from 4th 2012 to 12th 2013. In the apartment, there are 151 residents.

2. The demand data came from an apartment located in Tokyo area from 4th 2012 to 12th 2013. In the apartment, More than 4000 residents.

The minimum time span is 30 minutes, 48 steps for a day. We did the forecast and sum-up. Weather data is used in the forecast. Weather data is used in this chapter is published by Japan Meteorological Agency [JMA 2014]. Although we use forecasted weather data when we use this forecast algorism. In this case study, 90% of the data was utilized for the training and 10% of the data was used for the forecast validation. For the both cases, the training data is from 2012/1/25 to 2013/10/21, the test case is from 2013/10/22 to 2013/12/31

Input parameters are the following: parameters related to weather information (temperature and humidity), parameters related to power demand (power demand information of the previous day), and parameters related to human activities (holiday, time of day, a day of the week) and so on. The detailed indication for the features used in the forecasts are indicated in the Appendix 4.

For evaluation, the predictive error quantified it in MAPE indicated in 3-(1). The predictive technique used Gradient Boosted Machine. Also, we evaluated Support Vector Regression, Random Forest, GLM as a target for comparison.

$$M = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right|, \qquad 3\text{-}(1)$$

Actual Value: Ft
Forecasted Value: At
Number of Sample : n

3.4.2 Comparison between machine leanings

The forecast based on the previous day demand, GLM, Random Forest (RF),Support Vector Machine Regression (SVR) are conducted. Fig 3.4 shows the results for each forecast. We predicted the household demand data aggregating 151 homes in Kanto, Japan. In the first case, we cloud predict the one day aggregated demand with 6.4% (MAPE) for RNN and 6.8 %(MAPE) for GBM.

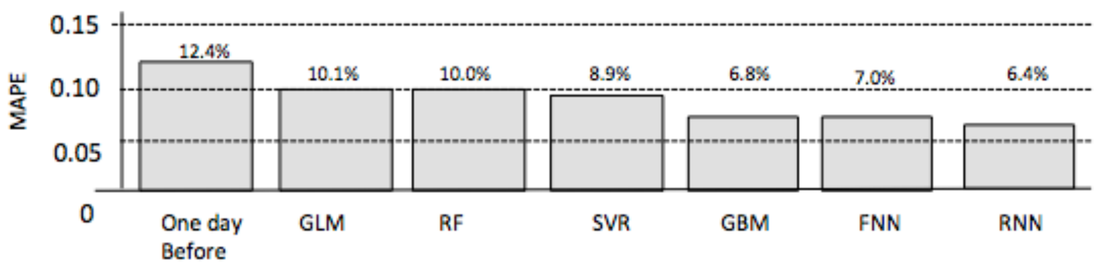


Fig 3.4 Demand Forecast comparison between Machine Learnings algorithms (Made by Author)

In the second case, for the demand forecast of 4000's houses.,we compared the GBM with FFNN and RNN. WE could found the RNN could show the best-forecast ability. The RNN could also indicate the best result that shows the accuracy for 3.5 % (MAPE). Comparing with the previous results, in 2013, Miyata from Chubu power provide a result that shows the 3.17%(MAPE) for next day demand curve forecast. Although our result is slightly below the result indicated by Miyata[Miyata 2013]. The data used in the research of Miyata was the amount of whole electricity power. As there is a tendency that the larger amount of electricity demand having less forecast error. It means that our result have achieved certain high or higher level. In Fig 3.5, we show Miyata's work in gray color and our color in light gray color.

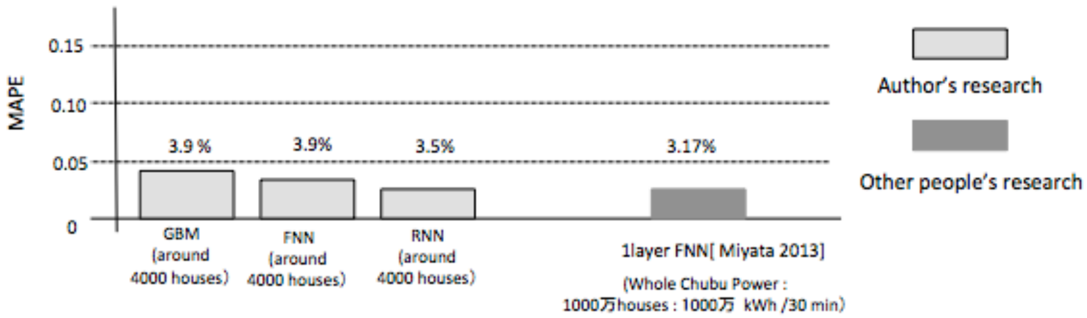


Fig 3.5 Demand Forecast comparison between Machine Learnings algorithms and house numbers (Made by Author)

Also, the actual forecasted demand curve is indicated in Fig 3.4 and 3.5. On the other hand, Comparing with the number of demanders, the gap of MAPE is much bigger if the there are a smaller number of demanders. The fact that the prediction error is bigger in a smaller number of the customer is caused by the less the consumers are, the higher the volatility of the demand curve becomes.

3.5 Discussion

3.5.1 The formulation of demand forecast error

As indicated in the Fig. 3.5, it is known that the forecasted error will be decreased. However, there is still a certain number of error left even though we have a large number of demanders in the demander portfolio. In this research, we found a new law between individuals demand forecast and total demand forecast. It explains the reason of limitation of the forecast is caused by non-independent covariance between the demanders.

To investigate the relationship between the number of customers and the prediction error, the following analysis was carried out.

We consider that there is no measuring error for the measuring device. First of all, the entire demand of the customers can be represented as x, the demand of individual consumers can be represented as x_1, x_2, x_3 ... x_n. Relationship of the total demand and the demand of individual customers is indicated as 3-(2).

$$x = x_1 + x_2 + \dots + x_n \qquad 3\text{-}(2)$$

Where x_f indicates the individual forecasted demands, x_a is the individual demands, and t is the length of time. The Root Mean Squared Error of the whole term is indicated as 3-(3).

$$\overline{\sigma}^2 = \frac{1}{t}\sum_{t=1}^{t}(\overline{x}_i^f - \overline{x}_i^a)^2 \qquad 3\text{-}(3)$$

Here, we consider the average of aggregated individual demand, and we derive root mean square error based on the calculation below,

Function 3-(3) will be expanded as function 3-(4) ~ (13).

$$\overline{x}^f = \frac{1}{n}\sum x^f \qquad 3\text{-}(4)$$

$$\overline{x}^a = \frac{1}{n}\sum x^a$$ 3-(5)

$$\overline{\sigma}^2 = \frac{1}{t}\sum_{i=1}^{t}(\overline{x}_i^f - \overline{x}_i^a)^2$$ 3-(6)

$$= \frac{1}{t}\sum_{i=1}^{t}[(\frac{1}{n}\sum_{k=1}^{n}x^f - \frac{1}{n}\sum_{k=1}^{n}x^a)^2]$$ 3-(7)

$$= \frac{1}{t}\sum_{i=1}^{t}\frac{1}{n^2}[(\sum_{k=1}^{n}x^f - \sum_{k=1}^{n}x^a)^2]$$ 3-(8)

$$= \frac{1}{t}\sum_{i=1}^{t}\frac{1}{n^2}[(\sum_{k=1}^{n}x^f - x^a)^2]$$ 3-(9)

$$= \frac{1}{n^2}(\frac{1}{t}\sum_{i=1}^{t}(\sum_{k=1}^{n}\sum_{l=1}^{n}\left(x_k^f - x_k^a\right)\left(x_l^f - x_l^a\right))))$$ 3-(10)

$$\overline{\sigma^2} = \frac{1}{n^2}\{(\sigma_{11}^2 + \sigma_{22}^2 + \ldots\ldots + \sigma_{nn}^2) + (\sigma_{12}^2 + \sigma_{13}^2 + \ldots\ldots + \sigma_{(n-1)n}^2 + \sigma_{n(n-1)}^2)\}$$ 3-(11)

$$\overline{\sigma^2} = \frac{1}{n^2}\{(n \times \frac{\sigma_{11}^2 + \sigma_{22}^2 + \ldots\ldots + \sigma_{nn}^2}{n}) + (n^2 - n) \times (\frac{\sigma_{12}^2 + \sigma_{13}^2 + \ldots\ldots + \sigma_{(n-1)n}^2 + \sigma_{n(n-1)}^2}{n^2 - n})\}$$ 3-(12)

Therefore, the Root Mean Square Error of the total demand can be represented as the average variance of individual demand and the average covariance.

$$\overline{\sigma^2} = \frac{1}{n^2}\{n\overline{\sigma_{nn}^2} + (n^2 - n)\overline{Cov}\}$$ 3-(13)

3.5.2 Independent and non-independent demand

Suppose that we consider the error of demand forecast is independent; the item of the covariance will be attenuated. Considering the demands are non-independent, it is not possible to reduce the item of covariance as the increase of n. The number of errors will be attenuated to a particular value in the end. Therefore, the relationship can be described as one between a systematic error and a non-systematic error, as shown in Fig 3.6 based on the 3-(14).

$$\overline{\sigma} = \sqrt{\frac{1}{n}\{\overline{\sigma^2_{nn}} + (n-1)\overline{Cov}\}} \qquad 3\text{-}(14)$$

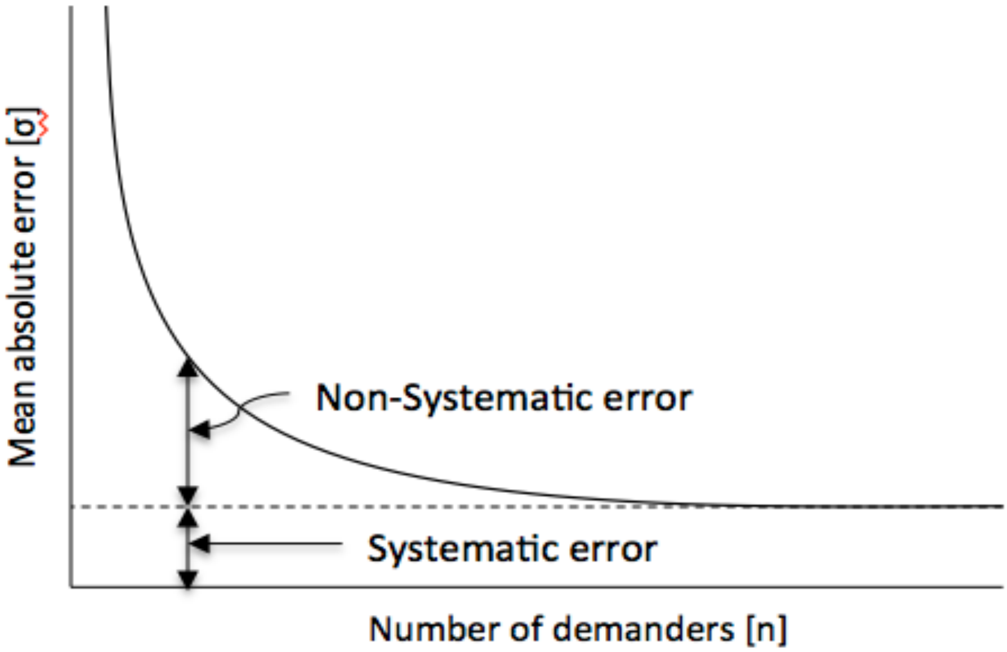


Fig 3.6 *N*on-Systematic error and Systematic error (Made by Author)

3.5.3 Comparison of the predicted results and the theoretical formulas

In Fig 3.7, we show the forecasted result for the three apartments and the sum demands of the three apartments. The vertical axis shows the RMSE and the horizontal axis represents the number of the demanders in each apartment. The final forecast result was around 75 kWh for 112 customers for apartment A. The accuracy of the forecast was gradually improved along with the increase in the number of demanders. Especially, there is a sharp decrease in the first ten demanders, but the slope of decrease started to be converged gradually after the sharp decline. On the other hand, the line is the expected the error calculated from the variance and covariance, and the dots are the exact RMSE calculated for each number of demanders. Fig 3.7 shows the theoretical value is consistent with the data value for each apartment and the sum of each apartment.

We also represent the change of covariance as the increase in the number of demanders in Fig 3.8. The horizontal axis (n) indicates the number of customers, and the vertical axis represents the value of covariance of the forecasted error of demands. When the number of demanders is small, the covariance is also little. But with the increase of the number of demanders, the covariance will attenuate to a particular value. This is equal to the root-mean-square error of each apartment and the sum of the demands of the apartments.

It can be seen that the overall error of each apartment is not significant because the covariance is not related to the number of demanders. Therefore, as a method of error mitigation, it is important to reduce the covariance and remove individual prediction errors. Besides, it is necessary to consider aggregating the demanders having different patterns of demand.

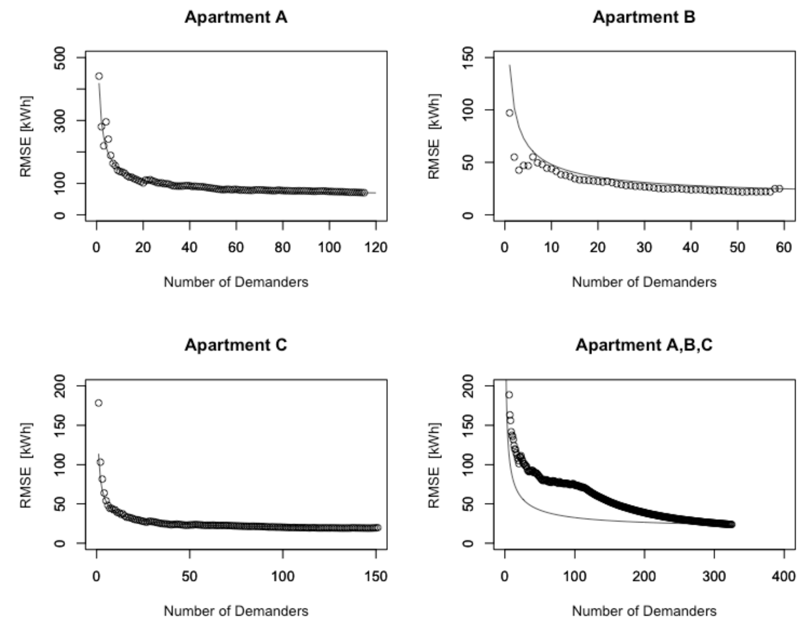


Fig 3.7 Root-mean-square error relationship between the number of customers in apartment A (Made by Author)

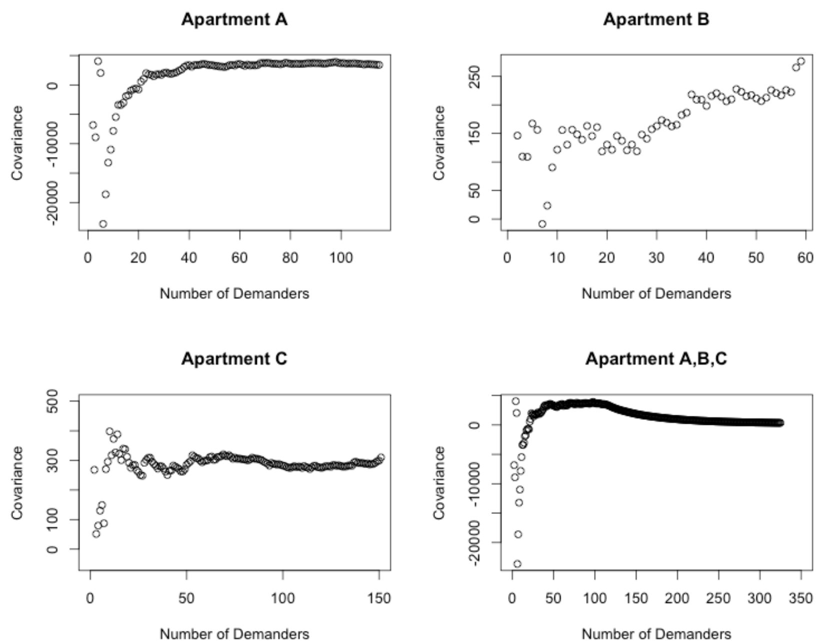


Fig 3.8 Root-mean-square error relationship between the numbers of customers in apartment B (Made by Author)

3.5.4 The analysis of the non-independent error

The reduction of forecasted error by aggregation can by explained by the law of large numbers. In this case, if the error is mutually independent, the error will decrease as n increases due to $1/\sqrt{n}$. However, in this demand forecast simulation, RMSE was attenuated to a constant value as n increased. We assume this was because of the non-independent case of the law of large numbers. Fig 3.9 and Fig 3.10 show the average forecasted error for each apartment. We can find apartment B and C have a more forecasted error in the morning and the evening. The error is not evenly distributed, and there is some bias occurring in each step. Therefore, we consider that there are common tendencies in behaviors of each household that causes the increase of the covariance of the error. The graph indicates the demand sources in the same apartment so that the behavior of each household might be much more similar than that of the random selection of demand sources in the individual districts.

We could demonstrate the mathematical reasons the forecast error cannot be eliminated with the increase of demand sources. As a result, we could understand that this issue is a particular case of the law of large numbers (the case of non-independence). This result can lead to the two policies for reducing the forecasted error. The first one is to improve the forecasting algorithm, and the other is to make a better portfolio for the demand forecasting.

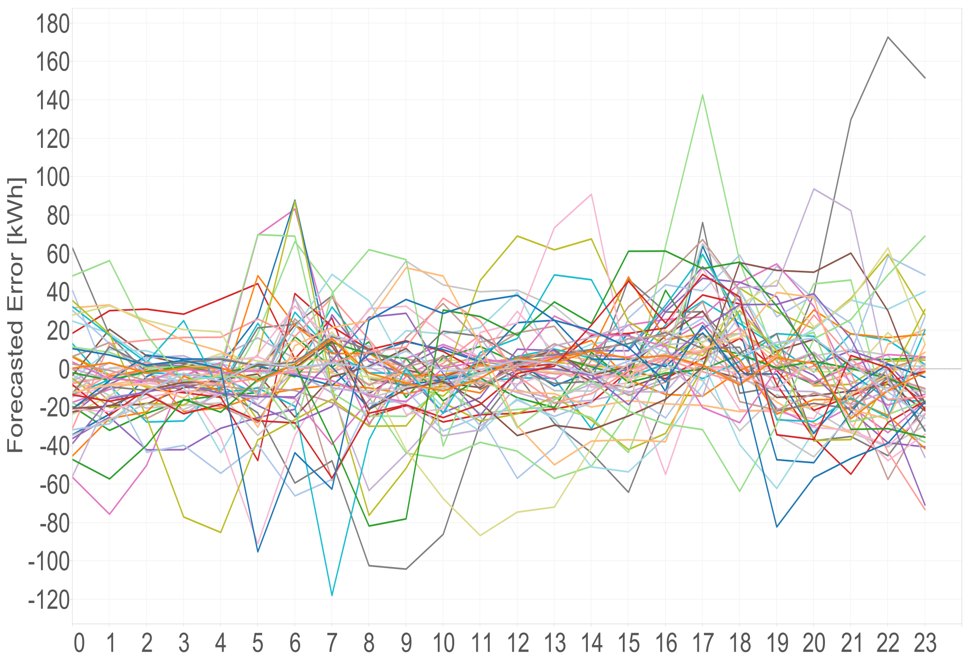


Fig 3.9 Average error for each time of the apartment B (Made by Author)

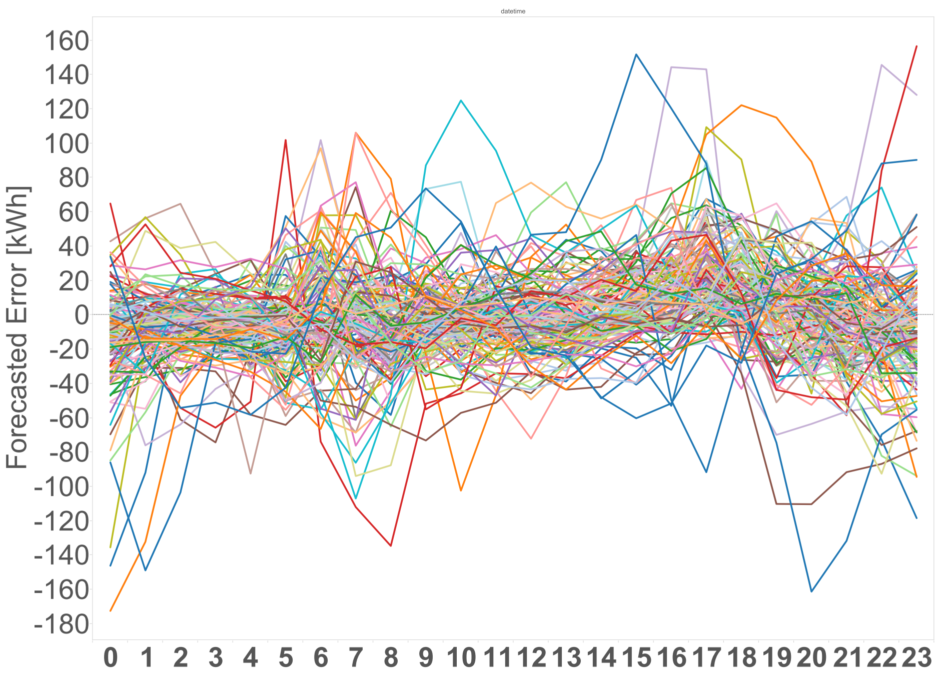


Fig 3.10 Average error for each time of the apartment C (Made by Author)

3.6 Summary

The necessity of accurate demand forecast is increasing in Japan after the market deregulation after 2016 for the new emerging electricity companies. We tested the method to forecast the one-day demand curve targeting for the new Private Power Supplier and tested the accuracy of the method by applying it to different kinds of Machine Learning. By adaption of the Deep Learning and Gradient Boosting, the predictive accuracy was improved .

In the process of examining the relationship between individual demand and the total demand, we could discover the relationship between the individuals and total demands in the electricity demand forecast. In this section, we could demonstrate that the mathematical reasons why the forecast error cannot be eliminated with the increase of demanders. As a result, we could understand that this issue is the particular case of the law of large numbers (the case of non-independence), and the error will be not eliminated because the correlation between the demanders.

As the future perspective, the weather data are the actual data in the past. In the actual situation, the actual weather in the next day cannot be obtained so that it is needed to acquire it from the weather forecast. Because weather forecast is not always correct, it will result in the decrease of the forecast accuracy. To consider this problem, it might be possible to use the actual data with random noise.

As indicated, the electricity market's requirement varies in term of the future forecast. In this chapter, we have indicated the forecast ability to forecast the 1day head demand curve. However, the demand for further short time forecast will occur depend on the usage of the demand forecast. In that case, it is easy to change the forecast target just by changing the training data to shorter span.

4 ELECTRICITY DEMAND FORECAST BASED ON THE LOCAL INFORMATION AND BOTTOM-UP APPROCH

4.1 Background and purpose of this chapter

After the electricity liberalization, we think that the demand forecast is necessary not only for demand adjustment at the power plant but before various electric liberalization, as shown in Figure 4.1, at various levels of the power grid. For example, in the procurement of electricity in PPS, besides that, it is expected to adjust the startup power at the village, city, shopping mall, and industrial park level. Also, have batteries in the apartment. It is also anticipated that each household possesses a battery, and in that case, it is an important question in which level of demand aggregation can make better-forecast result for adjustment for each power supply.

In this chapter, we performed a series of electricity demand foresting and could find that the error mainly occurs based on the non-independent case of the law of large numbers. Then, we check the accuracy of TD and BU model. Based on that result, we present a method based on the BU model and local parameters for the higher accuracy of the demand forecast.

4.2 Existing research

In the recent electricity forecast, especially the research are targeting to forecast for the shorter span like 30 minutes for the demand curve instead of the one-day pick forecast, and the Machine Learning technology is widely applied to it [Hong 2009][Chin 2014]. Usually, the forecast model is applied to the aggregated demand data. This method is widely used, and we can call this method as a Top-Down method (TD)[Dangerfield 2012].

In recent years, the introduction of smart meters has been actively conducted in various countries. With prevailing of the device of Internet of things, the temperature data that is necessary for the demand forecast can be collected in real time. Therefore, it is possible to perform the electricity forecast the each household demand at first and then sum up the results. Referring from another field like production planning and economics, this kind method can be called Bottom-Up method (BU) [Dangerfield 2012]. Whereas the BU model seems to be able to create the most fitted the model for the each household, the TD model is said to be more robust and have less influence on random data. In the field other electricity demand forecast such as production planning and economics [Borges 2012], it was a long- term discussion for the problem that which method can have more accurate result [Dangerfield 2012][Sevlian 2014]. There are few types of research that used the real demand data to have an analysis of which is the better. In this chapter, we applied the BU and TD the electricity demand forecast of the individual household data to evaluate and compare the advantage and disadvantage.

Recently, there are more attentions paid to the local behavior on the smart grid because the smart meter can provide individual demand for each household. There are a few types of research on TD and BU have been addressed in the research of the electricity demand forecast. Borges compared approaches, namely BU, TD in the smart grid [Borges 2013]. At the result, they could found that the BU could provide slightly better or equal result comparing with TD model. Furthermore, the weather parameter is different between geographic locations, and the human behavior is also varied between the households. However, there are a few researches which have examined the local and global relationship. Kobayashi considered the environmental change of in the process of demand forecast [Kobayshi 2006]. He adds the actual weather forecast for the different district in the process of the demand forecast and could show higher accuracy taking the environment change into account.

4.3 Method

4.3.1 Bottom-Up and Top-Down model

We consider that there is no measuring error for the measuring device. We performed the forecast following the procedure indicated in Fig 4.1. The BU forecast starts from the forecast of the local data while the TD forecast starts from the sum up the data and then forecast the sum-up data as illustrated in Fig. 4.1. We have chosen optimum input parameter for the learning of the Machine Learning algorithm following the previous research [Dangerfield 2012].

We have chosen optimum input parameter for the learning of the Machine Learning algorism following the previous research [Chin 2014]. Gradient Boosting is used as the method for the forecasting. Gradient Boosting is a method of a boosting in ensemble study. By combining the weak Machine Learning model. It is said that it is strong for over-fitting and create less variance error. For the evaluation, we used the Means Absolute Percentage Error (MAPE) as the evaluation method because a penalty is set to charge for the over 3% in Japan.

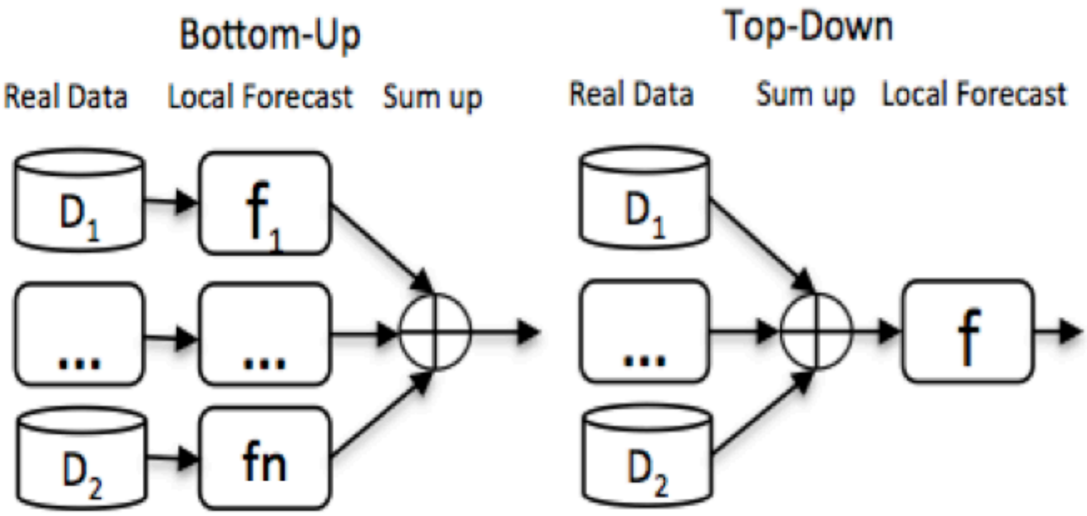


Fig 4.1 Bottom-up and Top-down method (Made by Author)

4.4 Case study

4.4.1 Demand forecast based on Bottom-Up and Top-Down

We did case studies to test the effectiveness of this method using the real demand data. The demand data came from an apartment located in Tokyo area from 4th 2012 to 12th 2013. In the apartment, there are 112 residents. The minimum time span is 30 minutes, 48 steps for a day. We did the forecast and sum-up. Weather data is used in the forecast. In this case study, 75% of the data was utilized for the training, and 25% of the data was used for the forecast validation. The regression model was Gradient Boosting. Input parameters are referring to the past of chapter 3. Input parameters are the following: parameters related to weather information (temperature and humidity), parameters related to power demand (power demand information of the previous day), and parameters related to human activities (holiday, time of day, day of the week).

4.4.2 Results of Demand forecast based on BU and TD

In the Fig.4.2, we show the forecast result for the apartment which residence 152 demanders. The vertical axis shows the MAPE and the horizontal axis shows the number of the demanders. The final forecast result was 6 % for 152 customers. The TD method and BU method were almost same. They have some fluctuation during the change of the size of demanders. The MAPE for 152 the number of demanders is 6.2% for BU and 6.5% for TD. The accuracy of the forecast was gradually improved along with the increase of the number of demanders. Especially, there is a sharp decrease in the first ten demanders, but the slop started to be converged gradually after the sharp decrease. The forecast is the actual data published by Japan Meteorological Agency (JMA). In this case study, 75% data was used for the training and 25% data used for the forecast validation. The parameter for the GBM is carefully tuned. We used R and the Machine Learning library H2O.

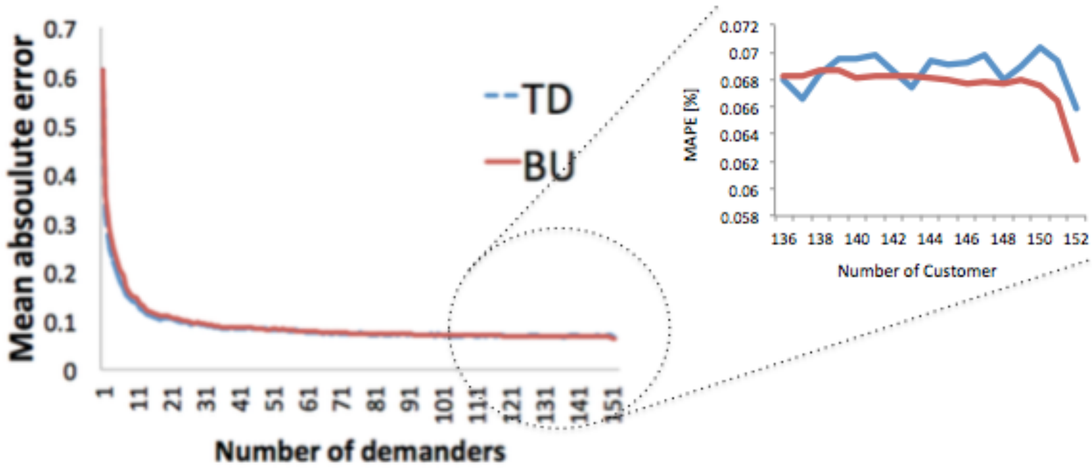


Fig 4.2 MAPE for the Bottom-up and Top-down case study (Made by Author)

We assume that the sharp decrease of the forecast error is due to the "Law of large numbers" in the statistics. To indicate the " Law of large numbers," The transition of the distributions for the BU and TD's error is demonstrated in Fig 4.3, and Fig 4.4, the distribution for the individual forecast error was high, after the aggregation of the error, the variance is lower than the individual one. Similarly, as for the TD case, we also find the decrease in the variance of the demand aggregation before the forecast process. On the other hand, from the practical point of view, the BU method has the disadvantage from the economical point under current electric infrastructure.

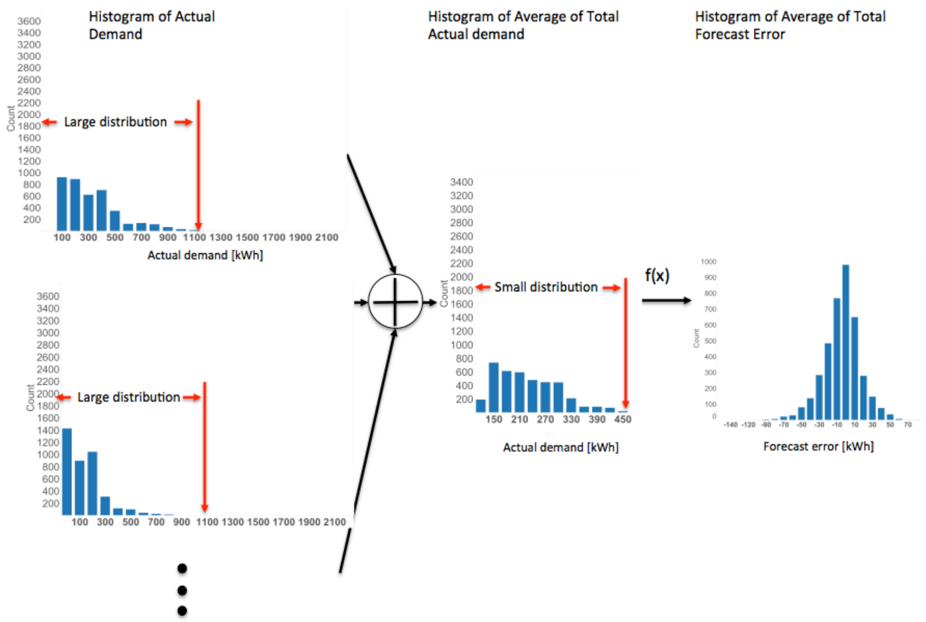


Fig 4.3 Data distribution of Top-down method (Made by Author)

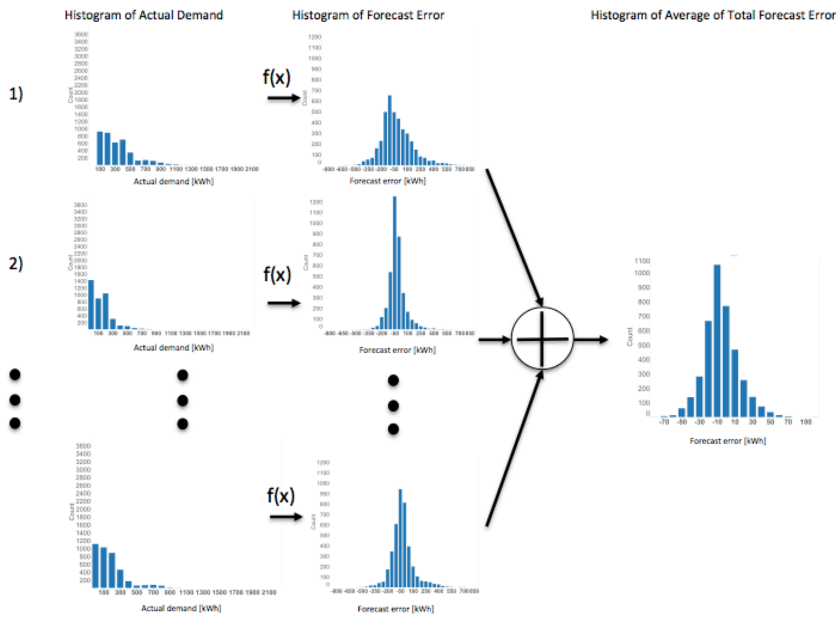


Fig 4.4 Data distribution of Bottom-up method (Made by Author)

4.4.3 Demand forecast based on the information from BU

As the merit of BU model, the BU model also can take advantage of the local data for further improvement of the demand forecast. Here, we have considered that if the forecast can conduct in the local with information from the local. The Local data stands for the local weather information, the local human activity (schedule, location information, and activity information).

For the first case, we find the in or off house information can be acquired. For the second case, we consider much precise temperature can be obtained from the local. Fig 4.5 shows the image for the BU to take advantage of the local information.

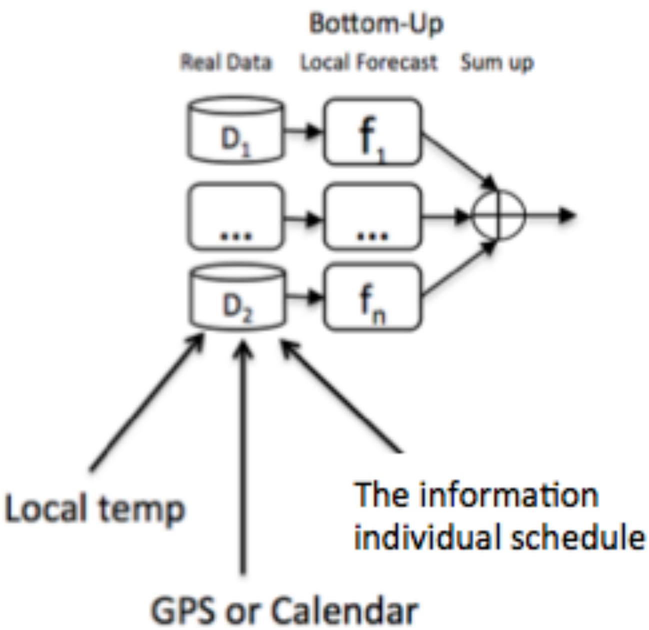


Fig 4.5 Bottom-up method with the local information (Made by Author)

For the simulation, at first, we add the in or off data to the training data set for every household.

1) The case that we know the schedule in advance

The First Case(Red) :We compared the two cases 1) The normal case of bottom-up method without local information.

The Second Case(Blue) :The in or off data was set by the demand level, we used the HMM to determine the in a house or off a house in advance, and then put the in or off house column to the training data set.

2) The case that we know more precise temperature forecasts

The First Case(Red) :To simulate the forecast error in the local, we put the 1.5 standard deviations in random normal distributed error to the TD model, because originally we are using the correct data.

The Second Case(Blue) : Use Accurate temperature forecasts.

4.4.4 Result of Demand forecast based on the information from BU

Fig. 4.6 shows the result of this experiment. At first, we found improvements both in the case of the local schedule case and the local temperature for a significant amount. Especially, to know the local schedule could improve the forecast largely.

By incorporating the absence information beforehand into the demand forecast, significant improvement was obtained. The improved result is about 2%. By inputting accurate weather information, we were able to obtain about 1% improvement.

In the practical case, the local data can be acquired from GPS, sensor at home or the web schedule calendar. Also, to combine the local temperature or humidity sensor has many possibilities to provide the capacity to improve the result.

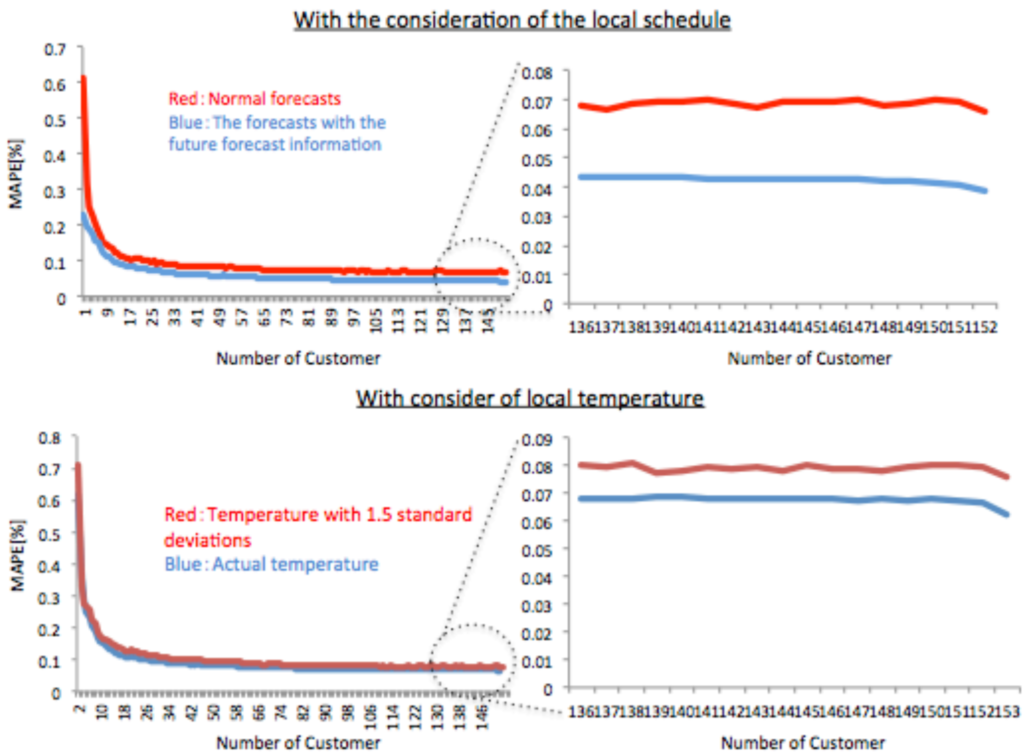


Fig 4.6 Forecast based on GBM (Upper side: forecasted value、down side: actual value (Made by Author)

4.5 Discussion

In this section, it is confirmed whether the demand prediction accuracy improves by using local actual data, using the local data proposed in the previous section. Incidentally, the local weather data (temperature) and the GPS data of the residents are considered as the local data this time. At this time,the validation of Demand forecast based on the local temperature from BU,Discussion(2) The validation of Demand forecast based on the local temperature from BU ,Discussion(3) GPS data and the demand forecast were validated and discussed.

4.5.1 Discussion (1) - the validation of Demand forecast based on the local temperature from BU

4.5.1.1 Method applied for validating the local temperature difference

In 4.3.5, we assumed that the temperature fluctuates randomly by 1 or 2 degrees, we did not know how much the temperature depends on the area. In this section, We verified how correct that assumption is.

To validate the temperature difference between the areas, we measured the temperature of two locations. First one is author's home and a second is the Kitanomamaru Park in Tokyo which is the official temperature measurement. The location of the two place is indicated in Fig 4.7. The two places are around 4km. Also, the in-house temperature and out-house temperature were measured by the sensor indicated in Fig 4.8.

Fig 4.7 Map showing the points that measuring the temperature data (Made by Author)

Fig 4.8 Sensor used for the validation of the local temperature and the central temperature gap

The specification of the temperature sensor is indicated below; we performed measurement from 10/31/2016 to 11/4/2016 every 1min in the three location.

- Measurement temperature range (° C): -30 to 60
- Temperature minimum indication (° C): 0.1
- Number of data memory: 16000
- Measuring accuracy: ± 1 ° C
- Operating temperature: -30 ° C to + 60 ° C
- Record interval: 10 seconds to 24 hours
- Sensor: internal NTC thermal resistance

4.5.1.2 Results for validating the local temperature difference

The comparison between The Temperature in Kitanomaru Park and The temperature on the out side of author's house were performed. As the Fig 4.9 indication, The Temperature in Kitanomaru Park and The temperature on the out side of author's house has some temperature gaps. The distribution of the gap is indicated in the Fig.4.10. The average of the gap is 2.2℃; the standard deviation is 2.4 ℃. That means the temperature might change depending on the location and the environment even in the very close location. As a matter of fact, the temperature and other weather condition are different depending on the measuring point so that the point-to-point weather forecast is necessary and the local temperature measurement is important. Right now, the measuring point of the temperature is very rough. However, the much precise measurement of the temperature, humidity and provide higher accuracy.

Fig 4.9 Measured the temperature data in the local and central (Made by Author)

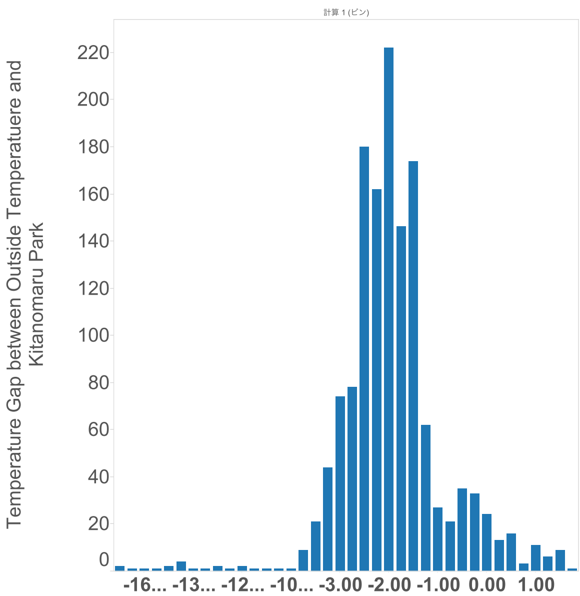


Fig 4.10 Gaps between the temperature in Kitanomaru Park and the temperature on the out side of author's house

The temperature gap between the temperature of the out-side of author's house and the temperature of the in-side of author's house is indicated in the Fig.11. It is considered that the temperature in the room can reflect the human sensible temperature more and there is a possibility of obtaining better prediction. In fact, the average temperature difference between room and outdoor was 5 ° C, and the standard deviation was 1.5 ° C. However, since this measurement was very simple and precision was lacking in some cases, it is necessary to carry out detailed measurements in the future and discriminate.

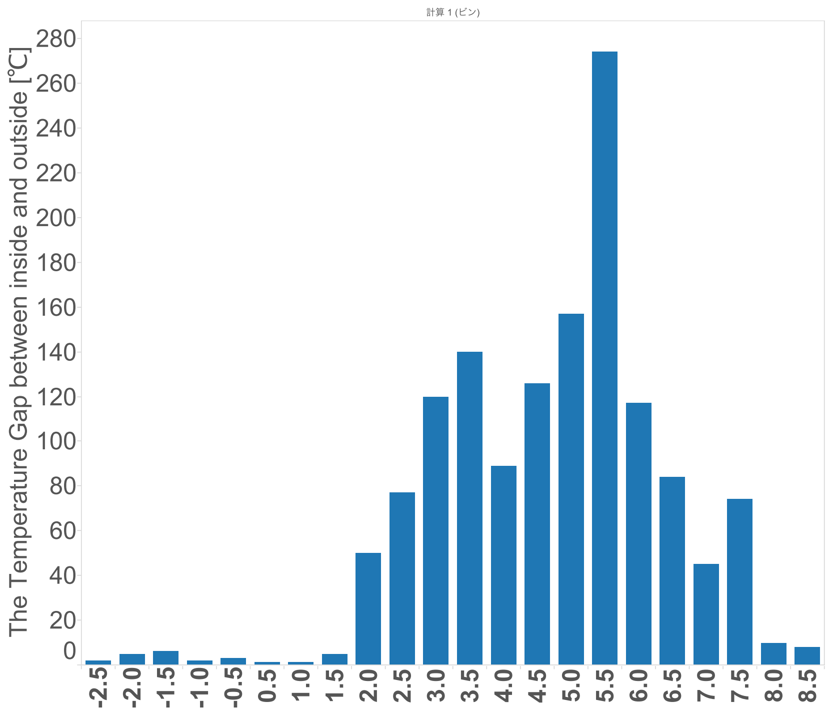


Fig 4.11 Temperature gap between the temperature of the out-side of author's house and the temperature of the in-side of author's house (Made by Author)

4.5.2 Discussion (2) - The validation of Demand forecast based on the local temperature from BU

As to whether the room temperature has prediction ability, verification was carried out using data of the energy consumption database in the house. It shows the relationship between temperature data of living room and demand for one year in a house in Kashiwa City, Chiba Prefecture(data set no.06 in Kanto area). This data utilized the data set provided by the Japanese Architectural Institute[JAA 2016].

The comparison was made using the energy consumption database in the housing provided by the Japanese Architectural Institute. Comparing the contents, we compare their fit rates by creating models with external temperature, internal temperature, and demand. I used the weather stations located in Abiko near Kashiwa outside. We used the internal temperature already provided in the data set.

A quadratic curve was used to show the relationship between temperature and demand. It was found that the fitness rate was higher for the internal temperature and the demand..As indicated in the table 4-1, It can be seen that the temperature of the leaving room was the best fitting for the temperature sensitive demand of this house. Fig 4.12 shows the plot between the temperature and temperature sensitive demand for three locations

As with Kobayashi's research, utilizing more detailed demand forecasting, rather than utilizing the weather parameter in the center leads to more accurate demand forecasts, but by utilizing local information it is possible to predict more accurate demand I think that it will be connected.

Table 4-1 Model fitness between Temp. measured in different places

(Made by Author)

	Tokyo Temp.	Abiko Temp.	Living room Temp.
MSE(Mean Square	169	169	127.6

Error)			
R^2	0.57	0.57	0.68

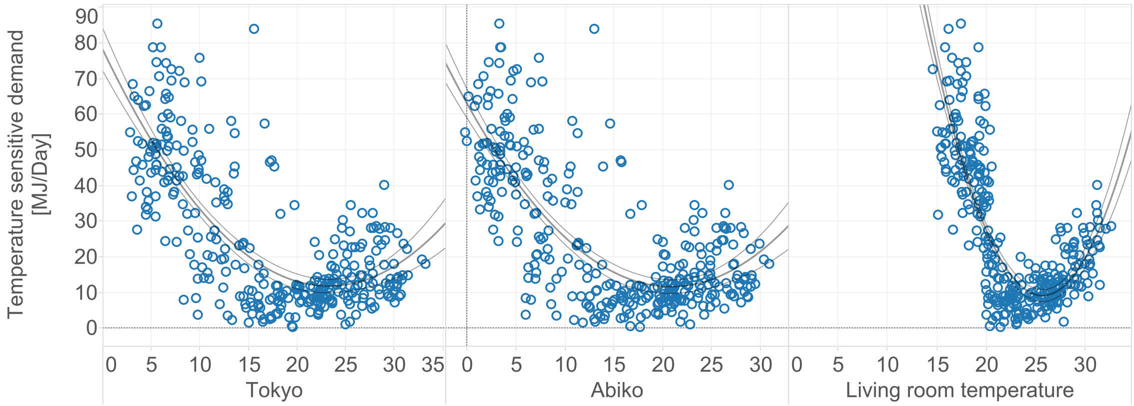


Fig 4.12 Plots between the temperature and temperature sensitive demand for three locations (Made by Author)

4.5.3 Discussion(3) - GPS data and the demand forecast

4.5.3.1 Method for the validation of the GPS model

The author is a university student living along in the Bunkyo area. The GPS data can have information for the electricity usage. We I am an out home. There are almost no appliances used, and I move close to my home. The possibility might be higher. It means that the GPS data can forecast the electricity demand. Moreover, it stands for that the local data for the human activity will affect the electricity demand.

I have recorded my GPS data from for every 5min(2016/10/24 ~2016/10/29, 1472 steps).Fig 4.13 shows the data plot for the GPS data base on the activity between 2016/10/24 ~2016/10/29. The data is recorded in the JSON format by the APP called “ZwiteGPS." Moreover, we performed the demand forecast based on GBM. The input parameter was time step dummy variable, demand itself and GPS data, the target parameter is the demand 10 min ahead. We took 70 % of data for training and 30% data for validation). Regarding missing values, we made up for the context. The input parameters are the distance from the home calculated from the demand in the past 30 minutes and the GPS information.

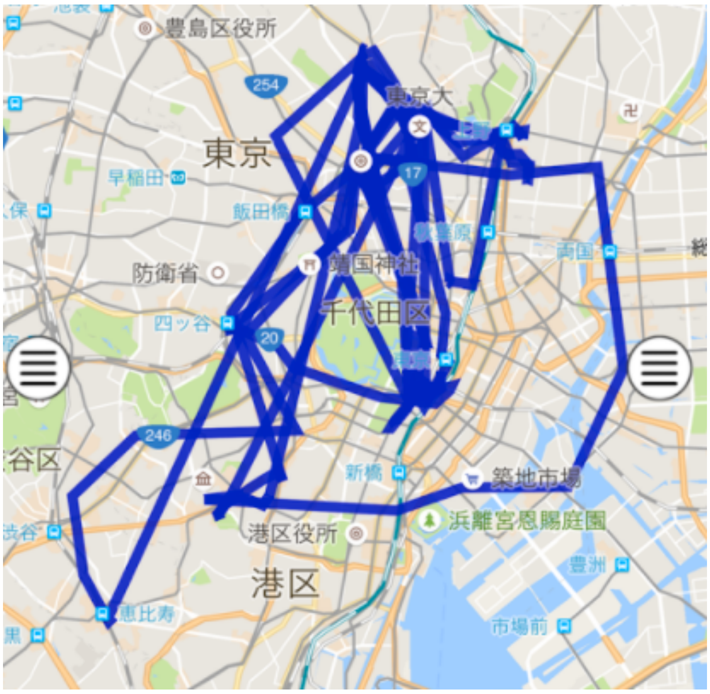


Fig 4.13 Data plot for the GPS data base on the activity between 2016/10/24 ~2016/10/29 (Made by Author)

4.5.3.2 Results for the validation of the GPS model

Due to the experiment limitation, I could not indicate that it is possible to improve the global demand forecast. The results showed that GPS have an ability to create the higher ability to forecast the local electricity demand. The result is indicated in the Fig 4.14. It shows the forecast result with GPS data and without GPS data. The result with GPS data is 22% in MAPE, and the result without GPS data is 27%. In this time, there are few data, and it is only showing the possibility, but I think that it is possible to more strictly show the relationship of demand by increasing the number of data.

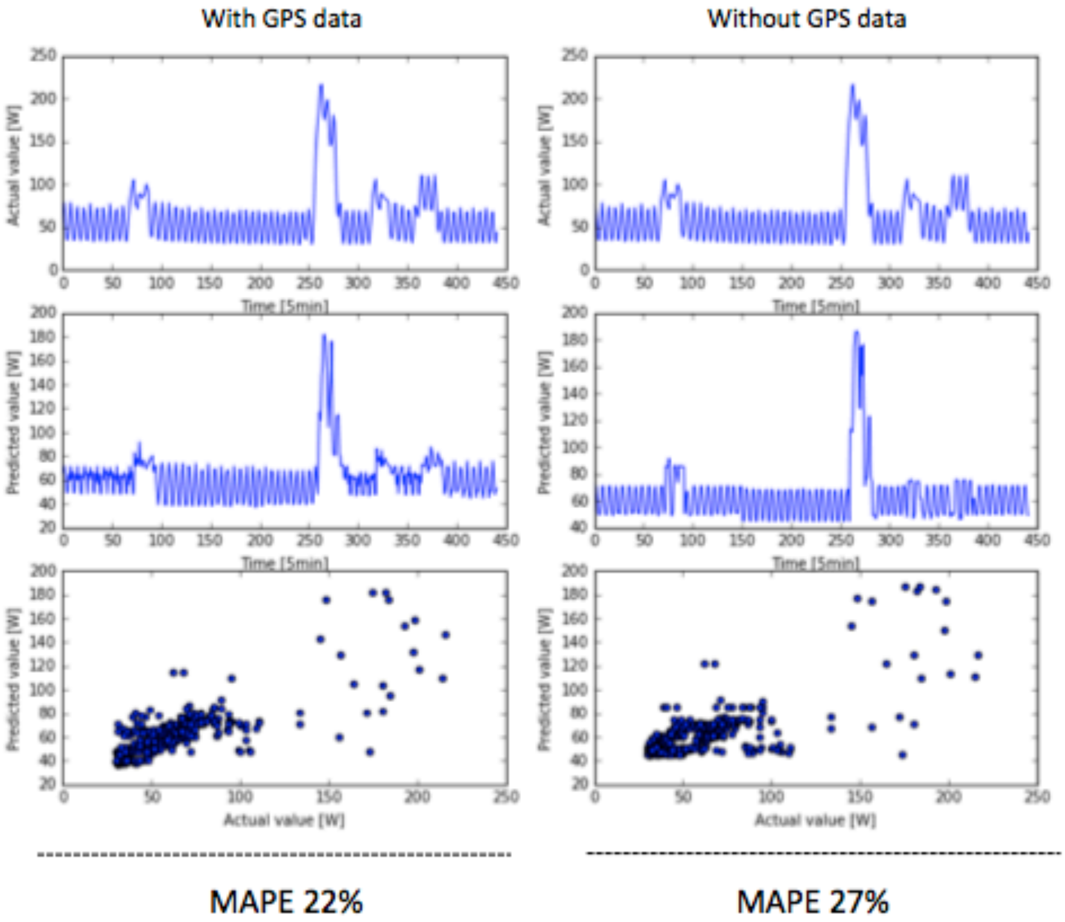


Fig 4.14 Result for the demand forecast based on GPS data (Made by Author)

4.6 Summary

In this chapter, we could demonstrate that the there is not a huge difference between the two methods in term of the accuracy of the forecast. However, it seems the BU method have slight accuracy than the TD method. For the future perspective, taking advantage of the result, we research the improvement of the forecast error by the accurate measurement of the local parameters for the forecast such as temperature. Fog computing based smart meter can enhance the BU model for better demand forecast.

This research shows the superiority of the bottom-up method which is not currently adopted in smart grid , showing the superiority of the bottom-up method which could not be analyzed in existing research. Especially, the local is overflowing with local information so that bottom-up method is well-matched, and it shows significance from the point that it is easier to distribute calculation resources in local. Forecasts of local weather and human activities would predict demand more than forecasting by top - down information alone.

5 HOUSEHOLD ELECTRICITY DEMAND DISAGGREGATION BASED ON LOW-RESOLUTION SMART METER DATA

5.1 Background and purpose of this chapter

The visualization and energy-saving diagnostic services such as electricity disaggregation based on smart meters have earned greater attention. If we can classify the electricity demand into possible groups, we can analyze the behavior of each state. The total research has many practical applications such as remote life pattern diagnosis, life pattern abnormal detection, in-house or off-house suggestion for the delivery service or targeted advice or demand response programs intended to reduce the demand of customers and make effective comparisons among electricity users

In this chapter, we propose a method that can extract electricity usage patterns based on the unsupervised method from the electricity disaggregation of low-resolution data. There are two kinds of disaggregation. First is based on the electricity demand itself; we disaggregate the demand based on the distribution and the amount of value. The second is based on the electricity demand and the related parameter. Here, we consider the related parameter is out-side temperature, and disaggregated the electricity demand based on it.

5.2 Existing Researches

Electricity disaggregation is a process for deducing the life patterns and usage of appliances by detecting and identifying changes in the voltage, current, and amount of power going through a house. The type of electricity disaggregation could be classified by the power-measuring interval of data [Armel 2012]. K. Armel et al. indicated a summary of patterns across existing electricity disaggregation work. A 1 min-1 second data frequency starts to be able to differentiate each appliance and the top 10 appliance types based on the information of steady state steps/transitions of power [Armel 2012]. As the data frequency gets finer, the capacity of the appliance recognition rises. Contrary to the various possibilities of the electricity disaggregation-based high-resolution smart meter, in Japan, the main electricity companies have decided to install the smart meter with 30 minutes as the measuring interval for households. Also, it is general to use smart meters based on a sample value with a 60~15 minute measuring interval in many other countries such as UK, Australia, and USA [AEC 2016][E UK 2016][PE USA 2016]. These facts show that in the future, the penetration of a low-resolution measuring (low sampling interval) smart meter will be much higher than the high-resolution smart meter. In previous research, electricity disaggregation using high-time resolution data was widely studied. On the contrary, data analysis methods for smart meters with low time resolution are not sufficiently developed [Armel 2012]. Furthermore, as the analysis method, the electricity demand clustering based on k-means or EM algorithm has been used for the purpose of marketing and grouping [Chicco 2003][Christoph 2012] to reveal the patterns and trends in the demander group. Kleiminger proposed a data set and supervised method for the occupancy detection. [Kleiminger 2015]. However, the clustering of the specific time series of the electricity demand has still not been researched. The comparison of electricity usage between residents is effective in energy saving, according to previous research [McLachlan 1997][Zhou 2013] [Laskey 2013].

In Japan, Central Research Institute of Electric Power Industry Japan has an active research on the field. As the occupancy detection, Hatorri has researched that actual demand estimating algorithm is therefore applied to low-resolution smart meter data and developed the research idea of supervised learning proposed by Kleiminger [Hatorri 2016]. Occupancy detection is implemented with the estimated demand data, and this result shows accuracy and precision are improved compared to the result with raw smart meter data. They show that supervised Machine Learning algorithms can forecast occupancy with accuracy between 83% and 94%. According to the method of Chen et al., The power demand data in the interval are determined using the maximum value, the standard deviation, the range (the difference between the maximum value and the minimum value), and three statistics A threshold value is set in advance, and a period exceeding the threshold is judged to be at home, and the another period is judged absent [Chen 2014]. However, it is more realistic to do unsupervised learning than supervised learning. Also, because the house base demand is different for each household, it is difficult to just give a threshold and to determine the absence of residence. Therefore, we think that a method like learning without teacher is required.

In the paper by CRIEPI in 2016, Kleiminger is cited as an example of HMM, but Kleiminger does not estimate transition probability and state probability unsupervised using the Baum-Welch algorithm, but instead uses a mixed Gaussian model while using teacher data at that time[Kleiminger 2015]. In addition, Kim's paper is a study of absence, but he is doing teacher learning for each event using high frequency data, and based on Hidden Markovs proposed in this research.　I

Komatsu noticed the importance for disaggregation of the temperature sensitive demand. He used the regression based on method for the disaggregation and compared the result with the actual data [Komatsu 2016]. However, Their model only calculates the temperature sensitivity demand on a daily basis and does not show the calculation method in each time zone.

5.3 Methods

A Hidden Markov model is a tool for representing probability distributions over sequences of observations [Eddy 2004]. Here, we have two rough steps; the first step is to calculate the hidden states for the time series data that was generated by the smart meter. The second step is to analyze and compare the disaggregated data so that it is possible to provide targeted energy-saving advice to a particular state. Also, comparing the time series of the residents is valid in energy saving, according to previous research [[McLachlan 1997]. Furthermore, we introduce the average electricity usage of the analysis. The point for this kind of clustering is that it is different from the typical clustering method because it is possible to separate and cluster the time series, depending on the pattern of the different time series. Furthermore, We can introduce the way to separate the demand for the state to more than three states to help the demander to identify the demand patterns and life patterns.

5.3.1 Hidden Markov Model

When the hidden states (A,B,C..) are defined as Q:={q_1,q_2,q_3...q_n},(1) is the posterior probability to have the observation:={ y_1, y_2, y_3,...y_n},and it can be defined as below 5-(1).

$$P(Y|Q) = \pi_{q_0} \prod_{t=1}^{n} a_{q_t q_{t+1}} b_{q_t}(y_t) \qquad \text{5-(1)}$$

Where,

π_{q_0} = The initial emission parameter in the state q_0.

$b_{q_t}(y_t)$ = Emission parameter for an observation associated with state q_t.

$a_{q_t q_{t+1}}$ = Probability of transition from state q_t.

Hidden Markov model can estimate the hidden status by Baum-Welch algorithm and Viterbi algorithm. Baum-Welch algorithm is used to find the each parameter including the initial parameter distribution, the transition distribution and described in the above Viterbi algorithm is a dynamic programming algorithm for finding the most likely hidden states for the coming the test sequence. The difference between the Hidden Markov model and another clustering model is that the Hidden Markov model is targeting the time-series to find the hidden states for each input data. Specially, the previous time series route will be considered in the decision process of the hidden status so that the distribution of the time series will be considered. Here, we consider the electricity demand (30 minutes) as input data, try to find the suitable hidden-state based on the emission parameter and probability of transition. The disaggregated hidden states cannot represent some specific appliance, but it is possible to show the certain state that has particular distribution and value. We call this hidden state life pattern. Life pattern can stand for active or in-active state or more specific pattern.

For the unsupervised occupancy disaggregation model based on Hidden Markov model. The data we used for the generation of the transition matrix state matrix and initial state parameters is the individual house demand data that has 48 steps per day. As the result, the total algorithm will estimate the 2 hidden states that stand for the occupancy of the house for each single data.

5.3.2 Temperature sensitive disaggregation

In Japan, the temperature sensitive demand is consisting of around 30% of the total demand of household [Eddy 2004]. Also, once the control device of the temperature demand has been reported, it can reduce the house energy consumption around 20% in the USA. It means that to indicate the approximate temperature sensitive demand has the potential to help the demanded to perform the energy saving. We performed the disaggregation for the temperature sensitive demand; the status can indicate the life activity that is sensitive to the temperature. The temperature sensitive demand can be calculated by the procedure below. The basic idea of temperature sensitive disaggregation is to take advantage of the gap of demand between the time (season) that is not temperature sensitive and the time (season) is temperature sensitive. We consider the gap is the temperature sensitive. Fig 5.1 shows that the process of Temperature sensitive disaggregation.

The data we used for the estimation of the temperature related demand are the demand 48 steps / day and the averaged temperature data 48 steps /day. Based on the 2 kinds of data we can calculate the approximate ratio for each step.

1. Build a model between average temperature per day and average electricity

demand per day based on more than one-year data. It can be represented in the Quadratic equation form (The case of electricity demand in Japan).

$Y_{load} = T^2 + T + c$, where T is the average temperature per day 5-(2)

2. Calculate the lowest average demand in a year, set it as Y_{low}, and calculate the ideal demand for each step ($Y_{ideal,t}$) for the temperature in that step (t) based on the equation 5-(2).
3. Calculate the Y_{gap} between ideal demand ($Y_{ideal,t}$)and lowest demand (Y_{low}).
4. Calculate the temperature sensitive demand $Y_{temp,t}$ for each step(t) based on the equation 5-(3)

$$Y_{temp,t} = Y_{actual,t} \ / \ Y_{ideal,t} * Y_{gap,t} \left(Y_{gap,t} >= 0 \right) \qquad (5.3)$$

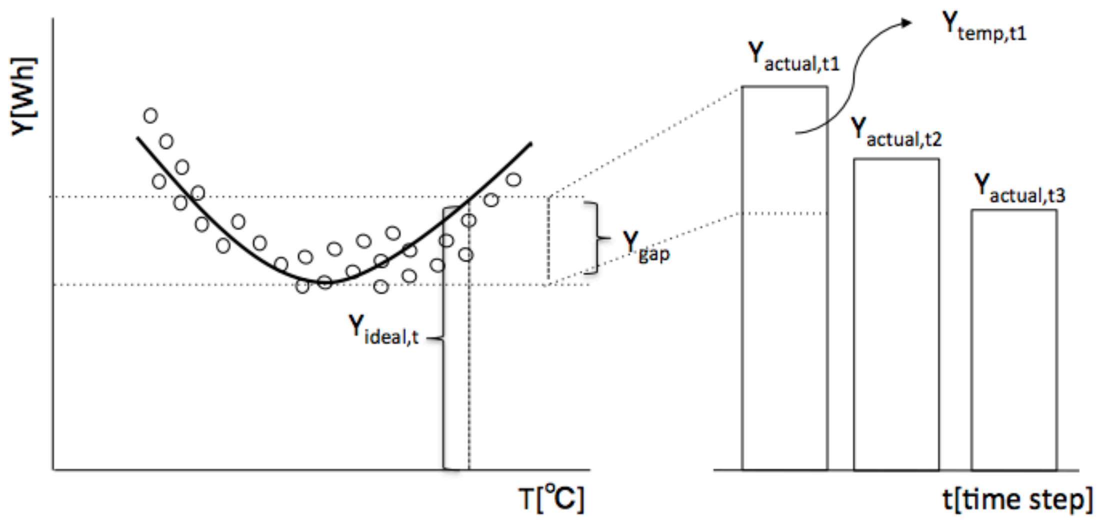


Fig 5.1 Process of temperature sensitive disaggregation (Made by Author)

5.4 Case Study

In the case study, we performed the disaggregation for the occupancy detection and the

5.4.1 Example of Eco data-set

To verify the accuracy of presence / absence judgment, ECO data set [Kleiminger 2015] which is a public data set is used. The ECO data set is a data set for occupancy detection research. It was collected in 6 households in Switzerland. The ECO data contains several houses demand data recorded in every 1 second for the summer time. This data set also contains the occupancy data. We performed the HMM occupancy disaggregation method to validate the accuracy of this method for the house 1 and house 2 in the data set. The accuracy is validated by accuracy (5-(4))and precision(occupancy) 5-(5)). The night time is eliminated because the sleeping time is hard to be detected just by the appliances activation.

- Accuracy

(TP: True Positive, FP: False Positive)

$$\frac{TP + TN}{TP + FP + FN + TN} \qquad 5\text{-}(4)$$

- Precision (Occupancy)

(TP: True Positive, FP: False Positive)

$$\frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \qquad 5\text{-}(5)$$

5.4.1.1 Validation of The example of Eco data-set

We performed the disaggregation for two houses. The data used in the ECO data set are no.1 house and no.2 house in the Switland. Due to the missing value problem. No.1 house in data is between 1st of August to 10th of August. No.2 house in data is between 20th of July to 30th of July. Fig 5.2 shows the example of the ECO data set for the No.1 house in the data. To separate this into two states on a computer, we consider the necessary algorithm to be a hidden Markov algorithm. In table 5-1, it shows the result of disaggregation that is possible to disaggregate the demand into two states. Following the previous research, night time 00:00 ~ 7:00 was taken off from the calculation because the sleeping time is hard to distinguish from off-house state just based on the electricity demand.

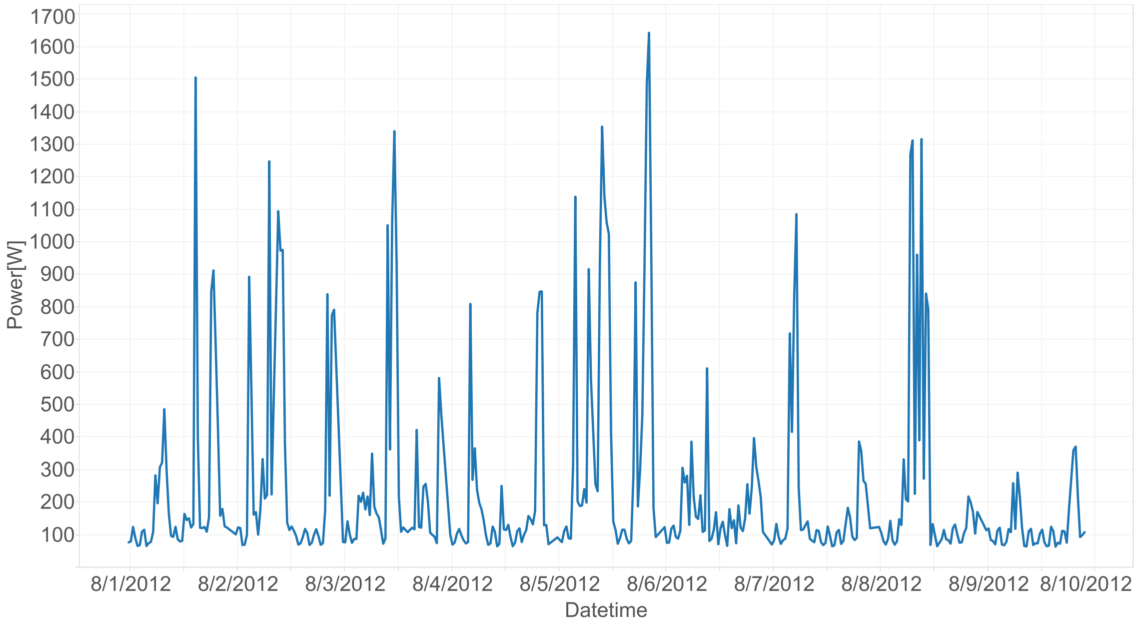


Fig 5.2 Electricity demand from the ECO data set for validation for house 1 (Made by Author)

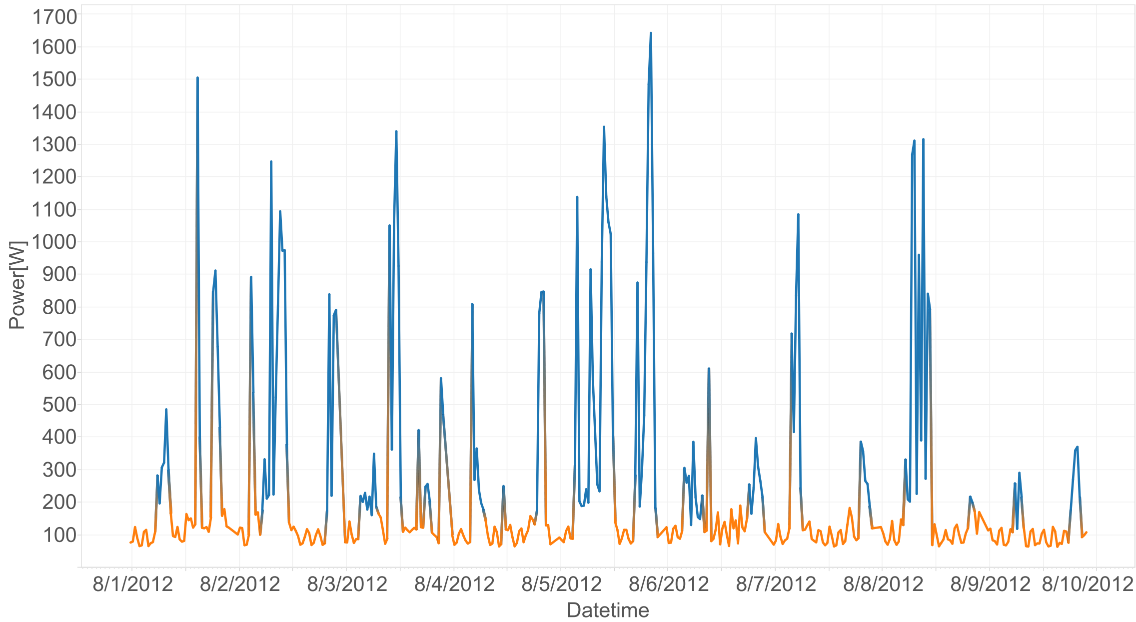


Fig 5.3 Result of disaggregation (HMM) for the ECO data set for house 1 (Made by Author)

We compared the result with the result shown in the Hattori's research (Central Research Institute of Electric Power Industry Japan)[Hattori 2016](Table 5-3). The estimation for the off-house is not that collect. The supervised method provides a better result than the HMM method. On the other hand, we could found that the precision of the two houses is worse than the supervised method. However, the occupancy forecast is as well as the result of the supervised forecast. Therefore, for the actual needs, we can utilize the result to show the in-house state.

Table 5-1 Result of disaggregation (HMM) for house 1 (Author' s work)

		Predicted Data	
		Off-house	In-house
Actual Data	Off-house	174	12
	In-house	191	190

Table 5-2 Result of disaggregation (HMM) for house 2 (Author' s work)

		Predicted Data	
		Off-house	In-house
Actual Data	Off-house	103	9
	In-house	29	189

Table 5-3 Comparison of result between previous research [Hattori 2016] and HMM (Made by Author)

	Accuracy	Precision (off-house)	Precision (In-house)
Previous research(SVM)	0.861	0.662	
House1	0.64	0.47	0.94
House2	0.88	0.78	0.95

5.4.2 Example of the condominium in Tokyo area

5.4.2.1 Disaggregation result of Occupancy demand in the condominium in Tokyo area

We used the data of a condominium in Tokyo area in Japan. The term of data is one year (2013/1/1~2013/12/31), and the time step of data is 48 steps per day (1 step is 30 minutes). The number of electricity demanded in the condominium is 75.We performed the calculation of the hidden state of the time series. Fig 5.4 shows the result of disaggregation based on HMM. We consider that there are two states in the time series. One state is the resident has active behavior (active state); another state is that the resident has inactive behavior (inactive state). It shows that the two states could be clearly separated (The darker part indicates the inactive pattern, and the light part indicates the active). In contrast, Fig 5.5 indicates the result of disaggregation based on the K-mans method that is a general method for the grouping and clustering for the electricity demand. Here, we can find that the k-means method could not classify the status of the active and inactive state. Also, the one advantage of using the Hidden Markov model is that the Hidden Markov model can take the duration of loads into consideration and do not have to make criteria for each time series. For instance, in Fig 5.4, the cycle part was not selected for an inactive state because of the fluctuation of the demand.

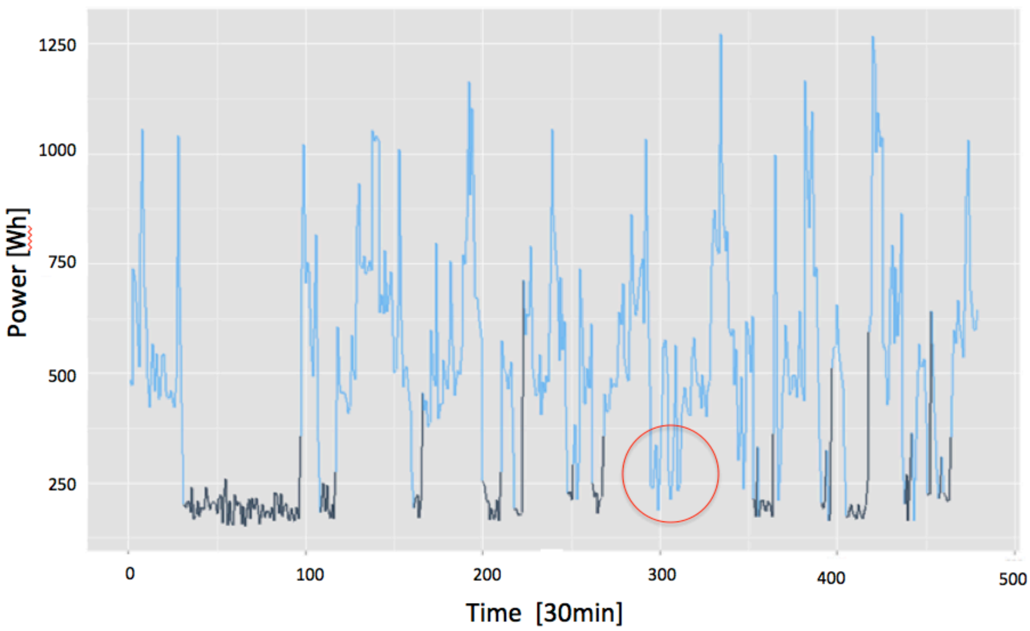


Fig 5.4 Result of disaggregation (HMM) for condominium in Tokyo area (room A) (Made by Author)

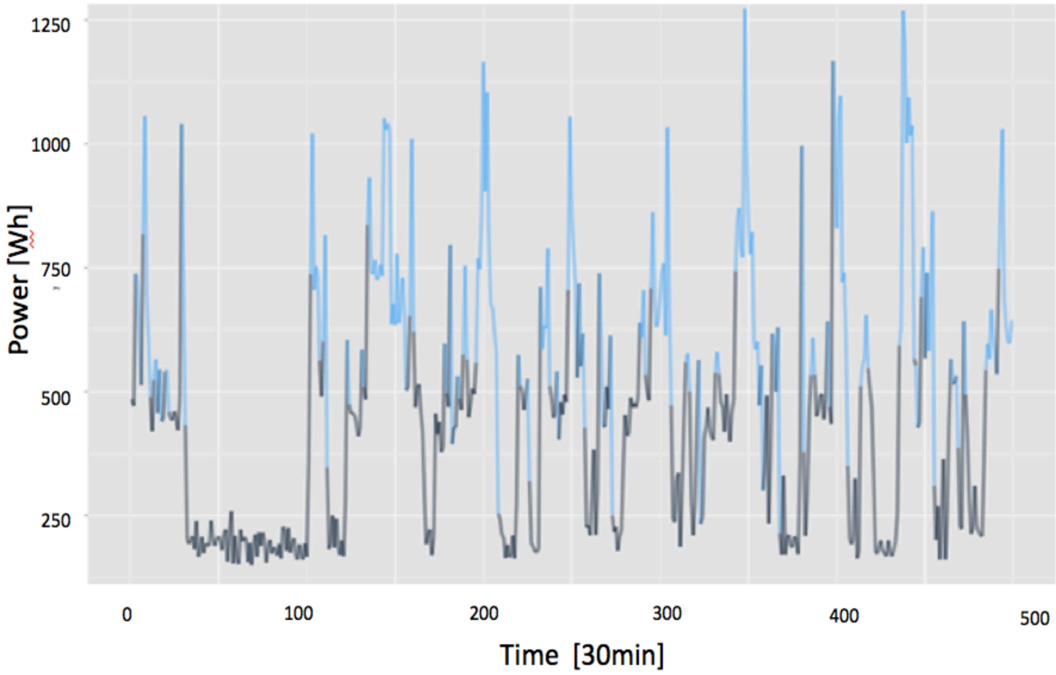


Fig 5.5 Result of disaggregation (k-means) for condominium in Tokyo area (room A) (Made by Author)

5.4.2.2 Classification of result of the Occupancy demand for the condominium in Tokyo area

Fig 5.6 and Fig 5.7 show that the result of disaggregation (HMM) for a condominium in Tokyo area room B and C, Confirming the demand in condominium data in Tokyo, it can be seen that the size of the demand estimated to be absent is different for each family. For example, in Fig.5.6 it is about 50 Wh of the base power supply, whereas in the household in Fig 5.7 it is found to be almost 200 Wh. Since the nature of the base power supply is different in this way, we think that the unsupervised HMM model is effective rather than a simple condition judgment.

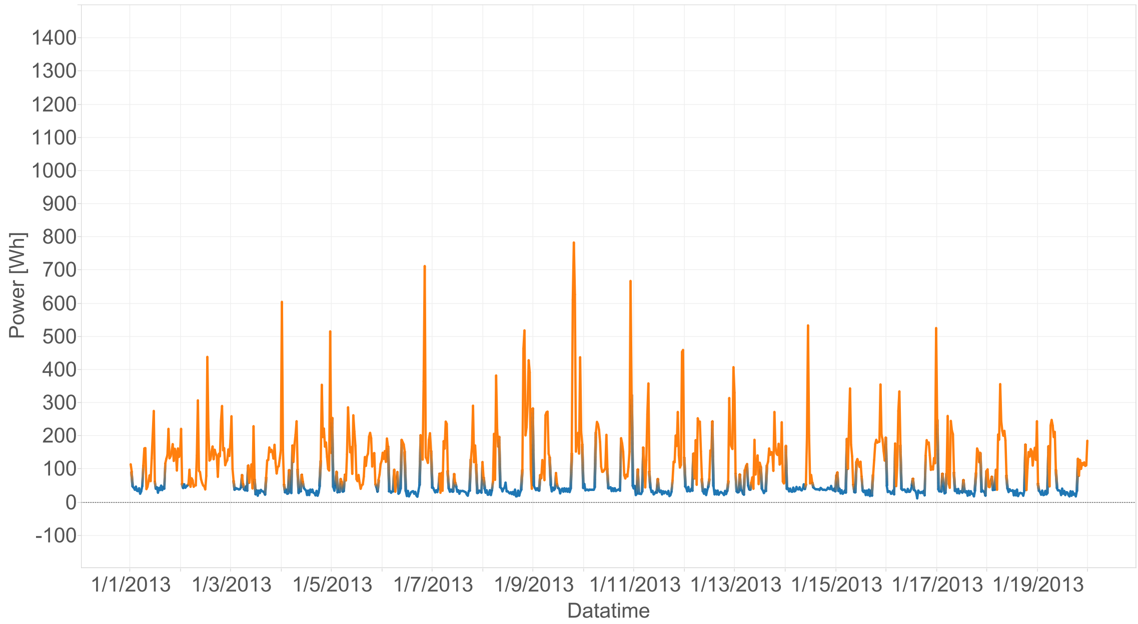


Fig 5.6 Result of disaggregation (HMM) for condominium in Tokyo area room B (Made by Author)

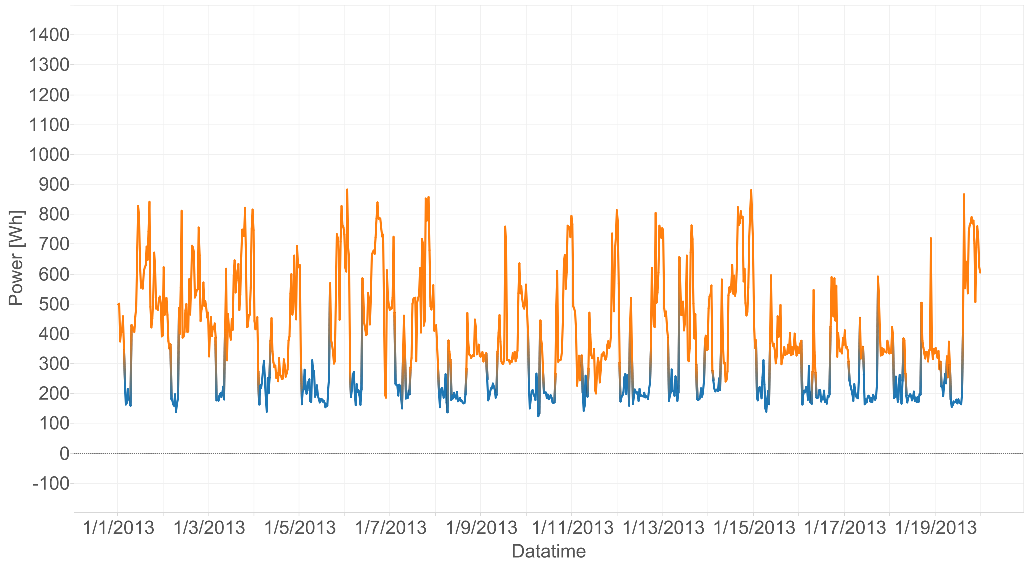


Fig 5.7 Result of disaggregation (HMM) for condominium in Tokyo area room C (Made by Author)

5.4.3 Temperature sensitive demand disaggregation

5.4.3.1 The example of data from Japan Architecture Academy

In this analysis, we obtained the electricity demand data from Japan Architecture Academy [JAA 2016]. This data set contains several household data that contains the total demand in a house, temperature sensitive demand and temperature recorded in the living. This house is located in the Kyoto (DB ID is WEB02). The number of the family is four people, and the area is 70 square meters. Fig 5.8 shows the one-year data of the total demand and temperature for this house. The one-year data is recorded every 30 min. Fig 5.9 shows the relationship between Temperature and total demand. We could find a slight dependency between the temperatures and total demand.

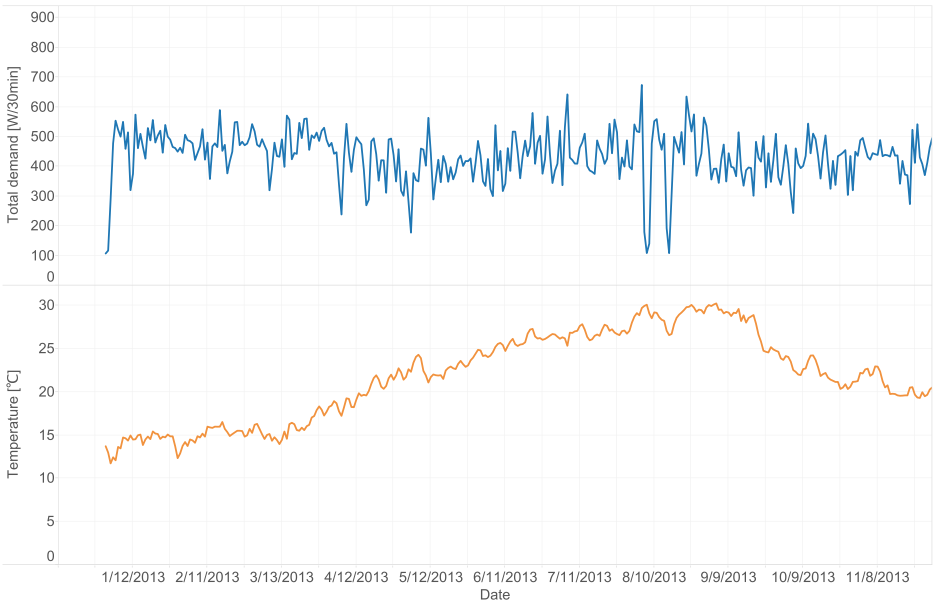


Fig 5.8 One-year time-series data of the total demand and temperature for the house in Kyoto (DB ID is WEB02) (Made by Author)

5.4.3.2 Result of temperature sensitive demand disaggregation for data from Japan Architecture Academy

1) We calculated the one-year demand forecast model based on the temperature.

Build a model between average temperature per day and average electricity demand per day based on more than one-year data. The Quadratic equation model is represented in the $0.783*T^2-35.84*T+835.43$,where *T* is the average temperature per day. (Fig 5.9 shows the relationship between Temperature and total demand.)

2) Calculate the lowest average demand in a year, set it as Y_{low}, and calculate the ideal demand for each step ($Y_{ideal,t}$) for the temperature in that step (t) based on the equation that we calculated.

3) Calculate the Y_{gap} between ideal demand ($Y_{ideal,t}$)and lowest demand (Y_{low}).

4) Calculate the temperature sensitive demand $Y_{temp,t}$ for each step(t) based on the equation derived in 1).

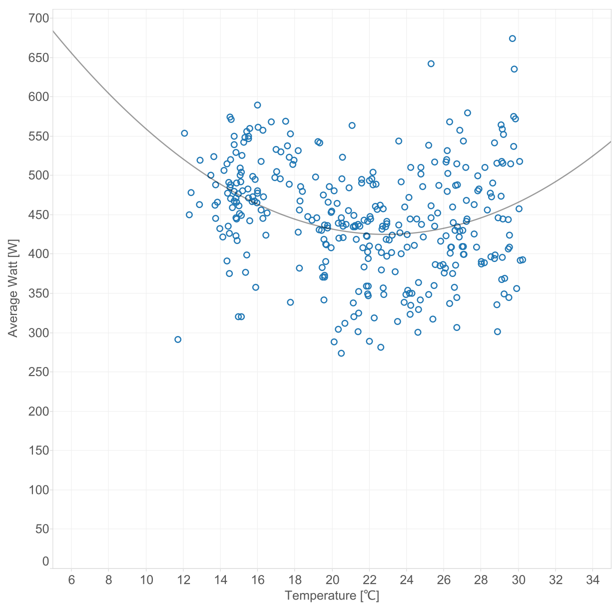


Fig 5.9 Relationship between Temperature and total demand for the house in Kyoto (DB ID is WEB02) (Made by Author)

5.4.3.3 Validation of temperature sensitive demand disaggregation

We validated the result of disaggregation comparing the previous result conducted by Central Research Institute of Electric Power Industry. In the Central Research Institute of Electric Power Industry's research [Kobayashi 2014], they could not indicate the way to estimate the temperature related per 30 min. But we could successfully calculate the number in 18% MAPE. The validation result of actual temperature sensitive demand and forecasted temperature sensitive demand is indicated in the Fig 5.10. And the time series value is illustrated in the Fig 5.11 We can find that the estimated value is slightly lower than the actual demand. The reason is the model between the temperature, and total demand could not describe the total demand. However, the rough estimation is enough to be used in the practical situation. Especially, as Fig 5.11 indication, the wintertime has better results than the summer time.

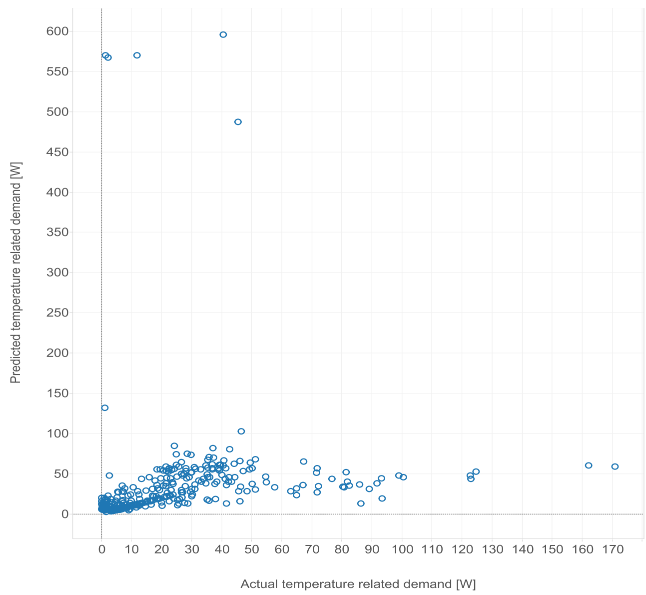


Fig 5.10 Plot of the actual temperature sensitive demand and the forecasted temperature sensitive demand for the house in Kyoto (DB ID is WEB02) (Made by Author)

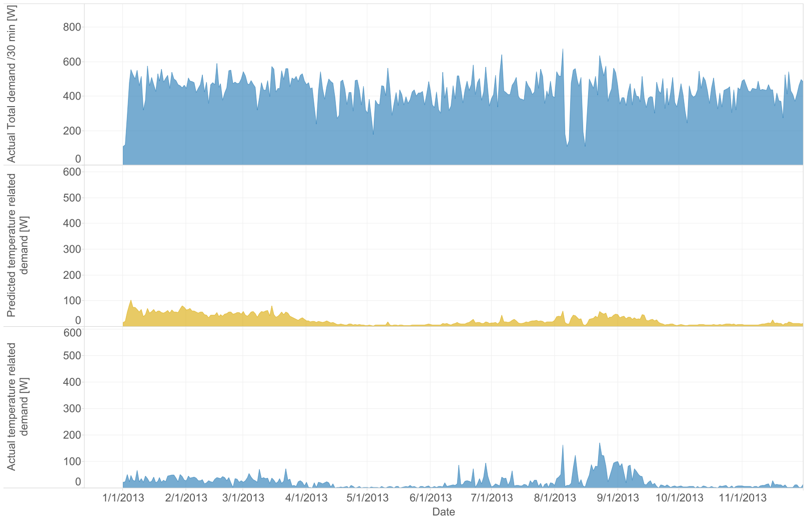


Fig 5.11 Result of actual temperature sensitive demand and forecasted temperature sensitive demand. for the house in Kyoto (DB ID is WEB02) (Made by Author)

5.4.3.4 Classification of Temperature sensitive demand for the condominium in Tokyo area

Fig 5.12 shows the different patterns of the temperature sensitive electricity. When checking the relationship between temperature and demand in condominium data in Tokyo, it can be considered that it can be divided into four types, important and weather. (Equivalent to A-1 in Fig. 13) In both winter and summer, families using electricity in summer (equivalent to B-1 in Fig. 12), households using more power in winter This corresponds to A-2 in 12), which corresponds to a household with much power in summer and winter (corresponding to B-2 in Fig. 12). The method proposed in this research can adapt to all these families.

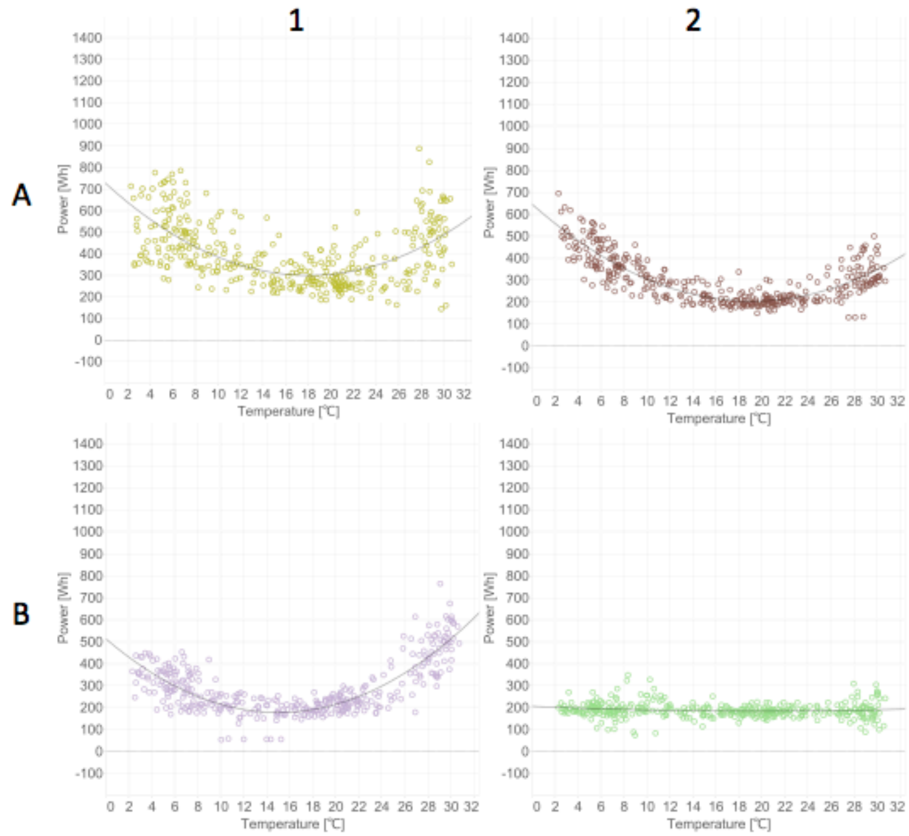


Fig 5.12 Different patterns of the temperature sensitive electricity for condominium in Tokyo area (Made by Author)

5.5 Discussion

We performed the analysis of the disaggregated data and had a comparison of the result. Fig 5.13 shows the comparison of the electricity usage of rooms in the condominium. The horizontal axis is the average of the state condition (1 stands for active status, 2 stands for inactive status). The vertical axis is for the average electricity usage per day. We can classify the two-dimensional graph to four domains to characterize the demanders as indicated in Fig 5.13 Primarily, we can estimate that there is a high potential to perform the energy saving for the room to improve the domain (right upper side) because we assume that these demanders use much electricity even though they are in an inactive state. Fig.5.14 indicates the comparison of the electricity usage of two rooms every day for a year, and it suggests that there is more potential to reduce the electricity for the demander (with large dot). The reason is that the average electricity usage of the user demander (with large dot) has a radical change in the mean of the state condition. Also, there is a high variance in electricity usage for the active state of the user demander (with large dot) so that we can assume there is room to improve the electricity usage.　All of this analysis can make a system that to provide the information.

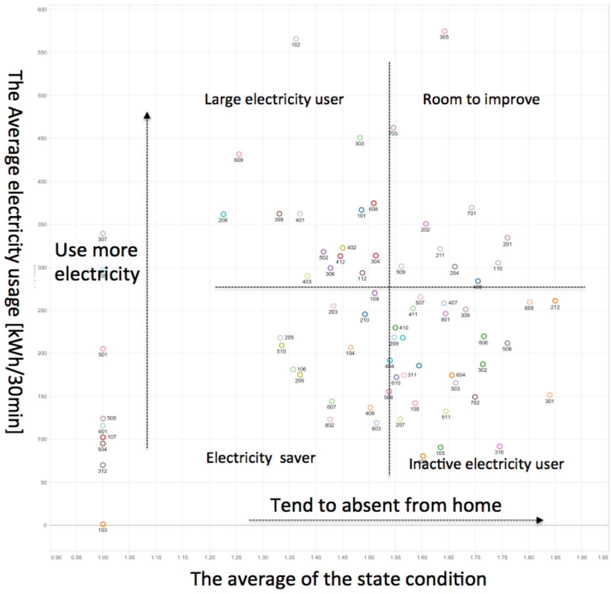


Fig 5.13 Comparison of the electricity usage of rooms　(Made by Author)

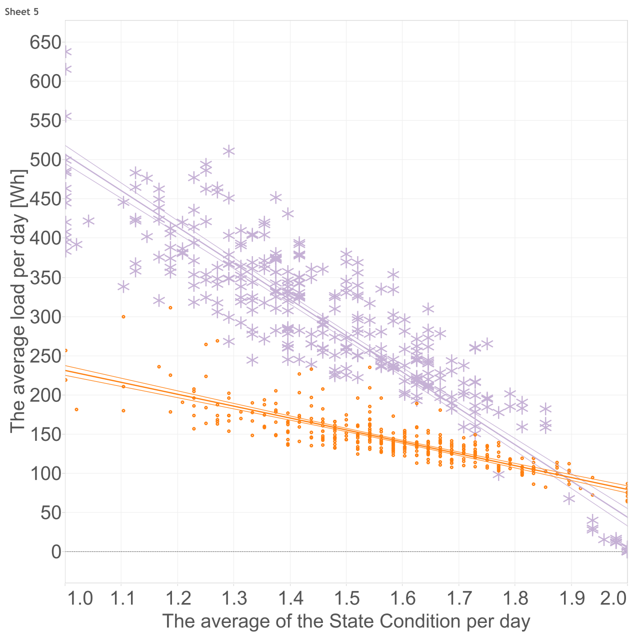


Fig 5.14 Comparison of electricity usage of 2 demanders (The average of the state condition versus the average electricity usage) (Made by Author)

5.6 Summary

The chapter shows an analysis method of electricity disaggregation on low-resolution smart meter data based on unsupervised method. The result of the disaggregation can be applied to some service such as remote life pattern diagnosis, life pattern abnormal detection, the in-house or off-house suggestion for the delivery service or targeted advice or demand response programs from the local calculation and real-time streaming. This result is much more feasible than using the finer sampling interval smart meter data because of the popularity of the low-resolution smart meter. As the future perspective, we use the result of disaggregation for the recommendation system for the energy-saving appliance recommendation based on the low-resolution smart meter data. The analysis should be considered from the local for the further number of utilizations for the reduction of central server calculation cost.

6 Household Electricity demand Disaggregation Based On High-Resolution Smart Meter Data

6.1 Background and purpose of this chapter

When it comes to making an energy-saving and low-carbon society a reality, it is important for customers to understand and utilize their energy usage information to raise energy-saving awareness and stimulate behavioral changes. To understand the shift of electricity consumption of each electrical appliance can provide much insight on the customer behavior. However, to figure out the energy consumption of all appliances of all point, it is necessary to install as the same number of sensors as appliances. The sensors cost of preparing Smart tabs is a problem resulting in that it's difficult to find out which appliance use how many power at what time.

In this chapter, we apply and consider using neural networks by focusing on simulating the pattern of the training data, which aims to provide the training data just based on the data acquired by the on /off of a switch of an appliance for a short time. Also, we show the accuracy improvement based on individually trained neural net works for each household comparing with the previous general training for the recognition of the appliances.

6.2 Existing researches

Studies regarding electricity disaggregation such as NIALM (Nonintrusive Appliance Load Monitoring) or Energy Disaggregation started in the early 1990s [Hart 1992], [Powers 1991], and various research has been done to this day. The position map of appliances based on the reactive power and real power and the estimation of the appliances power are introduced in Fig 6.1 and 6.2. For the problem of which feature amount to extract from observed data and how to decompose consumption using it, the application of Machine Learning approach is expected. There are many existing researches. For instance, approach using Factorial Hidden Markov Model [Gharmani 1997] to observed energy consumption, approach using NMF [Kolter 2012], approach to create non-linear projection using self-organizing map to the variation pattern of current value and cluster to appliance component [Iwafune 2011], and method to use Support Vector Machine to discern [Kato

2009] were proposed. Deep Learning has been tried for the new higher accuracy of disaggregation of electricity disaggregation. However, in the practical usage, a significant amount of data for the training was one of the biggest problems. Also, Kolter et al. [Kolter 2010] suggests the framework of semi-supervised learning under the condition that few patterned information of "typical shift of power consumption for each appliance." One of the most advanced research for the NIAM was conducted by Jack Kelly [Kelly 2013], Kelly used the three kinds of the DNN to predict the electricity demand, and showed the result of Deep Learning is superior the FHMM model. However, his work was based on one general classifier concept but not an individual classifier model.

In previous research, there were many types of research focused on the supervised learning algorithm for the disaggregation work. However, the disaggregation is not achievable based on supervised learning because it is almost impossible to measure the electricity usage of each appliance for individual homes. We could create the supervising data by taking advantage of the difference of electricity current of each appliance. After that, we used the supervised learning method to estimate the on/off status for each appliance.

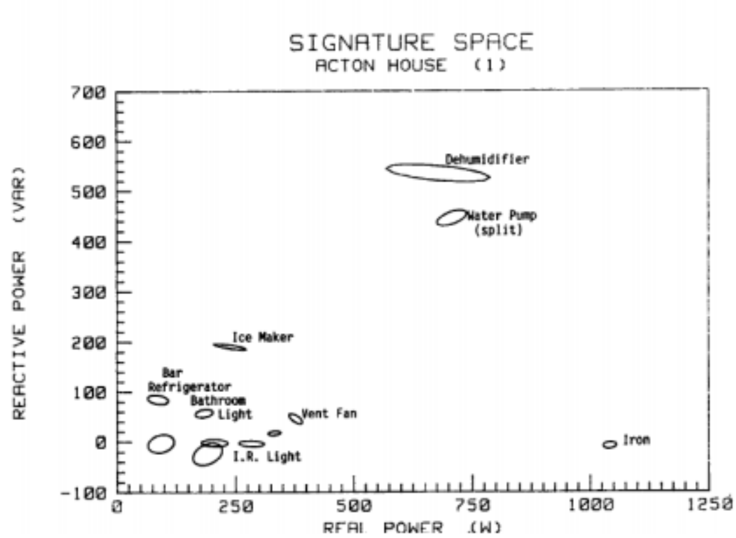


Fig 6.1 The Position map of appliances based on the reactive power and real power [Hart 1992]

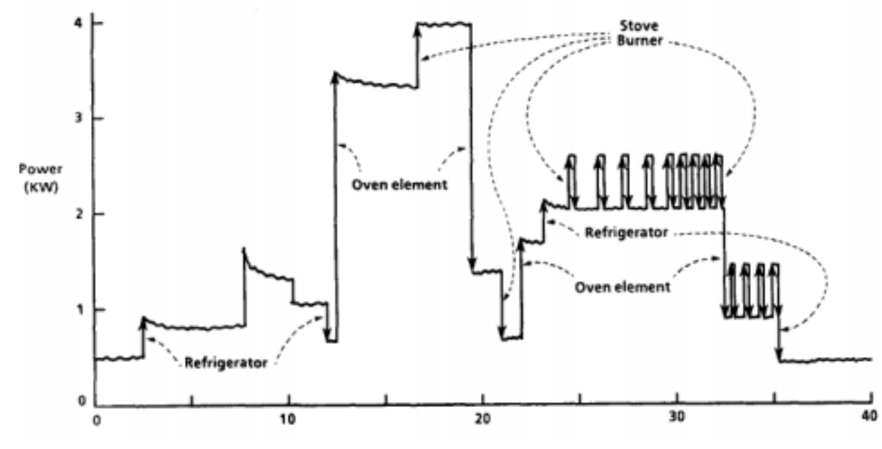


Fig 6.2 The Estimation of the appliance's power [Hart 1992]

6.3 Method

6.3.1 Analysis of the electricity current features for the appliances

There various feature can be acquired from the smart meter at this time; we tried to obtain the on / off feature from the current data. As indicated in Fig 6.3, each appliance does not change the pattern of power for the each time. However, they have slight fluctuation depending on the start condition.

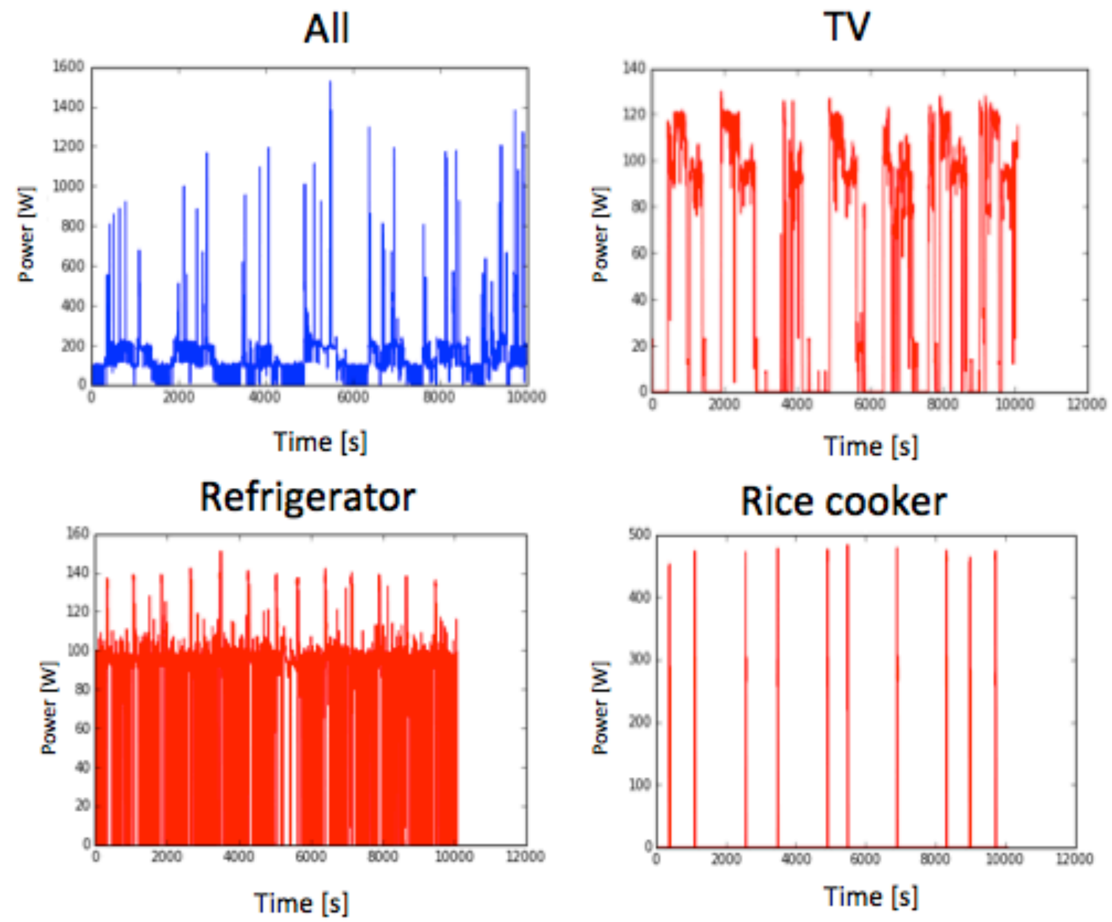


Fig 6.3 Visualization of each appliance power data and its spectrum (Made by Author)

6.3.1.1 Additive of electricity current

Because the plugs in the home are parallel circuit, the relationship between the total current and the individual currents in the circuit model can be described as the Fig 6.4. As the electricity voltage is approximately same in the circuit. The relationship between total and individual power consumed in the individual power consumed in the individual appliances. Therefore, it is possible to calculate the total power by the individual power. Formula 6-(1), 6-(2) show the relationship of the currents and powers.

$I = I_1 + I_2 + \ldots + I_n$ 6-(1)

$P = P_1 + P_2 \quad + \quad .... \quad + P_n$ 6-(2)

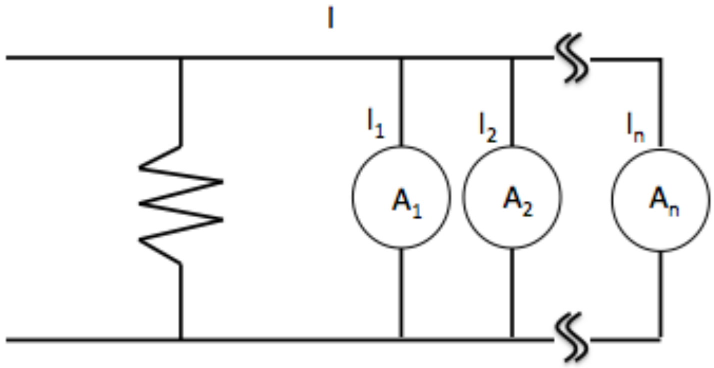


Fig 6.4 Circuit model in a general house (Made by Author)

6.3.2 Training data augmentation

To figure out the energy consumption of all appliances of all point of time, it is necessary to install as the same number of sensors as appliances, sensor cost of preparing Smart tabs is a problem resulting in that it's difficult to create the training data for the supervised electricity disaggregation.

Data augmentation is a method to increase the robustness by increasing the training data set for the Deep Convolutional Neural dealing with the image recognition by shit, transform, blur and change the color.

Here, we learn from the data augmentation to increase the data size. As addressed in the previous sections, if we can consider there is not a lot of changes between the each run for each appliance, it is possible to simulate the on / off shift for the appliance so that we can recognize the on / off of each appliance.

6.3.2.1 Window slide data preparation

At here, for the input of neural network. we used the window slide to create the input and output. Window slide is a general method of time-series analysis in which an input time-series is divided into a sequence of discrete time segments to indicate the underlying properties of its source. Fig. 6.5 shows the window slides data preparation for the electricity disaggregation.

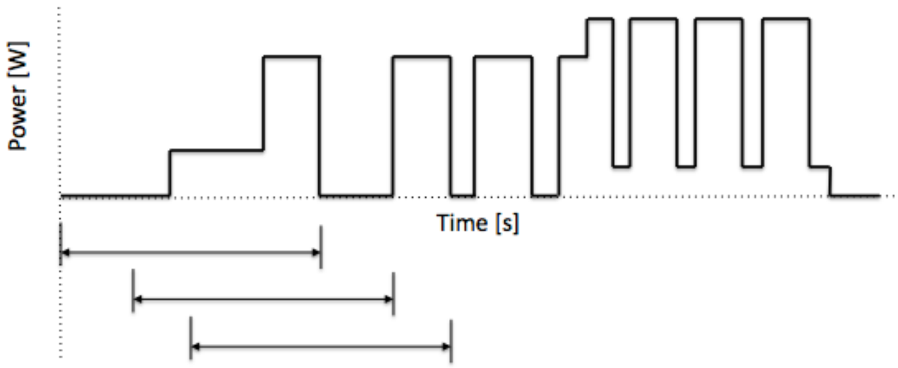


Fig 6.5 The window slides data preparation for the electricity disaggregation (Made by Author)

6.4 Training with Deep Learning

There are a lot of kinds of structure of Deep Learning. In this chapter, we only consider the normal structure of the Deep Learning. Fig 6.6 is the neural net work model for electricity disaggregation. The detail description of Deep Learning is indicated in Appendix 1.

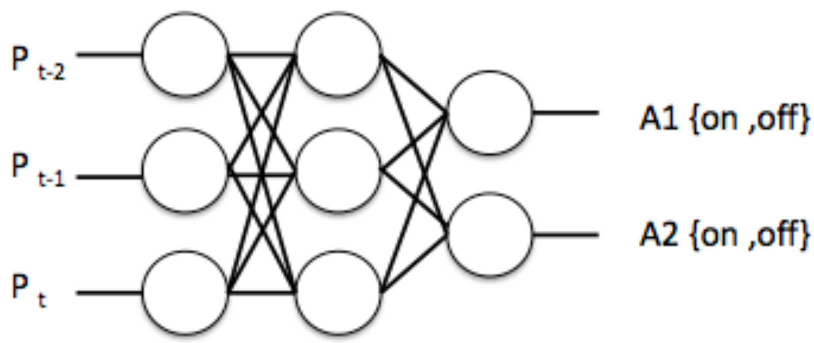
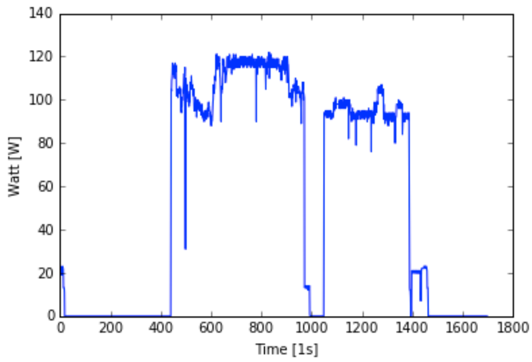


Fig 6.6 Neural net work model the electricity disaggregation (Made by Author)

6.5 Case study

6.5.1 Base data of the appliances

First, we used three target appliances in all our experiments: the fridge, rice cocker, and TV. Second, we used six target appliances in all our experiments: the fridge, rice cocker, TV, micro, air conditioner and laundry machine. The original data is power [W] measured in the 1-second interval, which was provided by the Informetis.inc. The data visualization result is indicated Fig 6.7 and the individual data of appliance serve as base data in the simulation process is indicated in Fig 6.8. The total power will serve as input data, and the each appliance data will transform to on/ off data and serve as output data.

Type	Base data for each appliance
TV	

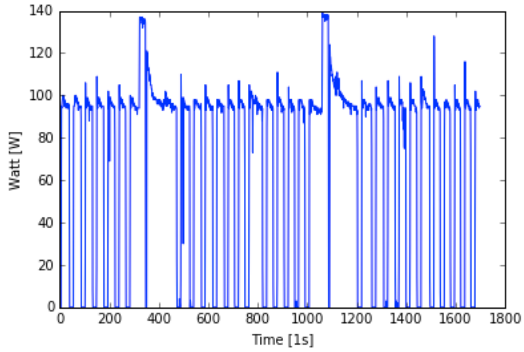
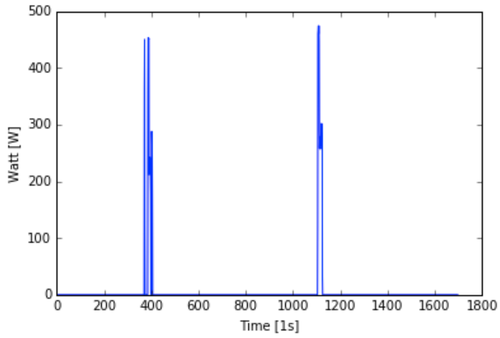
Refrigerator	
Rice cooker	

Fig 6.7 Base data of the three appliances　(Made by Author)

6.5.2 Data used in the disaggregation process

1) Training with actual data

We used the training data as indicated the in the Fig. 75% of total data was utilized for the training, and 25 % was used for the training. The power consumption (unit is W average power) of 6 equipment (air conditioner, washing machine, microwave oven, refrigerator, rice cooker, TV) for the homes of Infometis employees was targeted.

2) Training with simulated data

We used the training data simulated by the three appliances. Specifically, we have simulated it for 86400 step (which stand for one day). The possibility for turning-on were 80%. The simulated Total power was indicated in the 6.4.2. First of all, we trained the neural net works by the simulated data. Then, we used the same actual test data to test the trained neural net works. Fig 6.8 shows the actual and simulated total power.

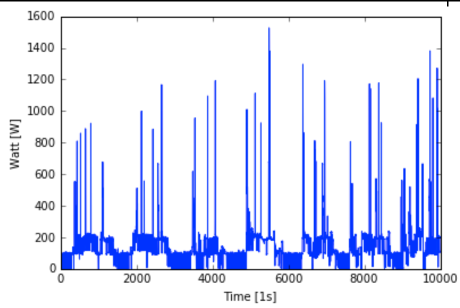
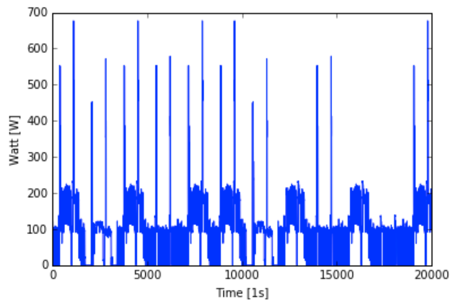
<table>
<tr><th>Type</th><th>Actual total power</th><th>Simulated total power</th></tr>
<tr><td>Total Power</td><td>
</td><td>
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Fig 6.8 Actual and Simulated total power (Made by Author)

3) Architecture of neural net works

Neural net works were used for the disaggregation. Three layered neural net work was used. The activation function was Relu, and the optimization method was Adam. We used the window size was 30 in time, and the window step size was 1. The batch size was 50, and the epoch size was 50. For the evaluation, we used the precision indicated in the formula (6.3).

$$\mathrm{Pr}ecision = \frac{TP}{TP+FP} \qquad 6\text{-}(3)$$

(TP: True Positive, FP: False Positive)

6.5.3 Disaggregation results

We show the disaggregation result is the Table 6.1, 6.2. This table shows two results; the first result is based on the result of neural net works trained by actual data. The second the result based on the neural net work trained by the simulated data based on the base data of each appliance. We can find both of the neural net works could indicate more than 80% precision. The neural net works trained by actual data provides slightly better accuracy than the trained by simulated data. The neural net works are trained with cross-validation manner and test with the test data. Therefore, we could show the electricity disaggregation can be done by the base data and simulations. In the previous paper, the forecast accuracy was around 50% or less than 50% for the 5 appliances disaggregation using one second data. Table 6.3 shows the result provided in the research conducted by Kelly [Kelly 2015]. Based on this result, we can conclude to create a model for each house individually and make predictions is an effective way for the electricity disaggregation.

Table 6-1 Result of disaggregation for three appliances(A: Classifier created using real data, B: Classifier created using simulation) (Made by Author)

	A	B
TV	97 %	96 %
Frige	90 %	85 %
Rice cocker	91 %	87 %

Table 6-2 Result of disaggregation for six appliances (A: Classifier created using real data, B: Classifier created using simulation) (Made by Author)

	A	B
TV	85 %	83 %
Frige	92 %	89 %
Rice cocker	98 %	97 %
Micro	86 %	83%
Air conditioner	92%	93%
Landry machine	94%	93%

Table 6-3 Result of disaggregation for five appliances from the research performed by Kelly [Kelly 2015]

	Kettle	Dish washer	Fridge	Micro wave	Washing machine
Precision score	70%	69%	79%	14%	29%

6.6 Discussion

In the actual, environment there are more noises, Small appliances which does not use much electricity such as phone chargers and small lumps are hard to be detected by a plenty of NILM algorithms because the result of the aggregation of small appliances on total power demand tends not to be recognized in the noisy condition. By definition, small appliances do not consume much energy individually. We have not researched if the neural nets perform well on small appliances based on high-frequency (Hz level) data, but we plan to research it in the future. There is also ongoing research into such things as a system for studying behavioral patterns and monitoring systems based on the disaggregation results.

In the actual situation, the individual electricity for each appliance can be obtained by the user. They can record each appliance by themselves and record the on and off status. The particular appliance power will be acquired by the subtraction.

There is a belief that if the IoT system or HEMS prevails, there is not a necessity for the disaggregation technology because people can get the signal from each appliance directly. However, that is just not the case. The reason is listed as follows.

1) It is impossible to install the IoT sensors for all appliances in recent years. Also, it is hard to consider that all of the households will install the IoT that can send the signal back to the server.
2) The data will be obtained by each electric appliance manufacturers. They will enclose data for them for the commercial reason. At the result, electricity disaggregation can be considered a way to acquire a perfect data set for the on/off information for the appliances.
3) The technology can be applied to the countries over the world.

6.7 Summary

How to estimate the individual appliance power consumption from collected data is essential for putting it into practical use and to prevail, and various approaches have been proposed. In this chapter, we aim to estimate energy consumption of single appliance at each point of time based on total energy consumption shift information acquired in from a second data. How to obtain the training data was a difficult problem for the electricity disaggregation. We have introduced a way to simulate the train data by recording the on / off. As a result, we could recognize the power consumption of each appliance only from the base data of total electricity consumption without recording the actual individual appliances data. As the future perspective, we can utilize finer second to kHz data to enhance the accuracy of the forecast. Based on the Fog computing scheme.

7 IMPLEMENTATION OF A SMART METER BASED ON FOG COMPUTING SCHEME

7.1 Background and purpose of this chapter

As mentioned in previous chapters, the recent smart meter is designed for the current electricity usage, and the solution is just specific ones. Although there are many services and usages can be implemented from the electricity data, it is not enough to realize all of the ideas based on the current system that has been introduced by the Japanese government. Also, it was not successful to define the hardware specification without clear view the data utilization. Specifically, based on the proposal on the new type smart meter we discuss the specific software application problems related to the data usage.

From the demand forecast part, we could understand the following necessity of the electricity.

1) The demand forecast should be done by high Machine Learning algorithm.
2) To have multi-time scale demand forecast (1 min head to 30 min head), there is necessity to obtain multi-scale demand data
3) BU is better than TD, especially when it is possible to take the local parameters into account, and the related local data acquisition is necessary (weather data ,human activity and etc.)

From the electricity disaggregation part, we could understand the following necessity of the electricity.

4) The demand disaggregation is better to be done each house base on the model trained by individual house data.

5) The fog computing system can reduce the burden for the individual calculation in the cloud server.
6) The real-time communication is necessary from the local machine control, DR and battery management.

To solve the problem above, we have proposed a new concept of the smart meter to manufacture a new type of based on fog computing scheme, which is called the Home Master. This device can modify the specifications of the software and can be managed externally through private 3G communication lines, and take advantage of API.

We show the actual implementation in this chapter. As a result, the analytics information scan is considered to be acquired from both from the local and cloud for the further number of utilizations.

7.2 Advantages of the Home Master

Table 7-1 shows the difference between the current smart meter in japan and the Home master. The differences can be illustrated from Processing , data transmission and data acquisition point of view as follows.

1) Processing

By utilizing Intel 's Edison module, we were able to create a platform that can utilize Linux OS. The Edison module integrates an Atom-based SoC (dual-core) operating at 500 MHz and 1 GB of memory, a 4 GByte eMMC (embedded SD card) storage, a Wi-Fi interface, etc. We can update smart meter software through the Edison module, and it is possible to install various software such as demand forecast and abnormality detection in this smart meter.

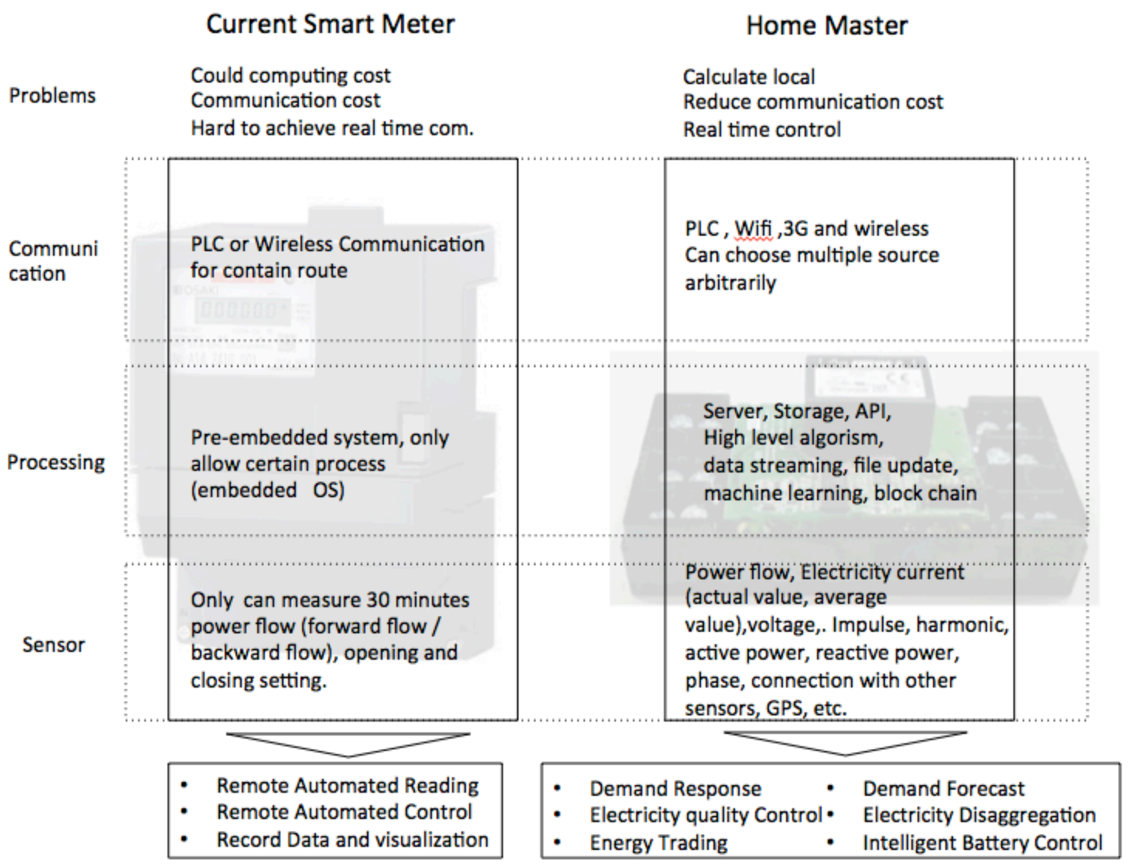
2) Data transmission

With this smart meter, it is possible to take various communication methods such as Wifi, Bluetooth, 3G, wireless communication and the like. It is possible to control communication easily from all Linux OS.

3) Data acquisition

With this smart meter, ADE7978 (3 phase energy meter IC, for meters using polyphase shunt resistors), a normal smart meter can also obtain various power parameters by using similar IC chip. In this research, we prepared a library that can utilize parameters from Edison so that we can acquire power related data freely.

Table 7-1 Difference between the current smart meter in japan and the Home master (Made by Author)



	Current Smart Meter	Home Master
Problems	Could computing cost Communication cost Hard to achieve real time com.	Calculate local Reduce communication cost Real time control
Communi cation	PLC or Wireless Communication for contain route	PLC , Wifi ,3G and wireless Can choose multiple source arbitrarily
Processing	Pre-embedded system, only allow certain process (embedded OS)	Server, Storage, API, High level algorism, data streaming, file update, machine learning, block chain
Sensor	Only can measure 30 minutes power flow (forward flow / backward flow), opening and closing setting.	Power flow, Electricity current (actual value, average value),voltage,. Impulse, harmonic, active power, reactive power, phase, connection with other sensors, GPS, etc.
	• Remote Automated Reading • Remote Automated Control • Record Data and visualization	• Demand Response • Electricity quality Control • Energy Trading • Demand Forecast • Electricity Disaggregation • Intelligent Battery Control

As proposed in chapter 2, here we illustrate the advantages of the Home Master.

1) To provide the development platform for HEMS, to provide a modifiable development platform for HEMS for the developer, enable the developers to join the development of HEMS service with ease. The difference between the current smart meter in japan and the Home master is indicated in the Table 7-1.

4) Information security :

The Home Master will enclose critical personal data inside of the home. Only necessary and available information will be passed to the cloud server.

5) API-based Control system :

Without building a LAN access port, the home appliances can be accessed from anywhere easily by API. Home Master connects sensor and consumer electronics of the house.

6) Integrated sensor data storage and computer calculation :

It is possible to treat the sensor data in the house in an integrated manner. Through the sensor data and analysis algorithms, it is possible to analyze the energy usage and efficiency of electricity in the house accurately. The developers can also utilize the data through the API that was provided.

7) Robustness Fixed home computer system on breaker and power line:

By attached to the switchboard, without having to worry about the operation power of Home Master its own. Also, it is possible to suppress the power failure of the entire house.

8) Scale effects the stationary feature is an outstanding point of this device.

Once a certain number of Home Masters prevails in society, Home Master can serve as a stationary sensor of each geographical point. In there, some stationary measurements are available. For instance, the atmospheric pressure and the humidity sensor big data can help to build correct weather forecasts.

7.3 Case study

In the case, to indicate the concept of Home Master (Electricity with General Operation System), we have implemented a hardware based system which can conduct very basic electricity disaggregation. Fig.7.1 is the concept picture for the actual usage. In this case, we have defined the Home Master as below. The specification is indicated in Table 7-2.

In this time, we define Home Master is a power measurement device utilizing the Intel Edison Compute Module and power measurement IC. To use the device such as for the estimating power demand, measurements data can be collected in short time intervals through the smart meter.

The Intel Edison is a small sized computer-on-module offered by Intel as a development system for IoT devices [Intel 2014] and Internet of Things devices. It has a high-speed electrical current waveform acquisition function. Rather than installing an ampere breaker in the distribution board, as it becomes unnecessary with the installation of the smart meter, measurements are taken using the attached terminal block. It can transmit information to a data acquisition device, such as an M2M server, through a 3G signal using the network function.

In the table, we indicate the specification that we have implemented this time. Based on the feature, we show the Fog Computing based smart meter with three main functions.1)With freedom of acquisition parameters,

2) computational ability. 3) The communicating in real time in multiple communication ways.

Tessera Co., Ltd. implemented the API from sensor to Edison,Home master itself, while the author implemented Edison to the cloud. In addition, the author made a conceptual design and Tessera Co., Ltd. made a detailed design and manufacture.

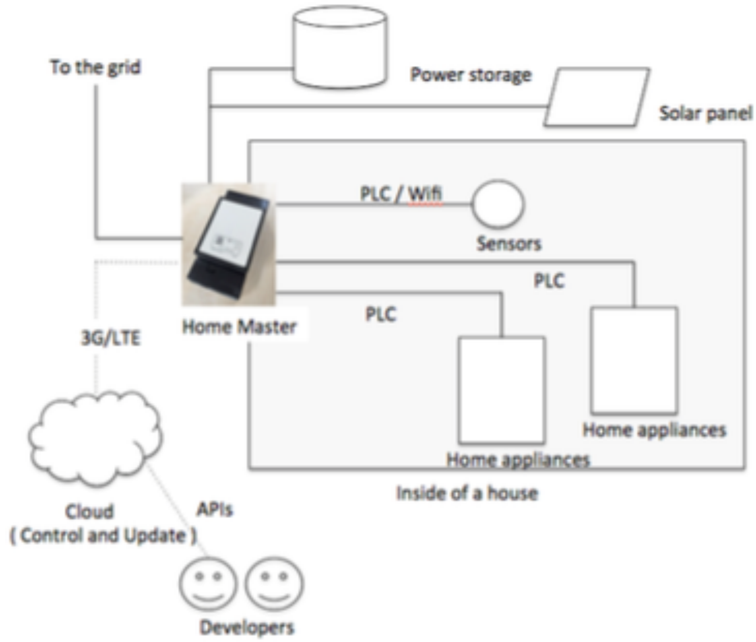


Fig 7.1 Position map of the Electricity Mater technology (Made by Author)

Table 7-2 Input feature used in the forecast process (Made by Author)

Item		Adapted Parts
CPU	CPU	Intel Edison Module (Atom 500MHz)
	Flash ROM	4GB eMMC
	RAM	1GB LPDDR3
	Wi-Fi	Broadcom 43340 802.11 a/bgn
	Bluetooth	BT 4.0
Current measurement		Single-wire 3-wire ADE7978+ADE7932+shant resistance
3G		3G module LISA-U200 ＋Micro SIM +U.FL connector + base antenna
SD card		Micro SD (Maximum 16GB)
USB host		USB 2.0
Ethernet		10BAse-T / 100Base-TX
Indication	LCD	ACM1602(16×2 columns)
	LED	2Pcs (Power, GPIO × 1)
Switch		Push Switch 2pcs, control board, system reset
Sensor	Temperature/ Humidity	BME280
	Acceleration	ADXL345
	Light	BH1710FVC
	Mic	LM48580
	Speaker	TLV320AIC3254
GPS		T.B.D UART (EXTENDABLE)
PLC		T.B.D UART (EXTENDABLE)
Size		65.6(W) ×150(D)×５０(H)
Power		AC85V-125V
Power consumption		10W(max)

7.4 Software Specifications

Linux OS is equipped with the Intel Edison chip; it will provide the programming environment for further development of the function. Here, we took advantage of the current measurement board. We have implemented the function for measuring the electricity current (5000 Hz ~ 1Hz), Voltage, Effective Current, Impulse,
Cumulative active energy

Fig 7.2 illustrates the ADE7978 device driver and the software configuration; this driver is about the current measure and the specification of the functions. As indicated, this driver communicates with ade7978 trough area library. Also, the driver is separated into two layers. 1) API layer: the interface between Python 2) Driver layer: the interface between Mraa library. The Internet layer and Device layer API were designed and implemented by author. On the other hand, the Device layer and Device Driver layer were implemented by Tessera Co., Ltd.

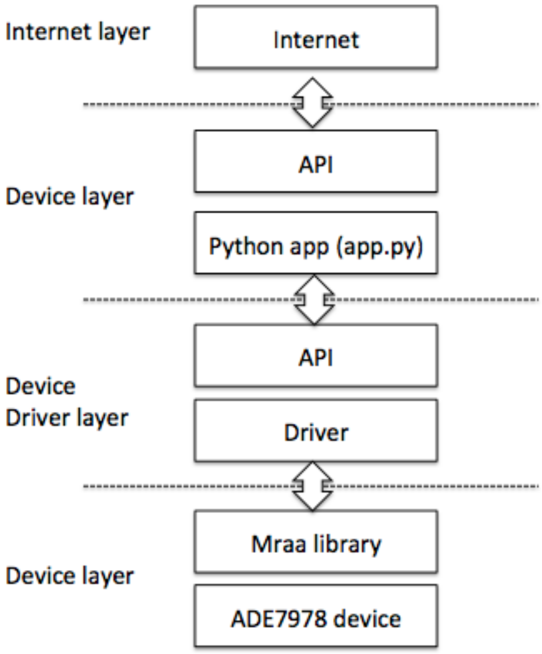


Fig 7.2 Software configuration for the Home Master Prototype (Made by Author)

7.5 Hardware Specifications

The hardware is consist of the four main boards; 1) main board, electricity measurement board, that resistant board and sensor board. The Intel Edison is equipped in the outside of the board due to the heat reason. Also, the sensor, 3G is equipped in the out side of the board. As the communication way, 3G and Wi-Fi can be applied, and connected to the cloud. Intel Edison provides 500 Mhz dual core processor, Intel Quark processor micro-controller 100 MHz, RAM 1GB, Storage 4GB, dual-band Wi-Fi and Blue4.9.For the electricity measure, we used the Shunt resistance, As the electricity measurement IC. We used ADE7978 + ADE7932. Detail materials are indicated in APPENDIX 3. Fig 7.3 indicates the actual image for the Home Master and its hardware. The Hardware conceptual design was performed by Mr. Chen ·and Prof.Abe; The Hardware detailed design was performed by Tessera Co., Ltd; Hardware Implementation was performed by Tessera Co., Ltd.

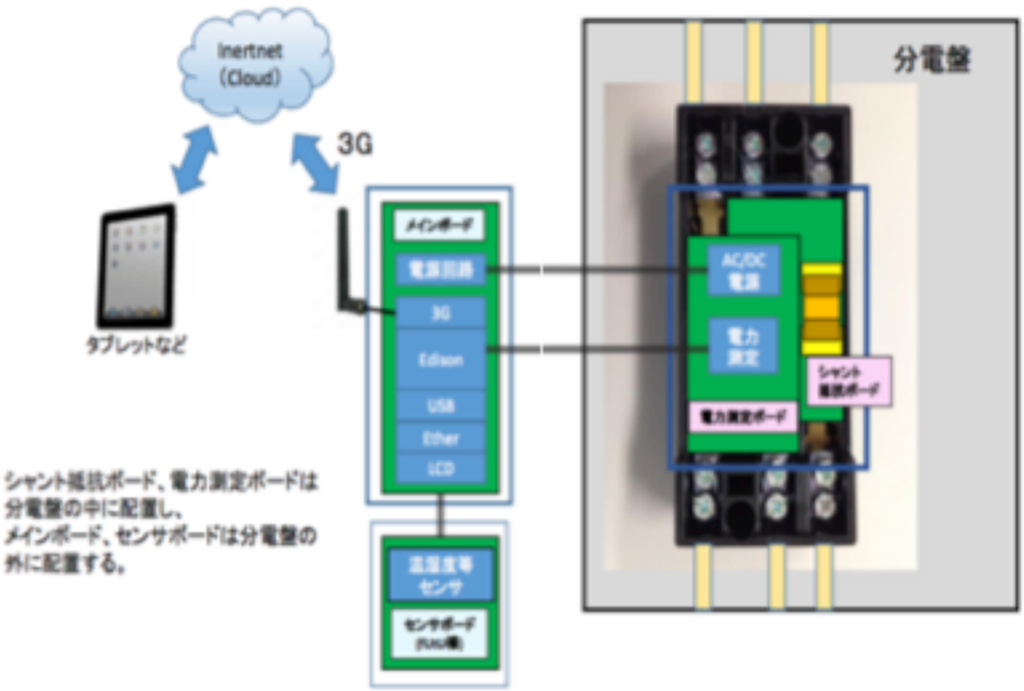


Fig 7.3 Actual image for the Home Master and its hardware (Made by Author)

7.6 Demos

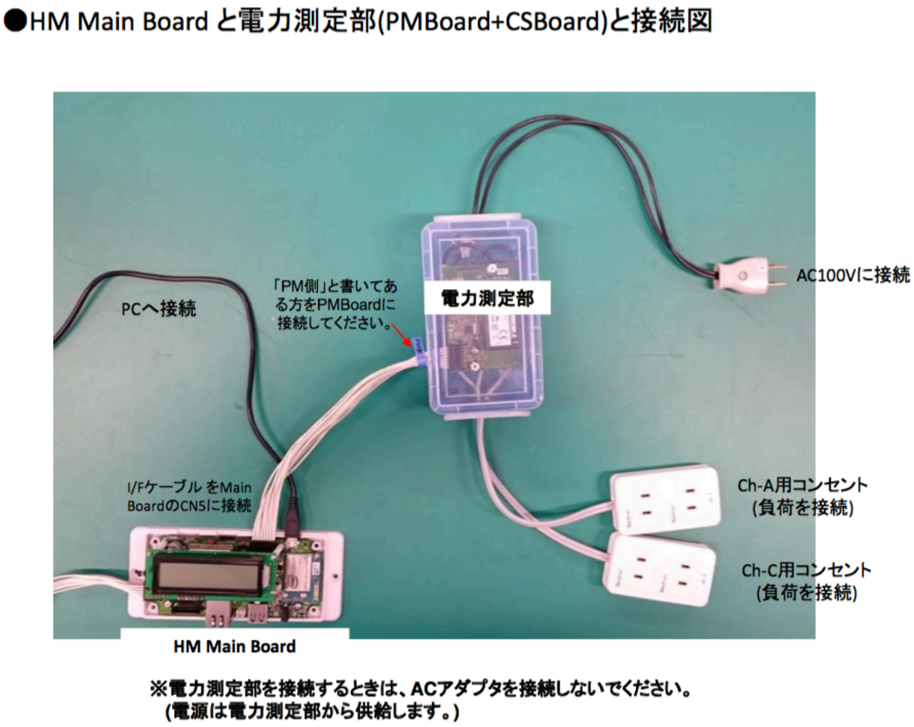


Fig 7.4 Actual image of Home Master (Made by Author)

The home master achieves three functions that cannot be done by the normal smart meter. They are the data variety, real-time data streaming, and Programmable device. I show the result in following sections. The actual image of Home Master is indicated in Fig 7.4.

7.6.1 Data variety

Just by changing the implemented functions, Home Master can measure different resolution electricity data. Fig 7.5 is the instantaneous current value of the cleaner and Fig 7.6 is the effective current value of cleaner. We can find a clear difference between the measurements. The change of setting can only be done by the change of the input of the function.

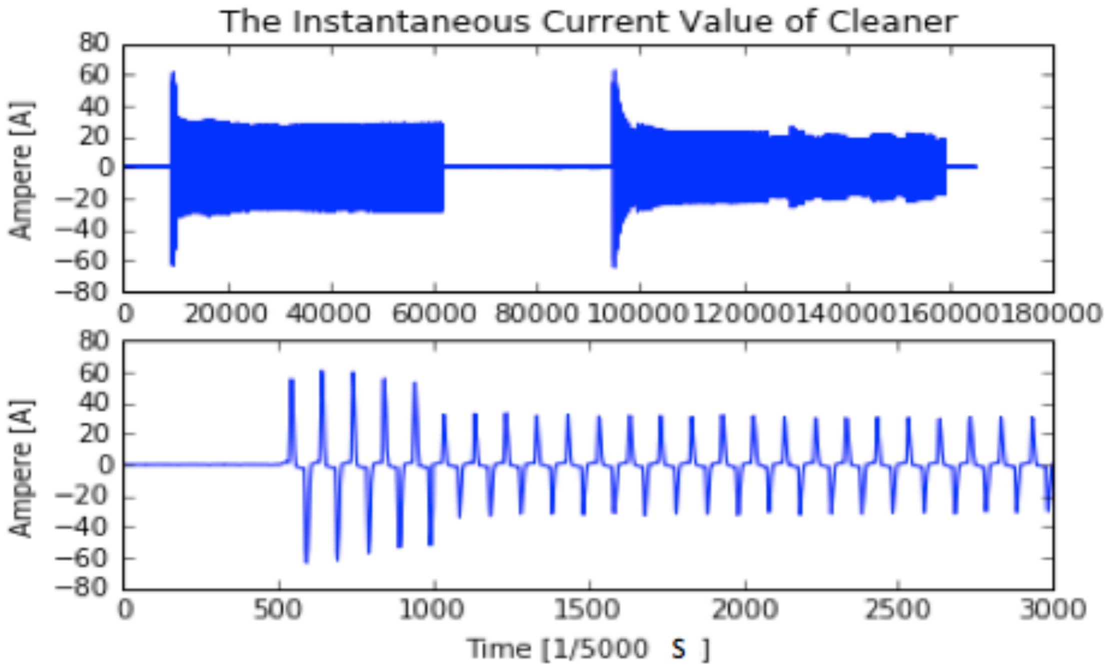


Fig 7.5 Instantaneous current value of cleaner (Made by Author)

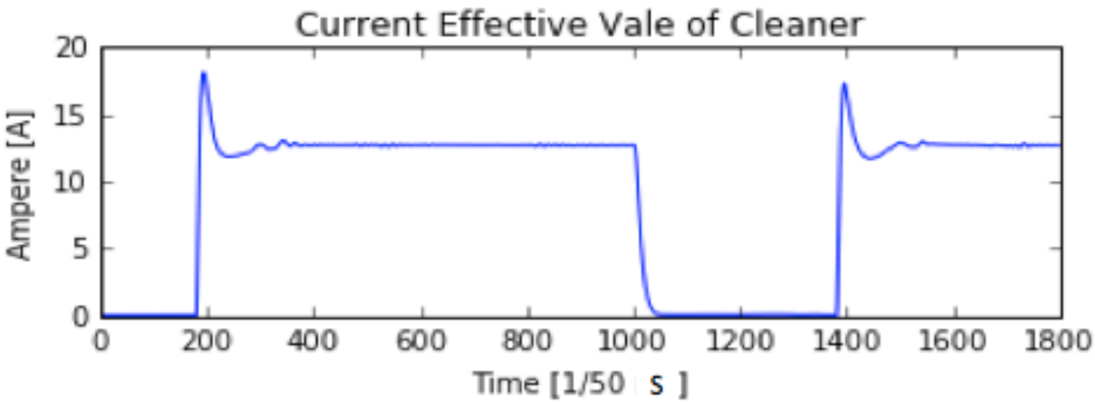


Fig 7.6 Effective current value of cleaner (Made by Author)

7.7 Discussion

As indicated in the Fig 7.11,12, the shorter time data of the electricity provides for information on the actual usage. It is better and efficient to use the shorter time data to perform the HEMS control.

It is possible to operate the appliance in home efficiently just depending on the usage and photovoltaic generation amount by providing the electricity data to control function of HEMS. As the control example, the HEMS can adjust the air conditioner's temperature. Also, it is possible to perform the optimum control the charge or discharge of the battery and the electricity vehicle. It could make it efficient by the demand forecast based on the smart meter data and weather data. The real time electricity data is not only can be applied to energy saving but also can be utilized for the other services such as the security, health care, and other marketing service.

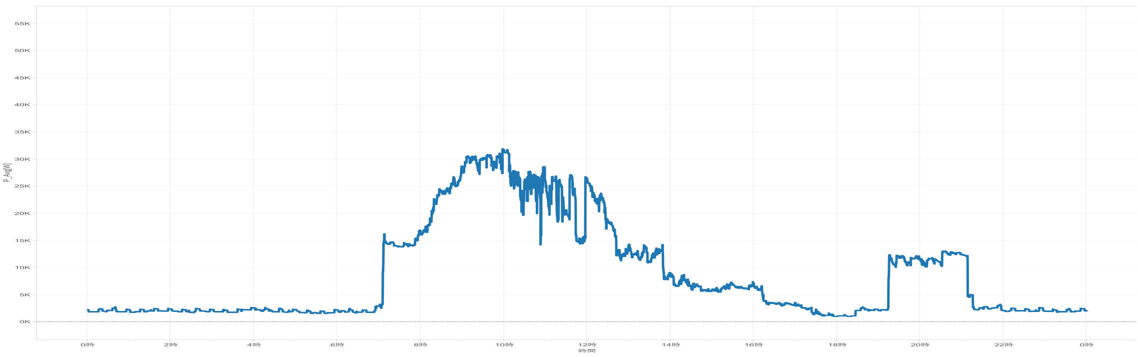


Fig 7.7 Image of electricity power measure in the Kooriyama for 10second (Made by Author)

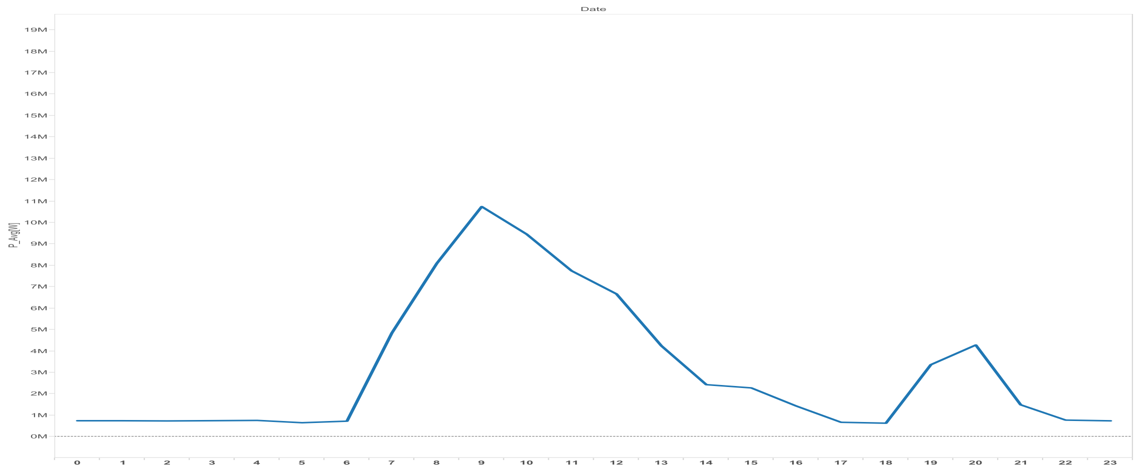


Fig 7.8 Image of electricity power measure in the Kooriyama for 1 hour (Made by Author)

7.8 Summary

In this chapter, we have shown the implementation of the proposed idea on the future smart meter. We called this smart meter as Home Master. The Home Master is a power measurement device utilizing the Intel Edison Compute Module and power measurement IC. This device can be used to estimate power demand as it measures power parameters including voltage, current, and electricity consumption and can be set to take measurements in short time intervals through the smart meter.Also, it has a high-speed electrical current waveform acquisition function. As a result, the analytics information scan is considered to be acquired from both from the local and cloud for the further number of utilizations with flexibility.

8 CONCLUSION

8.1 Final conclusion

We hoped that the utilization of electricity data bring economic stimulation through the creation of new industries and services. Indeed, the use of energy consumption information can have societal merits for both energy companies and customers, and it seems smart meters are the most popular and accessible IoT to collect the electricity information.

However, the practical research on smart meter data is still scarce in Japan. Moreover, we found that current scheme of a smart meter and their electricity measuring data can only bring limited benefits.

In this thesis, we aim at applying the data in a way that contributes to both society as well as the electrical industry by proposing a new concept of smart meter. For this, we take advantage of the emerging idea of computer architectures based on Fog computing scheme. We consider the future devices will be connected to the internet and process the locally generated data. Following this concept, we have proposed and implemented a smart: we called this smart meter Home Master. Specifically, The Home Master is a power measurement device utilizing the Intel Edison Compute Module with general-purpose OS and power measurement IC which could help the smart meter achieving the flexibility for changing measurement target, real communication, and computation in the local In previous studies only very limited concepts have been introduced, often lacked a specific discussion based on the data utilization and actual product.

We propose that the Fog Computing based smart meter should have three main functions. 1) With freedom of acquisition parameters, 2) computational ability. 3) Communication using multiple communication paths. Based on these requirements we implemented a prototype that called "Home Master."

We found that it is difficult to define the hardware specification without clear view the data utilization, and it is hard to define the specification of the new Smart Meter in the preparation of future necessity for the data. We focused on the electricity demand forecast and electricity demand disaggregation to find the characteristics of the electricity demand time series data and examined new applications and a methodology for smart meter data utilization.

As for the demand forecast part, we proposed a method of half-hourly electricity demand curve prediction of the following day and test the accuracy of the method by applying it to different kind of machine leanings. As a result, Gradient Boosting Machine and Deep Learning indicated the better result in the forecast of the demand-curve forecast. On the other hand, we could demonstrate that there is not a huge difference between the Bottom-Up and Top-Down method in term of the accuracy of the forecast. However, the BU method has the advantage that it can utilize local data.

For the demand disaggregation part, we presented an analysis method of electricity disaggregation on low-resolution smart meter data to reveal more precise personalized insights and analysis for energy saving. The result of the disaggregation can be applied to services such as remote life pattern diagnosis, life pattern abnormal detection, in-house or off-house suggestions for delivery services as well as targeted advice or demand response programs. Furthermore, in order to figure out individual energy consumption of each appliance, we considered a supervised learning algorithm which gives a data augmentation framework while allowing the use of a small training set regarding the use/non-use of individual appliances.

In conclusion, recent smart meters are designed for the current electricity usage and the solution provided is just for specific ones. Our proposed smart meter based on Fog Computing scheme can help realizing a much wider set of ideas than the currently planned infrastructure. Also, we could successfully determine the hardware necessity through examining individual algorithms. As a result, the analytics information scan is considered to be acquired from both from the local and the cloud for further utilizations.

8.2 Future perspectives

8.2.1 Future application of the Home Master

The information gained from smart meter data analysis has also been considered for use in creating behavior modification plans for reduced energy consumption and power conservation efforts. Especially, electricity disaggregation and electricity forecast based on Machine Learning can provide the much insight that for that usage.

For example, if the usage trend for heating and cooling demands can be estimated, it is possible to give selective power-saving advice in response to the usage patterns. Additionally, a plan is being considered for giving advice to those who are at home during the day on weekdays and guidance for when those who are not at home during the day return to their homes. The data can also be considered for use in the efficient operation of the Demand Response Program, in proposals for schedules of charges appropriate to each household, and in plans for new services that will improve living conditions.

8.2.2 Distribution system optimization based on Home Master

It is possible to utilize smart meters to make estimations of whether residents are at home or not and apply those methods to provide an even more sophisticated delivery system. There is no need to add additional functions or devices to existing electrical equipment already installed within households. It is also not necessary to acquire any information from the equipment within these households.

Due to the increase of sales via the Internet, delivery has been more important than ever. However, it is a fact that the absence of residents during delivery has been a significant cost factor. Therefore, it is essential to develop a system to help avoid delivering at times when the residents are not at home.

To achieve this goal, the delivery system, which applies estimation methods conducted by household smart meters and estimation devices, will accumulate measurement data of energy usage through these smart meters installed within designated households. The system will next provide a prediction of current and future states from previous measurement data. When it is decided whether the designated households are present or absent, the information then gets sent to servers and devices and then calculates the delivery schedules and routes. The estimated schedules and routes then get notified or control the parcel delivery service that is in charge of delivery of the commodity.

8.2.3 Blockchain based smart metering system

“Blockchains” unite transactions into one block, connecting these blocks together and saving them as chains. By connecting them like chains, this makes it impossible to change or manipulate the data contained within. It is an innovative technology especially as a ledger system, and Bitcoin, which utilizes this technology, is still now able to maintain a high level of security even during zero downtime. Currently, there has been a proposal for Blockchain 2.0, a program which is a Blockchain based smart contract, and if used with the point system, commissions will be reduced to almost zero compared with real currency. If smart contracts are implemented, then it would be possible to conduct demand shifts and switching for electricity companies to a smoother level. Researching these topics will lead to switching techniques for better-priced and groundbreaking innovation within the field of electricity.

8.2.4 Abnormal detection

The abnormal detection is also the main field for the future usage. The factors exerting an influence on the electricity transmission equipment capacity include the electricity demand from each household, as well as the presence or absence of solar power. Through proceeding with the accumulation of smart meter data such as voltage and frequency data, and understanding the demand in real time, we can plan for the streamlining of various forms of transmission equipment, such as transformers, service wires, meters, etc.

From the transmission equipment operation aspect, by taking the transmission equipment information (the state of the voltage, demand, and current) and continuing to build up the smart meter data at the same time, it will be possible to monitor the voltage, and monitor outages and determine equipment faults in the transmission system as the abnormal detection for the electricity suppliers.

Especially, the analytics for the reverse flow electricity can provide much more insight the PV based power generation.

8.2.5 Application for the digital grid and Ownership of smart meter

Recently, with the rise of the percentage of renewable energy in total energy supply in advanced countries, more and more small scale and unstable renewable energy resources will be integrated into the original power grid. As a future model of the electricity grid, the Digital Grid [Abe 2011] has been suggested. The Digital Grid realizes the convergence of power and information by utilizing Digital Grid Routers. It enables further efficiency and popularization of renewable energy through power interchange and electricity trade. Shortly, as indicated as the concept of Digital Grid, people are capable of generating power at home and trade it with other individuals freely. Following this idea, the demand and supply balancing will serve as one of the key technologies. For example, the balancing and trading electricity between the cells will be performed automatic. In there, the programmable smart meter can serve a key for the data provision. In that time, the ownership should be considered. Right now the ownership of the smart meter is only the electricity company, and the data will be monopolized. However, the data generated in the smart meter is owned by the demander, and the data has to be used for the total society. Therefore, the further deregulation should be conducted to enhance the democracy of the smart meter data. In that time, our proposed smart meter should serve a key role in there.

Finally, the ownership should be considered. Right now the ownership of the smart meter is only the electricity company, and the data will be monopolized. However, the data generated in the smart meter is owned by the demander, and the data has to be used for the total society. Therefore, the further deregulation should be conducted to enhance the democracy of the smart meter data. In that time, our proposed smart meter should serve a key role in there.

9 APPENDICES

Appendix 1 Explanation of Deep Learning

We briefly describe the structure of the neural network and how to train itself. Here we consider only the most fundamental feedforward type in which signals propagate in one direction from input to output. This is the most commonly used problem in many problems including image recognition. The explanation is referred from Deep Learning Technical report from The Institute of Image Information and Television Engineers. [Okatani 2014]

$$y = f(x) \qquad \text{A-(1)}$$

First, consider a unit imitating a neuron that is the model of human brain (Fig 9.1(a)). This has the function of taking one input x and returning one output y, and the relation between this input and output is determined by a nonlinear function called an activation function A-(1). In the activation function f, the sigmoid function $f(x) = 1 / (1 + e^{-x})$ which simulates the input / output response of the living body neuron has been used for a long time.

$$x_j = b_j + \sum_{i=1}^{m} y_i w_{ij} \qquad \text{A-(2)}$$

Consider a network in which such units are arranged in a layered fashion, and bonds are provided between the units only between the layers (Fig 9.1 (c)). One unit (j in the figure) adds a value called a bias to the weighted sum of outputs yi ($i = {}_{1, \ldots, m}$) from multiple units in the immediately preceding layerA-(2). This unit transmits the output via the activation function, yj = f (x_j) equally to the upper layer as shown in Fig 9.1 (c). An arbitrary number of such layers are arranged to create a multilayered network (Fig 9.2).

$$C = -\sum_{j=1}^{n} d_j \log p_j \qquad \text{A-(3)}$$

The input signal propagates sequentially through the layer, and the final result is output from the last layer. If the problem you solve is a classification class, only the last output layer is specially allocated the same number of units as the target class number n. Then let the outputs of these units be softmax-based on input x_j ($j = 1, ..., n$) to them, $p_j = e^{x_j} / \Sigma_{k=1} e^{x_k}$. This p_1, ..., p_n are probabilities for n classes, and they are classified into class j where p_j takes the maximum value. The neural network expresses one function as a whole. In order to make this function the desired one, neural net learning is adjusting the network weight w_{ij} and bias b_i using a large number of learning samples.

$$\Delta w_{ij}^{(i)} = -\varepsilon \frac{\partial C}{\partial w_{ij}^{(i)}} + \alpha \Delta w_{ij}^{(t-1)} \qquad \text{A-(4)}$$

A gradient descent method is generally used to minimize the error C defined in this way A-（3）. Gradient descent methods are used for large deep neural net works. In the gradient descent method, it is necessary to calculate the error gradient ($\partial C / \partial w_{ij}$, etc.) concerning the weight and the bias. This computes the derivative of the composite function in which the activation function is nested by the number of layers, which is simple in the layer closer to the output layer but becomes more complicated in the deeper layer away from the output layer. The system is called Back Propagation. A-（4）is the function of the backpropagation. By incorporating a chain rule resulting from differentiation of the composite function of activation function into the inside of numerical calculation, it becomes an algorithm that propagates errors of each unit in the output layer in the opposite direction from the side closer to the output layer.

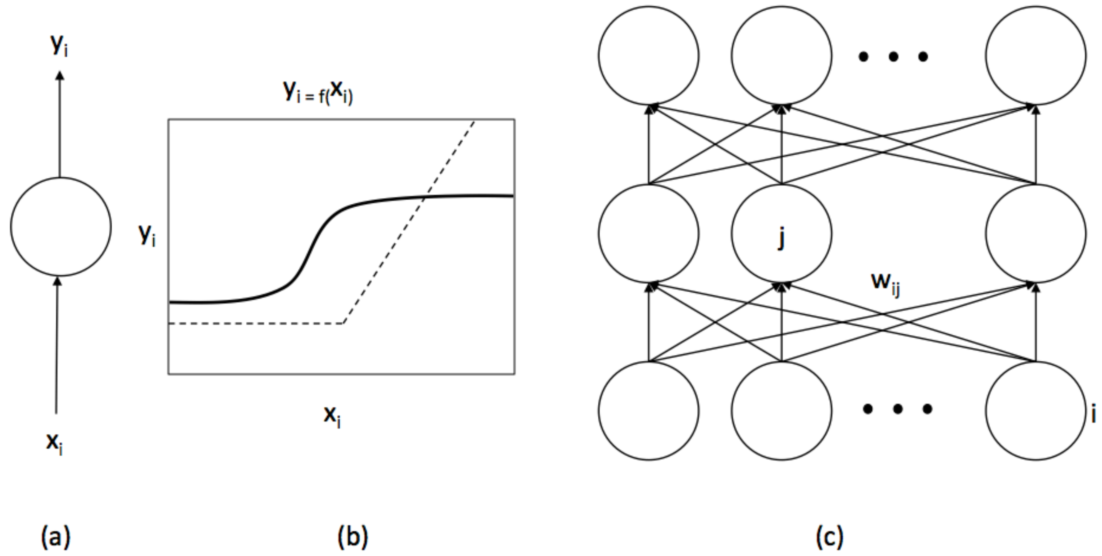


Fig 9.1 Image of neuron model in Neural net works [Okatani 2014]

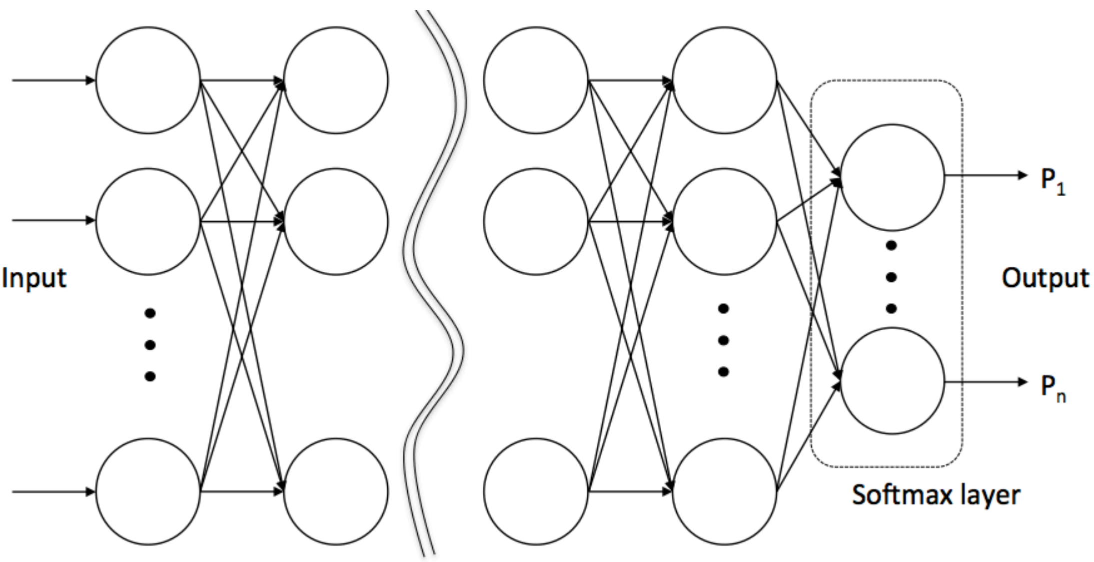


Fig 9.2 Image of total neuron model in Neural net works [Okatani 2014]

Appendix 2 Explanation of Gradient Boosting Machine

Gradient Boosting is a Machine Learning method that bases on two Machine Learning frameworks. They are gradient-based optimization and boosting. Gradient-based optimization uses gradient computations to reduce the loss function constructed by the training data. In boosting, it constructs a weak learner for each step and minimizes the loss function. At that time, the handling of each learning data is not even equal. It will increase the weight of each learning data to the one incorrectly identified in the previous step so that it can identify incorrectly well in the next step.

Fig 9.3 shows the algorithm used the Gradient Boosting based on example of K-class classification;

1. Initialize $f_{k0} = 0, k = 1,2,\dots,K$
2. For $m = 1\ to\ M$
   a. Set $p_k(x) = \frac{e^{f_k(x)}}{\sum_{i=1}^{K} e^{f_1(x)}}$ for all $k = 1,2,\dots,K$
   b. For $k = 1\ to\ K$
      i. Compute $r_{ikm} = y_{ik} - p_k(x_i), i = 1,2,\dots,N$
      ii. Fit a regression tree to the targets $r_{ikm}, i = 1,2,\dots,N$ giving terminal regions $R_{jkm}, 1,2,\dots,J_m$
      iii. Compute

$$\gamma_{jkm} = \frac{K-1}{K}\frac{\sum_{x_i \in R_{jkm}}(r_{ikm})}{\sum_{x_i \in R_{jkm}}|r_{ikm}|(1-|r_{ikm}|)}, j = 1,2,\dots,J_m$$

      iv. Update $f_{km}(x) = f_{k,m-1}(x) + \sum_{j=1}^{j_m}\gamma_{jkm}I\left(x \in R_{jkm}\right)$
3. Output value $f_k(k) = f_{kM}(x), k = 1,2,\dots,K$

Fig 9.3 Gradient Boosting based on example of K-class classification [Click 2015]

The explanation of the algorithms:

1) In the above algorithm for multi-class classification, It builds k-regression trees. That means one tree is made for each target class.

2) The index, M, stands for the number of iteration that defined by the users. The following explains that how weak learners added to the current ensemble. There is an inner loop within this outer loop for each of the K classes. Within this in loop(2.b in the algorithm indicated in Fig 9.3), 1) the first target is to calculate the residuals represented by rikm, which are the gradient values for each of the N bins that is made in the CART model(Decision Tree (CART model) is a method of Machine Learning that performs classification and regression using a data structure that is called a decision tree). Based on the, calculated rikm and updates, a regression tree based on CART model is then fit these gradient computations.

3) The last task in the inner loop is to add the model made in this step to the fitted regression tree to update the classification accuracy of the model based on gradient descent steps. Finally, After M iterations, the final model "boosted" model can be tested out on new data.

* The explanation is referred from Gradient Boosted Machines with H2O and The Elements of Statistical Learning. [Hastie 2009] [Click 2015]

Appendix 3 Drawings for Home Master

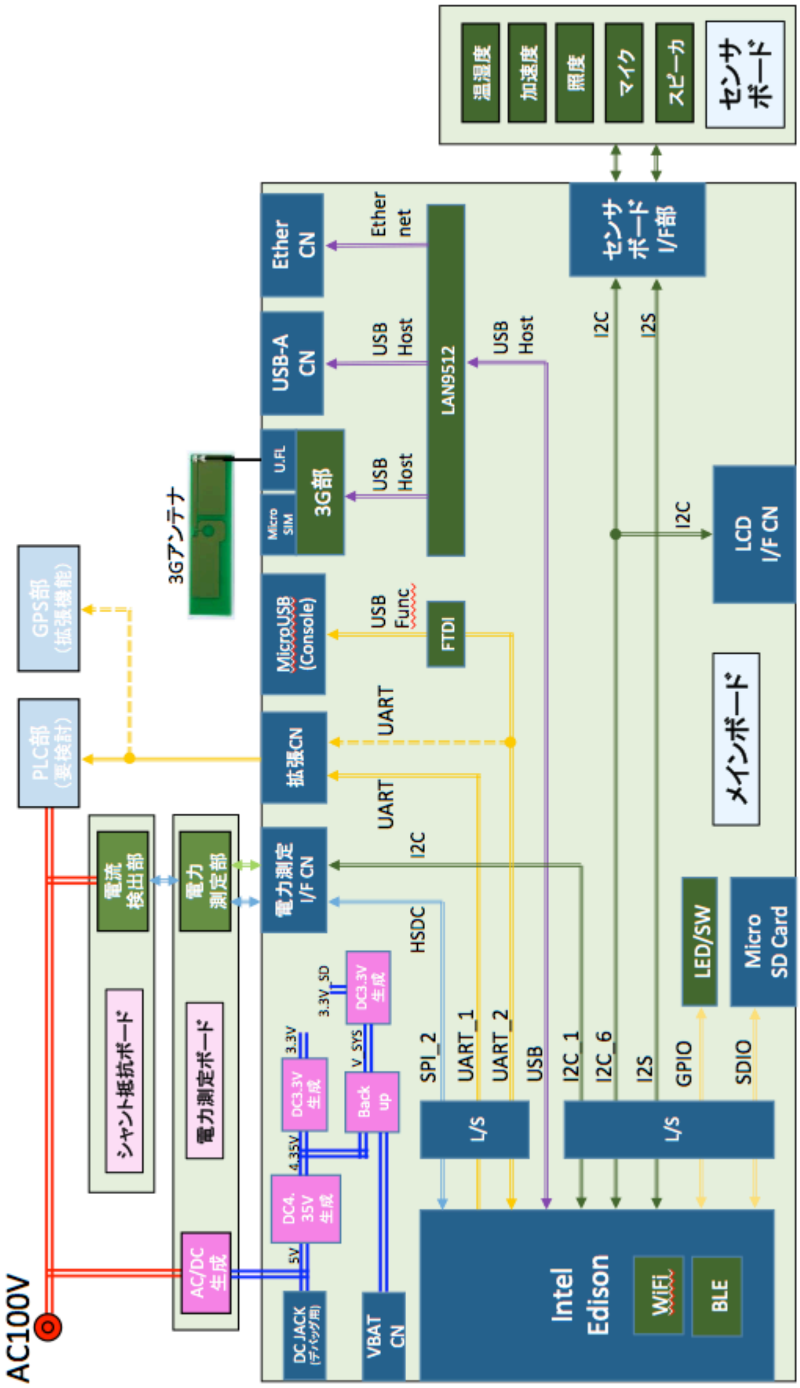


Fig 9.4 Circuit diagram for Home Master (Made by Tessera Co., Ltd)

Pin	信号名	兼用機能	使用機能	接続機能
1	GND	−	GND	
3	USB ID	−	USBホスト	プルダウン
5	GND	−	GND	
7	MSIC SLP CLK3	−	−	PAD (未使用)
9	GND	−	GND	
11	GND	−	GND	
13	GND	−	GND	
15	GND	−	GND	
17	PWRBTN#	−	−	SW
19	FAULT	−	−	PAD (未使用)
21	PSW	−	−	PAD (未使用)
23	V VBAT BKUP	−	−	PAD (未使用)
25	GP165	−	GPIO	LED
27	GP135	UART 2 TX	UART 2	コンソール用MicroUSB
29	−	−	−	未使用
31	RCVR MODE	−	−	SW
33	GP13 PWM1	PWM 1	GPIO (INT)	センサーボード
35	GP12 PWM0	PWM 0	GPIO (INT)	
37	GP182 PWM2	PWM 2	GPIO	
39	GP183_PWM3	PWM_3	GPIO (RESET) (Active=Low)	拡張コネクタ
41	GP19	I2C_1_SCL	I2C_1	電力測定IC
43	GP20	I2C 1 SDA		
45	GP27	I2C 6 SCL	I2C_6	センサーボード
47	GP28	I2C 6 SDA		
49	−	−	−	未使用
51	GP111	SPI2_FS1	GPIO (RESET) (Active=Low)	各機能
53	GP110	SPI2 FS0	SPI2	電力測定IC
55	GP109	SPI2 CLK		
57	GP115	SPI2 TXD		
59	GP114	SPI2 RXD		
61	GP130	UART 1 RX	UART_1	拡張コネクタ
63	GP129	UART 1 RTS		
65	GP128	UART 1 CTS		
67	OSC CLK OUT 0	−	−	PAD (未使用)
69	FW RCVR	−	−	SW

Pin	信号名	兼用機能	使用機能	接続機能
2	VSYS	−	VSYS	4.35V を入力
4	VSYS	−	VSYS	4.35V を入力
6	VSYS	−	VSYS	4.35V を入力
8	3.3V (OUT)	−	−	PAD (未使用)
10	3.3V (OUT)	−	−	PAD (未使用)
12	1.8V (OUT)	−	1.8Vout	各レベルシフタ
14	DCIN	−	VSYS	4.35V を入力
16	USB DP	−	USBホスト	USB-Ethernet ハブIC
18	USB DN	−		
20	USB VBUS	−	−	未使用
22	GP134	UART 2 RX	UART 2	コンソール用MicroUSB
24	GP44	−	GPIO	拡張コネクタ
26	GP45	−	GPIO	
28	GP46	−	GPIO	SW
30	GP47	−	INT (ZX)	電力測定IC
32	GP48	−	INT (IRQ 0)	
34	GP49	−	INT (IRQ 1)	
36	RESET OUT#	−	−	PAD (未使用)
38	−	−	−	未使用
40	−	−	−	未使用
42	GP15	−	GPIO (RESET) (Active=Low)	3G モジュール
44	GP84	SD 0 CLK FB	SDIO	MicroSDカード
46	GP131	UART 1 TX	UART 1	拡張コネクタ
48	GP14	−	GPIO	電源監視
50	GP42	I2S 2 RXD	I2S_2	センサーボード
52	GP40	I2S_2_CLK		
54	GP41	I2S 2 FS		
56	GP43	I2S 2 TXD		
58	GP78	SD 0 CLK	SDIO	MicroSDカード
60	GP77	SD 0 CD#		
62	GP79	SD 0 CMD		
64	GP82	SD 0 DAT2		
66	GP80	SD 0 DAT0		
68	GP83	SD 0 DAT3		
70	GP81	SD 0 DAT1		

Fig 9.5 Sensor specification for the sensor board (Made by Tessera Co., Ltd)

●HM Main Board 外観図

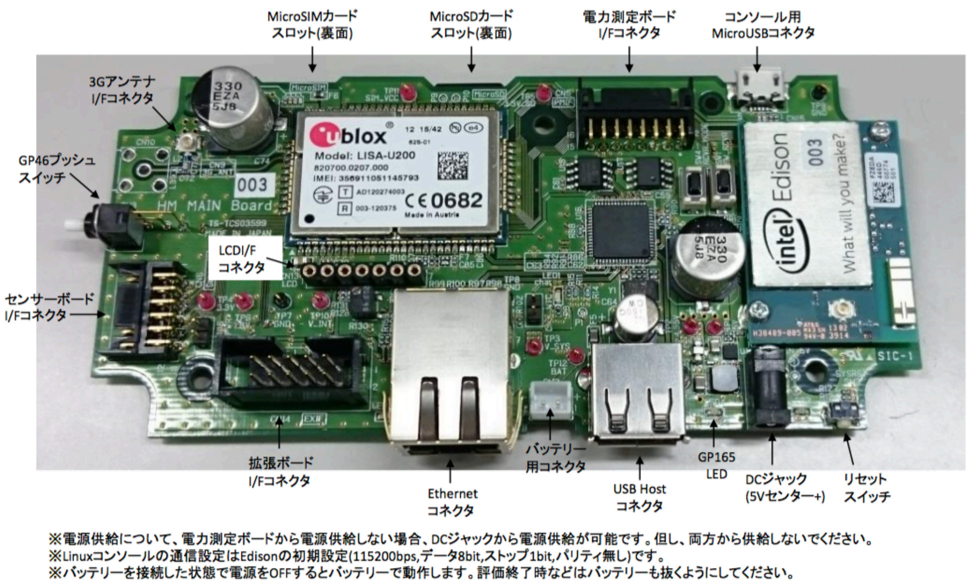


Fig 9.6 Main board outside image for the Home Master(Made by Tessera Co., Ltd)

●HM PM Board(電力測定) + HM CS Board(シャント抵抗)　外観図

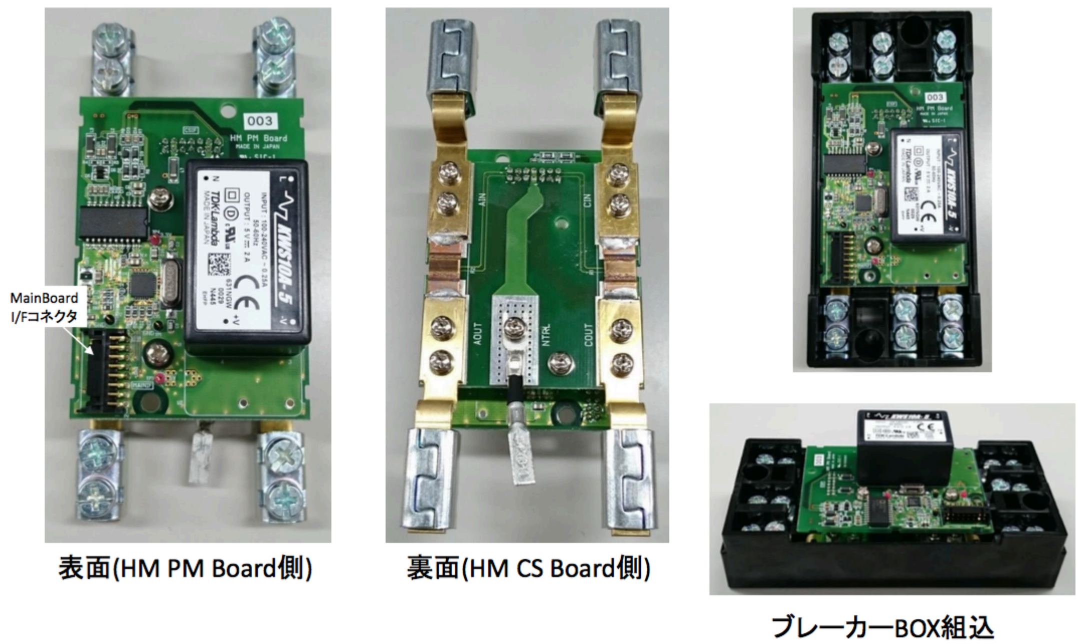


Fig 9.7　Outside image for the Home Master　(Made by Tessera Co., Ltd)

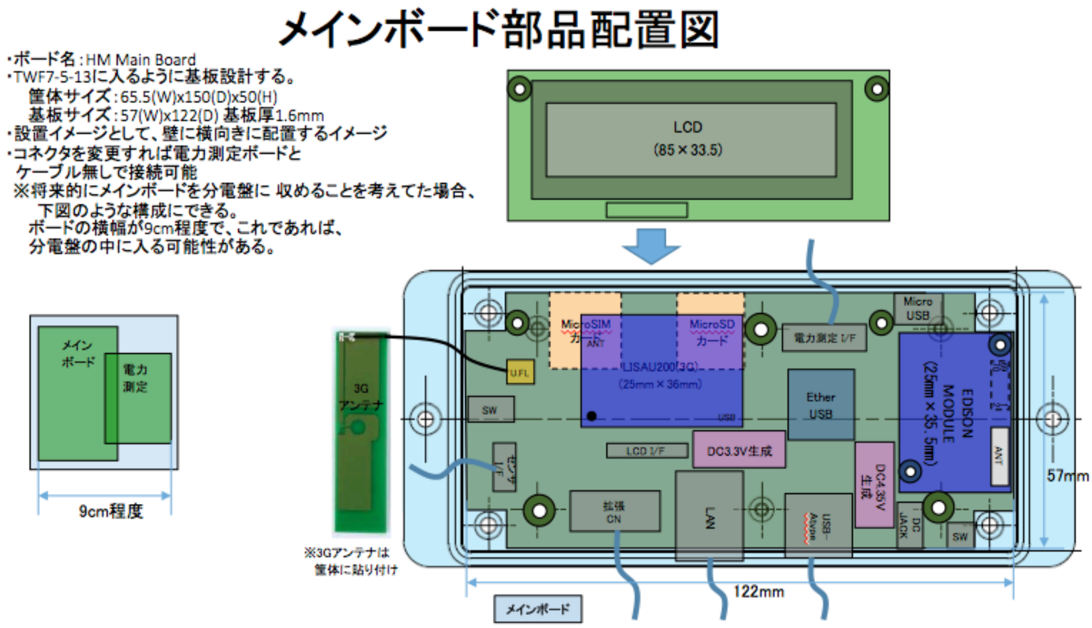


Fig 9.8　Parts location image　　(Made by Tessera Co., Ltd)

Appendix 4 Feature used in the demand forecast

4.1 Feature used for the demand forest in chapter 3.3.2

We selected the input parameter as follows for the chapter 3.3.2.These features are used in the calculation in Fig 3.4, 3.5.

Input parameters:

- $S_{(d,t)}$: The Time slot (48 steps Qualitative variable)
- $W_{(d)}$: Weekday (7 weekdays 4 Qualitative variable)
- $T_{(d,t)}$: Temperature for each step in the next day (Actual demand temperature)
- $H_{(d,t)}$: Humidity for each step in the next day (Actual humidity data)
- $WS_{(d,t)}$: Wind Speed for each step in the next day (Actual wind speed data)
- $T_{(d,t)}$: Temperature for each step in the day
- $H_{(d,t)}$: Humidity for each step in the day
- $WS_{(d,t)}$: Wind Speed for each step in the day
- $HF_{(d)}$:Holiday flag
- $HFT_{(d)}$: Tomorrow Holiday flag
- $HFY_{(d)}$: Yesterday Holiday flag
- $T_{AVE(d)}$: Average temperature for next day,
- $T_{MAX(d)}$: Maximum temperature for next day,
- $T_{MIN(d)}$: Minimum temperature for next day,
- $T_{AVE(d)}$: Average humidity for next day,
- $D_{(d-1,t-8)}$:The demand for 4 hours advanced time slot in previous day
- $D_{(d-1,t-8)}$:The demand for 4 hours advanced the time slot in previous day
- $D_{ave(d-1)}$:The average demand for the time slot in previous day
- $D_{ave(d-7)}$:The average demand for the time slot in previous week
- $D_{ave(d-14)}$:The average demand for the time slot in 14 days before

- $D_{(d-1,t)}$:The demand for the time slot in previous day
- $D_{(d-7,t)}$:The demand for the time slot in previous week
- $D_{(d-14,t)}$:The demand for the time slot in 14 days before

  * t stands for the 00:00, d stands for the day that the demand want to forecasted

Output parameters:

- $D_{(d,t)}$:The demand for the time slot

4.2 Parameter settings used for the demand forest in chapter 3.3.2

For the machine learning setting and configuration are indicated below for the chapter 3.3.2,

1) The input parameters for the Gradient Boosting Machine are used the parameters in indicated below for every individual data set:

- n.trees (The number of boosting stages to perform): 500
- interaction.depth(Maximum depth of the individual regression estimators) :5
- Shrinkage (learning rate):0.01

* The total calculation is based on R language. As the machine-learning library, H2O version 3.0.0.30.was used.

2) The input parameters for the Deep learning are used the parameters in indicated below for every individual data set:

Window slide system is adapted to the training process for the FNN. The configuration of the neural network is that the number of the first layer's neuron is

89, the mid layer has three layers; both of them have 100 neurons. Ignition function is Relu, and we used the Adam as the optimization method for the weight optimization.

We also applied the RNN for the demand forecast. Recurrent neural net (RNN) works widely used for the time series. The configuration of the neural network is as follows. The number of the first layer's neuron is 89; the mid layer has two layers; both of them have 100 neurons. The final layer has one output. The ignition function is called Relu, and we used the Adam as the optimization method for the weight optimization. Then for the term of recurrent we performed it for 48 steps, which stand for one day, and 337 which stands for 1week. Also, we performed the training while changing parameters of the batch size and number of trading. The result applied Deep Learning is indicated below. Table 9-1 shows the parameter setting and training for the demand forecast.

Table 9-1 Parameter setting for the demand forecast (Made by Author)

bath size	Epoch	recurrent size	MAPE(FFN)	MAPE(RNN)
100	300		3.94	
200	300		3.83	
200	600		4.4	
300	300	48		3.75
300	300	336		3.51

* The total calculation is based on Python.As the machine-learning library sklearn 0.17.1 and keras: 1.0.4

4.3 Feature engnieering performed the demand forest in chapter 3.3.2

For the feature engnieering, we used try and error approach for 18 cases based on Table 9-2. The prediction error largely depends on which feature is used. For this reason, it is necessary to select a feature strongly correlated with the electric power demand as the feature used for prediction. Generally, demand curve is said to be greatly affected by temperature. In addition, even if considering periodic fluctuations such as humidity and day of the week, there are many features with strong correlation. Also, it is reported that feature quantities such as combinations of exponentiation, logarithms, and arithmetic operations of them are effective for improving prediction accuracy. Table 9-2 shows each feature pattern tried, and Fig.9.9 shows thre result of the try and error approches for searching the best combination of the feature parameter for the reduction of prediction error. We have tried 18 cases for each parameter combination. The selected parameters are based on the previous researches. As indicated in Fig. 9.9, case 18 is shown the best forecast results and the analysis of this result is indicated later. As the result, we used the result based on the case 18 for the calculation for the Fig 3.4, 3.5 in the main part.

Table 9-2 The trial for the different feature cases(Based on the default parameterseting in GBM:tree number = 400, tree depth = 5) (Made by Author)

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
Slot	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Weekday	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Demand in 1 day advance		○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Temperature			○	○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Averaged temperature				○	○	○	○	○	○	○	○	○	○	○	○	○	○	○
Maximum temperature					○	○	○	○	○	○	○	○	○	○	○	○	○	○
Minimum temperature						○	○	○	○	○	○	○	○	○	○	○	○	○
Humidity							○	○	○	○	○	○	○	○	○	○	○	○
Averaged humidity								○			○	○	○	○	○	○	○	○
Sensible temperature								○	○		○					○	○	○
Holiday flag										○	○	○			○	○	○	○
Tomorrow holiday flag											○	○	○	○	○	○	○	○
Yesterday holiday flag														○	○	○	○	○
Demand in 14 days advance																		○
Demand in 7 days advance																	○	○

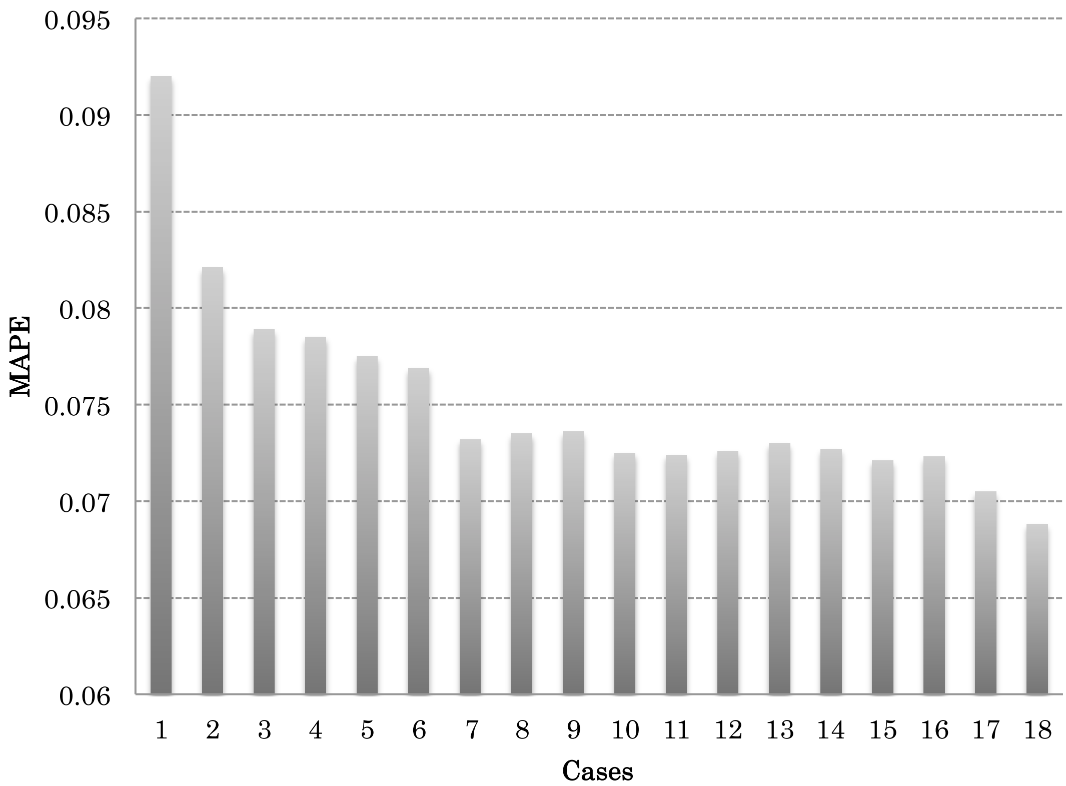


Fig 9.9 Result for different feature cases indicated in MAPE(Made by Author)

We analyzed the feature parameters used in the forecast process that should be used for the forecast based on the importance factor which can be calculated in the calculation process of the tree models such as Gradient Boosting Machine. The importance factor can be represented in IncMSE. The calculation process for IncMSE is indicated below. The main idea for IncMSE is to show the change of forecast error with and without the parameter.

- The algorithm for the calculation of the IncMSE.

1) Build regression forests. Calculate the mse (mse0).
2) For 1 to j variables: delete values of column j, then compute mse(j)

3) The percentage of IncMSE of j'th variable is calculated as (mse(j)-mse0)/mse0 * 100%

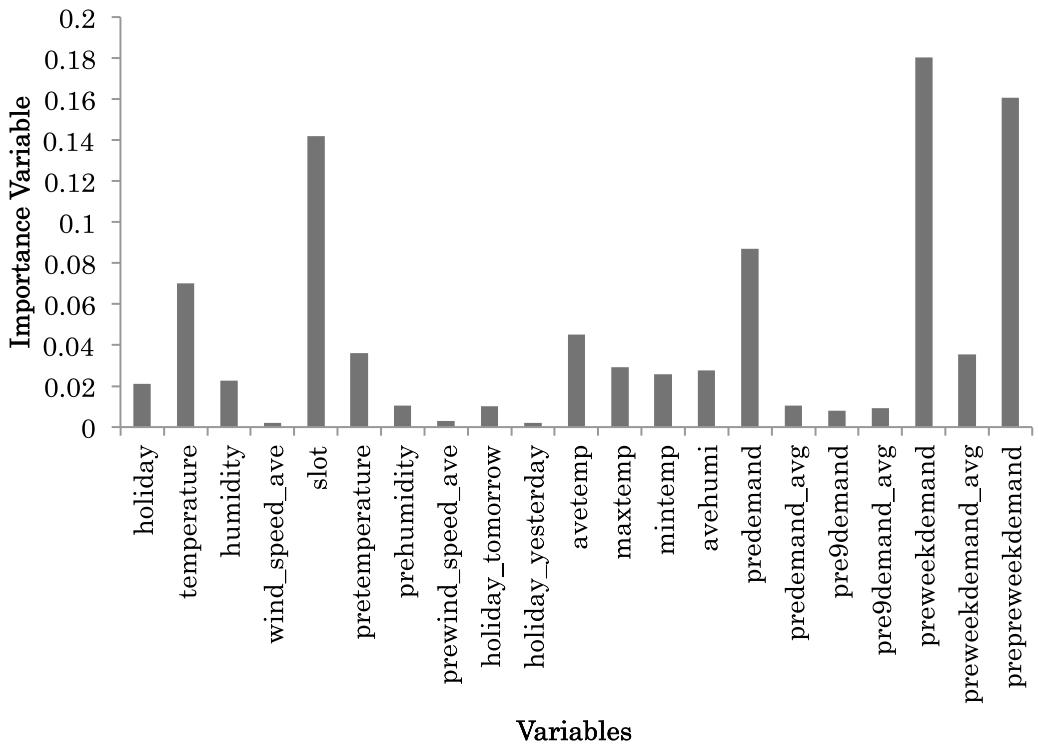


Fig 9.10 The importance variable for each input parameter (Made by Author)

The importance variable analysis performed for the Input parameter was indicated in the Fig 9.10. Previous week demand provided most significant information for the forecast as well as the demand in 2 weeks ago. Also the previous day demand provided information for the forecast. The weather information provided less information comparing previous demand information. In the weather parameters, temperature gives some information, while humidity provide less information. Next days averaged temperature, maximum temperature, and minimum temperature also provide certain information for the forecast.

4.4 Feature engnieering performed the demand forest in chapter 3.3.2 based on Generic Algorithm searching

Since the number of combinations of feature quantities is enormous, we investigated genetic algorithm (GA) parameter searching approach which is capable of efficient search for vast feature space. This time, the features listed in Table 9-3 were selected. Genes were expressed as 1,0 (1: included, 0: not included). GA was implemented. The objective function is MAPE. GA was executed as gene number 20. The gray frame is a feature which did not survive. It converges at cycle number 50. The final result shows that we could achieve MAPE 6.67%. However, due to the slight improvement, finally we used the input parameter indicated in the former process (Table 9-2). Table 9-3 shows the parameter used in the process for the parameter selection based on GA. As the result gray colored parameters were not selected.

Table 9-3 The trial for searching optimal parameter besed on GA (Based on the default parameterseting in GBM:tree number = 400, tree depth = 5) (Made by Author)

1	month	Month	The exact day	–
2	weekday	Weekday	The exact day	–
3	slot	Slot number	The exact day	The exact day slot
4	holiday	The exact day holiday flag	The exact day	–
5	holiday_tomorrow	Next day holiday flag	1 day after	–
6	holiday_yesterday	The advanced day holiday flag	1 day before	–
7	avetemp	The exact day maximum	The exact day	–

		temperature		
8	maxtemp	The exact day average temperature	The exact day	–
9	mintemp	The exact day average temperature	The exact day	–
10	avehumi	The exact day average humidity	The exact day	–
11	p2avetemp	1 day before temperatuere	2 day before	–
12	p3avetemp	2 day before temperatuere	3 day before	–
13	p4avetemp	3 day before temperatuere	4 day before	–
14	p5avetemp	4 day before temperatuere	5 day before	–
15	p6avetemp	5 day before temperatuere	6 day before	–
16	p7avetemp	6 day before temperatuere	7 day before	–
17	p2maxtemp	1 day before temperatuere	2 day before	–
18	p3maxtemp	2 day before temperatuere	3 day before	–
19	p4maxtemp	3 day before temperatuere	4 day before	–
20	p5maxtemp	4 day before temperatuere	5 day before	–
21	p6maxtemp	5 day before temperatuere	6 day before	–
22	p7maxtemp	6 day before temperatuere	7 day before	–
23	p2mintemp	1 day before temperatuere	2 day before	–
24	p3mintemp	2 day before temperatuere	3 day before	–
25	p4mintemp	3 day before temperatuere	4 day before	–
26	p5mintemp	4 day before temperatuere	5 day before	–
27	p6mintemp	5 day before temperatuere	6 day before	–
28	p7mintemp	6 day before temperatuere	7 day before	–
29	p2avehumi	1 day before temperatuere	2 day before	–
30	p3avehumi	2 day before temperatuere	3 day before	–
31	p4avehumi	3 day before temperatuere	4 day before	–
32	p5avehumi	4 day before temperatuere	5 day before	–

33	p6avehumi	5 day before temperatuere	6 day before	—
34	p7avehumi	6 day before temperatuere	7 day before	—
35	tempeff	Sensible temperature	The exact day	The exact day slot
36	temp	Temperature	The exact day	The exact day slot
37	temp_sq	The double of temperature	The exact day	The exact day slot
38	humi	Humidity	The exact day	The exact day slot
39	wind	Wind	The exact day	The exact day slot
40	rain	Rain	The exact day	The exact day slot
41	pressure	air pressure	The exact day	The exact day slot
42	sunshine	Sun shine	The exact day	The exact day slot
43	p2demand	1 day before demand	2 day before	The exact day slot
44	p3demand	2 day before demand	3 day before	The exact day slot
45	p4demand	3 day before demand	4 day before	The exact day slot
46	p5demand	4 day before demand	5 day before	The exact day slot
47	p6demand	5 day before demand	6 day before	The exact day slot
48	p7demand	6 day before demand	7 day before	The exact day slot
49	p2demand_log	1 day before demand	2 day before	The exact day slot
50	p3demand_log	2 day before demand	3 day before	The exact day slot
51	p4demand_log	3 day before demand	4 day before	The exact day slot
52	p5demand_log	4 day before demand	5 day before	The exact day slot
53	p6demand_log	5 day before demand	6 day before	The exact day slot
54	p7demand_log	6 day before demand	7 day before	The exact day slot
55	p2demand_avg	1 day before average demand	2 day before	—
56	p3demand_avg	2 day before average demand	3 day before	—
57	p4demand_avg	3 day before average demand	4 day before	—
58	p5demand_avg	4 day before average demand	5 day before	—
59	p6demand_avg	5 day before average	6 day before	—

		demand		
60	p7demand_avg	6 day before average demand	7 day before	—
61	p2demand_log_avg	1 day before averaged Logarithm power demand	2 day before	—
62	p3demand_log_avg	2 day before averaged Logarithm power demand	3 day before	—
63	p4demand_log_avg	3 day before averaged Logarithm power demand	4 day before	—
64	p5demand_log_avg	4 day before averaged Logarithm power demand	5 day before	—
65	p6demand_log_avg	5 day before averaged Logarithm power demand	6 day before	—
66	p7demand_log_avg	6 day before averaged Logarithm power demand	7 day before	—
67	p3demand_d	The electrcity gap between 2 before and 3 day before	2 day before	—
68	p4demand_d	The electrcity gap between 3 before and 4 day before	3 day before	—
69	p5demand_d	The electrcity gap between 4 before and 5 day before	4 day before	—
70	p6demand_d	The electrcity gap between 5 before and 6 day before	5 day before	—
71	p7demand_d	The electrcity gap between 6 before and 7 day before	6 day before	—
72	p2demand1	one day before slot 1	1day before	Slot 1
73	p2demand2	one day before slot 2	1day before	Slot 2
74	p2demand3	one day before slot 3	1day before	Slot 3
75	p2demand4	one day before slot 4	1day before	Slot 4
76	p2demand5	one day before slot 5	1day before	Slot 5
77	p2demand6	one day before slot 6	1day before	Slot 6
78	p2demand7	one day before slot 7	1day before	Slot 7

79	p2demand8	one day before slot 8	1day before	Slot 8
80	p2demand9	one day before slot 9	1day before	Slot 9
81	p2demand10	one day before slot 10	1day before	Slot 10
82	p2demand11	one day before slot 11	1day before	Slot 11
83	p2demand12	one day before slot 12	1day before	Slot 12
84	p2demand13	one day before slot 13	1day before	Slot 13
85	p2demand14	one day before slot 14	1day before	Slot 14
86	p2demand15	one day before slot 15	1day before	Slot 15
87	p2demand16	one day before slot 16	1day before	Slot 16
88	p2demand17	one day before slot 17	1day before	Slot 17
89	p2demand18	one day before slot 18	1day before	Slot 18
90	p2demand19	one day before slot 19	1day before	Slot 19
91	p2demand20	one day before slot 20	1day before	Slot 20
92	p2demand21	one day before slot 21	1day before	Slot 21
93	p2demand22	one day before slot 22	1day before	Slot 22
94	p2demand23	one day before slot 23	1day before	Slot 23
95	p2demand24	one day before slot 24	1day before	Slot 24
96	p2demand25	one day before slot 25	1day before	Slot 25
97	p2demand26	one day before slot 26	1day before	Slot 26
98	p2demand27	one day before slot 27	1day before	Slot 27
99	p2demand28	one day before slot 28	1day before	Slot 28
100	p2demand29	one day before slot 29	1day before	Slot 29
101	p2demand30	one day before slot 30	1day before	Slot 30
102	p2demand31	one day before slot 31	1day before	Slot 31
103	p2demand32	one day before slot 32	1day before	Slot 32
104	p2demand33	one day before slot 33	1day before	Slot 33
105	p2demand34	one day before slot 34	1day before	Slot 34
106	p2demand35	one day before slot 35	1day before	Slot 35
107	p2demand36	one day before slot 36	1day before	Slot 36
108	p2demand37	one day before slot 37	1day before	Slot 37
109	p2demand38	one day before slot 38	1day before	Slot 38

110	p2demand39	one day before slot 39	1day before	Slot 39
111	p2demand40	one day before slot 40	1day before	Slot 40
112	p2demand41	one day before slot 41	1day before	Slot 41
113	p2demand42	one day before slot 42	1day before	Slot 42
114	p2demand43	one day before slot 43	1day before	Slot 43
115	p2demand44	one day before slot 44	1day before	Slot 44
116	p2demand45	one day before slot 45	1day before	Slot 45
117	p2demand46	one day before slot 46	1day before	Slot 46
118	p2demand47	one day before slot 47	1day before	Slot 47
119	p2demand48	one day before slot 48	1day before	Slot 48

4.5 Parameter settings used for the demand forest in chapter 4.2

We used parameters indicated in the Table 3-1 based on the indication of the paper [Chin 2014] which selected the parameters based on the importance variables calculated in the Gradient Boosting Model. The features are indicated as below:

Input parameters:

- $S_{(d,t)}$: The Time slot (48 steps Qualitative variable),
- $W_{(d)}$：Weekday (7 weekdays 4 Qualitative variable),
- $T_{(d,t)}$: Temperature for each step in the next day (Actual demand),
- $H_{(d,t)}$: Humidity for each step in the next day (Actual demand) (Actual humidity),
- $T_{AVE(d)}$: Average temperature for next day,
- $T_{MAX(d)}$: Maximum temperature for next day,
- $T_{MIN(d)}$: Minimum temperature for next day,

- $T_{AVE(d)}$: Average humidity for next day,
- $D_{(d-1,t)}$:The demand for the time slot in previous day
- $D_{(d-7,t)}$:The demand for the time slot in previous week

Output parameters:

- $D_{(d,t)}$:The demand for the each time slot

The input parameters for the Gradient Boosting Machine are used the parameters in indicated below for every individual data set:

- n.trees (The number of boosting stages to perform): 500
- interaction.depth(Maximum depth of the individual regression estimators) :5
- Shrinkage (learning rate):0.1
- n.minobsinnode = 10

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ACKNOWLEDGEMENTS

ACKNOWLEDGEMENTS

I wish to express my sincere gratitude to the following persons who have made my learning experience an exceptional one.

Firstly, I must thank Prof.Abe, a very ambitious, experienced, and generous individual who is passionate about education. Thank you for the wealth of knowledge that you have imparted and for providing an environment for me to accomplish my Ph.D. and for the advice given in the every regular meeting.

To Professor Tanaka, a very kind and charming teacher. You have not only provided information that was helpful for my Ph.D. but also for my life. I miss the several days, and it was fun to have traveled with you for the academic conferences.

To Hashimoto-san and Umezu-San, my heartiest gratitude is extended to you. You were so generous and sometimes patient to take care of my life, extra problems and special issues during my studies. I wish to express my most sincere gratitude to you.

I have been truly blessed to have two of the most supportive roommates in the persons of Nguyen-san and Maida-san san. They listened to my discontent to the research and reassured me when things do not always turn out the way they should.

I not only got the company to share the suffering of my Ph.D. studies but I think I found my study soul mates in Annette, Brend, and Kitamura-san. You understood every hurdle; you helped me cried my secret tears and prevented me from getting much more weight on my body. We went through the teething pains together. Thank you for being my Ph.D. buddies.

For those other persons who have made even the simplest contribution to my precious school life and have supported me and shared with me throughout the period, I extend my sincere thanks. Your contribution and support are greatly appreciated.

I am happy that I could achieve one of the goals of my academic journey that I have been pursued. However, I am so sorry that my Ph.D. life in Todai is and will be the best part of the time in my life, and that will never come back again.

Thank you to everyone who has helped and supported this accomplishment.

PUBLISHMENTS AND AWARDS

1) Journals which have been reviewed

- H.Chin and Rikiya Abe, "Data Analysis of Spanish Electrical Grid System," International Journal of Electrical Energy, Vol. 4, No. 1, pp. 62-66, 2016.
- H.Chin and Rikiya Abe, “Household electricity load disaggregation based on lowresolution smart meter data”, International Journal of Smart Grid anInternational Journal of Smart Grid and Clean Energy, vol. 5, no. 3, pp. 188-195, 2016.

2) Presentation in the conferences which have been reviewed

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3) Presentation in the conferences

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- H.Chin, R.Abe,..etc, “Home Master – A degenderized Smart Meter”, Asian Utility Weeks 2016
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4) Awards from academia

- Best Ph.D Poster Award(First Prize), ” Demand forecast improvement based on the electricity demander portfolio management”, IEEE EEEIC 2016

5) Awards from extra -activity

- The Highest Popularity Award: Personal Micro Grid in Off-grid district, 2014 TECO Green Tech Contest, http://www.tecofound.org.tw/greentech-contest/2014/works_2014.php
- 関東経済産業局長賞：Automatic Power Change~電気料金メニュー自動切り替えサービス, 大学ベンチャーグランプリ関東大会 2014, http://www.cvg-nikkan.jp/index/tokyo/
- 大賞：Automatic Power Change~電気料金メニュー自動切り替えサービス,University Venture Grand Prix 2014, http://jeenet.jp/uvgp/

- 最優秀賞：Everysense システムをベースにしたクラウド型温度の提案、Everysense ハッカソン http://every-sense.com/
- FinalList : Tokyo Start Up Grand Prix 2014 http://tokyo-startup.jp/