Decarbonization cost of Bangladesh's energy sector: Influence of corruption

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Dedicated to my parents

Dr. Kalidas Debnath and **Mrs. Benu Debnath**

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Declaration and Statements

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This work has not been submitted in substance for any other degree or award at this or any other university or place of learning, nor is being submitted concurrently in candidature for any degree or other award.

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Abstract

As a rapidly developing lower-middle income country, Bangladesh has been maintaining a steady growth of +5% in the gross domestic product (GDP) annually since 2004, eventually reaching 7.1% in 2016. The country is targeting to become upper-middle-income and developed by 2021 and 2041 respectively, which translates to an annual GDP growth rate of 7.5–8% during this period. The bulk of this growth is expected to come from the manufacturing sector, the significant shift towards which started at the turn of this century. Energy intensity of manufacturing-based growth is higher, the evidence of which can be seen in the 3.17 times increase in national energy consumption between 2001 and 2014. Also, Bangladesh aims to achieve 100% electrification rate by 2021 against an annual population growth rate of 1.08%. With the increasing per capita income, there is now a growing middle class fuelling the growth in demand for convenient forms of energy. Considering the above drivers, the Bangladesh 2050 Pathways Model suggested 35 times higher energy demand than that of 2010 by 2050. The government and private sector have started a substantial amount of investments in the energy sector to meet the significant future demand. Approximately US$104 billion would be invested in the power sector of Bangladesh for establishing 33 GW installed capacity by 2030, the majority of which would be financed by national and international loans. However, Bangladesh is one of the most corrupted country in the world which may influence the energy planning development. The current policies of Bangladesh power sector paved the future direction towards predominantly coal-based energy mix which would augment the greenhouse gas (GHG) emissions five times (117.5 $MtCO_2e$) in 2030 than that of 2010. By increasing GHG emissions, the country would undermine the worldwide effort of keeping global temperature rise in 21st century below 2°C, as per the Paris agreement and COP21.

The objective of this research was to develop a framework to explore the cost of decarbonizing the Bangladesh's energy sector by 2050. For the study, six emissions scenarios —business as usual (BAU), current policy (CPS), high-carbon (HCS), medium-carbon (MCS), low-carbon (LCS) and zero-carbon scenarios (ZCS)—, and three economic conditions —high, average and low cost—were considered. The combination of emissions and economic scenarios rendered 18 different emissions-economic scenarios for the research. The results showed that Bangladesh would emit 343 $MtCO_2e$ by 2050 without any emissions reduction strategies under HCS. However, Bangladesh can reduce 23% GHG emissions by 2050 under LCS than that of HCS by adopting decarbonization strategies such as energy mix change towards renewable and nuclear. On the optimistic side, the emissions can be reduced 73% by 2050 under ZCS than that of HCS. The study demonstrated that a zero carbon future is not yet feasible for Bangladesh by 2050 because the operational fossil fuel based plants would be operational. Therefore, the GHG emissions are going to rise even if Bangladesh adopts renewables and nuclear dominating energy mix. However, it will be possible to keep the GHG emissions approximately 2 tCO_2e/capita threshold if the country adopts LCS. On the other hand, only MCS and LCS can meet the projected energy demand by 2050. The energy sector can meet the projected demand under ZCS only if the electricity consumption is reduced 26% by 2050. In terms total cost, the MCS was found to be 3.9% expensive than that of LCS by 2050. LCS would have a higher cost than that of MCS up to 2030, due to the high capital cost of renewable technologies. The total cost under LCS would start to be lower than of MCS after 2035 for the fossil fuel cost. Accumulated fuel cost would reach $250 billion in 2050 under HCS, which can be reduced 23% under ZCS. The cost of decarbonization would be 3.6, 3.4 and 3.2 times under average cost of MCS, LCS, and ZCS, than that of HCS. As the energy sector of Bangladesh is under rapid development, the accumulated capital would be comparatively high by 2050. However, fuel cost can be significantly reduced under LCS and ZCS which would also ensure lower emissions. The study suggested that energy mix change, technological maturity, corruption and demand reduction can influence the cost of decarbonization. However, the most significant influencer for the decarbonization of Bangladeshi energy sector would be the corruption. Results showed that if Bangladesh can minimize the effect of corruption on the energy sector, it can reduce the cost of decarbonization 45-77% by 2050 under MCS, LCS, and ZCS.

List of symbols

y	Years.
a	Energy generation technologies.
f	Fuels.
TCS_y	Total cost ($\$_{2010}$).
fd_y	Discount factor in a specific year.
fd_{2010}	Discount factor in 2010.
rd_y	Discount rate.
$IC_{(y,a)}$	Installed capacity (kW).
$F_{(y,a)}$	Fuel used (kWh).
$CC_{(y,a)}$	Capital cost per installed capacity ($\$_{2010}$/kW).
$OC_{(y,a)}$	Operation and maintenance cost per installed capacity ($\$_{2010}$/kW).
$FC_{(y,f)}$	Fuel cost per unit generation ($\$_{2010}$/kWh).

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Chapter 1

Introduction

Continued anthropogenic greenhouse gas (GHG) emissions have led to their unprecedented atmospheric concentrations (Pachauri *et al.*, 2014), contributing to and amplifying global climate change (Raupach *et al.*, 2007). Fossil fuels and land use change (for example, through deforestation and farming) are two primary sources of GHG emissions, of which the emissions from land-use has been nearly constant (Le Quéré *et al.*, 2009), while the emissions from fossil fuel based energy systems increased by 50% between 2000 and 2013 (IEA, 2015). Current energy and transportation systems can result in substantial GHG discharges (IPCC, 2014), with a likely global mean temperature increase between 2.0–4.9°C, with a median of 3.2°C by 2100 (Raftery *et al.*, 2017). Even if current GHG concentrations remain constant, the world will experience a few centuries of rising temperature and ocean level (Ramanathan and Feng, 2008; Clark *et al.*, 2016). Therefore, substantial reductions in global GHG emissions are essential to mitigate climate change.

In addition to the infrastructural elements of national energy systems (i.e. generation, distribution and transmission), access to grid electricity and purchasing power of the population influence energy end-use and GHG emissions. Figure 1.1A illustrates that both access to electricity and per capita CO_2 emissions are more significant in high-income countries, compared to low- and middle-income developing countries. Most developed countries can ensure 100% access to electricity, which only a few developing countries can match. In 2010, annual per capita CO_2 emissions ranged from 0.02–15.14 tCO_2 in low and middle-income countries, compared to 1.6–42.63 tCO_2 in high-income ones (Figure 1.1A). In general, there is a positive association between electricity access and GHG emissions. One notable exception is Costa Rica, an upper middle-income country, which had 98% access to electricity but per capita CO_2 emissions of 1.7 tCO_2, well below the average of 2.09 tCO_2 for all low and middle-income countries in 2010. This is due to 93.3% of Costa Rica's energy being from renewable resources, of which hydroelectric sources accounted for 75.8% (WB, 2017a).

As a result, future energy planning objectives of developed and developing countries are distinctly different. In developed countries, the focus today is on reducing emissions while enhancing energy security, primarily characterised by a shift from fossil fuels towards more renewable resources. However, developing countries are concerned with increasing access to electricity, which is considered a prerequisite for development and economic empowerment, as reflected by the inclusion of energy as a goal in the Sustainable Development Goals (IEA, 2017a). The current CO_2 emissions per capita of developing countries are low, often much below the global average (Figure 1.1B,C). Hence, emission reduction is not always on the agenda for developing countries, even at a cursory level, except for a few large countries such as China and India (CAT, 2014). The total CO_2 emissions in middle income countries has been higher than that of high income ones since 2007 (Figure 1.1D). As a result, despite the reduction in total emissions from high income countries, the global CO_2 emissions has been elevating continuously.

Bangladesh —the world's eighth most populous country in 2015—is now categorized as a least developed country (UN, 2017a) with lower middle income (WB, 2015b). With approximately +6% GDP growth-rate, Bangladesh is progressing towards being a developing economy from a least developed one by 2021 (MoF, 2011). Bangladesh demonstrated higher GDP growth than projected in 2016. GDP growth of Bangladesh reached 7.1% (WB, 2017a), exceeding the 6.9% estimation by the International Monetary Fund (IMF) (IMF, 2016). Bangladesh would have to maintain an annual GDP growth of 7.5%-8% against all exogenous and endogenous obstacles to reach upper-middle-income country status by 2021 (ADB, 2016). With 162 million population and approx. 1200 people living per square kilometre in 2016, Bangladesh is projected to have a population of 201 million by 2050 (UN, 2017b). Only 62% of the people have access to grid electricity in 2014 (WB, 2017a), and

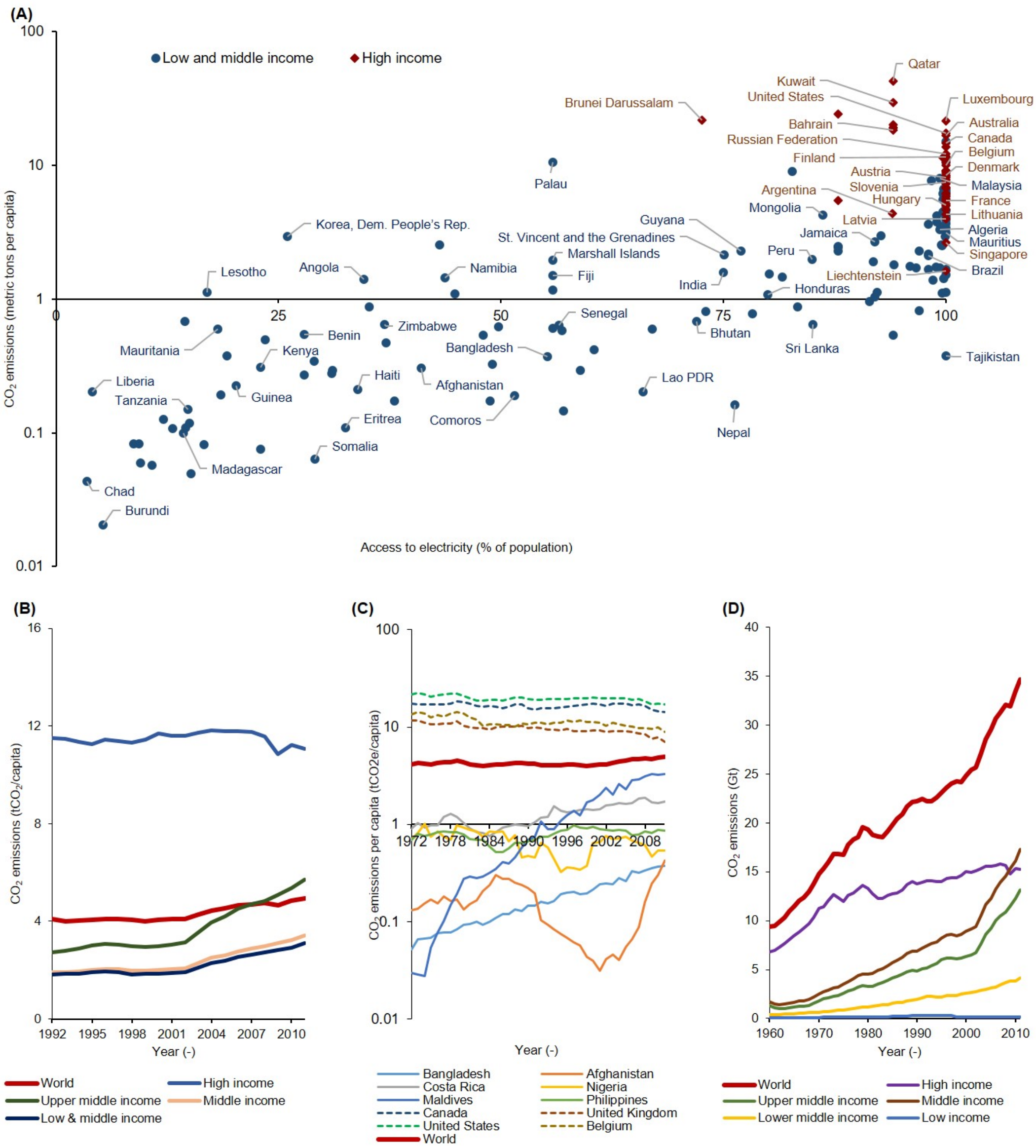

Figure 1.1: CO_2 emissions vs. access to electricity in high and low-income countries in 2010 (for the income classification World Bank list of economies was used); data source (WB, 2017a). Access to electricity in low and middle-income countries ranges from 3.5–100% of the population. In contrast, the figure is 72.6–100% in high-income countries.

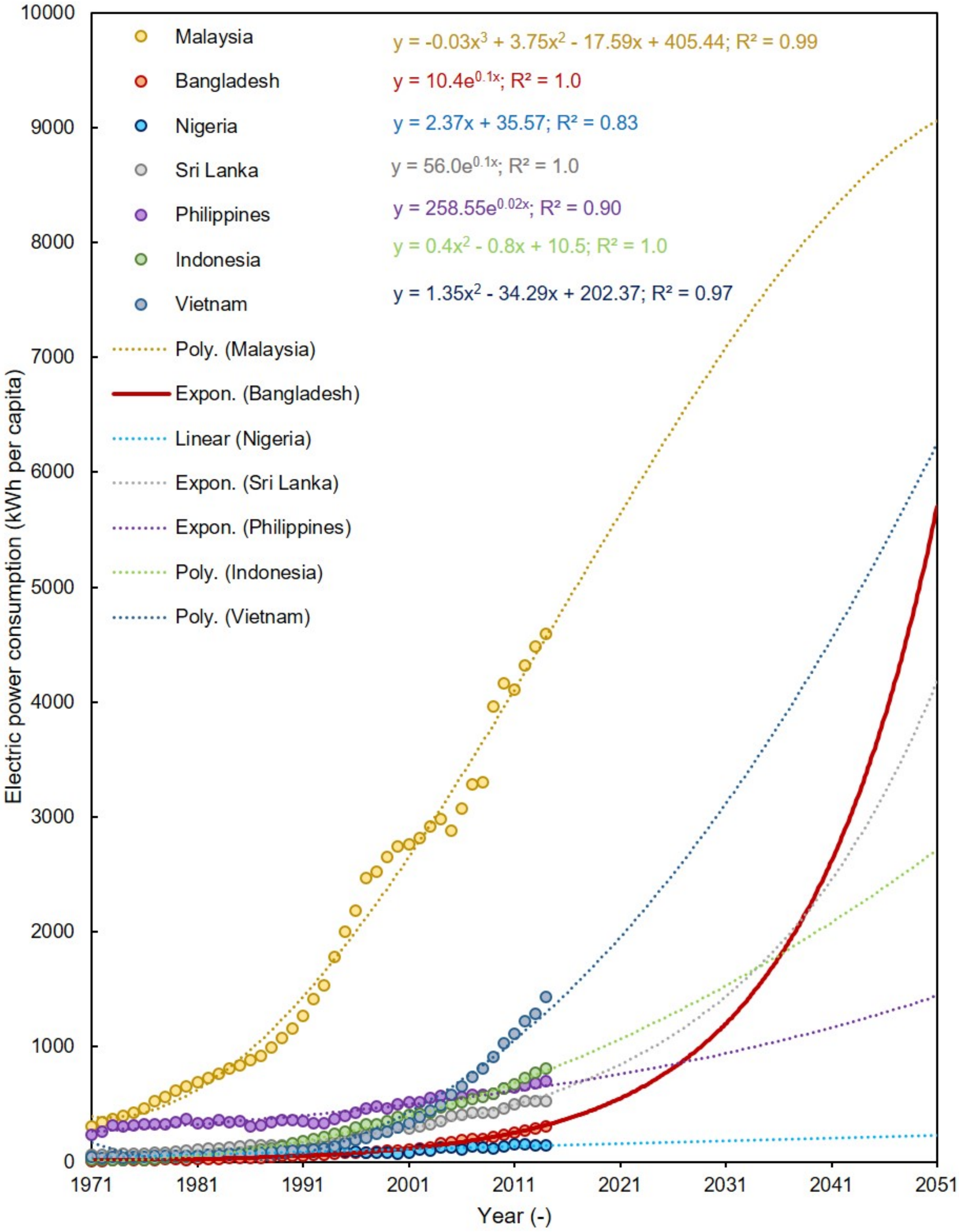

Figure 1.2: Electricity consumption per capita in different countries (1971-2014) and forecasting the trend up to 2051; data source (WB, 2017a)

the government is working on 100% grid connection by 2021 (EB, 2016). Historical data showed that electricity demand per capita has been increasing exponentially in Bangladesh and is projected to increase by 22 times in 2050 compared to 2014 (Figure 1.2). As shown in Figure 1.2, the electricity consumption in Bangladesh was 239.8 kWh per capita in 2010 that was approximately closer to the consumption of Malaysia in 1971. However, the projection showed that, by 2050, Bangladesh would have approximately similar electricity consumption as Malaysia in 2010. As a result, roughly estimation suggests that Bangladesh is heading towards a high energy consuming country and would cross the demand in Nigeria, Sri Lanka, Philippines and Indonesia by 2050 (Figure 1.2). Moreover, the electricity sector is investment intensive and has higher inertia, which means the capacity they have now will determine what they will have in the future, which makes it imperative to study the sector's evolution and plan especially in a developing context such as Bangladesh. Also, there has been limited investigation on the cost of deacrbonization and it's drivers for Bangladesh.

Greenhouse gas (GHG) emissions and CO_2 emissions per capita in developing contexts such as Nigeria, Bangladesh, Sri Lanka, Philippines and Indonesia are lower than the world average (WB, 2017a). However, the projected emissions per capita in developing contexts are going to rise quickly. By 2050, countries such as Bangladesh, whose CO_2 emissions per capita is as low as 0.46 tonnes in 2014 (WB, 2017a), are going to cross 2t/capita (Figure 1.3). In the view of the UN projected population (considering Medium Variant) (UN, 2017b), the total CO_2 emissions can reach up to 201 and 402 Million tonnes (Mt) by 2030 and 2050 respectively. That rough estimate is going to contradict the commitments[1] Bangladesh government agreed on reducing GHG emissions in Paris summit 2015. Decarbonization potential of the energy sector depends on emerging sources and fuel mix. As demand will be one of the highest in the world by 2050, a 2°C scenario would require that developing countries such as Bangladesh are already on a decarbonizing path.

GDP-electricity elasticity showed a positive linear relation (R^2=0.99) in Bangladesh

[1] Without international support Bangladesh will reduce its GHG emissions in the power, transport, and industry sectors by 12 $MtCO_2e$ by 2030 from BAU projection of 234 $MtCO_2e$. With international assistance, the reduction would be 36 $MtCO_2e$, which would result in a total GHG emissions of 198 $MtCO_2e$ by 2030(GoB, 2015b)

(Chapter 2), which means with elevated GDP per capita energy demand would augment rapidly. The government and private sector are investing significantly in the energy sector to satisfy this exponential demand growth (JICA and TEPCO, 2011). However, the government initiatives are more high emissions intensive, dominated by coal-based generation. Bangladesh is one of the highly vulnerable countries to sea level rise due to climate change. By adopting a GHG emission-intensive future energy generation master plan, Bangladesh would contribute to its inundation, as well as undermine the worldwide effort of keeping global temperature rise in 21st century below 2°C, as per Paris agreement and COP21.

In 2015, the majority of Bangladeshi power plants (68%) were natural gas fueled. The rest of the fuel mix was liquid hydrocarbon – coal- renewable (hydro)-imported electricity (24%-2%-2%-4%) (BPDB, 2017a). However, the energy planning master plan PSMP2010 has been stirring the energy sector towards an imported coal dominated energy generation mix where 50% would be coal-based (JICA and TEPCO, 2011). The government and the private sector have been establishing and will continue to build a significant number of new power plants within the next 12 years. The under construction and proposed power plants have been built on a significant amount of loan from international financial organizations such as World Bank (WB), IMF, ADB, as well as domestic ones. These loans would add enormous liabilities to the future economy of Bangladesh. Moreover, the Government's approach towards GHG intensive energy generation policies is already posing environmental threats in Bangladesh. As a result, conflicts between environmental activists and locals, and the government such as Rampal (EJA, 2017).

Different socioeconomic parameters such as political stability, corruption has direct or indirect implication on the energy development. Bangladesh is one of the most corrupted countries in the world, with many political instabilities and natural disasters. According to Transparency International (TI), Bangladesh was ranked 145th out of the 176 analyzed nations in corruption perceptions index 2016, compared to 134th out of 178 in 2010 (TI, 2017). Political stability in Bangladesh have been deteriorating over time. The country scored -1.24 on the scale of +2.5 to -2.5 in 2016, which was -0.90 in 2014 (WB, 2017b). The capital cost of establishing power plants in Bangladesh might be influenced by corruption in energy sector (Chapter

3). Therefore, the implication of corruption on the cost development of energy sector of Bangladesh was investigated in this study.

The present master plans, economic and environmental conditions trigger some questions on the policy development and their cost assessments, such as:

(i) Is high emissive fossil fuel-based generation the most viable solution for Bangladesh?

(ii) What is the expense of this high emission fossil fuel intensive based generation future?

(iii) What is the potential of a zero-carbon energy generation future for Bangladesh?

(iv) What would be the cost of decarbonizing future energy development in Bangladesh?

One of the first attempts at studying the cost of CO_2 emissions was undertaken by Dean et al. (1992) by analyzing six global energy planning models (EPMs) (Dean and Hoeller, 1992). The study was conducted for a long time horizon of 110 years (1990-2100) except for GREEN and IEA, and suggested different taxes and abetment costs across regions under different emissions reduction scenarios. However, the geographical extent of the study was limited to the USA, other organization for Economic Co-operation and Development (OECD), the former Soviet Union, China and the rest of the world. The decomposition of parameters for different regions for various models made the study more difficult and reduced accuracy of the outcomes. In the case of the energy sector of Bangladesh, few studies on decarbonization cost have been found. Mondal et al. (2010) analyzed the future energy generation technologies and their benefit on CO_2 emissions reduction in Bangladesh from 2005 to 2035 (Mondal *et al.*, 2010). The study utilized MARKAL model to analyze four scenarios. However, in a country where different socioeconomic factors such as population, GDP, corruption, political instability, and violence affect the energy demand and supply, adoption of a linear programming based optimization model may not offer reliable forecasting for Bangladesh.

In this study, a bottom-up cost model was developed with energy and emissions model BD2050 to explore different scenarios such as business-as-usual, current policy, high-, medium-, low- and zero-carbon scenarios, to investigate the cost of decarbonizing for Bangladeshi energy sector by 2050.

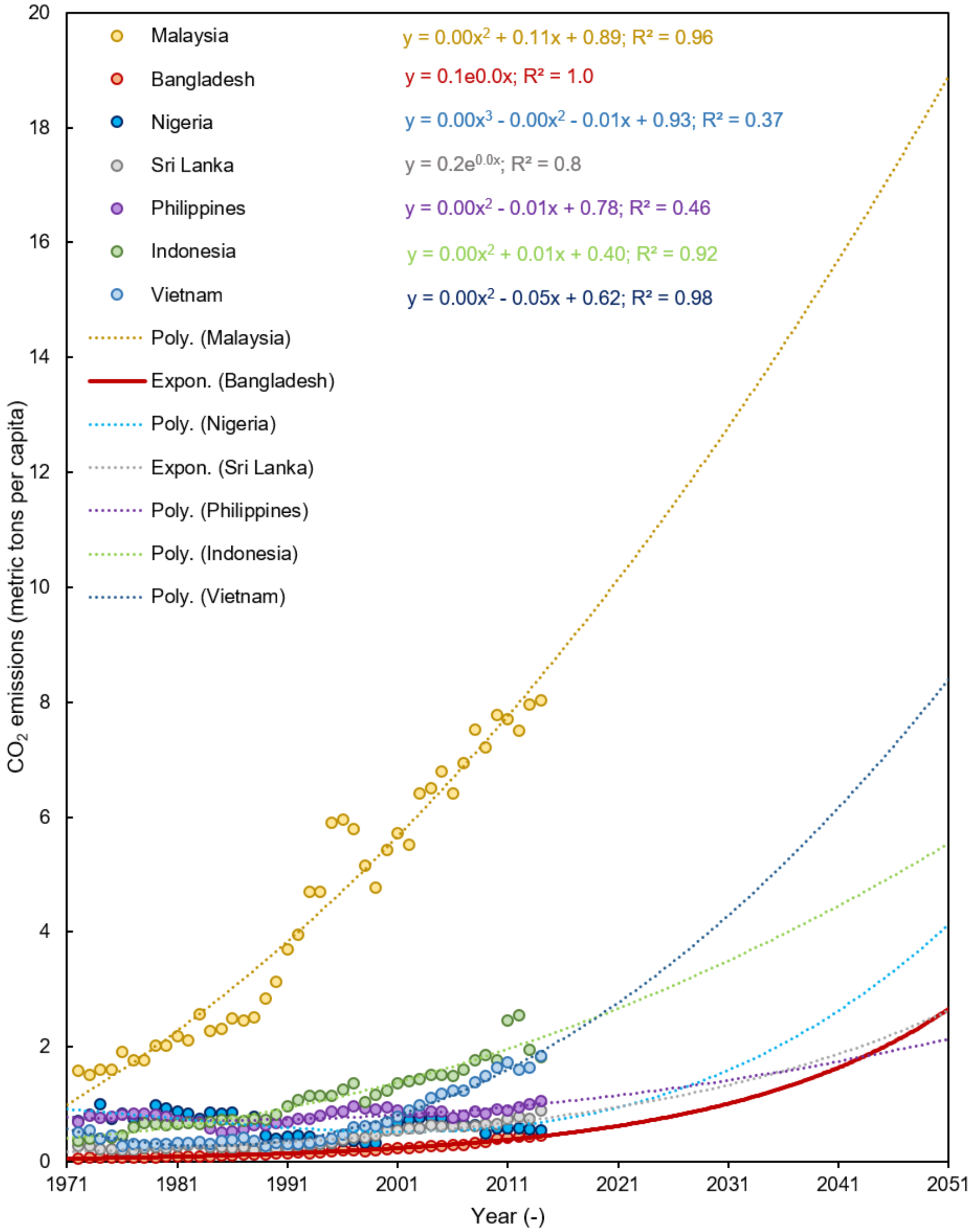

Figure 1.3: Electricity consumption per capita in different countries (1971-2014) and forecasting the trend up to 2051; data source WB (2017a)

1.1 Aim and objectives

The aim of this study was to investigate the energy generation sector development of Bangladesh from 2010 to 2050 under different emissions scenarios to estimate the cost of decarbonization.The objectives of the research were to:

(i) Review the state of the art of long horizon modeling and their forecasting methods;

(ii) Investigate the historical energy supply and demand scenarios, and cost development in energy sector of Bangladesh;

(iii) Develop long horizon emissions scenarios of Bangladesh;

(iv) Implement the interactions among the future plausible scenarios to find out the energy pathways from 2010 to 2050;

(v) Evaluate model pathways to find out potential low carbon development pathways; and

(vi) Evaluate cost of decarbonizing future energy sector development.

1.2 Research questions

The research questions addressed in this thesis are:

1. **What are the present state and future directions of the energy sector of Bangladesh?**

   The first research question addressed the contextual aspect of the energy sector of Bangladesh. It can be divided into two sub-questions as follows:

   (i) How did the energy demand and supply sector develop historically?

   (ii) What is the future direction of the energy sector development?

2. **What are the costs of developing different types of power plants in Bangladesh?**

   The second research question examined the cost development of the energy sector of Bangladesh. It can be divided into the two sub-questions, such as

(i) What is the capital cost of different energy generation technologies in Bangladesh?

(ii) How did the cost of power plants evolve in Bangladesh?

The cost evolution can render the opportunity to analyze the cost of private and public power plants, and compare them against the global average. This comparison can lead to the following sub-questions:

(i) What can we learn about the cost of energy sector in Bangladesh compared to the rest of the world?

(ii) If the cost is higher or lower, what are the reasons behind the difference?

3. **How can the cost of decarbonization be modeled for Bangladesh up to 2050?**

   The third question addressed the modeling aspect (methodology, assumptions) that are needed to be considered. The cost assumptions are based on the outcomes from the analysis of Research Question 2.

4. **What would be the total cost of decarbonizing the energy sector of Bangladesh?**

   The final research question centred on the outcomes from the model created in Research Question 3. The discussion on cost of decarbonization can be divided into three sub-questions.

   (i) What would be the impact of change in energy mix on the cost of decabonization, emissions and demand?

   (ii) What would be the effect of technological maturity on the cost of decabonization?

   (iii) What would be the influence of corruption on the cost of decabonization?

1.3 Structure of the thesis

The thesis is divided into eight chapters. Chapter 1 presents the research problem, aims and objectives, research questions and structure of the study. The synopsis of the energy supply and demand of Bangladesh is discussed in Chapter 2. Then the current energy supply structure and policies of Bangladesh is presented in Chapter

2. The cost analysis of the Bangladeshi supply is reviewed in Chapter 3. In Chapter 4, the existing and highly utilized energy planning models are reviewed to investigate their applicability in developing contexts such as Bangladesh. Chapter 5 presents the review on the forecasting methods utilized in energy planning models. The methodology, model structure and assumptions are explained in Chapter 6. Also, the results are discussed in Chapter **??**. Chapter 7 presents the conclusion of the study, main findings and recommendations for future works.

Chapter 2

Energy sector in Bangladesh

There were a number of previous studies that attempt at reviewing the energy scenarios in Bangladesh. Baten et al. (2009), reviewed the renewable energy scenario in Bangladesh including distribution, research and infrastructural development (Baten *et al.*, 2009). The objective of the study did not analyse the total electricity generation sector in depth. Islam et al. (2014), studied the contemporary energy mix, energy crisis and prospect of overcoming the crisis with the scenario of utilizing alternative renewable energy sources in Bangladesh (Islam *et al.*, 2014). Due to the focus on the renewable energy potential investigation, the study analysed the present energy scenario abruptly. There are some other studies which focus on the renewable resource potential and GHG emissions such as Ahiduzzaman and Islam (2011); Islam *et al.* (2008). The focus of the previous studies was not necessarily on the electricity generation and demand profile analysis, which encouraged the current study on the rapidly expanding electricity sector in Bangladesh. In this review, the focus was on the detailed analysis of the electricity generation and demand sector of Bangladesh. The review not only analysed the power plants and demand profiles, but it also examined the transmission and distribution infrastructure.

2.1 Historical context of energy sector of Bangladesh

The power sector in Bangladesh underwent several significant restructurings since its humble beginning at the turn of the 20th century. Originally, electricity was provided only to the wealthy residents in the capital with small power plants (Omprasad, 2016) but gradually shifted its focus towards serving essential businesses and industries by 1947 (Ebinger, 2011). When the Indian subcontinent was divided into India and Pakistan in 1947, East Pakistan (now Bangladesh) had an installed capacity of 21 MW, predominantly serving private companies and industry sector (Ebinger, 2011). Bangladesh Power Development Board (BPDB) was created on May 1, 1972 (BPDB, 2017a) after the liberation from Pakistan on December 16, 1971, with a total installed capacity of 200 MW (BPDB, 2017a). With limited generation, BPDB was supplying to urban centres and peripheries only. For providing electricity service to rural areas, the Rural Electrification Board (REB) was constructed in 1977 (BREB, 2016). The electricity generation was divided into East and West zones, which was connected with a 230KV transmission line in 1982 (Ebinger, 2011). The deregulation of the power sector was initiated in 1994 with National Energy Policy (Ebinger, 2011). A publicly owned company Rural Power Company Limited (RPCL) began its journey as the first independent power producer (IPP) in 1994 (Mourshed, 2013). Entirely private sector owned IPPs started in 1997, under build-own-operate (BOO) model of public-private partnership (PPP), which began to operate under rental agreements lasting between 3 and 15 years after further deregulation (MoF, 2009). First rental power plant (RPP) began its operation in 2008 and augmented rapidly in number, contributing to the total generation of Bangladesh.

At present power division of Ministry of Power, Energy and Mineral resources (MPEMR) act as the apex governmental organization. However, Bangladesh Energy Regulatory Commission (BERC) regulates the power sector. There are five electricity generation bodies involved in Bangladesh such as- Bangladesh Power Development Board (BPDB), Ashuganj Power Station Company Limited (APSCL), Electricity Generation Company of Bangladesh (EGCB), North West Power Generation Company Limited (NWPGCL) and Independent Power Producers (IPPs). The transmission of the power sector is operated and maintained by Power Grid Company of Bangladesh Limited (PGCB). BPDB is the sole purchaser of the generated electricity, which is then transmitted via the Power Grid Company of Bangladesh Limited (PGCB) and distributed by State-owned area-based distribution companies. There are five distribution companies currently operational in Bangladesh. They are- Bangladesh Power Development Board (BPDB), Dhaka Power Distribution Company (DPDC), Dhaka Electric Supply Company Limited (DESCO), West Zone Power Distribution Company (WZPDC) and Rural Electrification Board

(REB) through Rural Co-operatives. At present, bulk generation is centralized and mostly fossil fuel based. However, there are decentralized renewable power generation projects such as mini-grid, solar home systems (SHS) have been operational and under development for off-grid rural and remote areas. The government have targeted to generate 10% of the total electricity from renewable resources by 2021 (IDCOL, 2017). Although, IDCOL is aiming towards total SHS installed capacity of 200 MW by 2021, and installing 50 solar mini-grid by 2018 (IDCOL, 2017), the cumulative capacity of the off-grid generation will contribute very little to the electricity supply.

2.2 Electricity and economy

2.2.1 Population and economic growth

In 2015, Bangladesh was world's eighth most populous country with the population of approximately 161 million at the annually 1.2% growth rate (WB, 2017a) (Figure 2.1). With a total area of 0.148 million square kilometers (km^2), population density was $1236.8/km^2$ in 2015, making Bangladesh one of the world's highest densely populated countries. Therefore, Bangladesh outnumbered greater populous countries such as India and China, where population density was 441 and $146.1/km^2$ in 2015 (WB, 2017a).

The economy of Bangladesh has developed immensely since the liberation war of 1971. Before 1971, GDP growth was uneven and unpredictable (Figure2.2). After the war, the uneven growth continued. However, from the early 1990's the GDP growth started to stabilize, and from there it increased to 6.06% in 2010. In the past 50 years, the highest GDP growth was recorded 10.95% in 1964 (WB, 2017a). In 2013, Bangladesh's GDP was 7.81 times than that of 1960. According to World Bank, Bangladesh is categorized as lower middle income, with $972.88 (constant 2010 US$) GDP per capita in 2015 (WB, 2017a). The geographical position made Bangladesh vulnerable to natural disasters. Since 1971, there were major natural disasters such as floods, cyclones and hurricanes affected the economy of the country in 1984, 1985, 1987, 1988, 1991, 1994, 1995, 1998, 2007 and 2013 negatively (Figure 2.2). Moreover, political instabilities such as 1971 libation war, a military

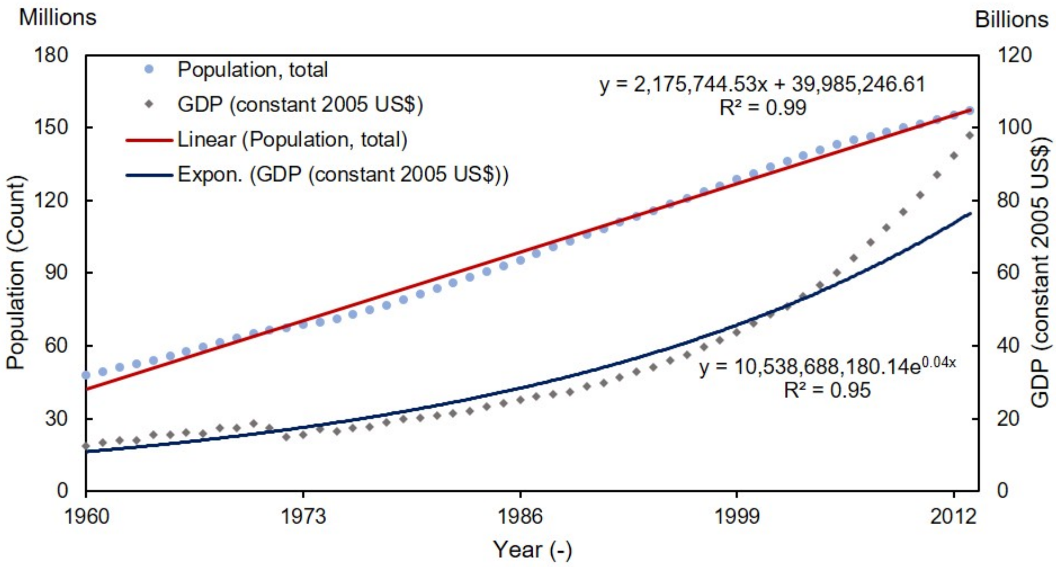

Figure 2.1: Population and GDP in Bangladesh form1960-2013 ; data source (WB, 2017a).The population has been rising at a positively linear trend. However, GDP is demonstrating an exponential trend.

coup (1975, 1977,1980, 1982, 1996, 2007), general election time protest and activates (1979, 1996, 2001), caretaker government crisis (2006-2008), and terrorist attack (2005) also contributed to reducing GDP growth in different times (Figure 2.2).

According to the World Bank, the country's poverty has decreased by 26% between 2000 and 2010 (WB, 2013). Despite an annual 7.1% GDP growth, 4.07% of the total labor force was unemployment in 2016, which was 2.2% in 1991 (WB, 2017a). The cause behind this higher unemployment rate may be the transition from the agriculture-based economy to manufacturing industry based one, as agriculture is more labor-intensive job sector than that of manufacturing industry in Bangladesh.

2.2.2 Energy use and effects on economy

Lee & Chang (2007), examined the economic growth in Taiwan (1955–2003) and concluded that the relationship between energy consumption and economic growth in Taiwan is characterized by an inverse U-shape (Lee and Chang, 2007). Moreover, where there was lower energy consumption in Taiwan, energy consumption promoted economic growth (Lee and Chang, 2007). In a different study, analysis of 16 Asian countries during the 1971–2002 also demonstrated a positive long-run co-integrated relationship between real GDP and energy consumption (Lee and Chang, 2008).

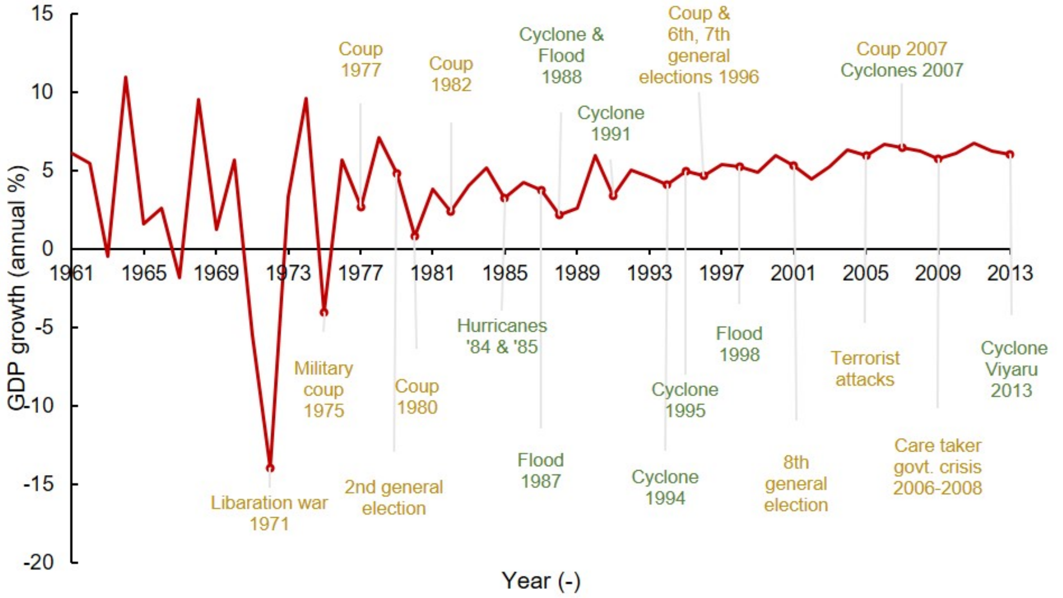

Figure 2.2: Historical GDP growth rate of Bangladesh; data source (WB, 2017a).and plausible reasons (the yellow coloured reasons are political and green ones are natural disasters)

Bangladesh was included in the least developed country category in 1975 (UN, 2017a). Bangladesh became lower-middle income country from lower income country in 2015 (WB, 2015b). Energy use per capita (kg of oil equivalent) and GDP per capita (constant 2010 US$) demonstrated a positive exponential correlation with $R^2 = 0.98$ (Figure 2.3). For the analysis, energy use and GDP per capita data from 1971 to 2013 were utilized by World Bank. Access to grid electricity in Bangladesh is the lowest among the NEXT 11 countries (WB, 2017a; GS, 2007). In 2012, only 60% of the total population had access to electricity. Therefore, 40% of the people in Bangladesh live in energy poverty. Increased energy consumption per capita has shown a high economic output in Bangladesh with one of the most massive energy poverty among it's population, which is resonating with the findings of the study conducted in Taiwanese context by (Lee and Chang, 2007).

Historical data on electricity demand indicated an exponential growth ($R^2 = 0.99$) in the last 42 years since 1971 (Figure 2.3). No data before 1971 was found. Electricity consumption in Bangladesh elevated to 293 kWh per capita in 2013 from only 11kWh in 1971 (WB, 2017a), which means a 27 times increase in 42 years. The GDP-electricity elasticity of the country exhibits a strong linear relationship ($R^2 = 0.99$); for one kWh/capita electricity consumption augmentation, GDP/capita in-

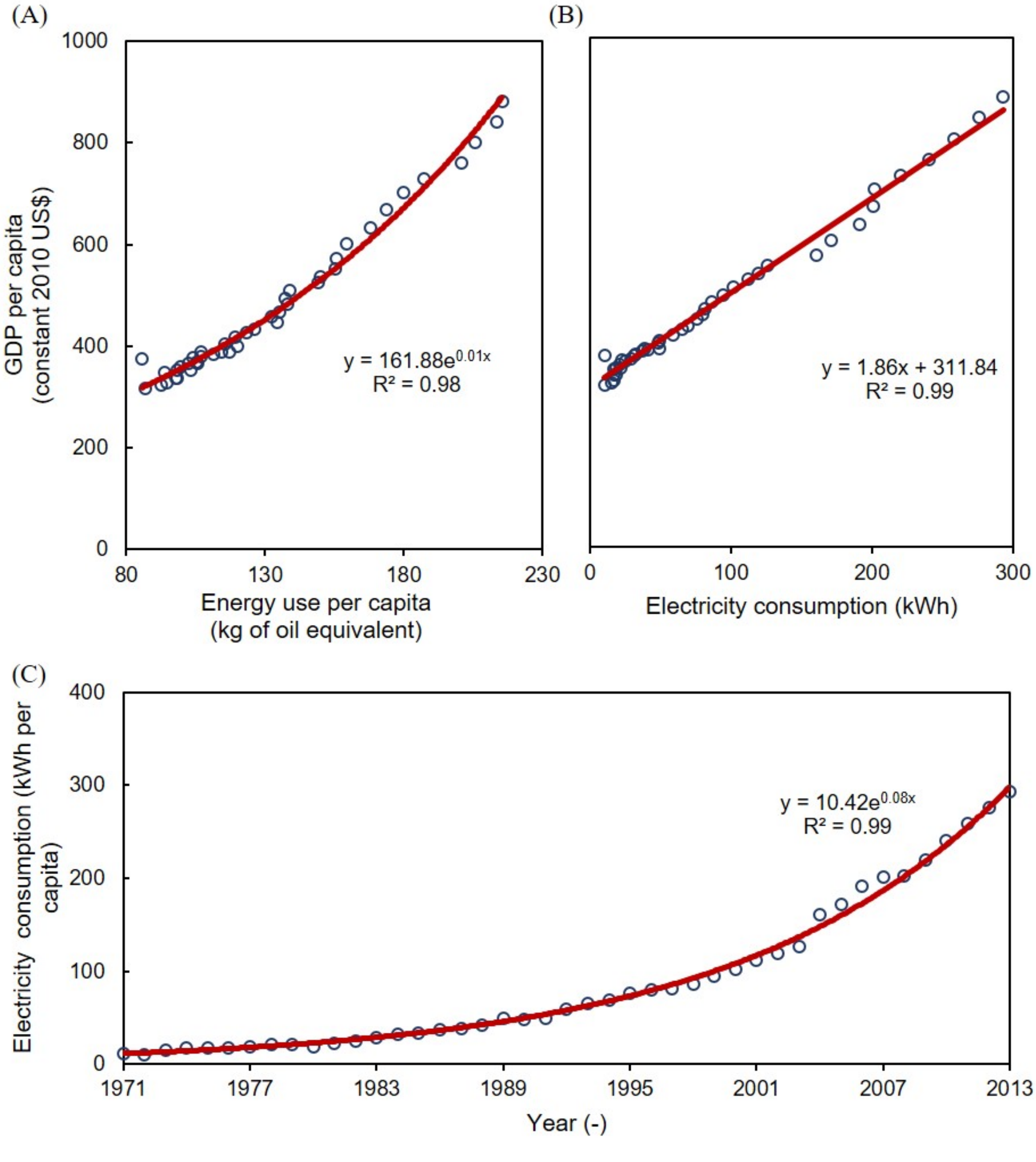

Figure 2.3: GDP elasticity with (A) energy use per capita, and (B) electricity consumption of Bangladesh. (C) Historical electricity consumption in Bangladesh (1971-2013); data source (WB, 2017a).

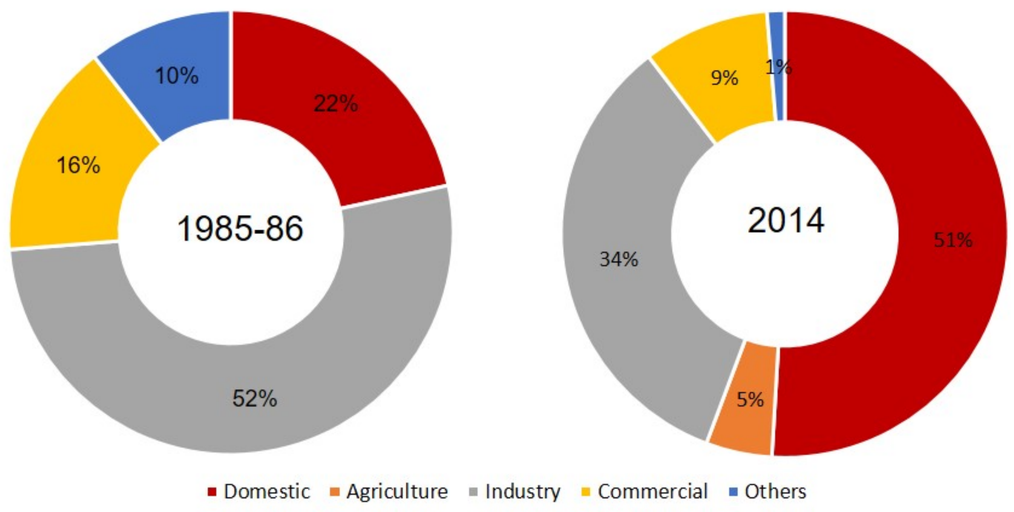

Figure 2.4: Electricity demand profile in 1985-86 and 2014; data source (BPDB, 2008, 2014).

creased US$1.8 on average in between 1971 and 2013 (Figure 2.3). The correlation from Figure 2.3 also resonates with another study where a unidirectional causality from per capita GDP to per capita electricity consumption in Bangladesh was concluded (Mozumder and Marathe, 2007).

2.3 Electricity demand

Domestic, industrial, commercial, agriculture and others are the demand sectors in Bangladesh. In 1985-86, 52% of electricity demand came from industry sector. Moreover, 22%, 16% and 10% of electricity demand were for domestic, others and commercial. By 2014, domestic electricity demand became the largest of all the sectors with 51%. The industry had the second most significant demand of 34% from the total electricity in 2014 (Figure 2.4).

Historical trends demonstrated exponential growth in all demand sectors (Figure 2.5). However, the domestic electricity demand reduced 46% in 1996-97 than that of 1995-96 because of two consecutive cyclones (in 1994 and 1995). Also, there was a sudden drop (153% reduction) in industry sector electricity demand in 1997-98, because of the collective influence of two consecutive cyclones (in 1994 and 1995), a military coup and the sixth & seventh national elections in 1996. Other than the two incidents the electricity demand elevated exponentially in Bangladesh.

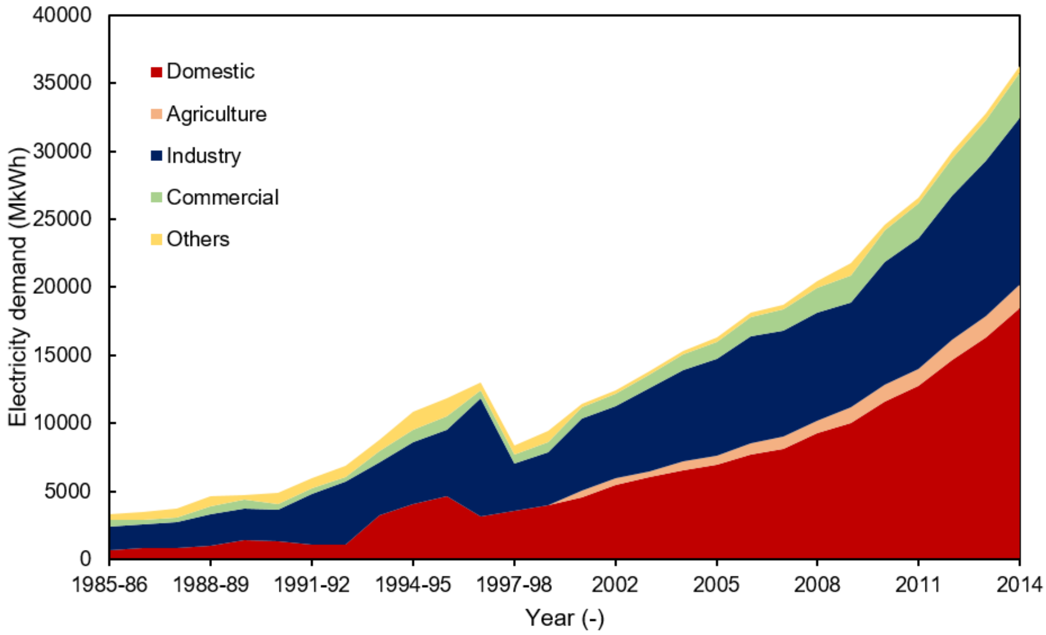

Figure 2.5: Electricity demand in different sectors; data source BPDB (2008, 2009, 2010, 2011, 2012, 2013, 2014, 2017a).

Despite the growing electricity demand, 62.4% of the population is yet to access grid electricity in 2014 (Figure 2.6A). Moreover, the generation sector cannot meet the demand resulting in growth in load shedding too (Figure 2.6C). Despite the maximum generation of 7356 MW in history (1974-75 to 2013-14), there was a 932 MW maximum load shedding in 2013-14. In 2005-06, the load shedding was highest of 1312 MW, while the maximum generation was 3721 MW. In eight years (2005-2013), the maximum generation elevated 1.9 times with a 29% reduction in load shedding. The load shedding is reducing in Bangladesh. However, suppressed demand can rise faster with more access to grid electricity and higher buying capacity (Rosnes and Vennemo, 2012), which is both going on in Bangladesh.

2.4 Electricity generation

In the case of electricity generation, the installed capacity is elevating exponentially to meet the demand (Figure 2.6B). Moreover, the derated installed capacity improved since 2009-10, because most of the newly built power plants became operational after 2009 and they are still in early stage of their lifespan (Figure 2.8). However, the present installed capacity is not sufficient, and the result is load shed-

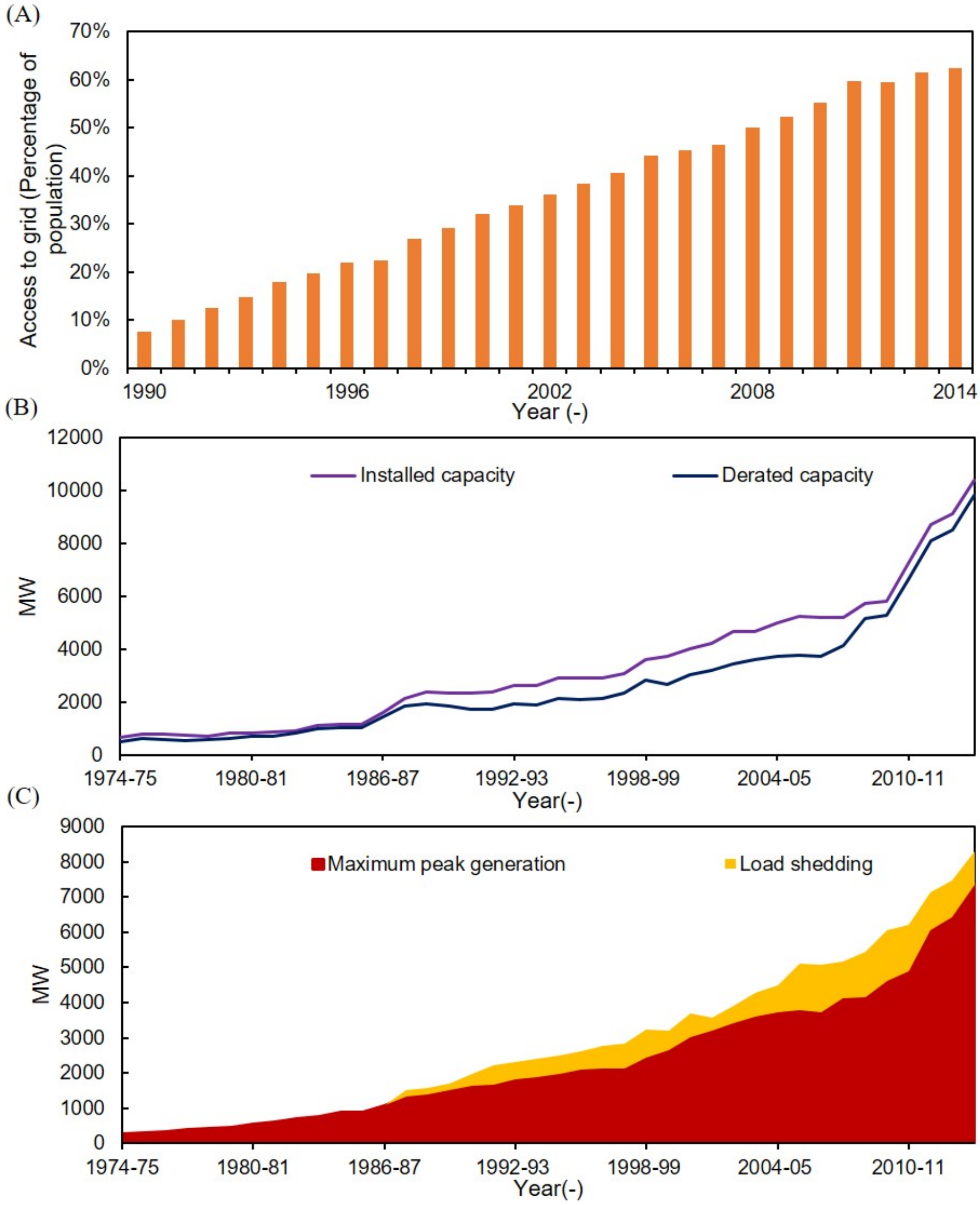

Figure 2.6: (A) Access to grid in Bangladesh; data source (WB, 2017a). (B) Installed and derated capacity in Bangladesh, (C) Maximum generation and load shedding in Bangladesh; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2017a).

ding. As per present energy sector planning, installed capacity will keep rising and rich to 33708 MW by 2030, which will be a 3.23 times higher than that of 2013-14 (JICA and TEPCO, 2011).

Public sector generation capacity has increased exponentially between 1970 and 1997 (Figure 2.7). The growth in the public sector slowed down when the private sector began supplementing generation in 1997 (Figure 2.7). Majority of the growth since 1997 came from the private sector and the trend is projected to continue up to 2030 with an installed capacity of 33.7 GW in 2030 (JICA and TEPCO, 2011) from 13.7 GW in 2017 (BPDB, 2017b). The installed capacity for public and private generation sector was 5803 and 4345 MW in 2015 respectively, with additional 500 MW imported from India (Table 2.1). The total generation capacity of Bangladesh was 10648 MW in 2015, which increased only 0.1% in 2016. However, the total installed capacity elevated to 12484 MW in 2017, which was 17.1% increase in a year. The public and private sector installed capacity were 6576 and 5308 MW respectively, with 600 MW imported electricity from India in 2017. The public sector installed capacity increased 13% between 2015 and 2017. APSCL and NWPGCL achieved 74.77%, and 19.6% increased installed capacity in two years (2015-17). On the other hand, the private sector had 22% increased installed capacity in 2017 than that of 2015. The IPP and QRPP installed capacity increased 60.6% and 26.9% in two years (2015-17). However, the total installed capacity of RPPs reduced 48% by 2017.

There were 74 public and 85 private owned power plant units operational in 2015. Among the public plants, 6% are older than 40 years. However, 23% and 25% of the plants are in 30-40 and 20-30 years old range. Moreover, 30% power plants are less than ten years old. On the other hand, 85% private power plants are less than ten years old (Figure 2.8). Altogether, 58% of the total power plant units are less than ten years old.

The majority of the existing thermal power plants are situated in north, north-west, east and middle-east part of the country (Figure 2.9). Among the existing power plants, the east zone has 9688 MW installed capacity, of which 4307 MW (44% of the east zone) was situated in Dhaka zone in 2017. However, the west zone

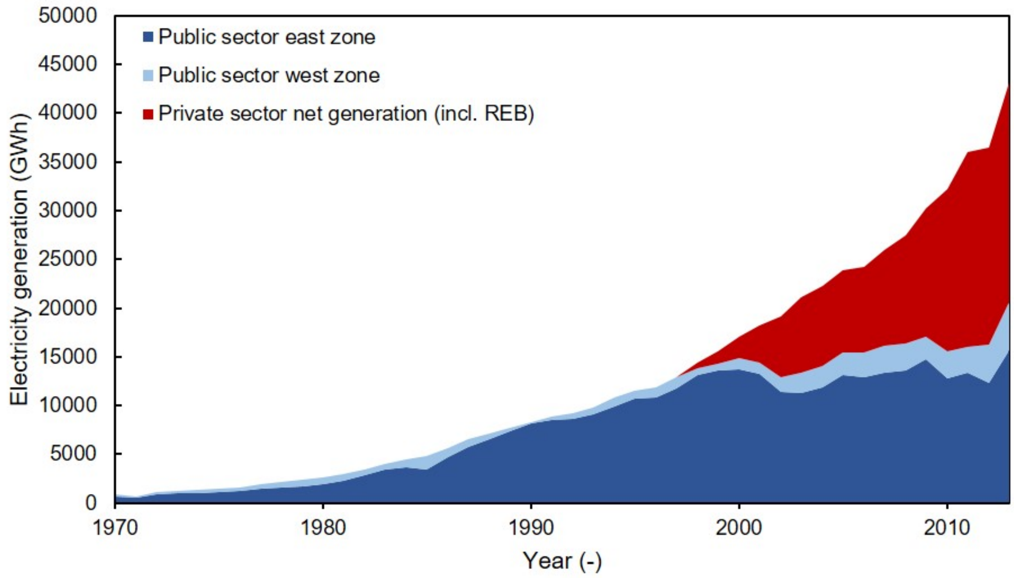

Figure 2.7: Public and private sector net generation; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2017a).

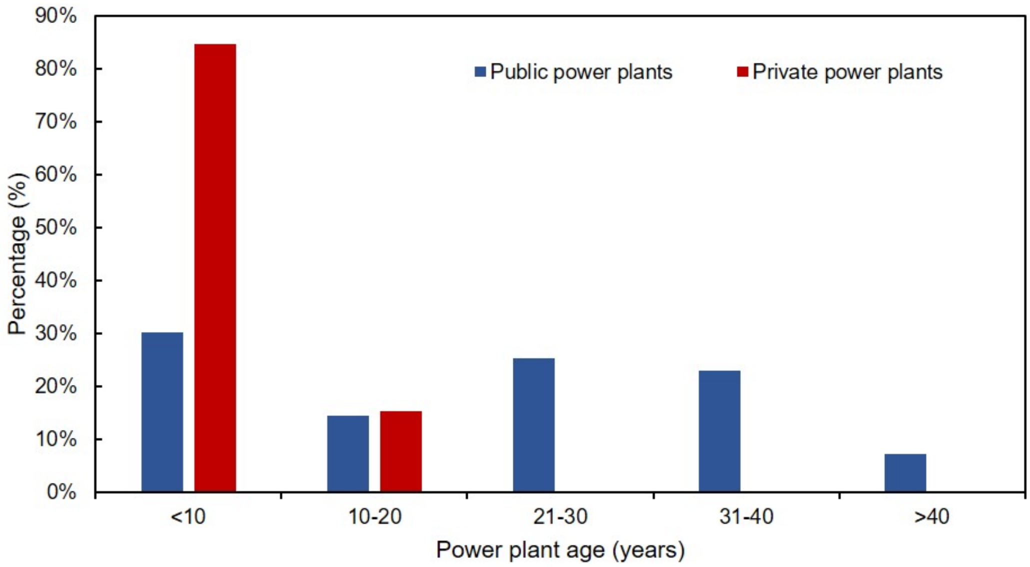

Figure 2.8: Age of public and private power plants; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2017a).

had only 2796 MW installed capacity in 2017. Therefore, the east zone has 3.5 times more installed capacity than that of west zone. The positions are mostly close to the fuel source such as gas, coal or liquid hydrocarbons. Close to a river is another requirement for thermal power plants due to the high water demand for cooling. In the case of the plants which fueled with imported liquid hydrocarbons, the rivers act as fuel transport medium. There is a significant number of fossil fuel based thermal power plants that are under construction and planned for the future by 2030 (Figure 2.9). However, there will be eight new thermal power plants built in the southern coastal areas of Bangladesh by 2030. Five of them will be near the south-east corner of the country, close to the port city of Chittagong. The other three are going to be constructed on the south-western side of the country, which will come very close to the world's largest mangrove forest Sundarbans. The proposed 1320 MW imported coal-fueled Rampal power plants would be constructed 14 km north of Sundarbans. There has been significant conflict between the government, local people and environmental activists due to the concern on the effect of GHG emissions on the forest (EJA, 2017). Moreover, the land acquisition and deforestation are also of major concern as 742 ha area would be built for the power plant by cleaning forest and adjacent lands. There were more conflicts regarding coal mining in Phulbari, Bangladesh in 2005. It was an open-pit coal mine project proposed by Asia Energy Corporation, which would have displaced 220000 local people and destroyed agricultural land. Due to the large protest from the local people and environmental authority the government had to stop this project. These conflicts around the only proven coal deposit in the north and geographical characteristic of Bangladesh may have influenced the future energy planning master plan PSMP2010. In PSMP2010, the government was suggested by JICA to move towards imported coal-based ultra-supercritical power plants (JICA and TEPCO, 2011). Due to the dependency on import, the future power plants were positioned in the coastal areas. However, the construction of coal power plant close to Sundarbans is still questionable from an environmental point of view.

In 1975, 78% of public electricity generation utilized natural gas. By 2013, the natural gas fuel use increased 21 times. Moreover, liquid hydrocarbon-based fuel use elevated 7.26 times in 2013 as compared to 1975. There has been an exponential growth in fuel use in public power plants between 1975 and 2013 (Figure 2.10).

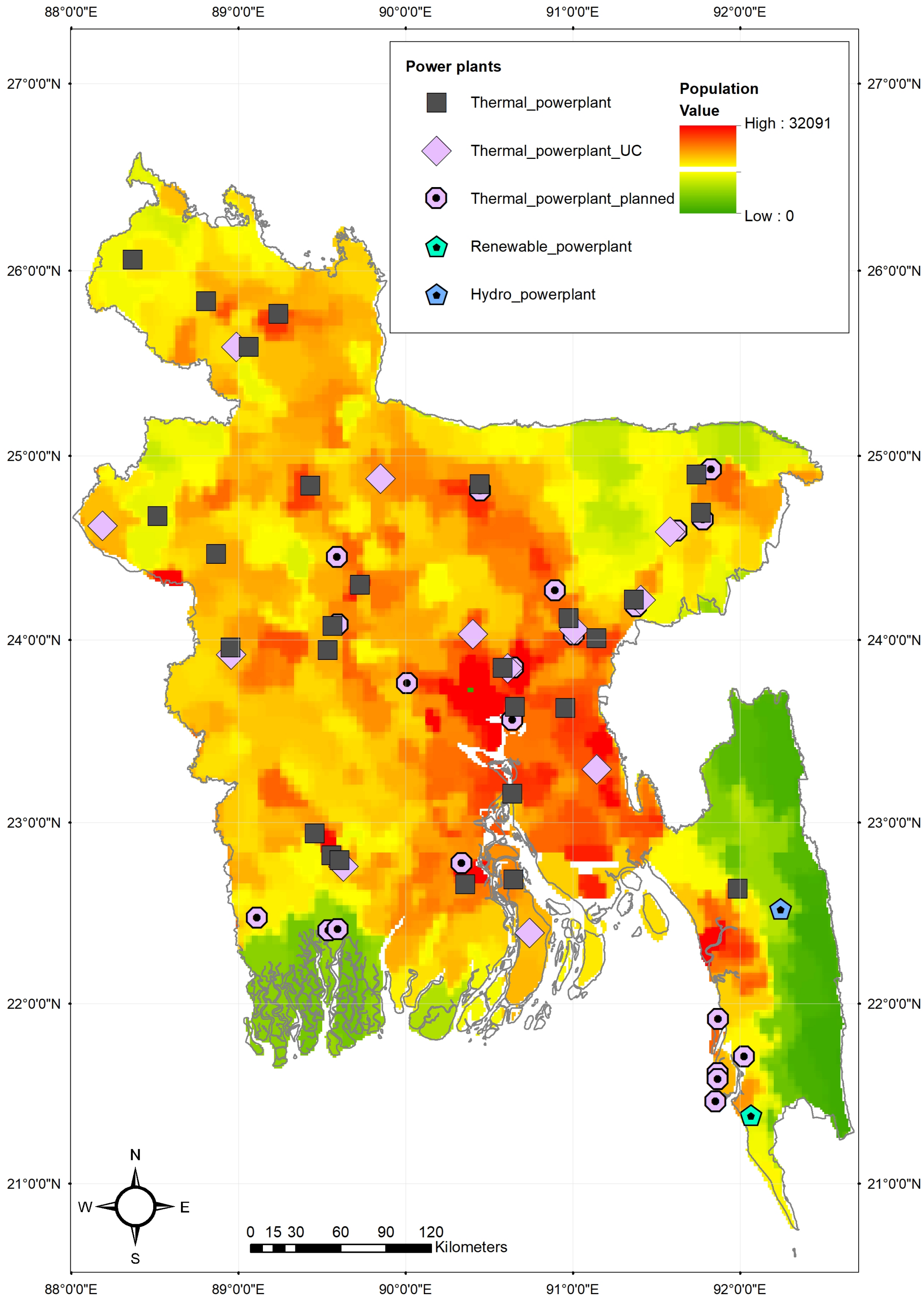

Figure 2.9: Power plants in Bangladesh including existing, under construction (UC) and planned (2015-2021); Map drawn by author using data from PGCB (2015); Hijmans *et al.* (2012); UNOCHA (2018)

Table 2.1: Electricity generation installed capacity; data source (BPDB, 2017b)

Generation authority	**Installed capacity (MW)**		
	2015	**2016**	**2017**
Public			
BPDB	4126	3758	4088
APSCL	687	840	1200
EGCB	622	210	622
NWPGCL	368	368	440
RPCL	0	77	77
PDB-RPCL	0	149	149
Private			
IPP	1883	2485	3025
SIPP-PDB	99	99	99
SIPP-REB	226	226	226
CIPP-REB	25	25	25
QRPP	1114	1414	1414
RPP	998	506	519
IMP	500	500	600
Total	**10648**	**10657**	**12484**

In 2015, 68% of the power plants were natural gas fueled (Figure 2.11). Moreover, 24% of the power plants were liquid hydrocarbon fueled. Only 2% generation was the renewable source (Hydro). Imported electricity is accounted for 4% of the electricity. However, the PSMP2010 proposed a shift from natural gas based electricity generation to coal-based (50%) one by 2030. Because the domestic natural gas reserve have been depleting and expected to reduce significantly after 2015 (JICA and TEPCO, 2011).

Most RPPs are oil based that relies on imported petroleum as Bangladesh has insufficient oil reserve. By increasing oil dependency (Mujeri *et al.*, 2014), the energy sector was exposed to the volatile international oil market (Mourshed, 2013). Energy sector subsidies have escalated because of growing import prices for fuels to encounter the accelerated energy demand (Mujeri *et al.*, 2014). Moreover, lack of transparency in public procurement process acted as an incentive for corruption to increase in the energy sector of Bangladesh (Khan and Rasheduzzman, 2013; Ahmed, 2011; Khatun and Ahamad, 2013). There were no data on how much fuel is used in private power plants separately.

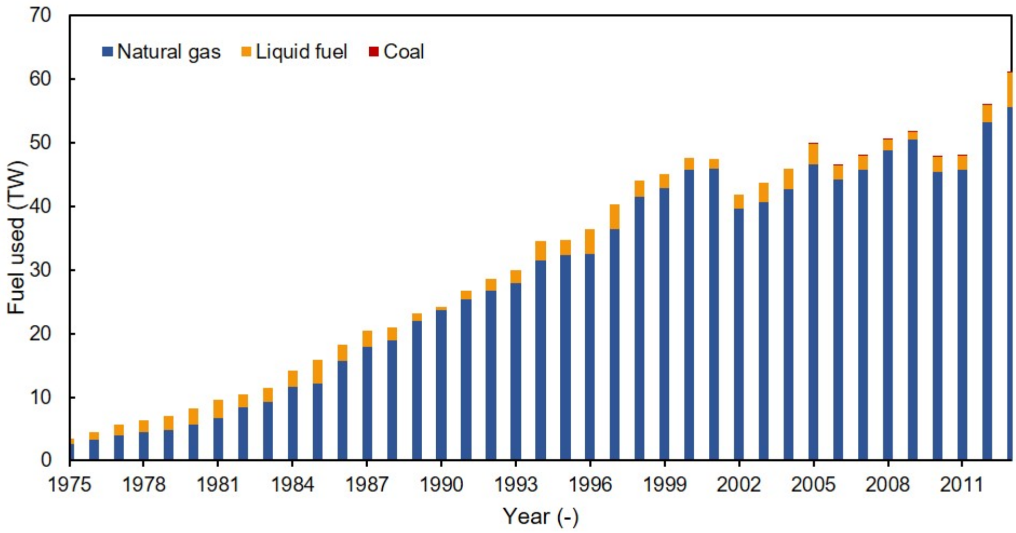

Figure 2.10: Fuel for public energy sector; data source WB (2014).

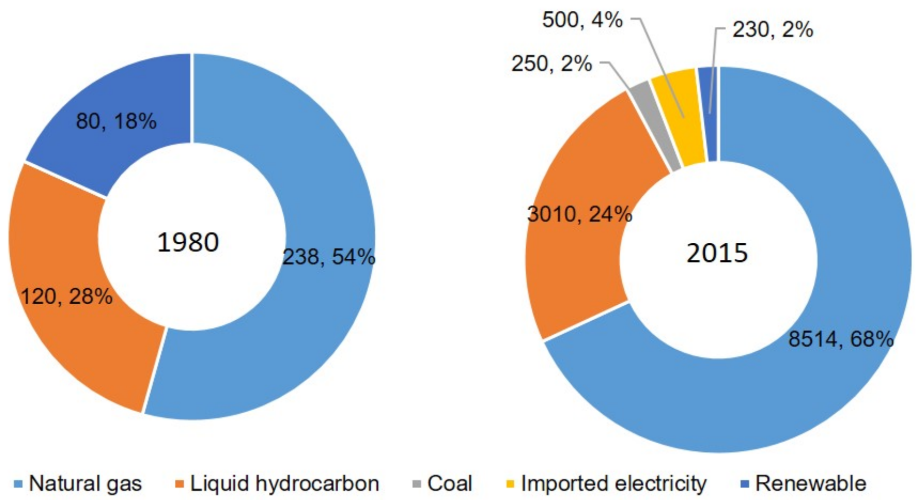

Figure 2.11: Installed capacity (MW) and fuel types; data source WB (2014).

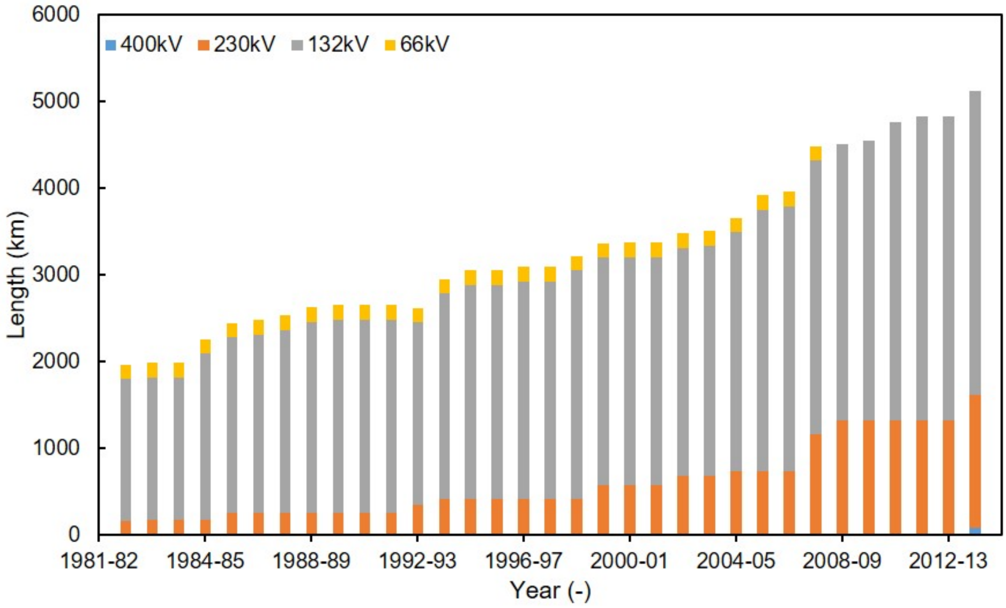

Figure 2.12: Transmission lines in Bangladesh; data source WB (2014).

2.5 Transmission and distribution

There are four types of transmission lines such as 400kV, 230kV, 132kV and 66kV that exist in Bangladesh by 2015. In 1981-82, 1967km of transmission line existed which increased to 2652km by 1990-91. However, only 22% of the population had access to grid electricity. By 2012-13, length of transmission line elevated to 4829km, a 1.8 times increase to supply electricity to 60% of the population (Figure 2.12).

The transmission line length is going to elevate because there are a substantial amount of lines that are under construction and planned for the future (Figure 2.13). Higher population density areas have access to grid electricity. However, a large number of rural and suburban regions does not have access to electricity (Figure 2.13).

There are three types of transmissions substations in Bangladesh, such as 230/132 kV, 132/33 kV, and 66 kV. Distribution substations are 33/11kV type. In the case of distribution transformers, two types of 33/0.4kV and 11/0.4 kV are present in Bangladesh. These substations numbers are also going to increase significantly by 2021 to supply most of the country (Figure 2.14). Moreover, HDVC stations are working in the interconnection between India and Bangladesh in Bheramara, Kushtia. Another one is under planning in the northern part of Bangladesh (Figure 2.14).

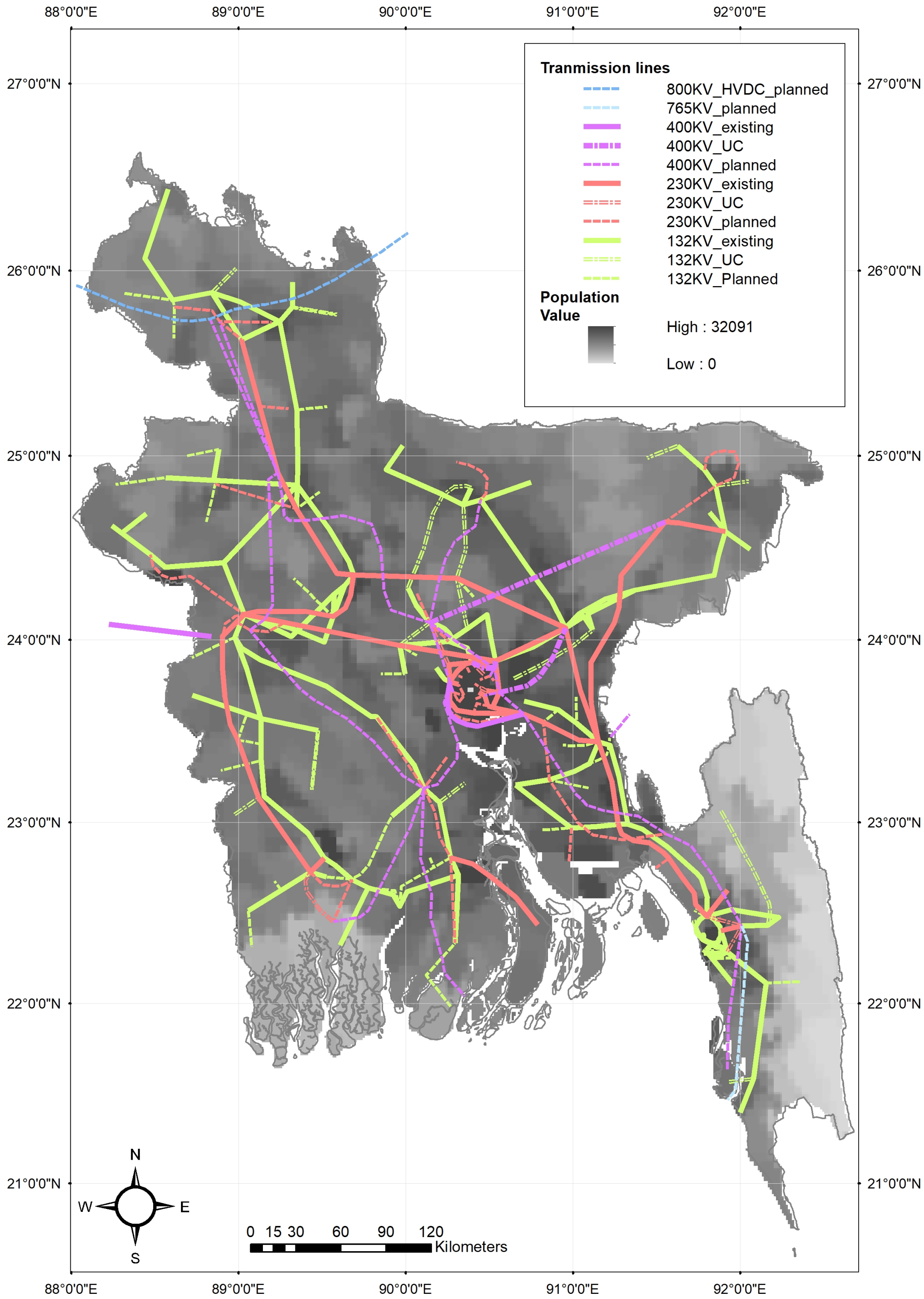

Figure 2.13: Existing, under construction and planned electricity transmission network in Bangladesh (2015-2021); Map drawn by author using data from PGCB (2015); Hijmans *et al.* (2012); UNOCHA (2018)

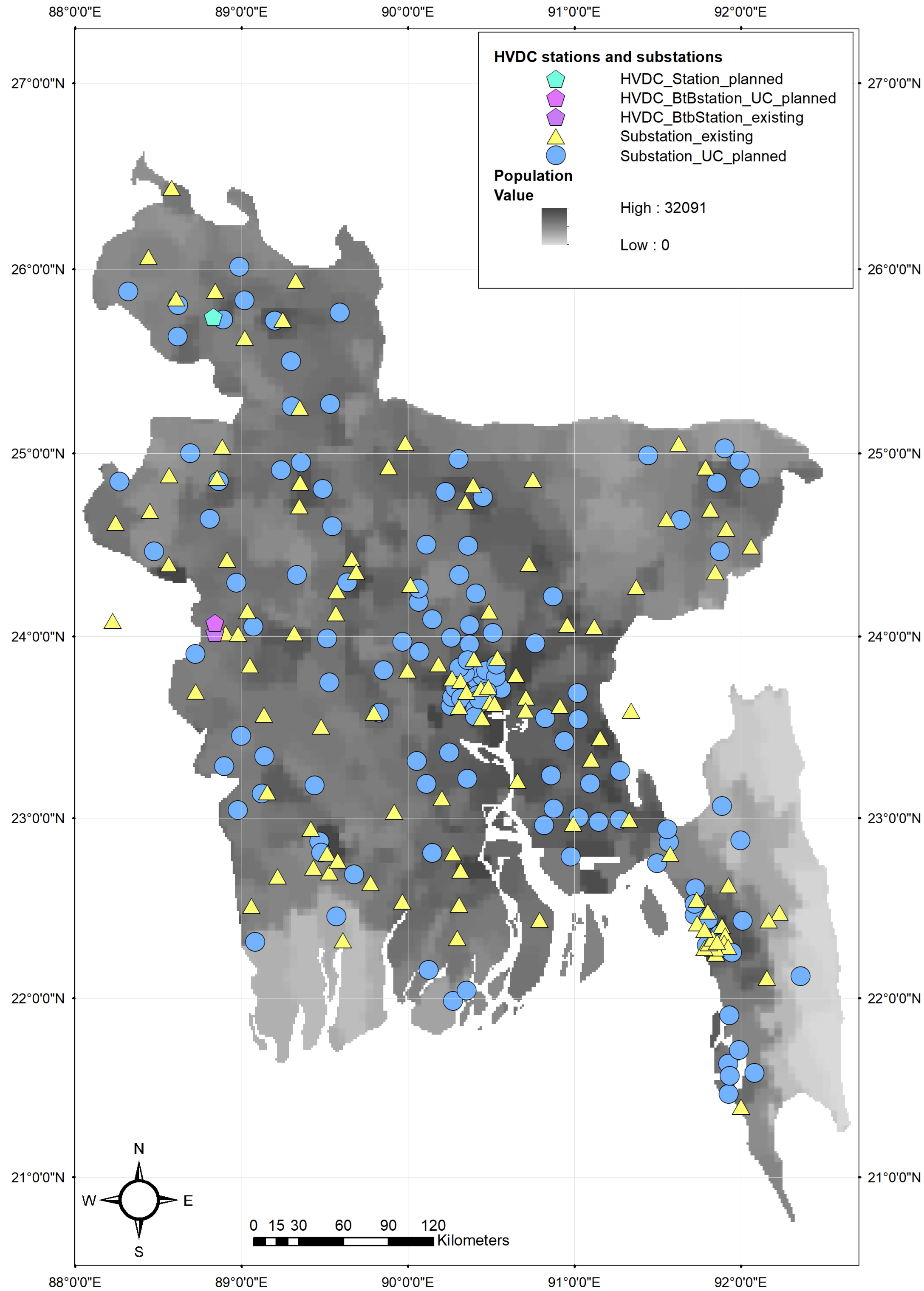

Figure 2.14: Substations and HVDC stations in Bangladesh (2015-2021); Map drawn by author using data from PGCB (2015); Hijmans *et al.* (2012); UNOCHA (2018)

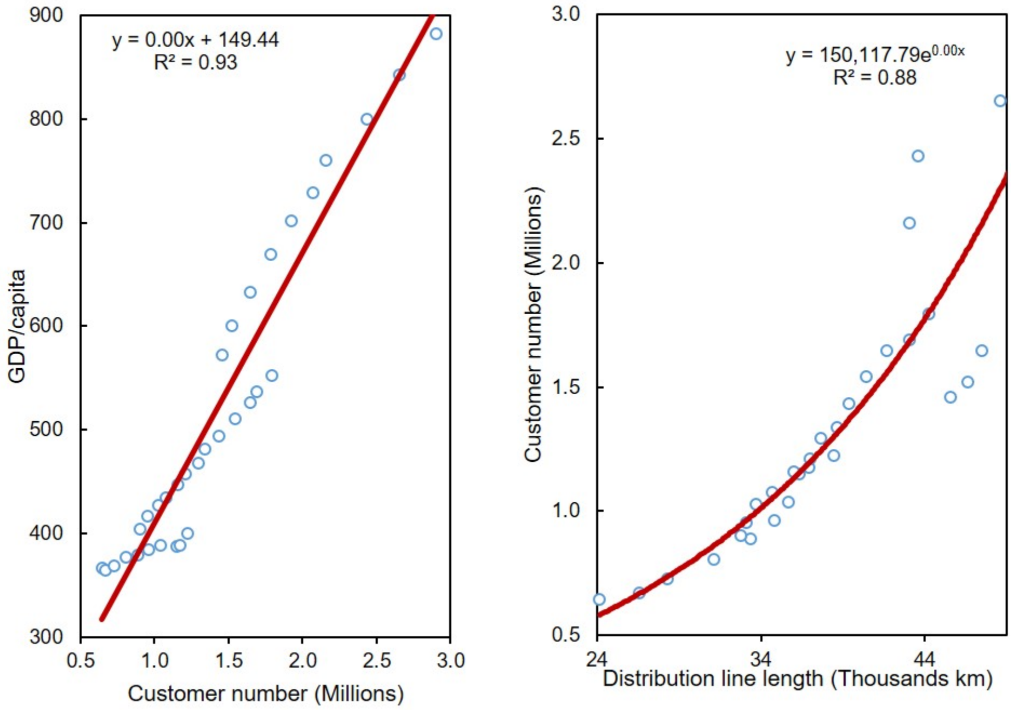

Figure 2.15: Relationship of electricity customer numbers with GDP per capita and distribution line length in Bangladesh; data source WB (2014).

Generally, distribution lines in Bangladesh are of three capacities- 33kV, 11kV and 0.4kV. In 1981-82, the total length of distribution line was 24156 km, which elevated two times to reach 49460 km by 2013-14. Customer number and GDP per capita showed a positive linear relationship in Bangladesh. The relationship can be interpreted as the higher buying capacity among the people elevates the number of electricity consumers (Figure 2.15), which resonates with the study conducted by (Hu and Hu, 2013). However, the customer number increases exponentially with the growth in distribution line length (Figure 2.15), which can be the result of suppressed demand in a country with high energy poverty. Moreover, distribution system loss in Bangladesh was 35.79% in 1991-92 which was reduced to 11.89% by 2013-14 with efficient maintenance and planning (BPDB, 2017a).

2.6 Summary

The historical and future energy sector development was analysed in this chapter. The historical data of energy demand and supply sector in Bangladesh showed an exponential growth over the past 40 years. The highest increase in the demand was in domestic sector. The domestic sector energy demand was 22% in 1985-86, which elevated to 51% of the total demand in 2014. Second highest demand share was 34% for industry sector. The historical demand profile denotes that there can be significant rise in electricity consumption. The supply sector have been developing in a rapid growth in the past 40 years. The trends showed that private sector was dominating the energy supply sector in 2014. However, the PSMP2010 is clearly leading towards a massive public electricity generation sector development in the next two decades, which would be dominated by fossil fuel especially coal. In addition to that energy supply sector development, the transmissions and distribution sector is growing rapidly to meet the target of giving access to grid electricity to all households by 2021.

Chapter 3

Cost analysis

Bangladesh takes a considerable amount of loans from national and international funding bodies for establishing power plants. Therefore, they would need to borrow a significant amount of loan to construct the substantial number of stations to achieve a 20 GW of additional installed capacity by 2030 than that of 2017 (BPDB, 2017a; JICA and TEPCO, 2011). With considerable capital costs involved and previous evidence of corruption in the energy sector (Khan and Rasheduzzman, 2013; Ruth, 2002) as well as in public procurement (Mahmood, 2010), the utilization of massive amount of money can prove to be a significant concern in Bangladesh. There have been different studies on the relationship between corruption and cost of big public projects. Study on Italian high-speed railways megaprojects demonstrated that corruption worsens both cost and temporal performance (Locatelli *et al.*, 2017). This study also identified the project contexts such as the discretionary power of officials, economic rents of policy/decision makers and weak institutions would make a country ideal for corruption. Another study demonstrated that capital cost of IPPs selected without competitive bidding was 44-56% higher than that of with competitive bidding in developing countries including Bangladesh (Phadke, 2009). However, only two projects with competitive bidding (4.87% of the total projects analysed) were considered in the case of Bangladesh. Therefore, the result was generic for developing countries, and the conclusion was not robust for Bangladesh. In another research, the Malaysian context was analysed to find the reasons behind corruption were an abuse of power, opportunity and moral compromise within the government officials (Othman *et al.*, 2014). Also, different studies suggest that the ongoing corruption can be controlled via random and regular supervision, severe punishment and prosecution of corrupt personnel, and anti-corruption awareness development (Zou, 2006; De Chiara and Livio, 2017). Although the literature suggests that government personnel are mostly responsible for active corruption by asking bribes, the private sector can also contribute by acting as passive corruption through approaching bureaucrats by offering bribes (Capasso and Santoro, 2017). However, there is a gap in the literature regarding studies on cost evolution of energy sector in developing economies such as Bangladesh, and their relation to corruption, due to the lack of political transparency and data. There are two objectives of this chapter. Initially, to investigate the capital cost of establishing various power plants in Bangladesh and compare with other countries, regions and world, to find any differences. Furthermore, to understand the reason behind the differences, it was hypothesized that corruption might have influenced the capital cost of power plants in Bangladesh. The correlation between the capital cost of the power plants and Corruption Perceptions Index (CPI)[1] of Bangladesh was examined to test the hypothesis.

3.1 Methodology

The study was conducted in three stages. First, annual (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014, 2017a; KPCL, 2014), project (APSCL, 2015; CPGCBL, 2015; EGCBL, 2015) and financial aid reports (IDCOL, 2015; WB, 2017c) from national bodies and international organizations were reviewed to develop a capital cost database of power plants in Bangladesh (Table B.1). Capital cost refers to all the expenses incurred before a plant becomes operational and comprises the cost associated with the acquisition of land; permits and legal matters; plant equipment and construction; financing; and the commissioning of the plant. Independent scrutiny of public expenditure does not feature strongly in Bangladesh's governance structure. Hence, the total capital cost or the breakdown of the capital cost of all the operational power plants is not publicly available. There were 100 public power plants in January 2016, of which 96 were operational (BPDB, 2017b). Primary data such as installed capacity, commissioning year, fuel and owner of 165 units from 113 public and private operational Bangladeshi power plants in January 2016 were

[1]Corruption Perceptions Index (CPI) was started in 1995. CPI is calculated from aggregated data to a standardized scale of 0-100, where '0' and '100' refers to highest and lowest level of corruption, respectively (TI, 2017).

collected for this analysis. The number of public and private owned units were 80 (6968 MW) and 85 (5566 MW) respectively. Among the operational units, ninety-five utilize gas, and seven are dual fuel type, of which four can use gas and heavy fuel oil (HFO). The rest of the three dual-fuel plants utilize high-speed diesel (HSD) and gas. Moreover, only HFO and HSD based units were 32 and 23 respectively. Two units were coal-based, and four units were hydroelectric. Also, there was a 500 MW interconnection with India in Khulna. Due to data constraints, the capital cost of 61 fossils (gas, coal and petroleum) and renewable (nuclear, hydro, the wind and solar) power plants in Bangladesh commissioned since 1962 and planned up to 2030, were collected (Table 3.1). Of the 61 plants, 34 are operational, and 27 are under construction, repair or future planned. The study had to test the hypothesis with lower data constrain and bias generated by it because of unavailability of cost data. The government has started to provide cost data since 2007 through the annual reports (BPDB, 2017b). With more data and transparency in the future, the studies regarding cost can be improved to make the power plants more cost-effective.

Among the analyzed 61 power plant units, gas, HFO/HSD/duel fuel, coal, nuclear and renewable based were 34, 17, four, one and five respectively. Moreover, 48 are public, and thirteen are privately operated. All the future and under-construction power plants are government owned. Among the nine analyzed duel fuel power plant units, three utilize HFO and gas, of which two are public, and one is privately owned. Six duel fuel power plant units use HSD and gas, of which one is private, and five are publicly owned. There are only nine HFO based power plant units, of which two are planned for future and rest of them are operational. All the HFO based functional power plants are privately owned. In the case of coal-based power plants units, only two are functional, and three are planned for future, and all of them are publicly owned. Similarly, all the renewable power plants are government owned, of which one is the Kaptai hydroelectric plant (5 units) and two small solar energy plants. The only planned nuclear power plant (Rooppur 1 and 2) would be publicly owned too. Three phases (Unit 1 and 2; Unit 3; Unit 4 and 5) of Kaptai hydroelectric power plant was considered separately because three stages had different cost individually. Among the coal power generation technologies, domestic coal-fueled subcritical plants were built in Barapukuria. Moreover, two new ultra-supercritical plants are under construction which would operate with imported coal. Cost per installed capacity in kW in a specific year of construction of the power plant was calculated and converted to the US dollar (USD) equivalent using the currency exchange rate with Bangladeshi Taka (BDT) on December 31 of the same year, obtained from Bangladesh Bank (BB, 2016). In cases where a power plant is going to be built after 2015, the cost was converted to 2015 USD using BDT to USD exchange rate on December 31, 2015. Then the historical cost data was converted using Consumer Price Index (Coinnews, 2016) of 2015 USD so that all cost can be compared on the 2015 USD basis.

Table 3.1: Background information on the cost data

Variable	Scale/ Category	Electricity generation technology							Total (n)	%
		GT	**CCPP**	**Sub-critical**	**Ultra-super-critical**	**Solar PV**	**Hydro**	**Nuclear**		
Commissioning year(-)	**1961-80**	-	-	-	-	-	1	-	1	1.6%
	1981-00	2	1	-	-	-	2	-	5	8.2%
	2001-10	2	2	1	-	-	-	-	5	8.2%
	2011-20	20	24	1	-	2	-	-	47	77.0%
	2021-30	-	-	-	2	-	-	1	3	4.9%
Ownership	**Public**	12	26	2	2	2	3	1	48	78.7%
	Private	11	2	-	-	-	-	-	13	21.3%
Fuel	**Natural gas**	10	24	-	-	-	-	-	34	60.7%
	Oil	9	-	-	-	-	-	-	9	16.1%
	Duel fuel	5	3	-	-	-	-	-	8	14.3%
	Coal	-	-	2	2	-	-	-	4	7.1%
	Nuclear	-	-	-	-	-	-	1	1	1.8%

Table 3.1: Background information on the cost data

Variable	**Scale/ Category**	**Electricity generation technology**							**Total (n)**	**%**
		GT	**CCPP**	**Sub-critical**	**Ultra-super-critical**	**Solar PV**	**Hydro**	**Nuclear**		
Installed capacity (MW)	**<10**	-	-	-	-	2	-	-	2	3.3%
	10-100	8	7	-	-	-	3	-	18	29.5%
	101-200	9	3	1	-	-	-	-	13	21.3%
	201-300	6	4	1	-	-	-	-	11	18.0%
	301-400	-	11	-	-	-	-	-	11	18.0%
	401-500	-	3	-	-	-	-	-	3	4.9%
	>500	-	-	-	2	-	-	1	3	4.9%
Capital cost (US$(2015) /kW)	**500-600**	1	2	-	-	-	1	-	4	6.6%
	601-700	4	1	-	-	-	-	-	5	8.2%
	701-800	2	1	-	-	-	-	-	3	4.9%

Table 3.1: Background information on the cost data

Variable	**Scale/ Category**	**Electricity generation technology**							**Total (n)**	**%**
		GT	**CCPP**	**Sub-critical**	**Ultra-super-critical**	**Solar PV**	**Hydro**	**Nuclear**		
	801-900	6	4	-	-	-	-	-	10	16.4%
	901-1000	2	4	-	-	-	-	-	6	9.8%
	1001-1100	-	5	-	-	-	1	-	6	9.8%
	1101-1200	2	2	-	-	-	-	-	4	6.6%
	1201-1300	1	3	1	-	-	-	-	5	8.2%
	1301-1400	2	1	-	-	-	-	-	3	4.9%
	1401-1500	2	1	-	-	-	-	-	3	4.9%
	1501-1600	-	-	-	-	-	-	-	0	0.0%

Table 3.1: Background information on the cost data

Variable	Scale/ Category	Electricity generation technology							Total (n)	%
		GT	**CCPP**	**Sub-critical**	**Ultra-super-critical**	**Solar PV**	**Hydro**	**Nuclear**		
	1601-1700	1	2	-	-	-	-	-	3	4.9%
	1701-1800	-	-	-	-	-	-	-	0	0.0%
	1801-1900	1	-	-	-	-	-	-	1	1.6%
	1901-2000	-	-	1	-	-	-	-	1	1.6%
	2001-3000	-	-	-	1	1	-	-	2	3.3%
	3001-4000	-	1	-	1	-	-	-	2	3.3%
	4001-5000	-	-	-	-	1	-	-	1	1.6%

Table 3.1: Background information on the cost data

Variable	**Scale/ Category**	**Electricity generation technology**							**Total (n)**	**%**
		GT	**CCPP**	**Sub-critical**	**Ultra-super-critical**	**Solar PV**	**Hydro**	**Nuclear**		
	5001-6000	-	-	-	-	-	-	1	1	1.6%
	>6000	-	-	-	-	-	1	-	1	1.6%

Second, country- and region-wise capital costs of power plants for the same technology used in Bangladesh were collected from the International Energy Agency's (IEA) World Energy Investment Outlook 2014 (IEA, 2014) for USA, Japan, Russia, China, India, Brazil, Europe, the Middle East and Africa. There were three data points for all the countries for 2012, 2020, and 2035. Data for Sri Lanka were collected from 'Long-Term Generation Expansion Planning Studies 2015- 2034' for 2015 (Samarasekara and Silva, 2015). In the case of USA, further data on cost and performance of power generation technologies were collected from National Renewable Energy Laboratory (NREL) to augment the IEA data (NREL, 2012). There were ten data points for the cost data from NREL for 2008, 2010, 2015, 2020, 2025, 2030, 2035, 2040, 2045 and 2050. Also, CPI score between 1995 and 2016 was collected from Transparency International (TI) (TI, 2017).

Third, the average cost of power plants in Bangladesh was compared with that of the identified countries, regions and the World using 2015 as a base year. The evolution of cost was also analysed for both public and private sectors in Bangladesh. Pearson's test was conducted at normalised capital cost and CPI score to examine the effect of corruption on power plant capital cost in Bangladesh. CPI data is available only from 1995, which reduced the sample size down to 31 for the correlation study. Among the collected cost data, power plants commissioned from 2004 to 2015 were considered. There were no cost data available for any power plants established between 1995 and 2003. There were also some cost data for power plants built before 1995. As the CPI index started in 1995, the cost data before that was not considered for the correlation study. As the sample size is less than 50, Shapiro-Wilk and Kolmogorov-Smirnov test of normality were conducted (Ghasemi and Zahediasl, 2012) and Table 3.2 indicated that the distribution of interval data was normal, supporting the selection of Pearson's test.

3.2 Cost of power plants in Bangladesh

Power generation technology is the critical factor for the variation in the capital cost. For this study, initially, capital cost of various public and private power plants in Bangladesh with varied technologies such as gas turbines (GT) and combined-

Table 3.2: Test of normality. The data is normal because of the Sig. Value of the Shapiro-Wilk Test was higher than 0.05.

CPI[a]		Kolmogorov-Smirnov[b]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
$/kW	25	.172	14	.200*	.882	14	.062
	26	.139	7	.200*	.974	7	.925
	27	.185	7	.200*	.916	7	.442

* This is a lower bound of the true significance.
[a]CPI,has been omitted when CPI Index are 15,20 and 24 because $/kW is constant.
[b] Lilliefors Significance Correction.

cycle power plant (CCPP); subcritical and ultra-supercritical plants; hydroelectric; nuclear and solar PV plants were compared with the world average, to find out the cost difference. When the cost of GT and steam turbines (ST) are compared, public power plants (hereafter plants) in Bangladesh are found to be approximately 2.2 times more expensive than that of the world mean (Figure 3.1A). The cost of public GTs is even higher, around 1.5 times than the private plants in Bangladesh. In the case of CCPP, public plants' mean is 1.2 and 1.7 times more expensive than that of the world mean and the private plants' mean respectively (Table 3.3).

The private CCPP with an average cost of $540 /kW, where publicly owned ones ranged from $853-3005 /kW (Figure 3.1B). Moreover, future planned public CCPP cost range from $554-1612 /kW. Therefore, public CCPP in Bangladesh can be built with as low-cost as China ($568 /kW between 2012 and 2020) to 19% greater than that of the highest cost of USA ($1358 /kW between 2015 and 2020). The difference between lowest and highest capital cost of CCPP (going to be commissioned in 2017) is $1058 /kW, the equivalent of constructing almost two CCPP plants in China. Cost difference can happen depending on the installed capacity. From long-term generation expansion planning study of Sri Lanka, two separate CCPP cost difference was $202 /kW depending on the installed capacity. The capital cost of CCPP-Auto Diesel of 144 and 288 MW was $853 and $1055 /kW respectively in Sri Lanka (Samarasekara and Silva, 2015), which means higher installed capacity may reduce cost. However, in the case of Bangladesh, Siddhirganj 335 MW and Bibiana (South) 383 MW CCPP plant would cost $1612 /kW and $873 /kW respectively (operational by 2017). Though Bibiana (South) has 48 MW higher installed capacity than that of the Siddhirganj, it would cost approximately half. On the other hand in the private sector, Meghnaghat 450 MW CCPP (Unit 2) was constructed with \$560 /kW in 2014.

Figure 3.1C&D compares the cost of coal power plants. The subcritical coal plant, capital cost range from \$1245-\$1923 /kW, which is higher than the expense of the USA in the upper bound, and Africa in lower bound. However, the cost of the proposed ultra-supercritical power plant is going to be highest compared to the rest of the world (Figure 3.1D).

In the case of renewable energy, Bangladesh has been utilizing hydroelectricity from Kaptai power plant since 1962, making it the oldest active power plant in Bangladesh with a capital cost of \$6408 /kW for Unit 1 and 2, and parts of Unit 3. Capital cost reduced with the construction of Unit 3 in 1982, from \$6408 /kW to \$543 /kW (Figure 3.2B). Unit 3 was partially built during the construction of Unit 1 and 2 in 1962, which reduced the capital cost of completion of Unit 3 in 1982. However, the capital cost for Unit 4 and 5 was \$1075 /kW, which was constructed in 1988. Unit 4 and 5 were constructed in an already established infrastructure with facilities such as dam, reservoir during the construction of Unit 1, 2 and 3. Therefore, Unit 4 and 5 had higher capital cost than that of Unit 3. While comparing the capital cost of Bangladeshi hydroelectric plants with the world, the cost reported for other countries were suggested for the construction of new plants.

Currently, Bangladesh has small-scale solar home systems in households, but no significant commercial, operational project. Two large solar PV plants are going to be constructed in 2016-17 with an installed capacity of 5 and 7 MW costing \$4906 /kW and \$2391 /kW respectively (Figure 3.2A). Despite the continuing descending trend in cost, one is costing higher than that of the highest in the world for that year. Also, it is not clear why the difference in cost would be \$2515 /kW for just 2 MW, almost two times more than the cost of establishing similar technology power plant in China in 2020.

In the case of nuclear power plants, the planned power plant in Bangladesh would be established with the assistance from Russia in 2024-2025. However, the capital cost would be 1.45 times than that of Russia and almost equivalent to Japan (Figure

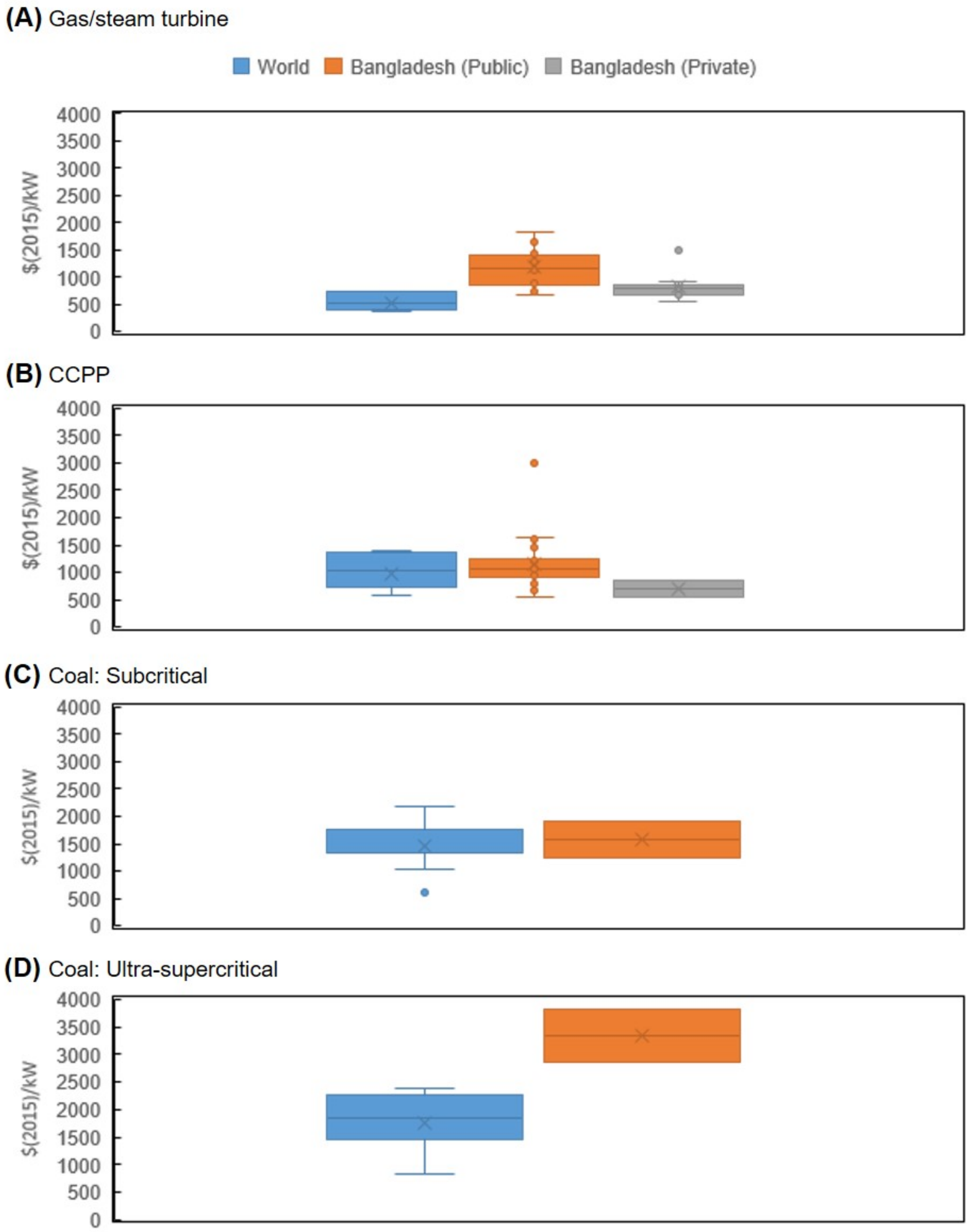

Figure 3.1: Capital cost comparison among fossil fueled power plants from the world with Bangladesh. In the case of GT/ST and CCPP, Bangladeshi public power plant's mean capital cost is higher than that of the mean of private and world counterparts. Surprisingly, private power plant's mean capital cost was lower than the world mean for CCPP. Subcritical coal plant means capital cost is slightly higher than that of global mean. However, ultra-supercritical mean capital cost of Bangladesh would be significantly greater than the world mean.

3.2C).

Although power plants cost more in Bangladesh, the public plants are significantly more expensive than the private ones, indicating that there may as well be other factors related to public sector governance in play (Table 3.3). Further studies may reveal other factors such as political instability, inefficient project management leading to construction delays and eventual increase in cost. However, the deep-rooted and widespread corruption culture could have a higher impact on the capital cost of the power plants, which needs further investigation with more data.

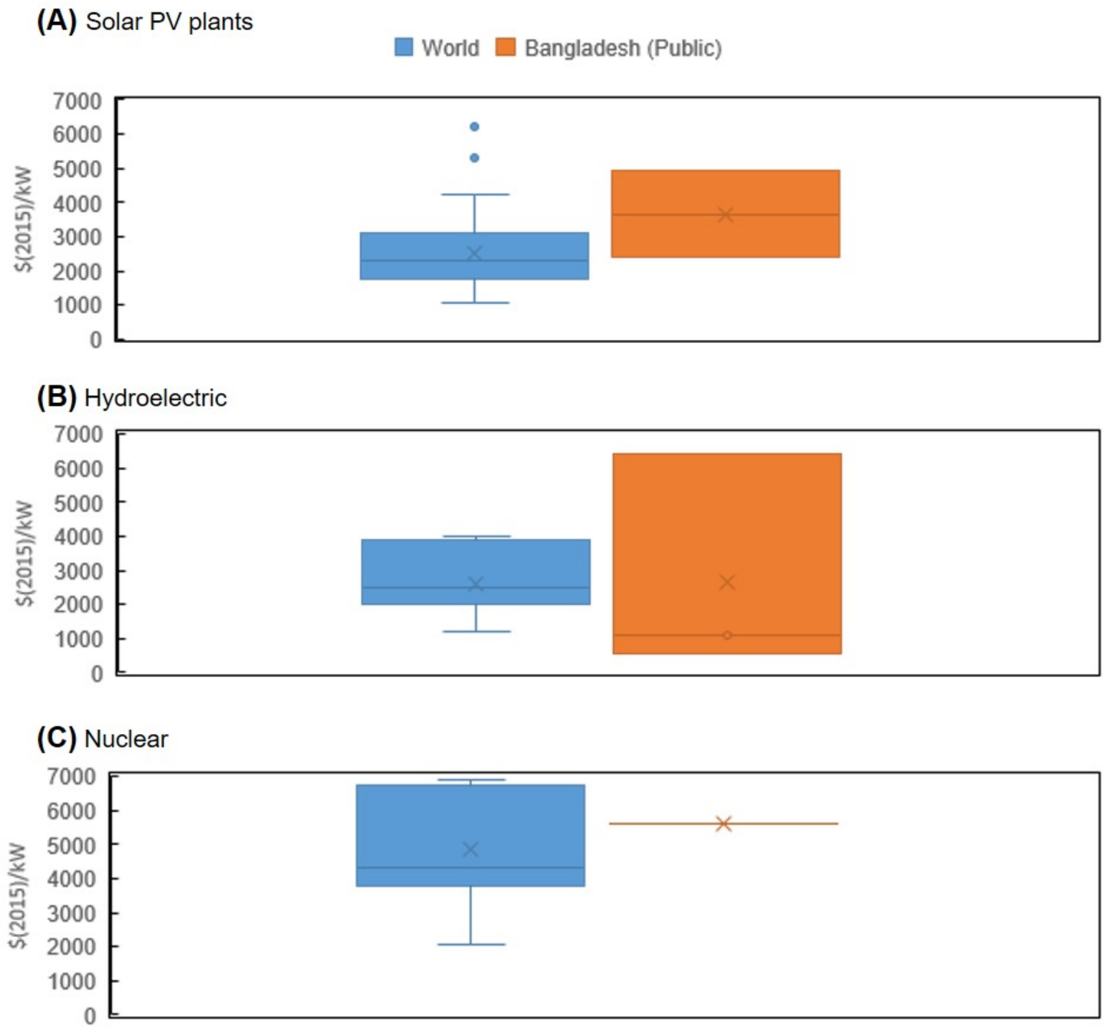

Figure 3.2: Capital cost comparison among nuclear and renewable power plants from different country/regions with Bangladesh. In the case of solar PV plants, mean capital cost of Bangladesh is lower than the world mean. However, the installed capacity is only 12 MW. Mean capital cost for hydroelectric plants is also lower than that of global mean capital cost. The reason behind this lower cost is the later units were in the same plant side, which reduced the ancillary cost. For nuclear only one plant is going to be built in Bangladesh by 2030 and its cost would be significantly higher than that of the world mean capital cost.

Table 3.3: The capital cost of power generation plants in the World and Bangladesh. Power plants in Bangladesh are further disaggregated into public and private. Historical and projected costs are rounded to the nearest US$(2015).

Fuel	**Technology**	**Capital cost (US$(2015)/kW)**														
		World				**Bangladesh (public)**				**Bangladesh (private)**				**Difference in Mean**		
		Min	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Min**	**Max**	**Mean**	**SD**	**Public & Private**	**World & Public**	**World & Private**
Natural gas, oil	Gas turbine (GT)	361	741	551	190	680	1823	1177	336	545	1495	819	235	258	-626	-268
	CCPP*	568	1381	974	407	545	3005	1164	505	560	848	704	144	460	-189	270
Coal	Subcritical	619	2168	1394	774	1245	1924	1584	479						-191	
	Ultra-supercritical	826	2374	1600	774	2867	3820	3343	477						-1743	
Renewable	Solar PV*	1910	6198	4054	2144	2391	4907	3649	1258						405	
	Hydro-electric*	1755	3977	2866	1111	543	6409	2676	2648						190	
Nuclear	Nuclear**	2065	6883	4474	2409		5625	5625								

* CCGT, Solar photovoltaics - Large-scale and Hydropower - large-scale in International Energy Agency's (IEA) World Energy Investment Outlook 2014 (IEA, 2014).

** There is only one planned nuclear power plant in Bangladesh. Caution should, therefore, be applied when interpreting the difference in mean.

3.3 Cost evolution

The cost evolution in Bangladeshi public and private plants do not follow the same trend. The cost of most of the power generation technology in the world reduces with time (Neij, 2008). However, in the Bangladeshi public plants, the cost appears to be increasing (Figure 3.3). Among the operational power plants, GT, ST and CCPP have been generating the most of electricity in Bangladesh in the last three decades in both public and private sectors. For the cost evolution analysis, the relatively new or less utilized technologies (subcritical, ultra-supercritical and hydro) are not considered. Solar PV, nuclear are new technologies compared to CCPP or GT in Bangladesh. The capital cost trend of CCPP is following a second order polynomial and augmenting after 2010. In the case of the similar technology, the private sector is showing a linear descending trend with only two data points. Establishing cost of public GT/ST trend is third order polynomial and increasing after 2014. However, private power plants with similar technology, demonstrating a second order polynomial trend with a reduction in cost.

Independent-samples t-test was conducted to compare the capital cost in public and private owned power plants. The cost of GT/ST and CCPP technologies were considered for the tests. In the case of GT/ST, there was a significant difference in the capital cost of public (M=1226.09, SD=360.62) and private (M=751.68, SD=108.80) owned power plants; $t(11.97)=4.16$, $p=0.001$. These results suggest that GT/ST power plant ownership depending on being public and private influences its capital cost. The test results suggest that public power plants have higher capital cost. In the case of CCPP, there was not a significant difference in the capital cost of public (M=1075.33, SD=263.21) and private (M=704, SD=203.60) owned power plants; $t(19)=1.92$, $p=0.070$. These results suggest that CCPP power plant ownership depending on being public and private does not influence its capital cost. However, the private CCPP power plants number was only two. With more data points in the future, this analysis may be improved.

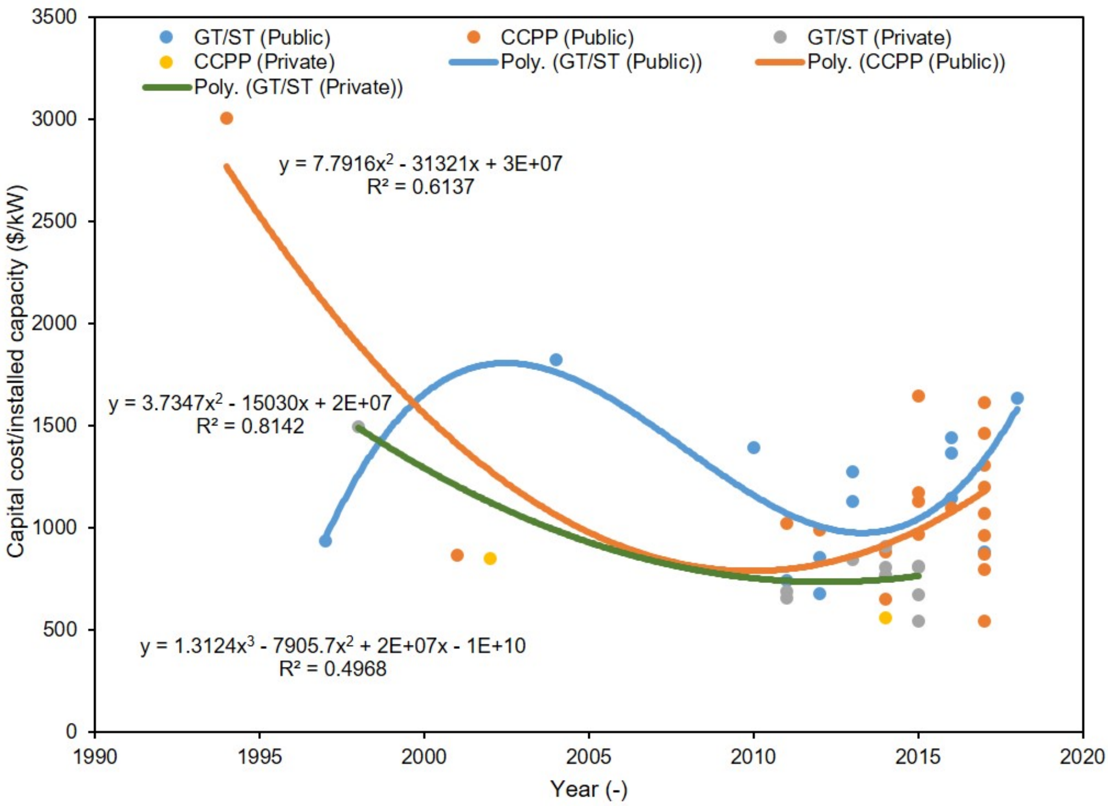

Figure 3.3: Cost evolution of different power generation technologies. In the case of coal, one subcritical power plants and two future ultra-supercritical ones not sufficient to see the cost evolution. For hydroelectric, solar PV and nuclear, the power plant numbers are insufficient for analysis of learning rate or cost evolution. Under these circumstances, highly utilized technologies such as gas turbine/engine and CCPP for public and private power plants were analyzed for cost evolution.

3.4 Effect of corruption on cost of power plants

Several reports and articles suggested that there has been significant evidence of corruption in electricity generation projects and operations, as well as in distribution system in Bangladesh (Khan and Rasheduzzman, 2013; TIB, 2016; Khan, 2007; Kenny, 2007; D'costa, 2012; IBP, 2012; Ruth, 2002; Hossain and Tamim, 2005/06). The measurement of corruption is complicated as it depends on complex variables (Galtung, 2006). Therefore, no single source or polling method has yet been developed that can provide a convincing methodology (Lambsdorff, 2006). Transparency International started CPI score for different countries in 1995 to put the issue of corruption on the international policy agenda (TI, 2017). For this study, CPI score for Bangladesh was adopted to be analysed with the capital cost of power plants in the same year to examine the effect of corruption on cost evolution. Before 2012, CPI scores were ranked 0-10. However, the scale was amended in 2012 to the range of 0-100, to demonstrate the better effect of corruption on the economy of a country (TI, 2012). The CPI scores before 2012 were converted to 0-100 scale by multiplying 10 with the scores to compare the data from 2004-16. Higher CPI score is interpreted as lower corruption, which may result in reduced capital cost and vice versa (Figure 3.4A&B). Only 42 public and private power plants (among studied 61) cost data, which were built within 2004-16, were found and analyzed in this correlation study. The cost data scarcity worked as a limitation in rendering a detailed relationship. With increased data available in the future, the correlation may improve. Independent-samples t-test was conducted to compare the capital cost in public and private owned power plants. There was a significant difference in the capital cost of public (M=1156.20, SD=332.40) and private (M=734.26, SD=118.29) owned power plants; $t(40)=4.09$, $p=0.000$. These results suggest that being public and private owned influences its capital cost. The test results suggest that public power plants have higher capital cost.

To assess the relationship between the CPI score and the capital cost of power plants in Bangladesh, Pearson's test for normally distributed interval data was conducted. There was a negative correlation between the two variables, $r = -0.477$, $n = 42$, $p = 0.001$ (Table 3.4). Figure 3.5 summarizes the results and demonstrated that corruption in Bangladesh is negatively related to a capital cost of power plants

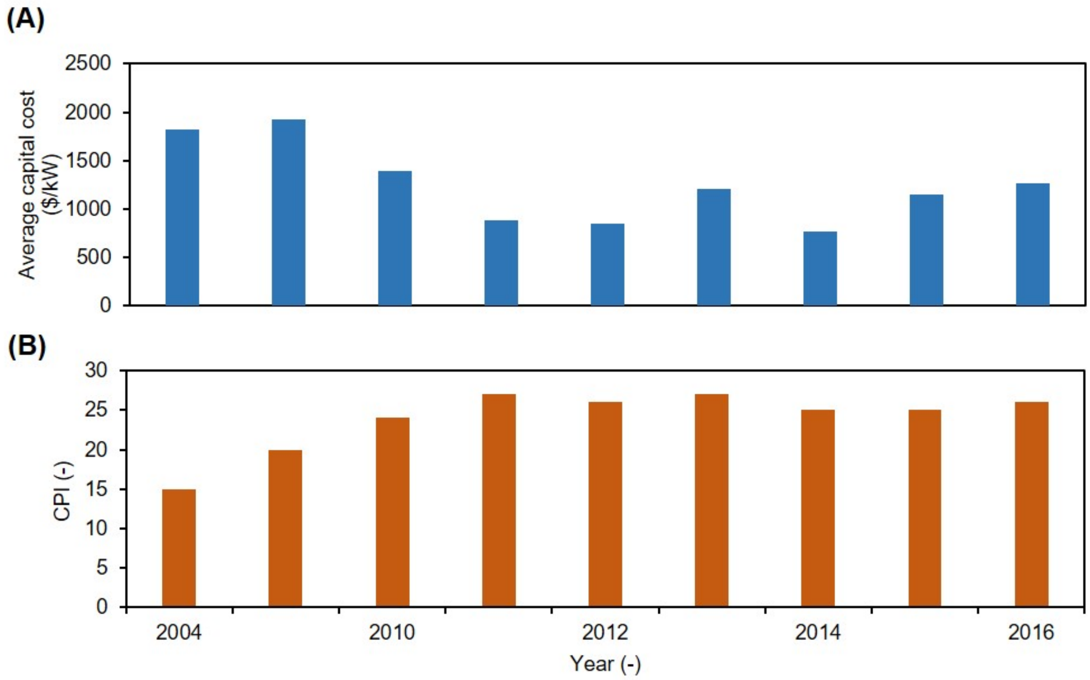

Figure 3.4: (A) Average capital cost (2004-2016) and (B) CPI score (2004-2016). Chart 'B' is demonstrating that CPI index is not gradually reducing. Moreover, the average capital cost of power plants is related to the change of CPI score. Here, higher CPI score means lower corruption.

with R^2=0.32 for annual CPI scores. Overall, there was a strong, negative correlation between corruption and capital cost of power plants. Decreases in corruption (increase in annual CPI score) were correlated with increased capital cost of power plants. Corruption is a continual socio-economic phenomenon traversing through years from megaproject construction and operation. CPI score represents an annual performance of a country. Whereas the power plant megaproject constructions usually go on for 2-7 years (GoB, 2015a). Furthermore to the Pearson's correlation test between annual CPI score and capital costs, additional correlation study was undertaken in this research to explore the relationship of the cost with biannual, triannual and quadrennial average CPI scores. The main objective of the study was to examine the correlation between different temporal CPI scores and capital costs. Table 3.4 summarizes the results. Figure 3.5 illustrated that the correlation R^2 value was better between the biannual CPI score and capital cost. However, the Pearson's correlation test showed that the best relationship was between the annual CPI scores and capital costs as the p-value was the lowest (Table 3.4).

The upper and lower limits of cost reduction per CPI score increase were \$116.94

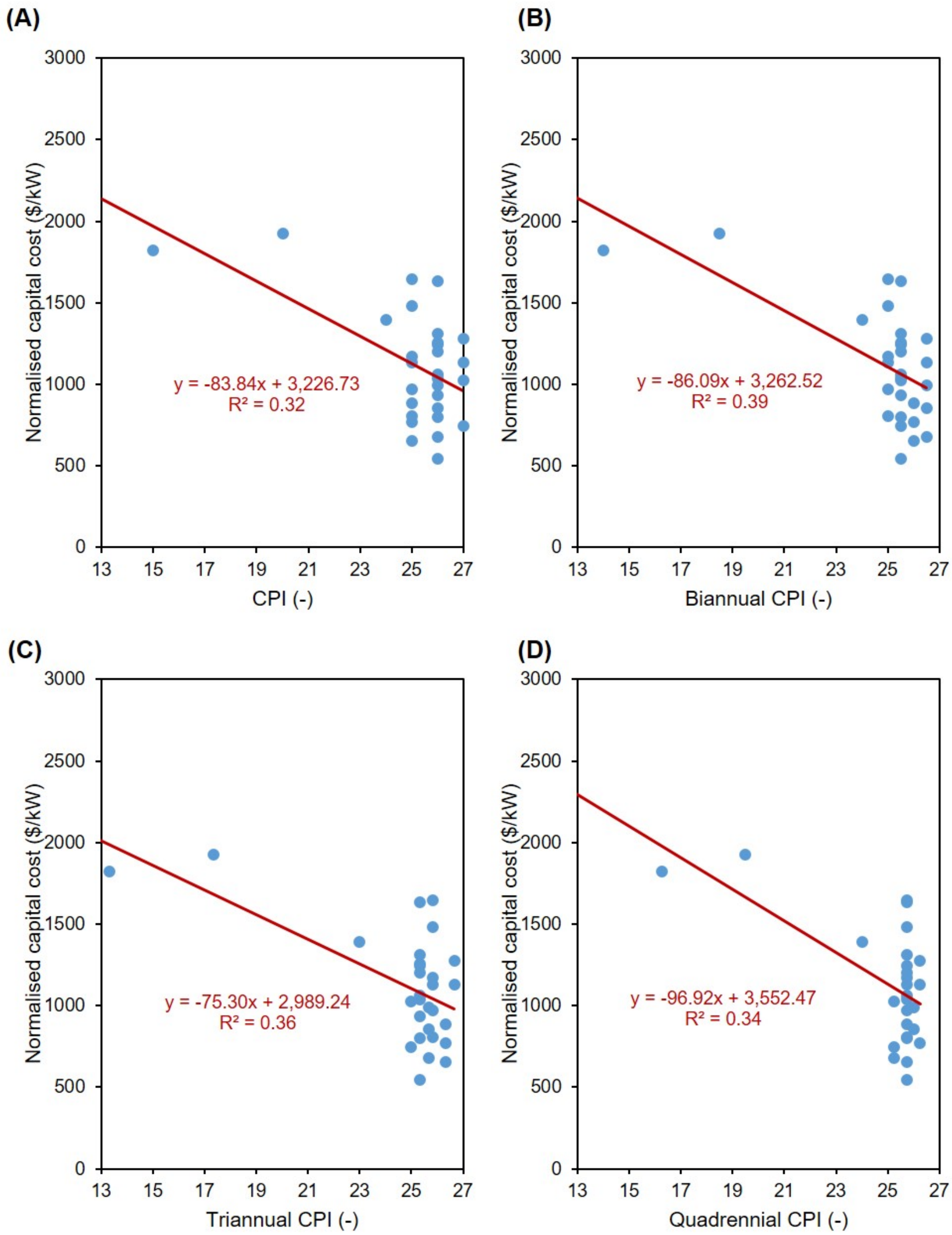

Figure 3.5: Corruption vs. capital cost analysis for Bangladeshi power plants; (A) Normalized capital cost vs. average annual CPI scores, (B) Normalized capital cost vs. average biannual CPI scores, (C) Normalized capital cost vs. average triannual CPI scores, and (D) Normalized capital cost vs. average quadrennial CPI scores.

Table 3.4: Pearson correlation test between CPI score and capital cost per installed capacity of power plants in Bangladesh

		Annual CPI (-)	**Biannual average CPI (-)**	**Triannual average CPI (-)**	**Quadrennial average CPI (-)**
Capital cost (\$/kW)	**Pearson Correlation**	-.565**	-.445**	-.430**	-.396**
	Sig. (2-tailed)	.001	.003	.004	.010
	N	42	42	42	42
**. Correlation is significant at the 0.01 level (2-tailed)					

/kW and \$45.47 /kW respectively. In some cases, the capital cost of public plants was two times higher than that of the private ones for the similar technology and time frame. Therefore, Bangladesh can reduce their cost of establishing power plants by reducing corruption. The power plant projects are expensive, and the government takes 66-94% (GoB, 2015a) of the total cost of loans from banks and aid organizations such as World Bank, Asian Development Bank. Higher capital cost means a more significant loan from funding bodies, which the government have to repay in the future from the revenues. Larger repayment can put pressure on the economy and people.

One of the reasons behind this significant corruption was the lack of governance in the energy sector. Implementing 'Quick Enhancement of Electricity and Energy Supply (Special Provisions) Act, 2010' enabled the government and responsible departments with authority to take rapid energy development initiatives while bypassing the 2006 public procurement law, with easy and quick procurement procedure for investing in the energy sector outside the bar of jurisdiction of the court (GoB, 2016). Laws such as 'Quick Enhancement of Electricity and Energy Supply (Special Provisions) Act, 2010' raised significant concern regarding transparency allowing enhanced scope for corruption among the donors (Choudhury *et al.*, 2010). The findings of this study suggest that the corruption may have influenced the higher cost of power plants in the past and increased after the implementation of the special provisions act (2010).

3.5 Summary

As a rapidly developing economy, Bangladesh has been establishing and will continue to build more power plants to support the growing demand for electricity. Literature suggested that there is a lack of research on the cost analysis of the rapidly growing energy sector in Bangladesh; partially because of the data inadequacy and lack of transparency in the government. Initially, a cost database was compiled from different resources for this study. For analyzing the cost of installing power plants in Bangladesh, the cost (public and private) data were compared with the world. The results demonstrated an intriguing aspect of a rapidly developing economy. Most of the public plants showed higher capital cost compared to the world average. Also, the cost of similar power generation technologies in private and public sector has a significant difference in Bangladesh. On top of the higher capital cost, the cost evolution demonstrated that cost of establishing public power plants is augmenting with time, whereas its opposite in private sector as well as in the world. In the case of expanding cost, the analysis of this chapter showed a significant correlation between corruption and higher cost of power plants. Higher corruption may increase the cost of a power plant in a developing context such as Bangladesh.

This chapter renders the opportunity to focus on the amendable condition of corruption within the governmental system to reduce the cost of establishing public power plants in Bangladesh. The government should implement more transparent and supervised system for establishing power plants to reduce the adverse influences of corruption on the megaprojects. Otherwise, there is a possibility the expensive power plants would become into 'white elephant' projects (Ross and Staw, 1993; Lewis and Williams, 1985), where the output is smaller than that of investment. The higher cost would impose an additional burden on the future economy.

Chapter 4

Energy planning models

Energy planning models (EPMs) play an essential role in the development of the energy sector at global, national and regional levels by enabling informed decision-making. EPMs are especially crucial as significant investments in innovative energy research and planning are required for decarbonisation (Amorim *et al.*, 2014). The development of EPMs started in the late 1950's and early 1960s (Sterner, 2012) but intensified after the oil crisis of the 1970s in light of the realization of the effects of exogenous political events on global and national energy supply (Barsky and Kilian, 2004). It was necessary, then, to critically assess the interrelationships between the sources of energy supply and demand, as well as to identify pathways for long-term development of the energy sector (Craig *et al.*, 2002). The drive for global sustainability in the 1990s –spurred in particular by the Rio Earth Summit in 1992 and the 1995 report of the Intergovernmental Panel on Climate Change (IPCC) (IPCC, 2002)–brought forward the issue of GHG emissions and their impact on the environment. As a result, further models were developed for projecting climate change and investigating the environmental impact and its mitigation. However, given that some two-thirds of global GHG emissions come from the electricity, heat, and transportation sectors (IEA, 2015), the integration of the environmental aspects of energy demand and supply within EPMs became necessary, providing a comprehensive picture of the interrelationships between energy, environment, and climate change.

Over the past four decades, a substantial number of EPMs have been developed by researchers and organizations in different countries, with various objectives and scopes. EPMs range from the holistic – modeling the partial or whole energy system of a country, region or the world – to the more sectoral – providing projections of the energy needs of, for example, transportation or industry. Given that the IEA estimates the growth in energy demand over the next 23 years will be higher in developing Asian countries than the rest of the world (IEA, 2017b) and future emissions from growth regions will be critical in the current 1.5°C temperature discourse (Pachauri *et al.*, 2014), it is essential to understand how EPMs reflect the challenges being faced by decision-makers in different parts of the world.

Previous work has reviewed EPMs of different types. Suganthi and Samuel (2012) categorised energy demand projection models based on their methods but misclassified bottom-up and top-down approaches. Bhattacharyya and Timilsina (2010) analysed available EPMs for application in developing countries but did not present details on relevant socio-economic parameters and their effect on policies. Pfenninger *et al.* (2014) categorised EPMs into four types: energy system optimization; energy system simulation; power system and electricity market and qualitative and mixed methods. They recommended further development and integration of innovative approaches into EPMs to address the complex interactions among disciplines such as social science, ecology, finance, and behavioural psychology. Urban *et al.* (2007) analysed twelve EPMs to investigate their suitability for developing contexts and suggested that critical characteristics of developing countries such as the informal economy and supply shortages were overlooked. The study identified a bias towards industrialised countries in the EPMs, yet specifics were not offered on socio-economic drivers such as political stability (or lack thereof) and corruption in energy markets in developing contexts.

In light of this, there is a lack of evidence-based analysis of contextual variations, model structures, and relevant emerging socio-economic variables for EPMs in the developing world context. To that end, thirty-four current, highly used, macro-level EPMs were reviewed to investigate their applicability and deficiency for energy systems in developing countries. Our focus is on the factors that affect the demand and supply of energy, as well as the rational development of the energy sector in a developing country.

4.1 Typology and structure of energy planning models

A meta-analysis of published literature on EPMs was conducted. The study focuses on models predominantly used for the planning of energy systems and infrastructures and that are more strategic, as opposed to operational. First, a preliminary study was conducted to gather an overview of the topics related to EPMs that resulted in the identification of two main themes: energy demand and supply; and energy information and emission models. Electronic databases namely Google Scholar, ScienceDirect, JSTOR, IEEE Xplore, Scopus, Web of Science and other official websites with energy databanks specifically United Nations (UN), World Bank, International Monetary Fund (IMF), International Energy Agency (IEA), Energy Information Administration (EIA) were searched for relevant publications using the keywords listed in Table 4.1. The keywords were categorised into five-word groups, which were combined using the Boolean operator 'AND', e.g. 'Energy planning model' AND 'Forecasting' AND 'Input variables' AND 'Organization' AND 'Global'. Based on the search and the available literature, thirty-four models developed by international organizations or institutions were selected for analysis (Table 4.2). In addition to the published journal articles and books, manuals of different models were investigated to explore their structure and key components. The reviewed models were categorized based on model objectives to contextualise the subsequent analysis and discussion. Model structures were then analysed to investigate their relevance and deficits in developing contexts. For the categorization by model objective, four categories were used: energy information systems, energy demand-supply, energy-economic and energy emissions models. Table 2 illustrates EPM types, and their inputs, outputs, and underlying methods. Five characteristics of input variables were analysed: qualitative, quantitative, financial, aggregated and disaggregated. Although financial data are typically classed as 'quantitative', based on the extensive use of these variables in different models it was deemed worthwhile to include them as a separate characteristic. The underlying methods were categorised into accounting framework, regression, optimization, econiomic, simulation, and equilibrium methods. Output variables were classified into energy, emissions, and cost measures.

Table 4.1: Searched keywords and associated groups

Model	**Objective**	**Components**	**Origin of development**	**Geographical applicability**
Energy planning	Forecasting	Input variables	Organization	Global
Energy information	Projection	Estimation methods	Country	Regional
Energy economic	Demand and Supply; Demand; Supply	Output variables		Country
Energy supply and demand	Economic			
Energy supply	Emission control			
Energy demand				
Emission reduction				

Among the analysed 34 models, quantitative and financial data are utilized in 34 and 32 models respectively. 27 models used disaggregated data as input variables. In the case of the output variables, most of the model's outputs are energy (30 models), emission (29 models), and cost (28 models). Model outputs are often normalised; e.g. cost/GDP, cost/capita, cost/generation, and emissions/GDP. Reviewed models adopted different underlying methods for estimation and projection. Optimization methods are widely utilized (13 models), followed by simulation (11 models) and economic (10 models) methods. Optimization methods are mostly applied to energy demand and supply, and economic models.

EPMs have three common components and a basic work flow: input variables $\rightarrow$ underlying estimation/projection methods $\rightarrow$ output variables. Key variations, however, lie in the type, resolution (temporal and spatial), scope and time frame of the input and output variables. Model objectives and the nature of the data most often determine the choice of estimation/projection methods.

Primary input variables in the studied EPMs are quantitative, financial and disaggregated. EPMs are numerical models and utilize quantitative data for calculation. Qualitative parameters are typically interpreted as ordinal data for modeling purposes. While modeling energy infrastructure in a holistic approach to cover a broader context, the supply, demand and socio-economic sectors require disaggregated data for a better interpretation of the existing systems.

Table 4.2: Characteristics of existing energy planning models

Model	Input variables*					Method†						Output variables‡			Total	Ref.
	Qul	Qua	Fin	Agg	Dagg	RE	OP	EC	SM	EQ	AF	En	Em	Co		
Energy information system																
E3		✓	✓						✓			✓	✓	✓	6	LBST (2008)
CO_2DB		✓	✓						✓				✓	✓	5	Strubegger (2003)
Energy economic model																
MAM		✓	✓	✓				✓††						✓	5	EIA (2014)
MARKAL-MACRO		✓	✓	✓	✓		✓	✓‡‡		✓		✓	✓	✓	10	Manne and Wene (1992)
MICRO-MELODIE		✓	✓	✓	✓		✓	✓‡‡				✓	✓	✓	9	Van Beeck (1999)
TIMES-MACRO		✓	✓	✓	✓		✓	✓‡‡				✓	✓	✓	9	Remme and Blesl (2006)
Energy demand-supply model																
DECPAC		✓	✓	✓			✓		✓			✓	✓	✓	8	IAEA (2003)

Table 4.2: Characteristics of existing energy planning models

Model	Input variables[*]					Method[†]						Output variables[‡]			Total	Ref.
	Qul	Qua	Fin	Agg	Dagg	RE	OP	EC	SM	EQ	AF	En	Em	Co		
IKARUS	✓	✓	✓	✓	✓		✓		✓			✓	✓	✓	10	Martinsen *et al.* (2004)
ENPEP		✓	✓	✓	✓			✓[‡‡]		✓[**]		✓	✓	✓	9	Van Beeck (1999); Sahir and Qureshi (2006)
LEAP		✓	✓	✓	✓			✓[††]	✓		✓	✓	✓	✓	10	Heaps (2012); Takase and Suzuki (2011); Cai *et al.* (2008)
POLES		✓	✓		✓			✓[††]		✓		✓	✓		7	Kitous (2006)
MESSAGE-III		✓	✓		✓		✓					✓		✓	6	Messner *et al.* (1996)
WASP		✓	✓		✓	✓	✓					✓		✓	7	IAEA (2001)

Table 4.2: Characteristics of existing energy planning models

Model	Input variables*					Method†						Output variables‡			Total	Ref.
	Qul	Qua	Fin	Agg	Dagg	RE	OP	EC	SM	EQ	AF	En	Em	Co		
MARKAL		✓	✓		✓		✓					✓	✓	✓	7	Loulou *et al.* (2004)
TIMES		✓	✓		✓		✓					✓	✓	✓	7	Loulou *et al.* (2005)
MEDEE		✓	✓		✓	✓					✓	✓			6	MacKenzie (1982)
MAED		✓			✓	✓						✓			4	IAEA (2006)
NEMS		✓	✓		✓		✓					✓	✓	✓	7	EIA (2009)
ENERPLAN		✓						✓††	✓			✓	✓		5	Van Beeck (1999); Sahir and Qureshi (2006)
MESAP		✓	✓	✓	✓		✓	✓††	✓		✓	✓	✓		10	Van Beeck (1999)
Energy emissions model																
UK 2050	✓	✓	✓		✓				✓			✓	✓	✓	8	DECC (2013)

Table 4.2: Characteristics of existing energy planning models

Model	**Input variables***					**Method†**						**Output variables‡**			**Total**	**Ref.**
	Qul	**Qua**	**Fin**	**Agg**	**Dagg**	**RE**	**OP**	**EC**	**SM**	**EQ**	**AF**	**En**	**Em**	**Co**		
BD 2050	✓	✓	✓		✓				✓			✓	✓		7	BD2050 (2015)
MESAP PlaNet		✓	✓		✓	✓			✓			✓	✓	✓	8	Schlenzig and Steidle (2001); Schlenzig (1999)
EFOM-ENV		✓	✓		✓	✓	✓					✓	✓	✓	8	Van Den Broek *et al.* (1992)
IMAGE		✓	✓		✓	✓							✓	✓	6	Stehfest *et al.* (2014)
AIM		✓	✓		✓	✓						✓	✓	✓	7	Kainuma *et al.* (1999)

Table 4.2: Characteristics of existing energy planning models

Model	Input variables*					Method†						Output variables‡			Total	Ref.
	Qul	**Qua**	**Fin**	**Agg**	**Dagg**	**RE**	**OP**	**EC**	**SM**	**EQ**	**AF**	**En**	**Em**	**Co**		
ASF		✓	✓						✓				✓	✓	5	Sankovski *et al.* (2000)
GREEN		✓	✓		✓					✓		✓	✓	✓	7	Burniaux *et al.* (1992); Weyant (1993)
ERM		✓	✓		✓					✓		✓	✓	✓	7	Dean and Hoeller (1992)
IEA		✓	✓		✓			✓††				✓	✓	✓	7	Dean and Hoeller (1992)
CRTM		✓	✓		✓					✓		✓	✓	✓	7	Weyant (1993); Dean and Hoeller (1992)

Table 4.2: Characteristics of existing energy planning models

Model	Input variables*					Method†						Output variables‡			Total	Ref.
	Qul	**Qua**	**Fin**	**Agg**	**Dagg**	**RE**	**OP**	**EC**	**SM**	**EQ**	**AF**	**En**	**Em**	**Co**		
MR		✓	✓		✓		✓					✓	✓	✓	7	Dean and Hoeller (1992)
WW		✓	✓		✓					✓		✓	✓	✓	7	Dean and Hoeller (1992)
SGM		✓	✓	✓		✓						✓	✓	✓	7	Brenkert *et al.* (2004)
Total	3	34	32	10	27	8	13	10	11	7	3	30	29	28		

* Input types: Qul (qualitative) Qua (quantitative), Fin (financial), Agg (aggregated) and Disag (disaggregated).

† Methods:RE (regression), OP (optimization), EC (economic – econometric, macroeconomic), SM (simulation), EQ (equilibrium) and AF (accounting framework)

‡ Output types: En (energy–demand and/or supply), Em (emissions) and Co (cost).

** Economic equilibrium

†† Econometric

‡‡ Macroeconomic

In the case of underlying methods, optimization was utilized in fourteen models because they would create an optimization loop as a way of testing whether the selected output satisfies the defined constraints. In some models, especially energy demand and supply models, the primary objective is to find the least cost solution for the energy market. Optimization methods in such models would render the opportunity to test different policies against the least cost option. However, simulation methods were also utilized in a significant number of models.

4.2 Deficiencies in existing EPMs

Most EPMs, if not all, were constructed in developed countries (Table 4.3) and considered their energy systems, economic assumptions, and the extent to which GHG emissions need to be reduced. While CO_2 emissions per capita in high-income countries are decreasing, they are increasing in the developing upper-middle and middle-income countries, whose primary objective often is to improve access to convenient forms of energy. Table 4.3 demonstrated that some EPMs such as ENPEP, LEAP, POLES, WASP, MARKAL, MAED and 2050 models were widely adopted than others. The major decision making behind the EPM selection for adopting in developing countries may depend on the availability of expertise of model development, complexity level of modeling, and recommendations from the donor organizations or consultants. Despite the fact that some EPMs have been widely adopted for energy system planning in developing countries, they lack consideration of a substantial number of issues affecting developing contexts; e.g. the effects of a lack of innovation, and the varying nature of privatisation, decentralisation and competition in the energy industry(Pandey, 2002). Policy priorities in EPMs need to be more country-specific or regional, because of the differences in objectives due to the common socio-economic vulnerability or conditions, and geographical and climatic characteristics. Indicators relevant to most developing economies include(Pandey, 2002): issues regarding resource management; assessment of energy alternatives; the economic and technical challenges associated with the transformation of the energy infrastructure from a centralised one to an intelligent and decentralised one; and financial vulnerabilities in households. Addressing these in EPMs is necessary to provide higher reliability of estimates.

Table 4.3: Origin and use of EPMs

Model	**Developer**	**Country of origin**	**Applied/ adopted in developing countries**	**Number of countries applied/ adopted**	**Ref.**
E3 Database	Ludwig-Bolkow-Systemtechnik GmbH	Germany	N/A		LBST (2008)
CO_2DB	International Institute for Applied Systems Analysis (IIASA)	Austria	N/A		Strubegger (2003)
DECPAC	International Atomic Energy Agency (IAEA)	Austria	N/A		IAEA (2003)
IKARUS	Former German Federal Ministry of Education, Science, Research, and Technology (BMFT)	Germany	N/A		Martinsen *et al.* (2004)
MAM	U.S. Department of Energy	USA	N/A		EIA (2014)
MARKAL-MACRO	Brookhaven National Laboratory	USA	Yes		Manne and Wene (1992)

Table 4.3: Origin and use of EPMs

Model	**Developer**	**Country of origin**	**Applied/ adopted in developing countries**	**Number of countries applied/ adopted**	**Ref.**
MICRO-MELODIE	The Commissariat à l'énergie atomique et aux énergies alternatives (CEA)	France	N/A		Van Beeck (1999)
TIMES- MACRO	The Energy Technology Systems Analysis Program (ETSAP), International Energy Agency (IEA)	France	N/A		Remme and Blesl (2006)
ENPEP	International Atomic Energy Agency (IAEA)	Austria	Yes	60	IAEA (2014)
LEAP	Stockholm Environmental Institute, Boston	USA	Yes	190*	SEI (2017)

Table 4.3: Origin and use of EPMs

Model	**Developer**	**Country of origin**	**Applied/ adopted in developing countries**	**Number of countries applied/ adopted**	**Ref.**
Mesap PlaNet	Institutes für Energiewirtschaft und Rationelle Energieanwendung (IER), University of Stuttgart	Germany	N/A		Schlenzig and Steidle (2001)
EFOM-ENV	Institut Economics et Juridigue de l'Energie (IEJE)	France	Yes	20	CEERD (2017)
POLES	First developed by CNRS (France) and now by CNRS / UPMF university, Enerdata, and IPTS (Spain, European Commission research center)	France	Yes	57*	Enerdata (2012)
MESSAGE-III	International Institute for Applied System Analysis (IIASA)	Austria	Yes		Munasinghe and Meier (1993)

Table 4.3: Origin and use of EPMs

Model	**Developer**	**Country of origin**	**Applied/ adopted in developing countries**	**Number of countries applied/ adopted**	**Ref.**
WASP	International Atomic Energy Agency (IAEA)	Austria	Yes	100	IAEA (2014)
MARKAL	International Energy Agency (IEA)/ ETSAP	France	Yes	70*	Munasinghe and Meier (1993); Giannakidis *et al.* (2015)
MEDEE	Institut Economics et Juridigue de l'Energie (IEJE), Grenoble	France	Yes		CEERD (2017)
MAED	International Atomic Energy Agency (IAEA)	Austria	Yes	40	IAEA (2006)
NEMS	U.S. Department of Energy	USA	N/A		EIA (2009)

Table 4.3: Origin and use of EPMs

Model	**Developer**	**Country of origin**	**Applied/ adopted in developing countries**	**Number of countries applied/ adopted**	**Ref.**
ENERPLAN	Tokyo Energy Analysis Group	Japan	Yes		Munasinghe and Meier (1993)
MESAP	Institutes für Energiewirtschaft und Rationelle Energieanwendung (IER), University of Stuttgart	Germany	Yes		Voß *et al.* (1994)
UK 2050	Department of Energy & Climate Change (DECC)	UK	Yes	24*†	DECC (2014a)
IMAGE	PBL Netherlands Environmental Assessment Agency/ Utrecht University	Netherlands	N/A		Stehfest *et al.* (2014)

Table 4.3: Origin and use of EPMs

Model	**Developer**	**Country of origin**	**Applied/ adopted in developing countries**	**Number of countries applied/ adopted**	**Ref.**
AIM	National Institute of Environmental Studies (NIES)	Japan	N/A		Kainuma *et al.* (1999)
CRTM	Joint Center for Satellite Data Assimilation (JCSDA)	USA	N/A		Dean and Hoeller (1992)
SGM	Pacific Northwest National Laboratory (PNNL) and is maintained by the PNNL Joint Global Change Research Institute (JGCRI)	USA	N/A		Brenkert *et al.* (2004)

Table 4.3: Origin and use of EPMs

Model	**Developer**	**Country of origin**	**Applied/ adopted in developing countries**	**Number of countries applied/ adopted**	**Ref.**

*Including all the countries that utilized the specific model

† Several 2050 pathways models have been constructed for the following developing countries: Vietnam, Bangladesh, Thailand, Nigeria, Mexico, Mauritius, Indonesia, India, Colombia, China and Brazil. These models are roughly based on the principles of UK2050 Pathways (DECC, 2014b), albeit with some minor country-specific additions. Except BD2050, where electricity consumption is modelled against various scenarios of GDP and population growth, all models lack the consideration of socio-economic parameters. Political instability, corruption, suppressed demand and climate change effects are not modelled in any of these developing country pathways.

In the following sections, the issue of suppressed demand in developing countries is analysed, followed by a discussion of the difference in socio-economic characteristics such as corruption and political stability, as well as their effect on the economy. Subsequent sections explore the impact of data inadequacy on the development of EPMs and the impact of climate change, focusing on the effect of energy planning on land development and food production, as well as the role of extreme weather events. Finally, the impact of poor characterisation of variables on EPMs is discussed.

4.2.1 'Suppressed' demand in developing countries

Suppressed demand refers to the incapability of the people or community or nation to meet minimum services levels (MSL) necessary for human development (CC-NUCC, 2012), such as clean and safe drinking water and adequate energy for cooking and lighting because of some host barriers (Gavaldão *et al.*, 2013). Barriers can be a lack of infrastructure, low technology penetration, and poverty, particularly the high costs of energy services compared to household incomes (Spalding-Fecher, 2015). Energy infrastructure barriers such as the lack of access to grid electricity can lead to minimal or no use of electrical appliances. The barriers can also interact to produce a situation where the population cannot afford energy for basic needs because of low income and high unit cost. On the other hand, studies show that the reduced unit cost often results in higher demand for energy. For example, the transition from kerosene to electric lighting in developing countries reduced the unit cost of light by more than 90% but augmented the consumption of lighting services (lumens) by a factor of 40 (Spalding-Fecher, 2015; Barnes *et al.*, 2002; IEG, 2008). In the case of the technology barrier, the penetration of specific technology among the population can be hindered by the higher initial cost. This cost can be compensated by high income and policy incentives (such as tax reduction on the technology or subsidies) by governments.

Emissions from developing countries are much lower than the global average because of suppressed energy demand. Energy consumption of many household needs, such as heating and cooking, and lighting, may not reflect the real demand. Additionally, suppressed electricity demand is hard to register in developing countries, for example- when the household have greater buying capacity how much the electricity demand is going to be increased is complex to model for developing contexts. Therefore, there is a lack of consideration of suppressed demand in EPMs which can result in an inaccurate estimation of baselines for Clean Development Mechanism (CDM) projects (UNFCCC, 2017). More specifically, CDM rules state that 'the baseline may include a scenario where future anthropogenic emissions by sources are projected to rise above current levels, due to the specific circumstances of the host Party' (UNFCCC, 2001). However, a UNFCCC report (paragraph 35 of Decision 2/CMP.5 (UNFCCC, 2010)) encouraged the CDM Executive Board 'to further explore the possibility of including in baseline and monitoring methodologies, as appropriate, a scenario where future anthropogenic emissions by sources are projected to rise above current levels due to specific circumstances of the host Party'. These guidelines explicitly differentiate energy contexts between developed and developing countries. None of the reviewed EPMs considered the CDM guidelines, which may increase error in future energy planning strategies for developing contexts.

4.2.2 Difference in socio-economic characteristics

Developed countries have different socioeconomic attributes than those of developing countries. The literature suggests that political instability affects the economic growth of a country(Alesina *et al.*, 1996), especially GDP growth(Aisen and Veiga, 2013). The rate of change of stability is lower in developed countries that are often characterised by steady GDP growth (Figure4.1a-e). However, all developing countries do not necessarily demonstrate a similar association between GDP growth and political stability, which varies substantially (Figure4.1f-j). There are also exceptions. Despite the negative progression of political stability, some countries have positive GDP growth (e.g. Japan, Germany, Philippines, and Bangladesh). Developed economies mostly maintain steady progress on the positive side of the political stability scale (that is, they have a political stability score of 0 to 2.5), while the same parameter is on the negative side of the scale in most of the developing countries (that is, the score ranges from 0 to -2.5). In most developed country EPMs, GDP is the only socio-economic parameter for demand projection. Considering GDP growth or GDP volume alone is thus unlikely to represent the nuances of the economic structure of a developing country. More integrative modeling is, therefore, required for predicting future energy demand while accounting for the structural changes in the economy. The increasing share of industry and services in the economic output with a corresponding rise in energy use and emissions in developing countries has the potential to further augment world GHG emissions, despite the decreasing trend for emissions in high-income countries.

Along with the stage of economic development, the intensity and distribution of economic activities influence a country's energy consumption. The analysis of GDP per capita against electricity consumption in Figure 4.2 shows a positive relationship; i.e. electricity consumption increases with the growth in GDP. The coefficients of determination (R2) in the plots are very high for low and lower-middle-income countries as compared to the upper-middle and high-income countries. In high-income countries, the change in GDP per capita has little influence on electricity consumption. In contrast, an increase in GDP per capita significantly amplifies electricity consumption in low and lower-middle-income countries, as previously reported (Debnath *et al.*, 2015). This amplification in energy consumption may have resulted from the presence of suppressed demand.

The trends in per capita gross national income (GNI) and energy consumption for the period 1960-2013 of eighteen randomly selected countries from four World Bank economic classifications are illustrated in Figure 4.3. The high and upper-middle-income countries, the relation between GNI per capita and electricity consumption per capita has a logarithmic progression, which denotes that when a country reaches a stable income level, the energy consumption becomes linear in characteristic (Figure 4.3). In the case of developing contexts with lower middle and low income, the increase in GNI boosts up the electricity consumption exponentially (Figure 4.3), because GNI/capita augmentation influences the 'suppressed' demand by allowing more people to access electricity. Moreover, improved buying capacity enables consumers to buy and utilize more electronic products, resulting in exponential electricity consumption growth. After reaching a stable economic stage, the energy consumption growth slows steadily (Medlock and Soligo, 2001), despite the fact that the GDP can keep rising.

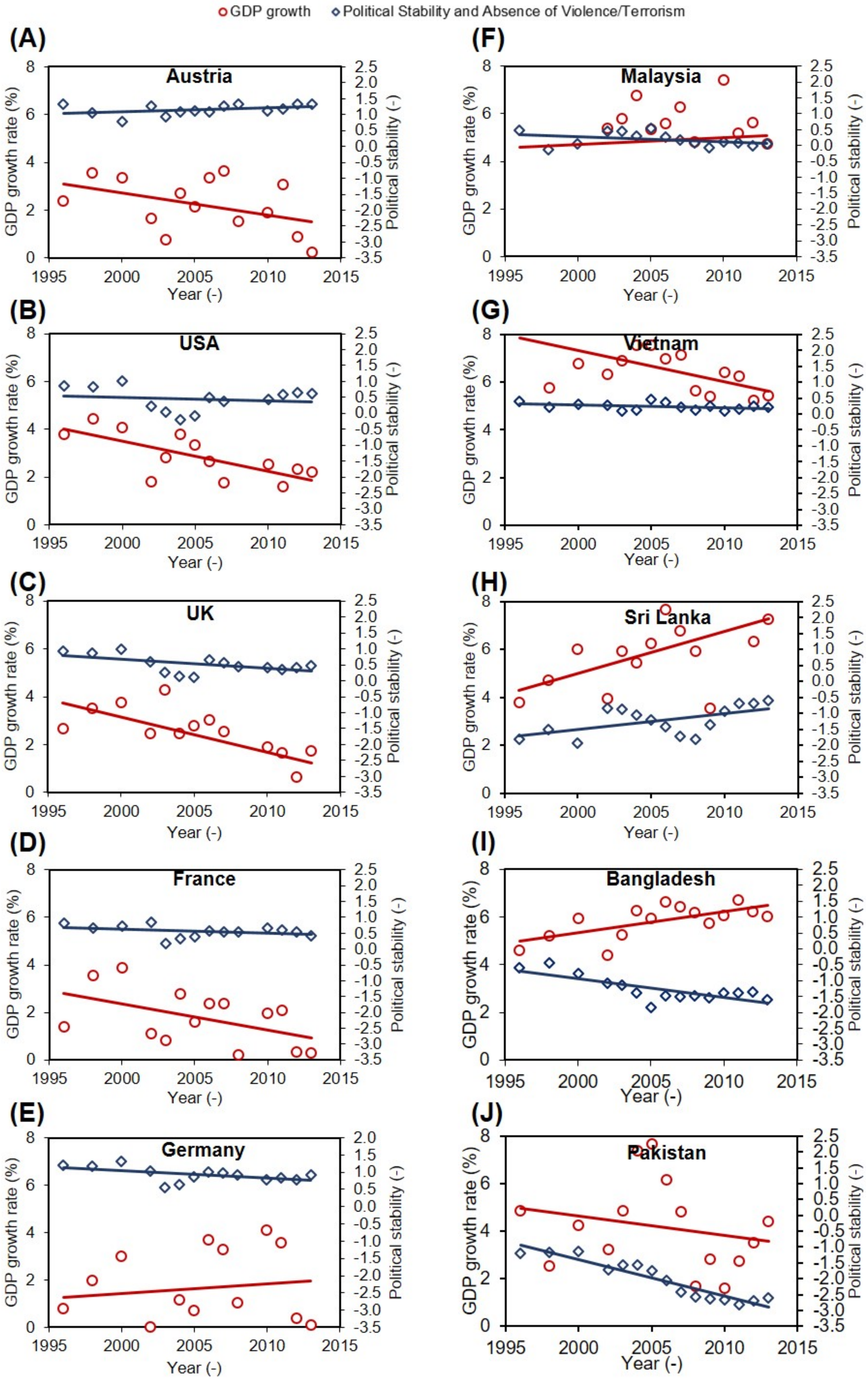

Figure 4.1: GDP growth vs political stability trends in developed (a-e) and developing countries (f-j). Here, the fitted regression line visually depicts the trend in the data. Data source WB (2014); Kaufmann and Kraay (2014)

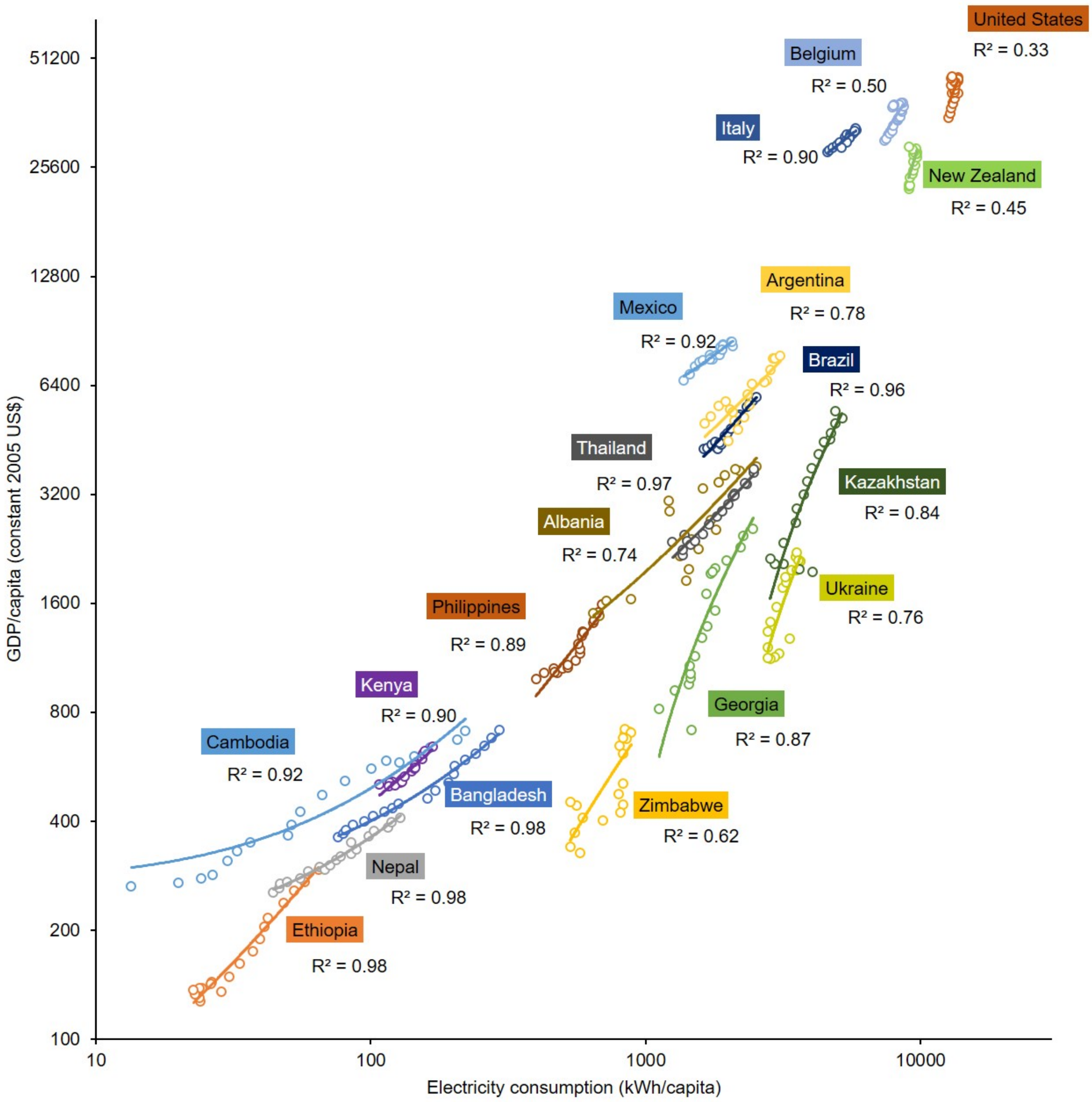

Figure 4.2: GDP per capita vs electricity consumption from 1995 to 2013. The R2 values denote the coefficient of determination, and it measures how close the data to the fitted regression line (The solid lines). Data source WB (2014)

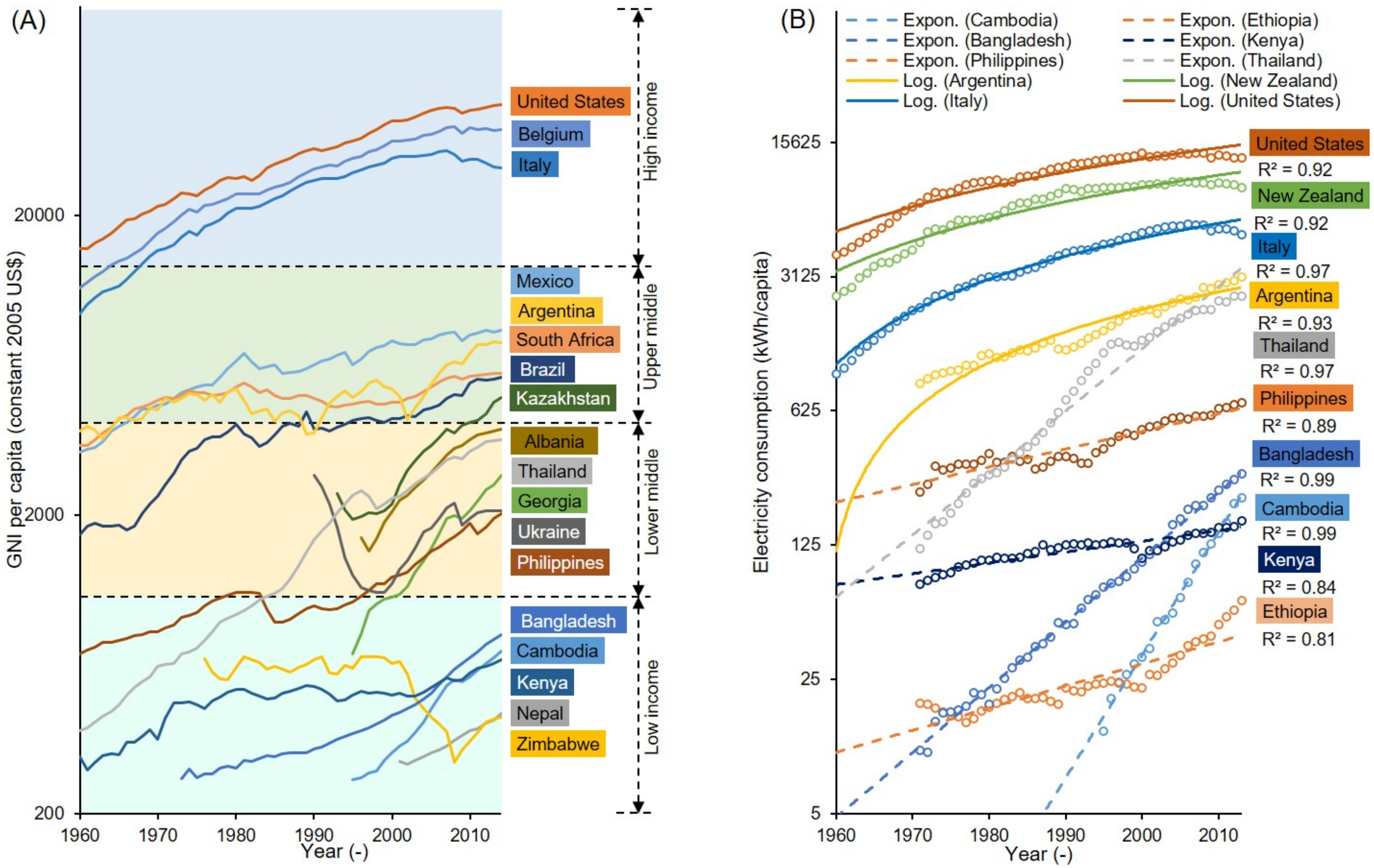

Figure 4.3: Growth trends across developed and developing countries. (A) Growth in GNI per capita of different countries from 1960 to 2014. (B) Growth trends in electricity consumption of different countries from 1960 to 2014. In panel (B), the trends in the data are visually depicted by fitted regression lines. The y-axis values are on a logarithmic scale, and the dashed and solid lines denote exponential and logarithmic progression of the data, respectively. The income group classification used here is that from the World Bank list of economies (July 2015): low income, \$1,045 or less; lower middle income, \$1,046–4,125; upper middle income, \$4,126–12,735; and high income, \$12,736 or more. Data source WB (2014)

In developing economies, corruption influences policy decisions, including the procurement of mega projects—often resulting in the selection of higher cost options (Mauro, 1995; Aladwani, 2016), that may benefit the decision maker(s) to the detriment of the environment and economy. For example, post-2009, Bangladesh's increased dependence on volatile international energy markets for oil imports was due to the growth in for-profit, private sector oil-based generation plants operating during off-peak hours that resulted in greater macroeconomic risks (Mourshed, 2013). The sub-optimal decision to increase oil-based electricity generation beyond peak generation capacity requirements has been reported as ad-hoc and short-sighted (Mourshed, 2013).

Evidence suggests that reduced corruption can result in a significant increase in GDP; e.g. if Bangladesh can enhance its bureaucratic integrity and efficiency to the level of Uruguay its annual GDP growth would elevate by over half a percentage (Mauro, 1995). Figure 4.4 compares inflation with the Corruption Perceptions Index (CPI) of different nations. Countries with higher CPI scores are less corrupt and more developed and in most cases, have less inflation. In contrast, countries with higher levels of corruption tend to have higher inflation. The economic inflation rate is associated with the size of the national debt of a country. Energy projects are typically big and require significant investments. Loans from international financial organizations such as the World Bank, Asian Development Bank (ADB) and International Monetary Fund (IMF), and local and international banks, constitute a large proportion of energy investments in developing countries. Corruption has been reported in all life cycle stages of energy projects, but most evidence on its existence and extent are reported for the tendering process, (Wells, 2015) which directly increases the project cost and corresponding loan amount. The terms of these loans are typically longer (e.g. decades) and interest rates are higher, due to the perceived risks of political instability and inflation—resulting in higher repayment cost and increased national debt. The consequences of increased pressures on public finance are the inevitable rise in personal and sometimes business tax rates, further increasing inflation. Another impact of a corruption-related increase in macroeconomic stress is the detrimental effect on social and economic development, as money intended for these sectors is often reallocated for debt repayment (Mourshed, 2013).

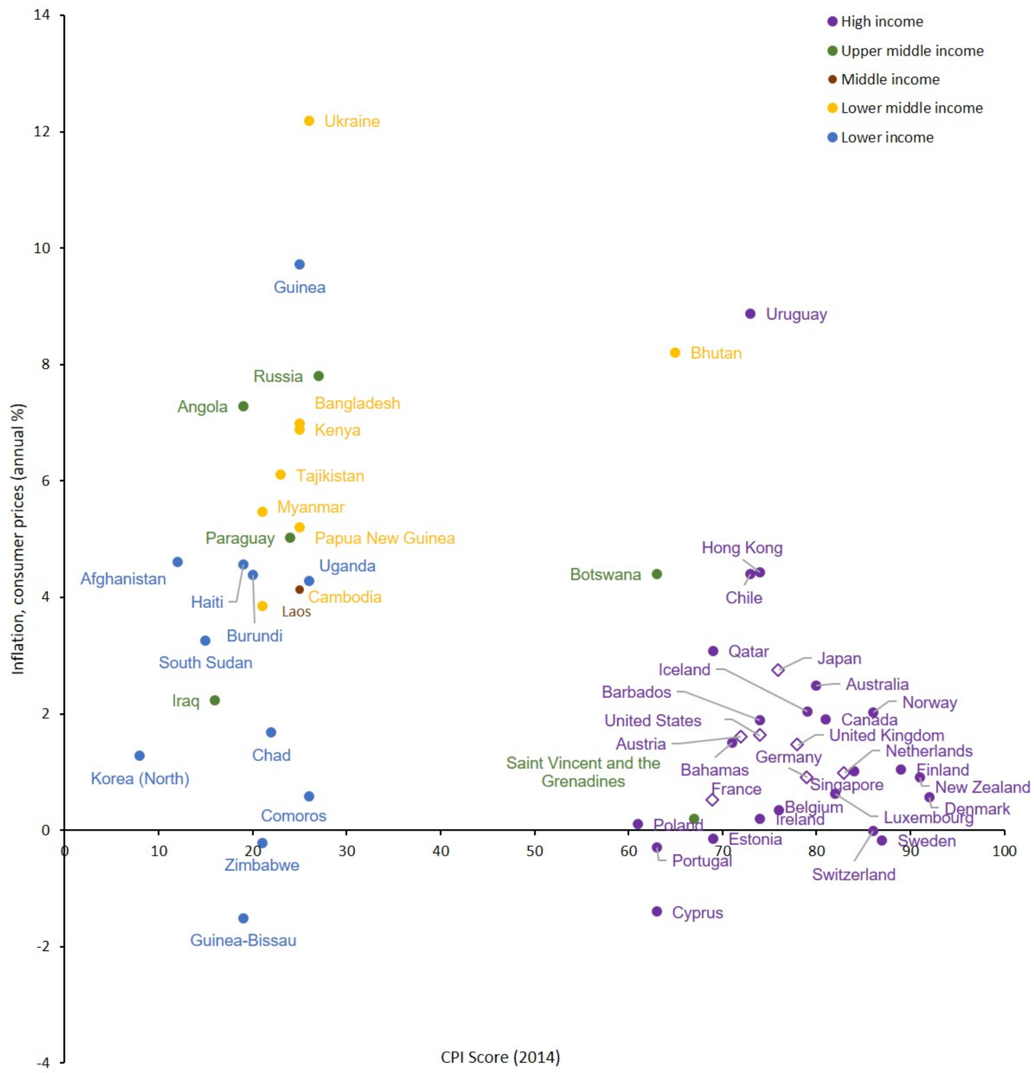

Figure 4.4: Comparison of corruption perceptions with inflation and consumer prices. Corruption Perceptions Index (CPI) 2014 vs. Inflation (2014) among the top and bottom 35 countries of the CPI list. High-income countries where EPMs have originated are illustrated by hollow purple diamond shapes. For detail, see Table 4.3. Data source WB (2014); TI (2014)

Comparatively low levels of corruption in developed countries have limited effects on energy projects and the economy, the modeling of which is, therefore, low in priority. In contrast, energy project procurement, management and operation in developing countries are evidently corrupted with severe impacts on the economy (Lovei and McKechnie, 2000). Corruption and its effects on micro- and macroeconomic performance in all life cycle stages of energy planning should, therefore, be an integral part of any modeling effort in developing countries.

Among the 34 reviewed EPMs, none of them addressed the implications of corruption on the energy economy. In addition to corruption, none of the reviewed models considered the effect of political instability on the economy, which was found to be prominent in developing contexts. Also, the influence of per capita income change drives energy consumption differently in developing economies than that of developed ones; this aspect was also found to be less elaborately modelled in the reviewed EPMs.

4.2.3 Data inadequacy

Estimation/projection quality in EPMs depend on data adequacy and accuracy, as historical trends determine the future projection. EPMs are mostly mathematical models in which data inadequacy can result in inaccurate estimation or at least increase the uncertainty of prediction. Also, incomplete data records hinder the assessment of potential interrelations among the variables, rendering the EPM development process difficult. Data inadequacy is reported to be more pronounced in developing contexts than that of developed ones (Nye, 1967; Vera and Langlois, 2007; Geng *et al.*, 2016), in particular regarding the required level of disaggregation and resolution, as well as the provenance of data. Careful considerations should be given, especially in developing contexts, to the collection of quality-assured data. On the other hand, modeling approaches should be flexible enough to accommodate incomplete historical data up to an acceptable limit while compensating for the possible variations in temporal and spatial resolutions.

4.2.4 Climate change impact

Climate change is projected to disproportionately impact some developing countries (e.g. Bangladesh, Philippines, Malawi and India) not only because of their development status and perceived shortcomings in adaptation capacity but also because of their inherent geographical and social vulnerabilities. Moreover, the global energy system is transitioning away from centralised generation and management to a more distributed, intermittent renewable energy and land-based system, where land and infrastructure resilience to natural hazards is becoming increasingly important, even for energy planning (McLellan *et al.*, 2012). The impacts of climate change on the broader economy and environment require the consideration of region- and country-specific parameters for resilience, adaptation, mitigation, and development in EPMs. None of the EPMs reviewed considers the impacts of climate change. Even energy emissions models consider only energy related emissions and may also consider their future evolution from decarbonisation perspectives.

Energy vs. land vs. food

Land-based economic sectors are particularly vulnerable to sea level rise, as well as natural disasters such as floods, tsunamis, and landslides due to increased precipitation, all of whose occurrence is projected to increase. Developing countries are particularly vulnerable to these impacts because of their tropical and sub-tropical locations and geomorphology (Alcántara-Ayala, 2002). For projected sea level rises of 45 and 100 cm, up to 15,600 and 30,000 km2 of land area respectively will be permanently flooded in Bangladesh (Butzengeiger and Horstmann, 2004), corresponding to up to about one-fifth of the country's total land area. The production of rice, the staple food, will decrease from 236 to 96 kg/capita-year if the sea level rises by 32 cm by 2050 and 30 kg/capita-year if the rise is 88 cm by 2100 (DoE, 2006). In the case of Maldives, the entire island country would drown if the sea level rises, as the highest point is only 2.4m higher than the sea level. Moreover, energy infrastructure in several countries is vulnerable to sea level rise (Khan *et al.*, 2013; Wadey *et al.*, 2013), as they are situated near the water resource such as river and sea for cooling purpose (Greenpeace, 2007). The direct impacts of climate change on energy systems are thus related to energy infrastructure resilience and energy production when vulnerable lands are used for energy crops.

As a matter of course, and in line with the theoretical discourse on stages of economic growth, the least developed and developing countries aim to become developing and developed respectively—representing a gradual shift in focus from agricultural towards more industrialised societies (Archibugi, 1997). Industrial development is often manifested in the transformation of agrarian lands into industries and energy infrastructures in the populated countries with severe shortages of buildable land—which affect food production. The situation is exacerbated when a significant share of arable land is allocated to energy crop production, leading to a conflict between the goals of energy and food securities—both of which are critical issues for developing countries with relatively large population and modest land mass, such as Bangladesh. Of the 34 studied models, only BD2050 considered the effects of energy sector development (e.g. land-based bioenergy) on food production (BD2050, 2015). Before BD2050's launch in 2015, the International Atomic Energy Agency's (IAEA) Wien Automatic System Planning package (WASP) was predominantly used for energy planning. WASP is essentially an optimum solution finder for the supply-side expansion and is mostly unsuitable for modeling land-based interactions. The increasing interactions between food, land and energy, therefore, need to be modelled and assessed holistically for informed decision-making.

Effects of extreme weather events

Extreme weather events are typically rare, yet climate change will make some of these events more likely to occur and more likely to be severe (EPA, 2016). Slow-onset events such as heatwaves and unexpected low temperatures have a direct effect on comfort related energy demand (Ravanelli and Jay, 2016), in addition to the resulting increased mortality, especially among the elderly, children and the infirm. While effects such as these are common to both the developing and developed countries, the amplitude and duration of extreme events, as well as the inability to cope with their sudden onset are often more pronounced in tropical and sub-tropical developing countries; e.g. heatwaves in India and Pakistan in 2015 (Herring *et al.*, 2016). Air conditioning accounts for 28% of electricity consumption in the hottest months in Delhi, India (Johansson *et al.*, 2012). Although India started its first energy efficiency rating for air conditioning and labelling programme in 2006

(Conti *et al.*, 2016), aimed at reducing annual electricity demand by 27 TWh by 2020 (McNeil and Iyer, 2008), a heatwave can escalate that demand (Miller *et al.*, 2008). Climate change impacts are seldom considered in EPMs likely because they originate in developed countries that have been shown to be less vulnerable than developing countries where climate change can cause immense damages (Yohe *et al.*, 2006). None of the reviewed EPMs considered the climate change impact. BD2050 only explored the implication of energy policies on food security. That does not necessarily explore the impact of climate change in Bangladesh. Energy demand projection and infrastructure resilience should, therefore, consider the probability of extreme weather events, especially in EPMs for developing countries.

4.2.5 Effects of poor characterisation

Poor characterisation of the energy system and its underlying socio-economic parameters can lead to inappropriate modeling of future energy and emissions scenarios in both developed and developing countries (Table 4.4). Inaccurate projections affect energy system planning and infrastructure development, especially in the long term. Furthermore, energy dynamics in developing countries are complicated because of the prevalence and different distribution of the following socio-economic and political parameters: political stability, energy use characteristics of the extremely poor, the pervasiveness of small unregistered businesses, the presence of large informal sectors, corruption, and subsidies. Moreover, most of these aspects have seldom been addressed in a reasonable level of detail in the literature. The gap in knowledge is exacerbated by the limited availability of modeling expertise in developing countries. Complexities such as these make the energy models in developing countries more vulnerable to poor characterization than that of the developed ones.

4.3 Implications and considerations for EPMs

Although developing countries have lower per-capita GHG emissions than those of developed countries, there is a marked increasing trend in emissions since 1990. The rate of change is often higher than previously projected. For example, despite the energy system being mostly based on renewable energy (93.3% of the total in

Table 4.4: Effect of poor characterisations of energy systems and economies of developing countries in energy planning models

Model typologies	**Effect of poor characterisations**
Mathematical procedures	
Regression, economic, simulations and accounting frameworks	Fragmented or inaccurate data and relations in the calculation can prompt incorrect results
Optimisation	Calculated best solutions may be incorrect, because of the inadequate interpretation of economy and resources framework.
Equilibrium	Overlooking the disequilibrium of business sectors and overestimate business sector impacts that prompt contorted results Urban *et al.* (2007).
Modeling approaches	
Top-down model	Incorrect or incomplete linkage or data in model frameworks results in incorrectly computed outputs
Bottom-up model	Influenced by inappropriate or incomplete relations and information in the frameworks, leading to incorrect results
Hybrid model	Hybrid models could lead to inconclusive results due to inappropriate interrelations of different parts of the system with economic and scientific data.

2010), per capita, CO_2 emissions in Costa Rica increased by 78.6% between 1990 and 2011 (WB, 2017a). Similarly, higher emissions growth rates can be found for United Nations Framework Convention on Climate Change (UNFCCC) non-Annex countries that did not have an emissions reduction target (WB, 2014). In contrast, most developed countries demonstrate a decreasing trend. CO_2 emissions from the middle-income nations already surpassed that of the high-income countries as illustrated in Figure 1d. Upper-middle-income nations are also about to exceed the emissions from high-income countries. Although India and China dominate in emissions growth at present, Brazil, India, Indonesia, China and South Africa are projected to eclipse global GHG emissions in 2050 (Marchal *et al.*, 2011). According to the 2017 IEA World Energy Outlook (IEA, 2017b), China will start to decrease CO_2 emissions from 2030 but will still emit 2.8 times more in 2040 than in 2000. On the other hand, CO_2 emissions from advanced economies started to decline in 2014, and by 2040, they will emit 0.3 times less than in 2000. However, CO_2 emissions from the rest of the world will keep increasing gradually, and will collectively emit 2.4 times more CO_2 by 2040 than in 2000.

The current discourse on economic development is that along with Brazil, Rus-

Table 4.5: Applicability of suggested variables in existing EPMs.

Variables	**Types of models**			
	Energy information systems	**Energy demand-supply model**	**Energy economic model**	**Energy emissions model**
Political stability		✓	✓	
Corruption			✓	
Suppressed demand	✓	✓	✓	✓
Climate change impacts		✓	✓	✓

sia, India, China and South Africa (BRICS), eleven further countries, known by the numeronym N-11— Bangladesh, Egypt, Indonesia, Iran, Mexico, Nigeria, Pakistan, the Philippines, Turkey, South Korea and Vietnam – have a high potential of becoming among the world's largest economies in the 21st century (Lawson *et al.*, 2007). Projections of energy demand growth in smaller economies but with more significant populations have primarily been inaccurate. For example, the 2010 Power Sector Master Plan (PSMP) projected that primary energy demand in Bangladesh in 2030 would be 616 TWh (JICA and TEPCO, 2011), which was later revised up in 2015 Plan to 860 TWh in the 'business as usual' (BaU) scenario—a 40% increase in the projected amount within five years (JICA and TEPCO, 2016). The updated projected demand can be ascribed to flawed assumptions of the probability of demand growth and the lack of the consideration of suppressed demand. Policies based on inaccurate projections are unlikely to be efficient and sustainable.

The consideration of the identified deficiencies in developing contexts and their treatment in energy planning models need to be context specific, both regarding integration with existing models and for the development of new ones. In cases where empirical relationships between deficient parameters and outcome variables are well established and accepted by the stakeholders, the decision on integration versus new EPM development will depend on the complexity of integration with the existing model and the potential for contribution in policy development and energy planning. On the other hand, not all deficiencies need to be accounted for in all model types. Table 4.5 provides an applicability matrix of the identified variables against model typologies.

A summary of potential considerations for the identified deficiencies for the development of or integration into future country/region specific localized EPMs follows.

Suppressed demand. Detailed relationships between the constituent variables of energy demand – such as the elasticity between income threshold and buying capacity and grid connectivity – need to be addressed in EPMs for developing contexts.

Dynamics between political stability and economic growth. Not all developing countries share similar political stability. If there exists an evident correlation between economic growth and political stability, it should ideally be explicitly modelled in the EPM. Where the relationship is not conclusive, further research needs to be conducted, even for implicit or proxy considerations.

Influence of corruption on the energy economy. The treatment of corruption in models should be context specific. Multiplier based modeling will be time and cost effective if a significant relationship exists between corruption and outcome indicators. In cases where the relationship is not apparent or cannot be mathematically formulated, conveniently, underlying causes can be investigated further.

Data gathering, validation and sharing. A structured data gathering and sharing system can contribute to the enhanced accuracy of the EPMs, as well as the effectiveness of the resulting policies.

Climate change impacts on energy infrastructure and systems. Depending on the country-specific impacts of climate change on energy systems and infrastructure, its degree of incorporation in EPMs can be varied. If the projected climate change has a significant effect on future energy infrastructure and systems, it should be modelled explicitly, especially for land-based variables such as land use, distributed energy generation, food production and bioenergy. In most cases, the explicit modeling of climate change impacts would require further investigations on the interactions between related variables.

In the case of Bangladesh, corruption was found to have greater impact on energy planning (Chapter 3) that should be modeled initially. After that, suppressed demand and climate change impact modeling should have more importance in the case of EPM development for Bangladesh. Political stability should also be modeled to increase the contextual consideration to elevate the accuracy of future planning of energy sectors in a cost effective way.

4.4 Summary

Distinct differences exist between the evolution of energy systems in developing and developed countries, as a response to varying social, technical, economic and environmental stimuli. Developed countries primarily aim to reduce climate-affecting GHG emissions while enhancing energy security. In contrast, developing countries are predominantly concerned with increasing access to conventional forms of energy through infrastructure expansion, which is often seen as a prerequisite for economic and social development. Despite the differences in overall policy goals, EPMs play a central role in energy sector development and transformation in both developing and developed countries. Current EPMs were mostly created in developed countries, often with the assumptions and biases of the country and region in which they were developed. Recognising the importance of EPMs in shaping the energy future, the analysis of 34 EPMs revealed several important shortcomings for the developing context.

A key finding from this chapter is the lack of consideration in the analysed EPMs of the unique socioeconomic characteristics in developing countries such as suppressed demand, corruption, and political instability. Disregarding suppressed energy demand can potentially underestimate total demand, rendering future planning inaccurate and ineffective, especially for long-horizon planning such as 2050 pathways. Corruption is a complex socio-economic factor and can increase capital and operation costs of energy projects and infrastructure in some developing countries, affecting sustainability. Also, the economy is sometimes linked with political instability which, on its own can affect energy infrastructure resilience.

Apart from the developing context-specific socio-economic deficiencies in the current EPMs, climate change impact on land availability and food production is likely to alter the dynamics of energy-food-emissions interactions, especially in the highly populated developing countries. Increasing penetration of distributed energy resources and bioenergy goals require that EPMs should now consider land-based interactions between energy, food, and environment for future planning and development.

Country-specific trends in GHG emissions are also evolving. Collectively, middle- and upper-income countries now emit more than that of the high-income countries since 2007. Emissions are increasing at a much faster rate in developing economies than previously projected. EPMs can play an essential role in setting the emerging economies towards a low-carbon pathway while enhancing access to energy. Most reviewed EPMs were initially intended for their country/region of origin in the developed world, embedding the contexts in which they were designed. Their later use in developing countries demonstrated their potential for informed decision-making on energy systems planning. However, the identified shortcomings in this chapter suggest that the formulation of localized EPMs are essential not only for the countries concerned but also for a low-carbon pathway for the world.

Chapter 5

Forecasting methods

Previous studies on forecasting methods of EPMs either divided the topic into its areas of application or the broad categories of underlying techniques. Application areas are always evolving – through the integration of new domains and concepts, as well as by expanding the breadth and depth of a modeled domain. The difficulty arises when previously categorized application areas are not flexible enough to accommodate a new area. For example, behavioral energy conservation is an important environmental psychology aspect of climate and energy debate; and widely considered for the modeling of energy use in buildings and transportation, as well as for national energy demand forecasting and policy making.[1] On the other hand, dividing forecasting methods based on the underlying techniques has similar issues. For example, Weron classified forecasting methods into two broad categories– statistical approaches and artificial intelligence (AI) based techniques (Weron, 2007). The developments in computing over the past decades have enabled the use of compute-intensive methods for improved accuracy and reduced computation time, thereby enhancing their applicability. AI techniques are now widely used to tune up parameters in statistical models. Moreover, some soft computing or computational intelligence[2] techniques routinely use advanced statistical concepts. Therefore, cat-

[1]Examples of the use of behavioral aspects of public energy conservation in policy making can be found in Japan's Third National Communication under the United Nations Framework Convention on Climate Change (UNFCC) (`http://unfccc.int/resource/docs/natc/japnc3.pdf`) and Energy Outlook of Vietnam through 2025 (`http://open_jicareport.jica.go.jp/pdf/11899796_02.pdf`)

[2]It can be argued that the so called AI methods used in forecasting are in fact, more specifically, computational intelligence (CI) techniques, also known as soft computing in AI. For further information on how computational intelligence branched out from general AI, initially to distinguish neural networks from hard AI but later to incorporate fuzzy systems and evolutionary computation, the reader is referred to the history of IEEE Computational Intelligence Society (CIS) at `http://ethw.org/IEEE_Computational_Intelligence_Society_History`

egorizing the forecasting methods as either statistical or artificial intelligence not only gives an inaccurate account but also hinders the informed comprehension of the strengths and weaknesses of different approaches. The hybridization of methods to suit application areas is characterized by data incompleteness and uncertainty; temporal and spatial variability; and domain features – all of which mandates a new classification scheme.

Existing reviews thus lack a comprehensive coverage regarding scope, accuracy, and applicability. The objective of this review is, therefore, to analyze the methods utilized in different EPMs to investigate their accuracy, objective, temporal and spatial extents with a view to identifying the factors behind the choice of forecasting methods. Findings of this study would benefit researchers in gaining an appreciation of the methods, as well as enable them to select appropriate forecasting methods for future research.

5.1 Methodology

A state-of-the-art systematic review was undertaken on published electronic resources for the study of underlying forecasting methods in EPMs. A preliminary study was conducted to gather an overview of the topics related to forecasting methods in energy planning. The identified main topics were: energy demand and supply model and forecasting; energy planning models; emission reduction models; time series analysis; and forecasting. These topics were used to identify relevant keywords, listed in Table 5.1. Keywords were then utilized to search electronic databases: Google Scholar, ScienceDirect, Scopus, Ei Compendex and Web of Science, for relevant publications on forecasting methods of EPMs.

Table 5.1: Searched keywords and associated groups

Model	**Objective**	**Geographical extent**	**Time horizon**
Energy	Forecasting	Global	Short
Electricity	Projection	Regional	Medium
Energy information		County	Long
Energy economic			
Energy supply and/or demand			
Emission reduction			
Energy planning			

An advanced search was conducted within the databases by categorizing keywords into four-word groups and by combining them using the Boolean operator 'AND.' The search was conducted in two stages. Firstly, the model, objective and geographical extent keywords were used. Secondly, the model, objectives, methods, and analysis measures were applied. The initial search results at each stage were refined by applying the following inclusion criteria:

(i) Objective: Energy forecasting

(ii) Language: English

(iii) Sources: Publications from journals related to energy and core forecasting and planning of energy; fossil fuel; renewable energy, and carbon emissions.

Abstracts of the selected publications were scrutinized. Articles were chosen for review if the substance was within the scope of the study. A further search was conducted on the recognized authors who had contributed noticeably in related fields. 600 publications were found from the search. The criteria for retention were:

(a) Studies covering energy demand and supply forecasting

(b) Studies with significant contribution in forecasting of GHG emissions

(c) Studies on forecasting methods for energy planning

(d) Key review articles from established authors/institutions in the area of energy forecasting and planning models

Finally, 483 publications and reviews on energy forecasting and planning were retained for analysis and interpretation.

5.2 Classification

Forecasting involves the predictions of the future based on the analysis of trends of present and past data, comprising three major components: input variables (past and present data), forecasting/estimation methods (analysis of trends) and output variables (future predictions), as shown in Figure 5.1. Based on the number of techniques used for trend analysis, the investigated methods can be broadly classified into two main types: stand-alone and hybrid. Stand-alone methods apply a single technique for analyzing trends whereas hybrid methods integrate more than one stand-alone techniques. In most cases, the purpose of hybridization is to rationalize or make reliable forecast output and to yield higher projection accuracy.

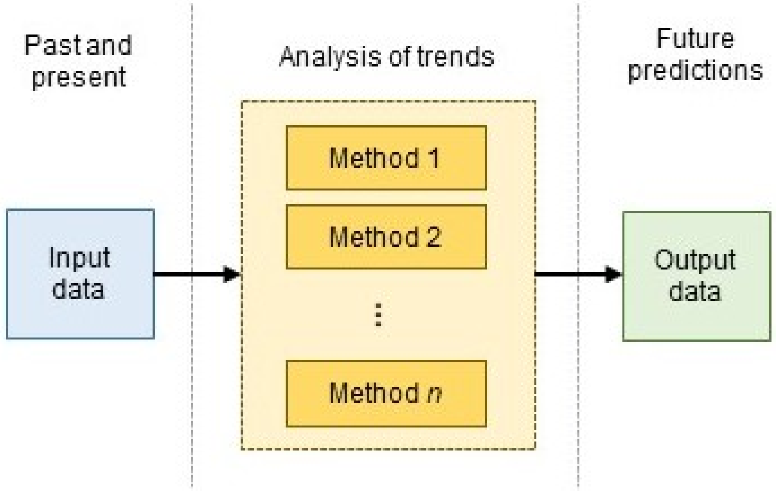

Figure 5.1: Basic forecasting or estimation model structure

Based on the type of techniques, stand-alone methods are divided into three categories: statistical, computational intelligence (CI) and mathematical programming (MP). Hybrid methods are divided into four: statistical-statistical, statistical-CI, CI-CI and statistical-MP methods. Some of the reviewed literature utilized multiple stand-alone and/or hybrid methods for comparison and critique. To obtain a comprehensive picture in this paper, underlying techniques in hybrid methods are also separately accounted for in the stand-alone method categories in Tables 5.2, 3.

The methods are also analyzed by geographical extent and forecasting time frame. Geographical extent was divided into three categories: global, regional and country. Global refers to the whole world; regional for a part of the world; e.g., Asia, Europe, G-8, and Sub-Saharan Africa; and country for an individual country. Models with geographical extent covering parts of a country are incorporated in the country category for brevity.

The time frame of the forecasted models ranges from hours to 100 years. Grubb *et al.* (1993) suggested five years or less for the short-term, between 3 and 15 years for the medium-term, and ten years or more for the long-term. However, this classification creates confusion for the medium- and long-term projections because of the overlapping time spans. This research, therefore, utilizes the following definitions for time span or modeling horizons: short- ($t < 3$), medium- ($3 \leq t \leq 15$) and long-term ($t > 15$), where t is time span in years.

The statistical and CI & MP based classification is presented in Tables 5.2 and 5.3 respectively, illustrating the techniques used, geographical extent and forecasting time frame, as well as the number of studies and references.

It is evident from the analysis of 483 studies that diversity in statistical methods is more prominent than computational intelligence and mathematical programming. 28 different statistical methods have been used, compared to 22 CI and one MP for forecasting. Among the statistical methods in Table 5.2, autoregressive integrated moving average (ARIMA) (46 models) followed by linear regression (LR) (39 models), autoregressive moving average (ARMA) (22 models) and logistic regression (LoR) (19 models). However, cointegration was widely used (48 models) technique to analyze the relationship among the variables. ARIMA, LR and other statistical methods were utilized to forecast.

With regard to CI techniques, ANN was used in 194 models, followed by SVM (58 models), FL (40 models), GA (39 models), PSO (34 models) and GM (29 models) (Table 5.3). In respect to geographical extent, global and regional models mostly adopt statistical methods. However, country-based models utilized a wide range of methods (statistical and CI) for forecasting (Tables 5.2 and 5.3).

Forecasting models, which adopted metaheuristic methods to develop a hybrid method, utilized genetic algorithm and particle swarm optimization most of the time. Also, global models utilized metaheuristic methods such as GA, PSO and Artificial bee colony optimization (ABCO). Moreover, country wise forecasting models utilized a wide range of methods both metaheuristic and MP. In case of the temporal span, statistical methods are suitable for short-term (Table 5.2), and CI methods are suitable for all temporal (Short, medium and long) forecasting (Table 5.3).

Table 5.2: Analysis of stand-alone statistical methods utilized in forecasting models (For more information on the source please check A.1)

Methods	Geographical extend			Time frame of forecasting			Number of models
	Global	Region	Country	Short	Medium	Long	
Linear regression (LR)	✓	-	✓	✓	✓	✓	39
Nonlinear regression (NLR)	-	-	✓	✓	✓	✓	3
Logistic regression (LoR)	-	✓	✓	✓	✓	✓	19
Nonparametric regression (NR)	-	-	✓	✓	-	-	3
Partial least squares regression (PLSR)	-	-	✓	-	✓	-	2
Stepwise regression (SR)	-	-	✓	✓	✓	-	7
Moving average (MA)	-	-	✓	-	✓	-	4
Autoregressive integrated moving average (ARIMA)	-	✓	✓	✓	✓	✓	46
Seasonal autoregressive integrated moving average (SARIMA)	-	-	✓	✓	✓	✓	13
Autoregressive moving average model with exogenous inputs (ARMAX)	-	-	✓	✓	✓	-	10
Autoregressive moving average (ARMA)	-	-	✓	✓	-	-	22
Vector autoregression (VAR)	✓	✓	✓	-	✓	✓	13
Bayesian vector autoregression (BVAR)	-	-	✓	✓	✓	-	4
Structural Time Series Model (STSM)	-	-	✓	-	✓	✓	3

Table 5.2: Analysis of stand-alone statistical methods utilized in forecasting models (For more information on the source please check A.1)

Methods	Geographical extend			Time frame of forecasting			Number of models
	Global	Region	Country	Short	Medium	Long	
VARIMA	-	-	✓	✓	-	-	1
Generalized autoregressive conditional heteroskedasticity (GARCH)	-	✓	✓	✓	✓	-	14
Seasonal exponential form of generalized autoregressive conditional heteroscedasticity (SEGARCH)	-	-	✓	✓	-	-	1
Exponential generalized autoregressive conditional heteroscedasticity (EGARCH)	-	-	✓	✓	-	-	1
Winters model with exponential form of generalized autoregressive conditional heteroscedasticity (WARCH)	-	-	✓	✓	-	-	1
Autoregressive distributed lag (ARDL)	-	✓	✓	-	✓	✓	6
Log-linear analysis (LA)	-	✓	✓	-	✓	✓	4
Geometric progression (GP)	-	-	✓	-	✓	✓	3
Transcendental logarithmic (Translog)	-	-	✓	-	✓	✓	2
Polynomial curve model (PCM)	-	-	✓	-	✓	-	1
Partial adjustment model (PAM)	-	-	✓	✓	✓	-	4
Analysis of variance (ANOVA)	-	-	✓	-	✓	✓	7

Table 5.2: Analysis of stand-alone statistical methods utilized in forecasting models (For more information on the source please check A.1)

Methods	Geographical extend			Time frame of forecasting			Number of models
	Global	Region	Country	Short	Medium	Long	
Unit root test and/or Cointegration	✓	✓	✓	✓	✓	✓	48
Decomposition	-	✓	✓	✓	✓	✓	16
Total number	3	8	28	18	22	14	
Percentage of all statistical methods (%)	11%	29%	100%	64%	79%	50%	

Table 5.3: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models (For more information on the source please check A.2)

Methods	**Geographical extend**			**Time frame of forecasting**			**Number of models**
	Global	**Region**	**Country**	**Short**	**Medium**	**Long**	
Computational intelligence (CI) methods							
Support vector machine (SVM)	-	✓	✓	✓	✓	✓	58
Decision tree*	-	-	✓	✓	✓	-	4
Artificial neural network (ANN)	✓	✓	✓	✓	✓	✓	194
Abductive networks	-	-	✓	✓	-	-	2
Expert system	-	-	✓	✓	✓	-	7
Grey prediction (GM/GP)	-	-	✓	✓	✓	✓	29
Fuzzy logic (FL)	-	-	✓	✓	✓	✓	40
Genetic algorithm (GA)	✓	-	✓	✓	✓	✓	39
Artificial bee colony optimization (ABCO)	✓	-	✓	✓	-	✓	4
Ant colony optimization (ACO)	-	-	✓	✓	✓	✓	10
Particle swarm optimization (PSO)	✓	-	✓	✓	✓	✓	34
Gravitational search algorithm (GSA)	-	-	✓	✓	-	✓	4
Chaotic ant swarm optimization (CAS)	-	-	✓	✓	✓	-	2

Table 5.3: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models (For more information on the source please check A.2)

Methods	**Geographical extend**			**Time frame of forecasting**			**Number of models**
	Global	**Region**	**Country**	**Short**	**Medium**	**Long**	
Differential evolution (DE)	-	-	✓	✓	✓	✓	4
Harmony search (HS)	-	-	✓	-	-	✓	1
Evolutionary algorithm (EA)	-	-	✓	✓	-	-	1
Memetic algorithms (MA)	-	-	✓	✓	-	-	1
Immune algorithm (IA)	-	-	✓	-	✓	-	1
Simulated annealing algorithms (SA)	-	-	✓	✓	✓	-	6
Firefly algorithm (FA)	-	✓	✓	✓	-	-	4
Cuckoo search algorithm (CSA)	-	✓	✓	✓	-	-	2
Mathematical programming (MP) methods							
Nonlinear programming (NLP)	-	-	✓	-	-	✓	1
Total number	4	4	22	19	13	12	

Table 5.3: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models (For more information on the source please check A.2)

Methods	**Geographical extend**			**Time frame of forecasting**			**Number of models**
	Global	**Region**	**Country**	**Short**	**Medium**	**Long**	
Percentage of all CI and MP methods (%)	18%	18%	100%	86%	59%	55%	
*Random forest was included under decision tree modeling as they are collection of decision trees in the modeling.							

5.3 Stand-alone methods

Most of the analyzed models adopted stand-alone methods, which can be divided into three categories- statistical, computational intelligence (CI) and mathematical programming (MP) methods.

5.3.1 Statistical methods

Statistics methods investigate the accumulation, examination, elucidation, presentation, and association of data [18] and can be divided into several categories from the analyzed models. For example:

Regression analysis

There are different regression methods for forecasting. Among, the regression methods six methods were utilized in the studied models. The methods were: Linear regression (LR), ordinary least squares (OLS), nonlinear regression (NLR), logistic regression (LoR), nonparametric regression (NR), partial least squares regression (PLSR) and stepwise regression (SR).

Thirty-nine reviewed models utilized linear regression (LR) method. LR is applied to model the relationship between two variables by fitting a linear equation to observed data (Song *et al.*, 2005). Among the reviewed models which utilized LR, 89.7% models forecasted energy and electricity demand.

Three forecasting models utilized non-linear regression (NLR). Bilgili et al. forecasted the electricity consumptions of Turkey with NLR (Bilgili *et al.*, 2012). Ghiassi et al. proposed a dynamic artificial neural network (DAN2) model for forecasting nonlinear processes and compared to NLR; the method was effective for forecasting nonlinear processes (Ghiassi and Nangoy, 2009). Tsekouras et al. developed a nonlinear multivariable regression to midterm energy forecasting of power systems of Greece (Tsekouras *et al.*, 2007). Logistic or logit regression (LoR) was applied in 19 reviewed models, of which 68.4% models forecasted energy and electricity demand.

Three models utilized nonparametric regression (NR) method. NR establishes model according to the data from larger sample sizes. Charytoniuk et al. developed a short-time load forecasting model by applying NR Charytoniuk *et al.* (1998). Another study applied NR model to short-term wind power forecasting (Wang *et al.*, 2010a). Jónsson et al. presented an analysis of how dayahead electricity spot prices are affected by day-ahead wind power forecasts. The author utilized NR to assess the wind power forecast (Jónsson *et al.*, 2010).

Partial least squares regression (PLSR) was applied in two forecasting models. Zhang et al. forecasted China's transport energy demand for 2010, 2015 and 2020 with PLSR method. The results demonstrated transport energy demand for 2020 will reach a level of around 433.13 million tons of coal equivalent (Mtce) and 468.26 Mtce, respectively (Zhang *et al.*, 2009). Meng et al. analyzed and forecasted China's annual electricity consumption with PLSR. It showed real estate and relative industry electricity consumption was affected by unusual development (Meng and Niu, 2011a).

Seven models forecasted with stepwise regression (SR) method. Ekonomou utilized SR to estimate energy consumption of Greece for 2005–2015 to compare with the results produced by LR and ANN method (Ekonomou, 2010). Tso et al. utilized SR method to predict electricity consumption in Hong Kong (Tso and Yau, 2007). Rao et al. utilized SR to select the relevant cross-products to be used in a non-homothetic Translog function to forecast and analysis of demand for petroleum products in India (Rao and Parikh, 1996). Aranda et al. utilized SR to select the correct model form to predict the annual energy consumption in the Spanish banking sector (Aranda *et al.*, 2012).

Univariate time series methods

Among the studied models, five univariate time series methods were utilized. The methods were: moving average (MA), autoregressive integrated moving average (ARIMA), seasonal autoregressive integrated moving average (SARIMA), autoregressive moving average model with exogenous inputs (ARMAX) and autoregressive moving average (ARMA).

Four forecasting models utilized moving average (MA). Azadeh et al. forecasted electricity consumption in Iran with moving average (MA) to make the data trend-free to train the ANN. Also forecasted electricity consumption to compare the predicted results (Azadeh *et al.*, 2007a). Xu et al. combined two statistical methods to model to forecast natural gas consumption in China from 2009 to 2015. One of the methods was MA (Xu and Wang, 2010). In another study, Zhu et al. developed an improved hybrid model (MA-C-WH) to forecast electricity demand in China, which utilized MA (Zhu *et al.*, 2011). Li et al. applied single and double MA for forecasting power output of a grid-connected photovoltaic system (Li *et al.*, 2014).

The general form of Autoregressive integrated moving average (ARIMA) is ARIMA (p,d,q) where p is the order of the auto-regressive part, d is the order of the differencing, and q is the order of the moving average process. Some ARIMA had the seasonal and non-seasonal part, and denoted as ARIMA (p,d,q) (P,D,Q)s where P, D, Q is the seasonal part of the model, S the number of periods per season. Among the analyzed models, ARIMA was applied in 46 models (Tables 5.2 and 5.4). Among the ARIMA models, 46% forecasted energy and electricity demand.

Table 5.4: ARIMA model objectives and structures

Objective	Year	ARIMA Structure		Ref.
		p,d,q	**(p,d,q) (P,D,Q)s**	
Electricity load	2005	2,2,1	-	Pai and Hong (2005)
Electricity load	2013	1,1,1	-	Ju and Hong (2013)
Electricity demand	2003	0,1,0	-	Hsu and Chen (2003a)
Wind speed	2010	1,0,0; 2,0,0	-	Cadenas and Rivera (2010)
Electricity demand	2006	0,1,1; 0,0,2; 3,2,0	(0,1,1)12	Gonzalez-Romera *et al.* (2006)
Electricity demand	2008	-	(0,1,1) (0,1,1)12	González-Romera *et al.* (2008)
Wind speed	2007	-	(0,1,1) (0,1,1)12	Cadenas and Rivera (2007)
Electricity demand	1997	-	(1,1,0) (1,1,0)12	Abdel-Aal and Al-Garni (1997)
Electricity load	2011	1,1,1	-	Hong (2011)
Electricity demand	2011	0,2,2; 1,2,1; 1,1,0; 0,2,0	-	Kandananond (2011)
Energy demand	1999	1,1,1; 1,2,1	-	Al-Saba and El-Amin (1999)
Global solar radiation	2000	-	(1,0,1) (0,1,1)	Sfetsos and Coonick (2000)
Electricity demand	1999	-	(0,1,1) (0,1,1)	Gonzales Chavez *et al.* (1999)
Electricity demand	1999	-	(1,1,0) (0,1,1)	Gonzales Chavez *et al.* (1999)
Black-coal production	1999	-	(1,0,1) (0,1,1)	Gonzales Chavez *et al.* (1999)

Table 5.4: ARIMA model objectives and structures

Objective	Year	ARIMA Structure		Ref.
		p,d,q	**(p,d,q) (P,D,Q)s**	
Antracite production	1999	-	(0,1,1) (0,1,1)	Gonzales Chavez *et al.* (1999)
Electricity generation	1999	-	(0,1,3) (1,1,0)	Gonzales Chavez *et al.* (1999)
Solar radiation	2009	-	(1,0,0) (1,1,0)	Reikard (2009)
Electricity demand	2015	1,1,1	-	Wang *et al.* (2015b)
Electricity price	2002	2,1,1	-	Ierapetritou *et al.* (2002)
Natural gas demand	2010	36,1,0	-	Erdogdu (2010)
Electricity demand	2007	13,2,0	-	Erdogdu (2007)
Power output of a grid connected photovoltaic system	2014	1,1,1	-	Li *et al.* (2014)
Load forecasting	2009	2,2,1	-	Hong (2009a)
Electricity demand	2006	0,1,0	-	Zhou *et al.* (2006)
CO_2 emissions, energy demand and economic growth	2012	-	-	Pao *et al.* (2012)
Electricity price	2010	-	-	Tan *et al.* (2010)

Table 5.4: ARIMA model objectives and structures

Objective	**Year**	**ARIMA Structure**		**Ref.**
		p,d,q	**(p,d,q) (P,D,Q)s**	
Energy demand	2007	-	-	Ediger and Akar (2007)
Electricity price	2008	-	-	Bowden and Payne (2008)
CO_2 emissions, energy demand, and economic growth	2011	-	-	Pao and Tsai (2011a)
Electricity load	2001	-	-	Amjady (2001)
Electricity price	2003	-	-	Contreras *et al.* (2003)
Fossil fuel production	2006	-	-	Ediger *et al.* (2006)
Electricity demand	2001	-	-	Saab *et al.* (2001)
Electricity load	1987	-	-	Hagan and Behr (1987)
Electricity demand	1993	-	-	Harris and Liu (1993)
Electricity load	1995	-	-	Cho *et al.* (1995)
Electricity price	2005	-	-	Conejo *et al.* (2005)
Electricity demand	2009	-	-	Sumer *et al.* (2009)
Wind speed	2009	-	-	Kavasseri and Seetharaman (2009)

Table 5.4: ARIMA model objectives and structures

Objective	**Year**	**ARIMA Structure**		**Ref.**
		p,d,q	**(p,d,q) (P,D,Q)s**	
Natural gas demand	1991	-	-	Liu and Lin (1991)
Electricity demand	2012	-	-	Lee and Tong (2012)
Wind speed	2011	-	-	Guo *et al.* (2011)
Wind speed and electricity generation	2012	-	-	Shi *et al.* (2012)

Seasonal autoregressive integrated moving average (SARIMA) was applied in 13 projection models (Table 5.2). Zhu et al. developed MA-CWH model to forecast electricity demand in China and utilized the results from a SARIMA model to compare the accuracy of the proposed model (Zhu *et al.*, 2011). Cadenas et al. forecasted wind speed with integrated ARIMA and ANN to compare with the results from SARIMA for Oaxaca, Mexico (Cadenas and Rivera, 2007). Jeong et al. applied SARIMA for determining the annual energy cost budget in educational facilities. In this study, models for elementary, middle, and high schools SARIMA (13, 1, 0) (0, 1, 0), SARIMA (6, 1, 1) (0, 1, 0), and SARIMA (6, 1, 1)(0, 1, 0) respectively were developed (Jeong *et al.*, 2014). Ediger et al. applied SARIMA methods to forecast primary energy demand of Turkey from 2005 to 2020 (Ediger and Akar, 2007). Monthly energy forecasting model for Thailand was developed with SARIMA $(l,0,1)(0,1,0)_{12}$ (Damrongkulkamjorn and Churueang, 2005). Ediger et al. applied SARIMA to forecast production of fossil fuel sources in Turkey (Ediger and Akar, 2007). Forecasting electricity demand with SARIMA (0,1,1)(1,1,1) by Sumer et al. in (Sumer *et al.*, 2009). Bouzerdoum et al. applied SARIMA for short-term power forecasting of a small-scale grid-connected photovoltaic plant (Bouzerdoum *et al.*, 2013). Guo et al. applied SARIMA for forecasting wind speed in Hexi Corridor of China (Guo *et al.*, 2011). Wang et al. developed electricity demand forecasting with SARIMA method for China (Wang *et al.*, 2012c). Boata et al. developed hourly solar irradiation forecasting model with SARIMA $(1,0,1)(1,0,1)_{24}$ (Boata and Paulescu, 2014). Wang et al. applied SARIMA to forecast electric load in (Wang *et al.*, 2010b).

Autoregressive moving average model with exogenous inputs (ARMAX) was utilized in 10 forecasting models (Table 5.2). Darbellay et al. applied ARMAX to forecast Czech electricity demand (Darbellay and Slama, 2000). Li et al. developed a forecasting model for the power output of a grid-connected photovoltaic system with ARMAX (Li *et al.*, 2014). González et al. applied SARMAX for forecasting power prices (González *et al.*, 2012). Bakhat et al. applied ARMAX for estimation of tourism-induced electricity consumption in Balearics Islands, Spain (Bakhat and Rosselló, 2011). For short-term load forecasting, Wang et al. utilized ARMAX based on an evolutionary algorithm and particle swarm optimization (Wang *et al.*, 2008). Lira et al. utilized ARMAX for short-term electricity prices forecasting of Colombia (Lira *et al.*, 2009). Hickey et al. developed four ARMAX–GARCH models for forecasting hourly electricity prices (Hickey *et al.*, 2012).

Autoregressive moving average (ARMA) is a statistical method consist of two polynomials- autoregressive (AR) and moving average (MA). Among the reviewed models, 22 utilized ARMA (Table 5.2), of which 32% and 27% were utilized for energy & electricity demand and load forecasting respectively.

Multivariate time series methods

Vector autoregression (VAR) was applied in 13 reviewed models (Table 5.2). Among these 13 models, 77% models forecasted energy and electricity demand. Bayesian vector autoregression (BVAR) was applied in four reviewed models (Table 5.2). Chandramowli et al. forecasted New Jersey's electricity demand with BVAR (Chandramowli and Lahr, 2012). To forecast energy consumption in China from 2004 to 2010, Crompton et al. applied BVAR and concluded energy demand would rise at an annual average rate of 3.8% (Crompton and Wu, 2005). Energy consumption and projected growth were modeled with BVAR for selected Caribbean countries in (Francis *et al.*, 2007). The Bayesian hierarchical model was developed for one-hour-ahead wind Speed Prediction in (Miranda and Dunn, 2006). Multivariate VARIMA (0,1,1) model was applied to model and forecast fossil fuels, CO_2 and electricity prices and their volatilities. VARIMA approach gives better results in the case of electricity prices. However, the time span of forecasting tends to be short (García-Martos *et al.*, 2013).

Structural time series model (STSM) was utilized by Dilaver et al. to predicted that Turkish industrial electricity demand would be somewhere between 97 and 148 TWh by 2020 industrial electricity demand (Dilaver and Hunt, 2011a). In another study, Dilaver et al. predicted Turkish aggregate electricity demand would be somewhere between 259 TWh and 368 TWh in 2020 by utilizing STSM (Dilaver and Hunt, 2011b).

Autoregressive conditional heteroscedasticity (ARCH) methods

Generalized autoregressive conditional heteroskedasticity (GARCH) was applied in fourteen models. GARCH can be both univariate and multivariate (Wang and Wu, 2012). Seasonal generalized autoregressive conditional heteroscedasticity (SEGARCH) and Winters model with an exponential form of generalized autoregressive conditional heteroscedasticity (WARCH) were applied to forecast energy consumption in Taiwan by developing nonlinear hybrid models with ANN (Pao, 2009). Exponential generalized autoregressive conditional heteroscedasticity (EGARCH) method was utilized by Bowden et al. for short-term forecasting of electricity prices (Bowden and Payne, 2008).

Others

Six analyzed model utilized autoregressive distributed lag (ARDL) (Table 5.2). Dilaver et al. forecasted industrial electricity demand (Dilaver and Hunt, 2011a) and aggregate electricity demand (Dilaver and Hunt, 2011b) in Turkey with ARDL. In another study, Dilaver et al. predicted Turkish aggregate electricity demand would be somewhere between 259 TWh and 368 TWh in 2020 by utilizing ARDL. Adom et al. utilized ARDL to forecast electricity demand in Ghana to be within 20,453 and 34,867 GWh by the year 2020 for analyzed three scenarios (Adom and Bekoe, 2012). Kim et al. forecasted energy demand of South Korea for 2000–2005 after reviewing the 1990s (Kim *et al.*, 2001). Zachariadis T. forecasted electricity consumption in Cyprus with ARDL (Zachariadis, 2010). Vita et al. developed ARDL bounds testing approach to estimate the long-run elasticities of the Namibian energy demand (De Vita *et al.*, 2006).

Among the reviewed models, four models applied log-linear analysis (LA) (Table 5.2). Parikh et al. used the LA to project the demand for petroleum projects and natural gas in India. The study projected the demand of petroleum products to be 147 and 162MT in the business as usual scenario (BAU) of 6% and optimistic scenario (OS) of 8% GDP growth, respectively for 2011–2012 (Parikh *et al.*, 2007). In another study, Pilli-Sihvola utilized the log-linear econometric model to project and examine the impact of gradually warming climate on the heating and cooling demand in five European countries form 2008–2050 (Pilli-Sihvola *et al.*, 2010). Limanond et al. project transport energy consumption in Thailand from 2010 to 2030 with LA (Limanond *et al.*, 2011). Wadud et al. projected natural gas demand in Bangladesh from 2009 to 2025 with log-linear Cobb–Douglas method (Wadud *et al.*, 2011).

Geometric progression (GP) was utilized in three studied models (Table 5.2). Mackay et al. forecasted crude oil and natural gas supplies and demands from 1995 to 2010 for France (Mackay and Probert, 1995b) and Denmark (Mackay and Probert, 1995a) by utilizing geometric progression method. In a separate study, Mackay et al. forecasted liquid fossil fuel supplies and demands for the UK with geometric progression method (Mackay and Probert, 2001).

Transcendental logarithmic (Translog) was applied in two forecasting models (Table 5.2). Rao et al. developed a translog model on a non-homothetic translog function to forecast and analyze the demand for petroleum products in India (Rao and Parikh, 1996). Furtado et al. forecasted petroleum consumption in Brazil up to 2000 with translog model along with logistic and learning model. The study demonstrated that translog model performed better than logistic and learning model (Furtado and Suslick, 1993).

Polynomial curve model (PCM) is one of the trend extrapolation methods best modeled with polynomial equations. Xu et al. combined two statistical methods to forecast natural gas consumption in China from 2009 to 2015; one of the methods was PCM (Xu and Wang, 2010).

Four reviewed models utilized partial adjustment model (PAM) for forecasting (Table 5.2). Nasr et al. utilized PAM to develop an econometric model to estimate electricity consumption of post-war Lebanon (Nasr *et al.*, 2000). Adom et al. identified the factors that affect aggregate electricity demand in Ghana and forecasted electrical consumption from 2012 to 2020 with PAM and ARDL (Adom and Bekoe, 2012). To analyze the demand for natural gas in Kuwait, PAM was utilized in (Eltony, 1996).

Seven models utilized analysis of variance (ANOVA) (Table 5.2). ANOVA was applied to compare the selected ANN, regression and actual data of forecasting electricity consumption (Azadeh and Faiz, 2011; Azadeh *et al.*, 2007a). ANOVA F-test was applied for ANN, simulated-based ANN, time series and actual test data for forecasting electrical energy consumption in Iran (Azadeh *et al.*, 2008b).

Cointegration implies restrictions on multivariate time series and is widely believed that it can produce better long-horizon forecasting (Christoffersen and Diebold, 1998). Unit root test and/or Cointegration was utilized in 48 models (Table 5.2). The major objective of applying cointegration method was to find the relations among the variables of a model. Nasr et al. utilized cointegration method to develop an econometric model to estimate electricity consumption of post-war Lebanon (Nasr *et al.*, 2000). Decomposition was utilized in 16 analyzed models (Table 5.2).

5.3.2 Computational intelligence (CI) methods

There were 22 methods utilized in the analyzed models. The real life problems have nonlinear characteristics while forecasting, especially for energy planning. Computational methods were used for prediction problems where mathematical formulae and prior data on the relationship between inputs and outputs are unknown (Curram and Mingers, 1994). The applied CI methods can be divided into four categories.

Machine learning methods

Artificial Neural Network (ANN) was highly utilized method for various objectives. Inspired by the human brain, ANN can learn and generalize from samples and analyses unpretentious useful connections among the information regardless of the possibility that the fundamental connections are obscure or difficult to portray (Zhang *et al.*, 1998). A schematic diagram of feed-forward neural network architecture is shown in Figure 5.2. ANN has three layers: input, hidden and output. In Figure 5.2, only one hidden layer is shown, and the number can be more than that depending on the complexity of the analyzed problem. Each neuron is connected to every other neuron of the previous layer through adaptable synaptic weight. A training process is carried out to train ANN by modifying the connection weights, and weights are adjusted to produce the desired outputs as shown in Figure 5.3. Description of basic ANN method can be found in (Ahmad *et al.*, 2016).

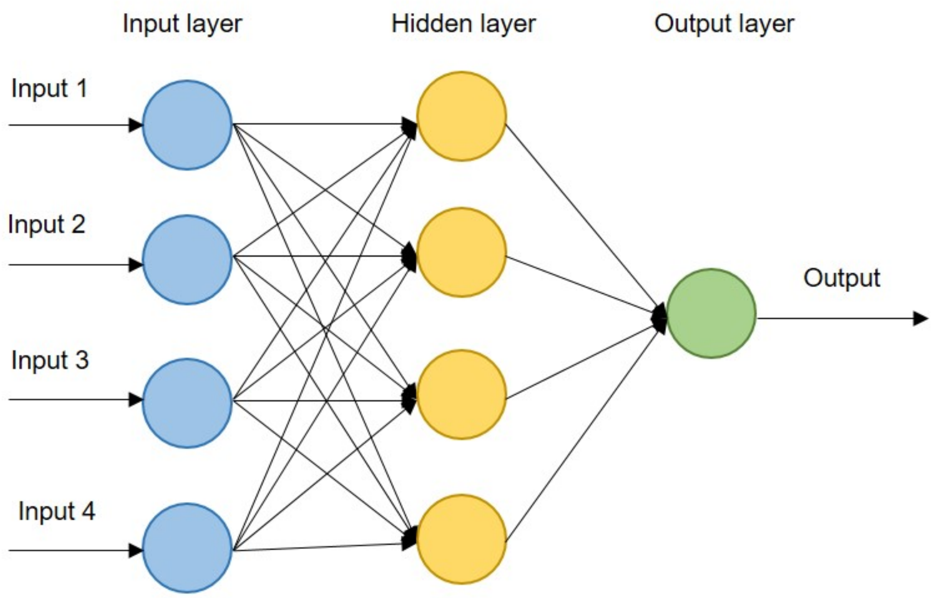

Figure 5.2: ANN schematic diagram

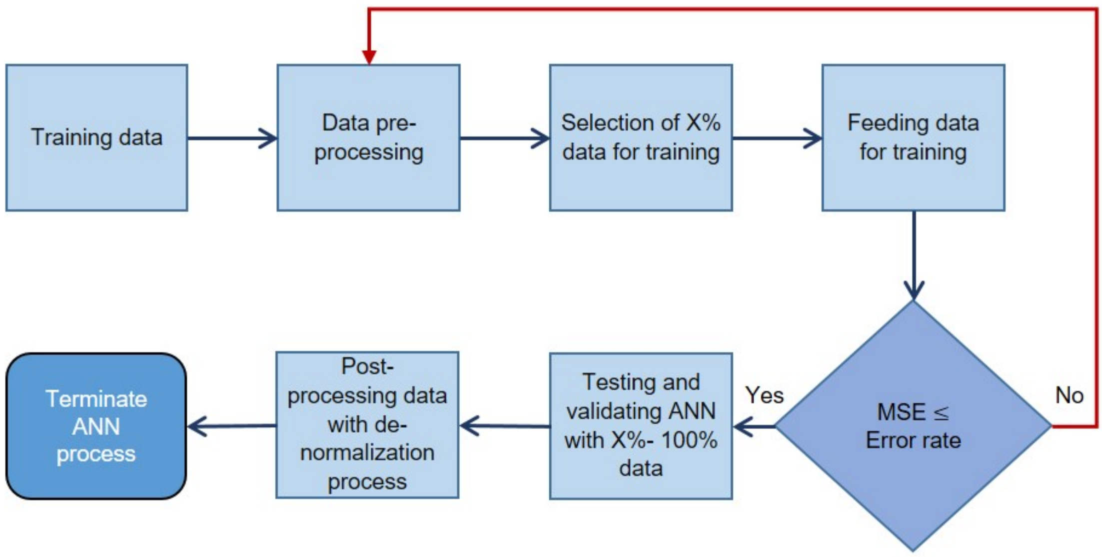

Figure 5.3: ANN process; adopted from (Ahmad *et al.*, 2016)

Among the reviewed models, 194 models applied ANN or different form of NN. The detailed analysis of ANN can be found in Table A.3, which is demonstrating layer number, neuron number in different layers and neuron composition of different

NN models, which differs depending on the objective. According to reviewed literature, NN structure with two hidden layers produced best results for the monthly load forecasting, the peak load forecasting and the daily total load forecasting modules (Yalcinoz and Eminoglu, 2005). However, one hidden layer is sufficient for most forecasting problems according to Zhang *et al.* (1998). In another study, the performance of the hierarchical model on long-term peakload forecasts outperformed the multilayer perceptron (Carpinteiro *et al.*, 2007). Analysis of reviewed models revealed that 83% models utilized three layer neuron structure with one hidden layer. Only 6% and 17% models used two and four neuron layers respectively. 49%, 38%, 78% and 11% of the neuron structures had less than five neurons respectively in the first, second, third and fourth layer. In the case of the first and second layer, 26% and 43% of the neuron structures respectively had neuron numbers between 5 and 10. Moreover, 23% and 18% neuron structures had more than ten neurons in the first and second layers respectively. Only 8% neuron structures had more than ten neurons in the third layer, which is only 1% in fourth layer (Table A.3).

Support vector machine (SVM) was utilized in 58 forecasting models (Table 5.3). Yuan et al. developed a short-term wind power prediction model with least squares support vector machine (LSSVM) because the kernel function and the related parameters of the LSSVM influence the greater accuracy of the prediction (Yuan *et al.*, 2015). Some of the models utilized Support vector regression (SVR), which is SVM applied to the case of regression. Ju et al. utilized SVR and seasonal SVR forecast electricity load in Taiwan (Ju and Hong, 2013). Among the reviewed models, 41.4%, 22.4%, and 20.7% forecasted electric load, renewable energy, and energy & electricity demand.

Abductive networks is a machine learning method. It was found to be applied in two forecasting models (Table 5.3). Abdel-Aal, R.E. utilized AIM (abductory inductive mechanism) and GMDH (group method of data handling) approach for forecasting monthly energy demand. AIM is a supervised inductive machine-learning tool. It automatically develops abductive network models form a database of input and output variables. GMDH is a learning algorithm and formalized paradigm for iterated (multi-phase) polynomial regression (Abdel-Aal, 2008). In another study, Abdel-Aal et al. utilized AIM monthly electric energy consumption in eastern Saudi

Arabia and demonstrated that AIM performed better than that of regression method (Abdel-Aal *et al.*, 1997).

Decision tree develops an empirical tree which represents a segmentation of the data and able to classify and predict categorical variables. The segment is developed by applying a series of simple rules/logic. The advantage of the decision tree is that it produces a model which have segments of the system with interpretable rules or logic statements (Tso and Yau, 2007). However, it performs poorly with nonlinear and noisy data (Curram and Mingers, 1994). Tso et al. utilized decision tree method to predict electricity consumption in Hong Kong (Tso and Yau, 2007). Yu et al. developed a building energy demand predictive model with a decision tree and demonstrated high accuracy with 93% for training data and 92% for test data (Yu *et al.*, 2010).

Knowledge-based methods

Expert systems were applied in seven models (Table 5.3). Most of the models utilized expert system for short-term load forecasting (Ho *et al.*, 1992; Rahman and Bhatnagar, 1988; Ho *et al.*, 1990; Rahman and Hazim, 1996; Jabbour *et al.*, 1988). Ghanbari et al. applied cooperative ant colony optimization-genetic algorithm (COR-ACO-GA) for energy demand forecasting with knowledge-based expert systems, which yielded better accuracy (Ghanbari *et al.*, 2013). In another study, Ghanbari et al. integrated ant colony optimization (ACO), genetic algorithm (GA) and fuzzy logic to develop a load forecasting expert system (Ghanbari *et al.*, 2011).

Uncertainty methods

Fuzzy logic was applied in 40 models (Table 5.3). In the analyzed models, the fuzzy method was proved to be efficient with the incomplete or limited dataset. The theory of fuzzy sets is the foundation of the fuzzy logic. The basic description of the method can be found in (Elias and Hatziargyriou, 2009).

Grey prediction (GM) belongs to the family of the grey system among which the GM (1, 1) model is the most frequently used. GM methods adopt essential part of the grey theory (GT) which deals with systems with uncertain and deficient data (Lin *et al.*, 2004; Deng, 1989). The real world systems are modeled with the assumptions based on the inadequate information (Liu and Lin, 2006). GM method has been successfully adopted for forecasting models in different disciplines. Among the reviewed models, twenty-nine models applied GM. The basic description of the method can be found in (Akay and Atak, 2007).

Metaheuristic methods

Evolutionary methods are a subset of metaheuristic methods which uses mechanisms inspired by natural biological evolution, such as reproduction, mutation, recombination, and selection. There were several types of metaheuristic methods applied in forecasting models-

Genetic algorithm (GA) was utilized in thirty-nine forecasting models. The basic description of the method can be found in (Canyurt and Ozturk, 2008). Forouzanfar et al. forecasted natural gas consumption for residential and commercial sectors in Iran with LoR. However, to make the process simpler, two different methods are proposed to estimate the logistic parameters, of which one was GA based (Forouzanfar *et al.*, 2010). Zhang et al. utilized stimulated annealing algorithms with chaotic GA to develop a hybrid method to assist an SVR model in improving load forecasting performance (Zhang *et al.*, 2012). Assareh et al. applied GA for forecasting energy demand (Assareh *et al.*, 2012) and oil demand (Assareh *et al.*, 2010) in Iran based on population, GDP, import, and export. Chaturvedi et al. applied GA for electric load forecasting (Chaturvedi *et al.*, 1995). The objective of themodels, the purpose of GA in that model and the publishing year can be found in Table 5.5. Among the reviewed models, 27% utilized GA for parameter optimization in the hybrid methods.

Table 5.5: The purpose of GA in the reviewed hybrid models

Forecasted variable	Purpose of GA									Year	Ref.
	Parameter tuning	Parameter optimization	Model structure optimization	Coefficients optimization	Weighting factors value	Learning rate	Database generation	Estimate the residual	Improve performance		
Electricity demand	✓	-	-	✓	-	-	-	-	-	2007	Azadeh *et al.* (2007b)
Electricity load	-	-	✓	-	✓	-	-	-	-	2009	Shayeghi *et al.* (2009)
Hydro energy potential	-	-	✓	-	✓	✓	-	-	-	2010	Cinar *et al.* (2010)
Electricity demand	-	✓	✓	-	✓	-	-	-	-	2015	Yu *et al.* (2015)
Electricity demand	-	-	✓	-	-	-	-	-	-	2015	Wang *et al.* (2015b)

Table 5.5: The purpose of GA in the reviewed hybrid models

Forecasted variable	Purpose of GA									Year	Ref.
	Parameter tuning	Parameter optimization	Model structure optimization	Coefficients optimization	Weighting factors value	Learning rate	Database generation	Estimate the residual	Improve performance		
Electricity load	✓	-	-	-	-	-	-	-	-	2013	Hu *et al.* (2013)
Energy demand	-	-	-	-	-	-	✓	-	-	2013	Ghanbari *et al.* (2013)
Electricity load	-	-	-	-	-	-	✓	-	-	2011	Ghanbari *et al.* (2011)
Electricity load	-	✓	-	-	-	-	-	-	-	2009	Hong (2009a)
NOx Emission	-	-	-	-	✓	-	-	-	-	2013	Samsami (2013)

Table 5.5: The purpose of GA in the reviewed hybrid models

Forecasted variable	Purpose of GA									Year	Ref.
	Parameter tuning	Parameter optimization	Model structure optimization	Coefficients optimization	Weighting factors value	Learning rate	Database generation	Estimate the residual	Improve performance		
Energy demand	-	-	-	✓	-	-	-	-	-	2012	Yu *et al.* (2012c)
Energy demand	-	-	-	✓	-	-	-	-	-	2012	Yu *et al.* (2012b)
Energy demand	-	✓	-	-	-	-	-	-	-	2012	Yu and Zhu (2012)
Energy demand	-	-	-	-	-	-	-	✓	-	2011	Lee and Tong (2011)
Energy demand	-	-	-	-	-	-	-	✓	-	2012	Lee and Tong (2012)

Table 5.5: The purpose of GA in the reviewed hybrid models

Forecasted variable	Purpose of GA									Year	Ref.
	Parameter tuning	Parameter optimization	Model structure optimization	Coefficients optimization	Weighting factors value	Learning rate	Database generation	Estimate the residual	Improve performance		
Energy distribution*	-	-	-	-	-	-	-	-	✓	2000	Da Silva *et al.* (2000)
Energy distribution*	-	-	✓	-	-	-	-	-	-	2006	Sirikum and Techanitisawad (2006)
Energy demand	-	✓	-	-	-	-	-	-	-	2004	Ceylan and Ozturk (2004)

Table 5.5: The purpose of GA in the reviewed hybrid models

Forecasted variable	Purpose of GA									Year	Ref.
	Parameter tuning	Parameter optimization	Model structure optimization	Coefficients optimization	Weighting factors value	Learning rate	Database generation	Estimate the residual	Improve performance		
Electricity demand	-	-	-	-	-	-	-	-	✓	2005	Ozturk and Ceylan (2005)
Electricity demand	-	✓	-	-	-	-	-	-	-	2005	Ozturk *et al.* (2005)
Petroleum exergy production & demand	-	-	-	-	✓	-	-	-	-	2004	Ozturk *et al.* (2004)
Transport energy demand	-	-	-	-	✓	-	-	-	-	2005	Haldenbilen and Ceylan (2005)

Table 5.5: The purpose of GA in the reviewed hybrid models

Forecasted variable	Purpose of GA									Year	Ref.
	Parameter tuning	Parameter optimization	Model structure optimization	Coefficients optimization	Weighting factors value	Learning rate	Database generation	Estimate the residual	Improve performance		
Oil demand	-	✓	-	-	-	-	-	-	-	2006	Canyurt and Öztürk (2006)
Electricity demand	-	✓	-	✓	-	-	-	-	-	2007	Azadeh and Tarverdian (2007)
Natural gas demand	-	✓	-	-	-	-	-	-	-	2009	Xie and Li (2009)
Global CO_2 emission	-	-	-	-	✓	-	-	-	-	2012	Kavoosi *et al.* (2012)

Table 5.5: The purpose of GA in the reviewed hybrid models

Forecasted variable	Purpose of GA									Year	Ref.
	Parameter tuning	Parameter optimization	Model structure optimization	Coefficients optimization	Weighting factors value	Learning rate	Database generation	Estimate the residual	Improve performance		
PV power generation	-	✓	-	-	-	-	-	-	-	2015	Chu *et al.* (2015)
Total number	2	9	5	4	7	1	2	2	2		
%	6%	26%	15%	12%	21%	3%	6%	6%	6%		
* Transmission network expansion planning (TNEP), Power generation expansion planning (PGEP)											

An evolutionary algorithm (EA) was utilized in only one forecasting model. Wang et al. utilized a hybrid optimization method based on evolution algorithm and particle swarm optimization to improve the accuracy of forecasting ARMAX model (Wang *et al.*, 2008).

Memetic algorithm (MA) was applied in one forecasting model. For forecasting electricity load, Hu et al. applied firefly algorithm (FA) based memetic algorithm (FA-MA) to determine the parameters of SVR model appropriately (Hu *et al.*, 2013).

Particle swarm optimization (PSO) was applied in 34 models (Table 5.3). Zhu et al. developed an improved hybrid model (MA-C-WH), which utilized MA and adaptive particle swarm optimization (APSO) algorithm to forecast electricity demand in China. APSO was utilized to determine weight coefficients of the MA-C forecasting model, and the objective function of this optimization problem was to minimize the MAPE (Zhu *et al.*, 2011). Kiran et al. applied PSO to develop an ACO-PSO hybrid method to forecast energy demand of Turkey (Kıran *et al.*, 2012). The proposed ACOPSO method by Kiran et al. was applied for to forecast the wind power output of Binaloud wind farm in Iran in Rahmani *et al.* (2013). Assareh et al. applied PSO for forecasting energy demand (Assareh *et al.*, 2012) and oil demand (Assareh *et al.*, 2010) in Iran based on based on population, GDP, import, and export. AlRashidi et al. constructed long-term electric load forecasting model with PSO (AlRashidi and El-Naggar, 2010). Also for modeling and forecasting long-term natural gas consumption in Iran PSO was utilized (Kamrani, 2010). Abdelfatah et al. constructed a global CO_2 emissions forecasting model with PSO (Abdelfatah *et al.*, 2013). The objective of the models, the purpose of PSO in that model and the publishing year can be found in Table 5.6. Among the reviewed models, 33% utilized PSO for parameter optimization in the hybrid methods. The basic description of the method can be found in (Boeringer and Werner, 2003; Niu *et al.*, 2009).

Table 5.6: The purpose of PSO in the reviewed hybrid models

Forecasted variable	**Purpose of PSO**							**Year**	**Ref.**
	Parameter tuning	**Parameter optimization**	**Model structure optimization**	**Coefficients optimization**	**Weighting factors value**	**Scenario optimization**	**Improve performance**		
Electricity load	-	-	-	-	-	-	-	2009	Niu *et al.* (2009)
Electricity demand	-	✓	-	-	✓	-	-	2015	Yu *et al.* (2015)
Electricity load	-	-	-	-	✓	-	-	2009	Bashir and El-Hawary (2009)
Electricity demand	-	✓	-	-	-	-	-	2012	Wang *et al.* (2012c)
Electricity load	-	-	-	-	-	-	✓	2008	Wang *et al.* (2008)
Electricity load	✓	-	-	-	-	-	-	2013	Hu *et al.* (2013)
Electricity load	-	✓	-	-	-	-	-	2009	Hong (2009a)
NOx emission	-	-	-	-	✓	-	-	2013	Samsami (2013)
Energy demand	-	✓	-	-	-	-	-	2014	Cao *et al.* (2014)
Energy demand	-	-	-	✓	-	-	-	2012	Yu *et al.* (2012c)
Energy demand	-	-	-	✓	-	-	-	2012	Yu *et al.* (2012b)

Table 5.6: The purpose of PSO in the reviewed hybrid models

Forecasted variable	Purpose of PSO							Year	Ref.
	Parameter tuning	**Parameter optimization**	**Model structure optimization**	**Coefficients optimization**	**Weighting factors value**	**Scenario optimization**	**Improve performance**		
Energy demand	-	✓	-	-	-	-	-	2012	Yu and Zhu (2012)
Economic emissions	-	-	-	-	-	✓	-	2013	Aghaei *et al.* (2013)
Electricity load	-	-	-	-	✓	-	-	2010	Wang *et al.* (2010b)
Electricity demand	-	-	-	-	-	-	✓	2008	El-Telbany and El-Karmi (2008)
Electricity consumption	-	-	✓	-	-	-	-	2011	Assareh *et al.* (2011)
Energy demand	-	-	-	-	✓	-	-	2014	Nazari *et al.* (2014)
Energy demand	-	✓	✓	-	-	-	-	2012	Yu *et al.* (2012a)
Wind power	✓	-	-	-	-	-	-	2015	Osório *et al.* (2015)
Electricity load	-	✓	-	-	-	-	-	2014	Bahrami *et al.* (2014)

Table 5.6: The purpose of PSO in the reviewed hybrid models

Forecasted variable	**Purpose of PSO**							**Year**	**Ref.**
	Parameter tuning	**Parameter optimization**	**Model structure optimization**	**Coefficients optimization**	**Weighting factors value**	**Scenario optimization**	**Improve performance**		
Total number of models	2	7	2	2	5	1	2		
%	10%	33%	10%	10%	24%	5%	10%		

Artificial bee colony optimization (ABCO) was applied in four forecasting models among the reviewed models (Table 5.3). For forecasting world CO_2 emissions, BCO was utilized for finding optimal values of weighting factors for forecasting (Behrang *et al.*, 2011a). Chaotic artificial bee colony algorithm was applied for electric load forecasting to determine suitable values of its three parameters for forecasting (Hong, 2011).

Ant colony optimization (ACO) was utilized in ten forecasting models (Table 5.3). For energy demand forecasting, Ghanbari et al. applied Cooperative Ant Colony Optimization (COR-ACO) to learn fuzzy linguistic rules (degree of cooperation between database and rule base), which would yield better accuracy (Ghanbari *et al.*, 2013). In another study, Ghanbari et al. applied ACO-GA to generate optimal knowledge base (KB) for an expert system to forecast load (Ghanbari *et al.*, 2011). Niu et al. applied ACO with SVM model to forecast short-term power load, where ACO to pre-process the data which influence uncertain factors in forecasting (Niu *et al.*, 2010). A NOx emission forecasting model for Iran utilized ACO to estimate optimal values of weighting factors regarding actual data in (Samsami, 2013). To estimate energy demand of Turkey, ACO was applied in (Duran Toksarı, 2007). In another study, to forecast energy demand of Turkey, ACO was applied to develop ACOPSO hybrid method (Kıran *et al.*, 2012). For estimating the net electrical energy generation and demand of Turkey, ACO was applied based on the GDP, population, import and export (Toksarı, 2009). ACO based hybrid method was applied for to forecast the wind power output of Binaloud wind farm in Iran in (Rahmani *et al.*, 2013). Yu et al. applied ACO to forecast energy demand of China (Yu *et al.*, 2012c) and primary energy demand of China (Yu *et al.*, 2012b).

Chaotic ant swarm optimization (CAS) is deterministic chaotic optimization method inspired by behaviors of real ants (Li *et al.*, 2006), which was utilized by two models (Table 5.3). Hong et al. for electric load forecasting. In the proposed model CAS was applied to improve the forecasting performance of SVR by searching its suitable parameters combination (Hong, 2010). For electric load forecasting with SVR model, Hong W. C. applied CAS to determine suitable parameter combination for the model (Hong, 2009a).

Differential evolution (DE) was applied in three of the analyzed models (Table 5.3). Wang et al. developed a load forecasting model with DE and SVR (Wang *et al.*, 2012b). In another study, adaptive differential evolution (ADE) was applied with BPNN for developing a method for electricity demand forecasting in (Wang *et al.*, 2015b). For short -term load forecasting, Xiaobo et al. developed a GRA-DE-SVR model, where DE to optimize parameters of SVR model (Xiaobo *et al.*, 2014).

Gravitational search algorithm (GSA) was applied assist to develop three demand estimation models to forecast oil consumption based on socio-economic indicators in (Behrang *et al.*, 2011b). GSA was utilized to forecast electricity load in Taiwan to assist the seasonal SVR model in (Ju and Hong, 2013). GSA was applied to optimize the parameters of the LSSVM model developed by Yuan et al. to short-term wind power prediction model (Yuan *et al.*, 2015). Gavrilas et al. proposed a model of electric load forecasting with GSA combined with regression method and Kohonen neural networks (Gavrilas *et al.*, 2014).

Harmony search (HS) was utilized to develop HArmony Search Transport Energy Demand Estimation (HASTEDE) model, in a study conducted by Ceylan et al. to project the transport sector energy consumption in Turkey. The results demonstrated overestimation of transport sector energy consumption by about 26%, and linear and exponential forms underestimate by about 21%, compared to Ministry of Energy and Natural Resources projections. The study pointed out the under, and overestimation might be the outcome of the choice of modeling parameters and procedures (Ceylan *et al.*, 2008).

Immune algorithm (IA) was applied for electric load forecasting model, where IA determined the parameter selection of SVR model (Hong, 2009b).

Simulated annealing algorithms (SA) is an evolutionary method was applied in six models (Table 5.3). Zhang et al. utilized SA with chaotic GA to develop a hybrid method to assist an SVR model in improving load forecasting performance [104]. Pai et al. utilized SA algorithms were employed to choose the parameters of an SVM model to forecast electricity load in Taiwan (Pai and Hong, 2005). Hong, W.-C. developed SVMSA model for load forecasting, where SA was applied to determining appropriate parameter combination for SVR model (Hong, 2009a).

Moreover, Firefly algorithm (FA) and Cuckoo search algorithm (CSA) are two metaheuristic methods utilized in four and two forecasting models respectively to develop a hybrid methodology in recent times (Table 5.3).

5.3.3 Mathematical programming (MP)

Mathematical programming or mathematical optimization prescribes best solution/s from a set of available alternatives under some conditions. Among the analyzed models, one mathematical programming methods were found- Nonlinear programming (NLP). Forouzanfar et al. forecasted natural gas consumption for residential and commercial sectors in Iran with LoR. However, to make the process simpler, two different methods are proposed to estimate the logistic parameters, of which one was GA based (Forouzanfar *et al.*, 2010).

5.4 Hybrid methods

In some models, for specific reasons (i.e., parameter tuning, elevating accuracy) different stand-alone methods were combined to construct hybrid methods. Hybrid methods were utilized to develop the assumptions and parameters in some forecasting models (Wang and Huang, 2007). The hybrid methods found in analyzed models can be divided into following four categories:

5.4.1 Statistical-statistical methods

Xu et al. combined MA and PCM to develop a Polynomial Curve and Moving Average Combination Projection (PCMACP) model to forecast natural gas consumption in China from 2009 to 2015. The model demonstrated, the average annual growth rate will increase, and the natural gas consumption will reach 171,600 million cubic meters in 2015 in China (Xu and Wang, 2010). To estimate the long-run elasticities of the Namibian energy demand, Vita et al. applied ARDL bounds testing approach to cointegration (De Vita *et al.*, 2006).

Tan et al. developed a day-ahead electricity price forecasting model by combining Wavelet (WT)–GARCH–ARIMA (Tan *et al.*, 2010). Bowden et al. applied ARIMA-EGARCH-M for short-term forecasting of electricity prices (Bowden and Payne, 2008). Hickey et al. developed four ARMAX–GARCH models for forecasting hourly electricity prices. The four models were- GARCH (1,1), EGARCH (1,1), APARCH (1,1) and CGARCH (1,1) power ARCH (PARCH), where EGARCH is exponential GARCH; APARCH is asymmetric power ARCH, and CGARCH is Component GARCH (Hickey *et al.*, 2012). Liu et al. developed ARMA-GARCH models (ARMA-SGARCH, ARMAQGARCH, ARMA-GJRGARCH, ARMA-EGARCH, and ARMA-NGARCH) and their form of ARMA– GARCH-in-mean to forecast short-term electricity prices (Liu and Shi, 2013).

5.4.2 Statistical-CI methods

Pao developed nonlinear hybrid models with SEGARCH and WARCH with ANN to forecast energy consumption in Taiwan (Pao, 2009). For wind speed forecasting Cadenas et al. developed a ARIMA-ANN model (Cadenas and Rivera, 2010). González-Romera et al. developed an hybrid method where the periodic behavior was forecasted with a Fourier series while the trend was predicted with a neural network (González-Romera *et al.*, 2008). For forecasting symbolic interval time series, Maia et al. developed an ARMA-ANN model, where it performed better than that of ARMA (Maia *et al.*, 2006). Kandananond, K. developed prediction models of the electricity demand in Thailand with NN, MLR and ARIMA methods to develop ANN-MLR and ANN-ARIMA hybrid methods (Kandananond, 2011). ANN model using statistical feature parameters (ANN-SFP) and historical data series (ANN-HDS) was applied for short-term solar irradiance forecasting (STSIF) (Wang *et al.*, 2012a). Shi et al. applied ARIMA with ANN and SVM to develop two hybrid models of ARIMAANN and ARIMA-SVM for forecasting of wind speed and wind power generation (Shi *et al.*, 2012). Bouzerdoum et al. developed SARIMA-SVM model for short-term power forecasting of a small-scale grid-connected photovoltaic plant (Bouzerdoum *et al.*, 2013). Guo et al. developed a hybrid Seasonal Auto-Regression Integrated Moving Average and Least Square Support Vector Machine (SARIMA-LSSVM) model for forecasting wind speed in Hexi Corridor of China (Guo *et al.*, 2011). Wang et al. applied PSO optimal Fourier approach on residual modification of SARIMA to develop F-S-SARIMA model to forecast electricity demand for China (Wang *et al.*, 2012c). Wang et al. developed a combined model to forecast electric load. For the model SARIMA, seasonal exponential smoothing (S-ESM) and Weighted SVM (W-SVM) was constructed by linear combination and APSO was utilized for determining weight coefficients of combined forecasting model (Wang *et al.*, 2010b). Wang et al. applied seasonal decomposition with LSSVR for hydropower consumption forecasting in China (Wang *et al.*, 2011).

Song et al. applied fuzzy regression analysis in the short-term load forecasting problem (Song *et al.*, 2005). Xu et al. applied GM (1,1) with ARMA to develop GM-ARMA model to forecast energy consumption for Guangdong Province of China (Xu *et al.*, 2015). Amin-Naseri et al. developed a model for daily electrical peak load forecasting (PLF) with feed-forward neural network (FFNN) method, where the Davies–Bouldin validity index was introduced to determine the best clusters (Amin-Naseri and Soroush, 2008). Forouzanfar et al. forecasted natural gas consumption for residential and commercial sectors in Iran by utilization of LoR. However, GA based approach was proposed to estimate the logistic parameters, to make process simpler (Forouzanfar *et al.*, 2010). Zhu et al. developed an improved hybrid model (MA-C-WH), which utilized MA and adaptive particle swarm optimization algorithm to forecast electricity demand in China (Zhu *et al.*, 2011). An electric load forecasting model was developed with regression method combined with GSA or Kohonen neural networks (Gavrilas *et al.*, 2014). GSA was applied to estimate optimal weighting factors for three demand estimation models to forecast oil consumption based on socio-economic indicators up to 2030 (Behrang *et al.*, 2011b).

5.4.3 CI-CI methods

To forecast solar radiation, Chen et al. developed a fuzzy neural network (FNN) model with ANN and fuzzy logic (Chen *et al.*, 2013). The fuzzy neural network was applied for day-ahead price forecasting of electricity markets in (Amjady, 2006). Bazmi et al. utilized adaptive neuro-fuzzy network (ANFIS) for electricity demand forecasting for the state of Johor, Malaysia (Bazmi *et al.*, 2012). In another study, Zahedi et al. applied neurofuzzy network for electricity demand forecasting for Ontario province, Canada (Zahedi *et al.*, 2013). Esen et al. utilized the neuro-fuzzy network for forecasting performances of ground-coupled heat pump system [151]. Forecasting model of mean hourly global solar radiation was developed with ANFIS (Sfetsos and Coonick, 2000). Akdemir et al. utilized ANFIS for long-term load forecasting (Akdemir and Çetinkaya, 2012). Chen et al. applied a collaborative principal component analysis and fuzzy feed- forward neural network (PCA-FFNN) approach for long-term load forecasting (Chen and Wang, 2012). In another study Chen, T. applied a collaborative fuzzy-neural approach for long-term load forecasting (Chen, 2012). Chang et al. applied weighted evolving fuzzy neural network for monthly electricity demand forecasting in Taiwan (Chang *et al.*, 2011). FNN was also applied for short-term load forecasting in (Bakirtzis *et al.*, 1995; Srinivasan *et al.*, 1995; Papadakis *et al.*, 1998). Padmakumari et al. applied FNN for long-term land use based distribution load forecasting (Padmakumari *et al.*, 1999).

In case of metaheuristic methods, genetic algorithm (GA), Particle swarm optimization (PSO) and Ant colony optimization (ACO) were mostly utilized methods. El-Telbany et al. applied PSO and BP algorithm to train NN model to forecast electricity demand in Jordan (El-Telbany and El-Karmi, 2008). Ghanbari et al. applied cooperative ant colony optimization-genetic algorithm (COR-ACO-GA) for energy demand forecasting with knowledge-based expert systems, which yielded better accuracy than ANFIS and ANN (Ghanbari *et al.*, 2013). Ghanbari et al. integrated ACO, GA and fuzzy logic to develop a hybrid method to construct a load forecasting expert system for Iran in Ghanbari *et al.* (2011). Niu et al. developed ACO-SVM model for forecasting short-term power load (Niu *et al.*, 2010). A NOx emission forecasting model for Iran, where GA, PSO, and ACO were applied to estimate optimal values of weighting factors regarding actual data in Samsami (2013). In another study, to forecast energy demand of Turkey, ACO-PSO based hybrid method was applied (Kıran *et al.*, 2012). Hybrid ACO-PSO method was applied for to forecast the wind power output of Binaloud wind farm in Iran in (Rahmani *et al.*, 2013). To forecast Annual electricity demand, Yu et al. utilized GA to optimizes the structure and PSO-GA to the parameters of the basis and weights of the Radial Basis Function (RBF) neural network (Yu *et al.*, 2015). Yu et al. applied PSO–GA approach for forecasting energy demand of China (Yu *et al.*, 2012c) and primary energy demand of China (Yu *et al.*, 2012b). In another study, Yu et al. utilized improved PSO-GA to forecast energy demand for China (Yu and Zhu, 2012). Lee et al. constructed a GP-based GM(1, 1) model (Lee and Tong, 2011) and hybrid dynamic GPGM model (Lee and Tong, 2012) to predict energy consumption.

Hu et al. applied firefly algorithm (FA) based memetic algorithm (FA-MA) to appropriately determine the parameters of SVR model for load forecasting [108]. Hong, W.-C. developed IA-SVR model for electric load forecasting (Hong, 2009b). Fan et al. integrated two machine learning techniques: Bayesian clustering by dynamics (BCD) and SVR to forecast the electricity load (Fan *et al.*, 2008).

Hsu et al. developed an improved GM (1, 1) model that combines residual modification with ANN sign estimations (Hsu and Chen, 2003a). For predicting hourly load demand Bashir et al. applied ANNs and utilized PSO algorithm to adjust the network's weights in the training phase of the ANNs (Bashir and El-Hawary, 2009). Xie et al. constructed improved natural gas consumption GM (1, 1) model by applying GM for optimizing parameters (Xie and Li, 2009).

Zhang et al. utilized SA with chaotic GA to develop a chaotic genetic algorithm-simulated annealing algorithm (CGASA), with an SVR model to improve load forecasting. The proposed CGASA was utilized for the internal randomness of chaotic iterations to overcome premature local optimum, which yielded better accuracy (Zhang *et al.*, 2012). SA algorithms were employed to choose the parameters of an SVM model to develop SVMSA method to forecast electricity load in Taiwan in Pai and Hong (2005). Ko et al. combined SVR, radial basis function neural network (RBFNN), and dual extended Kalamn filter (DEKF) to develop an SVR-DEKF-RBFNN model for short-term load forecasting (Ko and Lee, 2013). To forecast electric load, CAS was applied to improve the forecasting performance of SVR by searching its suitable parameters combination in Hong (2010). Azadeh et al. developed electrical energy consumption forecasting models with GM-ANN method, where GA tuned parameters and the best coefficients with minimum error were identified for ANN (Azadeh *et al.*, 2007b). Cinar et al. applied GA to determine the hidden layer neuron numbers for GA-FFBPNN model to forecast the hydro energy potential of Turkey (Cinar *et al.*, 2010). Xiaobo et al. developed a GRA-DE-SVR model for short-term load forecasting with DE and SVR (Xiaobo *et al.*, 2014).

For forecasting world CO_2 emissions, BCO was utilized for finding optimal values of weighting factors for forecasting with ANN (Behrang *et al.*, 2011a). In another study, chaotic artificial bee colony algorithm was applied to determine suitable values of its three parameters for electric load forecasting (Hong, 2011). Continue genetic algorithm was applied to determine the number of neurons in the hidden layer and connecting weights for ANN model to forecast short-term electricity load (Shayeghi *et al.*, 2009). For accurate forecasting of electric load, Hong W.-C. applied CAS, CGA, CPSO, and SA with SVR model, to determine suitable parameter combination for the model (Hong, 2009a).

GSA was utilized to assist the seasonal SVR model to develop SVRGSA and SSVRGSA for forecasting electricity load in Taiwan in Ju and Hong (2013). Yuan et al. developed an LSSVM-GSA model to short-term wind power prediction model where GSA was applied to optimize the parameters of the LSSVM (Yuan *et al.*, 2015). Niu et al. applied particle swarm optimization (PSO) as a training algorithm to obtain the weights of the forecasting methods (i.e., a method of proportional (MP), LR, GM, and BPNN) (Niu *et al.*, 2009). Wang et al. developed a load forecasting model with DE and SVR, where DE algorithm was used to choose the appropriate parameters for the SVR model (Wang *et al.*, 2012b). Wang et al. applied ADE-BPNN forecasting method for developing prediction for electricity demand ompared with different methods (i.e., ARIMA, BPNN, GA–BPNN, DE–BPNN, SSVRCGASA, and TF-e-SVR-SA) (Wang *et al.*, 2015b). Cao et al. applied quantum-behaved particle swarm optimization (QPSO) to optimize the parameters for the SVR model and developed an SVR-QPSO model to forecast the energy demand of China (Cao *et al.*, 2014).

5.4.4 Statistical-MP methods

Forouzanfar et al. forecasted natural gas consumption for residential and commercial sectors in Iran by utilization of LoR. However, NLP and GA based approach were proposed to estimate the logistic parameters, to make the process simpler (Forouzanfar *et al.*, 2010).

5.5 Discussion

5.5.1 Accuracy

An accurate forecasting of energy (demand and supply) and relevant parameters is critical to making informed decisions on energy infrastructure for power generation and distribution. Forecasting accuracy is determined using different performance evaluation measures. Root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage forecast error (MAPE) were mostly utilized (Pao, 2009; Niu *et al.*, 2009; Pai and Hong, 2005; Chen *et al.*, 2013; Nguyen and Nabney, 2010; Mohandes *et al.*, 1998a; Mandal *et al.*, 2006). Among other methods, mean absolute deviation (MAD), normalized root-mean-square error measure (NRMSE), standard error of prediction (SEP) and absolute relative error (ARE) were also applied (Wang *et al.*, 2012c; Pai and Hong, 2005; Xu *et al.*, 2015; Nguyen and Nabney, 2010). The accuracy evaluation methods were different in various models. The different choice of accuracy methods made is hard to categorize the methods from best to worst because the methods were not evaluated with same data or for the similar aim Under this circumstances, this study focused on the accuracy results of the reviewed models and their comparisons to find out which model performs better in specific objective (Table A.4).

This study found that combination of statistical methods performs better than that of stand-alone statistical methods and (Bianco *et al.*, 2013; Pao, 2009; Shen *et al.*, 2013; Li *et al.*, 2012; Wang and Wu, 2012; Bowden and Payne, 2008; Tan *et al.*, 2010; Rentziou *et al.*, 2012; Mohamed and Bodger, 2005b; Nguyen and Nabney, 2010)in most of the cases, CI methods outperformed statistical methods (Pao, 2006). Moreover, hybrid methods performed superiorly in accuracy to CI methods (Table A.4). In case of forecasting nonlinear and discontinuous data, machine learning methods performed better than that of statistical methods (Zhang *et al.*, 1998; Hsu and Chen, 2003a; Hill *et al.*, 1994). When the relationship between the variables is not known, or complex machine learning methods can forecast the data, which is difficult to handle statistically (Paliwal and Kumar, 2009). In some studies, authors combined machine learning methods with statistical methods to increase the accuracy (Abdel-Aal *et al.*, 1997; González-Romera *et al.*, 2008; Shi *et al.*, 2012;

Esen *et al.*, 2008a; Srinivasan, 2008). However, machine learning methods tend to be complex in learning and application, while statistical methods are easy to adopt (Zhao and Magoulès, 2012). Some authors noted the learning complexity of methods influence the choice of forecasting techniques (Forouzanfar *et al.*, 2010). Data availability also affects the choice of forecasting method.

ANN is a data-driven method and requires a large amount of data for higher forecasting accuracy (DominikSlezak and Mirkin, 2011). In case of incomplete data sets, fuzzy logic is better. However, the accuracy level is not always satisfactory (DominikSlezak and Mirkin, 2011). Grey prediction is another useful method while working with uncertainty problems with the small sample; incomplete and discrete data (Shen *et al.*, 2013; Li *et al.*, 2012). Significant numbers of authors advocated the utilization of hybridization methods to enhance the accuracy of the forecasting models. On the other hand, it would add more complexity in the model structure.

5.5.2 Temporal analysis

Based on the analysis of the previous EPMs, the research on forecasting models started in 1985, after the oil shock/crisis of 1970's (Figure 5.4). At the starting period, the number of models was low. After the United Nations Framework Convention on Climate Change (UNFCCC) committed State Parties to reduce GHG gas emission created by anthropogenic CO_2 emission systems, the development of forecasting EPMs started to rise from 1995 because energy sector has been one of the highest global emissions sources.

The number of models started to increase from 2005 when the Kyoto Protocol was entered into force in 2005. The number of models published escalated from 12 to 25 within 2004–2005. In the last 12 years, 76% EPMs were developed (Figure 5.4). The highest number of models (46) was developed in 2010. However, the number of EPMs reduced to 34 in 2011 & 2012. In 2013 and 2014, the published model number reduced to 20 and 24 respectively. The EPM number elevated to 27 in 2015. Up to June 2017, six models were published with the objective of forecasting in energy planning sector.

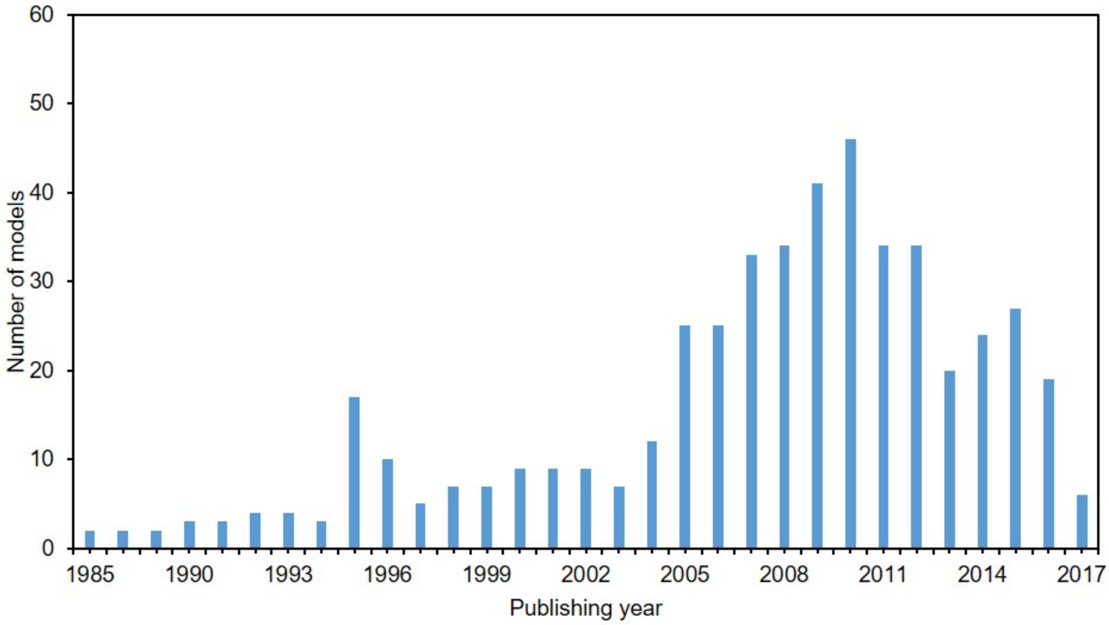

Figure 5.4: Publishing year of the studied models

Among the forecasting methods, statistical methods were the first to rise in use from 2005. Before 1990, statistical methods were mostly utilized (Figure 5.5). After 1990's use of machine learning methods started to rise. From 2007, the use of machine learning methods augmented significantly as well as with statistical methods. After 2009 the integration of metaheuristic methods in forecasting started to grow. In 2015, 56 models utilized CI methods which is four times more than that of the statistical ones (14 models). The CI method use is demonstrating an exponential growth in past 12 years, where statistical methods are showing a gradual descend since 2010 (Figure 5.5). A major cause of the growth may be the better accuracy of the CI methods (Table A.4) and higher speed in computational capabilities (Moewes and Nürnberger, 2013).

5.5.3 Geographical analysis

Continent-wise, all the continents with human habitation developed EPMs. According to United Nations, there 269 countries in the world (UN, 2013). Among these countries, forecasting models were developed for only 59 countries. Among all the countries, the highest number of forecasting models were developed in China. Total 122 models were developed in China with 27 of the 50 analyzed methods of this study.

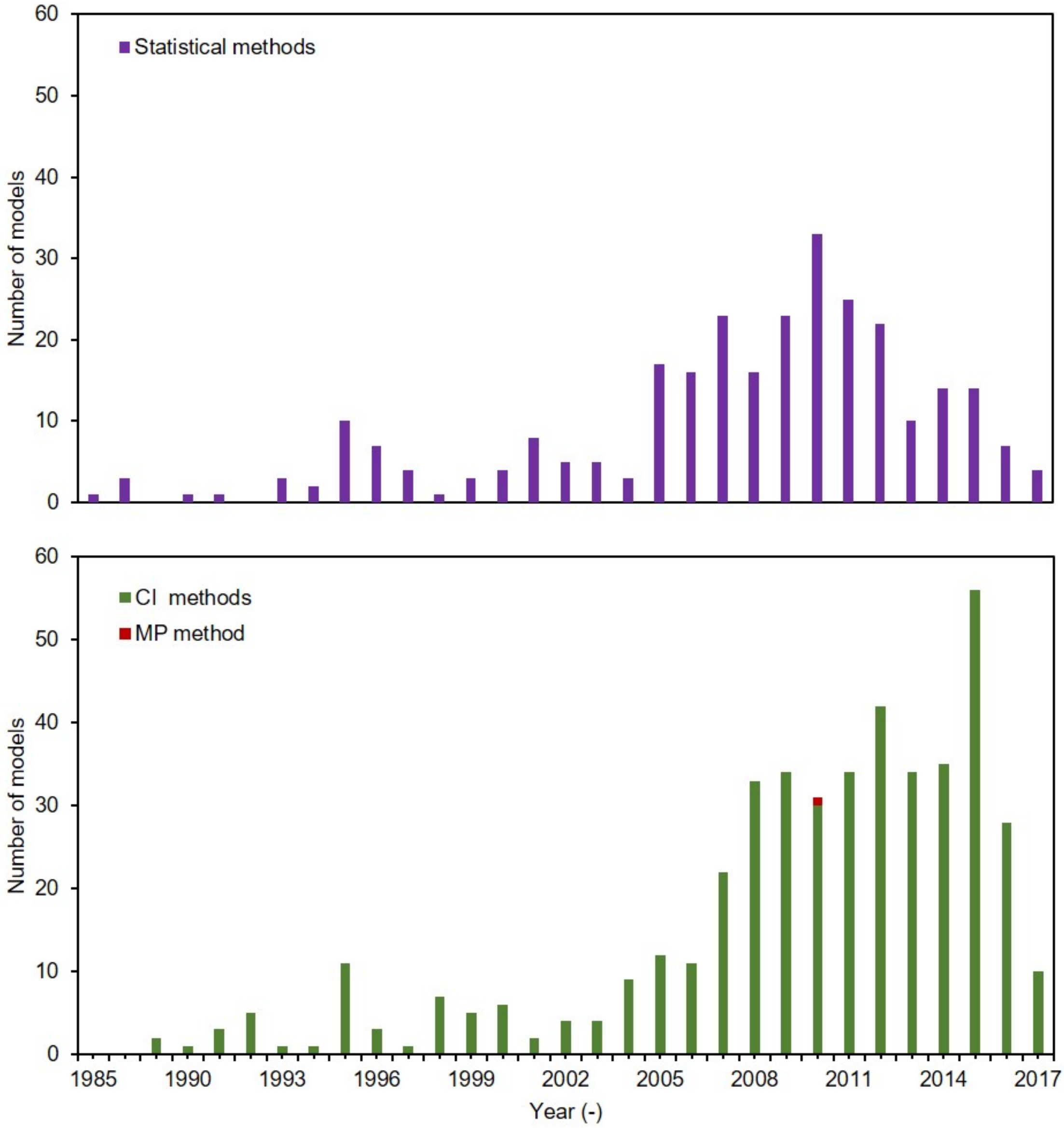

Figure 5.5: Publishing year of the models with methods utilized in energy planning models

In Europe, there are 53 countries (UN, 2013), but only 18 countries developed energy planning forecasting models. The countries were- UK, Ireland, France, Netherlands, Denmark, Germany, Spain, Portugal, Italy, Croatia, Romania, Russia, Czech Republic, Hungary, Poland, Cyprus, Greece, and Turkey. However, most of the models were developed in the UK, Turkey, Spain, and Greece (Figure 5.6).

There are 41 counties in North America (UN, 2013). However, only six countries (Haiti, Jamaica, Trinidad and Tobago, Mexico, USA and Canada) developed models for energy forecasting. Most of the models among these countries were developed in the USA (Figure 5.6).

The continent of Oceania contains 25 countries (UN, 2013), of which only Australia and New Zealand developed models. In this region other 23 countries of Melanesia, Micronesia and Polynesia are considered developing regions (UN, 2013). This concludes the fact that in this continent only developed countries established energy forecasting models.

In Asia, Japan, China, Hong Kong, Taiwan, South Korea, Jordan, Lebanon, Oman, Saudi Arabia, Kuwait, Iran, Pakistan, India, Bangladesh, Sri Lanka, Nepal, Indonesia, Singapore, Philippines, Malaysia, and Thailand developed forecasting models for energy planning. Therefore, 21 countries among 50 countries (UN, 2013) of the continents developed forecasting models. In Asia, the only developed economy is established in Japan. Along with Japan, other developing countries also established some models. In Asia, China, Taiwan, Iran, and India developed a higher number of forecasting models.

Africa has 58 countries, of which only five courtiers developed forecasting models. Namibia, Ghana, Algeria, Tunisia and South Africa established 2, 4, 2, 1 and five models respectively.

Among 14 countries of South America, Ecuador, Peru, Chile, Venezuela, Columbia, Argentina and Brazil adopted forecasting model for energy planning. Brazil developed the most number of models.

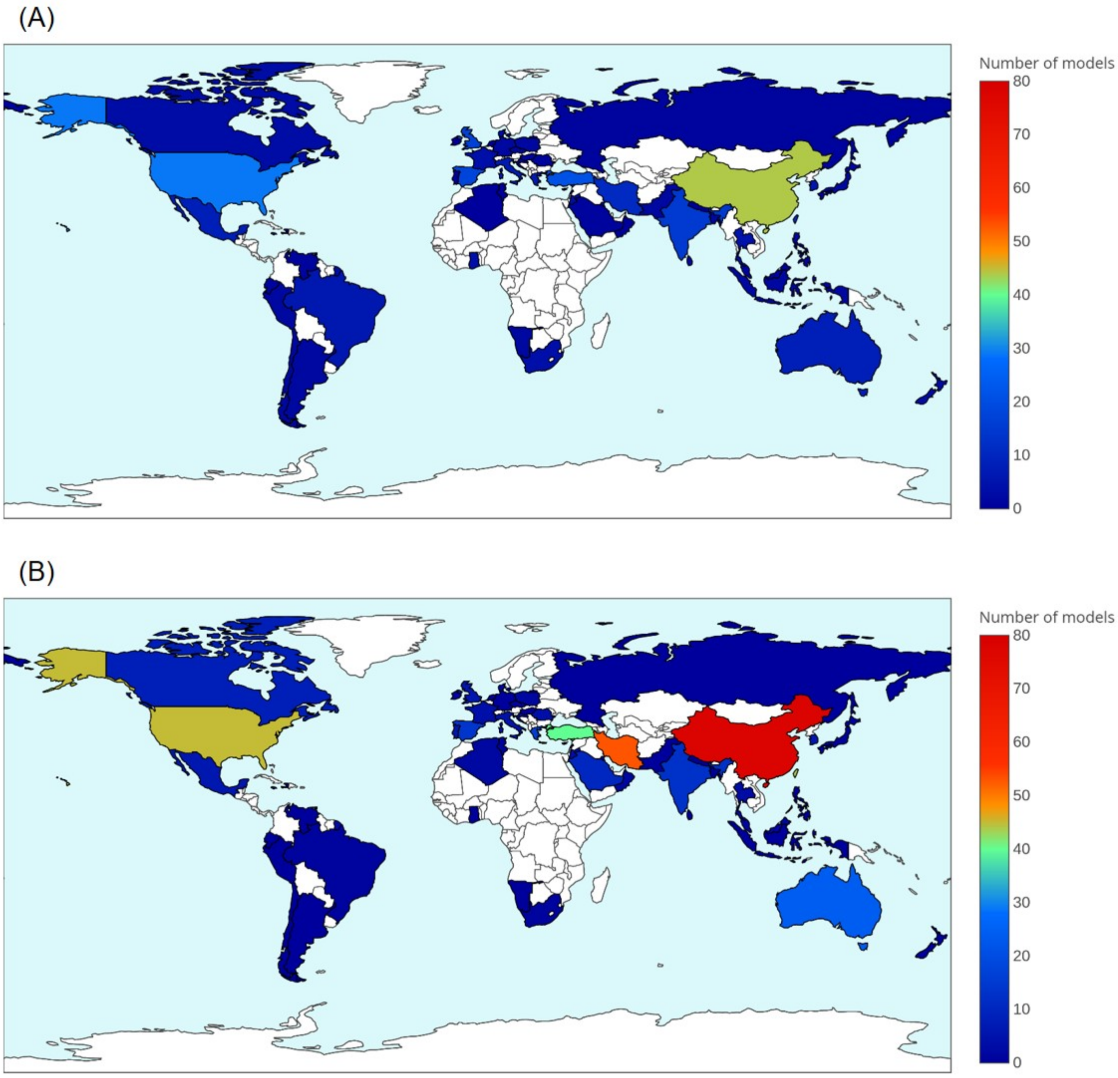

Figure 5.6: Country wise number of models utilizing (A) Statistical, (B) CI and MP forecasting methods

Among the studied 483 models, twelve models were developed for global forecasting (Table 5.2). LR, ANN, GA, ABCO, and PSO were utilized for forecasting for global geographical extent (Figure 5.6).

However, 30 models were established for regional geographical extent. The regions considered were- OECD countries, G-7 countries, Europe, CIS Countries, GCC countries, BRIC country, Middle East, North America, South America, Asia and developing countries. Among the 30 models, eight models were developed for Europe. From the analysis of the geographical extent, it is evident that developed economies have more EPMs than that of developing and least developed ones (Figure 5.6).

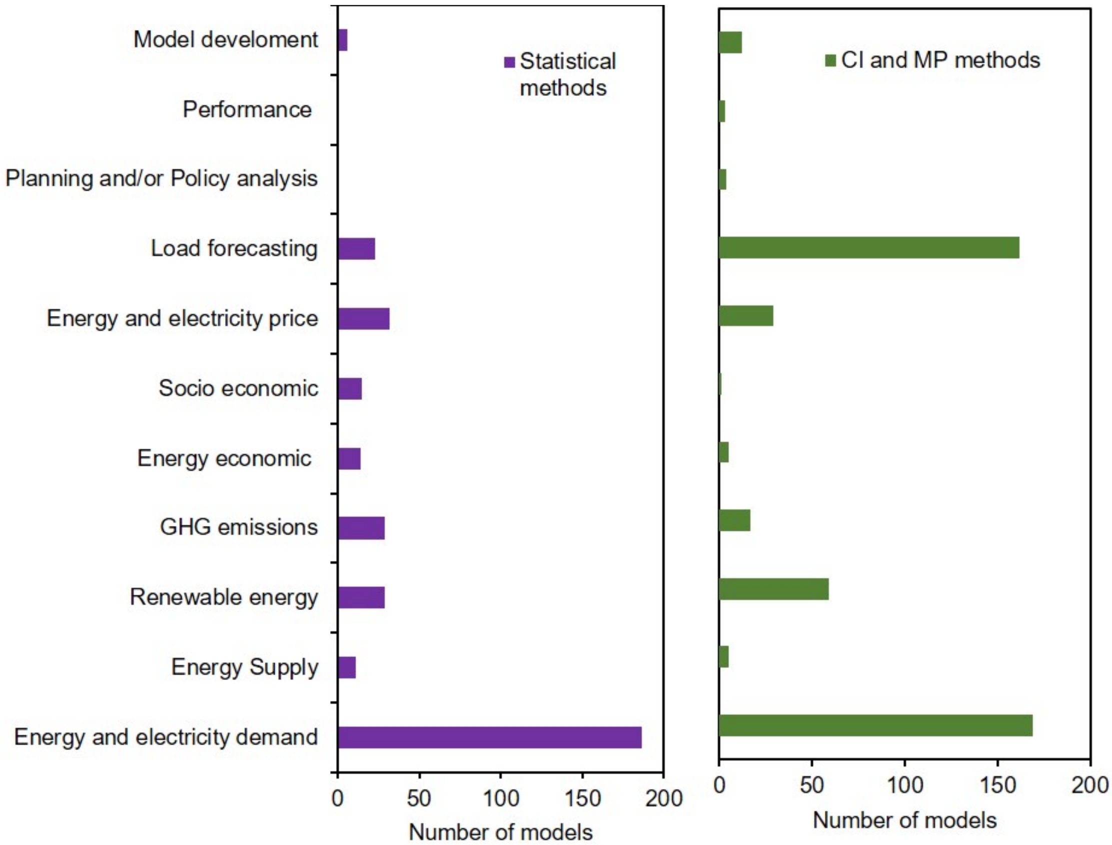

Figure 5.7: Objectives of the models

Statistical methods are utilized for developed, developing and least developed contexts. However, CI methods are widely used in developed contexts (Figure 5.6).

5.5.4 Objective based analysis

The studied EPMs had different objectives. From the analysis of 483 models, 11 objectives were identified (Table A.5). These were energy and electricity demand, energy supply, renewable energy, GHG emissions, energy economic, socio-economic, energy and electricity price, load forecasting, planning and policy analysis, performance analysis and model development. Among the 28 statistical forecasting methods, ARIMA was used for nine objectives, while LR complied with seven objectives, followed by ARMA (6 objectives) (Table A.5). Among the 28 statistical methods, 23 were utilized for energy and electricity demand forecasting in 53.9% of the reviewed 483 models (Table A.5).

Among the CI and MP methods, ANN was utilized for nine objectives, followed by GM for seven objectives. FL, SMV, PSO, and ACO were utilized for six objectives each. Moreover, GA was utilized for achieving five of the objectives (Table A.6). Among the 22 CI and MP methods, 13 and 18 methods were utilized for energy and electricity demand, and electric load forecasting respectively. In the reviewed 483 models, 73%, 38%, 18% and 13% of the model objectives were energy and electricity demand, electric load, renewable energy, and energy & electricity price forecasting respectively. For energy and electricity demand forecasting, statistical methods were used in 18% more models than that of CI and MP. However, CI methods were utilized in 28% and 4% more in electric load and renewable energy forecasting models respectively than that of statistical ones (Figure 5.7).

Among the 50 analyzed methods, a maximum number of methods (23 statistical, 12 CI and one MP) were utilized to develop energy and electricity demand forecasting models. Second highest number of methods (8 statistical and 18 CI) were utilized to forecast electric load. Third highest number of methods (7 statistical and 9 CI) were used for renewable energy forecasting (Tables A.5 & A.6).

5.6 Summary

Energy planning models assist stakeholders to assess the impact of current and future energy policies. The accuracy of EPMs depends on applying appropriate forecasting methods for demand and supply sector projections. Among all the forecasting methods, choice of appropriate one depends on different factors. The complexity and nature, as well as, the objective of the research problem are one of the critical determinants of method choice. Other important factors of forecasting method selection can be accuracy and estimation adaptability with incomplete data-set.

The review of 483 EPMs, revealed the use of fifty different methods between 1985 and June 2017. Among the 50 identified methods, statistical, computational intelligence (CI) and mathematical programming (MP) methods were 28, 21 and one respectively. Among CI methods, ANN was utilized in 194 EPMs, followed by SVM (58 models), FL (40 models), GA (39 models), PSO (34 models) and GM (29 models). In the case of statistical methods, ARIMA, LR, and ARMA were utilized in 46, 39 and 22 EPMs respectively for forecasting. Evidently, CI methods were widely utilized than that of statistical ones for electric load and renewable energy forecasting. However, statistical methods were used in 18% more models than that of CI and MP for energy and electricity demand forecasting. The accuracy of CI methods for forecasting was better than that of statistical ones. A significant number of forecasting models utilized multiple stand-alone methods to develop a hybrid approach because they yielded higher accuracy than that of stand-alone ones. In case of incomplete data-set, some CI methods such as fuzzy logic and grey prediction outperformed other stand-alone ones.

The analysis of the studied model objectives showed that most of the forecasting methods were applied to forecast energy demand and electrical load. The development of the forecasting models started from 1985, it spiked after 2005, and it is continuing. Most numbers of models were developed in 2010. In case of the geographical extent, although most of the models were established for developed countries, some of the developing countries also established forecasting models. The highest number of models were developed for China.

Chapter 6

Drivers for energy sector decarbonisation

Estimation and forecasting of the cost of reducing carbon emissions are significantly challenging due to the uncertainty of exogenous (e.g., population, GDP), and endogenous assumptions, as well as the volatility of the energy market (Weyant, 1993). The limitation of existing global models are (Weyant, 1993)—

- They exclude socioeconomic nuances of developing countries; and
- Typically treated simplistically. Sometimes aggregated together because the lack of appropriate data for the countries involved and computational constraints due to model size.

Cost models of decarbonization has four components- the baseline input assumptions to the analysis, the specification of the control scenario being considered, the structure of the model employed to make the projection and the cost measure(s) reported (Weyant, 1993). Based on the components, the structure of cost model would be an input-output model with a structure such as input $\rightarrow$ mathematical estimation and forecasting$\rightarrow$ Output.

The analysis of existing EMPs in chapter 4 revealed the shortcomings of models constructed with developed countries while adopted for developing contexts. The major shortcomings in generalized model structures were addressing the contextual local characteristics in a developing country such as corruption, political instability, suppressed demand and climate change impact. For this study, BD2050 energy and emissions model (BD2050, 2015) was utilized for baseline energy demand, supply and emissions assumptions form 2010 to 2050 for the projection of demand, energy generation and GHG emissions. Because BD2050 is a detailed bottom-up energy and emissions localized model developed for Bangladesh's energy demand and supply sector. The modeling approach of BD2050 was rendered to be particularly suitable for Bangladesh to establish a cost model and examine the effect of corruption on energy market. The supply sector assumptions for Bangladesh were updated to forecast the potential of generation resources for different scenarios. The cost model acts as an extension of the energy and emissions pathway model (Figure 6.1). The proposed model of decarbonization in this study has four interconnected layers, such as- policy, socioeconomic, energy and cost layer (Figure 6.1). For a reliable forecasting and decision making, all these layers are more or less significant for a cost of decarbonization model for developing and least developed countries. The socioeconomic, energy and cost layers have three parts- input variables, mathematical estimation and forecasting, and the output variables. Policy layer feeds into the input variables.

6.1 'BD2050 – Bangladesh 2050 Energy and Emissions Pathways' model

BD 2050 model was developed for the energy sector planning for Bangladesh from 2010-2050. The primary goal is to analyze the energy security in Bangladesh up to 2050 under different scenarios. The model has demand and supply domains. The demand domain is comprised of building, industry, transport, agriculture, and food sector. The supply domain is comprised of the operational and potential energy generation sources for Bangladesh, such as- coal, natural gas, liquid hydrocarbon, nuclear, wind, solar, geothermal, hydro, waste and biomass. Moreover, the energy fuel and transmission & distribution sectors were modeled in BD 2050. The building sector is divided into three categories- rural, urban household, and commercial building sector. Also, the transport sector has four categories- passenger, freight, international aviation, and shipping. There is also a socioeconomic sector, where demographic, economic analysis was undertaken to support the assumptions in other sectors. Assumptions from BD 2050 utilized for projecting electricity demand 2010-

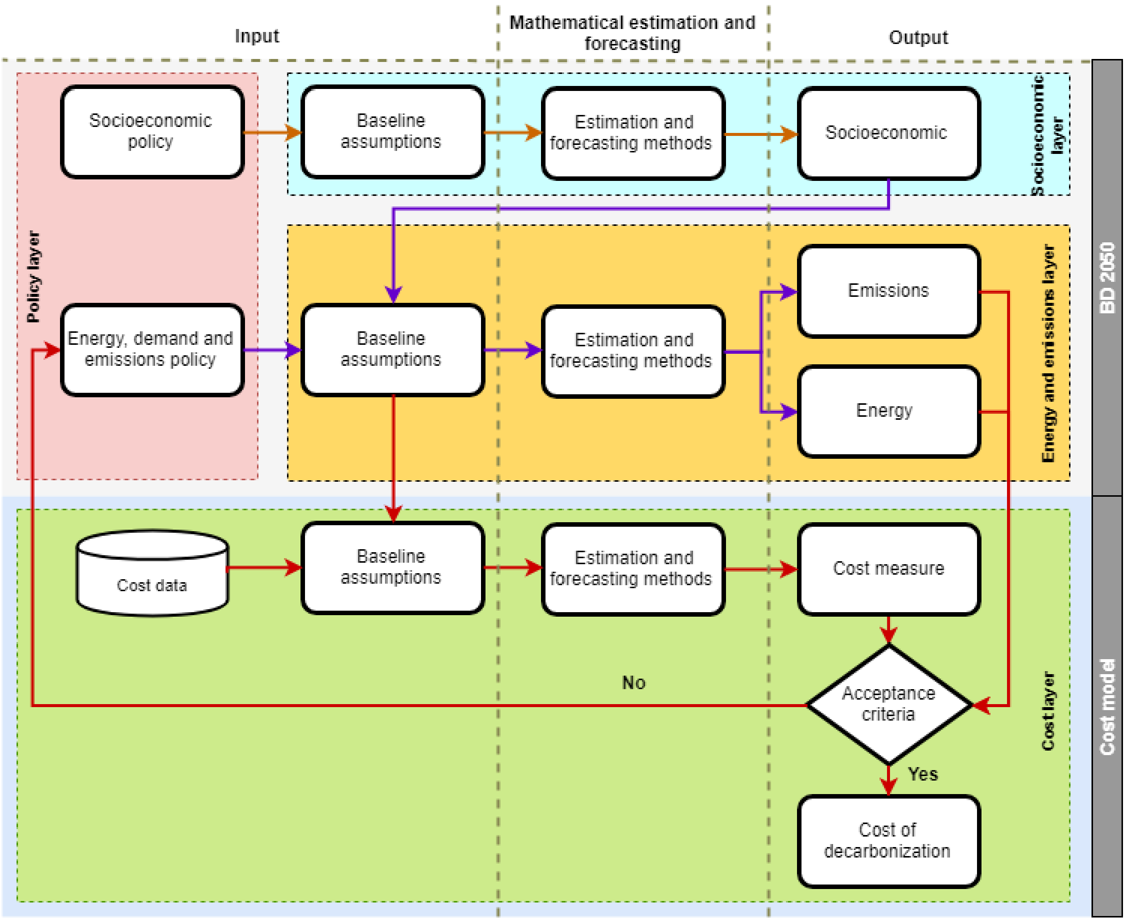

Figure 6.1: Cost model structure (red lines denote the possible links and flow between BD2050 – 'Bangladesh 2050 Energy and Emissions Pathways' model and proposed cost model

2050 (BD2050, 2015):

(i) Socioeconomic:

(a) The population of Bangladesh would be 245 million by 2050 (WB, 2015a), which will be 1.62 times than that of 2010.

(b) The rural and urban population would be 48% and 52% respectively by 2050. The household size would be 2.5 and 2.7 in urban and rural households respectively (BD2050, 2015).

(c) The annual GDP growth would be 7.3%. The GDP would be 16.94 times by 2050 than that of 2010.

(ii) Building sector:

(a) The GDP-electricity demand index would reach three and 2.5 times for rural and urban households respectively by 2050 than that of 2010.

(b) In a commercial building, heating technology mix would be 90%-10%-0% for gas-electric-solar respectively.

(c) The cooking technology mix would be 90%-10% for gas-electric respectively in commercial buildings.

(d) The lighting technology mix would be 40%-25%-30%-5% of the household and commercial spaces by 2050 for incandescent-fluorescent-CFL-LED respectively.

(e) The appliance assumptions for different types of commercial buildings were described in Table 6.1.

(iii) Transport sector:

(a) For passenger transport, the modal share would be walk-bike-car-motorbikes-bus-rail-IWT-domestic air-international air travel (15.6%-31.3%-20.0%-13.3%-7.0%-1.4%-2.0%-0.5%-8.9%) by 2050 (BD2050, 2015).

(b) Occupancies (pax/vehicle-km) in 2050 per mode: motorbikes, auto-rickshaws (1.2); cars, vans (2.2); buses (42); inland water travel (60); railways (0.37) and domestic air travel[1] (0.65). The 2010 estimations were based on (Karim, 1999).

[1]Unit for railways and domestic air travel was pax/seat-km

Table 6.1: Appliances for different commercial buildings (percentage of the total floor area) (BD2050, 2015)

Commercial building types	**Lighting (%)**	**Fans (%)**	**Air-conditioning (%)**	**Desktop PCs (%)**	**Refrigerators (%)**	**Boiler (%)**	**Cooking (%)**	**Others (%)**
Office	76.5	75	100	40.4	76.5	20	20	100
Retail	100	75	100	90	100	20	20	100
School	60.8	75	100	100	0	20	20	100
Hospital	100	75	100	100	100	100	100	100
Others	100	75	100	100	76.5	20	20	100

(c) The technology penetration in passenger transport sector of Bangladesh was described in Table 6.2.

(d) The rail, road and IWT freight capacity would be 0.8, 403 and 3 billion (bn) ton-km respectively by 2050. The modal share would be road-rail-IWT (88%-3%-9%). There will be no electric freight.

(e) The road and IWT freight efficiency would be 3.17 and 0.24 TWh per bn vehicle-km.

(f) In the case of international shipping, the number of barrels used per day for bunkering would be 72.95 by 2050, which would be 17.8 times than that of 2010.

(g) In the case of international aviation, the average number of occupancies would be 110 per flight by 2050, which would be two times than that of 2010.

(iv) Industry sector:

(a) The general index of manufacturing industries was described in Table 6.3.

(b) The energy mix in the industrial sector would be electricity-gaseous hydrocarbon-solar heating (60%-10%-30%).

(v) Agriculture sector:

Table 6.2: Penetration of Technology (Percentage of passenger-km) in the transport sector of Bangladesh (BD2050, 2015)

Mode	Technology	2010	2050
Bike	Bike	100%	100%
LMT	ICE	86%	94%
	CNG	14%	6%
	EV	0%	0%
Car	ICE	49%	78%
	CNG	51%	22%
	PHEV	0%	0%
	EV	0%	0%
	FCV	0%	0%
Bus	ICE	87%	94%
	CNG	12%	5%
	HEV	1%	0%
	EV	0%	0%
	FCV	0%	0%
Rail	Diesel	100%	100%
	Electric	0%	0%
IWT	Diesel	100%	100%
	EV	0%	0%
	FCV	0%	0%
Air	Air	100%	100%

Table 6.3: General index of manufacturing in Bangladesh; estimation based on (BBS, 2011, 2012, 2014, 2015, 2016)

Industry	**General index of manufacturing**	
	2010	**2050**
Food, beverage & tobacco	1	2.36
Jute, cotton, woven apparel & leather		11
Wood products including furniture		2.5
Paper and paper products		2.36
Chemical, petroleum & rubber		2.84
Non-metallic products		2.36
Basic metal products		4.95
Fabricated metal products		3.24
Telecom BTS tower		1.4

(a) The farm power index would be 1.57 times in 2050 than that of 2010.

(b) The fuel mix in agriculture sector would be electric-diesel-solar (8%-92%-0%) in 2050 for irrigation and vehicle operation such as a tractor, power tillers.

6.2 Cost model

The cost model has three parts- input, mathematical estimation and forecasting, and output (Figure 6.1). In the input, the baseline cost assumptions from the collected capital, operation and maintenance, and fuel cost data of power generation technologies (Table 6.4). The collected technology-wise cost data was estimated by multiplying with forecasted installed capacity of the energy supply sector from 2010 to 2050. The baselines cost and energy assumptions utilize equation 6.1 and 6.2, to forecast the total cost of energy generation sector development in Bangladesh in 2010-2050. The output from cost model is in USD (2010) value. The total energy demand, generation and GHG emissions from the BD 2050 model feed into the evaluation stage (Figure 6.1), where the total cost, unmet demand, and cost per unit emissions and per unit generation were evaluated according to the acceptance criteria to find the cost of decarbonization for Bangladesh under various emissions scenarios. For cost estimation the following equations were utilized:

$$TCS_y = \sum_{y \in Y} \sum_{a \in A} \sum_{f \in F} fd_y (IN_{(y,a)}.CC_{(y,a)} + IC_{(y,a)}.OC_{(y,a)} + F_{(y,a)}.FC_{(y,f)}) \quad (6.1)$$

$$fd_y = fd_{2010}/(1 + rd_y)^5 \quad (6.2)$$

For the discount factor calculation, the discount rate was considered 5% annually (CIA, 2018).

In the case of corruption, the cost analysis in chapter 3 demonstrated a statistically significant relationship between the capital cost of establishing power plants and the level of corruption in Bangladesh. Modeling a socioeconomic parameter such as corruption is complex as discussed in section 4.3. In this model corruption was not modeled as multiplier or index based. In chapter 3, private power plants demonstrated significant high capital cost and better association with corruption than that of private ones. The upper limit of the cost model assumption were from the capital cost of the public power plants as shown in table 6.4. Moreover, the lower limit of cost assumptions were mostly from private sector cost as they showed the lowest in Bangladesh as compared to the public ones. In the case of new generation technologies, the world lower limit from the IEA (2014) database was considered (Table 6.4).

Table 6.4: Baseline cost assumption for different energy generation technology; data source BPDB (2017a); GoB (2015a); IEA (2014); JICA and TEPCO (2011); NEI (2016)

Fuel type	**Generation technology**	**Capital cost (US$2010)/ Installed capacity (kW)**			**O&M cost (US$2010)/ unit generation (kWh)**			**Fuel cost(US$2010)/ unit generation (USD/kWh)**		
		High	**Low**	**Annual change rate (%)**	**High**	**Low**	**Annual change rate (%)**	**High**	**Low**	**Annual change rate (%)**
Natural gas	GT/ST, CCPP	1950	697	3	2.37*	0.26*	4.4	0.031		0.33
Coal	Subcritical	1924	1245	0.18	35**	21**	0.18	0.012		0.7
	Supercritical	2400	700	0.18	48**	28**	0.18	0.015		
	Ultra-supercritical	3845	800	0.18	56**	32**	0.18	0.015		
	Integrated Gasification Combined Cycle	2900	1100	0.18	77**	50**	0.18	0.015		

Table 6.4: Baseline cost assumption for different energy generation technology; data source BPDB (2017a); GoB (2015a); IEA (2014); JICA and TEPCO (2011); NEI (2016)

Fuel type	**Generation technology**	**Capital cost (US$2010)/ Installed capacity (kW)**			**O&M cost (US$2010)/ unit generation (kWh)**			**Fuel cost(US$2010)/ unit generation (USD/kWh)**		
		High	**Low**	**Annual change rate (%)**	**High**	**Low**	**Annual change rate (%)**	**High**	**Low**	**Annual change rate (%)**
Liquid hydrocarbon	GT/ST	1654	550	1.57	31.32*	4.23*	4.5	0.055		0.34
Nuclear	Nuclear	5625	2000	0.13	133**	112**	-0.13†	6.77**	0.8**	0.4
Renewable	Hydro	2128	1700	-0.3†	0.14*	0.053*	-0.6†	-		
	Solar PV	4938	1850	0.6	21**	18**	0.6	-		
	Geothermal	2980	2070	0.4	42**	41**	0.3	-		
	Offshore wind	5390	4440	2.8	163**	155**	2.8	-		

Table 6.4: Baseline cost assumption for different energy generation technology; data source BPDB (2017a); GoB (2015a); IEA (2014); JICA and TEPCO (2011); NEI (2016)

Fuel type	**Generation technology**	**Capital cost (US$2010)/ Installed capacity (kW)**			**O&M cost (US$2010)/ unit generation (kWh)**			**Fuel cost(US$2010)/ unit generation (USD/kWh)**		
		High	**Low**	**Annual change rate (%)**	**High**	**Low**	**Annual change rate (%)**	**High**	**Low**	**Annual change rate (%)**
	Onshore wind	1890	1300 (IEA, 2014)	0.4	39**	35 **	0.4	-		

* Unit: BDT/kWh

** Unit: USD/kW

† Cost increases

6.3 Limitations and scope

The modeling approach took comprehensive set of technologically and economically feasible energy generation alternatives into account to analyze different energy development pathways for Bangladesh up to 2050. Individually, the cost of decarbonizing the energy sector can be examined under different scenarios, as well as the capability of the scenarios in supplying the forecasted demand can be investigated.

There are some limitations of the model such as instead of modeling endogenous learning curve effects; the study adopted exogenous cost data for the technologies not applied in Bangladesh. Learning curve effect states that with average time cost of power plants reduce certain percentage when the cumulative volume of installed capacity of generation technology doubles in a geographical extent (i.e., Global, regional, country) (Jägemann *et al.*, 2013). In the case of Bangladesh, private and public natural gas and liquid hydrocarbon based power plants have been established in general. But the cost difference between private and public power plants were significant (Chapter 3). Moreover, the public plant cost for gas-based generations were found to be increasing in Bangladesh (Chapter 3). As per literature, the cost of power plants are supposed to reduce with time (Neij, 2008). For the inconsistency in the cost evolution in Bangladesh, the costs of different generation technologies were considered as constant variables in this cost model. However, coal and hydroelectric plants are one with several units. There are no nuclear, wind, wave, tidal, commercial solar PV or thermal at present in Bangladesh. For these renewable and nuclear technologies, the exogenous cost was adopted from reliable resources such as IEA, EIA and other studies. Another major limitations of the study was the lack of cost data for Bangladesh. For analyzing cost of the energy generation technologies, cost of the 61 power plants was collected and examined among the operational 113 power plants.

6.4 Scenario definition

The decarbonization of energy sector of Bangladesh can be achieved by various energy mixes. To analyze the implication of different decarbonization pathways for energy sector of Bangladesh under different economic conditions, six different emissions scenarios were examined in this study such as business as usual (BAU), current policy scenario (CPS), high-carbon scenario (HCS), medium-carbon scenario (MCS), low-carbon scenario (LCS) and zero-emissions scenario (ZCS) for the energy generation sector (Figure 6.2). The installed capacity assumptions of different scenarios were calculated form the potential analysis in each electricity generation sector of Bangladesh. The decarbonization scenarios are described in later part of this section. The cost of decarbonization critically depends on the economic conditions and there were three economic conditions such as low, average and high cost scenarios, considered in this research. The cost of decarbonization analysis scenarios are defined in Table 6.5.

Regarding future cost, the decarbonization scenario assumptions range from very pessimistic 'high cost' to optimistic projection 'low cost' as shown in Table 6.5. Low and high cost assumptions were mentioned in Table 6.4. The average cost is the mean of low and high cost assumptions. The high range of cost was assumed to be constant from 2010 to 2050. Lower range of cost was assumed to reduce over time with the annual rate mentioned in Table 6.4. The high range of cost assumptions in some but not all energy generation technologies denoted the public sector cost associated with corruption, and low assumptions were associated with global or Bangladesh's private sector lower assumptions from the cost data described in appendix B and discussed in Chapter 3. The difference in future pessimistic high and optimistic low cost assumptions is greater for less mature technologies for Bangladesh such as geothermal, offshore and onshore wind, nuclear, because of the higher uncertainty. Cost of decarbonization also depends on the electricity demand. If the demand is high the cost will increase to decarbonize the system. Reducing demand can also decrease the cost of decarbonization. In this model, the demand was considered to be constantly increasing under BAU scenario of BD2050 model. The effect of demand reduction on cost of decarbonization is out of the scope of this research.

In the cost model, the capital, O&M and fuel cost, and installed capacity of power plants were considered variable over time. Other parameters such as power plant's generation efficiency factor, GHG emissions factors and technical lifetimes were considered to be constant as par BD2050 model. The imported capacity was assumed to be 484 TWh in 2015 and unchanged afterwards up to 2050.

Table 6.5: Scenario matrix

Emissions Scenarios	Economic scenarios		
	Low cost	**Average cost**	**High cost**
BAU	B-L	B-A	B-H
CPS	C-L	C-A	C-H
HCS	H-L	H-A	H-H
MCS	M-L	M-A	M-H
LCS	L-L	L-A	L-H
ZCS	Z-L	Z-A	Z-H

6.4.1 Business as usual (BAU)

BAU scenario for energy sector of Bangladesh refers to the continuation of current installed capacity and no new build power generation capacity. Under this scenario, the derating capacity of the base year was considered in the baseline assumptions from 2010 to 2050.

In the case of coal power plant, there will be no new built, installed capacity in 2010-2050. The 250 MW installed capacity in 2010 would remain unchanged until 2050. Natural gas-based power plant installed capacity was 4821 MW in 2010. Moreover, there will be no new gas-based power plant built in Bangladesh up to 2050 under BAU. However, because of the derating of power plants over time and retirement, there will be no power plant operational after 2045. The installed capacity for liquid hydrocarbon based power plants was 1918 MW in 2010, which elevated to 2623 MW by 2015. Under BAU, there would be no new liquid hydrocarbon based power plant built after 2015, and the installed capacity would reduce to zero by 2040 due to derating and retirement. The retirement age of liquid hydrocarbon based power plants is 3-15 years because of the contracts with the government, where they were established to support peak load (MoF, 2009). On the other hand, Gas Turbines (GT) and Combined-Cycle Power Plants (CCPP) have an average lifespan of 30-40 years and additional 12-25 years after extension (Lipiak *et al.*, 2006). That is why cumulative liquid hydrocarbon based power plants would retire before natural gas-based power plants.

Nuclear power plants are not operational in Bangladesh at the moment. Although, there is a plan of building a new power plant in Rooppur by 2025, the model assumed no nuclear plant built in Bangladesh under BAU.

For wind-based power generation, there were no large offshore and onshore installed capacity in Bangladesh in 2010. For BAU, the installed capacity was assumed to be zero up to 2050. However, there were 20KW collective installed capacity established in Bangladesh as small hybrid and stand-alone applications at various public facilities (UNDP, 2013). The 20KW installed capacity was considered as small onshore generation capacity in 2010. Under BAU, small onshore installed capacity was assumed to remain same up to 2050 and no new wind turbine would be built.

There is no tidal range, tidal stream and wave-based power generation capacity in Bangladesh in 2010. The installed capacity for the tidal and wave-based generation capacity was assumed to remain to zero up to 2050.

There was no grid-connected Solar Photovoltaic (Solar PV) installed capacity in Bangladesh in 2010. However, there were off-grid Solar Home System (SHS) operational in 2010. The total installed capacity of SHS was 39.57 MW in 2010, which increased to 189.03 MW by 2015. Under BAU, the total installed capacity would reduce to zero by 2040 as the lifespan of solar cells was assumed to be 25 years (Jordan and Kurtz, 2013).

The only hydroelectric power plant situated in Kaptai (230 MW) was operational in 2010. It is assumed that under BAU, the installed capacity would remain same up to 2050. There are no geothermal, biomass and waste-based power plants in Bangladesh. Under BAU assumption, there will be no geothermal power plants operational by 2050.

6.4.2 Current policy scenario (CPS)

Current policy scenario (CPS) was developed with the present policies undertaken by the government of Bangladesh for the supply sector development up to 2030. The Power System Master Plan 2010 (PSMP 2010) paved the future planning of Bangladesh power sector from 2010 to 2030, which was prepared by JICA and TEPCO for BPDB (JICA and TEPCO, 2011). PSMP 2010 master plan focuses on coal-based generation increase to a fuel mix of coal-gas-others (50%-25%-25%) by

2030 (JICA and TEPCO, 2011). All energy generation technologies in the model would maintain current government policies as assumptions from 2010 to 2050.

In the case of coal power plants, installed capacity would be 250 MW up to 2015, which will increase to 4800 MW by 2020. The installed capacity would reach 8850MW by 2025 and 19650 MW by 2030. As the PSMP 2010 was planned for up to 2030, the installed capacity would follow the trend of the master plan after 2030 in the model. Moreover, due to the derating factor of the power plants, the installed capacity would reach increase 4600 MW every 10 years after 2030 and reach to 29050 MW by 2050.

According to PSMP 2010, Bangladesh would shift its natural gas (4821 MW in 2010) dominating energy generation sector towards coal-based one. For this reason, the natural gas based installed capacity of would reduce after 2020. The gas-based power plant capacity would be 12163 MW by 2020. No new gas-based power plants will be commissioned after 2020. The total installed capacity of gas-based power plants would reduce to 10771 MW by 2025 as the old power plants start to retire. By 2040, only 5610 MW installed capacity would be operational due to the derating factor and retirement of the old plants. There will be no natural gas-based power plant operational by 2050 under the CPS.

The installed capacity of liquid hydrocarbon based power plants was 1918 MW in 2010. According to PSMP 2010, the government would keep building liquid hydrocarbon-based plants up to 2030 to supply the peak loads. Under the CPS, no liquid hydrocarbon-based plant established after 2030 was assumed. So the installed capacity would reduce to 1200 MW by 2035 and 800 MW by 2040. Eventually, there would be no liquid hydrocarbon-based plants after 2045.

In the case of nuclear power plants, Rooppur nuclear power plant is one unit of 2000 MW would be operational by 2020 and another unit with 2000 MW would start supplying to the grid by 2025. Under CPS, we assumed that there would be no new nuclear power plants after 2025 and the installed capacity would remain 4000 MW up to 2050.

There were no large offshore and onshore installed capacity in Bangladesh in 2010. The installed capacity of large offshore wind power plants was assumed to be 100 MW by 2015 according to PSMP 2010 (JICA and TEPCO, 2011). The onshore wind installed capacity would increase 20 MW in 2015 and no more new built after that up to 2050. Under CPS, the installed capacity was assumed to remain 100 MW up to 2050. The small onshore generation capacity was 20 KW in 2010. For CPS, small onshore installed capacity was assumed to remain same up to 2050, and no new wind turbine would be built. There is no tidal range, tidal stream and wave-based power generation capacity in Bangladesh in 2010. Under CPS, the installed capacity for the tidal and wave-based generation capacity was assumed to remain to zero up to 2050.

The installed capacity of off-grid SHS was 39.57MW in 2010, which increased to 550 MW by 2015 because of the 500 MW solar irrigation project (GoB, 2013). According to IDCOL, there will be another 2000 MW grid-connected solar installed capacity in Bangladesh (IDCOL, 2017). Under CPS assumption, the total installed capacity would increase to 2550 MW by 2020, which will rise to 14550 MW by 2050 if additional 2000 MW is built every five years.

The only hydroelectric power plant situated in Kaptai (230 MW) installed capacity was operational in 2010. Under CPS the installed capacity would be 332 MW by 2015 and would remain same up to 2050. There are no geothermal, biomass and waste-based power plants in Bangladesh. Under CPS assumption, there will be no geothermal power plants operational by 2050.

6.4.3 High-carbon scenario (HCS)

Under the HCS, the supply sector would be dominated by fossil fuel such as coal, natural gas, and liquid hydrocarbon-based energy generation. Under the HCS, the installed capacity would maintain the PSMP 2010. The coal power plant installed capacity was 250 MW in 2010. According to PSMP 2010, the coal power installed capacity would be 8850 MW in 2025 and 19650 MW by 2030, which denotes a 10800 MW rise within five years. Under the HCS, we assumed that the installed capacity would elevate 10000 MW every five years up to 2050. The installed capacity for coal power plant would be 59650 MW in 2050.

In the case of natural gas-based power plants, the cumulative installed capacity would follow the PSMP 2010 masterplan and would be 8854 MW by 2030. The installed capacity was 4821 MW in 2010, which would be 9379 MW and 12163 MW in 2015 and 2020 respectively. After that, the installed capacity would start to reduce as there would be no new plant built. The installed capacity increased 4558 MW between 2010 and 2015. According to PSMP 2010, the gas-based installed capacity would elevate to 2784 MW between 2015 and 2020. Under HCS, we assumed that the installed capacity would increase 5000 MW every five years and reach to 28854 MW by 2050.

The installed capacity for liquid hydrocarbon based power plant was 1918 MW in 2010. According to PSMP 2010, the installed capacity would be 2623 MW in 2015, which would reduce to 1755 MW by 2020. The installed capacity would rise again to 2155 MW and 2240 MW in 2025 and 2030 respectively. According to PSMP 2010, there would be 400 MW rise between 2020 and 2025. Under HCS, the liquid hydrocarbon based power plant was assumed to have a 400 MW additional installed capacity every five years after 2030, which would result in 3840 MW capacity by 2050.

According to PAMP 2010, nuclear power installed capacity would be 2000 MW and 4000 MW in 2020 and 2025 respectively (JICA and TEPCO, 2011). Under the HCS, the installed capacity was assumed to remain 4000 MW up to 2050. In the case of solar PV, the total installed capacity would increase to 2550 MW by 2020, and it will remain same up to 2050.

In the case of large offshore, onshore and small onshore wind turbines, and hydroelectric plants, the installed capacity would be same as CPS. Under HCS assumption, there will be no geothermal power plants operational by 2050.

6.4.4 Medium-carbon scenario (MCS)

In the case of medium-carbon scenario (MCS), the energy mix would be dominated by fossil fuels with the support from renewables. The fossil fuel (coal, natural gas, and liquid hydrocarbon) and nuclear electricity generation installed capacity would remain same as HCS up to 2050. In the case of solar PV, the total installed capacity would increase to 2550 MW by 2020, which will gradually rise to 114.87 GW by 2050. For that 60% of the urban & industrial built space (525 km^2), and 40% of the rural settlement area (7064 km^2) is used for solar electricity generating in Bangladesh.

In the case of large offshore, onshore and small onshore wind turbines, and hydroelectric plants, the installed capacity would be same as CPS. Under MCS assumptions, there will be no geothermal power plants operational by 2050.

6.4.5 Low-carbon scenario (LCS)

Under the low-carbon scenario (LCS) renewable and nuclear energy dominate the energy generation sector of Bangladesh. As present PSMP 2010 masterplan proposes a fossil fuel dominating future supply sector, LCS would not be entirely fossil fuel free. The cumulative coal power installed capacity would maintain CPS up to 2030 and then additional 5000 MW would be built every five years, which will make the total capacity 39650 MW by 2050. Other than the coal-based power plants, there would be no gas and liquid hydrocarbon based power plants operational by 2045.

According to PSMP 2010, nuclear power installed capacity would be 2000 MW and 4000 MW in 2020 and 2025 respectively. Under the LCS, we assumed the installed capacity would increase 2000 MW every five years up to 2050. The total installed capacity for nuclear power generations would be 14000 MW in 2050. In the case of solar PV, the total installed capacity would increase to 2550 MW by 2020, which will gradually rise to 225.76 GW by 2050. For that 90% of the urban & industrial built space (789 km^2), and 80% of the rural settlement area (15895 km^2) are used for solar electricity generating in Bangladesh.

In the case of large offshore, onshore and small onshore wind turbines the installed capacity would be same as CPS. Under LCS assumption, there will be no geothermal, biomass and waste-based power plants operational by 2050. The hydroelectric power installed capacity was 230 MW in 2010 which would be 545 MW by 2050 because 140 and 75 MW plants would be operational in Sangu and Matamuhuri respectively by 2020 (Mondal and Denich, 2010).

6.4.6 Zero-carbon scenario (ZCS)

In the case of zero-carbon scenario (ZCS), the energy mix would be dominated by the renewable resources. The fossil fuel based (coal, natural gas, and liquid hydrocarbon) energy generation would follow the BAU.

The nuclear, solar PV based and hydroelectric installed capacity would follow the LCS. In the case of offshore and onshore large wind installed capacity would increase respectively 20 MW and 50 MW annually up to 2050 under the ZCS. Under ZCS, offshore and onshore installed capacity would reach 500 MW and 1150 MW respectively in 2050. The installed capacity of small wind turbines would increase 20 KW every five years from 2015 up to 2050. The total installed capacity would reach 0.18 MW by 2050.

In the case of geothermal energy generation, Bangladesh has a potential of 1000MW (Hasan *et al.*, 2013). Under ZCS, we assumed that there would be 200 MW (Hasan *et al.*, 2013) geothermal power generation plants would be operational in Bangladesh by 2020. Additional 200 MW installed capacity would increase every ten years to reach 800 MW by 2050.

6.5 Result and discussion

The results of the scenarios analysis are discussed in this section. The subsequent investigation and discussion are structured as follows: Section 6.5.1 provides an overview of the total cost and cost of decarbonization associated with six emissions and three economic scenarios. The implication of the change in the energy mix on GHG emissions and cost are discussed in Section 6.5.2. Section 6.5.3 analyzes the

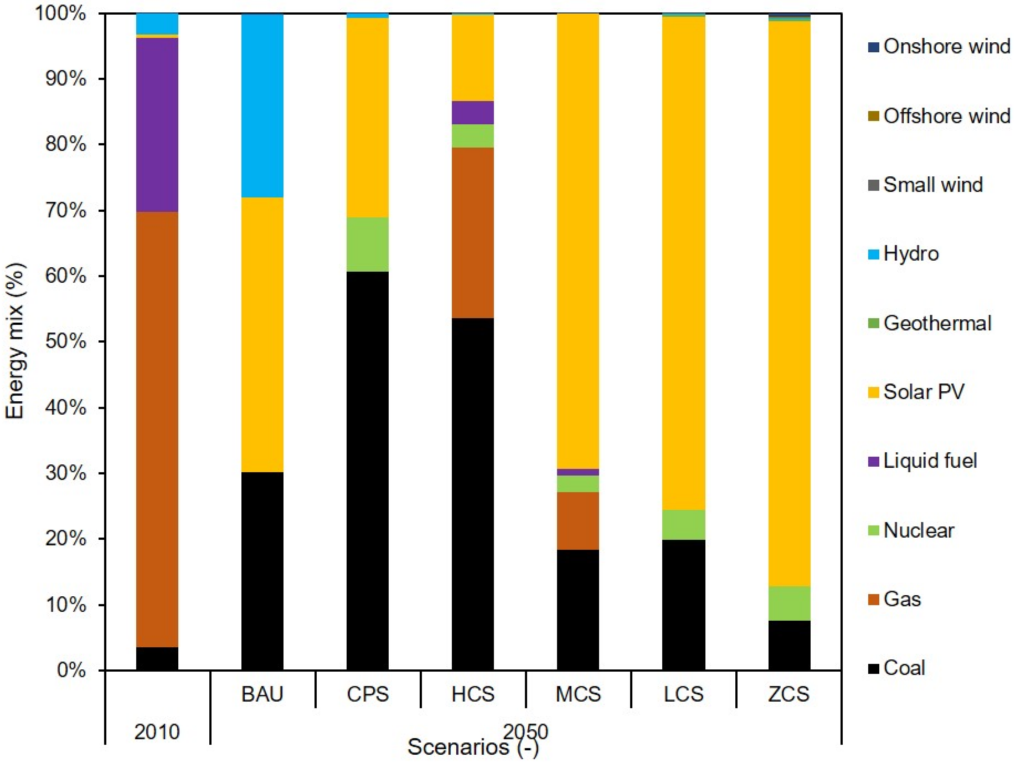

Figure 6.2: Energy mix of Bangladesh in 2010 and analyzed scenarios in 2050. The assumptions of different scenarios were calculated form the potential analysis in each electricity generation sector of Bangladesh with BD2050 (2015).

influence of generation technology maturity on the GHG emissions and cost. After that, the effect of corruption on the cost of decarbonization is discussed in Section 6.5.4. Finally, Section 6.5.5 provides the discussion on the influence of demand reduction on the cost of decarbonization.

6.5.1 Overview of total cost and cost of decarbonization of energy generation sector

The total cost comprises discounted capital, operation and maintenance (O&M), and fuel cost of Bangladesh's energy sector under different emissions scenarios in a specific year. Moreover, the total cost is illustrated with the range of expenditure in a specific year with low, average and high cost. The total cost was estimated in billions(bn) US$(2010). The total coat of the energy generation and distribution system development elevates in Bangladesh by 2050 under all the scenarios as it's a rapidly developing sector and still approximately 40% of the population does not have access to grid electricity. However, the cost varies significantly between scenarios with and without decarbonization policies because of adopting GHG emissions

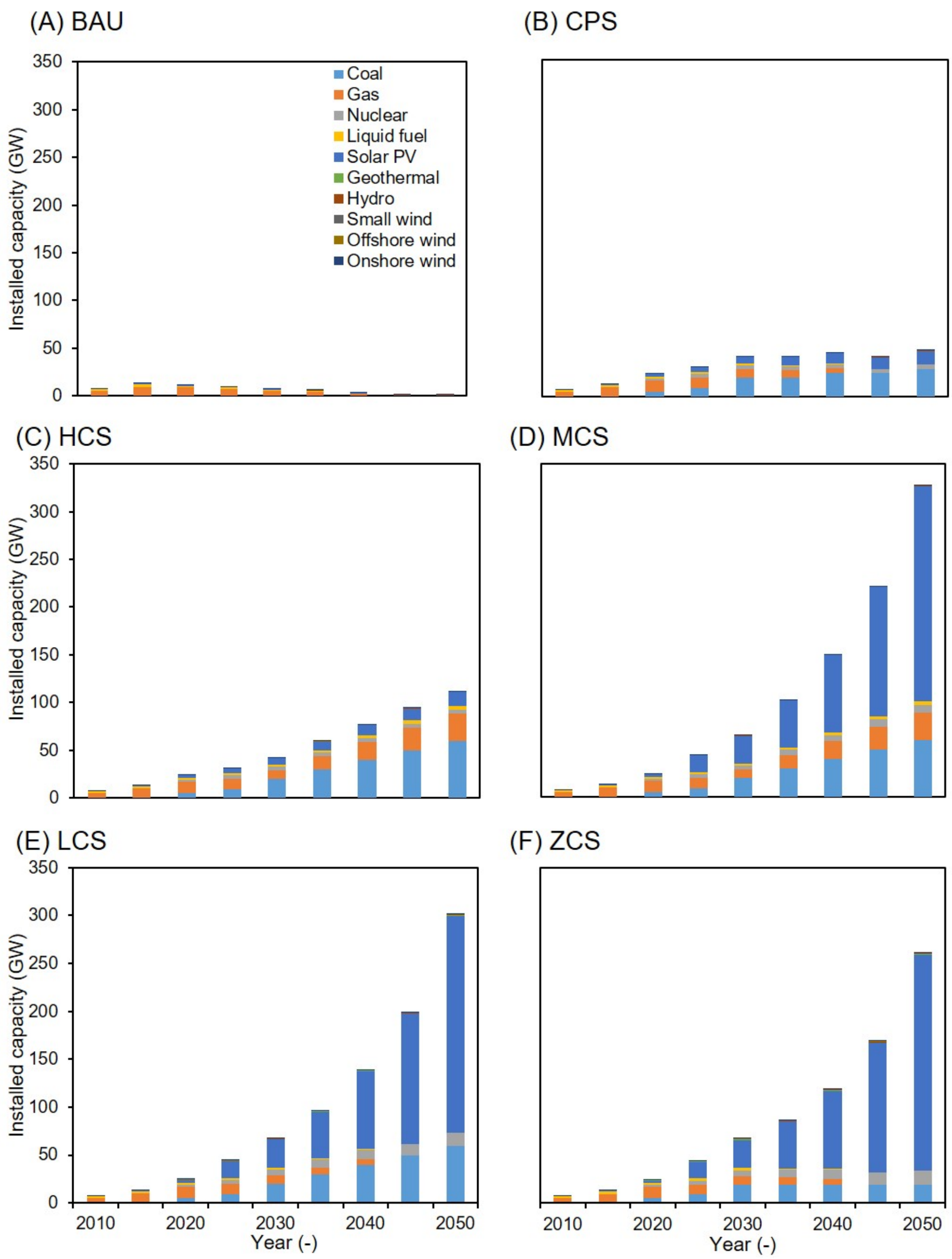

Figure 6.3: Installed capacity 2010-2050 under (A)BAU, (B)CPS, (C)HCS, (D)MCS, (E)LCS and (F)ZCS

reduction strategies such as changing the energy mix and establishing new generation technologies requires substantial investments. Therefore, the total cost is increasing linearly and would be approximately below $200 bn in 2050 under BAU, CPS, and HCS because there is no decarbonization policy involved. Whereas, the cost starts to rise exponentially with the adoption of emissions reduction strategies under MCS, LCS, and ZCS, and would reach up to approximately $716 bn by 2050 (Figure 6.4).

The total cost under B-A scenario would be $49 bn by 2050, which would be 2.4 times higher than that of 2010. The range of total cost would be $72 bn and $35 bn under the B-H and B-L scenarios (Figure 6.4). If Bangladesh maintains its present policies in action, the cost would be $66 bn by 2030 and eventually $75 bn in 2050 under C-A scenario which would be $26 bn higher than that of B-A. The total cost range would be $114 bn and $51 bn under the C-H and C-L scenarios, respectively (Figure 6.4). The total cost would increase to $119 bn in 2050, which would be 5.7 times higher than that of 2010, under H-A scenario. The total cost would have a linear growth under H-A between 2010 and 2050. The range of total cost would be between $183 bn and $79 bn under the H-H and H-L scenarios in 2050 (Figure 6.4). The total cost of energy sector development under H-A would be 2.4 and 1.5 times higher compared to B-A and C-A scenarios in 2050, respectively. Under M-A scenario, the cost of Bangladesh's energy sector development would be $419 bn in 2050, which would be 3.5 times higher than that of H-A. The total cost would be $403 bn by 2050 for L-A scenario, which would be 3.4 times higher compared to H-A, but 4% lower than that of M-A. The total cost range would be between $696 bn and $202 bn under L-H and L-L scenarios in 2050. Under the Z-A scenario, the total cost would reach to $638 bn in 2050, which would be 3 times higher than that of H-A. However, total cost under Z-A would be 13% and 9% lower than that of M-A and L-A respectively.

The cost of decarbonization refers to the difference between no emissions reduction scenario HCS and scenarios with emissions reduction strategies such as MCS, LCS, and ZCS. For example, the cost of decarbonizing Bangladesh's energy generation sector under ZCS would be derived by subtracting the total cost of ZCS from the total cost of HCS in a specific year. BAU and CPS were not considered for the analysis of the cost of decarbonization because HCS has the highest GHG emissions by 2050 among the three scenarios without any emissions reduction strategies

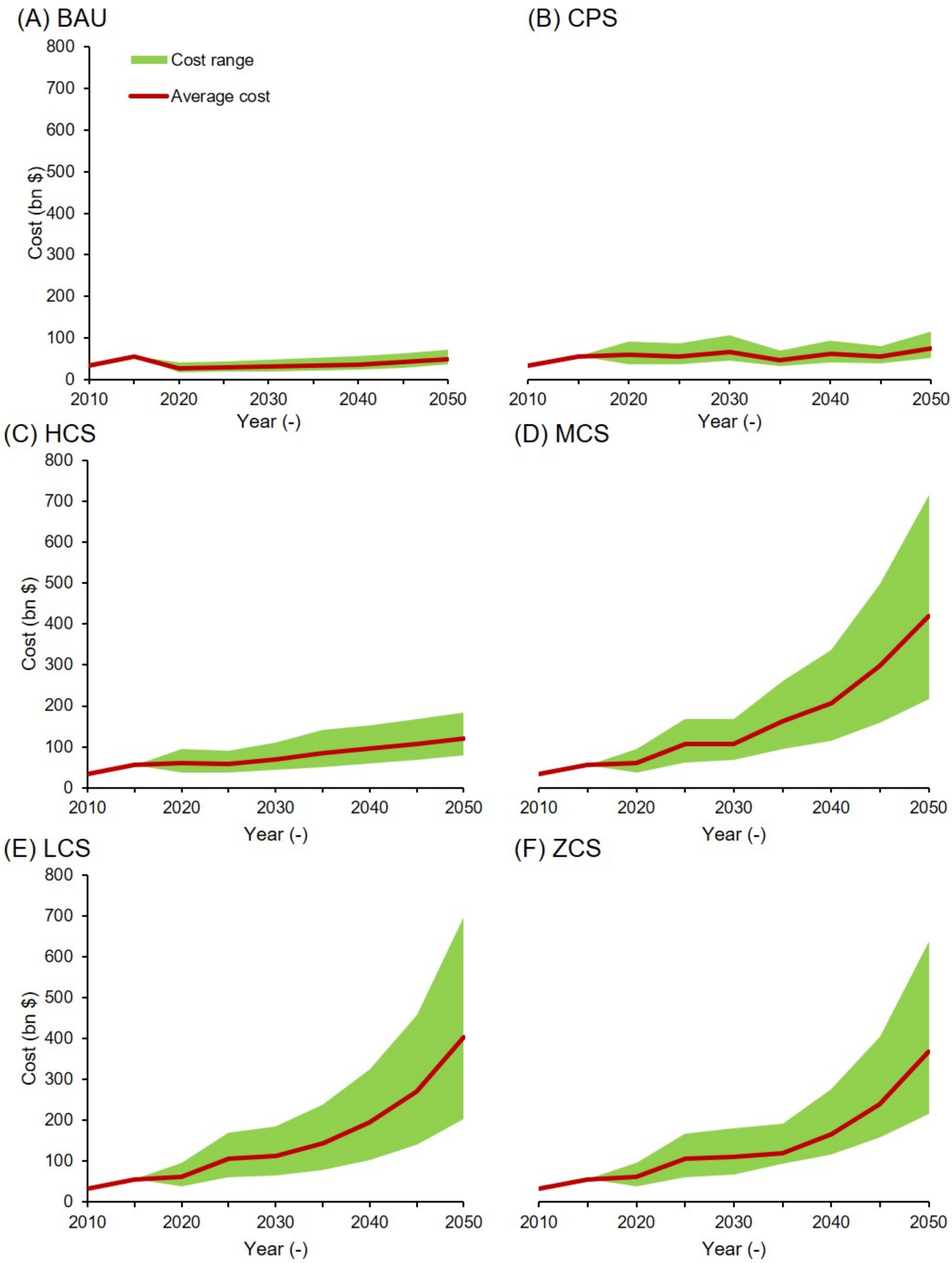

Figure 6.4: Total cost under (A)BAU, (B)CPS, (C)HCS, (D)MCS, (E)LCS and (F)ZCS from 2010 to 2050

(Figure 6.5D). The cost of decarbonization would be \$300 bn in 2050 under M-A (Figure 6.5A). The high and low range of the cost would be \$533 bn and \$137 bn by 2050, respectively. The cost of decarbonization would reduce to \$284 bn in 2050 under L-A, which would be a 5.5% reduction compared to M-A. The cost range would be between \$513 bn, and \$123 bn for LCS in 2050. Under the Z-A, the cost of decarbonization would reduce to \$251 bn by 2050, which would be 19.6% and 13.4% lower compared to M-A and L-A, respectively (Figure 6.5A). Moreover, the cost range of decarbonization for ZCS would be between \$456 bn and \$105 bn in 2050.

6.5.2 Change in the energy mix

Change in energy mix can significantly influence the GHG emissions in the future as well as contribute to the cost of decarbonization for Bangladesh.

Implication on GHG emissions

The electricity generation highly depends on fossil fuels in Bangladesh (BPDB, 2017b). The GHG emissions from electricity generation sector were 23.6 $MtCO_2e$ in 2010. Under the BAU scenario, the GHG emissions would reduce to 1.3 $MtCO_2e$, as there will be no new power plant established after 2010 (Figure 6.5D). Under the present government policies driven CPS, the total GHG emissions would rise to 129.7 $MtCO_2e$ by 2050, 5.5 times higher compared to 2010 (Figure 6.5D). The current policies direction towards fossil fuel dominating energy mix of Bangladesh would induce the rise in total GHG emissions. Under fossil fuel dominating HCS, the GHG emissions will reach 15 times by 2050 as compared to 2010 (Figure 6.5D), resulting in 1355% increase in total emissions from electricity generation. Under the MCS, the fossil fuel installed capacity will be same as HCS, and only renewables and nuclear capacity will increase 70 times by 2050. Therefore, the GHG emissions for MCS will be the same as HCS for 2010-2050.

In the case of LCS, the renewables and nuclear are going to dominate the energy mix of Bangladesh by 2050. Due to the partial fossil fuel dependency in energy mix, the total GHG emissions will rise 11 times by 2050 than that of 2010. Although, the total GHG emissions would reduce by 23% in 2050 under LCS compared to MCS

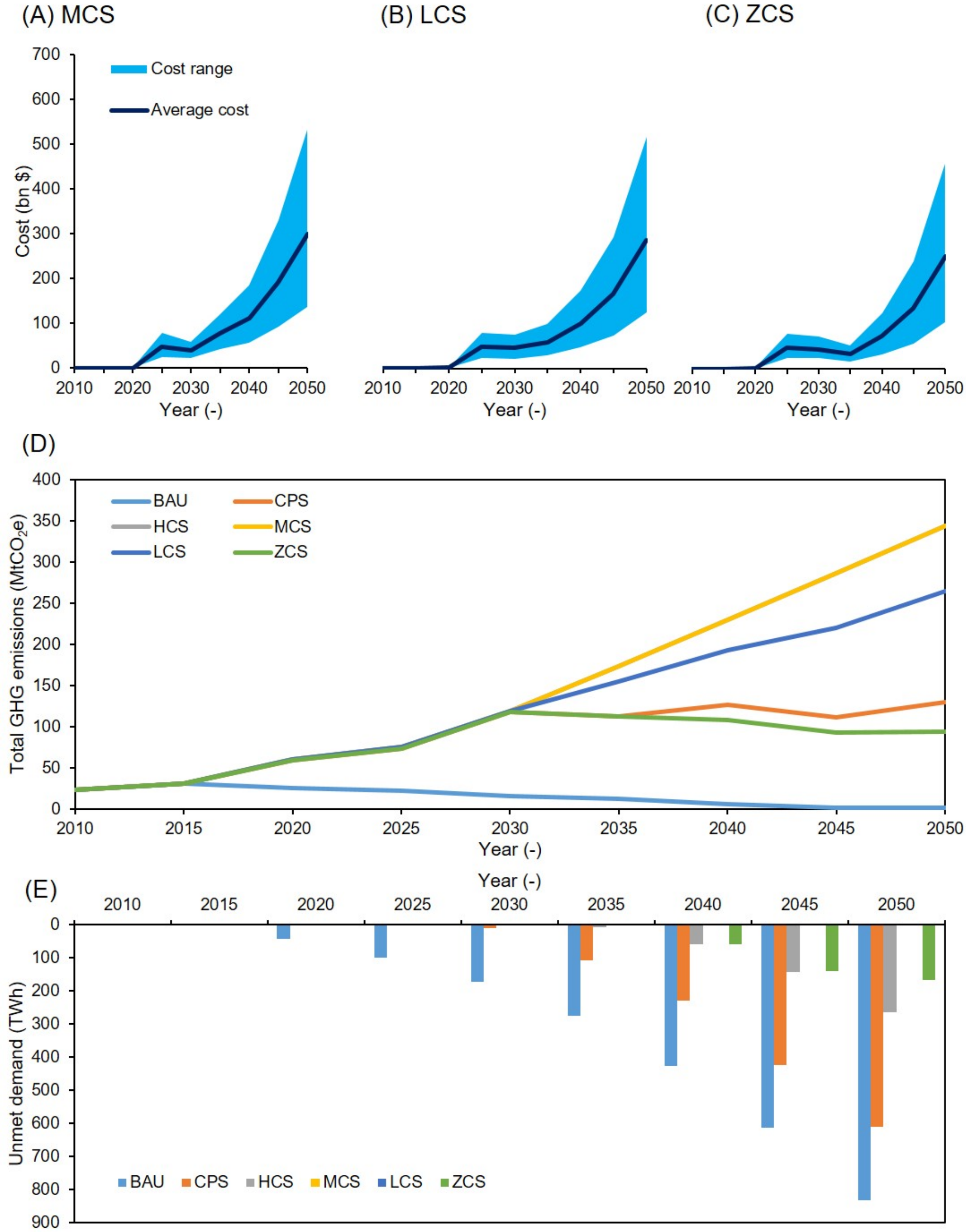

Figure 6.5: Cost of decarbonization under (A)MCS, (B)LCS and (C)ZCS from 2010 to 2050, (D) Total GHG emissions under different analyzed scenarios 2010-2050, (E) Unmet demand for analyzed scenarios.

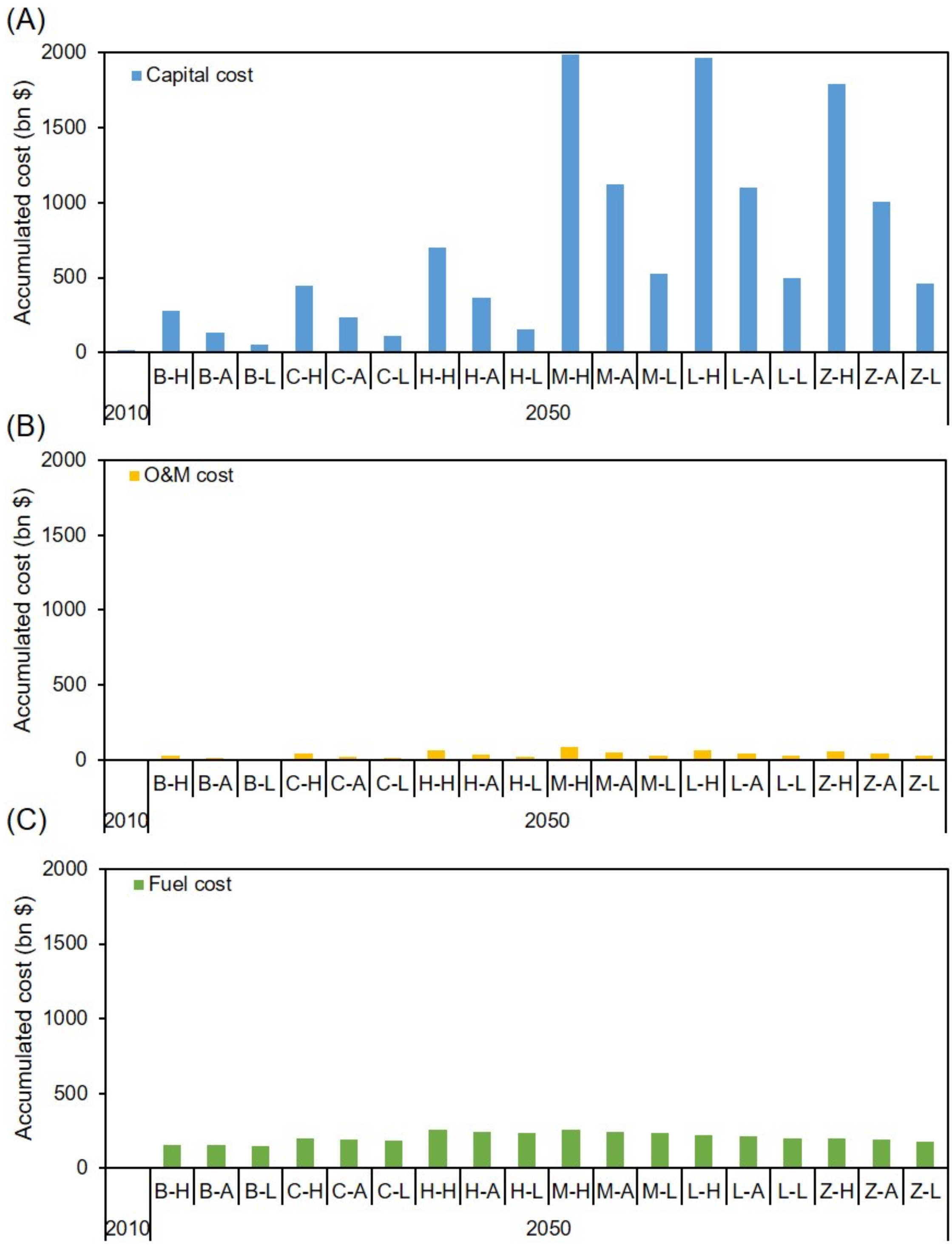

Figure 6.6: Accumulated (A) Capital, (B) O&M abd (C) fuel cost under different analyzed scenarios in 2050

and HCS. Under the ZCS, the total GHG emissions would not diminish entirely because of the already established and under construction coal and gas power plants by 2015. The coal-based power plants started to be established in Bangladesh in 2006 (BPDB, 2017b). All the coal power plants will be operational even after 2050 because of their more than 40 years lifespan (IEA, 2005). However, the total emissions would reduce by 73% and 65% in 2050 under ZCS as compared to MCS and LCS, respectively.

Emissions intensity of electricity generation was 0.79 $kgCO_2e/kWh$ in 2010, which would be 0.47 $kgCO_2e/kWh$ under BAU in 2050. The emissions intensity would increase to 0.55 and 0.60 $kgCO_2e/kWh$ under CPS and HCS in 2050, respectively. However, the emissions intensity would decrease to 0.34 and 0.28 $kgCO_2e/kWh$ for MCS and LCS, respectively. The LCS offers lower emissions per unit electricity generation because of the higher concentration towards renewable and nuclear technologies. The lowest emissions will be 0.14 $kgCO_2e/kWh$ under the ZCS in 2050.

The GHG emissions per capita were 0.47 tCO_2 in 2010. The emissions intensity per capita for HCS and MCS will be 2 tCO_2 2050, which will be 4.2 times that of 2010. In the case of LCS, the per capita GHG emissions will increase 3.5 times by 2050 than that of 2010. Moreover, the lowest emissions reduction from energy sector will be possible in Bangladeshi energy sector under ZCS. The per capita emissions will be 0.93 tCO_2e in 2050 under ZCS, which will be two times higher than that of 2010.

Implication on the total cost and cost of decarbonization

Cost is a driving factor for future energy policy development. The capital, O&M, and fuel cost was 57%, 15%, and 28% of the total cost of $33 bn in 2010, respectively. Under the B-A scenario, the total cost of electricity generation will increase 62.4% in 2050 in comparison to 2010. Although the installed capacity is reducing because of no new power plants being built after 2015, the fuel cost will elevate 236% in 2050 than that of 2010. Under B-A scenario, 63% and 35% of the total cost would be fuel and capital cost in 2050, respectively. In the case of C-A, the total cost would increase 23% by 2050 than that of 2010, of which 36%, 6%, and 60% will be capital, O&M, and fuel cost respectively.

In the case of H-A, the total cost of the supply sector will increase to \$119 bn by 2050 (Figure 6.7), of which 45% and 49% will be capital and fuel cost respectively. Under M-A, the total cost of the energy sector will rise to \$419 bn by 2050, which will be 3.8 times higher than that of H-A. Of the \$419 bn, 83% will be a capital cost, as the major investment will be in solar PV and nuclear electricity generation as well as the fossil fuel based ones. In the case of L-A, the total cost will reach \$404 Billion in 2050 (Figure 6.7), which is 4% less than that of M-A. Capital cost will be 87% of the total cost under L-A. The total cost of energy sector would be higher up to 2030 under L-A compared to M-A, because of the initial higher capital cost of renewable energy technologies. Under M-A, the total cost would surpass L-A in 2030-2050, mostly because of the fuel cost (Figure 6.6C). In the case of Z-A, the total expense will be \$368 bn in 2050 for energy system (Figure 6.7), of which 88% will be the capital cost (Figure 6.7). Among all the analyzed scenarios, M-A offers the highest total cost of energy system development by 2050 in Bangladesh.

In 2050, 83% of the energy generation would be fossil fuel based whereas only 17% would be nuclear and renewables under HCS. Shifting the energy mix from fossil fuel to renewables dominating, would exponentially increase the cost of decarbonization by 2050 for MCS, LCS, and ZCS (Figure 6.5 A, B, C), predominantly because of capital cost of renewable technologies (Figure 6.7). The energy mix would have 72% of the generated electricity from nuclear and renewables sources for MCS, which would elevate to 80% under LCS in 2050. Under the ZCS, the energy mix would have the highest amount (93%) of energy from nuclear and renewables sources. The capital cost of energy sector would be \$347 bn in 2050, a 6.6 times increment under M-A compared to H-A. The cost of decarbonization would be \$300 bn in 2050 under M-A, which translates into 60% of the total cost (\$419 bn) of the energy sector development. Under the L-A, the capital cost would be approximately similar to M-A. Moreover, the fuel cost would be 25% lower for L-A than that of M-A in 2050. However, the cost of decarbonization would be \$284 bn by 2050 under L-A, which means 58% of the total cost (\$404 bn). In 2050, the cost of decarbonization would reach to \$249 bn under Z-A, which would be 52% of the total cost (\$368 bn).

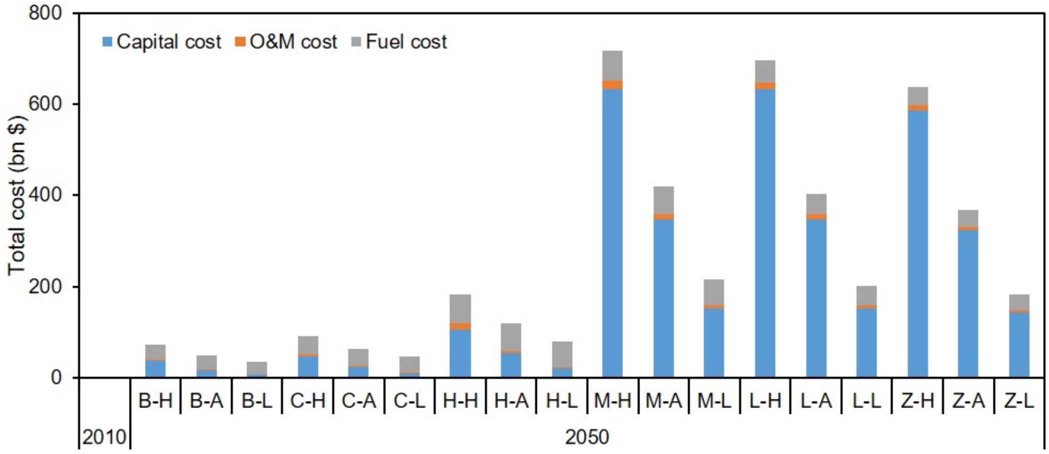

Figure 6.7: Cost breakdown in 2010 and under different scenarios in 2050

6.5.3 Implication of technological maturity on the cost of decarbonization

Most of the fossil fuel based power plants, particularly gas and liquid hydrocarbon based ones, have been operational in Bangladesh for last three decades. However, coal-based power plants started operating in 2006. The present Barapukuria coal-based power plant is a sub-critical power plant. The planned coal-based power plants are going to be ultra-supercritical. Therefore, gas and liquid hydrocarbon based power plants are matured technology; and coal, nuclear, solar, wind and geothermal are considered new technology in Bangladesh. The difference between the high and low cost for matured technology is lower than that of the new ones. As a result, the scenarios with emissions reduction strategies show higher cost difference than that of the HCS. The difference between the high and low range of capital cost would be \$86 bn in 2050 under HCS. The capital cost range from \$633 bn to \$153 bn in 2050 under the M-H and M-L scenarios, which means difference of \$480 bn under MCS. Moreover, the cost difference between the high and low range would be \$481 bn and \$445 bn in 2050 under LCS and ZCS, respectively. Studies suggest that over time the matured technology reduces cost (Neij, 2008), which denotes that the cost of energy sector development in Bangladesh may reduce in the future.

6.5.4 Influence of corruption on the cost of decarbonization

According to the correlation study in Chapter 3, the cost of public power plants showed a statistically significant relationship with corruption in Bangladesh. In the case of gas, liquid hydrocarbon, coal, solar and nuclear power plants, the cost range was derived from the cost database (Appendix B) developed for this study. The high cost range for gas, liquid hydrocarbon, coal, solar and nuclear power plants represented the public plants. The lower limit of the cost range is based on private or global average cost of establishing the power plant. Under the decarbonization scenarios, the county may develop the energy sector with a lower limit, if the corruption is under control.

The cost of decarbonization would be \$533 bn in 2050 under the M-H scenario (Figure 6.5). Under lower corruption assumptions, the cost of decarbonization can reduce 44% under M-A than that of M-H. If the corruption level can be minimized to maintain the lower limit of the cost of energy sector future development, the cost of decarbonization can be reduced 74% under M-L scenario compared to M-H. Similarly, the cost of decarbonization can be reduced 76% and 77% under L-L and Z-L scenarios compared to L-H and Z-H, respectively. If Bangladesh can control the level of corruption and build power plants with the lower limit, the total cost would be \$182 bn under the Z-L scenario, whereas the upper limit of energy sector development for H-H would be \$184 bn in 2050 (Figure 6.4). Therefore, control of corruption in the energy sector can significantly influence the cost of decarbonization in Bangladesh.

6.5.5 Influence of demand reduction on the cost of decarbonization

The scenarios were analyzed with the capability of meeting the projected demand for 2010-2050. Under the BAU scenario, the generation would reduce 89% in 2050 compared to 2010 (Figure 6.8). On the other hand, the electricity demand was projected to be 36 times greater within the similar time span, resulting in 830 TWh unmet demand by 2050 (Figure 6.5E). If Bangladesh follows CPS, the electricity generation would increase 7.4 times by 2050 (Figure 6.8) but there would be 615 TWh unmet demand (Figure 6.5E). Under CPS, the energy mix would be coal-based (57%) by 2030, as planned by PSMP 2010 (JICA and TEPCO, 2011), which would reach 61% by 2050 (Figure 6.8).

Under the HCS, the electricity generation would increase 19 times in 2050 than that of 2010 but the projected demand would not be met. The unmet demand would be 267 TWh in 2050 (Figure 6.5E). Under the HCS, the electricity generation will increase 19 times in 2050 compared to 2010. The total generation would be 1000 TWh by 2050 under MCS, which will be 33 times higher than that of 2010 (Figure 6.8). For LCS, the energy generation will elevate 31 times in 2050 than that of 2010. The ZCS also cannot meet the electricity demand by 2050. There would be 172 TWh unmet demand (Figure 6.5E) despite the 22 times generation increase in 2050 than that of 2010 under ZCS (Figure 6.8). The projected electricity demand would be met only under MCS and LCS (Figure 6.5E).

The electricity generation cost in 2010 was \$3/kWh, which will be \$48, \$1.19 and \$1.01 under BAU, CPS, and HCS respectively in 2050. However, generation cost will increase to \$2.75 and \$2.81/kWh under MCS and LCS respectively. Under ZCS, the generation cost will increase to \$3.63/kWh. The generation cost will be 32% and 29% lower under MCS and LCS respectively than that of ZCS, as well as these scenarios, will meet the electricity demand by 2050. Therefore, Bangladesh would need mixed energy generation sector of fossil fuel-based and renewable-based technologies. Although, zero-carbon energy generation sector is not going to be possible for Bangladesh by 2050, concentrating on LCS may pave the road towards a zero carbon future. Also, LCS would be cheaper than that of MCS by 2050 because of the lower fuel cost. This lower fuel cost incentive can also drive the energy sector towards lower dependency on the imported fuel and eventually on volatile international fossil fuel market.

Demand reduction can act as a important driver for reducing cost of decarbonization for Bangladesh. The cost of decarbonization would be \$300 bn and \$284 bn under M-A and L-A, respectively. The cost of decarbonization can be \$248 bn by 2050 under Z-A. Evidently, Z-A would not meet the projected demand (Figure 6.5E). However, 20% reduction in demand by 2050 can make the decarbonizaiton of Bangladesh's energy sector possible under ZCS with the cost range between \$454 bn and \$103 bn.

6.6 Summary

The cost model methodology and the cost assumptions was elaborated in this chapter. The cost model was developed as a extension of BD2050- energy and emissions pathway model. The total energy demand from 2010 to 2050 was estimated with the BD2050 model under BAU scenario. The major assumptions of the demand sector

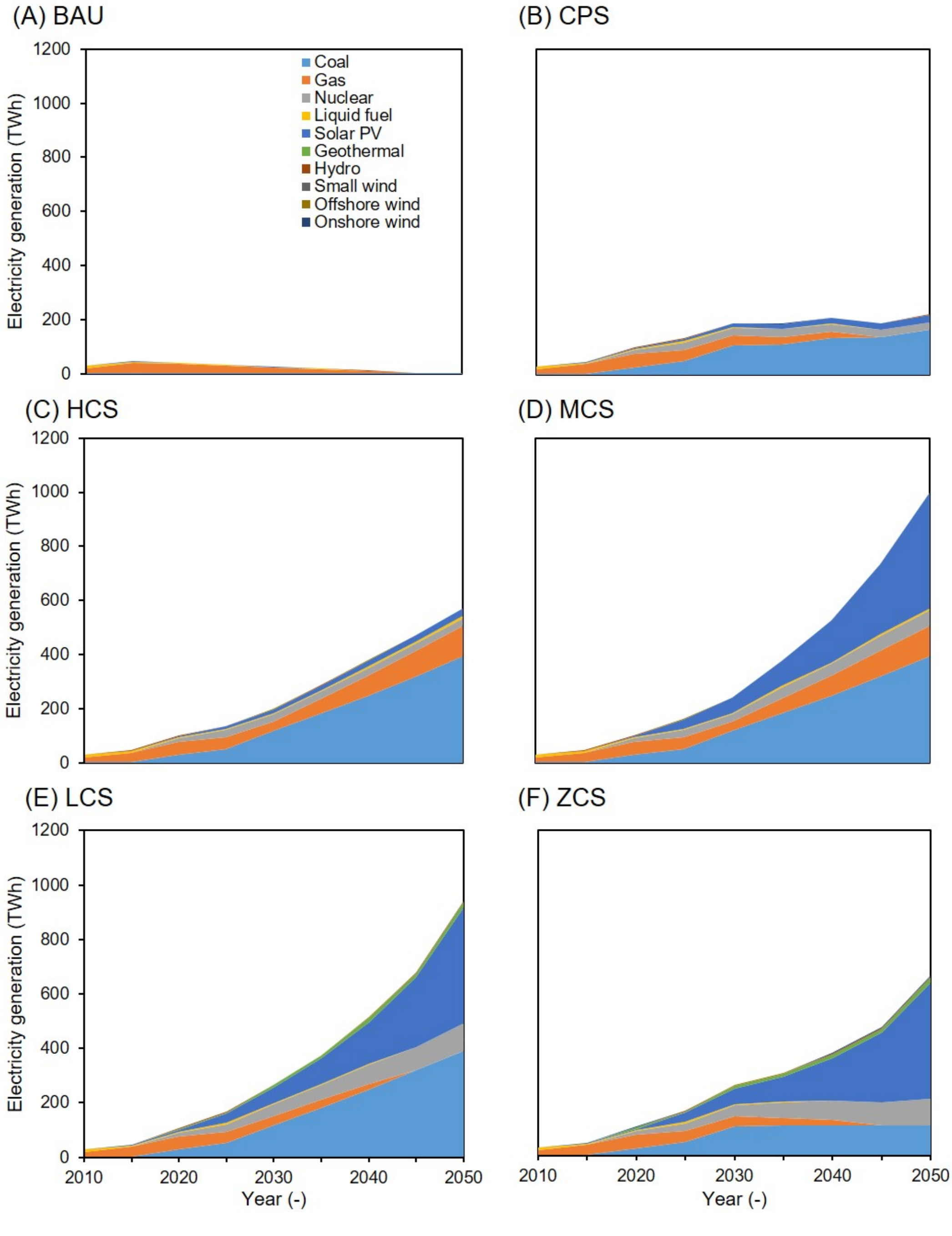

Figure 6.8: Total electricity generation from different supply sector 2010-2050 under (A)BAU, (B)CPS, (C)HCS, (D)MCS, (E)LCS and (F)ZCS

was also described in this chapter. Moreover, the scenario matrix, definition, and limitation of the cost model was discussed. At the end, the scenarios which were analyzed for the cost of decarbonization were elaborated.

The total cost and cost of decarbonization was described in the initial part of this chapter. The analysis showed the effect of a change in the energy mix, technological maturity, and corruption on the cost of decarbonization. The present direction of energy sector development has been fossil fuel dominating especially coal-based for the future energy mix in Bangladesh. The emissions analysis suggested that the GHG emissions will reach 15 times by 2050 under HCS as compared to 2010. Change in energy mix towards renewable and nuclear can reduce the future emissions by 23% in 2050 under LCS. The projected emissions can be reduced 73% under ZCS than that of HCS. The cost of decarbonization would be highest in 2050 under MCS, which would be 1.05 and 1.20 times than that of LCS and ZCS. Technological maturity also influences the cost of decarbonization. The cost range difference is lower for matured technologies compared to new technologies. The higher cost of decarbonization is also associated with the adoption of relatively new renewable technologies in the energy system. In the case of Bangladesh, corruption in energy sector found to be the biggest catalyst in reducing the cost of decarbonization. Results showed that if the country can minimize the effect of corruption in the energy sector, it can reduce the cost of decarbonization 45-77% by 2050 under MCS, LCS, and ZCS. Moreover, the analysis of generation and capability of the scenarios in meeting the projected demand suggested that reduction in demand may also reduce the cost of decarbonization.

Chapter 7

Conclusion and future work

The outcomes of the study are concluded in this chapter. The conclusion section summarizes the study outcomes and evaluates against the research questions. Moreover, the future prospect from this study is described in future work section.

7.1 Conclusion

A cost model was developed in this study to investigate the cost of decarbonization under different emissions and economic conditions for Bangladesh from 2010 to 2050. To conclude the findings of this study, the research questions addressed at the beginning will be answered in this section.

• ***What are the present state and future direction of energy sector of Bangladesh?***

(i) How did the energy demand and supply sector developed historically?

(ii) What is the future direction of the energy sector development?

Initially, the historical energy demand and supply scenario of Bangladesh was investigated in Chapter 2. Moreover, the future direction of the energy sector of Bangladesh was analyzed. Studies suggest that, Bangladesh is going to anticipate a high exponential increase in electricity demand because of the rapidly growing economy. The energy sector has been getting a massive makeover in the last decade to meet the high demand, which is going to continue up to next couple of decades. The electricity demand had been slowly growing since 1971, which took a significant leap in the 2000's, and it will eventually keep elevating. Not only the demand sector but also the supply and distribution component of the electricity sector have been observing a rapid growth. The present electricity generation is natural gas dominating and going for a mixed fueled scenario in the future, which would be predominantly coal-based. The majority of coal-based power plants would operate with imported coal. Already, the dependency on imported petroleum-based rental and quick rental power plants proved to be a questionable endeavor, which elevated the generation cost and exposed the Bangladeshi energy sector to the volatile global petroleum market. The further dependency on imported coal may pose more severe constraint on the generation sector as well as the economy of Bangladesh. The direction towards high GHG emissions intensive generation sector development is questionable at the time when significant discussion going on in Bangladesh as well as international stages about the future high emission-intensive energy development.

- ***What are the costs of developing different types of power plants in Bangladesh?***

  (i) *What are the capital cost of different energy generation technologies in Bangladesh?*

  (ii) *How did the cost of power plants evolved in Bangladesh?*

  (iii) *What can we learn about the cost of energy sector in Bangladesh compared to the rest of the world?*

  (iv) *If the cost is higher or lower, what are the reasons behind the difference?*

The cost dynamics of Bangladesh's energy sector was examined in Chapter 3. For analyzing the cost of establishing power plants in Bangladesh, the cost (public and private) data were collected and compared with the world. The results demonstrated an intriguing aspect of a rapidly developing economy. Most of the public plants showed higher capital cost compared to the world average. Also, the cost of similar power generation technologies in private and public sector has a significant difference in Bangladesh. On top of the higher capital cost, the cost evolution demonstrated that cost of establishing public power plants is augmenting with time, whereas its opposite in private sector as well as in the most of the cases globally. In the case of increased cost, a statistically significant correlation between corruption and higher cost of power plants was found. Therefore, corruption may increase the cost of a power plant in a developing context such as Bangladesh.

After the analysis of the energy sector and the cost of establishing power plants in Bangladesh, the state-of-the-art of energy planning models was undertaken in Chapter 4. Current EPMs were mostly created in developed countries, often with the assumptions and biases of the country and region in which they were developed. Recognising the importance of EPMs in shaping the energy future, the analysis of 34 EPMs revealed several important shortcomings for the developing context. A key finding from the review is the lack of consideration in the analyzed EPMs of the unique socioeconomic characteristics in developing countries such as suppressed demand, corruption, and political instability. Disregarding suppressed energy demand can potentially underestimate total demand, rendering future planning inaccurate and ineffective, especially for long-horizon planning such as 2050 pathways. Corruption is a complex socio-economic factor and can increase capital and operation costs of energy projects and infrastructure in some developing countries, affecting sustainability. Also, the economy is often linked with political instability, which on its own can affect energy infrastructure resilience. Apart from the developing context-specific socio-economic deficiencies in the current EPMs, climate change impact on land availability and food production is likely to alter the dynamics of energy-food-emissions interactions, especially in the highly populated developing countries. Increasing penetration of distributed energy resources and bioenergy goals require that EPMs should now consider land-based interactions between energy, food, and the environment for future planning and development. From the analysis, it was evident that localized EPMs are very important in energy sector development in developing contexts such as Bangladesh.

In addition to the analysis of EPMs, another systematic review was conducted on the forecasting methods of EPMs in Chapter 5. The review of 483 EPMs, revealed the use of fifty different methods between 1985 and June 2017. Among the 50 identified methods, statistical, computational intelligence (CI) and mathematical programming (MP) methods were 28, 21 and one, respectively. Among CI methods, ANN was utilized in 194 EPMs, followed by SVM (58 models), FL (40 models), GA (39 models), PSO (34 models) and GM (29 models). In the case of statistical methods, ARIMA, LR, and ARMA were utilized in 46, 39 and 22 EPMs respectively for forecasting. Evidently, CI methods were widely utilized than that of statistical ones for electric load and renewable energy forecasting. However, statistical methods were used in 18% more models than that of CI and MP for energy and electricity demand forecasting. The accuracy of CI methods for forecasting was better than that of statistical ones. A significant number of forecasting models utilized multiple stand-alone methods to develop a hybrid approach because they yielded higher accuracy than that of stand-alone ones. In case of incomplete data-set, some CI methods such as fuzzy logic and grey prediction outperformed other stand-alone ones. The analysis of the studied model objectives showed that most of the forecasting methods were applied to forecast energy demand and electrical load. The development of the forecasting models started in 1985, it spiked after 2005, and it is continuing. Most numbers of models were developed in 2010. In case of the geographical extent, although most of the models were established for developed countries, some of the developing countries also established forecasting models. The highest number of models were developed for China.

•***How can the cost of decarbonization be modeled for Bangladesh up to 2050?***

The objective of this study was to evaluate the current policies and future energy mix to investigate the cost of decarbonizing Bangladesh's energy sector. For the investigation, a cost model was developed in Chapter 6. The cost model was developed as an extension of the 'BD2050 – Bangladesh 2050 Energy and Emissions Pathways' model. BD2050 model was utilized for the energy demand, supply and emissions projection. The assumptions for demand sector in BD2050 to estimate and forecast the total electricity demand from 2010 to 2050, were briefly described in Section 6.1. The cost model structure and mathematical equations used in the model along with the cost assumptions were also described in Section 6.2.

Six different emissions scenarios were evaluated- business as usual (BAU), current policy scenario (CPS), high-carbon scenario (HCS), medium-carbon scenario (MCS), low-carbon scenario (LCS) and zero-emissions scenario (ZCS). The emissions scenarios were described in Section 6.4. In addition to the emissions scenarios, there were three economic scenarios such as low, average and high cost considered in the study. Total 18 emissions-economic scenarios were analyzed in this study.

• ***What would be the total cost of decarbonizing the energy sector of Bangladesh?***

(i) What would be the impact of change in energy mix on the cost of decabonization, emissions and demand?

(ii) What would be the effect of technological maturity on the cost of decabonization?

(iii) What would be the influence of corruption on the cost of decabonization?

The scenario-based analysis with the cost model developed in Chapter 6 was discussed in Section 6.5. The total cost of future development of energy sector and the cost of decarbonization of Bangladesh was discussed. Also, the discussion elaborated on the influence of change in the energy mix, generation technology maturity and corruption on the cost of decarbonization. The total cost and cost of decarbonization would elevate would elevate exponentially by 2050 under MCS, LCS, and ZCS because of adopting emissions reduction strategies for energy sector. The high capital cost of new renewable technologies would drive the elevated cost. The results showed that zero-carbon future might not be possible for Bangladesh by 2050. There will be operational coal power plants by 2050, which were established in 2006. Moreover, the projected demand cannot be met under ZCS, as well as BAU, CPS, and HCS. Only MCS and LCS can supply the projected energy needed for Bangladesh by 2050. The emissions intensity would be 0.34 and 0.28 $kgCO_2e/kWh$ for MCS and LCS respectively. The cost of decarbonizing the energy sector of Bangladesh would be \$2.75 and \$2.81/kWh under MCS and LCS respectively. In the case of total cost, the MCS is 4% expensive than that of LCS one. LCS would have higher coat than that of MCS up to 2030 due to the high capital cost of renewable technologies. However, the total cost under LCS would start to be lower than of MCS after 2035 for the fossil fuel cost. Although, the high dependency on fluctuating renewable resources such as solar PV may result in load-shedding under LCS. On the other hand, high dependency on imported fossil fuel under MCS may eventually expose the Bangladeshi energy sector to volatile international fossil fuel market.

The study suggests that the cost of decarbonization can be reduced by controlling the corruption in energy sector in Bangladesh. Reducing the effect of corruption on the energy sector can reduce the cost of decarbonization 45-77% by 2050 under MCS, LCS, and ZCS. Another major driver for reducing cost of decarbonization can be demand reduction. A 20% reduction in demand by 2050 can make the decarbonizaiton of Bangladesh's energy sector possible under ZCS with the cost range between $454 bn and $103 bn, which would also denote a 73% GHG emissions by 2050 than that of projected highest emissions under HCS and MCS.

7.2 Contribution of the thesis

The contribution of the thesis are as follows:

(i) The problems rising and may come out of the energy sector development in Bangladesh was pointed out by analyzing the mater plans and collected historical data.

(ii) A cost database was developed for the baseline assumptions. Data analysis demonstrated that the capital cost for public power plants were higher than that of private ones. Moreover, a statistically significant relationship between corruption and higher cost of public power plants was found.

(iii) Challenges and gaps in EPMs originated in developed countries were identified for implementing in developing contexts.

(iv) Analysis of the forecasting methods revealed the mostly utilized method among the reviewed 50 methods.

(v) Developing a cost model to calculate the cost of decarbonization as a extension with the BD2050 model.

(vi) The cost of decarbonization was analyzed under six emissions and three economic scenarios.

(vii) The drivers of total cost and cost of decarbonization for energy sector of Bangladesh were identified and analyzed.

(viii) The drivers of reducing the cost of decarbonization were identified.

7.3 Future works

Recommendations for further work are as follows:

(i) Collecting and Enriching the database with more cost data to analyze the relationship between capital cost and corruption.

(ii) Analysing the different components of capital cost such as land value, machinery cost, construction expanse should be analyzed in detail upon collecting detailed data to find which part is more prone to corruption based cost increase.

(iii) Collecting and analyzing the cost data of energy generation technologies which are new at present.

(iv) Analyzing the variables of suppressed demand, political stability, corruption, climate change impact in terms of food security and extreme weather, and their relationships with energy sector in Bangladesh to incorporate in the energy planning model

(v) Develop an optimization module to incorporate with BD2050 and cost model to find the least cost scenario under varied emissions scenarios.

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Appendix A

Forecasting methods analysis

Table A.1: Forecasting models analyzed for investigating stand-alone statistical methods

Methods	Ref.
Linear regression (LR)	Song *et al.* (2005); Bilgili *et al.* (2012); Ekonomou (2010); Mackay and Probert (1995a,b, 2001); Niu *et al.* (2009); Yu *et al.* (2012c,b); Xiaobo *et al.* (2014); Kandananond (2011); Amin-Naseri and Soroush (2008); Lee and Tong (2011); Nguyen and Nabney (2010); Bianco *et al.* (2009, 2013); Rentziou *et al.* (2012); Mohamed and Bodger (2005b); Pao (2006); Papalexopoulos and Hesterberg (1990); Melikoglu (2013); Bolton (1985); Sharma *et al.* (2002); Gori *et al.* (2007); Haida and Muto (1994); Yumurtaci and Asmaz (2004); Arsenault *et al.* (1995); Köne and Büke (2010); ZhiDong (2003); Egelioglu *et al.* (2001); Bianco *et al.* (2014b); Chi *et al.* (2009); Kankal *et al.* (2011); Elattar *et al.* (2010); Ramsami and Oree (2015); De Felice *et al.* (2015); Baldacci *et al.* (2016); Khan (2015); Zhang and Yang (2015)
Nonlinear regression (NLR)	Bilgili *et al.* (2012); Ghiassi and Nangoy (2009); Tsekouras *et al.* (2007)
Logistic regression (LoR)	Mackay and Probert (2001); Furtado and Suslick (1993); Forouzanfar *et al.* (2010); Melikoglu (2013); Mohamed and Bodger (2005a); Gutiérrez *et al.* (2005); Siemek *et al.* (2003); Bodger and Tay (1987); Purohit and Kandpal (2005); Carolin Mabel and Fernandez (2008); Bessec and Fouquau (2008); Meng and Niu (2011b); Nel and Cooper (2008); Skiadas *et al.* (1993); McNeil and Letschert (2005); Daim *et al.* (2012); Debnath *et al.* (2015); Bianco *et al.* (2014a); Shaikh and Ji (2016)
Nonparametric regression (NR)	Charytoniuk *et al.* (1998); Wang *et al.* (2010a); Jónsson *et al.* (2010)

Table A.1: Forecasting models analyzed for investigating stand-alone statistical methods

Methods	Ref.
Partial least squares regression (PLSR)	Zhang *et al.* (2009); Meng and Niu (2011a)
Stepwise regression (SR)	Ekonomou (2010); Tso and Yau (2007); Rao and Parikh (1996); Aranda *et al.* (2012); Ramsami and Oree (2015); Soldo *et al.* (2014); Potočnik *et al.* (2014)
Moving average (MA)	Azadeh *et al.* (2007a); Xu and Wang (2010); Zhu *et al.* (2011); Li *et al.* (2014)
Autoregressive integrated moving average (ARIMA)	Li *et al.* (2014); Cadenas and Rivera (2007); Ediger and Akar (2007); Ediger *et al.* (2006); Sumer *et al.* (2009); Guo *et al.* (2011); Darbellay and Slama (2000); Bowden and Payne (2008); Hu *et al.* (2013); Hong (2011, 2009a); Wang *et al.* (2015b); Pai and Hong (2005); Tan *et al.* (2010); Cadenas *et al.* (2010); González-Romera *et al.* (2008); Kandananond (2011); Shi *et al.* (2012); Lee and Tong (2012); Contreras *et al.* (2003); Pao and Tsai (2011a); Gonzalez-Romera *et al.* (2006); Ierapetritou *et al.* (2002); Erdogdu (2010); Abdel-Aal and Al-Garni (1997); Gonzales Chavez *et al.* (1999); Saab *et al.* (2001); Hagan and Behr (1987); Amjady (2001); Harris and Liu (1993); Erdogdu (2007); Cho *et al.* (1995); Conejo *et al.* (2005); Reikard (2009); Kavasseri and Seetharaman (2009); Liu and Lin (1991); Cadenas and Rivera (2010); Azadeh *et al.* (2007b); Zhou *et al.* (2006); Wang and Hu (2015); Nobre *et al.* (2016); Wang *et al.* (2016); Bracale and De Falco (2015); Barak and Sadegh (2016); Sen *et al.* (2016)

Table A.1: Forecasting models analyzed for investigating stand-alone statistical methods

Methods	Ref.
Seasonal autoregressive integrated moving average (SARIMA)	Zhu *et al.* (2011); Cadenas and Rivera (2007); Jeong *et al.* (2014); Ediger and Akar (2007); Damrongkulkamjorn and Churueang (2005); Ediger *et al.* (2006); Sumer *et al.* (2009); Bouzerdoum *et al.* (2013); Guo *et al.* (2011); Wang *et al.* (2012c); Boata and Paulescu (2014); Wang *et al.* (2010b); Yang *et al.* (2016)
Autoregressive moving average model with exogenous inputs (ARMAX)	Li *et al.* (2014); González *et al.* (2012); Bakhat and Rosselló (2011); Wang *et al.* (2008); Lira *et al.* (2009); Hickey *et al.* (2012); Pao (2006); Arciniegas and Rueda (2008); Yan and Chowdhury (2013, 2014b)
Autoregressive moving average (ARMA)	González *et al.* (2012); Xiaobo *et al.* (2014); Liu and Shi (2013); Maia *et al.* (2006); Xu *et al.* (2015); El-Telbany and El-Karmi (2008); Srinivasan (2008); Hagan and Behr (1987); Cadenas *et al.* (2010); Nowicka-Zagrajek and Weron (2002); Pappas *et al.* (2008); Fan and McDonald (1994); Al-Shobaki and Mohsen (2008); Topalli *et al.* (2006); Torres *et al.* (2005); Pappas *et al.* (2010); Taylor (2010); Crespo Cuaresma *et al.* (2004); Chu *et al.* (2015); Yang *et al.* (2017); Kavousi-Fard *et al.* (2014); Zhu *et al.* (2015)

Table A.1: Forecasting models analyzed for investigating stand-alone statistical methods

Methods	Ref.
Vector autoregression (VAR)	Chandramowli and Lahr (2012); Nasr *et al.* (2000); McAvinchey and Yannopoulos (2003); Ghosh (2006); Sari and Soytas (2004); Lee and Chien (2010); Kulshreshtha and Parikh (2000); Abosedra *et al.* (2009); Narayan and Prasad (2008); Inglesi (2010); García-Ascanio and Maté (2010); Athukorala and Wilson (2010); Baumeister and Kilian (2015)
Bayesian vector autoregression (BVAR)	Chandramowli and Lahr (2012); Crompton and Wu (2005); Francis *et al.* (2007); Miranda and Dunn (2006)
Structural Time Series Model (STSM)	Dilaver and Hunt (2011a,b); Amarawickrama and Hunt (2008)
VARIMA	García-Martos *et al.* (2013)
Generalized autoregressive conditional heteroskedasticity (GARCH)	Bakhat and Rosselló (2011); Hickey *et al.* (2012); Wang and Wu (2012); Tan *et al.* (2010); Liu and Shi (2013); Cao *et al.* (2014); Wang *et al.* (2016); Wei *et al.* (2010); Garcia *et al.* (2005); Kang *et al.* (2009); Sadorsky (2006); Diongue *et al.* (2009); Li *et al.* (2017); Zhang *et al.* (2015)

Table A.1: Forecasting models analyzed for investigating stand-alone statistical methods

Methods	Ref.
Seasonal exponential form of generalized autoregressive conditional heteroscedasticity (SEGARCH)	Pao (2009)
Exponential generalized autoregressive conditional heteroscedasticity (EGARCH)	Bowden and Payne (2008)
Winters model with exponential form of generalized autoregressive conditional heteroscedasticity (WARCH)	Pao (2009)

Table A.1: Forecasting models analyzed for investigating stand-alone statistical methods

Methods	Ref.
Autoregressive distributed lag (ARDL)	Dilaver and Hunt (2011a,b); Adom and Bekoe (2012); Kim *et al.* (2001); Zachariadis (2010); De Vita *et al.* (2006)
Log-linear analysis (LA)	Parikh *et al.* (2007); Pilli-Sihvola *et al.* (2010); Limanond *et al.* (2011); Wadud *et al.* (2011)
Geometric progression (GP)	Mackay and Probert (1995a,b, 2001)
Transcendental logarithmic (Translog)	Rao and Parikh (1996); Furtado and Suslick (1993)
Polynomial curve model (PCM)	Xu and Wang (2010)
Partial adjustment model (PAM)	Adom and Bekoe (2012); Nasr *et al.* (2000); Eltony (1996); Erdogdu (2007)
Analysis of variance (ANOVA)	Azadeh *et al.* (2007a); Azadeh and Faiz (2011); Azadeh *et al.* (2008b); Al-Ghandoor *et al.* (2008, 2009); Azadeh *et al.* (2008a); Trejo-Perea *et al.* (2009)

Table A.1: Forecasting models analyzed for investigating stand-alone statistical methods

Methods	Ref.
Unit root test and/or Cointegration	Adom and Bekoe (2012); De Vita *et al.* (2006); Nasr *et al.* (2000); Eltony (1996); Erdogdu (2007); Ghosh (2006); Athukorala and Wilson (2010); Amarawickrama and Hunt (2008); Li *et al.* (2017); Pao and Tsai (2011b); Kwakwa (2012); Narayan and Smyth (2007); Narayan *et al.* (2007); Smith *et al.* (1995); Masih and Masih (1996a); Fouquet *et al.* (1997); Glasure (2002); Hondroyiannis *et al.* (2002); Galindo (2005); Lee and Chang (2005); Al-Iriani (2006); Chen and Lee (2007); Lise and Van Montfort (2007); Zhao and Wu (2007); Feng *et al.* (2009); Sadorsky (2009b,a); Narayan *et al.* (2010); Apergis and Payne (2010); Sadorsky (2011); Hatzigeorgiou *et al.* (2011); Masih and Masih (1996b); Lin Chan and Kam Lee (1997); Eltony and Al-Mutairi (1995); Ramanathan (1999); Alves and De Losso da Silveira Bueno (2003); Akinboade *et al.* (2008); Park and Zhao (2010); Zou and Chau (2006); Ziramba (2010); Gallo *et al.* (2010); Silk and Joutz (1997); Narayan and Smyth (2005); Zachariadis and Pashourtidou (2007); Yuan *et al.* (2007); Odhiambo (2009); Yoo and Kwak (2010); Lim *et al.* (2014)
Decomposition	Damrongkulkamjorn and Churueang (2005); Dilaver and Hunt (2011a,b); Sánchez-Úbeda and Berzosa (2007); Ang (1995a,b); Ang and Lee (1996); Ang and Zhang (2000); Sun (2001); Tao (2010); Afshar and Bigdeli (2011); He *et al.* (2011); Kawase *et al.* (2006); An *et al.* (2013); Xiong *et al.* (2014); Wang *et al.* (2017)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
Computational intelligence (CI) methods	
Support vector machine (SVM)	Ekonomou (2010); Guo *et al.* (2011); Wang *et al.* (2010b); Yuan *et al.* (2015); Ju and Hong (2013); Zhang *et al.* (2012); Hu *et al.* (2013); Hong (2011,?); Niu *et al.* (2010); Hong (2009a); Wang *et al.* (2012b, 2015b); Xiaobo *et al.* (2014); Hong (2009b); Pai and Hong (2005); Shi *et al.* (2012); Wang *et al.* (2011); Fan *et al.* (2008); Ko and Lee (2013); Cao *et al.* (2014); Li *et al.* (2012); Elattar *et al.* (2010); De Felice *et al.* (2015); Soldo *et al.* (2014); Wang and Hu (2015); Wang *et al.* (2016); Yan and Chowdhury (2014b); Yang *et al.* (2017); Kavousi-Fard *et al.* (2014); Zhu *et al.* (2015); Zhang *et al.* (2015); Xiong *et al.* (2014); Kavaklioglu (2011); Wang *et al.* (2009); Mohandes *et al.* (2004); Niu *et al.* (2008); Hong *et al.* (2013); Patil and Patil (2015); Ji *et al.* (2007); KÜÇÜKDENİZ (2010); Chen and Chang (2004); Wu and Chang (2006); Ying and Pan (2008); Wang *et al.* (2015a); Hu *et al.* (2015a); Rana *et al.* (2016); Lauret *et al.* (2015); Feijoo *et al.* (2016); Hu *et al.* (2015c, 2014); Cecati *et al.* (2015); Yan and Chowdhury (2014a); Abdoos *et al.* (2015); Chen *et al.* (2015); Bai and Li (2016); Deo *et al.* (2016)
Decision tree*	Tso and Yau (2007); Yu *et al.* (2010); Ibarra-Berastegi *et al.* (2015); Lahouar and Ben Hadj Slama (2015)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
Artificial neural network (ANN)	Bilgili *et al.* (2012); Ghiassi and Nangoy (2009); Ekonomou (2010); Tso and Yau (2007); Azadeh *et al.* (2007a); Cadenas and Rivera (2007); Jeong *et al.* (2014); Darbellay and Slama (2000); Pao (2009); Limanond *et al.* (2011); Azadeh and Faiz (2011); Azadeh *et al.* (2008b); Yalcinoz and Eminoglu (2005); Carpinteiro *et al.* (2007); Abdel-Aal (2008); Ho *et al.* (1992); Ghanbari *et al.* (2013); Hu *et al.* (2013); Niu *et al.* (2009); Behrang *et al.* (2011a); Hong (2009a); Wang *et al.* (2012b, 2015b); Behrang *et al.* (2011b); Cadenas *et al.* (2010); González-Romera *et al.* (2008); Maia *et al.* (2006); Kandananond (2011); Wang *et al.* (2012a); Shi *et al.* (2012); Amin-Naseri and Soroush (2008); Chen *et al.* (2013); Amjady (2006); Bazmi *et al.* (2012); Zahedi *et al.* (2013); Esen *et al.* (2008a); Sfetsos and Coonick (2000); Akdemir and Çetinkaya (2012); Chen and Wang (2012); Chen (2012); Chang *et al.* (2011); Bakirtzis *et al.* (1995); Srinivasan *et al.* (1995); Padmakumari *et al.* (1999); El-Telbany and El-Karmi (2008); Yu *et al.* (2015); Hsu and Chen (2003a); Bashir and El-Hawary (2009); Ko and Lee (2013); Azadeh *et al.* (2007b); Cinar *et al.* (2010); Shayeghi *et al.* (2009); Cao *et al.* (2014); Nguyen and Nabney (2010); Mohandes *et al.* (1998a); Mandal *et al.* (2006); Srinivasan (2008); Li *et al.* (2012); Pao (2006); Kankal *et al.* (2011); Ramsami and Oree (2015); Soldo *et al.* (2014); Potočnik *et al.* (2014); Gonzalez-Romera *et al.* (2006); Cadenas and Rivera (2010); Wang *et al.* (2016); Barak and Sadegh (2016); Yang *et al.* (2016); Arciniegas and Rueda (2008); Topalli *et al.* (2006)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
	Chu *et al.* (2015); Yang *et al.* (2017); Kavousi-Fard *et al.* (2014); Zhu *et al.* (2015); García-Ascanio and Maté (2010); Azadeh *et al.* (2008a); Trejo-Perea *et al.* (2009); An *et al.* (2013); Mohandes *et al.* (2004); Patil and Patil (2015); KÜÇÜKDENİZ (2010); Ying and Pan (2008); Rana *et al.* (2016); Lauret *et al.* (2015); Cecati *et al.* (2015); Abdoos *et al.* (2015); Bai and Li (2016); Khashei and Bijari (2010); Sun *et al.* (2011); Hsu and Chen (2003b); Chakraborty and Simoes (2008); Al-Saba and El-Amin (1999); Es *et al.* (2014); Hamzaçebi (2007); Sözen *et al.* (2005b); Sözen (2009); Sözen and Arcaklioglu (2007); Murat and Ceylan (2006); Liu *et al.* (1991); Aydinalp *et al.* (2002); Ermis *et al.* (2007); Sözen *et al.* (2007); Geem and Roper (2009); Geem (2011); Xue *et al.* (2011); Hsu and Yang (1991); Park *et al.* (1991); Lee *et al.* (1992); Peng *et al.* (1992); Chen *et al.* (1992); Lu *et al.* (1993); Papalexopoulos *et al.* (1994); Sforna and Proverbio (1995); Mohammed *et al.* (1995); Khotanzad *et al.* (1995, 1996); Bakirtzis *et al.* (1996); Chow and Leung (1996); Vermaak and Botha (1998); Hobbs *et al.* (1998); Khotanzad *et al.* (1998); Gao and Tsoukalas (2001); Gareta *et al.* (2006); Kandil *et al.* (2006); Santos *et al.* (2007); Al-Shareef *et al.* (2008); Vahidinasab *et al.* (2008); Catalão *et al.* (2007); Pao (2007); Xiao *et al.* (2009); Kurban and Filik (2009); Siwek *et al.* (2009); Islam *et al.* (1995); González-Romera *et al.* (2007); AlShehri (1999); Ghiassi *et al.* (2006); Xia *et al.* (2010); Chaturvedi *et al.* (2010); Benaouda *et al.* (2006); Beccali *et al.* (2004); Amjady and Keynia (2008); Sözen *et al.* (2005a); Kavaklioglu *et al.* (2009); Dorvlo *et al.* (2002); Nizami and Al-Garni (1995); González and Zamarreño (2005); Mohandes *et al.* (1998b)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
	Ringwood *et al.* (2001); Esen *et al.* (2008b); Sideratos and Hatziargyriou (2007); Marquez *et al.* (2013); Fonte *et al.* (2005); Lee *et al.* (2012); İzgi *et al.* (2012); Szkuta *et al.* (1999); Cadenas and Rivera (2009); Wang and Liang (2009); Kermanshahi and Iwamiya (2002); Swarup and Satish (2002); Asgharizadeh and Taghizadeh (2012); Hamzaçebi (2008); Kiartzis *et al.* (1995); Sözen *et al.* (2005c, 2004); Saini (2008); Lauret *et al.* (2008); Assareh *et al.* (2011); Yu *et al.* (2012a); Pai (2006); Dolara *et al.* (2015); Mellit *et al.* (2014); Kashyap *et al.* (2015); Laouafi *et al.* (2016); Ortiz *et al.* (2016); Sandhu *et al.* (2016); Osório *et al.* (2015); Singh *et al.* (2017); Kouhi and Keynia (2013); Kouhi *et al.* (2014); Chaturvedi *et al.* (2015); Ghofrani *et al.* (2015); Rana and Koprinska (2016); Khwaja *et al.* (2015); Li *et al.* (2015, 2016); Liu *et al.* (2014); Hernández *et al.* (2014); Sharma *et al.* (2016); Kim (2015); Chae *et al.* (2016); Szoplik (2015); Panapakidis and Dagoumas (2017); Zjavka (2015)
Abductive networks	Abdel-Aal (2008); Abdel-Aal *et al.* (1997)
Expert system	Ho *et al.* (1992); Rahman and Bhatnagar (1988); Ho *et al.* (1990); Rahman and Hazim (1996); Jabbour *et al.* (1988); Ghanbari *et al.* (2013, 2011)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
Grey prediction (GM/GP)	Guo *et al.* (2011); Akay and Atak (2007); Niu *et al.* (2009); Xu *et al.* (2015); Lee and Tong (2011, 2012); Hsu and Chen (2003a); Xie and Li (2009); Li *et al.* (2012); Pao and Tsai (2011a); Zhou *et al.* (2006); Xue *et al.* (2011); Pao *et al.* (2012); Lin *et al.* (2011); Lu *et al.* (2009); Ma and Wu (2009); Kumar and Jain (2010); Lee and Shih (2011); Yao *et al.* (2003); Wang (2007); Yao and Chi (2004); Bianco *et al.* (2010); Mu *et al.* (2004); Pi *et al.* (2010); Hamzacebi and Es (2014); Wang (2009); Bahrami *et al.* (2014); Tsai *et al.* (2017); Wu *et al.* (2015)
Fuzzy logic (FL)	Song *et al.* (2005); Boata and Paulescu (2014); Lira *et al.* (2009); Ghanbari *et al.* (2011); Elias and Hatziargyriou (2009); Chen *et al.* (2013); Bazmi *et al.* (2012); Zahedi *et al.* (2013); Esen *et al.* (2008a); Sfetsos and Coonick (2000); Akdemir and Çetinkaya (2012); Chen and Wang (2012); Chen (2012); Chang *et al.* (2011); Bakirtzis *et al.* (1995); Srinivasan *et al.* (1995); Papadakis *et al.* (1998); Padmakumari *et al.* (1999); Wang *et al.* (2016); Barak and Sadegh (2016); Yang *et al.* (2016); Arciniegas and Rueda (2008); Ying and Pan (2008); Chakraborty and Simoes (2008); Sideratos and Hatziargyriou (2007); Pai (2006); Laouafi *et al.* (2016); Osório *et al.* (2015); Chaturvedi *et al.* (2015); Panapakidis and Dagoumas (2017); Kucukali and Baris (2010); Kiartzis *et al.* (2000); Miranda and Monteiro (2000); Mamlook *et al.* (2009); Ahmadi *et al.* (2012); Jain *et al.* (2009); Lau *et al.* (2008); Al-Ghandoor *et al.* (2012); Mori and Nakano (2016)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
Genetic algorithm (GA)	Ghanbari *et al.* (2013, 2011); Canyurt and Ozturk (2008); Forouzanfar *et al.* (2010); Zhang *et al.* (2012); Assareh *et al.* (2012, 2010); Chaturvedi *et al.* (1995); Hu *et al.* (2013); Samsami (2013); Yu *et al.* (2012c,b); Hong (2009a); Wang *et al.* (2015b); Chang *et al.* (2011); Yu *et al.* (2015); Yu and Zhu (2012); Lee and Tong (2011, 2012); Xie and Li (2009); Azadeh *et al.* (2007b); Cinar *et al.* (2010); Azadeh and Tarverdian (2007); Barak and Sadegh (2016); Chu *et al.* (2015); Kavousi-Fard *et al.* (2014); Hong *et al.* (2013); Ying and Pan (2008); Chaturvedi *et al.* (2015); Panapakidis and Dagoumas (2017); Da Silva *et al.* (2000); Sirikum and Techanitisawad (2006); Ceylan and Ozturk (2004); Ozturk *et al.* (2005); Haldenbilen and Ceylan (2005); Canyurt and Öztürk (2006); Ozturk *et al.* (2004); Ozturk and Ceylan (2005); Kavoosi *et al.* (2012)
Artificial bee colony optimization (ABCO)	Behrang *et al.* (2011a); Hong (2011); Kavousi-Fard *et al.* (2014); Li *et al.* (2015)
Ant colony optimization (ACO)	Ghanbari *et al.* (2013, 2011); Kıran *et al.* (2012); Rahmani *et al.* (2013); Niu *et al.* (2010); Samsami (2013); Duran Toksarı (2007); Toksarı (2009); Yu *et al.* (2012c,b)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
Particle swarm optimization (PSO)	Zhu *et al.* (2011); Wang *et al.* (2012c, 2010b, 2008); Assareh *et al.* (2012, 2010); Hu *et al.* (2013); Kıran *et al.* (2012); Rahmani *et al.* (2013); AlRashidi and El-Naggar (2010); Kamrani (2010); Abdelfatah *et al.* (2013); Niu *et al.* (2009); Samsami (2013); Yu *et al.* (2012c,b); Hong (2009a); El-Telbany and El-Karmi (2008); Yu *et al.* (2015); Yu and Zhu (2012); Bashir and El-Hawary (2009); Cao *et al.* (2014); Barak and Sadegh (2016); Zhang *et al.* (2015); Hu *et al.* (2014); Chen *et al.* (2015); Assareh *et al.* (2011); Yu *et al.* (2012a); Osório *et al.* (2015); Liu *et al.* (2014); Bahrami *et al.* (2014); Mori and Nakano (2016); Aghaei *et al.* (2013); Nazari *et al.* (2014)
Gravitational search algorithm (GSA)	Yuan *et al.* (2015); Ju and Hong (2013); Behrang *et al.* (2011b); Gavrilas *et al.* (2014)
Chaotic ant swarm optimization (CAS)	Hong (2010, 2009a)
Differential evolution (DE)	Wang *et al.* (2012b, 2015b); Xiaobo *et al.* (2014); Kouhi *et al.* (2014)
Harmony search (HS)	Ceylan *et al.* (2008)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
Evolutionary algorithm (EA)	Wang *et al.* (2008)
Memetic algorithms (MA)	Hu *et al.* (2013)
Immune algorithm (IA)	Ceylan *et al.* (2008)
Simulated annealing algorithms (SA)	Zhang *et al.* (2012); Hu *et al.* (2013); Hong (2009a); Pai and Hong (2005); Hu *et al.* (2015a); Wang *et al.* (2015b)
Firefly algorithm (FA)	Hu *et al.* (2013); Kavousi-Fard *et al.* (2014); Hu *et al.* (2015c,b)
Cuckoo search algorithm (CSA)	Wang *et al.* (2016); Kim (2015)
Mathematical programming (MP) methods	
Nonlinear programming (NLP)	Forouzanfar *et al.* (2010)

Table A.2: Analysis of stand-alone computational intelligence and mathematical programming methods utilized in forecasting models

Methods	**Reference**
*Random forest was included under decision tree modeling as they are collection of decision trees in the modeling.	

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
		2	**3**	**4**	**1st**			**2nd**			**3rd**			**4th**				
					<5	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
Electricity demand	2006	-	✓	-	-	✓	-	-	✓		✓	-	-	-	-	-	5-5-1	Pao (2006)
						✓	-	-	✓		✓	-	-	-	-	-	5-6-1	
					✓	-	-	-	✓		✓	-	-	-	-	-	4-8-2	
Electricity demand	2012	-	✓	-	✓	-	-	-	✓	-	-	-	✓	✓	-	-	4-20-17-1	Bilgili *et al.* (2012)
Energy demand	2010	-	-	✓	-	✓	-	-	-	✓	✓	-	-	-	-	-	8-36-1	Ekonomou (2010)
Electricity load	2008	-	✓	-		✓	-	-	✓	-	✓	-	-	-	-	-	9-10-1	Amin-Naseri and Soroush (2008)
					-	✓	-	-	-	✓	✓	-	-	-	-	-	10-31-1	
					-	✓	-	-	-	✓	✓	-	-	-	-	-	8-17-1	
					-	✓	-	✓	-	-	✓	-	-	-	-	-	9-2-1	

Table A.3: ANN model objectives and structures

Forecasted variable	Year	No. of layers			No. of neurons in layers												Neuron composition	Ref.
		2	3	4	1st			2nd			3rd			4th				
					<5	5-10	>10	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10		
					-	-	✓	-	-	✓	-	✓	-	✓	-	-	12-16-6-1	
Electricity demand	2007	-	-	✓		✓	-	-	✓	-	✓	-	-	-	-	-	5-5-1	Azadeh *et al.* (2007a)
Energy demand	2011	-	✓	✓		✓	-	-	✓	-	✓	-	-	-	-	-	5-10-1	Limanond *et al.* (2011)
					-	✓		-	✓	-	-	✓	-	✓	-	-	5-5-5-1	
					-	-	✓	✓	-	-	✓	-	-	-	-	-	12–4–1	
Energy demand	2008	-	✓	-		-	✓	-	✓	-	✓	-	-	-	-	-	12–5–1	Abdel-Aal (2008)
					-	-	✓	-	✓	-	✓	-	-	-	-	-	12–6–1	
					✓	-	-	-	✓	-	✓	-	-	-	-	-	3–5–1	
Energy demand	2009	-	✓	-		-	-	✓	-	-	✓	-	-	-	-	-	2-3-1	Pao (2009)
					✓	-	-	✓	-	-	✓	-	-	-	-	-	2-4-1	

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
					1st			**2nd**			**3rd**			**4th**				
		2	**3**	**4**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
Solar radiation	1998	-	✓	-		-	-	-	✓	-	✓	-	-	-	-	-	4-10-1	Mohandes *et al.* (1998a)
Wind speed	2010	✓	✓	-		-	-	✓	-	-	-	-	-	-	-	-	3-1	Cadenas and Rivera (2010)
					✓	-	-	✓	-	-	-	-	-	-	-	-	2-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	3-3-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	3-2-1	
Electricity demand	2000	-	✓	-	-	✓	-		✓		✓	-	-	-	-	-	6-6-1	Darbellay and Slama (2000)
Wind speed	2007	✓	-	-	✓	-	-	✓	-	-	-	-	-	-	-	-	3-1	Cadenas and Rivera (2007)

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
					1st			**2nd**			**3rd**			**4th**				
		2	**3**	**4**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
Electricity demand	2011	-	✓	-	-	✓	-	-	✓	-	✓	-	-	-	-	-	5-12-1	Azadeh and Faiz (2011)
Electricity demand	2013	-	✓	-	-	-	✓	-	-	✓	-	-	✓	-	-	-	48-97-48	An *et al.* (2013)
Electricity demand	2012	-	✓	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	1-2-1	Li *et al.* (2012)
Time-series forecasting	2010	-	✓	-		✓	-	✓	-	-	✓	-	-	-	-	-	8-3-1	Khashei and Bijari (2010)
					-	✓	-	✓	-	-	✓	-	-	-	-	-	8-4-1	
					-	-	✓	✓	-	-	✓	-	-	-	-	-	12-4-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	4-4-1	
					-	✓	-	-	✓	-	✓	-	-	-	-	-	7-5-1	

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
					1st			**2nd**			**3rd**			**4th**				
		2	**3**	**4**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
Electricity demand	2007	-	✓	✓		-	-	✓	-	-	✓	-	-	-	-	-	2-2-1	Azadeh and Tarverdian (2007)
					✓	-	-	-	✓	-	-	✓	-	✓	-	-	2-10-10-1	
					✓	-	-	-	-	✓	-	-	✓	✓	-	-	2-20-20-1	
Electricity demand	2008	-	✓	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	3-2-1	Azadeh *et al.* (2008b)
Electricity demand	2008	-	-	✓	✓	-	-	✓	-	-	✓	-	-	✓	-	-	5–3–2–1	Azadeh *et al.* (2008a)
Electricity load	2003	-	✓	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	3-2-1	Hsu and Chen (2003b)

Table A.3: ANN model objectives and structures

Forecasted variable	Year	No. of layers			No. of neurons in layers												Neuron composition	Ref.
					1st			2nd			3rd			4th				
		2	3	4	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10		
Electricity load	2005	-	-	✓		✓	-	-	✓	-	-	✓		✓	-	-	6-5-8-1	Yalcinoz and Eminoglu (2005)
					-	✓	-	-	✓	-	-	✓	-	✓	-	-	9-5-8-1	
Energy demand	2009	-	✓	-		-	-	-	✓	-	✓	-	-	-	-	-	4-5-1	Trejo-Perea *et al.* (2009)
					✓	-	-	✓	-	-	✓	-	-	-	-	-	4-4-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	4-3-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	4-2-1	
Electricity demand	2011	-	✓	-		-	-	-	✓	-	✓	-	-	-	-	-	4-10-1	Kandananond (2011)
					✓	-	-	-	✓	-	✓	-	-	-	-	-	4-6-1	
					✓	-	-	-	✓	-	✓	-	-	-	-	-	4-8-1	
					✓	-	-	-	✓	-	✓	-	-	-	-	-	4-6-1	

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
		2	**3**	**4**	**1st**			**2nd**			**3rd**			**4th**				
					<5	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
					✓	-	-	-	✓	-	✓	-	-	-	-	-	4-5-1	
Energy demand	1999	-	✓	-		-	-	-	✓	-	✓	-	-	-	-	-	2-7-1	Al-Saba and El-Amin (1999)
					✓	-	-	-	✓	-	✓	-	-	-	-	-	3-7-1	
					✓	-	-	-	✓	-	✓	-	-	-	-	-	4-7-1	
					-	✓	-	-	✓	-	✓	-	-	-	-	-	5-7-1	
Electricity demand	2007	-	✓	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	4-2-4	Hamzaçebi (2007)
Energy demand	2005	-	-	✓		✓	-	✓	-	-	✓	-	-	✓	-	-	5-4-4-1	Sözen *et al.* (2005b)
					-	✓	-	✓	-	-	✓	-	-	✓	-	-	7-4-4-1	

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
					1st			**2nd**			**3rd**			**4th**				
		2	**3**	**4**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
Energy demand	2002	-	✓	-		-	✓	-	-	✓	✓	-	-	-	-	-	55-27-1	Aydinalp *et al.* (2002)
					-	-	✓	✓	-	-	✓	-	-	-	-	-	55-02-1	
Electricity load	1994	-	✓	-	-	-	✓	-	-	✓	-	-	✓	-	-	-	77-24-24	Papalexopoulos *et al.* (1994)
Electricity load	1996	-	✓	-	-	-	✓	-	-	✓	-	-	✓	-	-	-	63-24-24	Bakirtzis *et al.* (1996)
Electricity load	1993	-	✓	-		-	✓	-	✓	-	✓	-	-	-	-	-	29-8-1	Lu *et al.* (1993)
					-	-	✓	-	✓	-	✓	-	-	-	-	-	22-5-1	
					-	-	✓	-	-	✓	-	-	✓	-	-	-	39-10-24	
Electricity load	1992	-	✓	-	-	✓	-	-	✓	-	✓	-	-	-	-	-	5-8-1	Peng *et al.* (1992)

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
					1st			**2nd**			**3rd**			**4th**				
		2	**3**	**4**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
Electricity load	1996	-	✓	-	-	-	✓	-	-	✓	-	-	✓	-	-	-	81-81-24	Chow and Leung (1996)
Electricity load	1998	-	✓	-		-	✓	-	-	✓	✓	-	-	-	-	-	15-(7-12)*-1	Vermaak and Botha (1998)
					-	-	✓	-	-	✓	✓	-	-	-	-	-	7-(10-16)†-1	
Electricity load	2006	-	✓	-	-	-	✓	-	-	✓	✓	-	-	-	-	-	32-65-1	Kandil *et al.* (2006)
Electricity load	2008	-	✓	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	4-3-1	Al-Shareef *et al.* (2008)
Electricity price	2007	-	✓	-	✓	-	-	-	✓	-	✓	-	-	-	-	-	5-7-1	Pao (2007)

Table A.3: ANN model objectives and structures

Forecasted variable	Year	No. of layers			No. of neurons in layers												Neuron composition	Ref.
					1st			2nd			3rd			4th				
		2	3	4	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10		
Electricity load	2009	-	-	✓	-	-	✓	-	-	✓	-	-	✓	-	-	✓	19-20-15-24	Siwek *et al.* (2009)
Electricity demand	1999	-	✓	-	✓	-	-	-	✓	-	✓	-	-	-	-	-	3-5-1	AlShehri (1999)
Electricity demand	2015	-	✓	-	-	✓	-	✓	-	-	✓	-	-	-	-	-	5–3–1	Yu *et al.* (2015)
Solar energy potential	2005	-	✓	-	-	✓	-	-	✓	-	✓	-	-	-	-	-	6-6-1	Sözen *et al.* (2005a)
Electricity demand	2001	-	✓	-		-	-	-	✓	-	✓	-	-	-	-	-	2-6-1	Ringwood *et al.* (2001)
					✓	-	-	-	✓	-	✓	-	-	-	-	-	3-9-1	

Table A.3: ANN model objectives and structures

Forecasted variable	Year	No. of layers			No. of neurons in layers												Neuron composition	Ref.
					1st			2nd			3rd			4th				
		2	3	4	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10		
					✓	-	-	-	✓	-	✓	-	-	-	-	-	3-5-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	1-3-1	
Wind speed	2005	-	✓	-	-	-	✓	-	-	✓	✓	-	-	-	-	-	14-15-1	Fonte *et al.* (2005)
Wind speed	2012	-	✓	-	-	✓	-	-	✓	-	✓	-	-	-	-	-	5-10-1	Lee *et al.* (2012)
Wind speed	2009	✓	✓	-		-	-	✓	-	-	-	-	-	-	-	-	3-1	Cadenas and Rivera (2009)
					✓	-	-	✓	-	-	-	-	-	-	-	-	2-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	3-3-1	
					✓	-	-	✓	-	-	✓	-	-	-	-	-	3-2-1	

Table A.3: ANN model objectives and structures

Forecasted variable	**Year**	**No. of layers**			**No. of neurons in layers**												**Neuron composition**	**Ref.**
					1st			**2nd**			**3rd**			**4th**				
		2	**3**	**4**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**	**<5**	**5-10**	**>10**		
Electricity price	1999	-	✓	-	-	-	✓	-	-	✓	✓	-	-	-	-	-	15-15-1	Szkuta *et al.* (1999)
Electricity demand	2013	-	✓	-	✓	-	-	-	✓	-	✓	-	-	-	-	-	4-6-1	Ghanbari *et al.* (2013)
Natural gas demand	2013	-	✓	-	✓	-	-	-	✓	-	✓	-	-	-	-	-	3-5-1	Ghanbari *et al.* (2013)
Oil products demand	2013	-	✓	-	✓	-	-	✓	-	-	✓	-	-	-	-	-	2-3-1	Ghanbari *et al.* (2013)
Energy demand	2009	-	✓	-	-	✓	-	-	✓	-	✓	-	-	-	-	-	7-8-1	Wang and Liang (2009)

Table A.3: ANN model objectives and structures

Forecasted variable	Year	No. of layers			No. of neurons in layers												Neuron composition	Ref.
					1st			2nd			3rd			4th				
		2	3	4	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10	<5	5-10	>10		
Electricity load	2008	-	-	✓	-	-	✓	-	✓	-	-	✓	-	✓	-	-	11-5-5-1	Saini (2008)
Electricity demand	1999	-	✓	-		-	-	✓	-	-	✓	-	-	-	-	-	3-2-1	Padmakumari *et al.* (1999)
					✓	-	-	✓	-	-	✓	-	-	-	-	-	3-1-1	
Electricity demand	2015	-	✓	-	-	-	✓	✓	-	-	✓	-	-	-	-	-	12-4-1	Wang *et al.* (2015b)
Total number		3	44	9	48	25	22	37	42	17	76	6	8	11	0	1		
%		6%	83%	17%	49%	26%	23%	38%	43%	18%	78%	6%	8%	11%	0%	1%		

* Number of hidden layer neurons form week 1 to 21 ranged from 7 to 12 for feedforward networks

† Number of hidden layer neurons form week 1 to 21 ranged from 10 to 16 for recurrent networks

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Electricity price	WT-GARCH-ARIMA	1.61	-	-	-	-	-	-	WT-GARCH-ARIMA	Tan *et al.* (2010)
	ARIMA	10.61	-	-	-	-	-	-		
	ARIMA-GARCH	8.65	-	-	-	-	-	-		
	WT-ARIMA	6.37	-	-	-	-	-	-		
Electricity consumption	AR (1)+HPF	-	4.64†	-	-	-	-	-	AR (1)+HPF	Saab *et al.* (2001)
	AR (1)	-	7.23†	-	-	-	-	-		
	ARIMA	-	6.11†	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Power from PV system	ARMAX	38.88	-	104.77	77.27	-	-	-	ARMAX	Li *et al.* (2014)
	ARIMA	76.66	-	172.96	140.9	-	-	-		
	Single moving average	82.09	-	190.59	153.8	-	-	-		
	Double moving average	88.1	-	180.25	152	-	-	-		
	Single exponential smoothing	72.93	-	180.95	141.5	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	MAE (-)	RMSE (-)	MAD (-)	NRMSE (-)	SEP (-)	ARE (%)		
	Double exponential smoothing	72.85	-	181.04	141.5	-	-	-		
	Holte Winter's additive	72.36	-	185.1	144.6	-	-	-		
	Holte Winter's multiplicative	75.94	-	185.43	146.5	-	-	-		
Electricity consumption (48 historical data)	LR	8.6	1341.57	1508.96	-	-	-	-	ANN	Pao (2006)
	RSREG**	9.51	1489.72	1701.9	-	-	-	-		
	ARMAX	4.83	764.9	931.13	-	-	-	-		
	ANN	3.19	460.74	635.38	-	-	-	-		
Electricity consumption (132 historical	LR	8.84	1376.26	1542.43	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
	RSREG**	7.58	1171.78	1295.43	-	-	-	-		
	ARMAX	8.88	1386.99	1566.34	-	-	-	-		
	ANN	4.02	598.65	709.25	-	-	-	-		
Energy consumption	WARCH	2.9	-	-	-	-	-	-	WARCH-ANN	Pao (2007)
	SEGARCH	3.65	-	-	-	-	-	-		
	WARCH-ANN	2.56	-	-	-	-	-	-		
	SEGARCH-ANN	2.98	-	-	-	-	-	-		
Electricity demand	PSO (training)	2.42	-	-	-	-	-	-	PSO	El-Telbany and El-Karmi (2008)

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
	PSO (test set)	2.52	-	-	-	-	-	-		
	BP algorithm (training)	3.2	-	-	-	-	-	-		
	BP algorithm (test set)	2.82	-	-	-	-	-	-		
	ARMA (training)	3.98	-	-	-	-	-	-		
	ARMA (test set)	3.93	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Energy consumption	GPGM (1, 1) (training)	2.59	-	-	-	-	-	-	GPGM (1, 1)	Lee and Tong (2011)
	GPGM (1, 1) (test set)	20.23	-	-	-	-	-	-		
	GM(1,1) (training)	4.13	-	-	-	-	-	-		
	GM(1,1) (test set)	26.21	-	-	-	-	-	-		
	LR (training)	4.2	-	-	-	-	-	-		
	LR (test set)	27.76	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Energy consumption	Hybrid dynamic GM	0.4	874.19	1383.11	-	-	-	-	Hybrid dynamic GM	Lee and Tong (2012)
	GM (1,1)	16.94	26945.07	30384.99	-	-	-	-		
	NDGM(1,1)	33.33	73052.8	93230.75	-	-	-	-		
	ARIMA	17.99	41890.49	59271.76	-	-	-	-		
	GP	5.12	10631.51	13325.14	-	-	-	-		
	Hybrid GM(1,1)	4.93	9949.13	12054.78	-	-	-	-		
Mid-term load forecasting	DLS-SVM	1.082	-	-	-	-	-	-	DLS-SVM	(Niu *et al.*, 2008)
	LS-SMV	1.101	-	-	-	-	-	-		Wu and Chang (2006)

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
	SMV	2.149	-	-	-	-	-	-		Chen and Chang (2004)
Solar radiation	FNN	6.03-9.65	-	-	-	-	-	-	FNN	(Chen *et al.*, 2013)
	ARIMA and descriptive statistics	Around 30	-	-	-	-	-	-		Nomiyama *et al.* (2011)
	Fuzzy logic	13.9 - 20.2	-	-	-	-	-	-		Chen *et al.* (2013)
	ANN	10.9-20.3	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Power demand	GM (1,1)	3.88	-	-	-	-	-	-	Improved GM (1,1)	Hsu and Chen (2003a)
	Improved GM (1,1)	1.29	-	-	-	-	-	-		
	ARIMA	2.27	-	-	-	-	-	-		
CO_2 emission	ARIMA	2.75	9.81	11.25	-	-	-	-	GP (4 year)	Pao and Tsai (2011a)
	GP (4 year)	2.46	8.78	11.25	-	-	-	-		
	GP (5 year)	4.22	15.27	17.6	-	-	-	-		
	GP (6 year)	2.6	9.29	11.75	-	-	-	-		
Energy consumption	ARIMA	1.75	158.11	174.36	-	-	-	-	ARIMA	
	GP (4 year)	4.4	427.07	627.61	-	-	-	-		
	GP (5 year)	3.32	320.06	455.69	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
	GP (6 year)	2.45	231.23	304.28	-	-	-	-		
Economic growth (GDP)	ARIMA	4.17	32.06	41.49	-	-	-	-	GP (4 year)	
	GP (4 year)	1.81	13.69	19.15	-	-	-	-		
	GP (5 year)	3.41	26.17	36.9	-	-	-	-		
	GP (6 year)	5.44	41.45	55.84	-	-	-	-		
Energy consumption	GM	-	-	-	-	-	-	7.17	GM-ARMA	Xu *et al.* (2015)
	ARMA	-	-	-	-	-	-	7.62		
	GM-ARMA	-	-	-	-	-	-	4.39		
Wind speed	SARIMA-LSSVM	6.76	-	-	-	-	-	-	SARIMA-LSSVM	(Guo *et al.*, 2011)
	ARIMA	18.08	-	-	-	-	-	-		
	SARIMA	11.08	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	MAE (-)	RMSE (-)	MAD (-)	NRMSE (-)	SEP (-)	ARE (%)		
	LSSVM	8.83	-	-	-	-	-	-		
	GM	8.93	-	-	-	-	-	-		
	ARIMA-SVM	14.81	-	-	-	-	-	-		
Electric load	ARIMA	6.044	-	-	-	-	-	-	SSVRCGA	Zhu *et al.* (2011)
	SVRCGA	3.382	-	-	-	-	-	-		
	SSVRCGA	2.695	-	-	-	-	-	-		
Electric load	SVRCPSO	1.61	-	-	-	-	-	-	SVRCPSO	Hong (2009a)
	SVRPSO	3.14	-	-	-	-	-	-		
	SVMSA	1.76	-	-	-	-	-	-		
	ARIMA	10.31	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Electricity demand	SARIMA	6.08	-	-	-	-	-	-	MA-C-WH	Zhu *et al.* (2011)
	MA-C-H	3.86	-	-	-	-	-	-		
	MA-C-WH	3.69	-	-	-	-	-	-		
Electric load	SSVRCGASA	3.73	-	-	-	-	-	-	SSVRCGASA	Zhang *et al.* (2012)
	TF-ε-SVR-SA	3.799	-	-	-	-	-	-		
	ARIMA	6.04	-	-	-	-	-	-		
Electric load (Eastern regional)	SVRCAS	2.23	-	-	-	-	-	-	SVRCPSO	Hong (2010)
	SVRCPSO	2.19	-	-	-	-	-	-		
	SVRCGA	2.57	-	-	-	-	-	-		
	Regression	4.1	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
	ANN	3.6	-	-	-	-	-	-		
Electric load	ARIMA	6.04	-	-	-	-	-	-	SRSVRCABC	Hong (2011)
	TF-ε-SVR-SA	3.8	-	-	-	-	-	-		
	SSVRCABC	3.06	-	-	-	-	-	-		
	SRSVRCABC	2.39	-	-	-	-	-	-		
Electric load	ARIMA	10.31	-	-	13788	0.105997	-	-	SVMSA	Pai and Hong (2005)
	GRNN	5.18	-	-	6758	0.054732	-	-		
	SVMSA	1.76	-	-	2,448	0.026357	-	-		
Electric load	SSVRGSA	2.587	-	-	-	-	-	-	SSVRGSA	Ju and Hong (2013)
	ARIMA	6.044	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
	SVRGSA	3.199	-	-	-	-	-	-		
	TF-ε-SVR-SA	3.799	-	-	-	-	-	-		
Electricity demand	ADE-BPNN	1.725	3.0623	3.9925	-	-	-	-	ADE-BPNN	Wang *et al.* (2015b)
	ARIMA	6.044	10.6641	12.3787	-	-	-	-		
	BPNN	3.341	5.9958	6.987	-	-	-	-		
	GA-BPNN	3.168	5.5618	6.9285	-	-	-	-		
	DE-BPNN	3.08	5.4004	6.8622	-	-	-	-		
	SSVRCGASA	1.901	3.4347	4.1822	-	-	-	-		
	TF-ε-SVR-SA	3.799	6.9694	8.6167	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Electric load	SVM	-	-	12.37†	-	-	-	-	GRA-DE-SVR	Xiaobo *et al.* (2014)
	GRA-DE-SVR	-	-	10.85†	-	-	-	-		
	ARMA	-	-	10.93† -	-	-	-			
	LR	-	-	11.99†	-	-	-	-		
Natural gas consumption	PCMACP	-3.42	-	-	-	-	-	-	PCMACP	Xu and Wang (2010)
	Polynomial Curve (2nd order)	-10.75	-	-	-	-	-	-		
	BP neural network	-10.68	-	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	**Methods**	**Accuracy***							**Best method**	**Ref.**
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
	GM	-39.61	-	-	-	-	-	-		
Energy consumption	WARCH-ANN	2.56	404184.2	531545.14	-	-	-	-	WARCH-ANN	Pao (2009)
	WARCH	2.9	474189.2	643744.33	-	-	-	-		
	SEGARCH	3.65	606629.3	824500.08	-	-	-	-		
	SEGARCH-ANN	2.98	464632.4	596013.96	-	-	-	-		
Petroleum consumption	WARCH-ANN	3.51	112542.5	134832.21	-	-	-	-	WARCH-ANN	
	WARCH	4.08	134300.1	165753.68	-	-	-	-		
	SEGARCH	4.88	167031.1	204369.84	-	-	-	-		
	SEGARCH-ANN	3.71	122320.1	148234.91	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	MAE (-)	RMSE (-)	MAD (-)	NRMSE (-)	SEP (-)	ARE (%)		
Electricity demand	F-S-SARIMA***	2.19	-	4.91	-	-	2.65	-	F-S-SARIMA	Wang *et al.* (2012c)
	SARIMA	3.28	-	6.67	-	-	3.74	-		
	F-SARIMA	2.75	-	6.57	-	-	3.68	-		
	S-SARIMA	2.91	-	6.25	-	-	3.37	-		
Electricity demand	COR-ACO-GA	-	-	1292.381	-	-	-	-	COR-ACO-GA	Ghanbari *et al.* (2013)
	ANFIS	-	-	4563.398	-	-	-	-		
	ANN	-	-	6323.944	-	-	-	-		
Natural gas demand	COR-ACO-GA	-	-	648.31	-	-	-	-		
	ANFIS	-	-	1206.816	-	-	-	-		
	ANN	-	-	2178.246	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	**MAE (-)**	**RMSE (-)**	**MAD (-)**	**NRMSE (-)**	**SEP (-)**	**ARE (%)**		
Oil products demand	COR-ACO-GA	-	-	3.750578	-	-	-	-		
	ANFIS	-	-	8.795963	-	-	-	-		
	ANN	-	-	11.05846	-	-	-	-		
Electricity price	BPANN	29.46	8.5021	-	-	-	-	-	DCANN	Wang *et al.* (2016)
	FNN	22.03	6.8929	-	-	-	-	-		
	LSSVM	9.5	4.4632	-	-	-	-	-		
	ARFIMA	35.08	8.8737	-	-	-	-	-		
	GARCH	25.11	7.2425	-	-	-	-	-		
	DCANN	8.87	4.2611	-	-	-	-	-		
Electric load	ARMA	2.3688	34.0608	2.9198	-	-	-	-	SVR-MFA	Kavousi-Fard *et al.* (2014)

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	MAE (-)	RMSE (-)	MAD (-)	NRMSE (-)	SEP (-)	ARE (%)		
	ANN	1.9569	28.8032	2.6396	-	-	-	-		
	SVR-GA	1.8501	27.3499	2.1943	-	-	-	-		
	SVR-HBMO	1.8375	26.5383	2.0007	-	-	-	-		
	SVR-FA	1.8051	26.1718	2.5667	-	-	-	-		
	SVR-PSO	1.7381	24.0145	2.1399	-	-	-	-		
	SVR-MFA	1.6909	22.5423	2.0604	-	-	-	-		
Energy demand	SC-SVR	2.36	3913.88	-	-	-	-	-	SC-SVR	Bai and Li (2016)
	LSSVR	4.77	8285.22	-	-	-	-	-		
	BPNN	3.61	4549.69	-	-	-	-	-		
Energy demand	ARMA	6.1	13.6	-	-	-	-	-	FNF-SVRLP	Zhu *et al.* (2015)
	ANN	5.3	11.9	-	-	-	-	-		

Table A.4: Method-wise accuracy of the selected reviewed models

Forecasting objective	Methods	Accuracy*							Best method	Ref.
		MAPE (%)	MAE (-)	RMSE (-)	MAD (-)	NRMSE (-)	SEP (-)	ARE (%)		
	SVRLP	4.4	10.4	-	-	-	-	-		
	FNF-SVRLP	3.8	9.2	-	-	-	-	-		

*,Accuracy metrics: Mean absolute percentage forecast error (MAPE), mean absolute error (MAE), root mean square error (RMSE), mean absolute deviation (MAD), normalized root-mean-square error measure (NRMSE), standard error of prediction (SEP) and absolute relative error (ARE)

** Response surface regression model (RSREG)

*** PSO optimal Fourier approach on residual modification of SARIMA was applied

† The values in the study was reported in percentage (%)

Table A.5: Statistical method-wise objective of the reviewed models

Objectives	Energy Demand	Energy Supply	Renewable energy	GHG emiss-ions	Energy economic	Socio economic	Energy and electricity price	Load foreca-sting	Planning and/or Policy analysis	Perfor-mance	Model develop-ment	Total	%
Methods													
LR	✓	✓	-	✓	✓	-	✓	✓	-	-	✓	7	9.0%
NLR	✓	✓	-	✓	✓	-	-	-	-	-	✓	5	6.4%
LoR	✓	✓	✓	✓	-	-	-	-	-	-	-	4	5.1%
NR	-	-	✓	-	-	-	-	✓	-	-	-	2	2.6%
PLSR	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%
GP	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%
Log linear analysis	✓	-	-	-	✓	-	-	-	-	-	-	2	2.6%
Translog	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%
Polynomial curve model	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%

Table A.5: Statistical method-wise objective of the reviewed models

Objectives / Methods	Energy Demand	Energy Supply	Renewable energy	GHG emiss-ions	Energy economic	Socio economic	Energy and electricity price	Load foreca-sting	Planning and/or Policy analysis	Perfor-mance	Model develop-ment	Total	%
MA	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%
ARIMA	✓	✓	✓	✓	✓	✓	✓	✓	-	-	✓	9	11.5%
SARIMA	✓	✓	✓	-	✓	-	-	✓	-	-	-	5	6.4%
ARMAX	-	-	✓	-	-	-	✓	✓	-	-	-	3	3.8%
ARMA	✓	-	✓	✓	-	-	✓	✓	-	-	✓	6	7.7%
ANOVA	✓	-	-	✓	-	-	-	-	-	-	-	2	2.6%
SR	✓	✓	-	-	-	-	-	-	-	-	-	2	2.6%
VAR	✓	-	-	-	-	-	✓	-	-	-	-	2	2.6%
ARDL	✓	-	-	-	-	✓	✓	-	-	-	-	3	3.8%
PAM	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%
GARCH	✓	-	-	-	✓	-	✓	-	-	-	-	3	3.8%
SEGARCH	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%

Table A.5: Statistical method-wise objective of the reviewed models

Objectives	Energy Demand	Energy Supply	Renewable energy	GHG emiss-ions	Energy economic	Socio economic	Energy and electricity price	Load foreca-sting	Planning and/or Policy analysis	Perfor-mance	Model develop-ment	Total	%
Methods													
EGARCH	-	-	-	-	-	-	✓	-	-	-	-	1	1.3%
WARCH	✓	-	-	-	-	-	-	-	-	-	-	1	1.3%
Decompo-sition	✓	✓	-	✓	-	-	✓	✓	-	-	✓	6	7.7%
Unit root test and/or Cointegr-ation	✓	-	-	✓	✓	✓	✓	-	-	-	-	5	6.4%
BVAR	✓	-	✓	-	-	-	-	✓	-	-	-	3	3.8%
Number of methods	23	7	7	8	7	3	10	8	0	0	5		

Table A.5: Statistical method-wise objective of the reviewed models

Objectives	Energy Demand	Energy Supply	Renewable energy	GHG emiss-ions	Energy economic	Socio economic	Energy and electricity price	Load foreca-sting	Planning and/or Policy analysis	Perfor-mance	Model develop-ment	Total	%
Methods													
Number of models	186	11	29	29	14	15	32	23	0	0	6		
Percentage of model (%)	53.9%	3.2%	8.4%	8.4%	4.1%	4.3%	9.3%	6.7%	0.0%	0.0%	1.7%		

Table A.6: CI and mathematical method-wise objective of the reviewed models

Objectives	Energy Demand	Energy Supply	Renewable energy	GHG emiss-ions	Energy economic	Socio economic	Energy and electricity price	Load foreca-sting	Planning and/or Policy analysis	Perfor-mance	Model develop-ment	Total	%
Methods													
SVM	✓	-	✓	-	✓	-	✓	✓	-	-	✓	6	8.7%
Decision tree	✓	-	✓	-	-	-	-	✓	-	-	-	3	4.3%
ANN	✓	✓	✓	✓	✓	-	✓	✓	-	✓	✓	9	13.0%
Abductive networks	✓	-	-	-	-	-	-	-	-	-	-	1	1.4%
Grey prediction	✓	✓	✓	✓	-	✓	✓	✓	-	-	-	7	10.1%
Fuzzy logic	✓	-	✓	-	-	-	✓	✓	✓	✓	-	6	8.7%
Expert system	✓	-	-	-	-	-	-	✓	-	-	-	2	2.9%
GA	✓	-	-	✓	-	-	-	✓	✓	-	✓	5	7.2%
ABCO	-	-	-	✓	-	-	-	✓	-	-	-	2	2.9%

Table A.6: CI and mathematical method-wise objective of the reviewed models

Objectives	Energy Demand	Energy Supply	Renewable energy	GHG emiss-ions	Energy economic	Socio economic	Energy and electricity price	Load foreca-sting	Planning and/or Policy analysis	Perfor-mance	Model develop-ment	Total	%
Methods													
ACO	✓	✓	✓	✓	-	-	-	✓	✓	-	-	6	8.7%
PSO	✓	-	✓	✓	-	-	✓	✓	✓	-	-	6	10.1%
GSA	✓	-	✓	-	-	-	-	✓	-	-	-	3	4.3%
CAS	-	-	-	-	-	-	-	✓	-	-	-	1	1.4%
DE	-	-	-	-	-	-	-	✓	-	-	✓	2	2.9%
HS	✓	-	-	-	-	-	-	-	-	-	-	1	1.4%
EA	-	-	-	-	-	-	-	✓	-	-	-	1	1.4%
MA	-	-	-	-	-	-	-	✓	-	-	-	1	1.4%
IA	-	-	-	-	-	-	-	✓	-	-	-	1	1.4%
SA	-	-	✓	-	-	-	-	✓	-	-	-	2	2.9%
FA	-	-	-	-	-	-	-	✓	-	-	-	1	1.4%
CSA	-	-	-	-	-	-	✓	-	-	-	-	1	1.4%

Table A.6: CI and mathematical method-wise objective of the reviewed models

Objectives	Energy Demand	Energy Supply	Renewable energy	GHG emiss-ions	Energy economic	Socio economic	Energy and electricity price	Load foreca-sting	Planning and/or Policy analysis	Perfor-mance	Model develop-ment	Total	%
Methods													
NLP	✓	-	-	-	-	-	-	-	-	-	-	1	1.4%
Number of methods	23	7	7	8	7	3	10	8	0	0	5		
Number of models	186	11	29	29	14	15	32	23	0	0	6		
Percentage of model (%)	53.9%	3.2%	8.4%	8.4%	4.1%	4.3%	9.3%	6.7%	0.0%	0.0%	1.7%		

Appendix B

Cost data

Table B.1: Cost database of different power plants of Bangladesh; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

Generation technology	**Power plants**	**Future/ existing**	**Public/ private**	**Types of fuel**	**Year**	**Installed capacity**	**Capital cost/ installed capacity**
Gas turbine	Ghorasal ST: Unit-6	Future	Public	Gas	2018	206	1634.24
	Ghorashal 365 MW CCPP	Future	Public	Gas	2017	363	881.53
	Ghorashal 365 MW CCPP	Future	Public	Gas			
	Siddhirgonj ST	Existing	Public	Gas	2004	150	1822.94
	Siddhirganj: 2×120MW Peaking power plant	Existing	Public	Gas	2012	210	680.21
	Raozan: Unit-2	Existing	Public	Gas	1997	210	937.29
	Sikalbaha Peaking GT	Existing	Public	Gas	2010	150	1392.32
	Ashuganj : 50 MW GE	Existing	Public	Gas	2011	53	743.52
	Sylhet 150 MW GT	Existing	Public	Gas	2012	142	856.90
	Bhola 225 MW CCPP ST	Future	Public	Gas		75	
	Raozan 25 MW Dual Fuel Power Plant	Existing	Public	Gas/HFO	2013	25	1131.14
	Sikalbaha 225 MW CCPP	Future	Public	Gas/HSD	2016	225	1145.04
	Khulna 150MW GT	Existing	Public	Gas/HSD	2013	158	1277.31
	Sirajganj 225 MW CCPP: Unit-2	Future	Public	Gas/HSD	2016	220	1439.95

Table B.1: Cost database of different power plants of Bangladesh; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

Generation technology	**Power plants**	**Future/ existing**	**Public/ private**	**Types of fuel**	**Year**	**Installed capacity**	**Capital cost/ installed capacity**
	Chapainababgaonj 100 MW	Future	Public	HFO	2016	104	1363.57
	Ghorashal (Regent)	Existing	Private	Gas	2014	108	767.58
	Ashuganj 195MW Modular (United)	Existing	Private	Gas	2015	210.7	806.83
	Katpotti 52.50 MW power plant	Existing	Private	HFO	2015	51	544.52
	Nababganj55 MW power plant	Future	Private	HFO	2015	55	814.39
	Patenga 50MW (Barakatullah)	Existing	Private	HFO	2014	50	809.17
	Chittagong ECPV 108 MW	Existing	Private	HFO	2013	108	843.81
	Lakdhanvi-52.2 MW	Existing	Private	Gas/HFO	2015	52	673.08
	Khulna (KPCL-1)	Existing	Private	HFO	1998	110	1495.31
	Khulna (KPCL-2)	Existing	Private	HFO	2011	115	687.19
	Noapara (Khanjahan Ali-KPCL-III)	Existing	Private	HFO	2011	40	658.56
	Rajlanka 52 MW	Existing	Private	HFO	2014	52	911.67
	Ghorasal : Unit-3	Future	Public	Gas	2017	400	798.87
	Haripur CCPP: Unit 1	Existing	Public	Gas	2001	273	865.25

Table B.1: Cost database of different power plants of Bangladesh; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

Generation technology	**Power plants**	**Future/ existing**	**Public/ private**	**Types of fuel**	**Year**	**Installed capacity**	**Capital cost/ installed capacity**
	Haripur CCPP: Unit 2	Existing	Public	Gas		139	
	Haripur CCPP: 412 MW	Future	Public	Gas	2014	360	884.97
	Siddhirganj: 335 MW	Future	Public	Gas	2017	335	1612.12
	Ashuganj : 225 MW GT, ST	Existing	Public	Gas	2015	225	969.49
	Ashuganj : 450 MW (South)	Future	Public	Gas	2015	375	1132.23
	Ashuganj : 450 MW (North)	Future	Public	Gas	2017	450	962.50
	Chandpur CCPP (Cengda eng. Co., China)	Existing	Public	Gas	2012	106	991.09
	Chandpur CCPP (Cengda eng. Co., China)	Existing	Public	Gas	2012	57	
	Fenchugonj CCPP 1: Unit 1	Existing	Public	Gas	1994	32	3005.26
	Fenchugonj CCPP 1: Unit 2	Existing	Public	Gas	1995	32	
	Fenchugonj CCPP 1: Unit 3	Existing	Public	Gas		33	
	Fenchugonj CCPP 2: Unit 1	Existing	Public	Gas	2011	35	1024.62
	Fenchugonj CCPP 2: Unit 2	Existing	Public	Gas		35	
	Fenchugonj CCPP 2: Unit 3	Existing	Public	Gas		35	

Table B.1: Cost database of different power plants of Bangladesh; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

Generation technology	**Power plants**	**Future/ existing**	**Public/ private**	**Types of fuel**	**Year**	**Installed capacity**	**Capital cost/ installed capacity**
	Shahjibazar CCPP	Existing	Public	Gas	2017	80	544.59
	Shahjibazar 330 MW CCPP	Future	Public	Gas	2016	330	1097.75
	Sylhet 150 MW to 225 MW CCPP	Existing	Public	Gas	2017	75	1201.75
	Bibiana 400 MW CCPP: Unit 3	Future	Public	Gas	2017	400	1069.45
	Bibiana 383 MW CCPP: South	Future	Public	Gas	2017	383	873.43
	Bheramara 360 MW CCPP	Future	Public	Gas	2017	360	1465.14
	Bhola 225 MW CCPP GT-1,2	Future	Public	Gas	2015	150	1170.06
	Baghabari 100 MW to 150 MW	Existing	Public	Gas	2017	50	1308.99
	Khulna 150MW to 225 MW	Future	Public	Gas/HSD	2015	75	1643.04
	Sirajganj CCPP	Existing	Public	Gas/HSD	2014	225	653.50
	Sirajganj 225 MW CCPP: Unit-3	Future	Public	Gas	2018	225	1035.28
	Ashuganj : 450 MW (South)	Future	Public	Gas	2017	450	1059.31
	Shahjibazar 2x35 to 105 MW conversion	Future	Public	Gas	2016	35	1244.77
	Ashuganj : 400 MW (East)	Future	Public	Gas	2020	400	933.55

Table B.1: Cost database of different power plants of Bangladesh; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

Generation technology	**Power plants**	**Future/ existing**	**Public/ private**	**Types of fuel**	**Year**	**Installed capacity**	**Capital cost/ installed capacity**
	Khulna 330 MW CCPP	Future	Public	Gas	2019	330	1256.04
	Meghnaghat CCPP	Existing	Private	Gas	2002	450	847.97
	Meghnaghat 450 MW CCPP (Unit 2) Summit	Existing	Private	Gas/HSD	2014	335	560.04
Sub critical coal	Barapukuria ST: Unit-1	Existing	Public	Coal	2006	125	1923.84
	Barapukuria ST: Unit-2	Existing	Public	Coal		125	
	Barapukuria ST: Unit-3	Future	Public	Coal	2018	275	1245.14
Ultra Super Critical	Maheshkhali: Coal Fired power plant	Future	Public	Coal	2022	1200	2866.95
	Matarbari 1200 MW coal based power plant	Future	Public	Coal	2021	1200	3820.01
Solar	Kaptai 5 MW solar power plant	Future	Public		2016	5	4906.75
	Hatia 7 MW solar power plant	Future	Public		2016	7	2391.08
Hydro	Kaptai Hydro: Unit-1	Existing	Public		1962	40	6408.55

Table B.1: Cost database of different power plants of Bangladesh; data source (BPDB, 2008, 2009, 2010, 2011, 2012, 2013, 2014)

Generation technology	**Power plants**	**Future/ existing**	**Public/ private**	**Types of fuel**	**Year**	**Installed capacity**	**Capital cost/ installed capacity**
	Kaptai Hydro: Unit-2	Existing	Public			40	
	Kaptai Hydro: Unit-3	Existing	Public		1982	50	543.38
	Kaptai Hydro: Unit-4	Existing	Public		1988	50	1075.95
	Kaptai Hydro: Unit-5	Existing	Public			50	
Nuclear	Rooppur 1	Future	Public		2024	1200	5625.00
	Rooppur 2	Future	Public		2025	1200	

Appendix C

Publications

The publications from this study are as follows-

(i) Debnath, KB and Mourshed, M. (2018) **Challenges and gaps for energy planning models in the developing-world context**. Nature energy, Nature Publishing Group. DOI: 10.1038/s41560-018-0095-2.

Reprinted in 'Grand Challenges: India's research solutions to real-world problems' (April 2018) published by Nature India.

(ii) Debnath, KB and Mourshed, M. (2018) **Forecasting methods of energy planning models**. Renewable and sustainable energy reviews, Elsevier BV. DOI: 10.1016/j.rser.2018.02.002

(iii) Debnath, KB and Mourshed, M. (2018) **Corruption significantly increases the cost of power plants in developing contexts**. Frontiers in Energy Research, Frontiers. DOI: 10.3389/fenrg.2018.00008