CPD Working Paper 139

Proposed Power and Energy System Master Plan (PESMP)

Perspective on Analytical Frame, Methodology and Influencing Factors on Demand Forecasting

Khondaker Golam Moazzem
Helen Mashiyat Preoty

CENTRE FOR POLICY DIALOGUE

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Centre for Policy Dialogue (CPD)
House 40/C, Road 11 (new)
Dhanmondi, Dhaka-1209, Bangladesh
Telephone: (+88 02) 48118090, 55001185, 58156979
Fax: (+88 02) 48110414
E-mail: info@cpd.org.bd
Website: www.cpd.org.bd

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The present paper titled *Proposed Power and Energy System Master Plan (PESMP): Perspective on Analytical Frame, Methodology and Influencing Factors on Demand Forecasting,* has been prepared by *Dr Khondaker Golam Moazzem*, Research Director, CPD (moazzem@cpd.org.bd) and *Ms Helen Mashiyat Preoty*, Programme Associate, CPD (preoty@cpd.org.bd).

Series Editor: *Dr Fahmida Khatun*, Executive Director, CPD.

Executive Summary

The new Power and Energy System Master Plan (PESMP) is on the process of drafting by the Ministry of Power Energy and Mineral Resources (MoPEMR). The new PSEMP aims to promote a low or zero-carbon transformation of the total energy supply and demand system. The successive PSMPs (2005, 2010 and 2016) have been criticised to have an inappropriate demand projection which led to different types of challenges. The paper reviews the successive PSMPs (PSMP 2005, 2010 and 2016) to find out the methodological weaknesses and suggests the alternative methodology for demand-side analysis of the power sector for the new plan. Based on the literature of developing countries and the findings of the key informant interviews (KIIs) the paper finds that Bangladesh needs to consider a sound methodology for proper forecasting of electricity demand. A number of methods which are methodologically well-recognised and applied to different countries such as bottom-up approach which could be more appropriate in the context of Bangladesh to forecast the power demand in the PESMP 2021. This paper concludes with a number of recommendations for the next PESMP.

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Acronyms

ADB	Asian Development Bank
ANN	Artificial Neural Network
ARIMA	Auto Regressive Integrated Moving Average
BBS	Bangladesh Bureau of Statistics
BNN	Bayesian Neural Network
BPDB	Bangladesh Power Development Board
FS	Fuzzy System
FTS	Fuzzy Time Series
FYP	Five Year Plan
GDP	Gross Domestic Product
GHSA	Global Harmony Search Algorithm
JICA	Japan International Cooperation Agency
KII	key informant interview
KBES	Knowledge Based Expert System
LSSVM	Least Squares Support Vector Machine
LNG	Liquefied Natural Gas
MLR	Multiple Linear Regression
MAPE	Mean Absolute Per cent Error
OLS	Ordinary Least Square
PESMP	Power and Energy System Master Plan
PSO	Particle Swarm Optimisation
PSMP	Power System Master Plan
SSA	Singular Spectrum Analysis
SRM	Structural Risk Minimisation
SVM	Support Vector Machine
SVR	Support Vector Regression
TAIEX	Technical Assistance and Information Exchange

1. INTRODUCTION AND OBJECTIVES

The Ministry of Power Energy and Mineral Resources (MoPEMR) has initiated the process of drafting the new plan for the future.[1] At present, the power sector is guided by the PSMP 2016 and after five years, a new plan is due in 2021.[2] According to the MoPEMR, the Plan will be broadened from the Power System Master Plan (PSMP) to the Power and Energy System Master Plan (PESMP).[3] This would help to formulate an integrated plan on the whole production network of the power sector. The importance of formulating a new master plan has further increased due to aggravated structural and operational challenges and changing power demand amidst the COVID-19 pandemic in the country.[4] The new plan is expected to deliver the future outlook of the power sector in the context of transitioning the power sector towards clean power.

The power sector has been guided by the five year-long PSMP since 1995. Over the last 25 years, a total of five PSMPs have been formulated (PSMP 1995, 2005, 2010 and 2016).[5] These PSMPs have provided the direction of the power sector development considering the demand and supply-side issues. However, successive PSMPs have confronted several criticisms including those related to weak demand-side analysis. The projection of electricity demand has been made based on weak benchmark analysis owing to lack of methodological rigor and over-projection on long-term economic growth and per capita income (World Bank, 2017). Both the power sector and the economy have been confronted with multiple challenges because of weak demand projection under the PSMPs.

Against this backdrop, a proper analysis of the demand-side and supply-side issues is of critical importance intended to make rational power demand under the new PESMP. The main objective of this paper is to identify the weaknesses and challenges, and to suggest an alternative methodology for demand forecasting. In this regard, the study reviews the demand and supply-side issues of the earlier PSMPs (i.e. 2005, 2010 and 2016). The demand side projections made in different countries have also been reviewed to identify possible alternate methods for Bangladesh's power demand analysis. Based on the analysis the study put forward a set of suggestions on the new plan's analytical frame, factors and methodology for undertaking demand-side analysis.

The study has been carried out based on the framework of demand-side analysis of the power sector. Necessary primary and secondary data have been used to conduct the study. Secondary data and information include structure and composition of GDP and their year-wise growth, sector-wise demand for electricity, inter-linkages between economic growth and electricity demand, electricity generation, energy mix, tariff and institutional reform. Primary information is gathered through a number of key informant interviews (KIIs) with academics and professionals related to the power sector mainly on issues related to weaknesses of the PSMPs and possible alternate methods for demand-side analysis.

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[1] Drafting of the New Plan issue has been reported in the media over the last six months. The State Minister for the MoPEMR mentioned about this in a web-based discussion in June, 2020 which was organised by the CPD. It was subsequently reported in the national media (20 August, 2020; 13 March, 2021).

[2] A revised version of PSMP 2016 was published in 2018. However, the version is not referred due to its various limitations.

[3] Government has signed an agreement with JICA in this regard. Japan International Cooperation Agency (JICA) mentioned on its website (15 March, 2021) that the aim of the new plan is to promote a low or zero-carbon transformation of the total energy supply and demand system.

[4] The steady-state electricity demand and standard consumption values would fall by 8–10 per cent and 6 per cent, respectively (Amin et al., 2021).

[5] First PSMP was formulated by the Planning Commission; since 2005, it had been prepared by the MoPEMR.

2. REVIEW OF DEMAND-SIDE ISSUES OF PREVIOUS POWER SYSTEM MASTER PLANS (PSMPS): 2005-2016

The successive PSMPs have highlighted demand- and supply-side issues of the power sector. In case of demand-side issues, the PSMPs focused on GDP growth, per capita income and per capita electricity consumption etc. On the other hand, the supply-side issues focus on fuel requirements such as fossil fuel, renewable energy, imported electricity, cost of fuel etc. Demand-side weaknesses and challenges as observed during the period of implementation of PSMPs have also been discussed.

The generation of power is usually determined based on the projection of power demand. This is why the aspects of the power demand forecast are really important for higher level of projection accuracy. Even though different methodologies have been used in previous PSMPs, GDP growth rate is always considered to be the core variable for demand projection.

2.1 Methodological Approaches

The different mathematical formula had been used for projecting demand for electricity. In PSMP 2005 correlation analysis[6] was done by using the following formula: Ln (Estimated net energy generation (n)) = - 11.919 + 1.482 Ln (GDP (n)). The result showed that sales grew faster than generation. In the case of high and low demand cases the optimal mix of new resources did not change significantly. Costs and fuel requirements followed the same trend as well.

Table 1: PSMPs demand-side issues

	PSMP 2005	**PSMP 2010**	**PSMP 2016**
Methodology	Correlation analysis	Electricity Intensity Method	GDP Elasticity Method
GDP growth rate	Base case: 5.2% High case: 8% Low case: 4.5%	Base case: 7% High case: 8% Low case: 5.5%	Base case: 4.4% High case: 5% Low case: 4%
Variables	1. GDP 2. Historical electricity consumption	3. GDP per capita 4. Power consumption 5. Maximum load	6. GDP 7. GDP elasticity
Used Formula	Ln (Estimated net energy generation (n)) = - 11.919 + 1.482 Ln (GDP (n))	$e = \alpha + ßy + xy^2 (+\lambda 1D1 + \lambda 2D2 + \cdots + \lambda n—1Dn—1)$	The projected GDP * the GDP elasticity of peak demand.
Findings	The result showed that sales grew faster than a generation. In the case of high and low demand cases, the optimal mix of new resources did not change significantly. Costs and fuel requirements followed the same trend as well.	The test showed that the increase in electricity intensity slowed down with the increase in GDP per capita. The second coefficient of GDP per capita was a negative value, as assumed.	Data showed that the total electricity consumption was greater than the available supply from the grid. The reason was total electricity consumption included the factories' self-consumption from captive power generation.

Source: PSMP 2005, 2010, 2016.

[6]Correlation Analysis: Correlation analysis is a statistical method used to evaluate the strength of relationship between two quantitative variables. A high correlation means that two or more variables have a strong relationship with each other, while a weak correlation means that the variables are hardly related.

The PSMP 2010 used a different method called the "Electricity Intensity Method".[7] The study showed that as the country exceeds the GDP per capita income of USD1000, it tends to show a decreasing pattern in electricity density. Bangladesh at that time had a GDP per capita income of more than USD700 and was soon to exceed USD1000. Therefore, the Electricity Intensity Method was used. The used formula was: $e=\alpha+\ss y+xy^2$ $(+\lambda 1D1+\lambda 2D2+\cdots+\lambda n\text{-}1Dn\text{-}1)$. The test showed that the increase in electricity intensity slowed down with the increase in GDP per capita. The second coefficient of GDP per capita was a negative value, as assumed.

The latest PSMP 2016 used another approach based on GDP which is easier to use. This time the used methodology was "GDP Elasticity Method"[8] and used formula was: projected GDP * GDP elasticity of peak demand. Results showed that the total electricity consumption was greater than the available supply from the grid. The reason was total electricity consumption included the factories' self-consumption from captive power generation. Variables that can influence power demand were omitted in this method.

2.2 Key Variables Considered: GDP, GDP Growth and Per Capita Income

GDP growth rate is considered to be the most influential variable to project the power demand in different PSMPs throughout the years. A linear relationship is considered between the electricity demand and GDP growth rate in the case of Bangladesh. In contrast, often such linear relationship is not applicable in low income and lower middle-income countries like Bangladesh where power demand usually experiences a gradual rise.[9] The adopted GDP growth rate varies from time to time based on the projected or targeted GDP growth rate of Bangladesh.

Table 2: GDP growth rate used in different PSMPs (high, base and low case)

	PSMP 2005	PSMP 2010	PSMP 2016
Low case	5.3 per cent	5.5 per cent	4 per cent
Base case	6 per cent	7 per cent	4.4 per cent
High case	6.5 per cent	8 per cent	5 per cent

Source: PSMPs of 2005, 2010 and 2016.

Successive PSMPs projected GDP growth under three different scenarios—base case, low case and high case scenarios. Under the PSMP 2005, the GDP growth rates projected between 5.3 per cent and 6.5 per cent during the targeted period; on the other hand, PSMP 2010, the GDP growth rates projected between 5.5 per cent and eight per cent respectively; and PSMP 2016 the GDP growth rates ranged between four per cent and five per cent respectively. This GDP growth projection particularly in the PSMP 2016 did not match with the projection made in the 7th Five Year Plan (for the period of 2016-2020). This is mainly happened owing to differences in target period 7th Five Year Plan (2016-2020) while PSMP considered 25 years (2016-2020).[10] However, the actual GDP growth rates during these periods were much lower compared to what is projected under the PRSPs (Figure 1).

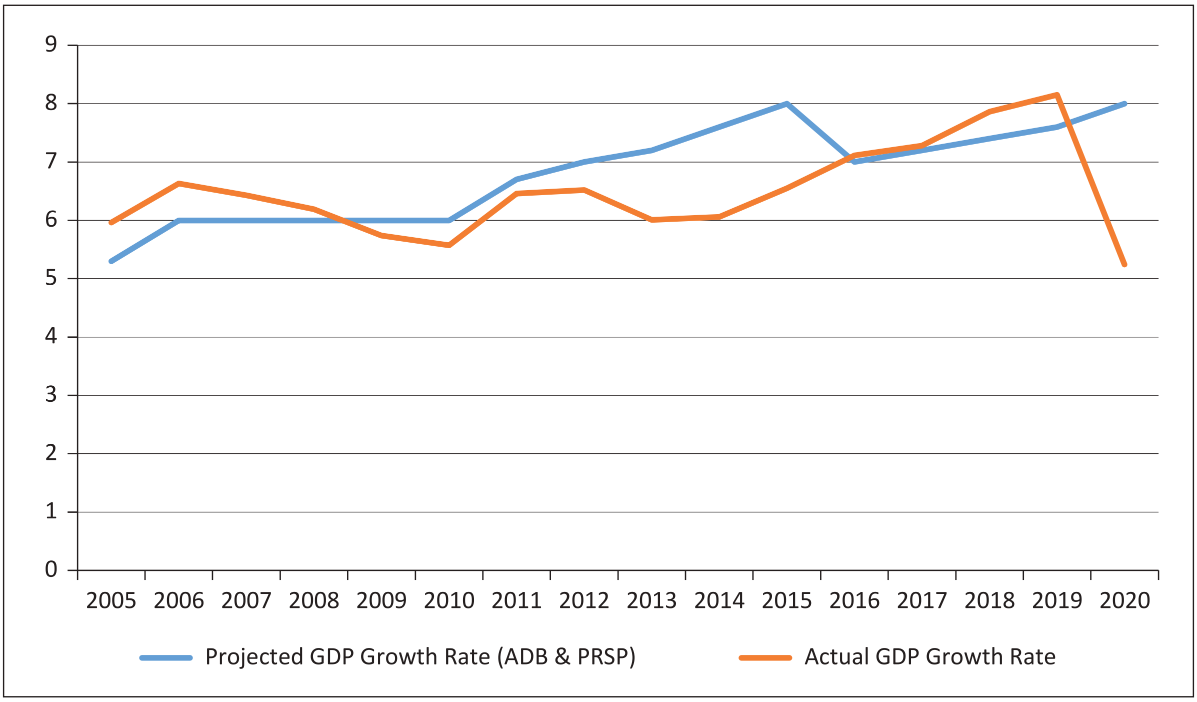
[7]Electricity Intensity: It is a measure of the electricity inefficiency of an economy.

[8]GDP Elasticity Method: It is a measure of the elasticity of power demand with respect to GDP of an economy.

[9]In other words, it happens in a non-linear way—initially a low power demand is observed in low income and lower middle-income countries, it starts to rise as the country starts to develop slowly and gradually and finally the country tends to consume less power as it becomes more developed. Hence the relationship between economic growth rate and power demand is likely to be an 'inverted U' shaped curve.

[10]According to the 7th FYP period, projected GDP growth rates for 2016-2020 were as follows: FY2015-16: 7 per cent, FY2016-17: 7.2 per cent, FY2017-18: 7.4 per cent, FY2018-19: 7.6 and FY2019-20: 8 per cent.

Figure 1: Differences in GDP growth: Projected in PSMPs and actual



Source: Authors' illustration based on different PSMPs, 2021.

The difference between actual and projected GDP growth rates was partly related to which data source has been utilized for this projection. There is no specific mention in PSMP 2005 about the sources of data of GDP growth while the following two PSMPs—PSMP 2010 and 2016 used Asian Development Bank (ADB) Key Indicator for Bangladesh and 7th Five Year Plan (for the period of 2016-2020) respectively. It is observed that the difference between projected GDP growth rates mentioned in PSMP 2016 (based on the 7th FYP) was lower compared to that of the earlier projections and actual GDP growth rates.

Apart from GDP growth rate, several other variables are considered for estimating projection of electricity demand; however, the variables are not the same for all PSMPs. PSMP 2005 used GDP and historical electricity consumption data to forecast power demand. PSMP 2010 used GDP per capita instead of GDP, power consumption and maximum load data to do so. PSMP 2016 used the elasticity of GDP along with GDP as per the need of methodology. The type of variables indicate that the power demand projection is mainly based on GDP or economic growth rate.

2.3 Projection of Electricity Demand and Actual Demand

Successive PSMPs have forecasted maximum demand for electricity using different methodological approaches. Bangladesh Power Development Board (BPDB, 2020) had taken into consideration three cases—'base case', 'low case' and 'high case' scenarios of electricity demand for different years. From the successive PSMPs it can be concluded that forecasted demand has been revised downward (Table3). A comparative assessment can be made on projected electricity demand mentioned in different PSMPs for 2015—2020—the period which is covered under different PSMPs. A major observation is—demand projections in PSMP 2005 and PSMP 2010 in the long term (between 2015 and 2020) were significantly higher compared to that of PSMP 2016. The difference between base case and high case projections in PSMP 2005 and 2010 were unimaginably high which is difficult to explain even non-linear demand projection of electricity.

Table 3 Projection of electricity demand under different PSMPs

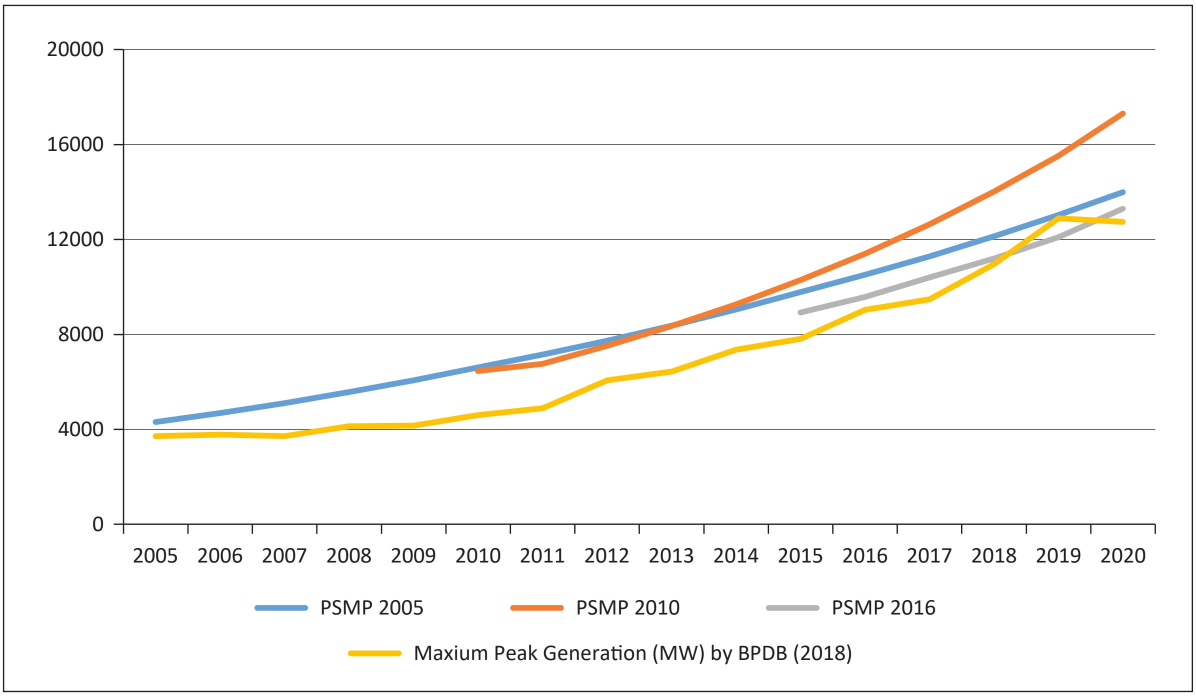
Year	PSMP 2005			PSMP 2010			PSMP 2016			Maximum forecasted demand (MW) by BPDB
	Base	Low	High	Low	High	Govt. Policy	Base	Low	High	
2005	4308	4308	4381	-	-	-	-	-	-	-
2006	4693	4627	4839	-	-	-	-	-	-	-
2007	5112	4970	5345	-	-	-	-	-	-	-
2008	5569	5339	5904	-	-	-	-	-	-	-
2009	6066	5734	6467	-	-	-	-	-	-	-
2010	6608	6160	7355	6454	6454	6454	-	-	-	-
2011	7148	6569	8237	6756	6869	6765	-	-	-	6,765
2012	7732	7007	9288	7083	7329	7518	-	-	-	7,518
2013	8364	7473	10473	7436	7837	8349	-	-	-	8,349
2014	9047	7970	11810	7819	8398	9268	-	-	-	9,268
2015	9786	8501	13408	8232	9019	10283	8920	8920	8920	8,920
2016	10512	9066	15223	8680	9705	11405	9584	9600	9600	9,600
2017	11291	10313	17166	9165	10463	12644	10400	10400	10400	10,400
2018	12128	11000	19357	9689	11300	14014	11200	11200	11200	11,200
2019	13027	11732	21827	10255	12224	15527	12100	13300	12100	12,100
2020	13993	12424	24445	10868	13244	17304	13300	13300	13300	13,300

Source: PSMPs of 2005, 2010 and 2016.
Note: In the case of PSMP 2016, in comparing the power demand projection between the "GDP elasticity method" and the "Sectorial analysis method", this study concluded that the results are almost identical, though the latter exceeded the former by about five per cent. Therefore, this study adopted a peak demand projection using the "GDP elasticity method", which is an easier approach and thus easy for technology transfer to local counterpart agencies who are expected to take over the work in a rolling plan.

A very unique feature of forecasted and maximum demand served has been noticed. The difference between forecasted demand and maximum demand served has been narrowed down over the years whereas installed capacity against that of projected demand has been widening over the years. The gap between forecasted demand and maximum demand was 38.3 per cent in Financial Year Plan 2011 which has reduced to as low as 4.4 per cent in FY2019-20. Even the gap was found negative in a year (FY2018-19) which means that the generated electricity has served all the demands within the country. At the same time the reserve capacity is way above the installed capacity (53.3 per cent vs. 25 per cent). The generation capacity has increased overtime with little consideration of projection made in the plan documents. The difference in projected power demand under different PSMPs have been gradually reduced; in other words, the projection has been made in successive PSMPs considering lower level of demand for electricity over the years.

The difference is observed in the case of the projected power demand in PSMP 2010 and 2016. The actual demand for power in 2015 was less than the projected demand for power. When PSMP 2010 was formulated, the demand was estimated to increase to around 9768 MW by 2015. However, the actual demand in 2015 was approximately 80 per cent of the estimate, around 8,000 MW. This is partly linked with an assumption of a high GDP growth rate based on which the power demand is forecasted- actual GDP growth rate was much lower compared to that of the projected GDP growth rates. (Figure 2)

Figure 2: Power demand forecast in PSMP and actual demand served



Source: PSMPs of different years

In Financial Year Plan 2016-17 actual GDP growth rate was 7.1 per cent which was higher than the base case GDP growth rate (6 per cent) in PSMP 2016. A further increment in GDP growth rate was expected as mentioned in the 7th Five Year Plan. This evidence indicates that economic development is taking place faster than the prediction of PSMP 2016 so is the actual power demand. An overwhelming dependence on GDP growth for estimating power demand is found to be faulty.

2.4 Major Weaknesses of Demand-Side Issues Related to PSMPs

2.4.1 Questionable estimation of GDP/GDP growth rate

Over-dependence on GDP growth rate to estimate the projected electricity demand is a major weakness in demand-side analysis. Moreover, the official estimate of the GDP growth rate is not out of question. Different GDP growth estimates prepared by national and international organizations have found notable differences from that of the official estimates of the government (CPD, World Bank, IMF and ADB). Often official estimates are found to be higher than that of other estimates. Such ambiguity and discrepancy in GDP estimates have caused the projection of power demand faulty. Moreover, neglecting important variables other than GDP growth and per capita income, for example, sectoral GDP growth, sectoral demand for power and other variables caused the estimate of power demand problematic in successive PSMPs.

2.4.2 Limited number of variables considered

The main difference that was observed between the methodologies used in Bangladesh and that of other countries is the variables that were used as the exploratory factors of power demand. GDP or economic growth is the most important variable that influences the electricity or power demand but is not the only factor that causes power demand. According to the official data, the main sources of

Bangladesh's GDP/GDP growth is service sector related economic activities followed by manufacturing and agricultural activities. However, major service-related activities are less electricity-intensive such as wholesale and retail trade, transport and public administration (Table 4). In the case of industries, construction contributes a major share in incremental GDP; however, its power demand is much lower. Without having detailed data on proper understanding of electricity consumption by different sectors, a simple approach of GDP and GDP growth would not properly reflect the electricity demand.

Table 4: Incremental contribution to GDP growth

Incremental contribution to GDP growth: 100%					
Agriculture	**7.8%**	**Industries**	**41.6%**	**Services**	**50.1%**
Agriculture & forestry	3.9%	Mining & quarrying	1.4%	Wholesale & retail trade; repair of motor vehicles, motor cycles, and personal and household goods	12.8%
Fishing	3.9%	Manufacturing	25.8%	Hotel & restaurant	0.9%
		Electric. & water	1.8%	Transport, storage & communications	12.5%
		Construction	12.7%	Financial intermediation	2.8%
				Real state, renting and business activities	5.5%
				Public administration & defence	4.0%
				Education	2.8%
				Health & social works	3.5%
				Community, social & personal services	5.4%

Source: Authors' calculation.

2.4.3 Faulty way of undertaking sectorial approach

The sectorial approach is used in the revised version of PSMP 2016 which was released in 2018; however, the revised PSMP 2016 was not much appreciated by the experts.[11] Though such an approach is said to be a better approach, due to limited information on electricity consumption by different sectors, the estimates could not provide a better forecast. Experts rather criticised the high projection of electricity demand made for 2030 and 2041 under the revised PSMP 2016.

2.4.4 Longer-term demand projection weakens the plan

Given the dynamic nature of changing demand even within a short period, a long-term projection for 20 years is a weak analytical basis for estimating power demand. There is no need for setting a projection of the demand for the longer-term (e.g. next 20 years). Since the power sector plan has been updating and reviewing in every five years, necessary changes could be accommodated in the successive PSMPs. Instead, a long-term projection provided a faulty demand projection based on which investment in generation, transmission and distribution has been made. These caused excess investment in power generation particularly by the private sector.

2.4.5 Long wish list

In the absence of detailed sectoral estimates of GDP and sectorial consumption of electricity, different anecdotes on sectoral energy and power demand particularly driven by the policymakers and

[11]According to the KIIs with power sector experts, the revision of the PSMP 2016 has made the projection of electricity demand much weaker.

government high-ups influence the estimates of electricity demand. Often that anecdotal information has limited implications in undertaking rationale estimates. As there are no proper methodological approaches utilised, considering such anecdotes would make a bias estimates of electricity demand.

2.4.6 Limitation of Data collection, process and use

Lack of data of important variables particularly those related to sectoral estimates is a major weakness in undertaking appropriate estimates of power demand. Besides, panel data of important variables are not available such as the number of home appliances, how many industries are on pipeline, weather conditions, household size etc. There is no dedicated wing for data collection and preserving those data in the BPDB. Often data related activities have been carried out on an ad-hoc basis.

3. ANALYTICAL FRAMEWORK AND METHODOLOGIES FOR PROJECTION OF FUTURE POWER DEMAND

The projection of future electricity demand requires a well-developed forecasting model. Good forecasting is the prior condition for efficient and effective power demand prediction. Forecasting with the minimum error depends on the selection of an appropriate model. The power demand can be forecasted considering the aggregate demand of a country or considering sector-wise demand, or even both. The forecasting can be based on a top-down approach or a bottom-up approach.

3.1 Top-Down Approach

The top-down approach of forecasting uses national-level data at its point of the centre for necessary analysis. In a top-down approach, aggregate level forecasts are proportioned down to individual per sector forecast. The top-down approach achieves a better forecast at the aggregate level. Under this approach, power demand data are first aggregated to produce a combined forecast at the national level, then the forecast is disaggregated in a top-down approach.[12] Top-down approach works best at the lowest level.

This approach begins with a bigger aspect and then narrows in on a specific sector. Upholders of top-down forecasting favour smoothing lower-level data by aggregating it to develop a better fitting model. It is assumed that the top-level model will reflect a better R^2 value (goodness of fit) than other models. The limitation of top-down models is it is poor in forecasting at lower forecast levels (e.g., purpose-specific individual demand level).[13] As the aggregated data at the top level is an artificial representation of the true nature of the variable, such data does not typically reflect sales low level "peaks and valleys," which are cancelled by aggregation.

3.2 Bottom-Up Approach

Contrarily in the bottom-up approach, the forecast is developed for each series individually and then combined to generate a cumulative forecast of the aggregated demand. Since it is made up of the combination of the individual forecasts of each series, it is called a cumulative forecast. Proponents of bottom-up forecasting point to the fact that one can achieve a better mean absolute per cent error (MAPE) value at the lower level (Gordon et al., 1997). This is due in part to the fact that the lower

[12] A derived forecast is established for each data series usually by means of proportions.

[13] Assumption of top-down approach is: one seasonal pattern fits all, that is, the seasonal pattern both at the aggregate and disaggregate levels are the same, which is often not the case.

level models reflect the actual nature of the business. A bias also has been documented in regression co-efficient when aggregated data is used.

Often very poor accuracy is observed in the bottom-up approach at higher forecast levels. This is may be due to forecast error at intermediate (middle) levels accumulating as data moves up to higher levels. In a bottom-up approach, item per location (i.e. individual level power demand) forecasts are aggregated up to create a national forecast.

Various opinions support either approach (Table 5). Dangerfield and Morris (1992), for example, found that the bottom-up forecasting outperformed the top-down forecasting in nearly three out of four cases and that the relative superiority of the bottom-up forecasting was more pronounced as the correlation between the two items increased and/or one item increasingly dominated the family class. These findings were also supported by Gordon et al. (1997), Weatherford et al. (2001) and Diebold (1998, p. 188). However, Gross and Sohl (1990) numerically found that the top-down strategy (with a proper disaggregation method) provided better estimates than the bottom-up forecasting in two out of three product lines examined.

Table 5: Difference between bottom-up and top-down approaches

Issues	Top-down Approach	Bottom-up Approach
Definition	In TD, series are first aggregated to produce a combined forecast, then the forecast is disaggregated and a derived forecast for each series is established usually using proportions. The top-down approach achieves a better forecast at the aggregate level.	In BU, the forecast is developed for each series individually and then these are combined to generate a cumulative forecast of the aggregated series. This is referred to as the cumulative forecast since it is made up of the combination of the individual forecasts of each series.
Assumption	One seasonal pattern fits all, that is, the seasonal pattern both at the aggregate and disaggregate levels are the same.	No prior assumption is made.
Strength	Proponents of top-down forecasting favour smoothing lower-level data by aggregating it so that one can develop a better fitting model (the top-level model will reflect a better R2 value than lower-level models). It is also felt that top-down models often reflect better accuracy for top-level forecasting.	Proponents of bottom-up forecasting point to the fact that one can achieve a better Mean Absolute Per cent Error (MAPE) value at the lower level (Gordon, Morris, and Dangerfield 1997). This is due in part to the fact that the lower-level models reflect the actual nature of the business. A bias also has been documented in regression coefficients when aggregated data is used.
Weakness	The problem is top-down models typically do a poor job of forecasting at lower forecast levels (e.g., ' at the item per location level). The reason: aggregated data at the top level is an artificial representation of the true nature of the business because such data does not typically reflect sales low level "peaks and valleys," which are cancelled by aggregation.	Bottom-up forecasting often has very poor accuracy at higher forecast levels. This may be a result of forecast error at intermediate (middle) levels accumulating as data moves up to higher levels.
Objective of usage	If the company uses forecasts to develop strategic plans and budgets.	If production and distribution schedules (electricity generation and distribution) are driven by forecasts.
Forecast automation method	State Space Models.	ARIMA

Source: Authors' compilation based on different kinds of literature.

3.3 Load Forecasting Techniques for Projection of Power Demand

Methodology plays a vital role in predicting the most accurate demand for power and energy. Many advanced methodologies are used to determine the demand and supply of power in developed or developing countries. Not to mention the accuracy of the power forecast depends on the adopted model. A single forecasting method can improve the forecasting accuracy in some aspects if the right model is being adopted. But it is more difficult to yield the desired accuracy in all-electric load forecasting cases. Load forecasting plays an important role in electric system planning and operation. In recent years, lots of researchers have studied the load forecasting problem and developed a variety of load forecasting methods. Load forecasting algorithms can be divided into three major categories (Ghayekhloo et al., 2015).

3.3.1 Traditional methods

The traditional methods mainly include Autoregressive (AR), Autoregressive Moving Average (ARMA), Autoregressive Integrated Moving Average (ARIMA), semi-parametric[14], Gray model[15], similar-day models[16], and Kalman filtering method[17] (Kouhi & Keynia, 2013). The algorithms applied in these models have few theoretical limitations—it is difficult to improve the power demand forecasting accuracy using these forecasting approaches. ARIMA is one of the broadly used forecasting methods in time series analysis (Hong Chen et al., 2016). One drawback of ARIMA, often noticed while using it with the purpose of forecasting power demand is, the inability to capture the rapidly changing process underlying the electric load from historical data patterns (Chen et al., 2015). Kalman filter-based estimation is used to estimate the model parameters using the previous history of load and weather data (Al-Hamadi & Soliman, 2004). Even though Kalman filters have been demonstrating their usefulness in various fields of applications including the power sector, one major limitation of the Kalman filter model is, it cannot avoid the observation noise. The Gray model, on the other hand, doesn't provide an appropriate forecast when the data has a high level of discretion which is very often observed in the case of power load demand.

3.3.2 Modern forecasting techniques

The modern forecasting techniques (Table 6) mainly include Artificial Neural Networks (ANN)[18], fuzzy systems[19], Knowledge-Based Expert System (KBES) approach[20], wavelet analysis, Support Vector

[14]Semi-Parametric Model: A semi parametric model is intermediate between parametric and nonparametric models and contains finite-dimensional and infinite-dimensional parameters (School of Public Health, University of Michigan).

[15]Gray Model: Gray prediction model is that through the monotone sequence has been given, by means of once additive generates a group of new albinism differential equation (Mingyue Zhao et al., 2015).

[16]Similar-Day Model: It first selects similar historical days with similar characteristics, and then uses weighting and extrapolation to forecast the daily load (Qingqing et al., 2010).

[17]Kalman Filtering Method: Kalman Filtering is an algorithm that provides estimates of some unknown variables given the measurements observed over time. Kalman filters have been demonstrating its usefulness in various applications. Kalman filters have relatively simple form and require small computational power (Kim & Bang, 2018).

[18]ANN: An Artificial Neural Network (ANN) is the piece of a computing system designed to simulate the way the human brain analyzes and processes information.

[19]Fuzzy System: The fuzzy system approach is presented as a basis for the design of systems far superior in artificial intelligence to those we can conceive today. The concepts of controllability, observability and minimalism are developed, and conditions for the realisation of an input-output map by such a system are given (Negoita & Ralescu, 1974).

[20]KBES: A Knowledge-Based System (KBS) is a form of Artificial Intelligence (AI) that aims to capture the knowledge of human experts to support decision-making. Examples of knowledge-based systems include expert systems, which are so called because of their reliance on human expertise (John Moore Year?).

Table 6: Advantages and disadvantages of power demand forecast methods

Name of the methods	Advantages	Disadvantages
Artificial Neural Networks (ANN)	Can easily handle nonlinear relationships between dependent and independent variables and are best suited for complex information processing.	Has a black-box nature. The black box implies that while approximating a function, there is less information on the internal structure of the ANN and how it approximates the function. Faces difficulty in choosing parameters. ANN also has high computational complexity.
Fuzzy system	Can be coded using less data, so they do not occupy huge memory space. As it resembles human reasoning, these systems can solve complex problems where ambiguous inputs are available and take decisions accordingly. These systems are flexible and the rules can be modified.	Completely dependent on human knowledge and expertise. The accuracy of these systems is compromised as the system mostly works on inaccurate data and inputs. There is no single systematic approach to solve a problem using Fuzzy Logic. As a result, many solutions arise for a particular problem, leading to confusion.
Autoregressive Integrated Moving Average (ARIMA)	Uses the autocorrelation between series of values while the trends and seasonality of the latter target.	Fails to capture the rapidly changing process underlying the electric load from historical data pattern.
Multiple Linear Regression (MLR)	Really easy to utilise.	May not always provide the accurate forecast.
K mean clustering	Produce tighter clusters than hierarchical clustering, especially if the clusters are globular.	Implemented by considering different factors like seasonal consumption, type of consumer and area of consumption.
Holt- winter	Used to cater for seasonal changes in predicting electricity demand.	Best suited for forecasts that are short-term rather than seasonal or cyclic.
Singular Spectrum Analysis (SSA)	Useful to implement in a densely populated country.	SSA method is non-parametric and makes no prior assumptions about the dataset.
Support Vector Machine (SVM)	Effectiveness with high-dimensional spaces and memory efficiency.	Computational complexity irrespective of the dimensionality of its input space.

Source: Authors' compilation based on different kinds of literature.

Machine (SVM)[21], and so on. A KBES is the combination of knowledge and experience of numerous experts to maximise the experts' ability, but the method does not have self-learning ability. Besides, KBES is limited to the total amount of knowledge stored in the database and it is difficult to process any sudden change of the conditions.

The ANN has some very unique abilities like nonlinear approximation, self-learning, parallel processing and higher adaptive ability (Narciso & Steven, 2003). Despite these abilities, it also has some problems, such as it faces difficulty in choosing parameters and suffers from high computational complexity. The advantages of ANN makes it superior to all other methods. It is widely used in India, Thailand and Turkey for power demand forecasting. SVM is a machine learning method proposed by Cortes and Vapnik (1995) which is based on the principle of Structural Risk Minimisation (SRM) in statistical learning theory. The practical problems such as small sample, nonlinear, high dimension, and local minimum point could be solved by the Support Vector Machine (SVM) via solving a convex Quadratic Programming (QP) problem (Cortes & Vapnik, 1995). However, traditional SVM also has some shortcomings. Such that, SVM cannot determine the input variables

[21]SVM: A Support Vector Machine (SVM) is a supervised machine learning model that uses classification algorithms for two-group classification problems. After giving an SVM model sets of labeled training data for each category, they're able to categorise new text.

effectively and reasonably and it has slow convergence speed and poor forecasting results while suffering from strong random fluctuation time series. That is why in the case of power demand forecast it is not used as widely as ANN.

3.3.3 Hybrid Algorithm

As single algorithm method doesn't give appropriate forecasting always, two or more models can be hybridized according to the purpose of the researcher with the aim of forecasting the most accurate load. A new hybrid forecasting method, namely ESPLSSVM (Zhai, 2015), based on empirical mode decomposition, seasonal adjustment, PSO and LSSVM model was proposed. Hybridization of support vector regression (SVR) with chaotic sequence and EA is able to avoid solutions trapping into a local optimum and improve forecasting accuracy successfully (Zhang et al., 2012). Ghofrani et al. proposed a hybrid forecasting framework which was a combination of new data preprocessing algorithm with time series and regression analysis to enhance the forecasting accuracy of a Bayesian neural network (BNN). A hybrid algorithm based on fuzzy algorithm and imperialist competitive algorithm (RHWFTS-ICA) is also developed (Enayatifar et al., 2013), in which the fuzzy algorithm is refined high-order weighted. Yan Hong Chen et al. used a combination of the global harmony search algorithm (GHSA) with LSSVM to optimise the parameters of LSSVM in their study.

Fuzzy Time Series (FTS) has been utilized broadly in electric load forecasting as a significant quantitative forecasting model. Lee and Hong (2015) proposed a new FTS approaches for electric power load forecasting. Efendi et al. (2015) discussed the fuzzy logical relationships used to determine the forecast of electric load in the FTS modelling. Sadaei et al. (2014) presented an enhanced hybrid method based on a sophisticated exponentially weighted fuzzy algorithm to forecast short-term load. A combination of FTS with other models are often used with the aim of forecasting. A new method for forecasting the TAIEX (Technical Assistance and Information Exchange) is presented based on FTS and SVMs (Chen & Kao, 2013).

4. DEMAND FOR ELECTRICITY IN DEVELOPING COUNTRIES

Khanna & Rao (2009) stated that variables like GDP, prices, income, the level and characteristics of economic activity/urbanisation, and seasonal factors influence the electricity demand. *A Review of Electricity Demand Forecasting in Low and Middle-Income Countries: The Demand Determinants and Horizons* reviewed and analysed a total of 69 research articles for last 20 years 2000-2020 opined that the population, GDP, weather, and load data over different time horizons are the key drivers of demand determinants of electricity. The author used the time series modelling approach to forecast long and medium-term power demand. For shortterm forecasts, artificial intelligence-based techniques remain prevalent in the literature.

Early work in Paraguay (Gleen & Westly, 1977) discovered that electricity demand can be determined by GDP per household, the real marginal price of electricity, house size, and household size. In the paper titled, *Electricity Demand in Developing Countries,* OLS with a combination of the log, linear, inverse and interaction variables were used as the methodology to predict the power demand. Pakistan has a relatively low power supply reliability compared to other countries. A study conducted in Pakistan in 2011 discovered that GDP, income per capita and population influence electricity consumption (Gul et al., 2011). Univariate Time Series Model and MLR based econometric model was used as the main methodology in this study. Another study conducted in Pakistan in 2015 found that the main electricity consumption sectors in Pakistan are the household, government sector, street lights, commercial, industrial, agriculture (Hossain et al., 2016). The study titled *Forecasting electricity consumption in Pakistan: The way forward* used Winter Holt and ARIMA as the forecasting model.

On the other hand, a study conducted in China in 2015 found some new factors to determine the power demand. Hu et al. (2016) found that historical data, weather/temperature data can also affect the demand for electricity. The study used decreasing step fruit fly optimization algorithm to estimate the demand of power—a short-term power load forecasting model based on the generalized regression neural network with decreasing step fruit fly optimisation algorithm, 2017. Another study done in the same year based on Turkey found a similar result. Hamzaçebi et al. (2019) in their study named *Forecasting of Turkey's monthly electricity demand by seasonal artificial neural network* concluded that load data and weather of Turkey contribute to the power demand. This particular study utilised Seasonal Artificial Neural Network (ANN) as a methodology to forecast power demand.

In Thailand, Panklip et al. (2015) found that GDP and population effects electricity consumption. The study titled *Electricity Consumption Forecasting in Thailand Using an Artificial Neural Network and Multiple Linear Regression*, used ANN and MRL exactly how the name suggests.

Electric load demand forecasting for Aborlan-Narra-Quezon distribution grid in Palawan using MLR, a study by Supapo et al. (2017) concluded that historical data, number of consumers for past five years, development plans (commercial, industrial etc.) for next 10 years influences Philippine's electricity consumption by using MLR model. Another study was done in a developing country, Indonesia by Subanar et al. (2020) found load data determines the electricity demand in Indonesia by using Singular spectrum analysis, fuzzy systems and neural networks (*Indonesian electricity load forecasting using singular spectrum analysis, fuzzy systems and neural networks, 2020*).

In an article titled *Malaysia electricity load demand forecasting using exponential smoothing methods,* previous load data and seasonal patterns were used to determine the load demand of electricity (Jalil et al., 2013). Holt-Winters Taylor (HWT), Holt-Winters, modified Holt-Winters exponential smoothing were mainly used to forecast the power demand of Malaysia. A study based on Malaysia exposed in *Electricity energy outlook in Malaysia* (2013), power demand determined by population and income growth (Tan et al., 2013).

Silva et al. in 2017 found out that previous load data (1995–2015), electric consumption by process, value-added of different sectors, electricity price, production and value addition forecasts until 2050 contribute to the electricity consumption by using the Bottom-Up Approach (*Bottom-up methodology for long-term electricity consumption forecasting of an industrial sector-Application to pulp and paper sector in Brazil).* In Venezuela, the electricity load demand is determined by load data according to Zio et al. (2013) (*Singular spectrum analysis for forecasting of electric load demand, 2013*). By name, it is understandable that the authors used Singular Spectrum Analysis as the core methodology.

a) Based on the analysis, several key findings of demand-side analysis of projection of power demand can be drawn.
b) Economic growth or GDP is one of the key drivers of electricity demand in developing countries but it is not the only variable that affects power consumption.
c) Variables such as the income of a household, population, historical load data weather or temperature also heavily influence the demand for electric power.
d) Traditional methods like Ordinary Least Square (OLS), MLR are mostly used by the reviewed countries to forecast the demand and supply of power because of the feasibility but they don't often provide an accurate forecast of power demand.

e) ANN and FTS give the most accurate forecast of power. ARIMA is found to be the best-fitted model of power demand forecasting but for a short period. Similarly, the Fixed Effect Model is the most used model for forecasting the supply of electricity.
f) ANN, FTS, ARIMA, MLR and Singular Spectrum Analysis are the most used methodology in India, Thailand, Turkey, Indonesia, Malaysia, China, Pakistan, Philippines and Venezuela. In other words, those are the dominant methodologies in developing countries.

5. CONCLUDING REMARKS: RECOMMENDATIONS FOR PESMP 2021

The decision taken by the MoPEMR for preparing the integrated power and energy system master plan is a welcome initiative. This is particularly important when the sector needs to address several emerging challenges because of COVID 19 pandemic—excess capacity due to poor electricity demand, huge capacity payment, inefficiency, use of expensive energy and consequent high financial burden on BPDB. Such a policy is important as the country is in the process of the energy transition to scaled-down the usages of fossil fuel and scaling up the usages of renewable energy. Based on the analysis of earlier PSMPs and power demand analysis carried out on different developed and developing countries, the study put forward a number of recommendations

a) ***A review of the earlier PSMPs has revealed several important observations which needs serious consideration while drafting the new PESMP:*** According to the PSMPs and BPDB, the power sector is almost close to meet the demand with its existing generation. In the future, the power sector needs to create capacity only to cater for the prospective incremental demand in different activities. PSMPs have been projected power demand based on only one variable—GDP/GDP growth which seems to be a weak method.
b) ***Several weaknesses have been observed in the demand side analysis in the PSMPs***. These include—(a) Longer projection weaken the plan, (b) Mismatch in demand, (c) Limited number of variables considered, (d) Differences in weights of sectors between GDP and electricity consumption, (e) Faulty longer projection, questionable GDP estimates, (f) Long wish list of the government, (g) Faulty of undertaking sectorial approach, (h) Limitation of data and (i)Lack of dedicated institutional support for data.
c) ***Principles for the new PESMP 2021 should take into account a number of issues:*** The new power and energy system master plan should be drafted based on the following principles—(i) Applied advanced method for estimating the demand forecast; (ii) Taking into account the limitations/ weaknesses of earlier methods; (iii) Aiming to reduce excess installed capacity in a phased approach, and (iv) Ensuring due importance in transitioning towards clean power by gradual phase-out of fossil-fuel and phased-in of renewable energy.
d) ***Reviewing the ToR of PESMP 2021 will be required:*** As in the earlier cases, JICA has agreed to work with the ministry in preparing the PSPEMP. JICA mentioned on its website (15 March 2021) that the aim is to promote a low or zero-carbon transformation of the total energy supply and demand system. It will have an inclusive and long-term view, working for sustainable development, and will contribute to Sustainable Development Goals (SDG) 7 and 13. This time the master plan project will also strengthen the capacity required for policy and planning development and energy data management so that in the future the Bangladesh government can carry out energy and electrical development independently. Against this backdrop, it is important to review the ToR how the zero-carbon emission initiatives have been designed in the preparatory process to incorporate that under the new plan. It is expected that BPDB will ensure sufficient consultation with the private sector and CSOs.
e) ***Bangladesh should undertake a bottom-up approach with micro predictions:*** This micro-prediction will cover each sector and sub-sector by using a bottom-up approach. The projection

need not be required to do for a long period rather should be for the short to medium term. A doable and practical planning should be for five years and a mid-term of 10 years.

f) ***Detailed growth prediction and forecast of the industrial sector and the domestic sector should be done:*** The industrial sector and residential sector are the two most important sectors that consume the highest amount of electricity. Agricultural, commercial and service sectors' growth can be figured out from past trends as the proportion is small.

g) ***Limitations of data on each sector and sub-sectors will need to be addressed:*** In case the data are not available, a necessary survey should be conducted by an independent institute, particularly the Bangladesh Bureau of Statistics (BBS). Data management of the ministry (MoPEMR) needs to be strengthened with the appropriate institution, human resources and logistics.

h) ***The new plan shall specifically mention the required installed capacity:*** The new PESMP shall specifically mention the required installed capacity (lower case and upper case) and how to phase out the excess capacity. Given the availability and cost of fuel mix, the capacity can be a little bit higher than 25 per cent but no need of being where it is today. It will provide how the energy mix could be gradually made balanced with an increasing share of renewable energy.

i) ***The demand-side of the new plan should highlight weaknesses in creating huge excess installed capacity and way out of the excess capacity:*** Phasing out of investment in power generation in fossil-fuel-based plants through a way-out of the excess capacity has to be done. The plan should strictly mention no extension of quick rental power plants after the existing contracts expire. The plan should strictly mention the discontinuation of power plants which are dated, inefficient and using expensive energy. The new PESMP should strictly take its stance that Liquefied Natural Gas (LNG)-based power plants will not be set up in the land earlier planned for coal-based power plants.

j) ***A dedicated monitoring team should be formed:*** A dedicated monitoring team should be formed so that changes in electricity demand can be observed and altered accordingly. Government should make a high-powered committee with concerning public offices to monitor the implementation of the new PESMP.

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Telephone: (+88 02) 48118090, 55001185, 58156979
Fax: (+88 02) 48110414
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Website: www.cpd.org.bd