Master's Thesis

Aggregate Electricity Consumption in Iran and Japan: A Multiple Approach Comparison of Time series Forecasting Models and an Analysis of Accumulated Expertize measured in terms of Learning Rates

By

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September

2017

A Thesis presented to Graduate School of Management at Ritsumeikan Asia Pacific University in Partial Fulfilment of the Requirements for the Degree Master of Business Administration

Acknowledgment

While pursuing my MBA studies in Ritsumeikan APU, I have received a tremendous amount of support from many people and organizations alike. Without their memorizing help, this thesis would have never seen the light and my vocation would have never been achieved. Therefore, I want to thank everyone who have made this thesis possible.

First and foremost, I would like to thank Japan International Cooperation Organization (JICA) for providing me the outstanding opportunity of studying a Master's Degree in Ritsumeikan Asia Pacific University and allowing me to benefit from a study scholarship that has covered virtually all the required expenses for this thesis to be completed.

Of course, I would like to express my sincere gratitude to my supervisor, Professor ASGARI Behrooz, he has been a very good teacher and a second father to me. He supervised my thesis and pushed me to present my work in various conferences, which I did, and which were very valuable experiences. He has actually provided the Data for Electricity Consumption in Iran. It was a real struggle for Pr ASGARI to collect this data. Normally I should go through the hassles of data collection, but Pr ASGARI gently went through it instead of me for half of the required data for this thesis. So, I want to thank him for his kindness and willingness to assist me each step of the way.

Finally, I would like to address a special thanks to my family and friends who has supported me and advised me throughout my stay abroad in Japan.

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DECLARATION

I, ENNAJIH Yassin (Student ID 52115601) hereby declare that the contents of this Master's Thesis are original and true, and have not been submitted at any other university or educational institution for the sake of degree or diploma.

All the information derived from other published or unpublished sources has been cited and acknowledged appropriately.

ENNAJIH Yassin

2017/07/31

List of Abbreviations

KWh	Kilo Watt Hour
MW	Mega Watt
GW	Giga Watt
GWh	Giga Watt Hour
OPEC	Organization of the Petroleum Exporting Countries
GDP	Gross Domestic Product
ARMA	Auto Regressive Moving Average
MSE	Mean Squared Error
SMA	Simple Moving Average
SES	Simple Exponential Smoothing

Abstract

This thesis has been broken down into two major parts, in the first one, Iranian and Japanese annual electricity consumption data has been analysed with the purpose of developing a viable and accurate forecasting model for energy consumption. In case of Iran, the data spans from 1967 up until 2009. The data concerning Japan however spans from 1963 up until 2015. For both data sets, different regression models have been developed while only considering time as the main variable that influences the overall trend of electricity consumption. Seven types of time series were being compared in terms of their relative mean errors to the actual consumption data in order to select the most accurate model. Then we broke down our analysis to account for different sectors that has different consumption needs and thus would require appropriate analysis. For this matter, a thorough S-curve analysis was conducted for all the different sectors in order to assess the development and the growth phase of every single one of them.

In the second part, we have analyzed the learning rates of the different electricity consumption sectors in both Iran and Japan in order to measure their progress ratios using both the Linear and the Cubic learning curves that have been carefully constructed and brought back to an easier manipulation format through a logarithmic transformation. The purpose is then to determine if those sectors follow a specific learning behavior different from each other, or is there a general trend that seems to engulf everything under the same progress. Then we will be able to distinguish which sectors would perform better than the others. Those learning patterns have mainly been judged upon various combinations of attributes such as convexity or concavity, and assimilation or forgetting throughout the accumulative process of electricity production.

The results show that the best fit model for short term electricity forecasting in both countries is the brown model, while the best fit forecasting method for long-term electricity forecasting is the logistic model in case of Japan and the quadratic model in case of Iran. The s-curve analysis has showed that the studied sectors in Iran are still in their developing stages, while Japanese sectors have already reached the stagnating stage. In terms of learning potential, Iranian sectors exhibited a great potential for technological learning while the Japanese sectors exhibited a somewhat sluggish capacity for sustained learning and growth.

CHAPTER ONE: INTRODUCTION

1.1. Context of the Study

In an era where “Data Mining” and “Data Science” are gaining momentum through the venue of the so-called Industry 2.0, predicting the future with a relative accuracy has become one of the many main data analytics tools for every organization to have for its strategy and planning. In fact, Forecasting has been called upon as “one of the 10 grand challenges of modern science” (Cheng, et al., 2015). If it is performed rigorously, forecasting can have a tremendous impact. In fact, forecasts are primordial tools for decision making. For instance, they provide foresight on the expected production quantity, the resources and capacity needed for such a quantity, which products should benefit from more attention, and how much time is required to develop them further. It has been showed that a 10% improvement in forecasting accuracy can have positive repercussions on revenues by up to 4% (Yu, 2012). The research goes on to say that for large companies, even a 1% improvement translates into an increase in millions of dollars of revenue, which accentuates even more the impact that forecasting can have on organization’s performance.

In this Thesis, we will not be performing forecasts for companies, but for organizations as wide in scope as their respective countries. In fact, we will be attempting to forecast electricity consumption in both Iran and Japan, in order to find the best model that can accurately predict the needs for the upcoming years which will definitely save huge costs for the organizations responsible for electricity purchases, production, and distribution.

Another scope of this thesis is to be able to assess the accumulated expertize through technological capability. Technological capability itself stems from the continuous process of technological learning (Madanmohan, Kumar, & Kumar, 2003) which itself is defined by (Kim, 2001) as the ability to put the technological knowledge into effective use in production, engineering and innovation so as to maintain high competitive standards in terms of pricing and quality. In fact, we will be attempting to perform a learning curve analysis upon the aggregate electricity consumption data of all consuming sectors in Iran and Japan in order to assess whether electricity prices are going down throughout cumulative consumption or not, which in turn will indicate to the respective government which sectors need more attention and which sectors are actually benefiting from technological learning.

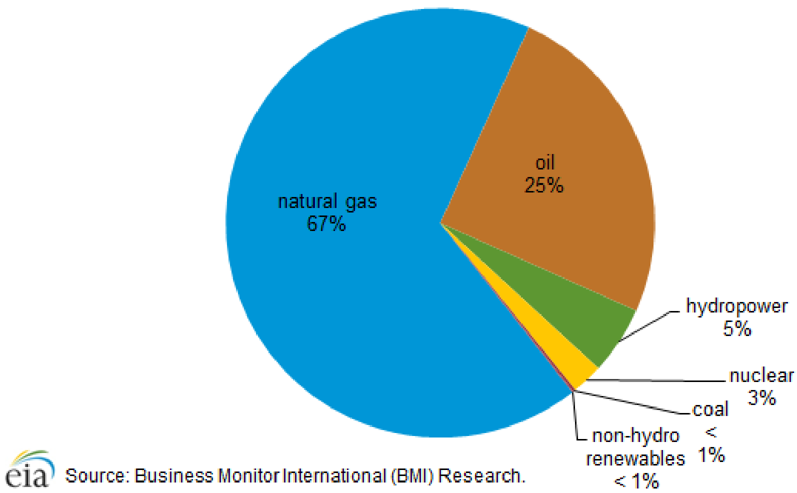
1.2. Study Contributions

Several contributions are made by this study. First, this is the first study of Iran electricity consumption sector that uses seven different forecasting models, and that is based on real world data coming from actual electricity bills and not from some widely available data in World Bank databases. Second, most studies on electricity forecasting do not take into account the S-curve analysis to further develop on the idea of stagnation or maturity, studies only provide the best forecasting model for the given data set, without further exploring the development stage the studied process is witnessing, but this thesis does. Third, the majority of studies that research the technological learning always focus on industries and manufacturing, very few of them actually apply dynamic technological learning rates to analyse electricity consumption patterns this study fills the literature gap on technological learning for electricity consumption Plus it offers a unique comparison of two very different countries, a developing country that is member of OPEC (Iran) and a developed country that is not a member of OPEC (Japan), OPEC membership will play an important role while analysing price learning curves.

1.3. Iran's Electricity Sector

Iran's electricity demand is still growing. In fact, Iran is experiencing a steady increase in electricity domestic demand, which has led to some supply shortcomings especially when electricity demand was at its peak. Moreover, Iran has recently pumped up the price of electricity which is part of its reform concerning energy subsidy in order to hinder the impact of the growing demand. Iran relies heavily on natural gas as its primary fuel source for electricity production, it almost engulfs two thirds of the total production capacity in 2013 as seen in figure 1.1.

Figure 1.1. Iran's Electricity Generation Capacity, by fuel in 2013



In 2013, Iran has produced 224 billion kWh worth of electricity, 92% of this amount was generated using fossil-fuel sources (EIA, March 2015). Coal, nuclear, hydropower, and non-hydropower renewables make up for the remainder of the other sources utilized to produce electricity. Following that year, early in 2014, the Iranian government made it clear that the price of electricity would go up approximately by 25% and that later on during 2015, price would experience another increase of another 20%, which is part of Iran's energy reform to scale back subsidies (EIA, March 2015). The government seems to believe that increasing the price would balance out the demand growth and relieve a good amount of pressure on its production ecosystem, especially during the climax of electricity demand. Nevertheless, it is highly anticipated that Iran's electricity consumption will still experience growth that has to be met by both fossil-oil sources and other renewable energy sources.

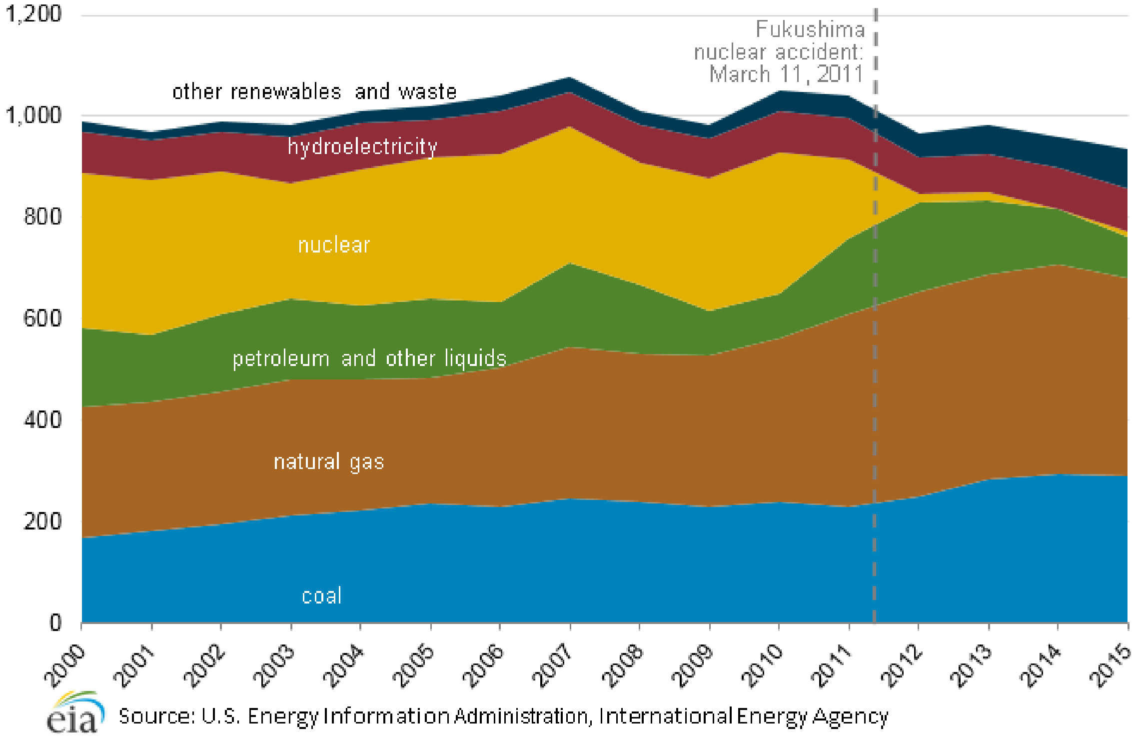
Iran's energy ministry offered as a solution to build 35 new scattered power generating plants, for which the cost has been estimated at $250 million. It is expected that is surplus in electricity production will mainly be targeted for the domestic consumption market, but Iran has bigger plans to also expand its electricity exports to the neighbouring countries. Iran exported 11 billion kWh worth of electricity during 2012, which was 25% more than the previous year of 2011. The main countries to which Iran exports electric power are Armenia, Turkey, Iraq, Pakistan, and Afghanistan. On the other hand, Azerbaijan and Armenia provide electric power to Iran following the formalities of a swap contract.

Electricity generated through nuclear power is a very recent practice in Iran, it is achieved by Bushehr power plant that has a capacity of 700 MW and that started production at the end of 2013 (EIA, March 2015). Initially, the construction has begun during the 1970s, but operations were postponed several times because of external coercive reasons, such as the Iranian Revolution, the war between Iran and Iraq, and very recently because of problems emanating from the Russian consortium that was given the contract of the project. When Iran's government has taking over the plant in late 2013, the nuclear power plant immediately begun generating power for commercial purposes. Two more power stations are planned at the same location, each single one of them is expected to have a capacity of 1000 MW, which contracts are again expected to be handed over to the Russians (EIA, March 2015). Even if Iran is trying to expand its nuclear power plants, the international sanctions forced on Iran might hinder the ambitions of the country to develop its nuclear program (World Nuclear Association, April 2015).

1.4. Japan's Electricity Sector

Before the big incident of Fukushima nuclear reactor in May 2011, Japan was the third biggest producer of nuclear power in the world just behind the United States and France. However, and after the Fukushima disaster, Japan has radically shifted its composition of energy sources used to generate power to fossil fuels, especially LNG as a prime substitute to nuclear power, as we can see in figure 1.2.

Figure 1.2. Japan's Electricity Generation by fuel, 2000-2015 in terawatt hours (TWh)



Despite Japan having the third highest electricity demand in Asia, its demand growth rate is counted amongst the lowest in the region. During the last decade, Electricity generation was on average steady around 1000 terawatt hours (TWh), but in 2015, Japan registered a drop of pace to 935 TWh. Now Japan is very dependent upon fuel imports to satisfy its electricity production needs. However, it stills strives to pursue an optimal energy mix of sources that can strike an optimal balance between cost, security and environment. It is good to mention that before the Fukushima disaster, Japan enjoyed one of the best energy mix models for power generation amongst the top power consumers of the world (The Federation of Electric Power Companies of Japan, 2014). In fact, Japan never had any particular energy source account for more than a third of all of its power generating fuel sources.

Once Japan dropped nuclear power generation vocation, other source of fuel such as LNG, oil, and coil started gradually replacing it. Some Financial incentives targeted towards clean energy projects ignited the growth and the interest on renewable energy which has definitely shacked the composition of Japan's energy generation portfolio. Although Japan doesn't have clear ideas on how much nuclear fuel will weight in the future country's portfolio, the government still aspires to incorporate it within the energy mix pretexting that it will have an optimal balance concerning cost, safety, and environment (Japan's Ministry of Economy, Trade, and Industry, 2014). As of now, government's targets for 2030 of the energy mix portfolio are as follows: 27% of LNG, 26% of coal, 22-24% of renewable energy, 20-22% of nuclear, and 3% of oil (FACTS Global Energy, 2015).

In 2014, electricity generating capacity in Japan toped at 313 GW, most of this capacity was accounted for at 62% by fossil fuel power plants at around 193 GW. Nuclear capacity was 42 GW in that same year, which is 13% of the total capacity. However, nuclear capacity is expected to drop by approximately 2 GW by 2017 because there are still plenty of reactors that are still scheduled for withdrawal from service. Hydroelectric plants accounted for 16% of the total capacity, while the remainder came from renewable energy facilities such as solar, wind, and geothermal (International Atomic Energy Agency, 2016).

In terms of electricity pricing, Japan has experienced some reforms in order to achieve lower electricity prices for consumers through fostering competition between the main actors of the sector, and through enhancing the sector's operations and investments. The goal of the Japanese government through those electricity reforms are mainly target for end consumers, which are meant to be able to choose their suppliers in order to dismantle the monopolies that exist in each major region of the country and that are vertically integrated. This reform will go through several steps, the last of which is to deprive the transmission and distribution divisions from the generating divisions so as to replace the fuel cost-recovery scheme with a market based pricing system by April 2020 (METI, 2015). Since Japan in now increasing its purchases of fossil fuel, the cost of electricity generation is also increasing. Therefore, Japan seems to pursue the same strategy of increasing electricity prices in order to cover the ever higher generating costs. In fact, retail electricity tariffs has gone up by 20% and 30% for residential and industrial customers respectively since 2011 (World Nuclear Association, 2014).

1.5. Statement of Problem

On the one hand, Iran’s electricity demand has been increasing tremendously throughout the last decade, which indicates a real economic prosperity and growth. Nonetheless, it is important to be able to assess the future development of such growth, for how long would it keep on growing, and what is the best model we can use to capture this development process. Another problematic is the repercussion of the increased demand on electricity prices, whether or not this growth translates into cheaper energy for Iranian consumers. And finally, we would like to shed the light on whether or not Iran benefits from being an OPEC member when it comes to technological learning and experience curve.

On the other hand, Japan’s electricity growth rate is one of the lowest amongst Asian countries, which indicates an economy that is out of breath. The problematic here is to be able to construct a forecasting model that might give us an insight on whether Japan’s electricity demand will increase in the future or will it continue stagnating. Another issue here is the Fukushima disaster that might have a great impact on electricity prices which might hinder the capacity of Japanese consumers to benefit from cheaper energy that originates from technological capability especially when the government intends to bring the prices higher to cover the increasing generating costs. Finally, we would also like to generally assess the impact of OPEC decisions on Japan's energy prices, especially during the 1973 oil crisis and could Japan use technological learning to bring the prices down after such major incident.

1.6. Research Questions

Being able to accurately forecast energy consumption will lead into huge cost savings in the electricity production sector and will provide an insight on how the economy of the country will perform in the future as electricity consumption and economic health are closely related. Also, being able to assess the accumulated knowledge throughout any productive process is an important aspect not only for designing the technological framework of that process, but also for providing insights about policy management. In that regard, this thesis's research questions are as follows:

- What is(are) the best forecasting model(s) for electricity consumption patterns in both countries?
- Which sector(s) have already reached its(their) full development capacity and which is(are) still in its(their) early developing stages?
- Which sectors are experiencing a reduction in electricity cost throughout their cumulative consumption (a favourable learning process), and which are not (an unfavourable forgetting process)?

CHAPTER TWO: LITERATURE REVIEW

2.1. Forecasting Background

There are mainly two separate types of forecasting methods: qualitative and quantitative techniques. On one hand, quantitative forecasting engulfs the study of time series and analysis of different predicting models that are mainly backed up by consistent historical data. For example, moving average forecasting method is one of the many models that are considered quantitative forecasting techniques. On the other hand, qualitative forecasting engulfs techniques that don't rely that much on methodical approaches, but rather are based on judgement. For example, the Delphi method can be considered as a quantitative forecasting technique. In this thesis, we will mainly be using qualitative forecasting techniques as it suits our approach of time series analysis and use of historical data.

In this study, we will be using seven different forecasting models that will be detailed later on in the next chapter. One of these models is autoregressive moving average, or ARMA for short. It is very popular amongst researchers and is very much widely used, its popularity stems not only from its statistical attributes but also from the famous Box-Jenkins methodology (G.E.P. Box, 1970) that is used as a process for constructing the ARMA model. But since we have chosen to perform a relatively simple ARMA model with lower degrees of seasonality, there is no need in using the Box-Jenkins method in our case. In fact, various exponential smoothing models can be derived from ARMA models (McKenzie, 1984), which allow researchers to implement different time series models using the same technique, i.e., pure autoregressive (AR), pure moving average (MA), combined AR and MA (ARMA) series, and double exponential smoothing called Brown model. We will be using the later three models in this thesis.

There are several challenges when performing time series forecasting. Indeed, it is often hard to spot whether or not a time series being studied is originated from a linear or nonlinear process, or whether or not a specific model is in general better than all the others when applied to data that is outside the sample used data. Therefore, it is laborious for researchers in general and forecasters in particular to decide on the right model for their particular situations. Normally, a bunch of various techniques are used, and the one that presents the least amount of error or the best degree of accuracy is chosen. However, that selected model is not always the best for never-before seen situations, because of many issues such as model uncertainty, structural change, and sampling variation. That is why it is unanimously agreed in the science literature that there is no single best forecasting model for every situation (Chat/eld, 1988) (Jenkins, 1982) (S. Makridakis, 1982).

Some researchers have tried to work out methods to improve the performance of the forecasts. (Bates & Gramger, 1969), (Granger, 1977), and (Granger C. a., 1984) proved that taking the average of various models has the potential to refine the results given by the forecasts when all the models are approximations. The procedure of aggregating varies by the value of the weight that has been assigned to the model with the actual best performance, which also considers giving the same weight to all models, giving weights in way that is reversely proportional to their actual MSE, using median forecasts, and giving weights to the forecasting models with the least value of simulated MSE. In this thesis, we will not only use MSE as our decision-making tool, we will use two more error measurement metrics that will be defined and explained in detail in the next chapter.

Many studies in the forecasting literature yielded many different results as of which is the best forecasting model for the given data set. (S. Makridakis, 1982) has put many univariate models in various series into the test in order to study their performance, some of those series were economic time series at the same country-like scale as the data sets used in this thesis. Their study concluded that more often than not, exponential smoothing was yielding the best results. (Meese, 1984) has made a comparison of different linear techniques by using approximately 150 macroeconomic time series, and discovered that the best model was the AR model with lag lengths selected by the Akaike Information Criterion (AIC). Which again stresses the idea that there is no single best solution for one type of data.

Recently, during the last couple of decades, a new forecasting method has emerged and has benefited from much attention and effort to its development and enhancement. This is new time series forecasting model is called artificial neural network (ANN) model (Zhang, Patuwo, & Hu, 1998). ANNs are one of the most interesting types of nonparametric nonlinear time series models. A set of various researches concerning large-scale forecasting models have demonstrated that combining different forecasting methods, for example an ANN with ARMA, would improve the accuracy of the forecasts compared to performance each individual method when performed separately, which eliminates the need to find the "best" forecasting model (Clemen, 1989) (S. Makridakis C. C., 1993) (P. Newbold, 1974). Which somehow indicates that ANNs might be a better model than all the other linear forecasting methods. However, in a comparison study performed under the auspices of the Santa Fe Institute, (Weignad & Gershenfeld, 1994) has compared the performance of the linear forecasting models against a lot of other nonlinear models such as ANNs; even though they have seen that nonlinear models are much more dynamic in different non-economic time series, the nonlinear models had poor results for the economic time series that has been studied that consisted of a data set of exchange rates. Moreover, (Swanson, 1997) made another comparison analysis between multivariate ANN models and other linear auto regression models, and concluded that the auto regression linear models present less forecasting errors, and thus have smaller values of MSEs when compared to the ANN models in simulated real time. Which means that the linear forecasting models that have been selected for this thesis can still yield better results than their nonlinear counterparts. Thus, we have decided to drop the ANN model in favour of the linear forecasting techniques.

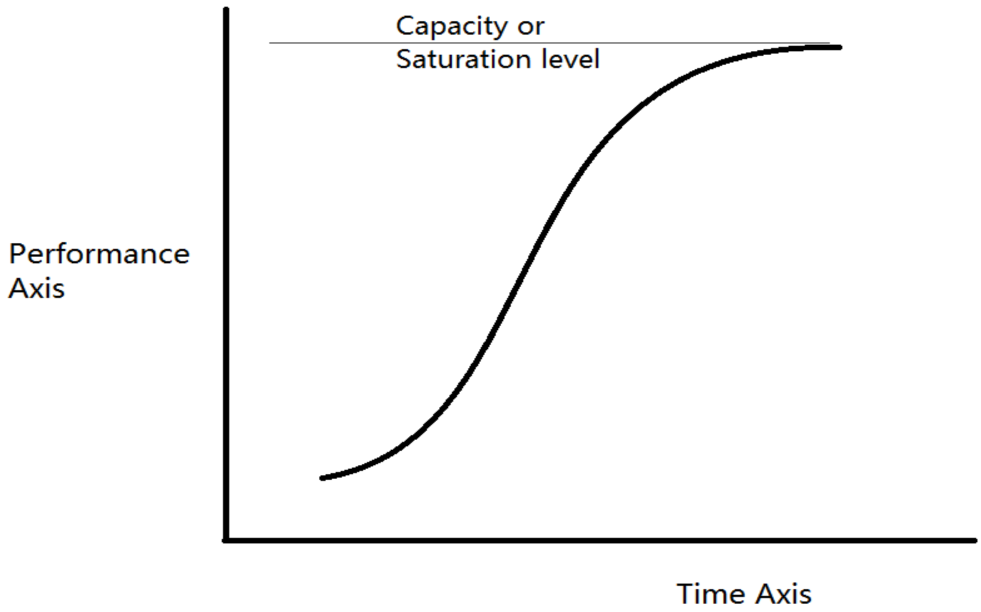
2.2. S-Curve Analysis Review

Amongst all the studies published in the field of technology management, several pathways have been explored about methods to smooth the relation between technology and strategy. One of the pathways that have been proposed, and that has been widely used since then, is the S-Curve analysis model that allows researchers to assess the performance development of any given technology throughout time. For instance, a wide variety of manuals and textbooks rely on this model for their strategy and technology management contributions. (Betz, 1993); (Dussauge, Hart, & Ramanantsoa, 1992); (Goodman, 1994); and (Twiss, 1986) all have used this model and recommend it in order to have insights on how the rate of technological change evolves throughout time, how to spot potential technological failures, and how to predict the saturation capacity of a given technology.

In fact, S-curve models have not only been used to assess technological progress, but have also been used in various management areas, such as marketing and production, so as to shape up the evolution of industries and/or their products. The most famous area of application is the attempt to depict product sales evolution throughout time by assessing the different stages of development through the lenses of a life cycle model. Indeed, using this framework of life cycle analysis, some researchers came up with various models that describe the performance evolution of the studied phenomenon (Abernathy & Utterback, 1975); (Ford & Ryan, 1981); (Roussel, 1991). These models are heavily inspired by the concept of biological life cycle. They make the assumption that industries and products have similar patterns when compared to a biological cycle of a living being, and thus technological evolution can be predicted in a straightforward manner.

The technological evolution theory stipulates that the performance progress rate is in general quite sluggish during the preliminary stage of the technology's development. When the technology has got time to improve through better management and control, the performance progress rate soars significantly (Sahal, 1981). However, as shown in the figure 2.1, the theory also states that when the technology arrives to a certain level, called the maturity stage, the progress rate declines drastically as the technology reaches its own saturation capacity. Thus, at maturity stage, in order to improve the performance of the technology, more efforts have to be deployed compared to the efforts needed to achieve the same amount of increase whilst in the early development stages.

Figure 2.1. S-Curve Graphical Representation (Source: Authors Concept)

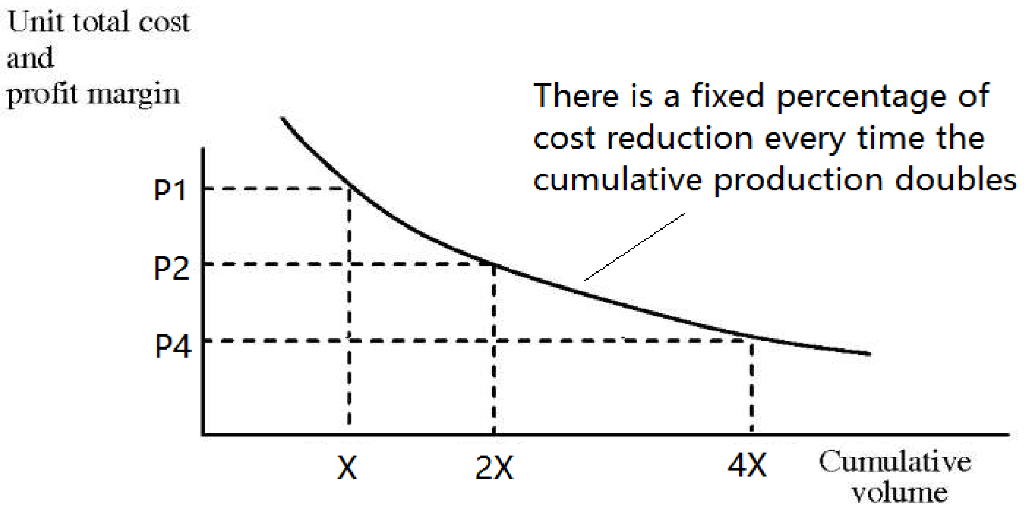


Practically speaking, S-curve analysis has been applied at the industry level in order to assess technology maturity. For example, (Constant & W., 1980) studied the aircraft industry, especially by focusing on aircraft engines, (Roussel P. A., 1984) studied the rubber industry by having a closer look at the foam products, (Foster, 1986) studied various industries simultaneously, and (Van Wyk, Haour, & Japp, 1991) studied the utilities industries, especially the permanent magnets line of products. In this thesis, we intend to apply the S-curve model to a country level, not only to an industry level. Indeed, we will perform S-curve analysis in order to assess the different evolution stages of different electricity consumption sectors in both Iran and Japan. This will allow us to spot the sectors that need more attention and care by the government in order to squeeze better performance out of them by implementing sound strategy and technology management practices. Literature in s-curve analysis applied to electricity consumption process is very scarce, as the majority of S-curve analysis studies that have been conducted so far mainly focus on service and manufacturing industries. Nonetheless, we have been able to find a valuable study conducted in New Zealand by (Bodger & Tay, 1987). In this study, a logistic curve model has been developed to analyse electricity consumption patterns with reference to New Zealand sectorial data. The fitting method used to construct the model is based on the Fibonacci search technique in order to allow the historical consumption data to produce optimal curve asymptotes. By the end of the study, it has been concluded that overall electricity consumption in New Zealand is in the arc that is near the maturity stage. That logistic s-curve model has been used to describe the historical time trends of electricity consumption data, such a model has proven itself to be the best model to use in order to perform technological forecasting (Baines & Bodger, 1984). In our study of Iran and Japan electricity consumption sectors, we will be using the same logistic s-curve model, but instead of the Fibonacci fitting technique, we will construct our model based on the Monte-Carlo fitting method.

2.3. Technological Learning Literature

According to many studies that has been carried throughout a wide set of different industries, it has been proved that technology performance gets better while production increases, which leads to reduced unit cost and decreased prices. This concept is usually referred to as the “Learning Curve”. This fruitful observation was first made by (Wright, 1936) in the aircraft industry. As shown in figure 2.2, the curve points to a reduction of unit cost as the cumulative produced volume doubles (Jackson, 1998).

Figure 2.2. An Illustration of the Learning Curve Effect (Source: Authors Concept)



The learning curve theory has been adjusted to the likings of the (Boston Consulting Group, 1970) which resulted in the emergence of the experience curve. The main difference is that the original learning curve puts the emphasise on individual inputs during the production process, while the experience curve takes into account various inputs in order to describe the learning phenomenon throughout cumulative production. This variation has allowed the learning concept to be applied to the industry level rather than single plants or factories, which has created a new tool for managers that will help them deciding on long-term strategic matters.

Table 2.1 gives the historical review of the articles so far written on the concept of learning-by-doing. The list is by no mean exhaustive. This suggest the relevancy of this very important phenomenon in cost saving and technological progress review.

Table 2.1. List of Articles focusing on Learning Curve Theory (*Source: Asgari & Jose Luis Gonzalez-Cortex, 2012)*

Year	Researcher	Publication
1936	Wright, T. P.	Factors affecting the cost of airplanes
1953	Wyer, R.	Learning curve helps figure profits, control costs
1954	Andress, F. J.	The learning curve as a production tool
1961	Taylor, M. L.	The learning curve - A basic cost prediction tool
1962	Arrow, K.	The Economic Implications of Learning by Doing
1966	Baloff, N.	The learning curve - Some controversial issues
1967	Baloff, N. and J. W. Kennelly.	Accounting implications of product and process start-ups
1972	Consulting, Boston.	Perspectives on Experience
1974	Henderson, B.	The experience curve reviewed: V. price stability
1978	Harris, L. C. and W. L Stephens.	The learning curve: A case study
1979	Yelle, L. E.	The learning curve: Historical review and comprehensive survey
1982	Ramanathan, R.	Lecture Notes in Economics and Mathematical Systems
1986	Belkaoui, A.	The Learning Curve
1989	Bailey, C. D.	Forgetting and the learning curve
1991	Adler, P. S., & Clark, K. B.	Behind the Learning Curve: A Sketch of the Learning Process
1992	Badiru, A. B.	Computational Survey of Univariate and Multivariate Learning Curve Models
1997	Hornstein, A., & Peled, D.	External vs. Internal Learning-by-Doing in an R&D Based Growth Model
2000	Pramongkit, P., Shawyun, T., & Sirinaovakul, B.	Analysis of Technological Learning for the Thai Manufacturing Industry
2001	Ruttan, V. W.	Technology, Growth, and Development. An Induced Innovation Perspective
2005	Karaoz, M., & Albeni, M.	Dynamic Technological Learning Trends in Turkish Manufacturing Industries
2009	Asgari, B., & Yen, L. W.	Accumulated Knowledge and Technological Progress in Terms of Learning Rates: A Comparative Analysis on the Manufacturing Industry and the Service Industry in Malaysia
2012	Behrooz Asgari, Jose Luis Gonzalez-Cortez	Measurement of Technological Progress through Analysis of Learning Rates; the Case of Manufacturing Industry in Mexico

Different studies suggest that technological learning is needed in order to achieve technological capability enhancement (Arrow, 1962). Technological learning refers to the process of accumulation of information, skills, experience, and competencies so as to create some positive changes in the production system (Platt & Wilson, 1999). It also embodies the pathway through which the technological capability is being accumulated. In fact, this trajectory is not constant and is subject to variation, which means that technological capability accumulation might happen in various paths and at various rates (Figueiredo, 2002).

Many scholars claim that technological knowledge gain is a cumulative and costly process. First, it is cumulative because it uses the already existing knowledge foundation which lies not only in the organization's human resources but also in its non-formal documents, its machinery, and its organizational structure in a different ways that are all considered inputs for the experience curve model. Which means that technological learning process will be faster and deeply rooted when the existing knowledge foundation and the provided efforts present high standards of operations (Kim, 2001). Second, it is a costly process because it needs a considerable amount of financial backing in order to obtain the required inputs such as materials and working hours that will foster the creation of various needed tangible and intangible resources for building a solid technological capability. The ability to learn is always mentioned as the main reason for long-term sustainable growth, especially if it occurs at different levels such as the individual level, the firm level, and the country level. (P. Conceicao, 2003).

There are various internal and external factors that directly impact the capacity of an organization to benefit from technological learning (Rothwell, 1996). On the one hand, internal elements are all those factors that consist of practical efforts that are deployed inside the organization, such as research and development, management approach, and production process. On the other hand, external technological elements occur when the organization interacts with the other ones within its operations reach through complementarity and networking, such as the customers, the consultants, the competitors, the suppliers of capitals, and the research institutions. Many of those interactions are very important and are based on formal relational skills, others are informal are solely based on trust (Malecki, 1997).

Government policy support is a pivotal external element. Indeed, all the regulations and institutions that consist of local and global innovation systems directly impacting the pathway of technological advancement, are crucial and directly concerned by the standardization and acceleration of the technological learning capability of all the players that are under its authority, from individuals to nations passing by firms and other organizations. In this study, we will try to assess the technological capability of the electricity production sector, by measuring the experience curve of the electricity cost against the cumulative production. The results are expected to comprise a solid guideline for policy makers that seek reinforcement of technological learning. In fact, this thesis will underline the electricity consumption sectors that need more development and attention, in order to foster the creation of new policies from government and management practices from organizations so as to enhance the technological learning capability of the various electricity consumption sectors in both Iran and Japan.

CHAPTER THREE: RESEARCH METHODOLOGY

3.1. Data Collection

In this study, four sets of data have been used to conduct our research. The first set of data consists of the National Electricity Consumption Data in Iran that spans from 1967 up until 2010, which is 44 years of historical data. This data has been carefully collected by Pr. Asgari directly from the final bills that consumers had to pay for their electricity expenses, which means that the data is reliable and doesn’t include any sort of electrical distribution and/or transmission losses. Therefore, the data only comprises the real net electricity consumption figures thanks to Pr. Asgari, which means the data doesn’t need further processing in order to account for the losses that would have occurred during electricity distribution. The data is also carefully split into 6 different sectors namely Industrial Sector, Agriculture Sector, Street Lighting Sector, Residential Sector, Public Service Sector, and Other sectors. The second set of data consists of Electricity Prices Data in Iran from 1968 to 2007. However this data requires more processing, which we will discuss in the upcoming section of this chapter.

The second set of data consists of the National Electricity Consumption Data in Japan that spans from 1963 up until 2015, which is slightly more consistent than the first set since it comprises 53 years of historical data. This data was collected from Federation of Electric Power Companies of Japan (FEPCJ) official website (FEPC, 2017). This set of data also accounted for the distribution and/or transmissions losses that could occur when dispatching electricity to final consumers. Therefore, no further processing of this set of data is needed. This data is also split into 6 different sectors namely Lighting Sector, Power sector, Manufacturing Sector, Mining Sector, Railways sector, and other sectors. The fourth and last set of data used in this study is the Electricity Prices Data in Japan from 1970 to 2015. However, and similarly to the second set of data, it requires more processing, which mainly consists of deflating the price values.

3.2. Data Processing

To stabilize the variance of random or seasonal fluctuation in price inputs that are mainly due to the process of inflation, the data sets that comprise electricity prices for both Iran and Japan were deflated using consumer price index (CPI). The advantage being that it will enable us to uncover the real tendency of electricity price changes over time in these consumption sectors during the different periods under consideration. Due to the long period considered, the time series CPI for all items published by International Monetary Fund, International Financial Statistics with 2010 as the base year, were used to deflate the second and the forth sets of data.

For the third data set, the data was aggregate into six sectors, two of them are power sector and lighting sector. This aggregation is the same one adopted by the FEPCJ in order to conglomerate the data into big clusters. According to FEPCJ, the power sector comprises several subsectors namely temporary power, agricultural power, construction power, business use power, and residential use power. The lighting sector on the other hand consists of temporary lighting, agricultural lighting, and public street lighting. This aggregation is not exactly similar to the one used for the first data set, but it is still valuable because it will allow us to perform a comparison between the sectors in Iran to those in Japan.

It is also good to mention that the data has been processed through different applications. The benefit of which is to compare the validity of the results yielded by standard software that are widely used (such as MS Excel) to the results given by more specialized software (Such as Minitab).

3.3. Forecasting Models

Before advancing any further in this thesis, we have to mention that the only variable that has been taken into account in our regressions analysis is the time variable. We are aware that there are a lot of factors that heavily influence energy consumption trends, and that time alone is not representative of a deterministic variation that can capture the overall picture of energy consumption patterns. A country's Gross Domestic Product (GDP) growth, population growth, Technology diffusion, households income, government policy, all impact at different levels the expected upcoming energy consumption that will occur in the years to come. Incorporating those kind of parameters to accurately model with higher certitude the exact trend that electricity consumption is following is way beyond the scope of this study, this would imply more regression analysis work with multiple parameters and would even yield distorted results as more than 3 parameters in a regressions analysis isn't famous for its results' robustness. Our goal here is to identify, using only time as out independent variable, the best time series model that yields the minimum amount of forecasting error.

The data that has been explained earlier will be used to conduct our time series analysis as explained below. From now on we will refer to the energy consumption data as Y, and we will refer to time as t. We will also use the symbol "Y-hat" to stand for a forecast of the time series Y made at the earliest possible prior date by a given model. The formulas that will be displayed in this section are from the work of Mr Robert F. Nau, professor in Duke University: The Fuqua School of Business, retrieved from his official webpage (Nau, 2017).

3.3.1. Linear Model

The linear forecasting model, also called the trend-line model is a simple regression model in which the dependent variable is modeled through a linear equation with an intercept and a slope multiplied by the independent variable. This model is usually evaluated by regression, which means that the trend line corresponds to the only possible line that minimizes the squared errors when compared against the actual data. The model equation is as follows:

$$\hat{Y}_t = a \times t + b \quad (1)$$

Where "a" is the slope and the "b" is the intercept.

3.3.2. Quadratic Model

The quadratic forecasting model is a subset of the polynomial models. It is a more advanced regression model in which the independent variable is modelled as the 2nd degree polynomial of the dependent variable. Similarly to the linear model, the quadratic model is also evaluated by regression, which tries to find the equation of the parabola (2nd degree polynomial) that minimizes the deviation from the actual data and thus fits the overall quadratic trend. The model equation is as follows:

$$\hat{Y}_t = a \times t^2 + b \times t + c \quad (2)$$

Where "a" is necessarily non null, however "b" and "c" can still equate to zero.

3.3.3. Exponential Model

The exponential forecasting model is a nonlinear model that shouldn't be confused with the exponential smoothing model that will be explained later in section 3.3.6of this chapter. The exponential model is often used in growth or decay events because it captures perfectly both the upward and the downward trends of an event's evolution throughout time. The model equation is as follows:

$$\hat{Y}_t = A \times e^{rt} \quad (3)$$

Where "A" is the intercept, and "r" is the growth or decay rate of the observed phenomenon.

3.3.4. Logistic Curve

The forecast for the value of Y at time t+1 that is made at time t equals:

$$\widehat{Y_{t+1}} = \frac{\mathrm{K}}{1+e^{-a-bt}} \tag{4}$$

Where K represents the curve's maximum value or commonly known as the optimum capacity of the logistic curve. The parameters "a" and "b" are linear equation parameters that hold some information about the Sigmoid midpoint and the steepness of the logistic curve.

In this thesis, K will be determined by utilizing Excel Solver in order to minimize the Mean Squared Error (MSE, which formula will be seen later). Both parameters "a" and "b" will be determined by operating a logarithmic transformation on consumption data and then using two Excel functions "INDEX" and "LINEST" in order to get the exact values of those two parameters. This logistic time series curve is very useful to describe phenomenon's that tend to rise quickly at early stage of development, then starts to deteriorate or slow down at advanced stages of its development. We think that energy consumption can follow this kind of trend, and thus the forecasting of its future values might be well approximated by logistic time series analysis.

3.3.5. 5-Period Moving Average

The forecast for the value of Y at time t+1 that is made at time t equals the simple average of the most recent m observations:

$$\widehat{Y_{t+1}} = \frac{Y_t+Y_{t-1}+\cdots Y_{t-m+1}}{\mathrm{m}} \tag{5}$$

Note that if m=1, the simple moving average (SMA) model is equivalent to the random walk model (without growth). If m is very large (comparable to the length of the estimation period), the SMA model is equivalent to the mean model. As with any parameter of a forecasting model, it is usual to adjust the value of m in order to obtain the best "fit" to the data, i.e., the smallest forecast errors on average. But since we will deal with this kind of error later, for now, we will set m=5, which means if we use a simple moving average of 5 terms, we get a smoother-looking set of forecasts. The 5-term simple moving average yields significantly smaller errors than the random walk model in this case. The average age of the data in this forecast is 3 (= (5+1)/2), so that it tends to lag behind turning points by about three periods.

3.3.6. ARMA (0, 1, 1) Time Series

The simple moving average model described above has the undesirable property that it treats the last m observations equally and completely ignores all preceding observations. Which means that the most recent observation should get a little more weight than 2nd most recent, and the 2nd most recent should get a little more weight than the 3rd most recent, and so on. The simple exponential smoothing (SES) model accomplishes this.

Let α denote a "smoothing constant" (a number between 0 and 1). We can express the next forecast directly in terms of previous forecasts and previous observations, in any of the following equivalent versions. The forecast is an interpolation between previous forecast and previous observation, as shown in the equation (6) above:

$$\widehat{Y_{t+1}} = \alpha Y_t + (1-\alpha)\widehat{Y_t} \tag{6}$$

A SES model is actually a special case of an ARIMA model, so the statistical theory of ARIMA models provides a sound basis for calculating confidence intervals for the SES model. In particular, a SES model is an ARIMA model with one non-seasonal difference, an MA(1) term, and no constant term, otherwise known as an "ARIMA(0,1,1) model without constant". The MA(1) coefficient in the ARIMA model corresponds to the quantity 1-α in the SES model. Where α can be greater or equal to 1. In this study, α will be determined by using Excel Solver in order to minimize the Mean Squared Error (MSE) as it is the case in the maximum capacity of the logistic time series analysis.

3.3.7. Brown Model

The SMA models and SES models seen earlier, assume that there is no trend of any kind in the data. But what about short-term trends? If a series displays a varying rate of growth or a cyclical pattern that stands out clearly against the noise, and if there is a need to forecast more than 1 period ahead, then estimation of a local trend might also be an issue. The simple exponential smoothing model can be generalized to obtain a linear exponential smoothing (LES) model that computes local estimates of both level and trend.

The simplest time-varying trend model is Brown's linear exponential smoothing model, which uses two different smoothed series that are centered at different points in time. The forecasting formula is based on an extrapolation of a line through the two centers.

The algebraic form of Brown's linear exponential smoothing model, like that of the simple exponential smoothing model, can be expressed in a number of different but equivalent forms. The "standard" form of this model is usually expressed as follows: Let S' denote the singly-smoothed series obtained by applying simple exponential smoothing to series Y. That is, the value of S' at period t is given by:

$$S'_t = \alpha Y_t + (1-\alpha)S'_{t-1} \tag{7}$$

Under The ARMA (0, 1, 1), this would be the forecast for Y at period t+1.

Then let S" denote the doubly-smoothed series obtained by applying simple exponential smoothing (using the same α) to series S':

$$S''_t = \alpha S'_t + (1-\alpha)S''_{t-1} \tag{8}$$

Finally, the forecast for Yt+k, for any k>1, is given by:

$$\widehat{Y_{t+k}} = L_t + kT_t \tag{9}$$

Where: $L_t = 2S'_t - S''_{t-1}$ is the estimated level at period t, and

$T_t = (\frac{\alpha}{1-\alpha})(S'_t - S''_{t-1})$ is the estimated trend at period t.

A mathematically equivalent form of Brown's linear exponential smoothing model, which emphasizes its non-stationary character and is easier to implement on a spreadsheet, is represented in the following equation:

$$\widehat{Y_t} = 2Y_{t-1} - Y_{t-2} - 2(1-\alpha)e_{t-1} + ((1-\alpha)^2)e_{t-2} \tag{10}$$

Where: $e_t = Y_t - \widehat{Y_t}$ (called the forecast error)

In other words, the predicted difference at period t is equal to the previous observed difference minus a weighted difference of the two previous forecast errors. In this study, α will be determined by using Excel Solver in order to minimize the Mean Squared Error (MSE).

3.3.8. Error Formulas

Once all seven forecasting models constructed, we will calculate for each one of them three types of deviations and errors in order to estimate the degree of accuracy that each forecasting model exhibits when compared to the other. The formulas are as follow:

- Mean absolute percentage error (MAPE)

$$\frac{\sum \left|(y_t - \hat{y}_t) \;/\; y_t\right|}{n} \times 100, (y_t \neq 0) \tag{11}$$

- Mean absolute deviation (MAD)

$$\frac{\sum_{t=1}^{n} \left|y_t - \hat{y}_t\right|}{n} \tag{12}$$

- Mean squared error (MSE)

$$\frac{\sum_{t=1}^{n} \left|y_t - \hat{y}_t\right|^2}{n} \tag{13}$$

In order to recognize the model that best fits the electricity consumption data, we will use these three error values to select the forecasting model that exhibits the least amount of deviation from the actual data across all three of these error measures. However, we will make sure to weight our decision by relying on some insights on the common error of "over fitting", especially when selecting the best models that are best suited for short term forecasting and those that are convenient for long term forecasting.

3.4. The Logistic S-Curve Model

The logistic function or logistic curve that is being constructed is a common "S" shape curve, with the following equation:

$$Y = \frac{K-d}{1+e^{-r(t-t_m)}} + d \tag{14}$$

Where:

e = the natural logarithm base (also known as Euler's number),

t_m = the time value of the s-shape's midpoint,

K = the curve's maximum value (saturation point),

r = the steepness of the curve,

d = an adjustment parameter.

The software used to plot the s-shape curve is called "Loglet Lab" which is a software package for analysing logistic behaviour in time-series data. It was part of the Program for the Human Environment that was undergone by The Rockefeller University, the software is available to access for free from the university's website (Program for the Human Environment, 2017).

While using the Loglet lab software, we will mainly focus on t_m the midpoint and K the saturation level. Loglet lab also displays a very good attribute referred to as "a" which indicates the time needed for the curve to go from 10% of its saturation point to reach 90% of the same saturation level, it indicates the expected lifecycle of the studied time series.

3.5. The Learning Curve Model

3.5.1. Linear Model of the Learning Curve

The linear learning curve estimation will be used to estimate the progress ratio under the traditional linear experience curve assumption. The measure the level of learning, the following mathematical formula is used:

$$C_t = C_1 X_t^{-\alpha}, \tag{15}$$

Which can be written in logarithmic form as follows:

$$lnC_t = lnC_1 - \alpha lnX_t \tag{16}$$

Where

Ct is the current level of time cost as time t, C1 is the production cost of the first unit of output, Xt is the cumulative production of units produced up until time t, and α is the learning elasticity or progress index to be estimated.

Equation 16 suggests that the current level of unit cost at time t (Ct), is a function of cumulative production level Xt, and the cost of producing the first unit C1 in the production process (Karaoz & Albeni, 2005).

A vey import parameter that doesn't appear in equation 16 is called "progress ratio" (d) and is derived from the learning elasticity α. The progress indicates that every doubling of total production reduces unit production by a factor of $2^{-\alpha}$. This is expressed as;

$$d=2^{-\alpha} \qquad (17)$$

When the process of learning takes in place into the production system, "d" is expected to vary between 0 and slightly less than 1 (i.e. $0 \leq d < 1$). When the value of "d" approaches 0, the learning potential is improving, however when the value of d is closer to 1, it implies that the production process exhibits a low learning rate.

When d=1, it has a specific connotation of stagnation, which means that there is neither learning nor forgetting, i.e. no cost saving at doubling of unit production or equivalently in economic terms, it means there is neither improvement nor worsening of unit production cost (Karaoz & Albeni, 2005) .

Finally, when the value of d is strictly superior to 1, it implies a forgetting process which means an increase in the unit cost of production whenever production is twice its previous scale.

As an example, if d=0.7, this means that value of per unit production cost would decrease by 30% when the production is doubled. A value of d superior to 1, say d=1.2, means that the value of per unit production cost would increase by 20% whenever the production is doubled. The interpretation of the progress ratio d, is somewhat straightforward. Table 3.1 summarises all the possible values of the progress ratio "d" and all its possible implications on the learning process.

Table 3.1. Boundary of Progress Ratio and its Meaning (*Source: Behrooz Asgari 2012)*

d<1	d=1	d>1
Learning state	No learning, no forgetting	Forgetting stage
Unit production cost decrease as output decreases	Unit production cost remains the same as output increases	Unit production cost increases as output increases
Efficiency increases	No change in efficiency	Efficiency decreases
Productivity increases	No change in productivity	Productivity increases

In the learning literature, the neoclassical production function is readily used to quantify the learning curve effect, following the assumption that learning is part of productivity (Pramongkit, Shawyun , & Boonmark , 2000), (Karaoz & Albeni, 2005).

As stated by the neoclassical production function, the production level Qt in time t, is a function of labor Lt, employed at time t, and capital Kt, invested at time t. This can be expressed as:

$$Q = A_t . L^{\beta} . K^{\gamma} \tag{18}$$

Where β and γ define the elasticity of labor and capital respectively, the parameter At is called multifactor productivity. It encompasses the actual level of technology or advances in knowledge base in a given time t.

The logarithmic form of equation 18 is expressed as:

$$lnQ_t = lnA_t + \beta lnL_t + \gamma lnK_t \tag{19}$$

Equation 18 assumes existence of a functional relationship between At and cumulative production Xt which is formulated as follows:

$$A_t = HX_t^{\alpha} \tag{20}$$

Where H represent the proportionality constant, and X_t^{α} is the inverse of $X_t^{-\alpha}$ expressed in equation 15. The natural logarithmic form of equation 20 can be expressed as:

$$lnA_t = lnH + \alpha lnX_t \tag{21}$$

Moreover, we can rearrange equation 15 and equation 20 to obtain:

$$X_t^{\alpha} = \frac{C_1}{C_t}, \tag{22}$$

$$A_t = H\frac{C_1}{C_t}, \tag{23}$$

When applying the natural logarithmic transform, equation 23 can be written in a linear form:

$$lnA_t = lnH + \ln(\frac{C_1}{C_t}) \tag{24}$$

If we combine both equations number 24 and 21, by substituting for A_t, we have:

$$lnQ_t = lnH + \alpha lnX_t + \beta lnL_t + \gamma lnK_t \tag{25}$$

By adding lnL_t from both sides of equation 25 and multiplying the results by -1, the following algebraic expressions ensues;

$$lnQ_t - lnL_t = lnH + \alpha lnX_t + \beta lnL_t + \gamma lnK_t - lnL_t$$

$$(lnQ_t - lnL_t = lnH + \alpha lnX_t + \beta lnL_t + \gamma lnK_t - lnL_t) \times -1$$

$lnL_t - lnQ_t = -lnH - \alpha lnX_t - \beta lnL_t - \gamma lnK_t + lnL_t$ or equivalently as;

$$ln\left(\frac{L}{Q}\right)_t = -lnH - \alpha lnX_t + (1 - \beta lnL_t) - \gamma lnK_t \tag{26}$$

The relation between capital and labor is assumed to be as follows:

$$K_t = \mu L_t^{\lambda} \tag{27}$$

Where the parameters $\mu \; and \; \lambda$ are constants.

Again, by applying the logarithm form to equation 27, we get:

$$lnK_t = ln\mu + \lambda lnL_t \tag{28}$$

Combining 26 and 28, and substituting for lnK_t will result to 29 in the form;

$$ln(\frac{L}{Q})_t = -lnH - \gamma ln\mu - \alpha lnX_t + (1 - \beta - \gamma\lambda)lnL_t \tag{29}$$

Equation 29 is the equation for empirical estimation of the learning curve. It can be expressed in a simpler way as follows:

$$lnC_t = \theta_0 + \theta_1 lnX_t + \theta_2 lnL_t + \varepsilon_t \tag{30}$$

Where $lnC_t = ln(\frac{L}{Q})_t$, $\theta_0 = -lnH - \gamma ln\mu, \theta_1 = -\alpha$, $\theta_2 = 1 - \beta - \gamma\lambda$, and ε_t is the stochastic term.

3.5.2. The Cubic Learning Model Construction

There is a significant drawback to the linear curve model. Indeed, it only offer a single learning rate value for a given event and thus fails to capture the variability of the learning potential throughout time. To bypass this weakness, some scholars have developed and used the cubic learning models (Karaoz & Albeni, 2005), (Behrooz Asgari, 2012). The cubic learning model take its root from the more generic S curve learning model since it is assumed to vary over time, and can be approximated using cubic cost function. Carlson, 1973 justifies the use of S curve function to estimate cubic learning rates as, improvement in tooling, methods of work, materials, design and workers experience. The cubic function states that; per unit cost of output at time t is a function of a cumulative production up to a third order polynomials (cubic term) (Badiru, 1992).This form of cubic cost function can be expressed as;

$$lnC_t = lnC_1 + \mathrm{B}lnX_t + \mathrm{C}(lnX_t)^2 + D(lnX_t)^3 \tag{31}$$

If we derive equation 31, we get the learning elasticity for the cubic models which can be expressed as:

$$-\alpha = \frac{dlnC_t}{dlnX_t} = B + 2\mathrm{C}(lnX_t) \quad + 3D(lnX_t)^2 \tag{32}$$

The proof of equation 32 was explained in detail by (Karaoz & Albeni, 2005).

To proceed, we expressed 32 in a ratio between a unit cost of producing the first unit (C1) and the unit production cost in time t (Ct). To do this, we subtract lnC1 from both side of 32 and rearrange as follows:

$$lnC_t - lnC_1 = lnC_1 + \mathrm{B}lnX_t + \mathrm{C}(lnX_t)^2 + D(lnX_t)^3 - lnC_1 \tag{33}$$

Or equivalently as:

$$ln\left(\frac{C_1}{C_t}\right) = -(\mathrm{B}lnX_t + \mathrm{C}(lnX_t)^2 + D(lnX_t)^3) \tag{34}$$

Recall from 24 that $lnA_t = lnH + \ln(\frac{C_1}{C_t})$, hence by substituting for $\ln(\frac{C_1}{C_t})$, we have a new relation as:

$$lnA_t = lnH - \mathrm{B}lnX_t - \mathrm{C}(lnX_t)^2 - D(lnX_t)^3 \tag{35}$$

Furthermore, by substituting for lnA_t, we have the following expression:

$$lnQ_t = lnH - \mathrm{B}lnX_t - \mathrm{C}(lnX_t)^2 - D(lnX_t)^3 + \beta lnL_t + \gamma lnK_t \tag{36}$$

By using the already established relation between labor and capital, we can express equation 36 entirely in terms of labor, which will lead us to a new relation in the form:

$$lnQ_t = lnH - \mathrm{B}lnX_t - \mathrm{C}(lnX_t)^2 - D(lnX_t)^3 + \beta lnL_t + \gamma\ (ln\mu + \lambda lnL_t) \tag{37}$$

And by adding lnL_t to both sides of 30 and rearranging in terms, we have a final empirical model for cubic learning model as follows:

$$ln\left(\frac{L}{Q}\right)_t = -lnH - \gamma ln\mu + \mathrm{B}lnX_t + \mathrm{C}(lnX_t)^2 + D(lnX_t)^3\ (1 - \beta - \lambda)lnL_t \qquad (38)$$

or equivalently in a simpler form as:

$$lnC_t = \theta_1 + \mathrm{B}lnX_t + \mathrm{C}(lnX_t)^2 + D(lnX_t)^3 + \theta_2 lnL_t \qquad (39)$$

Where $\theta_1 = -lnH - \gamma ln\mu$, $\theta_2 = (1 - \beta - \lambda)$ and $lnC_t = ln\left(\frac{L}{Q}\right)_t$

CHAPTER FOUR: RESULTS AND DISCUSSION

4.1. Preliminary Data Analysis

4.1.1. Total Electricity Consumption in both Countries

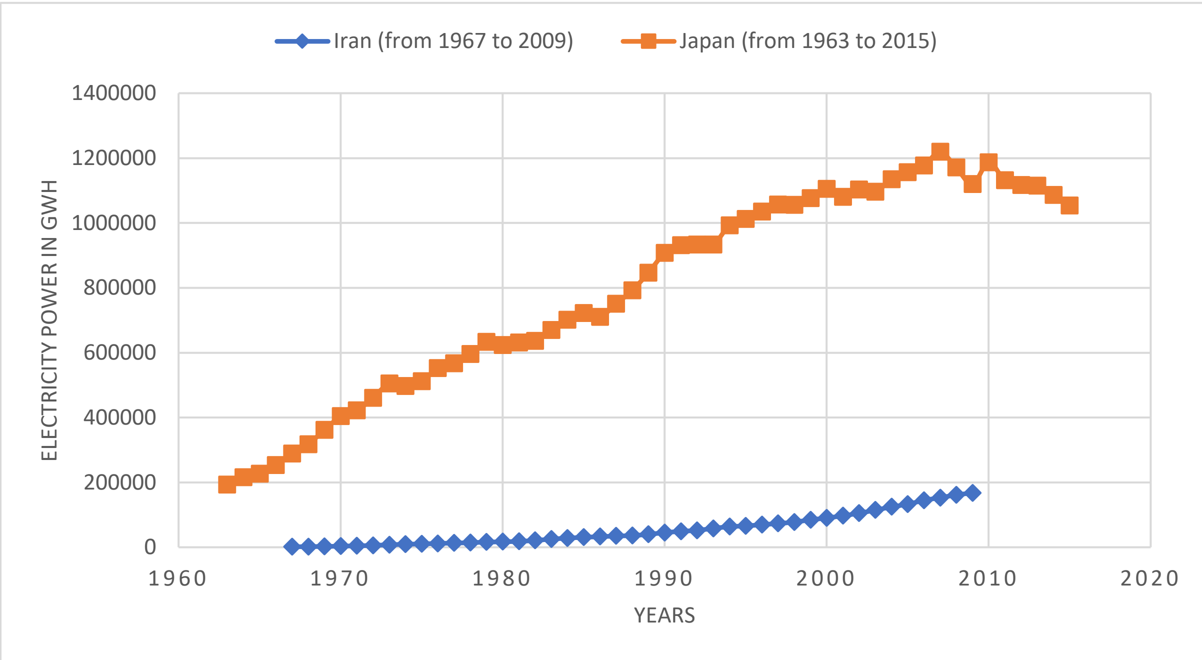
Iran and Japan are two very different countries. Not only in terms of geographic, religious, cultural, and historical ties, but also in terms of economics, population, political alignment, and technology development.

Iran is a Middle East country that is a member of the OPEC, and accordingly to the International Monetary Fund predictions, it will enjoy in 2017 a GDP of $1.551 trillion in purchasing power parity standard (International Monetary Fund, 2017). Its population is estimated at 82.8 million people by (World FactBook, 2016). Overall, Iran is categorised as an upper-middle income economy by the World Bank (World Bank, 2013). In the early 21st century, Iran's economy was mainly lead by the service sector, which had the lion share in terms of GDP contribution, then comes the industry (mining and manufacturing) and agriculture in second and third places respectively (Turquoise Partners, 2012).

Japan on the other hand is a north-east Asian archipelago that doesn't belong to any international energy consortium. Accordingly to the IMF, it will enjoy a GDP of $5.420 trillion in purchasing power parity standard (International Monetary Fund, 2017). Japan population is estimated at 126,76 million people by (Statistics Bureau of Japan, 2016). The service sector accounts for three quarters of the GDP (Statistical Handbook of Japan., 2011).

All those reports that offer valuable analysis about the macroeconomic health of country, seem to have omitted one econometric parameter that is as valuable as the standard GDP econometric. That parameter is "electricity consumption". In fact, electricity consumption is a very powerful indicator of the macroeconomic development of a country, of a sector, of and industry or even of a factory. The standard GDP measure focuses on the output of an entity to measure its economic progress. However, there will be no output without a substantial input to support it, indeed, energy is the main driver of the output, and it can be a good indicator of predictions for the upcoming expected output. Here we focus on electricity consumption as the main energy input that drives the economic output, figure 4.1 shows the total electricity consumption in both studied countries, each in its respective study time span.

Figure 4.1. Total Electricity Consumption in GWh



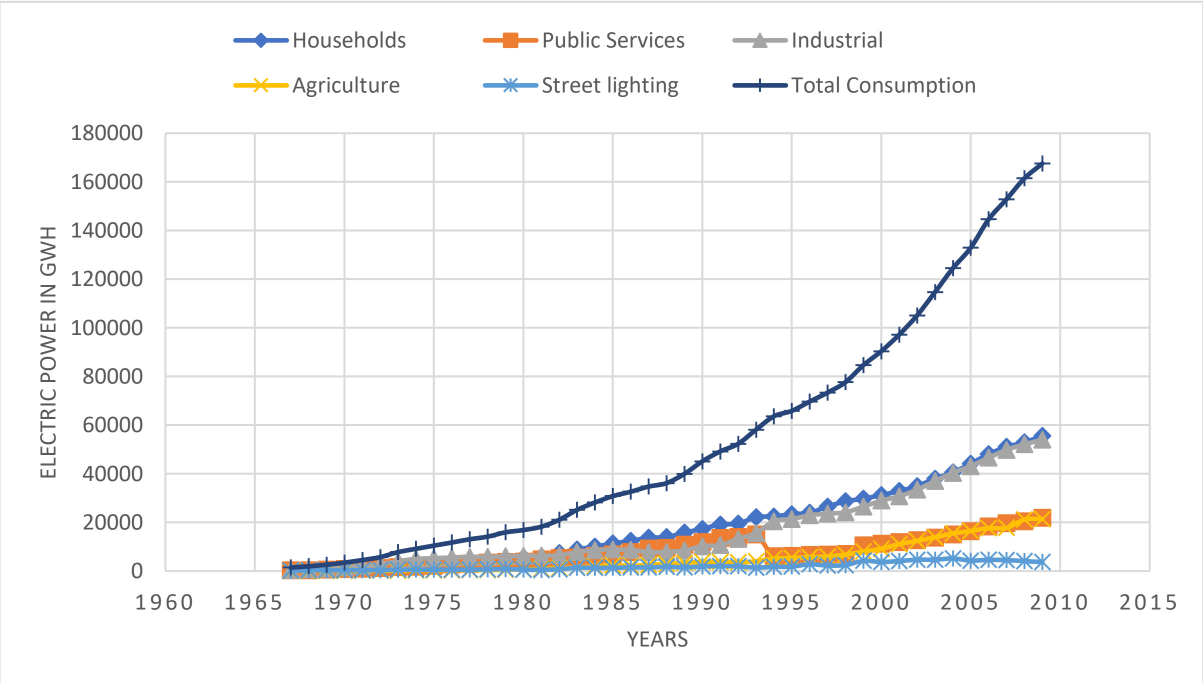
Having a quick preliminary look at figure 4.1, we immediately understand that Japan is a country that consumes electricity much more than Iran, and it has been enjoying and upward trend from 1963 until 2005, which means that Japan enjoyed economic prosperity of sustainable output during that period. However, we can see that after 2005, Japan's upward electricity consumption trend has slowed down in recent years, which means a stagnation economy that is finding difficulties pursuing more growth rates. On the other hand, Iran experienced a relatively flat electricity consumption trend from 1967 until the mid-1980s, which indicate a state of non-economic-improvement throughout the years. However, Iran started enjoying an upward trend from the early 1990s that is still going forward up until now, which indicates that Iran is enjoying economic growth at a sustainable rate.

All in all, forecasting electricity consumption will not only yield precise values of the energy needed for a future prospect period of consumption and thus help tailor down the costs of electricity production and/or consumption, but it will also yield a concise idea about the economic performance of the countries in general and the specific sectors in particular.

4.1.2. Electricity Consumption per Sector in Iran

As said in earlier chapters, we will not only study electricity consumption is Iran as a whole, but we will also break down the trend to account for the different sectors that has the lion share in energy consumption. Indeed, our data allows us to divide Iran's overall electricity consumption into 5 different sectors, plus a sixth one that represents all the other unlabeled sectors. The sectors considered are shown in figure 4.2 along with their respective electricity consumption.

Figure 4.2. Electricity consumption per sector in Iran (from 1967 until 2009)

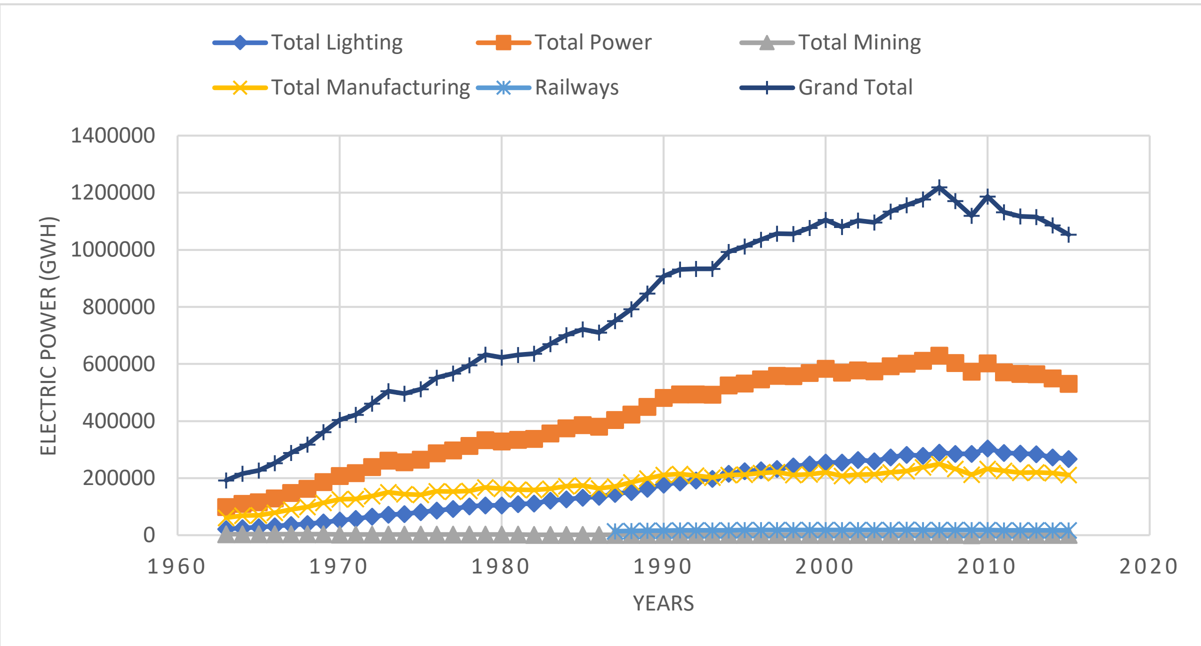


As expected, the industrial and the households sectors are the ones that account for the largest consumption amounts amongst all the different sectors. The street lighting sector is the lowest consuming sector in Iran, it experiences a constant trend throughout the duration of the study time span. The agriculture sector is also enjoying a constant growth rate but not as steep as the industrial and households sectors. We notice a sudden drop of electricity consumption in the public services sector going from 1993 to 1994. The consumption dropped by more than half from 14984 GWh to 6060 GWh, which is mainly attributed to changing some sub-sectors within the public service category to another sector.

4.1.3. Electricity Consumption per Sector in Japan

The sectors considered for Japan are not completely similar to those considered for Iran, and that is understandable. For example Railways in Japan are a major sector and consumes power as much as the other sectors do. However in Iran, the railways sector is a subsector included in the sector labeled as “other sectors”. Figure 4.3 shows all the sectors considered along with their respective electricity consumption.

Figure 4.3. Electricity consumption per sector in japan (from 1963 until 2015)



The power sector which comprises several subsectors; namely temporary power, agricultural power, construction power, business use power, and residential use power; is the main driver of electricity consumption is Japan. The second driver is the lighting sector that consists of temporary lighting, agricultural lighting, and public street lighting. Although, before the mid-1990s, the manufacturing sector was the second most energy hungry sector in the country. However after the mid-1990s, we can see that the lighting sector overtook the manufacturing sector as the second electricity consumption driver in Japan. Even though the railways sector consumes much more energy than the mining sectors, both of them are at the bottom of the chart with relatively constant trends.

4.1.4. Electricity Prices in Iran and Japan

As explained in Chapter 3, the third data set is comprised of nominal electricity prices in Iran from 1968 until 2007 in Rial/GWh, while the fourth data set consists of nominal electricity prices in Japan from 1970 to 2015 in JPY/KWh. This data needs further processing. In fact, we have to account for inflation before starting our learning curve analysis. Indeed, we will use the Consumer Price Index (CPI) retrieved from the official website of the IMF (IMF, 2016)in order to deflate all the values to obtain the real value of electricity prices. Table 4.1 and 4.2 shows the deflated values using the price index adjusted to 2010 (2010=100).

Table 4.1. Real Electricity Prices in Iran (Rial/GWh)

Year	*Nominal Electricity Price (Rial/GWH)*	*Price Index Adjusted to 2010 (2010=100)*	*Decimal Form*	*Real Electricity Price (Rial/GWH)*
1968	289	0.16	0.0016	180625.00
1969	221	0.16	0.0016	138125.00
1970	166	0.17	0.0017	97647.06
1971	183	0.17	0.0017	107647.06
1972	168	0.18	0.0018	93333.33

1973	147	0.2	0.002	73500.00
1974	142	0.23	0.0023	61739.13
1975	153	0.26	0.0026	58846.15
1976	170	0.29	0.0029	58620.69
1977	217	0.37	0.0037	58648.65
1978	228	0.41	0.0041	55609.76
1979	234	0.45	0.0045	52000.00
1980	282	0.55	0.0055	51272.73
1981	316	0.68	0.0068	46470.59
1982	386	0.81	0.0081	47654.32
1983	354	0.96	0.0096	36875.00
1984	353	1.09	0.0109	32385.32
1985	359	1.13	0.0113	31769.91
1986	385	1.34	0.0134	28731.34
1987	517	1.73	0.0173	29884.39
1988	535	2.22	0.0222	24099.10
1989	537	2.72	0.0272	19742.65
1990	568	2.92	0.0292	19452.05
1991	849	3.42	0.0342	24824.56
1992	1050	4.31	0.0431	24361.95
1993	1706	5.22	0.0522	32681.99
1994	3240	6.86	0.0686	47230.32
1995	3882	10.27	0.1027	37799.42
1996	4656	13.24	0.1324	35166.16
1997	5593	15.54	0.1554	35990.99
1998	6706	18.32	0.1832	36604.80
1999	8030	21.99	0.2199	36516.60
2000	8935	25.18	0.2518	35484.51
2001	9852	28.01	0.2801	35173.15
2002	11410	32.03	0.3203	35622.85
2003	13176	37.3	0.373	35324.40
2004	15106	42.81	0.4281	35286.15
2005	15208	48.56	0.4856	31317.96
2006	15278	54.36	0.5436	28105.22
2007	16498	63.72	0.6372	25891.40

The real value is obtained by dividing the nominal value by the price index in its decimal form.

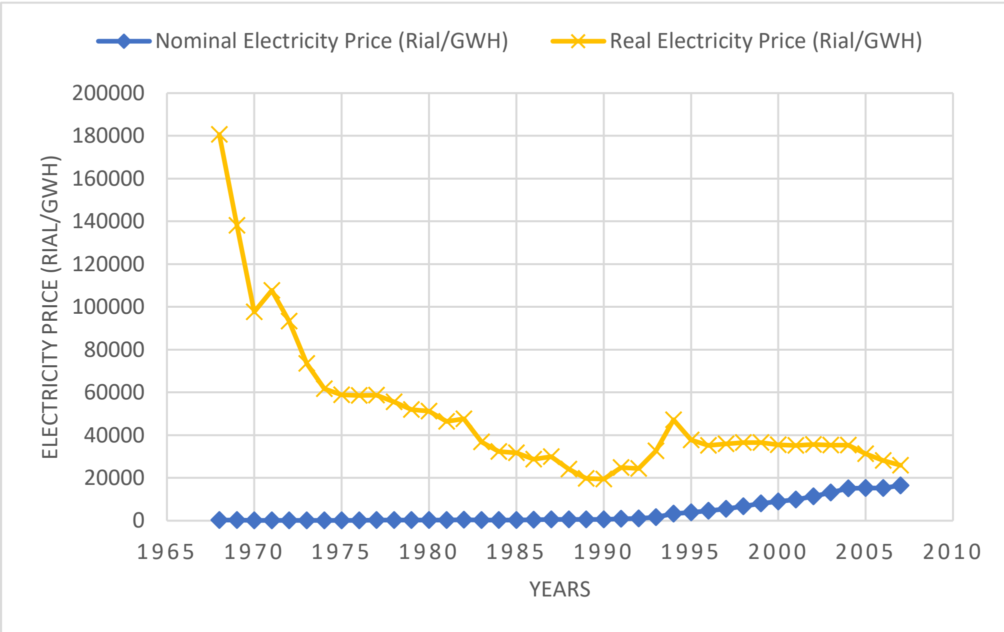
Year	***Nominal Electricity Price (JPY/KWH)***	***Price Index Adjusted to 2010 (2010=100)***	***Decimal Form***	***Real Electricity Price (JPY/KWH)***
1970	6.69	32.68	0.3268	20.47
1971	6.83	34.75	0.3475	19.66
1972	6.91	36.43	0.3643	18.98
1973	7.29	40.67	0.4067	17.93
1974	11.25	50.09	0.5009	22.47
1975	12.27	55.99	0.5599	21.92
1976	13.85	61.25	0.6125	22.62
1977	15.15	66.23	0.6623	22.87
1978	14.65	69.03	0.6903	21.22
1979	15.39	71.58	0.7158	21.49
1980	23.51	77.17	0.7717	30.46
1981	24.28	80.96	0.8096	29.99
1982	24.13	83.16	0.8316	29.01
1983	24.51	84.72	0.8472	28.93
1984	24.37	86.66	0.8666	28.12
1985	24.73	88.43	0.8843	27.97
1986	22.87	88.96	0.8896	25.71
1987	21.36	89.08	0.8908	23.98
1988	20.46	89.68	0.8968	22.81
1989	19.90	91.72	0.9172	21.69
1990	20.00	94.5	0.945	21.16
1991	20.38	97.62	0.9762	20.88
1992	20.64	99.28	0.9928	20.79
1993	20.66	100.54	1.0054	20.55
1994	20.28	101.23	1.0123	20.04
1995	20.26	101.11	1.0111	20.04
1996	19.77	101.24	1.0124	19.53
1997	20.04	103.03	1.0303	19.45
1998	19.22	103.71	1.0371	18.53
1999	18.82	103.37	1.0337	18.21
2000	18.81	102.69	1.0269	18.31
2001	18.83	101.87	1.0187	18.49
2002	17.74	100.53	1.0053	17.65
2003	17.35	100.70	1.007	17.23
2004	17.10	100.69	1.0069	16.98
2005	17.01	100.42	1.0042	16.94
2006	17.17	100.66	1.0066	17.05
2007	17.19	100.72	1.0072	17.06
2008	18.80	102.1	1.021	18.41

Table 4.2. Electricity Real Prices in Japan (JPY/KWh)

2009	17.27	100.73	1.0073	17.15
2010	17.23	100	1	17.23
2011	21.41	99.72	0.9972	21.47
2012	20.83	99.68	0.9968	20.89
2013	24.39	100.04	1.0004	24.38
2014	24.96	102.79	1.0279	24.29
2015	23.96	103.6	1.036	23.12

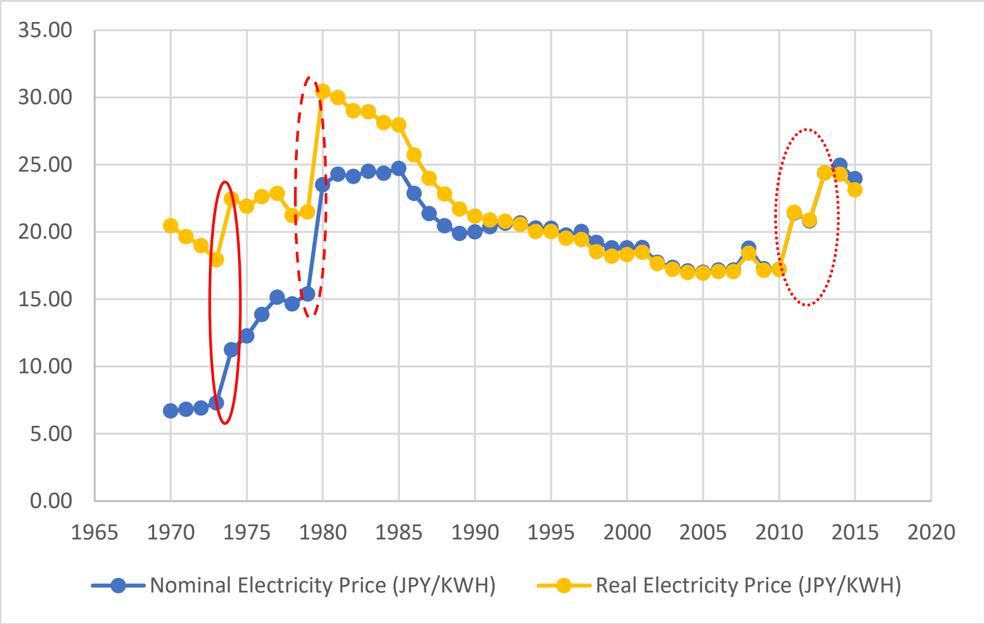
Once the real electricity prices obtained, we plot them against time to observe the evolution trend of electricity cost in both countries. Figure 4.4 and 4.5 show both trends of nominal and real electricity price.

Figure 4.4. Trend of Electricity Price Change in Iran (from 1968 to 2007)



Real and nominal electricity prices in Iran have very different values and trends, because the inflation rate in Iran has been quite high throughout the years fluctuating widely around 20% since the early 1990s, with a peak of 30% in 2009 and another peak of 44% in 2013 (Trading Economics, 2017). We can clearly see that the overall trend of real electricity prices in Iran is a downward slopped trend. Which is a good sign indicating that Iran benefits from sound electricity production management and that both economies of scale and technological learning are helping the prices the decrease. We will explain in detail the role of technological learning in the next sections of this chapter.

Figure 4.5. Trend of Electricity Price Change in Japan from (from 1970 to 2015)



Real and nominal electricity prices in Japan match each other since the early 1990s, because from that year on, Japan has always kept its inflation rate below 2% near the 0% mark. However, before that period, Japan had an inflation rate fluctuating around 5% with a peak to 25% in the mid-1970s, which explains why real and nominal electricity prices were drifting apart before the year 1990 (Trading Economics, 2017).

During the period from 1980 until 2010, electricity prices in Japan were decreasing at a relatively steady rate. However, the overall trend is not a downward one, in fact there are 3 major milestones that perturbed the normal evolution of electricity prices in Japan. All three of them have been displayed in figure 4.5 with the circle annotations. From the right to the left, the dotted-line circle that connotes a sudden electricity price increase, coincides with the Fukushima disaster in May 2011 that has led to a shortage of energy and has perturbed the balance of electricity prices within the energy production portfolio of Japan. The two circles from the left also indicate a sudden spike in electricity prices, the solid-line circle coincides with the first oil-crisis in 1973, while the dashed-line circle coincides with the second oil-crisis in 1979. Although both oil-crisis had a worldwide reach, so practically every country was affected by its repercussions. Except Iran, as the smooth downward slope of figure 4.4 suggests. This is mainly due to the international consortiums that each country belongs to. Iran belongs to the OPEC, so it is one of the countries that produce and provide oil all over the world, thus Iran can dictate the oil prices, and therefore it cannot be affected by any crisis related to fuel shortage. However, Japan doesn't belong to OPEC, and thus it undergoes all the fluctuations in price that the producing countries place on it. This will have an impact when performing the learning curve analysis, as it will hinder the technological learning potential of each electricity consuming sector in Japan.

4.2. Forecasting Results

4.2.1. Electricity Consumption Forecasting

After fitting the data of electricity consumption from Iran and Japan to all the forecasting models developed in the methodology section, we have calculated the three error and deviation errors in order to evaluate the model that is best fit for the studied data. In fact, the model that will yield the least amount of square error, would be the best fit model for forecasting future values of electricity consumption in the upcoming years.

Refer to Appendix 1 and Appendix 2 for the full graphical plot of all the constructed forecasting models for both Iran and Japan respectively. We have made sure to also display the actual consumption data alongside the time series forecasting model in order to judge the fitness of the model. Table 4.3 and 4.4 show the calculated error measurement of the constructed models.

Table 4.3. Squared Error values of the constructed Forecasting Models for Electricity Consumption Data in Iran

Type	*Model*	*MAPE*	*MAD*	*MSE*
Independent from actual consumption data	Logistic	14.69	4057.18	25021825.35
	Linear	63.24	14510.86	283982891.58
	Quadratic	16.83	3402.30	17163541.64
	Exponential	22.38	11216.49	383789287.42
Dependent from actual consumption data	5 Period Moving Average	35.28	12716.27	235974854.91
	ARMA(0,1,1)	6.69	2533.09	14353745.29
	Brown	3.64	1149.22	3140082.72

Amongst these seven constructed models, we can see that "Brown Model" presents the least amount of deviation across all three measurements of squared errors. Which means that the best forecasting model that will yield the most accurate electricity consumption prediction for the upcoming years is the "Brown Model". It is also worth noting that the model that yields the highest amount of squared error is the linear model, which implies that electricity consumption in Iran doesn't follow a linear trend at all, in fact, it follows a quadratic trend which best explains its overall growth rate.

In order to forecast electricity consumption for a short term period, say two or three years, Brown model is the best suited model for this operation, because it is the most accurate model amongst those that are dependent from the actual consumption data and thus can't accurately predict far ahead in the future from the set of data that it has been given. However, the models that are independent from the actual consumption data can forecast for long term periods, as they can capture the overall development trend of the consumption and are not locked down by previously available data. This observation yields some balanced contrasts in our results:

- The models that are dependent from actual consumption data yield the least amount of squared errors, but are only best fit for short-term forecasting.

- The models that are independent from actual consumption data yield the highest amount of squared errors, but are still best fit for long-term forecasting.

Table 4.4. Squared Error values of the constructed Forecasting Models for Electricity Consumption Data in Japan

Type	*Model*	*MAPE*	*MAD*	*MSE*
Independent from actual consumption data	Logistic	5.17	34823605.44	1.78E+15
	Linear	7.95	58107730.86	6.03E+15
	Quadratic	5.19	37318825.54	2.10E+15
	Exponential	15.31	115138738.93	2.22E+16
Dependent from actual consumption data	5 Period Moving Average	10.97	64660487.12	5.07E+15
	ARMA(0,1,1)	3.78	25088494.94	9.64E+14
	Brown	3.10	21789019.53	7.53E+14

In the case of Japan, we can also conclude that the "Brown Model" presents the least amount of deviation across all three measurements of squared errors. Which means that brown model will yield the most accurate predictions when forecasting electricity consumption in Japan. It is the same model that was selected as the best fit forecasting model in Iran. However, there is a difference between Iran and Japan in terms of global trends, which means that the best forecasting model for long term periods won't be the same. Indeed, from table 4.4, we can see that the model with the highest squared error measurement is the exponential model, which indicates that the rate of growth of electricity consumption in Japan is decreasing and doesn't have the potential to grow exponentially any longer.

In terms of long term forecasting, the best model that captures Japan's electricity consumption overall trend is the logistic model. Indeed, as mentioned earlier, Japan's electricity consumption potential to grow exponentially has reached a ceiling, and logistic curves are the best models that can capture this kind of situation for the long run. Table 4.5 summaries these findings.

Table 4.5. Summary of the Best fit Models for each Forecasting Scenario

	Best fit model for short term Forecasting	*Best fit model for long term Forecasting*
Iran	Brown Model	Quadratic Model
Japan	Brown Model	Logistic Model

4.2.2. Validity of using Excel for Constructing the Models

In order to study all the seven models, we have constructed them using Microsoft Excel with manual manipulation and linear programing in order to calculate the parameter values of the different forecasting models. However, these values might be biased and could be different from the optimal values, especially for the two most complex constructed models namely ARMA(0,1,1) and Brown. Therefore, we decided to construct those models using more specialized data processing software in order to check the validity of the results given by Microsoft Excel. The software that has been used is Minitab version 17, the student trial edition.

We have decided to check the validity of those two models only, because they are the ones that present the highest amount of complexity within all he studied models. Moreover, the algorithm that is build inside Minitab and which purpose is to find the best parameters for each model, tries to minimize all squared errors at once. Our linear program that we wrote in Excel Solver only minimizes the MSE, which only partially mimics the process of a specialized software and might not yield optimal results.

We have constructed the exact same models in Minitab 17. ARMA(0,0,1) model is referred to in Minitab as “Single Exponential Smoothing”, while Brown model is referred to as “Double Exponential Smoothing”. Refer to Appendix 3 for the plots of constructed models in Minitab. Table 4.6 shows a comparison between the results obtained in Excel and those obtained in Minitab.

Table 4.6. Minitab Results for Electricity consumption data in Iran

		Excel Results		*Minitab Results*	
	Models	Parameters	Squared Errors	Parameters	Squared Errors
Iran's Consumption Data	ARMA(0,1,1) Model	α = 1.75133	MAPE= 6.69 MAD=2533.09 MSE=1.44E+07	α = 1.75133	MAPE=6 MAD=2534 MSE=1.40E+07
	Brown Model	α = 0.911165 γ = 0.596103	MAPE=3.64 MAD=1149.22 MSE=3.14E+06	α = 0.920804 γ = 0.523457	MAPE=3 MAD=1134 MSE=3.05E+06
Japan's Consumption Data	ARMA(0,1,1) Model	α = 1.29035	MAPE=3.78 MAD=2.51E+07 MSE=9.64E+14	α = 1.29321	MAPE= 3.72 MAD= 2.51E+07 MSE= 9.45E+14
	Brown Model	α = 0.752481 γ = 0.995023	MAPE=3.10 MAD=2.18E+07 MSE=7.53E+14	α = 0.817326 γ = 0.209057	MAPE= 2.71 MAD= 2.03E+07 MSE= 6.93E+14

Table 4.6 shows the accuracy of Microsoft Excel results when compared to Minitab ones. In fact, Excel yields very accurate results that are very close to those given by the specialized software. Although Minitab might yield slightly better results in terms of goodness of fit, it doesn't justify the purchase of the software, as Excel's performance is still viable and can be used to construct the forecasting models with confidence. The only minor discrepancy that can be noticed, is the significant difference in the value of brown's model trend parameter gamma (γ) in the case of Japan's electricity consumption data. Indeed, Excel yields a value of γ = 0.995023 while Minitab gives a value of γ = 0.209057. These different values didn't seem to wildly affect the squared error results. Despite Minitab yielding inferior values for the measurement of squared errors, the difference is not significant enough to completely disapprove Excel results.

4.3. S-Curve Analysis

In this section, we will showcase the results of the S-Shape curve Analysis in order to assess the life span of each electricity consumption sector and observe their future development patterns. This analysis mainly consists of spotting which stage of the s-shape curve each sector belongs to. There are 4 distinct stages in an S-shape curve, the infant stage, the developing stage, the stagnating stage and then the maturity stage. The main measurements are the midpoint, the saturation level and the lifecycle timespan. Based on those measurements, one can be able to judge whether a consumption sector is still performing well and thus has many years to continue flourishing, or is it lagging behind and is losing its momentum and thus going straight through stagnation, maturity or even decline.

Recall that in equation 14, we have previously defined the parameters that we will have to estimate in order to construct the s-curve model. The results of this study were obtained by setting the value of "d" (the adjustment parameter) to zero, because we don't see the need to include an adjustment parameter that will bias the value of the model's saturation capacity. We have also set the fitting method to "Monte-Carlo" method, and made sure to set a high value for the number of iterations needed to converge towards the best fit s-curve that matches our cumulative data, in fact we have set the iteration setting to 1000 iterations, any higher value would only use more computational power for practically the same result. Finally, we have set the objective function setting to "sum of squares" which means that the software tries to find the s-curve that minimizes the sum of all the squared error measurements. Table 4.7 and table 4.9 show a quick overview of all the resulting parameters for the different electricity consumption sectors in Iran and Japan respectively. Refer to Appendix 4 and Appendix 5 to check all the plots and detailed parameters yielded by the Logletlab software for Iran and Japan consumption sectors respectively.

Table 4.7. Summary of the S-Curve Model Parameters for Electricity Consumption sectors in Iran

Sector	*Saturation Production (GWh)*	*Dt (Life Time in Years)*	*Midpoint (Year)*	*Saturation Date (Year)*
Other Sectors	177759.1	20.98	2004.76	2015.25
Public Service	458836.14	36.59	2001.19	2019.485
Residential	1372521.97	34.17	2007.04	2024.125
Street Lighting	181964.12	40.56	2010.1	2030.38
Agriculture	799928.46	32.51	2015.67	2031.925
Industry	2762540.45	41.72	2018.67	2039.53
All sectors	5131248.52	37.68	2010.91	2029.75

The majority of electricity consumptions sectors in Iran, have reached their cumulative development midpoint within the recent years. The industry sector is the only consuming sector that hasn't reached its midpoint yet, but will soon attain it within the second half of the year 2018. This indicates that these studied Iranian sectors are relatively "young", in the sense that they still have big development potential ahead and can still sustain a significant growth rate for the years to come. The average life time of electricity consuming sectors in Iran is around 35 years. The sector that enjoys the longest lifetime is the industry sector with nearly 42 years of development and growth after which it will reach a state of maturity at the year 2039 where further production will not yield any more growth and where the inner processes that previously drove this production would have to be changed in order to start a new cycle of sustained growth. Table 4.8 depicts the different development stages that every single consumption sector in Iran belongs to.

Table 4.8. Summary of the S-Curve Model Development Stages for Electricity Consumption sectors in Iran

Infant Stage	*Developing Stage*	*Stagnating Stage*	*Maturity Stage*
Industry Sector	Agriculture Sector	Public Service Sector	Other Sectors
	Street Lighting Sector		
	Residential Sector		
	All sectors		

If we compound each cumulative electricity consumption data for all the sectors in one general cumulative data, we can perform the s-curve analysis for this data that will account for all the sectors at once. Table 4.8 shows that "All sectors" belongs to the "developing stage", which means that those studied sectors in Iran are still in their early stages of development, and their production and management processes are relatively. Therefore, apart from the Public Service sector, the majority of the sectors can still maintain a relatively high growth rate and won't reach maturity until the year 2030.

Table 4.9. Summary of the S-Curve Model Parameters for Electricity Consumption sectors in Japan

Sector	*Saturation Production (MWh)*	*Dt (Life Time in Years)*	*Midpoint (Year)*	*Saturation Date (Year)*
Mining	92289421.05	43.98	1979.8	2001.79
Manufacturing	11053699924.75	50.15	1997.18	2022.255
Railways	551737624.60	27.49	2002.08	2015.825
Others	1380921489.27	50.81	1996.32	2021.725
Agricultural	69895482.45	41.97	1990.85	2011.835
Public Lighting	260654057.64	35.49	1999.18	2016.925
Residential	1575566765.42	37.61	1998.37	2017.175
All sectors	52814921830.67	49.15	2000.83	2025.405

In contrast to Iran's studied sectors, some of the electricity consumptions sectors in Japan have already reached their cumulative development midpoint before the 21st century, while only the railways sector have reached its midpoint in the year 2002. Moreover, the mining sector is the first sector to reach its maturity stage of development, it has done so in 2001. This indicates that these studied Japanese sectors are somewhat "old", in the sense that their development potential is becoming rusty and they can no longer sustain a significant growth rate for the years to come. The average life time of electricity consuming sectors in Japan is around 45 years, which is higher than its Iranian counterpart, about 35 years. This means that Japan can sustain growth with the same production processes and management styles for a much longer time span than Iran can. This is an indication of how efficient Japanese production and management systems are, when compared to the Iranian ones. Table 4.10 depicts the different development stages that every single consumption sector in Japan belongs to.

Table 4.10. Summary of the S-Curve Model Development Stages for Electricity Consumption sectors in Japan

Infant Stage	*Developing Stage*	*Stagnating Stage*	*Maturity Stage*
		Residential	Mining
		Manufacturing	Railways
		Others	Agriculture
		All sectors	Public Lighting

Right away from table 4.10, we can see that all the Japanese sectors belong to the second half of the development spectrum. Mining, railways, agriculture, and public lighting sectors have already reached maturity in 2001, 2015, 2011, and 2016 respectively, all the other sectors are in the stagnating stage and will reach the maturity stage within the year 2020 on average. It is worth noting that the shortest lifetime is attributed to the railways sector, indeed, it has only lasted for 27 years compared to the 45 years of average lifetime of all the other sectors. Which means that railways in Japan have practically been well established and can't grow anymore. In order to foster a new cycle of sustained growth, a new technology should take over. That's why the Shinkansen makes its entry into the railway sector to reignite the industry. The same can be said about the mining sector, although there has been no new innovation in the mining processes, therefore, we might observe a severe stagnation in the growth of the mining sector of the years to come.

4.4. Learning Curve Findings

Recall in figure 2.2 when a graph definition of a learning curve has been presented, the plot exhibited is a downward slopped curve that shows the decrease of the unit production cost through cumulative production. The plot of the learning curve as portrayed earlier is displayed by figures 4.6 And 4.7. Both figures show the polynomial form of the learning curve that will be subject to a logarithmic transformation in order to extract the learning elasticity information. The polynomial form of the learning curve is written as: Price= $A \times Cumul, Production^{-\alpha}$. This polynomial curve is shown in figures 4.6 and 4.7 by the dotted line curve referred to in the graph legend as “Power (learning Curve).”

Figure 4.6. Learning Curve of Electricity Consumption Process in Iran

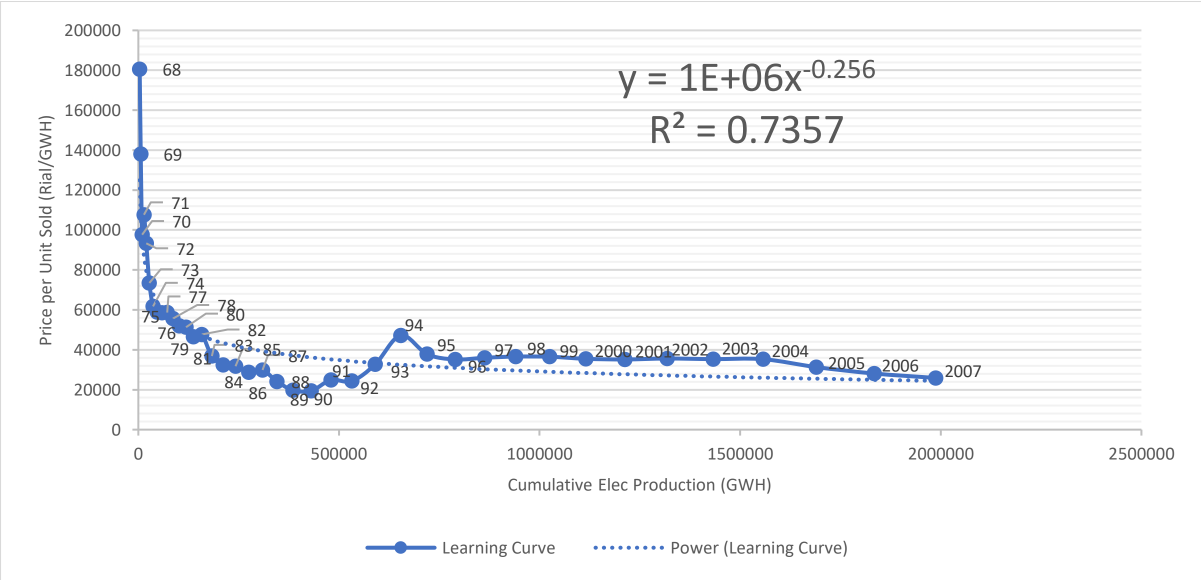
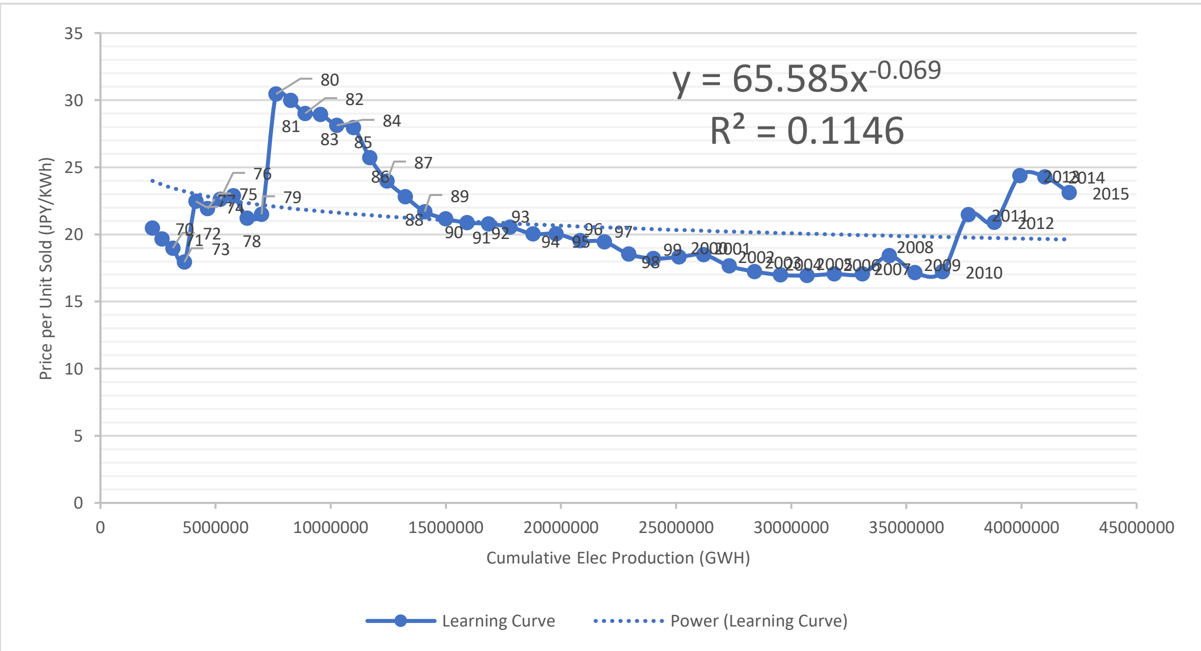


Figure 4.7. Learning Curve of Electricity Consumption Process in Japan



We can see that figure 4.6 matches the concept explained using figure 2.2, which means that Iran experiences an electricity cost drop for every doubling of the amount consumed. However, figure 4.7 doesn't portray the same decreasing pattern as figure 2.2, we observe a lot of fluctuations in the learning curve. In fact, the slope is a decreasing one, but it is not as steep as the slope in figure 4.6. This is mainly due to external factors, such as the two oil-crisis in 1973 and 1979 and the Fukushima disaster in 2011. Which means that the learning curve doesn't only depend from the internal capacity of the studied entity to learn and to foster technological advances, but it also depends from external non-controllable factors such as fuel shortages and natural disasters.

4.4.1. The Linear Elasticity Model Estimation

This section focuses on the estimation of annual technological learning elasticities (learning coefficient) and the progress ratio (d) or learning levels in Iranian and Japanese electricity consumption sectors. This study will enable us to uncover the trend and pattern of technological learning in different sectors in both countries. To achieve this, we utilized the various models constructed for learning elasticity and progress ratio (for linear and cubic respectively) as earlier shown in the methodology section. The results are presented hereunder.

Table 4.11. Learning elasticities and levels (progress ratio) estimated using linear model for all the studied sectors in Iran

Sector	φ0	φ1	φ2	R^2	Significance F	d
Households	-0.6250	-0.7095	0.9684	0.9652	1.02E-27	0.6115
Public Service	7.4220	-0.3923	0.3874	0.7997	1.20E-13	0.7619
Industrial	5.3420	-0.4797	0.5405	0.9734	7.04E-30	0.7171
Agriculture	2.5881	-0.6659	0.7857	0.9524	3.46E-25	0.6303
Street Lighting	5.2899	-0.4994	0.5635	0.9141	1.92E-20	0.7074
All sectors	0.6744	-0.6188	0.8401	0.9885	1.29E-36	0.6512

Table 4.12. Learning elasticities and levels (progress ratio) estimated using linear model for all the studied sectors in Japan

Sector	φ0	φ1	φ2	R^2	F	Significance F	d
Residential	-3.4631	-0.1419	0.6216	0.7631	62.8293	6.34E-13	0.9063
Mining	-9.4553	0.5575	0.6149	0.8300	104.9900	2.84E-17	1.4717
Manufacturing	-9.4613	-0.2596	1.0819	0.9010	195.7178	2.54E-22	0.8353
Public Lighting	-5.0288	-0.2799	0.9602	0.8112	83.7667	7.65E-15	0.8236
Agriculture	-0.1756	-0.0311	0.3467	0.7300	39.5430	4.15E-10	0.9787
Railways	-13.3251	-0.0652	1.3410	0.9217	153.1075	4.13E-15	0.9558
All sectors	-8.6658	-0.4327	1.1302	0.8758	151.5407	3.37E-20	0.7409

Tables 4.11 and 4.12 shows the model estimation for linear learning elasticity for each sector in Iran and Japan respectively. The regression statistics (R2 and F) suggest a good fitting across practically all the sectors in both countries. Although in Iranian sectors, R2 presents much higher values when compared to those of their Japanese counterparts. In fact, the lowest R2 value in table 4.10 is around 0.8 for the Public service sector in Iran, while all the other values in the same table are higher than 0.9. However, when compared to table 4.11, the lowest R2 value is 0.73 for the agriculture sector, while only two sectors presented values that exceeded the 0.9 R2 threshold value. This indicates that the linear elasticity model fit the Iranian sectors better than the Japanese ones.

The last column of Tables 4.11 and 4.12, show the estimated progress ratio for each sector in both countries. Unshaded cells indicate learning scenario with per unit cost efficiency gain (real cost savings) in the energy consumption process by the corresponding sector. Grey shaded cells however, indicate forgetting scenario with loss in efficiency and increase in per unit energy cost. As we can see in Table 4.12, only the mining sector presents a progress ratio value that is higher than 100%, while all the other sectors in both countries present some learning potential. As explained in the methodology chapter, progress ratio gets better when its value gets lower and lower. In that regard, Iranian sectors present some very promising progress ratio values when compared to the values presented by the Japanese sectors. Indeed, progress ratio values in Table 4.11 go as low as 61.15% for the Households sector and only tops out at 76.19% for the public services sector. However, in table 4.12, the lowest progress ratio value is at 82.36% while the highest is at 147.17% for the mining sector. This indicates that the Iranian sectors present much higher learning potential than the Japanese sectors. On aggregate, the same conclusion can be made. Indeed, the "all sectors' rows in both tables present a progress ratio of 65.12% and 74.09% respectively.

Those are some valuable information, but it still doesn't portray the overall picture as accurately as one would expect. Indeed, the weakness of the linear learning curve model is that it assumes the learning to be constant and hence ignores the time variance (dynamic) of the learning system. Some studies have proven that linear learning curve does not always give the true picture of technological learning when time series data is involved, as it lacks the capacity to check the dynamism of learning over time. The next section of this thesis will consist of the study of technological learning potential within the different sectors in Iran and Japan via non-linear (log-linear) cubic models.

4.4.2. The Cubic Learning Model Estimation

Tables 4.13 and 4.14 show the learning elasticities of all the studied sectors in Iran and Japan estimated using the cubic model. Similarly to the linear model, the cubic models seem to fit the data just as well as the previous models judging by the regression statistics (R2 and F). Most sectors had somewhat similar coefficient of determination R2, even though R2 values for the cubic model were slightly higher, implying that higher percentage of the variations in the data set was explained by the model. F statistic on the other hand shows that the model significantly fit the data at very low percentage levels for all the sectors in both countries.

Table 4.13. Learning elasticities and levels (progress ratio) estimated using Cubic model for all the studied sectors in Iran

Sector	*φ1*	*φ2*	*B*	*C*	*D*	*R^2*	*Significance F*
Households	-11.5293	2.8690	0.9243	-0.3570	0.0117	0.9817	7.33E-30
Public Service	2.1251	3.3028	0.1106	-0.4254	0.0160	0.8642	1.08E-14
Industrial	15.9985	-4.160	0.6215	0.3636	-0.0118	0.9815	8.54E-30
Agriculture	0.6940	-0.03	0.8006	-0.0771	0.0030	0.9555	3.95E-23
Street Lighting	-2.2641	2.3755	0.5346	-0.3358	0.0129	0.9187	1.43E-18
All Sectors	2.2959	-2.008	0.9945	0.1365	-0.0045	0.9941	1.86E-38

Table 4.14. Learning elasticities and levels (progress ratio) estimated using Cubic model for all the studied sectors in Japan

Sector	*φ1*	*φ2*	*B*	*C*	*D*	*R^2*	*Significance F*
Residential	-46.8225	10.3896	0.723	-0.8718	0.023	0.7969	2.45E-12
Mining	-1049.87	290.477	0.702	-26.9391	0.8339	0.8822	1.74E-18
Manufacturing	-193.379	37.4228	1.105	-2.5733	0.0585	0.9232	2.83E-22
Public Lighting	-25.0539	5.3154	1.107	-0.5574	0.0182	0.8419	2.51E-14
Agriculture	-282.972	82.1430	0.301	-7.9298	0.2546	0.7300	4.37E-10
Railways	-34.1799	6.3400	1.180	-0.5909	0.0180	0.9848	1.99E-21
All sectors	-275.296	49.8531	1.284	-3.1809	0.0668	0.9620	1.61E-28

The annual technological learning level (progress ratio) for all sectors were calculated and presented in Tables 4.15 and 4.16 for Iran and Japan respectively. Grey shaded cells emphasize a forgetting process during the period under review. Refer to Appendix 6 and Appendix 7 for the full display of the cubic model curve plots concerning every studied sector in Iran and Japan respectively. From table 4.15, we can see that only the public service sector exhibits a forgetting phenomenon with progress ratio values higher than 1 starting from 1995 up until

2007. All the other sectors exhibit a good learning potential throughout the years. However, the learning path connoted by the trend of the progress ratio throughout the years differs from a sector to the other. Indeed, households sector, agriculture sector, and public lighting sector, all exhibit a decreasing trend in the progress ratio in the early periods of the study, then experience an increasing trend towards the end periods of the study. During this change in progress ratio trend, no forgetting was displayed. We call this learning path a convex learning path with a minimum, with no forgetting at any period. On the other hand, the public service sector exhibits the same path as those previously mentioned sectors. However, we notice that the progress ratio goes beyond 1 at the end of the study periods. In this case, the learning path of the public service sector is characterized as a convex learning path with forgetting at some end period. Finally, the industrial sector exhibits an increasing trend in the progress ratio in the early periods of the study, then experiences a decreasing trend towards the end periods. Yet again, during this progress ratio change, all values stayed well below 1. We call this learning path a concave learning path with a maximum, with no forgetting at any period.

From table 4.16, we can see that all the all the sectors follow a convex learning path judging from the variation of the progress ratios for each sector during the studied periods. However, some sectors exhibit some values of progress ratio that are superior to 1, which means that they experience forgetting. Indeed, the residential sector, the mining sector, the manufacturing sector, the agricultural sector, and the railways sector, all follow a convex learning path with forgetting at some end periods. The remaining sector, namely the public lighting sector exhibits a convex learning path with no forgetting at any period. It is worth noting that the mining sector exhibited a forgetting pattern not only in some periods, but throughout all the studied timespan. Moreover, the mining sector exhibited the highest progress ratios in all the sectors, in fact, in 2015 the progress ratio was estimated at 2.957, which means that for every doubling of the consumed electricity amount in that sector, the cost of electricity becomes 295.7% of the value at which it was valued before, the cost of electricity nearly triples every time the mining sector doubles its consumption, which indicates a complete lack of technological learning in that sector.

When compared to the progress ratios from the studied sectors in Iran, the learning potential in Japan is clearly inferior to its Iranian counterpart. In fact, when we consider the aggregate consumption data for all the sectors at once, we observe that all the compounded sectors in Iran follow a concave learning curve with maximum, and with no forgetting at any period. Which means that the cost of electricity was decreasing in the early periods by an increasing cost cutting percentage, then it started decreasing at a very early stage, precisely in 1973 when it has reached a maximum value of 64.9%. Then from 1974, the progress ratio started decreasing rapidly to reach 54.3% in 2007. This indicates that all the studied sectors in Iran have experienced electricity cost cuts early on, but those savings were not efficient enough, it only started being efficient from 1974 where electricity costs started decreasing at a cascading rate. On the other hand, if we consider the aggregate consumption data for all the studied sectors in Japan, we observe that they follow a convex learning with minimum, and with no forgetting at any period. Which means that the cost of electricity was decreasing very efficiently in the early periods, then the progress ratio started increasing when it reached a value of 66% in 1982, and the cost savings were not as efficient as they used to be. From 1983, the progress ratio was increasing year in year out to reach a value of 98% in 2015. This indicates that all the studied sectors in Japan have experienced very efficient electricity cost reductions early on, but those savings stopped being efficient since 1983. If the progress ratio keeps on increasing at the same momentum, we expect it to go beyond 1, and thus the cost of electricity in Japan would increase in the studied sectors for every doubling of electricity consumption. Tables 4.17 and 4.18 show a summary of the findings.

Table 4.15. Annual Technological Learning Level Estimates for the different Iranian Electricity Consumption Sectors

Years	*Households*	*Public Service*	*Industrial*	*Agriculture*	*Street Lighting*	*All Sectors*
1968	0.750	0.878	0.577	0.689	0.824	0.625
1969	0.700	0.800	0.626	0.666	0.772	0.636
1970	0.669	0.760	0.666	0.654	0.745	0.643
1971	0.647	0.740	0.694	0.645	0.726	0.647
1972	0.630	0.730	0.714	0.638	0.714	0.648
1973	0.618	0.725	0.729	0.632	0.703	0.649
1974	0.609	0.724	0.737	0.627	0.696	0.648
1975	0.601	0.727	0.740	0.624	0.691	0.646
1976	0.595	0.732	0.741	0.621	0.689	0.644
1977	0.591	0.739	0.741	0.619	0.687	0.642
1978	0.589	0.748	0.739	0.618	0.686	0.640
1979	0.587	0.758	0.737	0.617	0.685	0.637
1980	0.588	0.768	0.735	0.616	0.685	0.634
1981	0.589	0.780	0.732	0.615	0.686	0.632
1982	0.591	0.793	0.729	0.615	0.687	0.629
1983	0.594	0.806	0.725	0.615	0.689	0.625
1984	0.598	0.820	0.721	0.616	0.691	0.622
1985	0.602	0.834	0.717	0.617	0.694	0.619
1986	0.607	0.850	0.713	0.618	0.697	0.615
1987	0.613	0.868	0.710	0.619	0.701	0.612
1988	0.618	0.885	0.707	0.620	0.705	0.609
1989	0.624	0.904	0.703	0.622	0.708	0.605
1990	0.630	0.923	0.699	0.623	0.713	0.602
1991	0.637	0.944	0.695	0.625	0.717	0.598
1992	0.644	0.965	0.690	0.626	0.722	0.595
1993	0.651	0.985	0.684	0.628	0.725	0.591
1994	0.658	0.994	0.677	0.630	0.729	0.588
1995	0.664	1.002	0.670	0.632	0.732	0.584
1996	0.671	1.010	0.663	0.633	0.738	0.581
1997	0.678	1.019	0.657	0.635	0.743	0.577
1998	0.686	1.028	0.650	0.637	0.748	0.574
1999	0.693	1.040	0.644	0.639	0.756	0.571
2000	0.701	1.054	0.637	0.642	0.763	0.567
2001	0.708	1.068	0.630	0.644	0.771	0.564
2002	0.716	1.082	0.623	0.647	0.779	0.561
2003	0.724	1.097	0.616	0.650	0.787	0.557
2004	0.732	1.112	0.609	0.653	0.795	0.554
2005	0.741	1.129	0.601	0.656	0.802	0.550
2006	0.750	1.147	0.594	0.659	0.809	0.547
2007	0.759	1.166	0.586	0.661	0.815	0.543

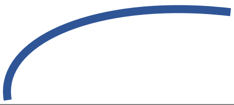
Table 4.16. Annual Technological Learning Level Estimates for the different Japanese Electricity Consumption Sectors

Year	*Residential*	*Mining*	*Manufacturing*	*Public Lighting*	*Agriculture*	*Railways*	*All sectors*
1970	-	2.314	0.946	-	-	-	0.813
1971	-	1.959	0.904	-	-	-	0.770
1972	-	1.732	0.872	-	-	-	0.737
1973	-	1.587	0.848	-	-	-	0.712
1974	1.139	1.489	0.831	0.985	1.736	-	0.695
1975	0.978	1.419	0.819	0.858	1.523	-	0.682
1976	0.917	1.371	0.809	0.813	1.369	-	0.673
1977	0.886	1.342	0.802	0.790	1.246	-	0.666
1978	0.867	1.325	0.798	0.778	1.145	-	0.662
1979	0.857	1.320	0.795	0.771	1.075	-	0.659
1980	0.853	1.324	0.793	0.767	1.030	-	0.658
1981	0.850	1.335	0.793	0.766	0.991	-	0.659
1982	0.850	1.352	0.793	0.766	0.960	-	0.660
1983	0.851	1.371	0.794	0.767	0.935	-	0.662
1984	0.853	1.396	0.796	0.769	0.914	-	0.666
1985	0.856	1.423	0.799	0.771	0.898	-	0.670
1986	0.860	1.453	0.801	0.774	0.888	-	0.674
1987	0.864	1.483	0.805	0.778	0.880	0.983	0.679
1988	0.869	1.514	0.809	0.781	0.876	0.931	0.685
1989	0.874	1.549	0.813	0.785	0.874	0.917	0.692
1990	0.880	1.588	0.819	0.789	0.874	0.915	0.699
1991	0.886	1.630	0.824	0.794	0.876	0.918	0.708
1992	0.892	1.674	0.830	0.798	0.880	0.924	0.716
1993	0.898	1.720	0.836	0.803	0.885	0.931	0.725
1994	0.905	1.770	0.843	0.808	0.895	0.938	0.734
1995	0.912	1.822	0.849	0.813	0.904	0.946	0.744
1996	0.918	1.878	0.856	0.818	0.915	0.955	0.754
1997	0.925	1.934	0.863	0.824	0.927	0.963	0.765
1998	0.932	1.990	0.870	0.829	0.939	0.971	0.775
1999	0.939	2.048	0.877	0.834	0.952	0.979	0.787
2000	0.946	2.108	0.884	0.840	0.966	0.988	0.798
2001	0.953	2.165	0.891	0.845	0.981	0.996	0.809
2002	0.960	2.216	0.898	0.851	0.997	1.004	0.821
2003	0.966	2.263	0.906	0.856	1.011	1.011	0.832
2004	0.973	2.313	0.913	0.862	1.027	1.019	0.844
2005	0.979	2.366	0.921	0.867	1.037	1.027	0.857
2006	0.985	2.424	0.929	0.873	1.047	1.035	0.869
2007	0.991	2.477	0.938	0.878	1.057	1.042	0.882
2008	0.996	2.531	0.946	0.883	1.067	1.050	0.895
2009	1.001	2.583	0.954	0.889	1.078	1.057	0.907
2010	1.007	2.640	0.962	0.894	1.088	1.064	0.920
2011	1.012	2.697	0.970	0.898	1.099	1.070	0.932
2012	1.017	2.757	0.978	0.903	1.110	1.076	0.945
2013	1.022	2.823	0.986	0.907	1.121	1.083	0.957
2014	1.026	2.891	0.993	0.912	1.132	1.089	0.969
2015	1.031	2.957	1.001	0.916	1.142	1.095	0.980

Table 4.17. Paths of Learning in Iranian Electricity Consumption from 1968 to 2007

Paths	Shape	Forgetting	Sector
Convex learning path with a minimum		With forgetting at some end periods	• Public Service
		With no forgetting at any period	• Households • Street Lighting • Agriculture
Concave learning path with maximum		With forgetting at some mid periods	-
		no forgetting in any period	• Industry • Overall Compound Sectors
Concave learning path that either have not reached or have no maximum		With forgetting after the beginning period	-
		with forgetting at some mid period	-

Table 4.18. Paths of Learning in Japanese Electricity Consumption from 1970 to 2015

Paths	Shape	Forgetting	Sector
Convex learning path with a minimum		With forgetting at some end periods	• Residential • Mining • Manufacturing • Agriculture • Railways
		With no forgetting at any period	• Public Lighting • Overall compound Sectors
Concave learning path with maximum		With forgetting at some mid periods	-
		no forgetting in any period	-
Concave learning path that either have not reached or have no maximum		With forgetting after the beginning period	-
		with forgetting at some mid period	-

CHAPTER FIVE: CONCLUSION

5.1. Results of similar Forecasting Studies

This section discusses the results of the data analyses in comparison with the literatures that has conducted similar studies concerning electricity demand forecast for Iran and Japan. Indeed, our results indicated that the best fit forecasting models for electricity demand differ from a country to other and from a forecasting scenario to the other. Indeed, as shown in table 4.4, the best fit model for electricity consumption forecasting in Iran for a long-term prediction scenario is the quadratic model, while the best fit model for the same scenario in the case of Japan is the logistic model. This indicates the variability of the concept of “best fit model”. In fact, we can’t assess by certainty that a specific model can predict the observed phenomenon more accurately than all the others. It depends on so many variables that the studied forecasting models can’t always account for. Indeed, some studies has shown that other models are best fit for electricity consumption forecasting in Iran and Japan alike.

A study has used an integrated algorithm based on ANN and time series analysis in order to forecast electricity consumption in Iran. In this study, the actual consumption data that has been used spans from 1994 to 2005, but instead of counting periods in years, the periods have been counted in months, so a total of 130 moths were used to show the performance and eminence of the proposed model. In this study, multilayer perceptron networks have been used, from which the back propagation algorithm had the best results with a calculated error of approximately 0.012 on the test dataset (Azadeh, Ghaderi, & Sohrabkhani, 2008). All in all, the results proved that ANN is better performing than both the standard time series models and the simulated-based ANN models. This observation was made accordingly to the statistical tests that have been conducted during the study, namely MAPE, Duncan's Multiple Range Test (DMRT), and Analysis Of Variance (ANOVA F-Test). However, the study has also made sure to mention that the utilization of various models is key in order to construct a better overall picture of the predictions. Indeed, the study emphasized on the fact that ANN is the best model, but relying solely on it will not enhance the overall validity of the forecasts. Therefore, in order to minimize the biases of using only one approach, different models should be considered. This was precisely the reason behind our recommendation of more than one model for each data set studied, as shown in table 4.4.

Another study has focused on the short-term load forecasting (STLF) in order to predict future values of electricity demand in Iran. The proposed framework is basically an improved version of the singular spectral analysis (SSA) in which the time series are broken down to their principal components, their tendency, and their oscillation components. The data set that has been considered are the total load time series of Iran electricity market, and is considered long and consistent enough to yield robust forecasting results. All in all, the results show that the proposed model offers great performance in short-term forecasting when put against some other models (Afshar & Bigdeli, 2011). However, since this study was only conducted with short-term forecasting in mind, no further consideration has been made concerning the performance of the model in other forecasting scenarios.

In the case of Japan, a study has used a Bayesian approach to examine the regional electricity demand in Japan. The forecasting model that was proposed is a spatial autoregressive (SAR) ARMA model, which parameters were estimated by relying on a Markov Chain Monte Carlo (MCMC) method. The results show that the spatial autoregressive ARMA(1,1) model performs better than the univariate ARMA model (Ohtsuka, Oga, & Kakamu, 2009). Moreover, a further observation has been made about the importance of spatial interaction between different regions, as it directly impacts the forecasts of future electricity demand in Japan.

5.2. Policy implications of the S-curve Analysis

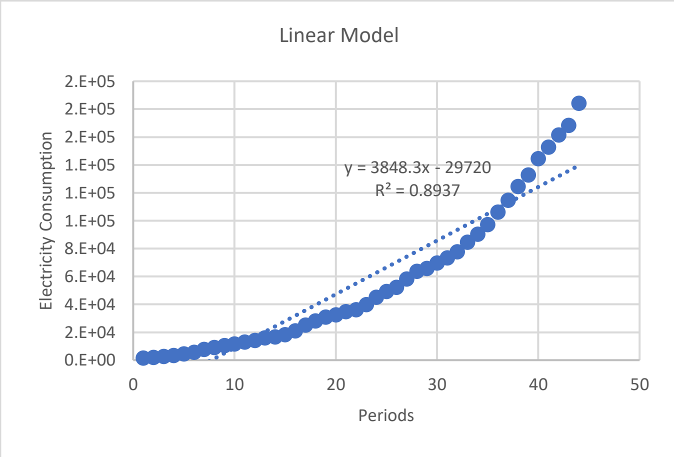
Comparing tables 4.7 and 4.9, we can conclude that different electricity consuming sectors have reached different stages of their developing path in different countries. Indeed, while the agriculture sector is still in its developing stage in Iran, the same sector has already reached its maturity stage in Japan. The same observation can be made about the residential and the public lighting sectors that are still in the developing stage in Iran, but have already reached the stagnating stage in Japan. Another sector also belongs to two different ends of the development stages spectrum in both countries. Indeed, manufacturing sector is in an infant stage in Iran, while it is in a stagnating stage in Japan. Finally, the mining and the railways sectors in Japan, which are not represented in our Iranian data set, both have already reached maturity in 2001 and 2015 respectively. All these observations indicate that Iran is still a developing country and has all the potential to experience sustainable growth during the upcoming years, while Japan is starting to be economically out of breath, especially in the sectors studied in this thesis. Concerning policy recommendations, the Iranian government could focus on starting new international campaign about FDI attraction in order to accelerate the development of its industry and increase the saturation point capacity level to a higher amount which will undoubtedly extend the lifespan of those sectors. Concerning the residential and agriculture sectors, population growth will play a great role of fostering growth in these sectors without specific government implication. Finally, regarding the public services sector, recommendations would concern the infrastructure and the organization of the sector more than government policy itself. In fact, reforms should be instituted about the structures and the underlying organization of the sector in order to foster more efficiency and growth so as to start a new s-curve life cycle. Regarding the Japanese government however, we have a whole different set of recommendations to make. The Japanese government should focus on improving the export capacity of its agriculture sector, for example Japanese mushroom and rice could easily reach the Southeast Asian markets and foster more growth in the sector. For sectors that can't afford going market extension outside japan, such as the railways sector. A new development cycle has to be created by relying on new technologies, and that is exactly what Japanese government is fostering, the new Japanese maglev train would start a new sustainable growth in the sector. The manufacturing sector however needs a combination of outside market extension measures and internal technology innovations. Indeed, Japanese manufacturers should seriously consider implementing their businesses abroad in order to harness the potential of the new fertile markets of Southeast Asia and Africa. Moreover, the government should provide some facility measures to foster this kind of industry globalization, in one hand, startups should benefit from less restrictive regulations and incumbents should benefit for low interest rate loans provided that the loan will serve the company to expand outside of Japan.

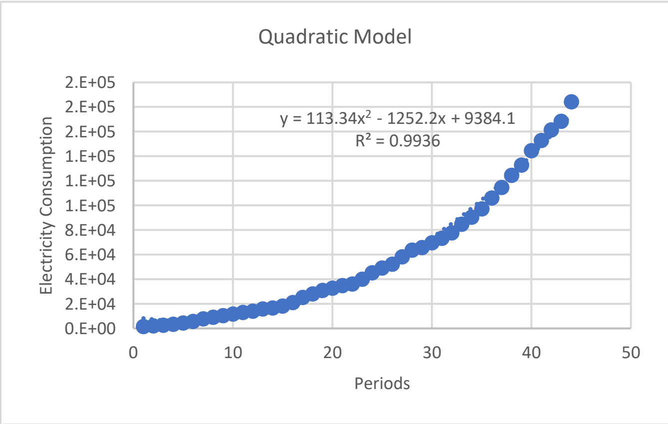
5.3. Policy implications of the learning curve Analysis

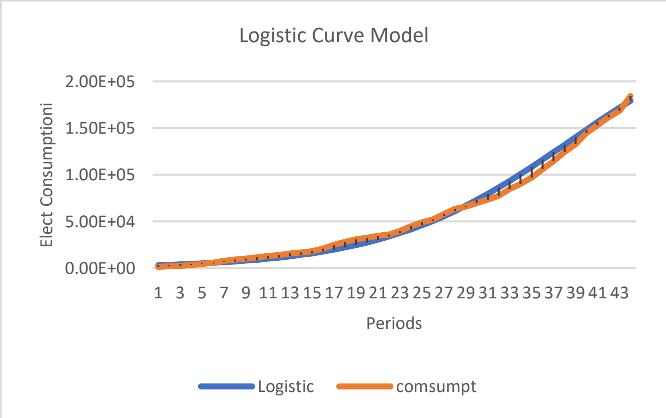
In this study, electricity consumption data was collected and incorporated in a learning model that estimated the dynamic technological progress of different sectors in Iran and Japan alike. The findings demonstrated that the learning trend in each sector in both countries behaved in two distinct manners: (1) convex with a minimum, (2) concave with a maximum. No studied sector behaved in the standard concave with no maximum manner. However there has been one exception to this general categorization, indeed the remaining electricity data set that has been aggregated under the "other sectors" label in Japan, follows a constant decreasing curve that is neither convex nor concave. In the case of Iran, the industry sector presented a concave progress ratio with a maximum, while all the other sectors presented a convex progress ratio curve, with the public services sector presenting a forgetting pattern at the end of the studied periods. This indicates that the industry sector is the better performing sector within Iran in terms of technological capability and driving costs down. Surprisingly, the overall progress ration in Iran follows a concave trend with maximum, which means that the industry sector in Iran is driving by its own the majority of the technological capability and learning potential in the country. In case of Japanese sectors, all sectors seem to have a progress ratio that is following a convex shape with a minimum, except the "other sectors" that is exhibiting a constant decreasing trend. Agriculture and residential sectors present forgetting patterns at both ends, the railways sector presents a forgetting pattern at the right side of the curve, while the mining sector presents forgetting pattern throughout the whole curve. We can see that the minimum level of progress ratio has been reached unanimously by all the sectors within the early 1980s, which shows that the peak of technological learning of the studied Japanese sectors has been reached in the early 1980s, and was on a decline since then.

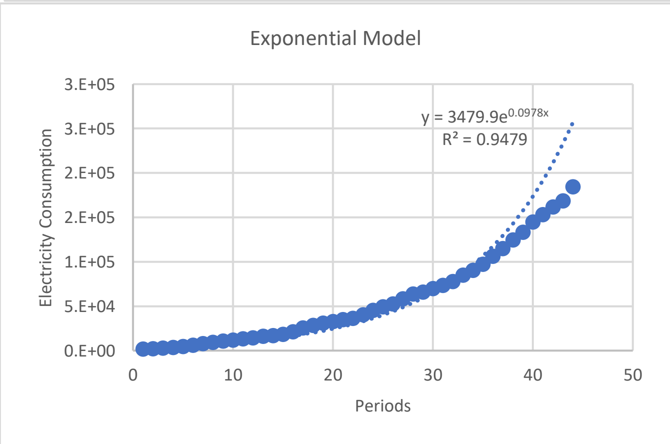
Concerning policy recommendations, since the industry sector is the main driver of technological learning in Iran, the Iranian government could adopt a deregulation strategy for the industry sector, which will attracts foreign technologies and boost learning. Moreover, Iranian government shouldn't solely rely on the country's low labor cost to draw FDI, regulation and adoption of new policies are required to attract a constant stream of FDI to ensure the proper growth of Iranian industry sector. Regarding Japan, in order to ignite once again the economic growth, more focus should be attributed to a cluster of sectors that encompass the best learning potential to the detriment of those lacking in technological capability. But none of the studied sectors in Japan seems to exhibit this kind of potential. Which lead us to the conclusion that further consideration and comprehensive exploration of a wider set of parameters that could be behind this lack of technological progress in the sectors alike. Some probable factors may include bad industry structures, changing attributes of demand, increasing technological barriers, external energy prices fluctuation, great dependency from energy import, degradation of efficiency and increase in electricity distribution losses within the network grid, not trying to diversify the power generating technologies and so on and so forth. Once all of these parameters are factored in, a proper understanding of the electricity demand in Japan will emerge, and can be used in policy frameworks in order to drive electricity costs down. All in all, demand and costing are all subject to variation, and comprise a significant level of uncertainty within them, that the framework presented in this thesis didn't necessarily take into consideration. As a further development of this learning model that measures technological progress, uncertainty can also be incorporate in future models in order to take the highly variable and probabilistic nature of demand into consideration.

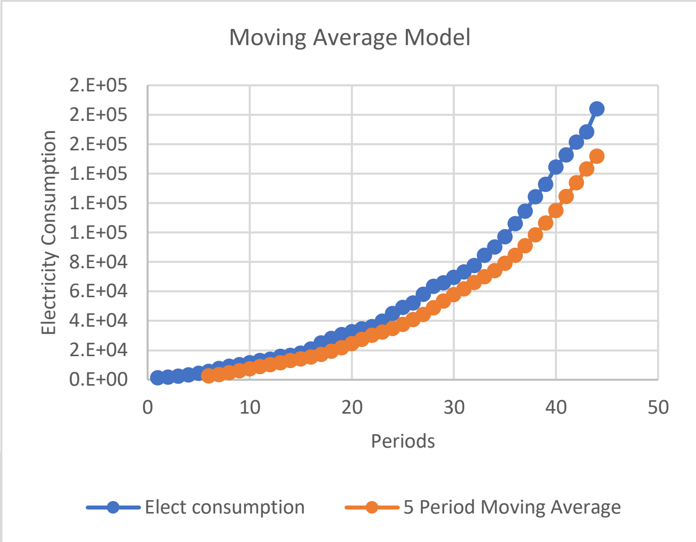
APPENDIX 1: Plots of Forecasting Models for Iran Consumption Data

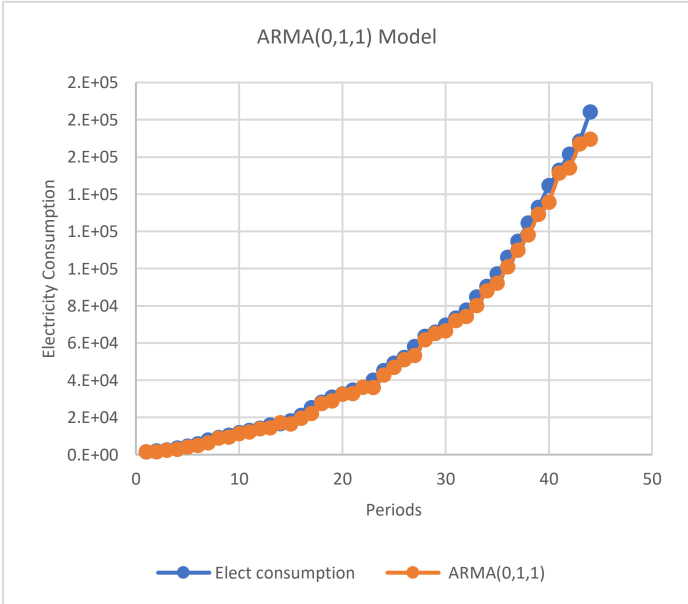


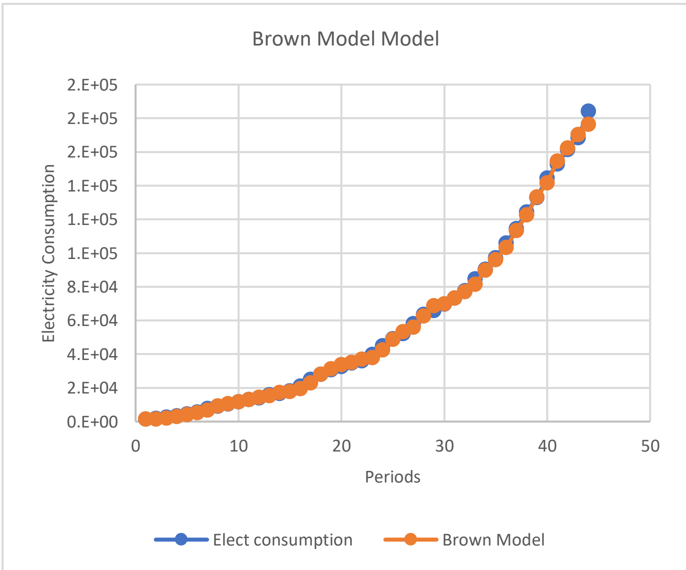




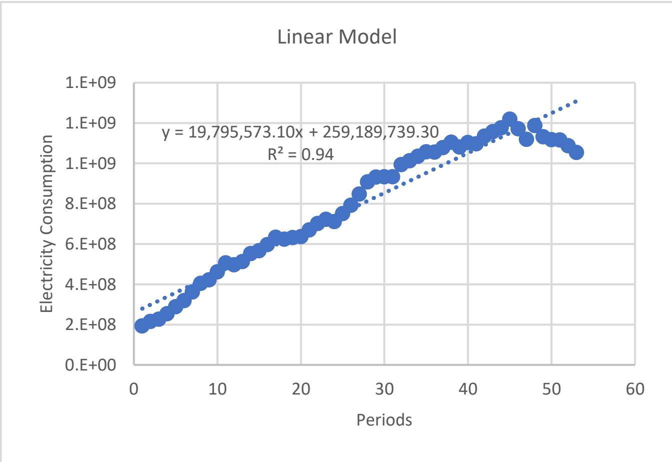


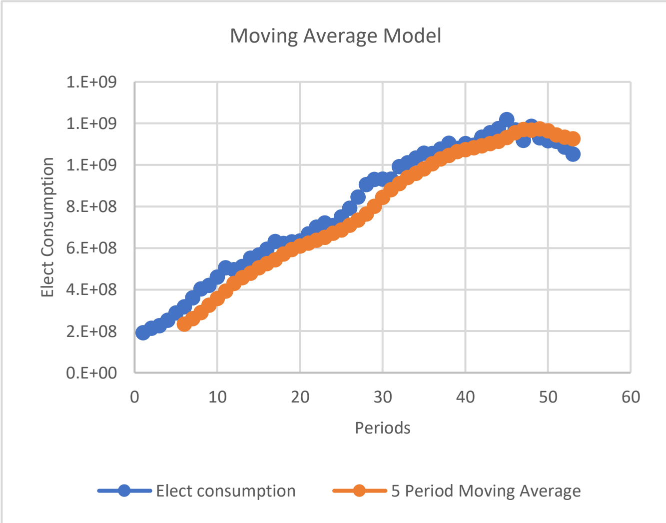


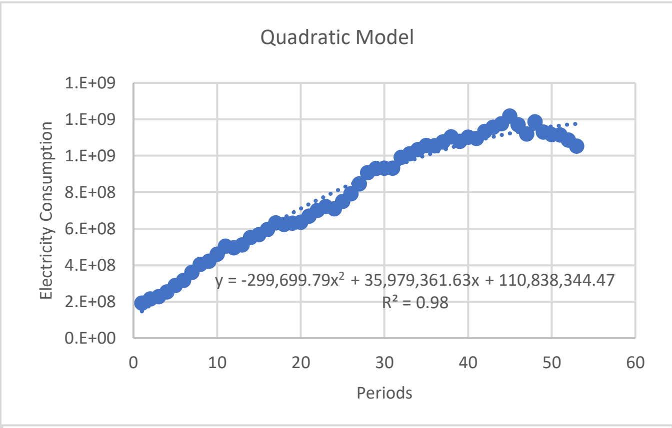


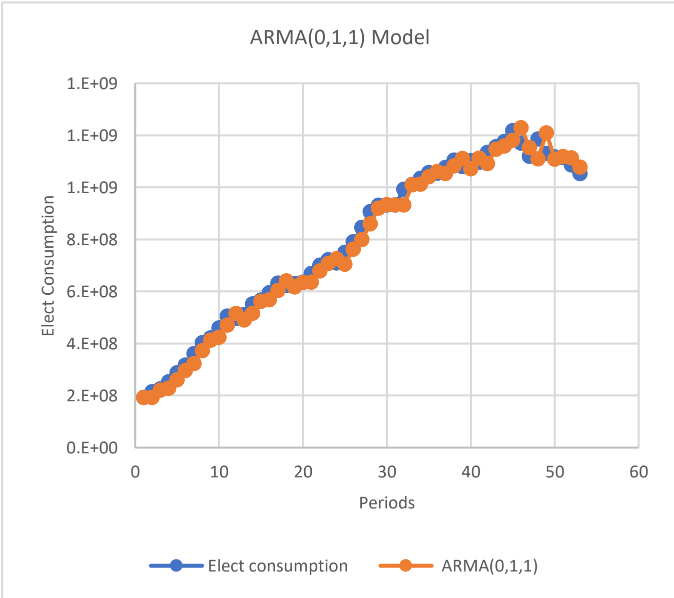


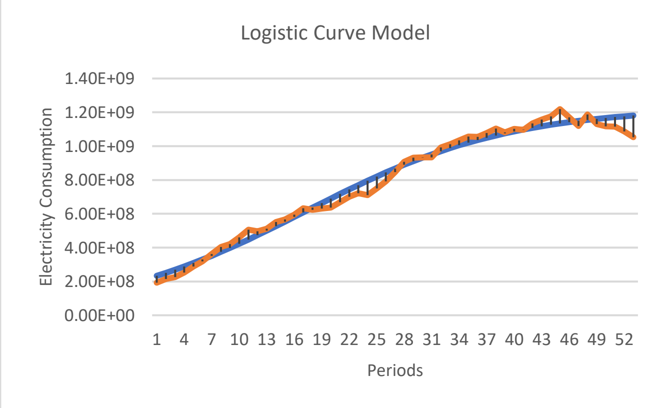
APPENDIX 2: Plots of Forecasting Models for Japan Consumption Data

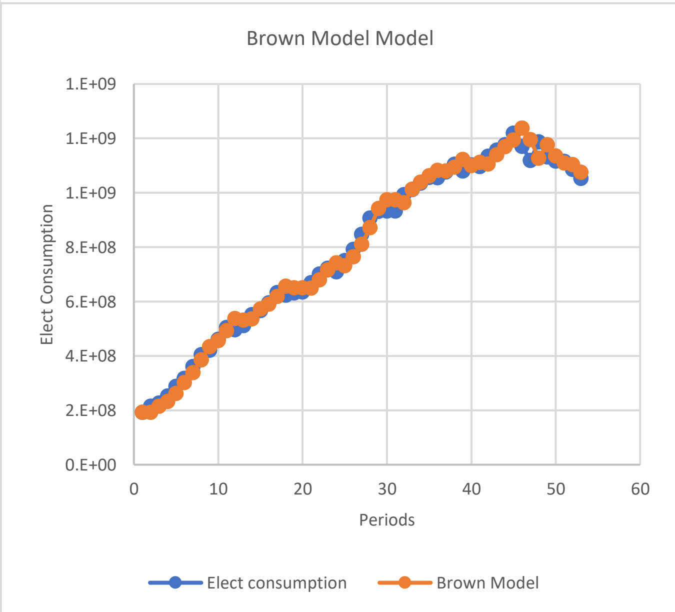


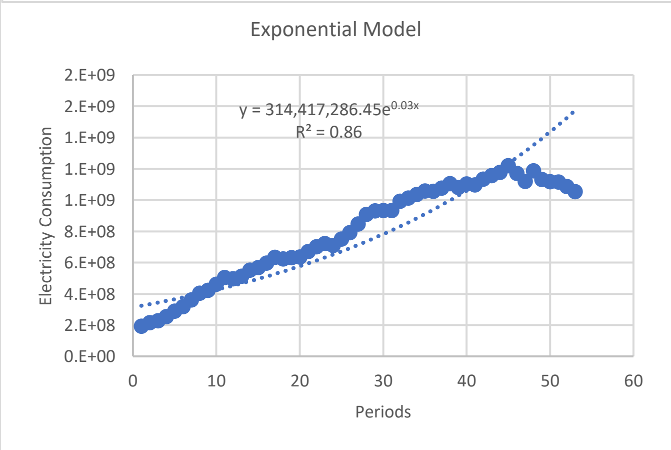




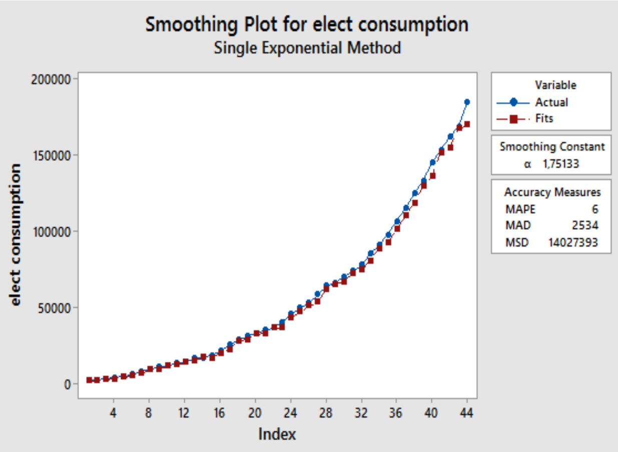


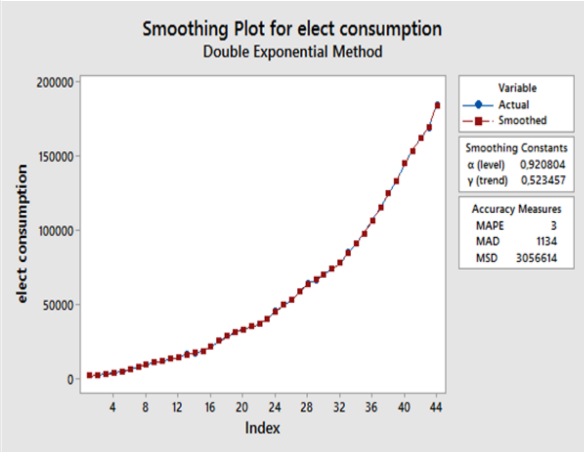


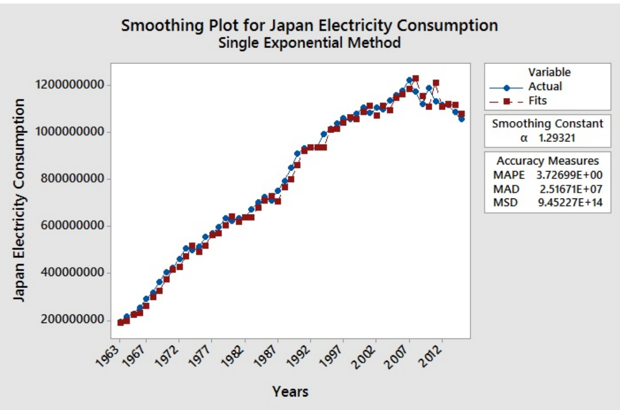


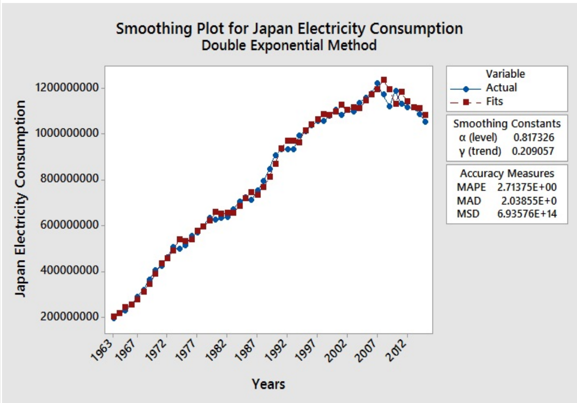


APPENDIX 3: Minitab Plot and Results for ARMA(0,1,1) and Brown Forecasting Models



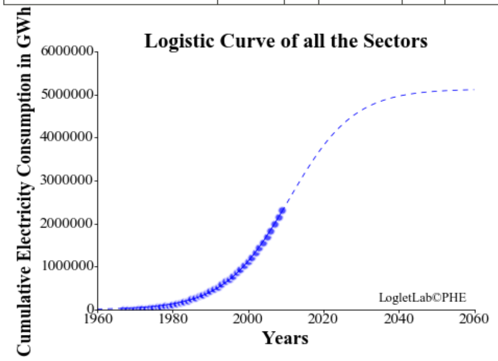






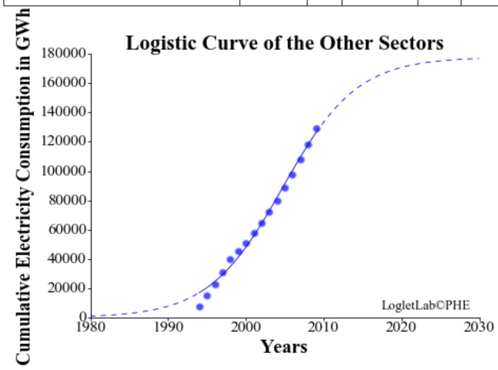
APPENDIX 4: S-Curve Analysis Plots for the Studied Sectors in Iran

Logistic		d	K	a	tm	r
Logistic Curve of all the Sectors	Phase 1 •	0.00	5131248.52	37.68	2010.91	0.12



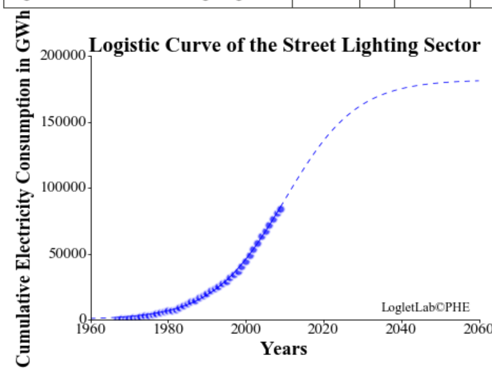
Total time including network latency: 1519 ms.Total computation time: 598.0 ms. Fit time: 231.391 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Other Sectors	Phase 1 •	0.00	177759.10	20.98	2004.76	0.21



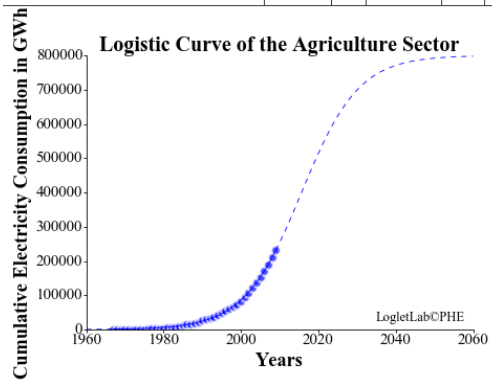
Total time including network latency: 1424 ms.Total computation time: 557.0 ms. Fit time: 202.679 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Street Lighting Sector	Phase 1 •	0.00	181964.12	40.56	2010.10	0.11



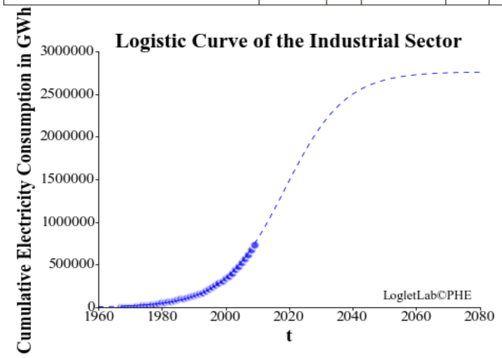
Total time including network latency: 1321 ms.Total computation time: 594.8 ms. Fit time: 225.040 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Agriculture Sector	Phase 1 •	0.00	799928.46	32.51	2015.67	0.14



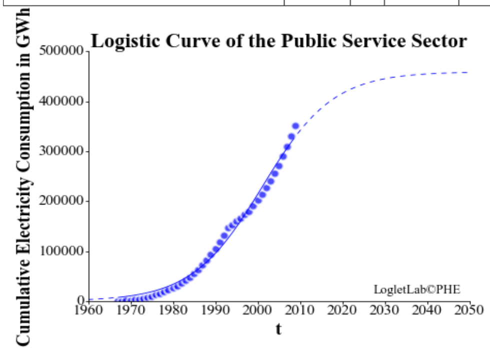
Total time including network latency: 1426 ms.Total computation time: 590.3 ms. Fit time: 227.780 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Industrial Sector	Phase 1 •	0.00	2762540.45	41.72	2018.67	0.11



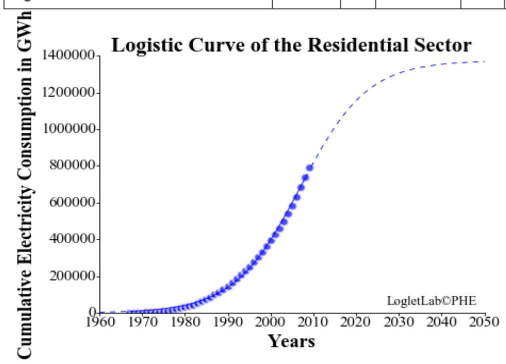
Total time including network latency: 1299 ms.Total computation time: 595.6 ms. Fit time: 228.875 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Public Service Sector	Phase 1 •	0.00	458836.14	36.59	2001.19	0.12



Total time including network latency: 1291 ms.Total computation time: 593.7 ms. Fit time: 219.313 ms.

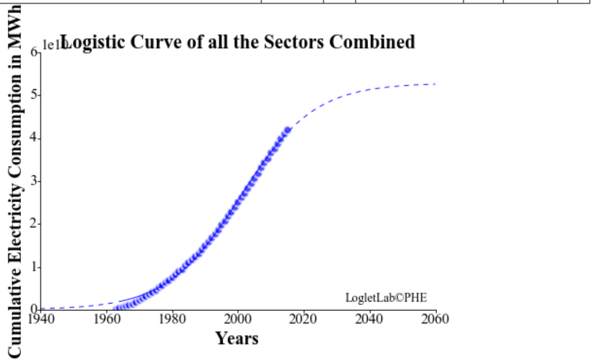
Logistic		d	K	a	tm	r
Logistic Curve of the Residential Sector	Phase 1 •	0.00	1372521.97	34.17	2007.04	0.13



Total time including network latency: 1372 ms.Total computation time: 678.7 ms. Fit time: 218.647 ms.

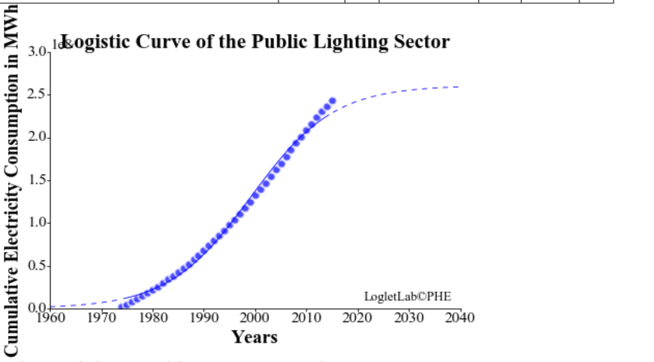
APPENDIX 5: S-Curve Analysis Plots for the Studied Sectors in Japan

Logistic		d	K	a	tm	r
Logistic Curve of all the Sectors Combined	Phase 1 •	0.00	52814921830.67	49.15	2000.83	0.09



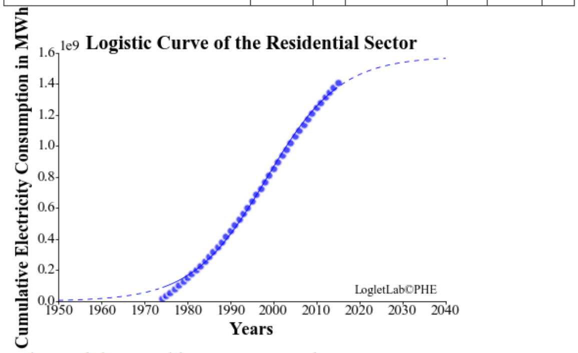
Total time including network latency: 1272 ms.Total computation time: 613.4 ms. Fit time: 229.378 m

Logistic		d	K	a	tm	r
Logistic Curve of the Public Lighting Sector	Phase 1 •	0.00	260654057.64	35.49	1999.18	0.12



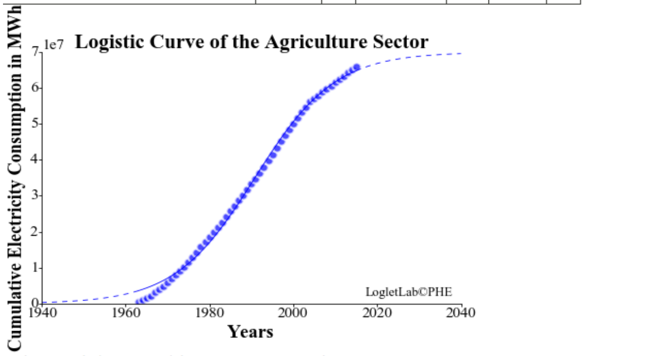
Total time including network latency: 1600 ms.Total computation time: 603.9 ms. Fit time: 230.381 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Residential Sector	Phase 1 •	0.00	1575566765.42	37.61	1998.37	0.12



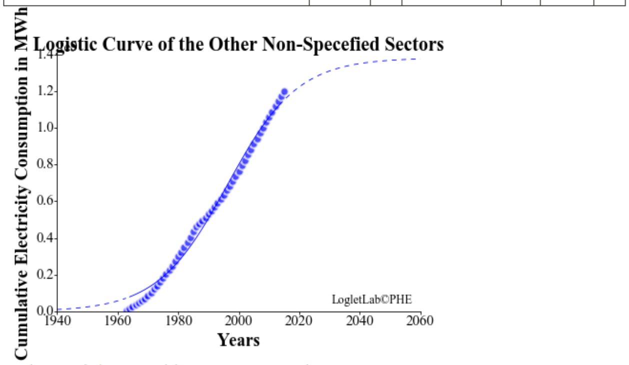
Total time including network latency: 1641 ms.Total computation time: 619.4 ms. Fit time: 234.573 ms.

Logistic		d	K	a	tm	r
.ogistic Curve of the Agriculture Sector	Phase 1 •	0.00	69895482.45	41.97	1990.85	0.10



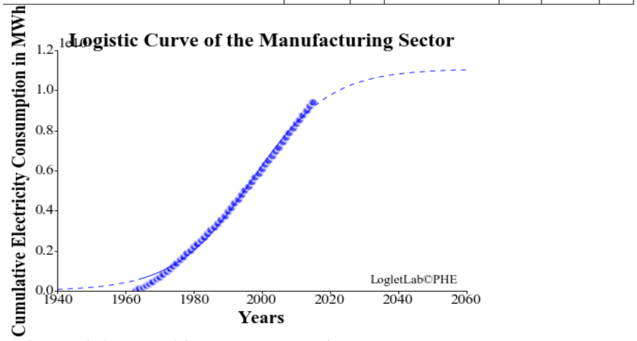
otal time including network latency: 1567 ms.Total computation time: 617.3 ms. Fit time: 239.764 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Other Non-Specefied Sectors	Phase 1 •	0.00	1380921489.27	50.81	1996.32	0.09

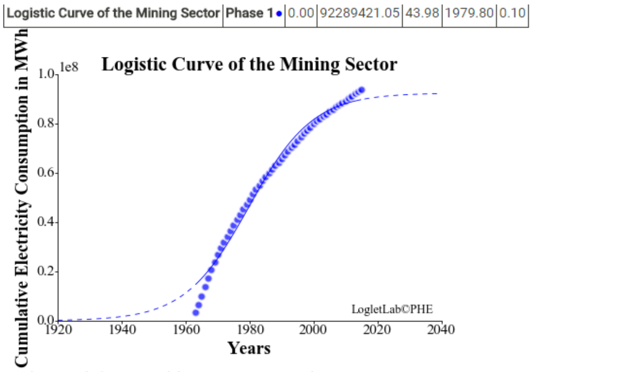


Total time including network latency: 1220 ms.Total computation time: 586.8 ms. Fit time: 213.314 ms.

Logistic		d	K	a	tm	r
Logistic Curve of the Manufacturing Sector	Phase 1 •	0.00	11053699924.75	50.15	1997.18	0.09

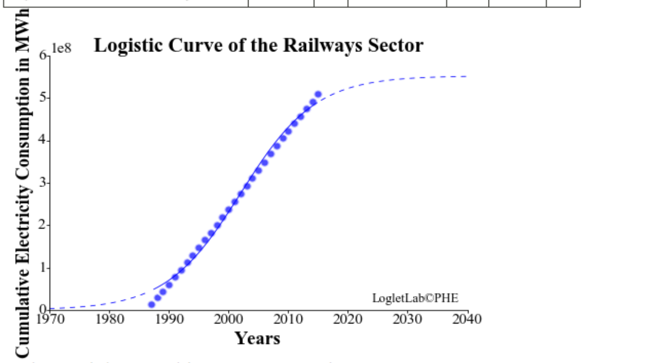


Logistic Curve of the Mining Sector	Phase 1 •	0.00	92289421.05	43.98	1979.80	0.10



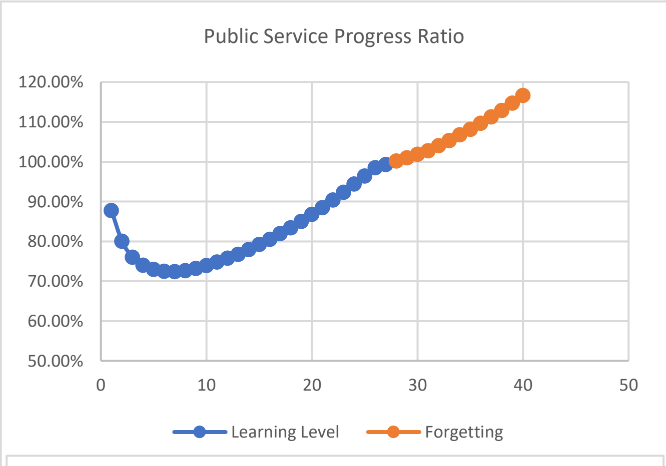
Total time including network latency: 1405 ms.Total computation time: 680.8 ms. Fit time: 315.931 ms.

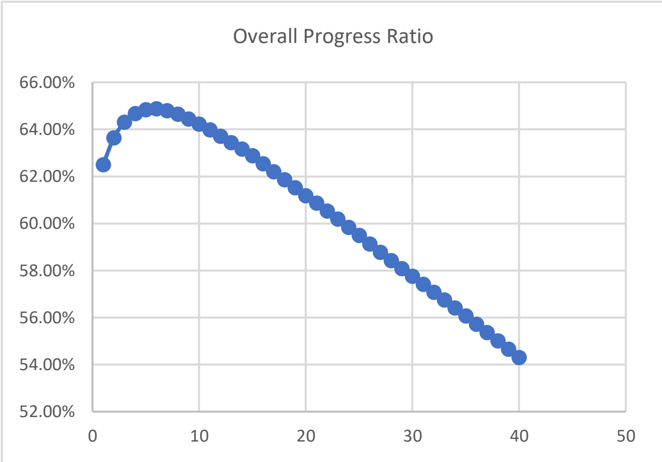
Logistic		d	K	a	tm	r
Logistic Curve of the Railways Sector	Phase 1 •	0.00	551737624.60	27.49	2002.08	0.16

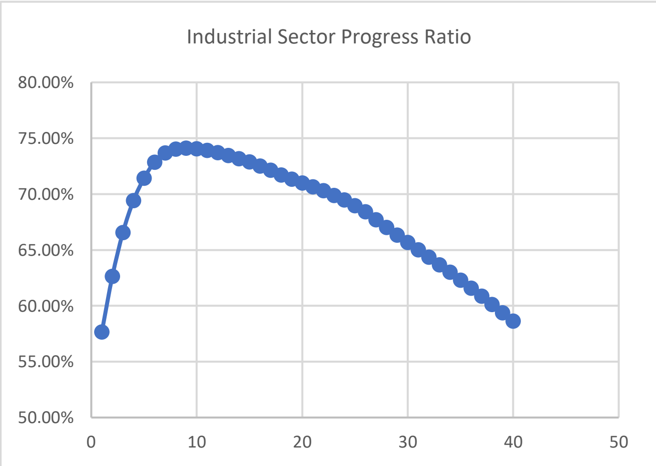


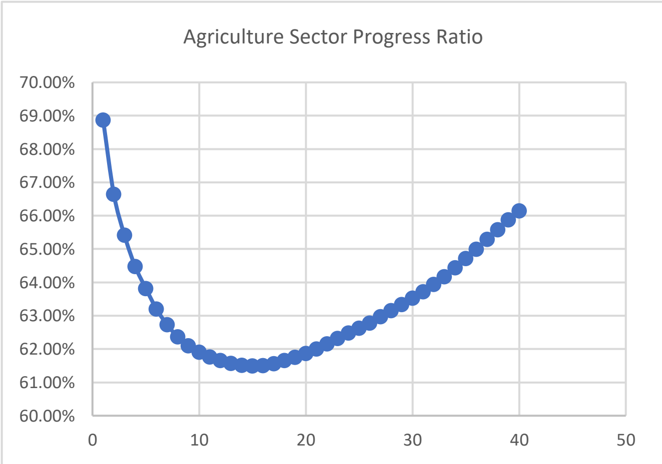
Total time including network latency: 1151 ms.Total computation time: 542.4 ms. Fit time: 190.593 ms.

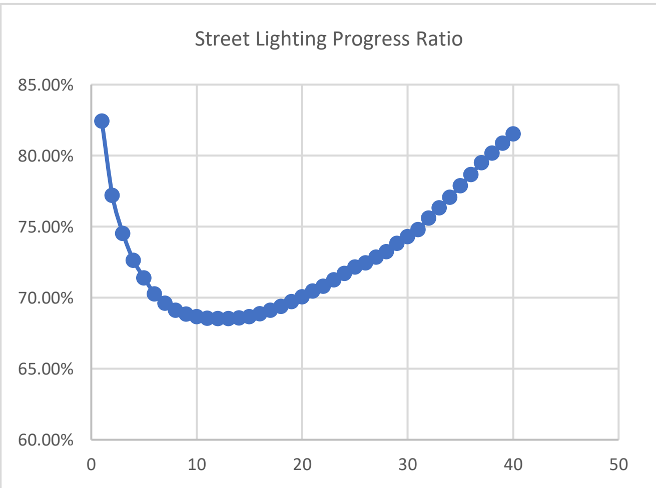
APPENDIX 6: Learning Curve Analysis Plots for all the Sectors in Iran

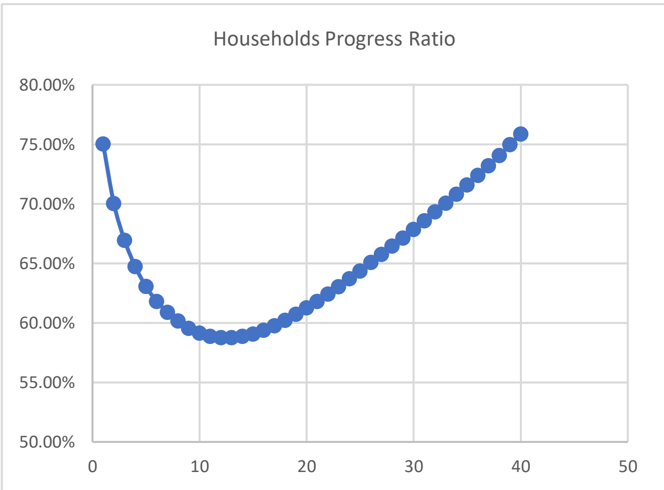




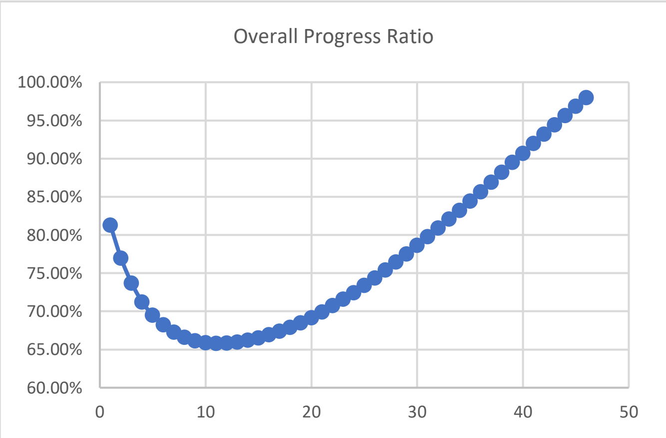


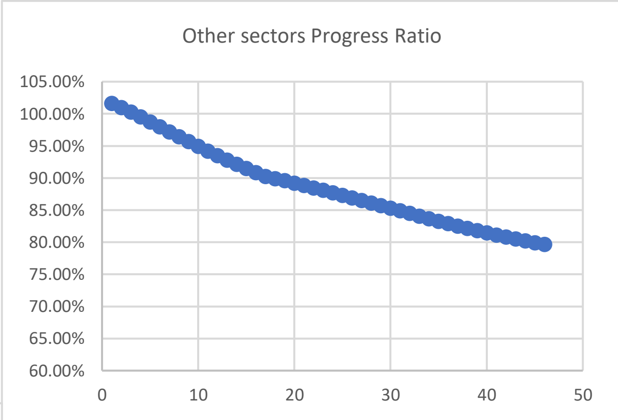


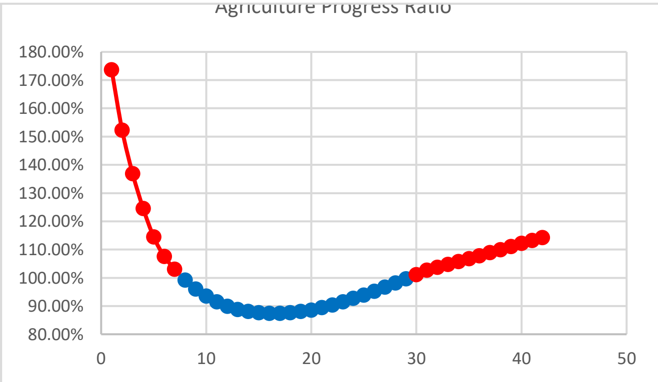


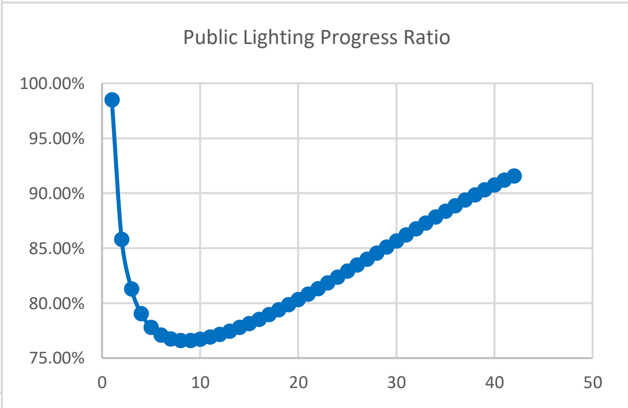


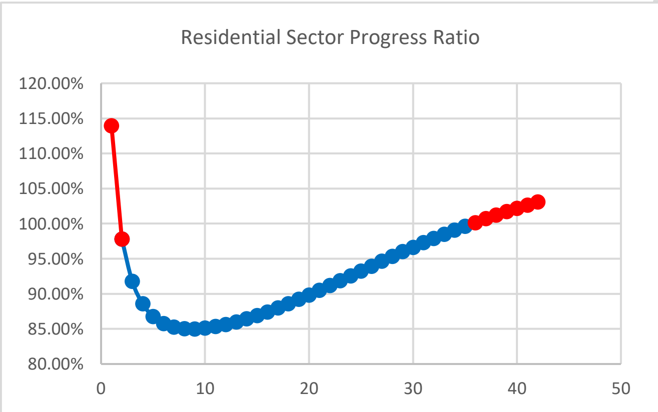
APPENDIX 7: Learning Curve Analysis Plots for all the Sectors in Japan

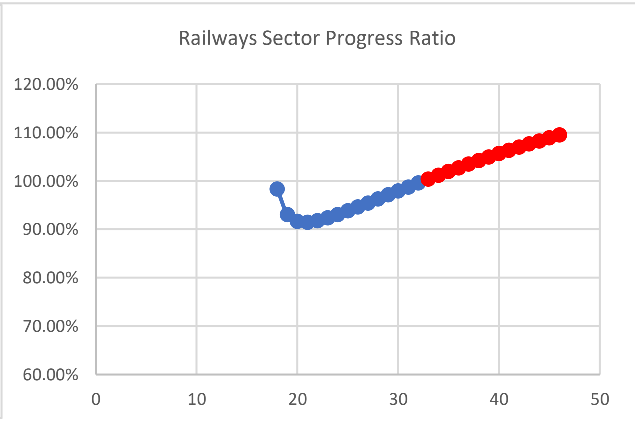


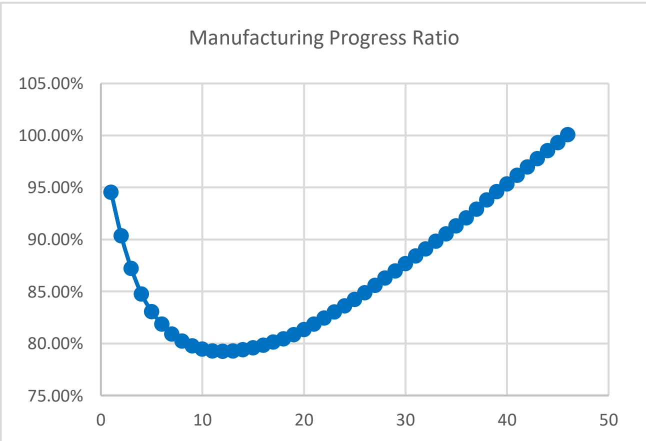


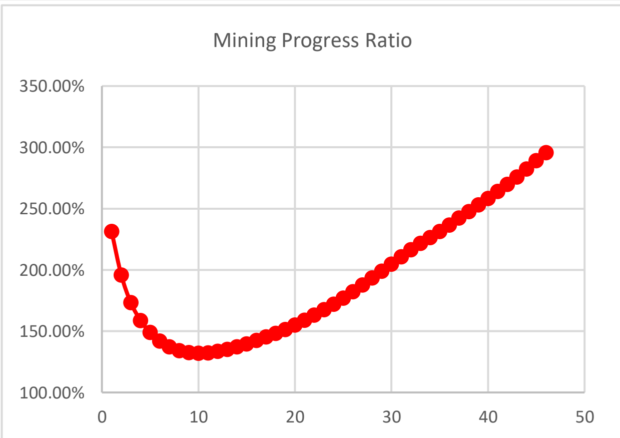












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