

Impact of electric vehicles on the operation of the Sri Lankan power system

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Abstract: It is anticipated that with the global trend towards decarbonizing the transport sector, depletion of fossil fuel resource and due to many other technical factors, Electric Vehicles (EVs) will increase in the car market in the future. The charging of a large number of EVs poses various technical challenges and requires special integration measures for power system operation. It is anticipated that depending on the charging regime EV will increase the operating reserve requirements. Quantifying the extent of incremental reserve requirement is vital for secure operation of the power system. This paper focuses on a methodology to estimate the regulating reserve requirement to compensate for the variations in the system load and EVs. Two different EV uptakes and two different charging regimes were considered. From extensive simulations studies it was found the increase in the regulating reserve is minute for the two scenarios considered. However, the long term scenario exhibits an increase in the regulating reserve thus alarming about a possible future issue with more EVs.

Keywords: Electric Vehicles, Operational flexibility, Regulating reserve.

INTRODUCTION

Mainly due to environmental pollution and rising oil prices, many governments are encouraging an increase in the share of Electric Vehicles (EVs) in their transport sector. Globally, a number of EVs exceeded 2 million in 2016. A number of newly registered EVs were 750 thousand worldwide. In terms of energy efficiency, an Internal Combustion (IC) engine based vehicle is estimated to transfer only around 50% of the input energy to the vehicles driven wheel. An EV is estimated to be able to transfer over 90% of the input energy to the driven wheel. This is a significant difference in efficiency. With the global trend, and due to many other technical advances over ICs, EVs will take over the market in the future. The number of EVs in Sri Lanka is exponentially growing and it is estimated that they may reach 2-3% of the vehicle stock by 2030.

The use of EV can bring immediate carbon savings. However, the introduction and widespread use of EVs could potentially lead to significant impacts on power systems (Lopes *et al.*, 2011). Battery charging of electric vehicles will generally increase electricity demand. If the process of EV battery charging is left uncontrolled, it is

likely that the time that EV owners will plug their EVs in sockets or dedicated charging points to charge them will coincide with peak demands (BERR, 2008).


In Qian *et al.* (2011), the effect of EV battery charging on the grid demand of the Great Britain is investigated. Three charging regimes are considered: uncontrolled regime (charging of EV batteries occurs at the last daily trip home arrival time), off-peak charging regime (charging of all EV batteries starts between 21:00-22:00 and stops at 06:00) and smart charging regime (charging of all EV batteries occurs during the cheapest hours of the day in terms of electricity prices). Results show that a 10% market penetration of EVs in the studied system would result in an increase in daily peak demand by up to 17.9%, while a 20% level of EV penetration would lead to a 35.8% increase in peak load, for the scenario of uncontrolled domestic charging.

The European project Mobile Energy Resources in Grids of Electricity (MERGE) examine the effect of residential EV battery charging on electricity demand of six European countries (Downing *et al.*, 2010). Two EV charging regimes are considered: dumb charging (EV owners would plug-in their EVs as soon as they return home from the last daily trip) and smart charging (a valley filling approach is adopted).

Electrical load demand data of six US regions are used by Denholm and Short (2006) to use EV charging for valley filling in electricity demand. It is assumed that 40% of the average distance travelled in each region would be by EVs and that the energy consumption of EVs would be 0.21 kWh/km. The findings show that EV charging would imply an increase in minimum load, of between 18% and 40% depending on the region under investigation.

Meyer *et al.* (2007) compare the number of EVs that could be charged using a valley filling control, to the number of EVs that could be charged only during the period 18:00 and 06:00. The results showed that 84% of the vehicle fleet could be charged under the valley filling control, compared to 43% that could be charged during the period 18:00 to 06:00.

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Hadley and Tsvetkova (2008) studied the effect of EV battery charging on the generation system of 2020 and 2030 for 13 US regions. Evening and night charging regimes are used. In the evening regime, half of the EV fleet would start the charging process at 17:00 and the rest at 18:00 p.m. In the night charging regime, half of the EV fleet would start charging at 22:00 and the rest at 23:00.

Parks *et al.* (2007) considered the application of multiple charging regimes in order to study the effects of EV utilisation on grid demand for the area of Colorado in US. The charging of 500,000 EVs with 0.21 kWh/km energy consumption and 7.2 kWh battery capacities is simulated. Four charging regimes are used: uncontrolled regime (charging of EVs starts as soon as they return home), delayed regime (charging of EVs starts at 22:00), off-peak regime (charging of EVs starts at 23:00 and stops at 07:00), and continuous regime (EVs are charged throughout). The uncontrolled regime case resulted in an increase of 2.5% in peak demand. The continuous regime would increase the peak demand by 4.6%.

In Su *et al.* (2017), an artificial fish swarm algorithm (AFSA) is applied to optimize the distribution network load curve in the restricted SOC range and charging time scope. An algorithm based on a nested optimization approach to characterize the optimal offline EV charging schedule to valley-filling is proposed in Chen *et al.* (2013).

As discussed above, many studies were carried out to estimate the effect of EV charging on peak demand reduction, valley filling and optimizing load curve. However, with the increase of EV charging the load curve shows different rate of changes during different time intervals depending on the charging regime used. This change in the rate of change of load curve demands different operational flexibility in the network. The operational flexibility is normally enhanced by maintaining an operating reserve which compensate for the upward and downward variation of the load curve.

There are two main approaches, namely deterministic and probabilistic methods, for estimating the operating reserve (Holttinen *et al.*, 2012). In deterministic approach which is simple and traditional, derives a fixed percentage of reserve based on the largest event in the required time frame. However this approach does not consider the probability of occurrence of other smaller events, and the dependence between events thus can often overestimate the reserve requirement. The probabilistic approach can be adopted when the time series data is available for load and EV. In the probabilistic method, the variability of load and EV output is statistically analysed and a reserve level is set so that an intended amount of variations are covered by reserve. In the standard deviation method which is also known as *n-sigma* method, assuming that load and EV variations can be represented by normal uncorrelated distributions, a multiple of standard deviation is taken as the reserve level. In many integration studies, three times the standard deviation (*3sigma*) is adopted to theoretically cover 99.7% of the variations (Holttinen *et al.*, 2012; Weber *et al.*, 2009). However that is based on the assumption that the variability information follows a normal Gaussian distribution. Certain detailed studies have

also paid attention on estimating correct number of sigma in this regard. However, stronger conclusion can be made for different systems if such data is analysed in detail to determine the reserve level (Wijekoon, 2017). Improving from the *n-sigma* method, exceedance level method first defines the expected confidence level at which reserves should cover the variations and then determine the exact reserve levels. Instead of applying a number of sigmas to a data set, the use of exceedance level can yield more accurate results since various load and EV variability characteristics can represent various probability distributions.

Even though the operating reserve is categorised into many forms (Era *et al.*, 2010; Holttinen *et al.*, 2012), the regulating reserve is particularly influenced by the rate at which load curve changes. In maintaining the regulating reserve, different systems adopt different techniques. However with increased penetration level of EV, estimating extra regulating reserve required is crucial and requires system specific studies in detail. Therefore, in this paper exact load distribution was evaluated based on historical data and EV penetration studies. Then the regulating reserve requirement was estimated using the exceedance level of variations.

MATERIALS AND METHODOLOGY

EV penetration estimation

Three methods were used to predict the EV penetration. They are;

a) *Double exponential Smoothing Method* (Christou, 2012).

This method is based on two smoothed values, one is a single exponential, S_t' , and the other is a double exponential, S_t'' . In this method the forecasted value at year $t + m$ was obtained by

$$F_{t+m} = a_t + mb_t \quad (1)$$

where

$$a_t = 2S_t' - S_t''$$

$$b_t = \frac{\alpha}{(1-\alpha)}(S_t' - S_t'')$$

$$S_t' = \alpha Y_t + (1-\alpha)S_{t-1}'$$

Y_t is the historical data

$$S_t'' = \alpha S_t' + (1-\alpha)S_{t-1}''$$

α is taken as 0.6 as it the optimum value to give the minimum error. The sum of squared error method was used to find the appropriate alpha value.

b) *Holt's Double exponential Smoothing Method* (Nazim and Afthanorhan, 2014).

This method is based on two smoothed constants, one is a process value, L_t , and the other is a trend value, T_t . The forecasted value at year $t + m$ was obtained by

$$F_{t+m} = L_t + kT_t \quad (2)$$

where

$$L_t = \alpha Y_t + (1-\alpha)(L_{t-1} + T_{t-1})$$

$$T_t = \beta(L_t + L_{t-1}) + (1-\beta)T_{t-1}$$

α is the process smoothing constant and taken as 0.5

β is the trend smoothing constant and taken as 0.9

c) *Moving Average and Double exponential Smoothing Method* (Nazim and Afthanorhan, 2014).

Initially the actual data were pre-processed to obtain the moving average. For the new set of data double Exponential Smoothing Method was applied.

EV load curve estimation

In order to obtain the EV load curve the model shown in Figure 1 was considered (Marra et al., 2012). The battery was represented by a voltage source behind a resistance and the EV battery charger was represented by its efficiency. The power on the grid side P_{ac} was kept constant during the charging process until the cell voltage threshold is reached. This was achieved by regulating i as the grid voltage is constant. The current i was calculated as follow:

$$i = \eta \cdot \frac{P_{ac}}{V_{pack}} \tag{3}$$

where η is the efficiency of the charger

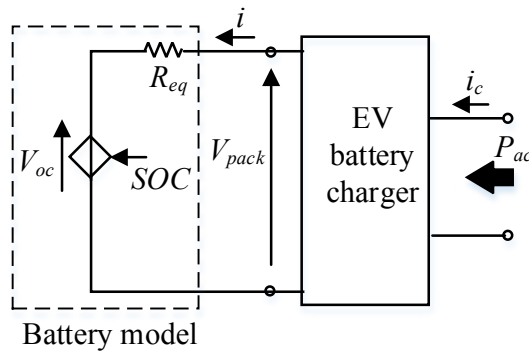


Figure 1: The equivalent circuit of the battery and the charger.

Iterative method was derived to obtain the battery SOC level and the terminal voltage, V_{pack} . Initial SOC level, SOC_i was generated as a random number between 20% and 90% to represent the travelling pattern of the population. Then SOC at the k^{th} iteration was obtained by:

$$SOC(k) = \sum_{k=1}^N \frac{i(k) \times T}{Q_{norm}} + SOC_i \tag{4}$$

where

Q_{norm} is the nominal capacity of the battery, Ah

T is the reference time step considered as 10 minutes

$i(k)$ was obtained from equation (3) with $V_{pack}(k-1)$

Then the open circuit voltage of the battery V_{oc} was obtained by (Marra et al., 2012),

$$V_{oc}(k) = V_o + \frac{K \times SOC(k)}{1 - SOC(k)} + Ae^{-[B \times SOC(k) \times Q_{norm}]} \tag{5}$$

where

A is the exponential zone amplitude (V)

B is the exponential inverse time constant (Ah⁻¹)

V_o is the battery voltage constant (V)

K is the polarization voltage (V)

The terminal voltage of the battery cell V_{pack} was derived by

$$V_{pack}(k) = V_{oc}(k) + i(k) \times R_{eq} \tag{6}$$

where

R_{eq} is the equivalent resistance of the battery pack

It was assumed that the charging pattern is constant power charging with a domestic charging unit of 3.7 kW until the terminal voltage reach 4 V. Therefore in this phase, $V_{pack}(k) \times i(k)$ was taken as a constant of 3700 W. Then it was assumed that the charging pattern is constant voltage of 4 V, i.e. $V_{pack}(k) = 4$ V until the SOC level reach 100%.

Reserve estimation

Estimating the regulating reserve services due to the integration of RES requires the analysis of both load and RES characteristics. Initially, it is essential to assess the regulating reserve required for load variability alone and that establishes the basic regulating reserve levels needed for the normal system operation. Further analysis on extra regulating reserves for EV penetration was then estimated and compared.

RESULTS

EV predictions

In order to define the EV predictions, the following two scenarios were defined:

1. Business as usual (2019 – 2022)

The historical data of cars imported to the country was obtained from the Department of Motor Traffic, Sri Lanka. According to the Nationally Determined Contributions (NDCs) in accordance with Decision 1/CP.21 of the 21st session of the Conference of the Parties to the United Nations Framework Convention on Climate Change, the readiness phase till 2020 is provided for allowing the country to prepare for the full-scale implementation of chosen NDCs. However, in this scenario it was assumed that the car import will be as usual until 2022 (NDC, 2016). The car stock in the country was predicted using double exponential smoothing method up to 2022. Figure 2 shows the historical data and predictions obtained. It is worth noting that the peak in 2015 is due to the reduction of importation tax to 5%.

2. Long-term (2025 – 2030)

Nationally Determined Contributions (NDCs) is reducing the GHG emissions against 2010 values by 10% in transport sector by 2030. According to car fuel data provided by Vehicle Certification Agency of the UK¹, CO₂ emissions from different cars change from 100 – 400 g/km. The total car population in Sri Lanka in 2010 was about 400,000

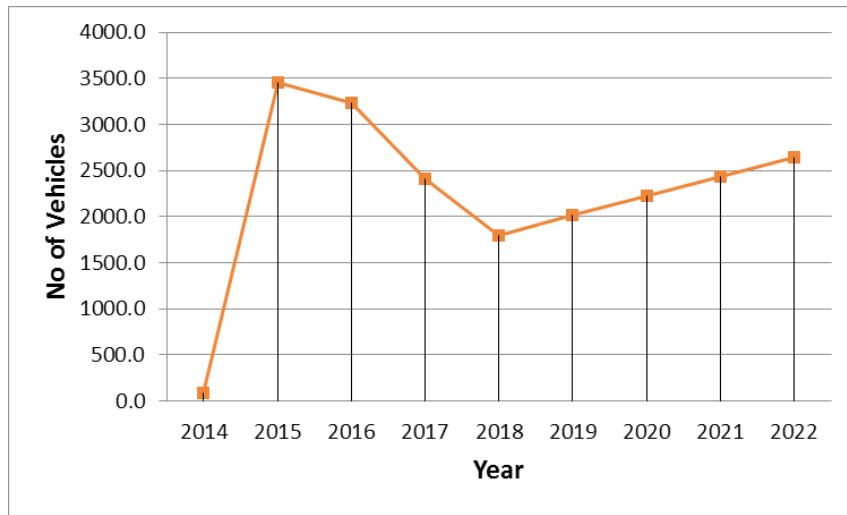


Figure 2: EV predictions up to 2022.

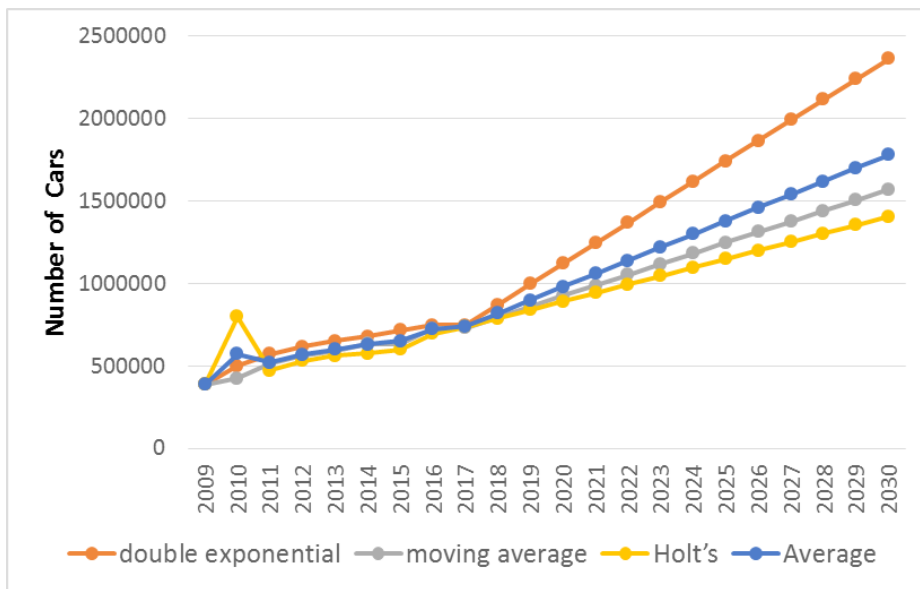


Figure 3(a): Car stock prediction.

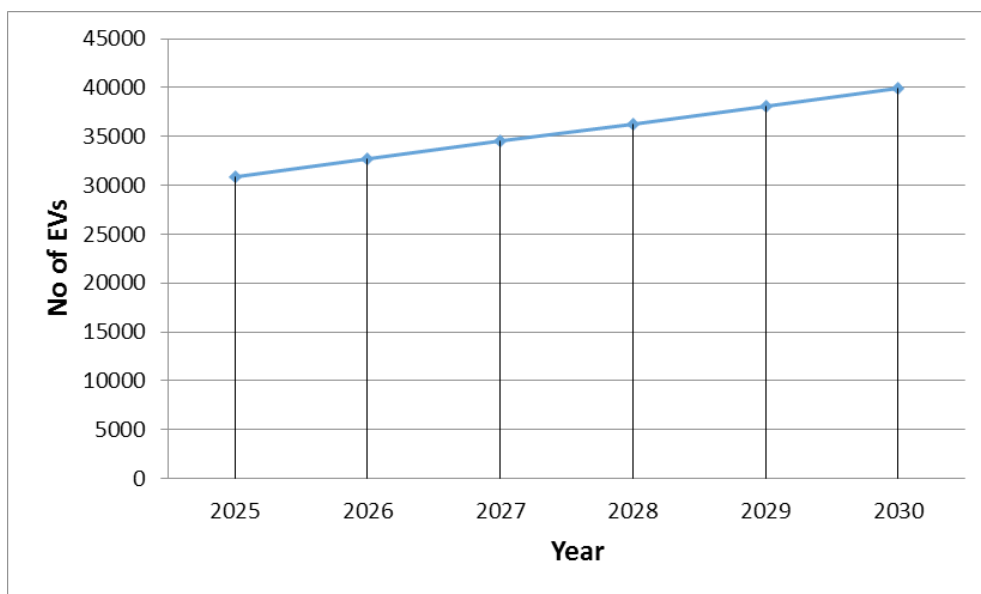


Figure 3(b): EV predictions from 2025 - 2030.

(Department of Motor Traffic, 2011). With an average daily distance of 50 km and average CO₂ emissions of 250 g/km, the total emission from cars at 2010 is 5000 tonnes per day. In order to achieve our NDC, emissions should be reduced by 500 tonnes and that translates into replacing 40,000 petrol or diesel cars by electric cars by 2030. Therefore in this scenario it was assumed that the Government will introduce tax reductions to promote EVs.

In order to predict the EV population from 2025 to 2030, first the total car population of the country was predicted using double exponential smoothing method, Holt’s double exponential smoothing method, and moving average & double exponential smoothing method up to 2030. Figure 3(a) shows the predictions obtained. The average value of

the results obtained from three models was taken as the car stock in the country. Then, it was assumed that 2.24% of the car stock is EVs. This percentage was obtained by assuming EV stock in the country in 2030 is 40,000. The predicted EV population from 2025 to 2030 is shown in Figure 3(b).

When one compares Figure 2 and Figure 3(b), it can be seen that in order to achieve our NDCs during the transitional period (i.e. from 2022 to 2025), 27,500 EVs should be added. Therefore, it was assumed that during these three years the Government introduces different initiatives to promote EVs.

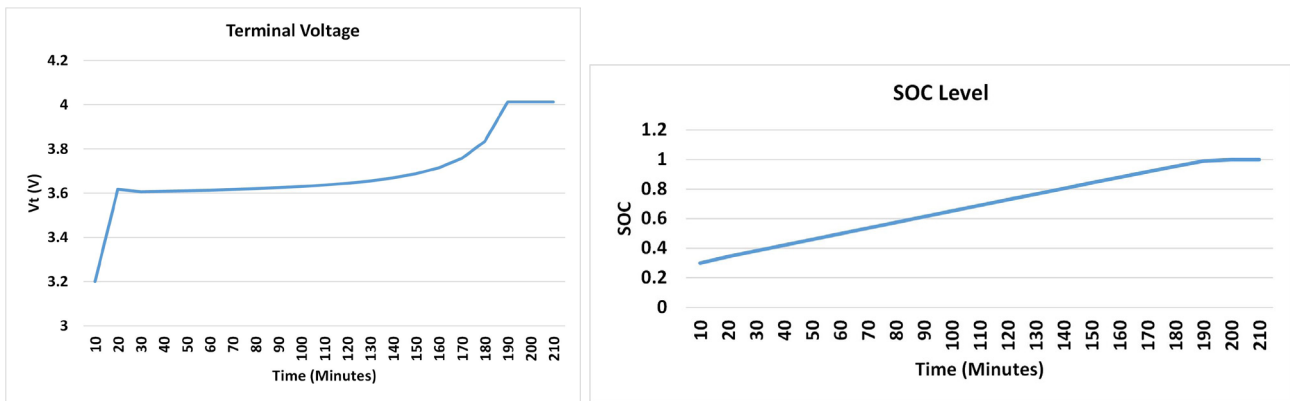


Figure 4: Terminal voltage and SOC values of one EV.

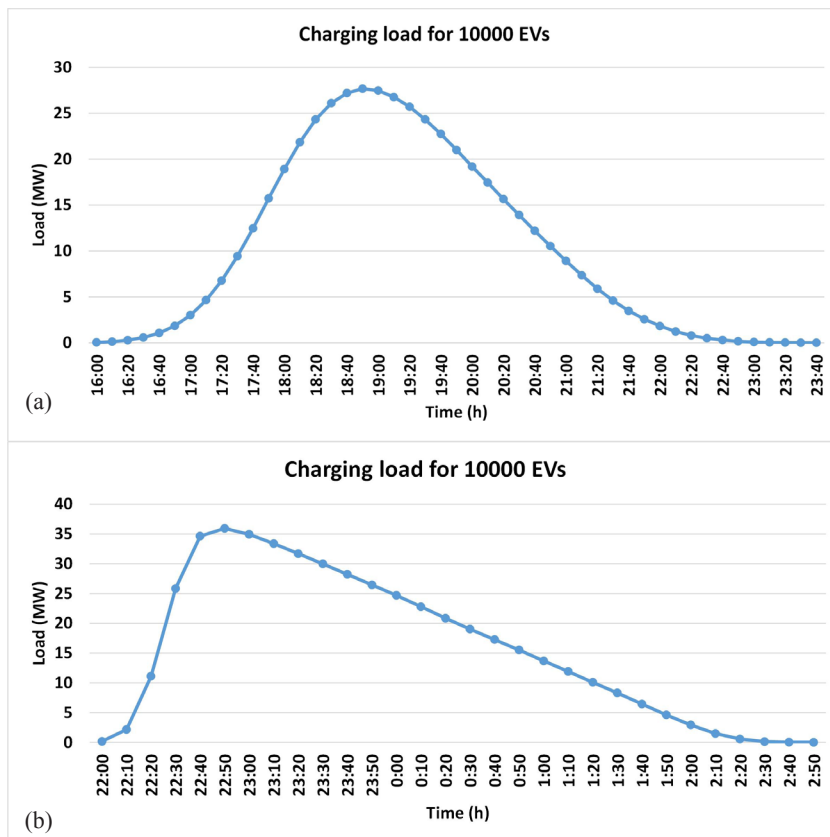


Figure 5: Charging load of 10,000 EVs (a) Dump charging (b) ToU charging

EV load profile

For this study it was assumed that all the vehicles are Nissan Leafs. The battery pack composed of 110 series-connected 3.2 V - 40 Ah LFP cells and has a total battery pack nominal voltage of 352 V. The battery pack has the following parameters: (Marra *et al.*, 2012)

$$V_o = 3.5 \text{ V}, \quad R_{eq} = 0.01 \Omega, \quad K = 0.025 \text{ V}, \quad 0.2 \text{ V}, \\ B = 0.375 (\text{Ah})^{-1} \text{ and } \eta = 0.88$$

For each EV, a load profile was generated using a randomly generated SOC value. The profile obtained for one EV is shown in Figure 4.

The model given in section 2.2 was run for 10,000 EVs taking the SOC as a random number between 20% to 90%. The charging load was observed for the following two scenarios:

- Assuming all 10,000 EVs Plug-in between 16:00h to 20:00h and Normally Distributed – Dump charging
- Assuming all 10,000 EVs plug-in between 22:00h to 23:00h and Normally Distributed (this is based on the current Time of Use (ToU) tariff) –ToU based charging

Sri Lankan daily load profile with EV load

For two EV scenarios considered in Section 3.1, the Sri Lankan load profiles were generated under Dump charging and ToU charging. Demand forecast given in ‘Long term generation expansion plan: 2018-2037’ of CEB was used as the base load. According to CEB Long Term Generation Plan, for the medium term as first four years, time trend modelling has been adopted by capturing recent electricity sales pattern and the anticipated near term demand growth.

For the long term, econometric approach has been adopted by analysing past electricity sales figures with significant independent variables and this exercise produces the long term electricity demand forecast considering the driving factors at macro level. Sector level behaviour of the GDP is considered in this process and the services sector GDP reflects the contribution from the overall transport sector in a business as usual scenario. However, significant changes such as rapid penetration of electric vehicles and electrification of other transport modes that affect the sector performance and ultimately the electricity demand have to be analysed separately. Electric vehicle charging function can potentially change the daily electricity demand profile. Therefore, the electricity demand profiles developed for future years based on the demand forecast of the long-term generation expansion plan: 2018-2037 has been used as the base demand profile in this work.

The forecasted EV charging loads given in Figures 5 (a) and 5(b) were added to obtain the future load. As the Figure 5 was generated for 10,000 EVs, in order to generate EV charging profiles under Business as Usual (BaU) and long term scenarios, the curves given in Figures 5(a) and 5(b) were multiplied by a factor equal to EV population in the year of consideration/10,000. Figures 6(a) and (b) shows the load profile of the country for the period 2019-2022 under BoU, dump charging and ToU charging. Similar figures for long term, dump charging and ToU charging for the period 2025-2030 is given in Figures 6(c) and (d).

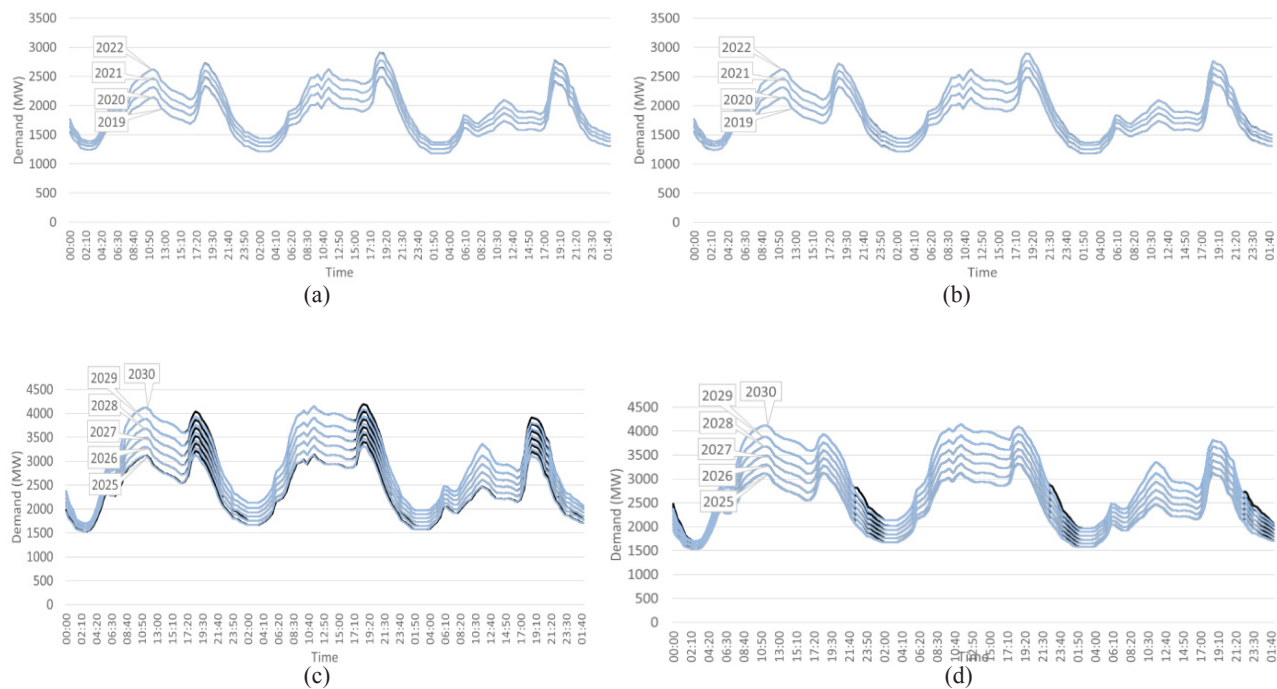


Figure 6: Load curve of Sri Lanka under different EV penetrations and charging profiles. (a) BaU – Dump charging (b) BaU – ToU charging (c) Long term – Dump charging (d) Long term – ToU charging.

Regulating reserve requirement for load variation

The time series data of the total load (as shown in Figure 6) is available in 30 minute resolution. Interpolation was used to generate time series data in 10 minute resolution based on the assumption that the total system is large enough to approximate the linearity between smaller time intervals. Figure 7 illustrates the duration curves of the 10 minute variabilities of the total load for year 2022 under two BaU scenarios and for the year 2030 under the two Long Term scenarios. Figure also shows the variability of the base case load, i.e. assuming that the EV penetration is negligible.

In order to understand the impact on the total load variability at the regulating time frame and the resulting regulating reserve requirement, the positive end of the above duration curves were closely examined. For the BaU scenario, Figure 8 shows the largest end of the upward variations (largest 1% portion of the duration curve) of the demand as it is the most interested portion reflecting the impact on regulating reserve requirement. Figure 9 illustrates the same for the two Long term scenarios.

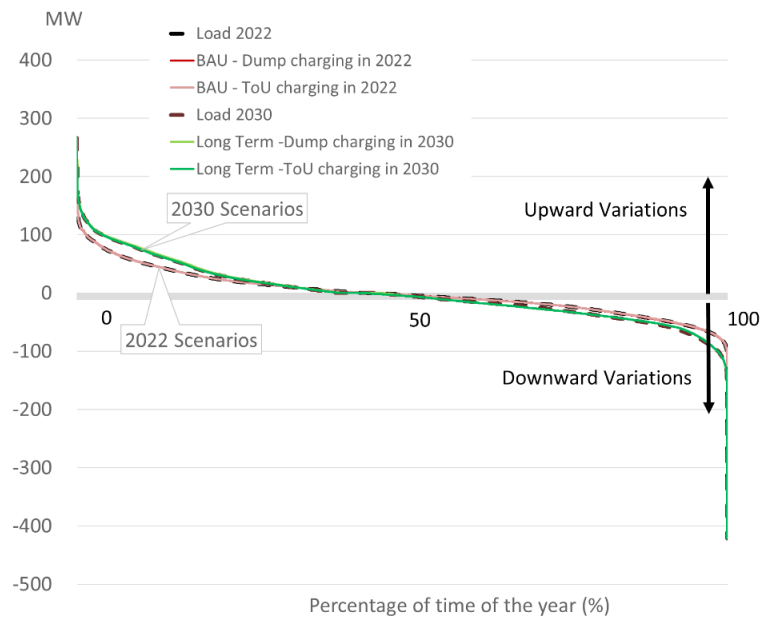


Figure 7: Duration curves of the variability.

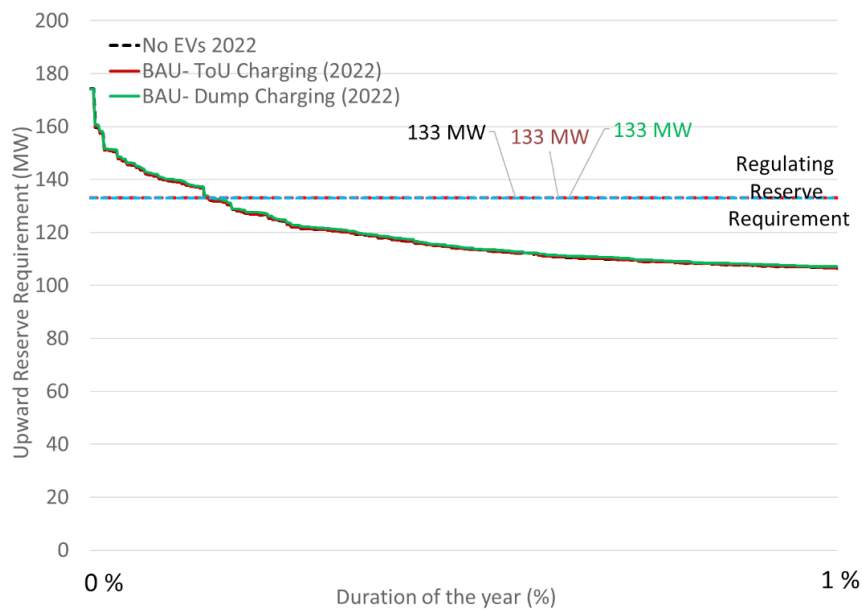


Figure 8: The largest 1% of upward variation of load in BAU scenario.

It is observed that under the BaU scenario, the EV charging load does not affect the regulating reserve requirement. The charging load is not significant enough under both dump and ToU charging regimes to cause major changes to the daily electricity demand pattern and the resulting load duration curve. However, EV penetration levels in the Long term scenario slightly affect the demand profile and its duration curve in the future years.

After obtaining the variability information from the generated demand profiles, the exceedance level method was applied to determine the required regulating reserve levels. Figures 10 and 11 shows the results obtained on the additional regulating reserve requirement for different scenarios for upward and downward directions respectively. The same results on the additional regulating reserve requirement are presented in Table 1.

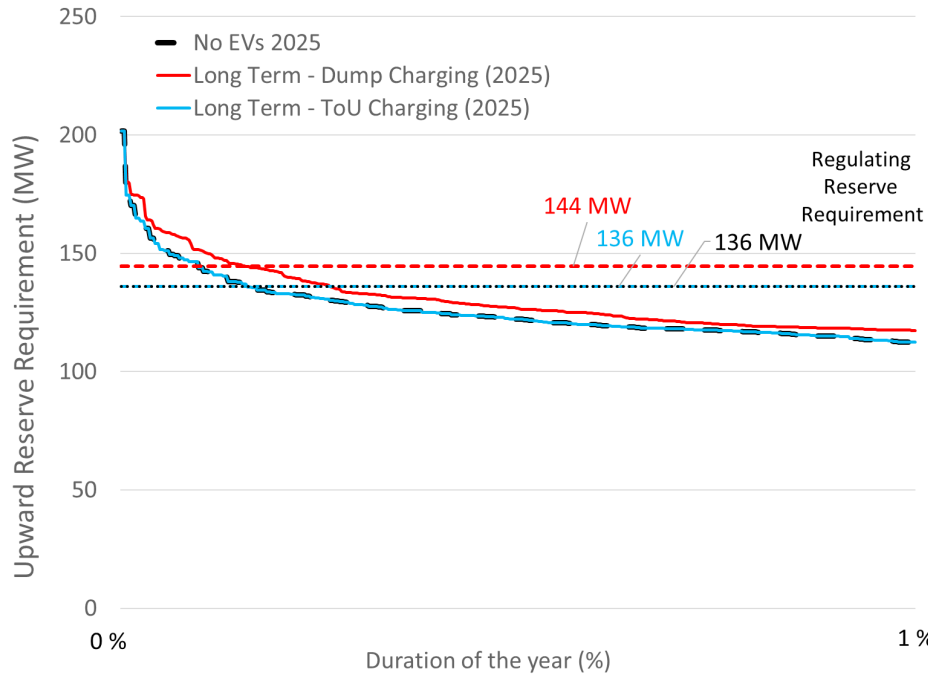


Figure 9: The largest 1% of upward variation of load in Long term scenario.

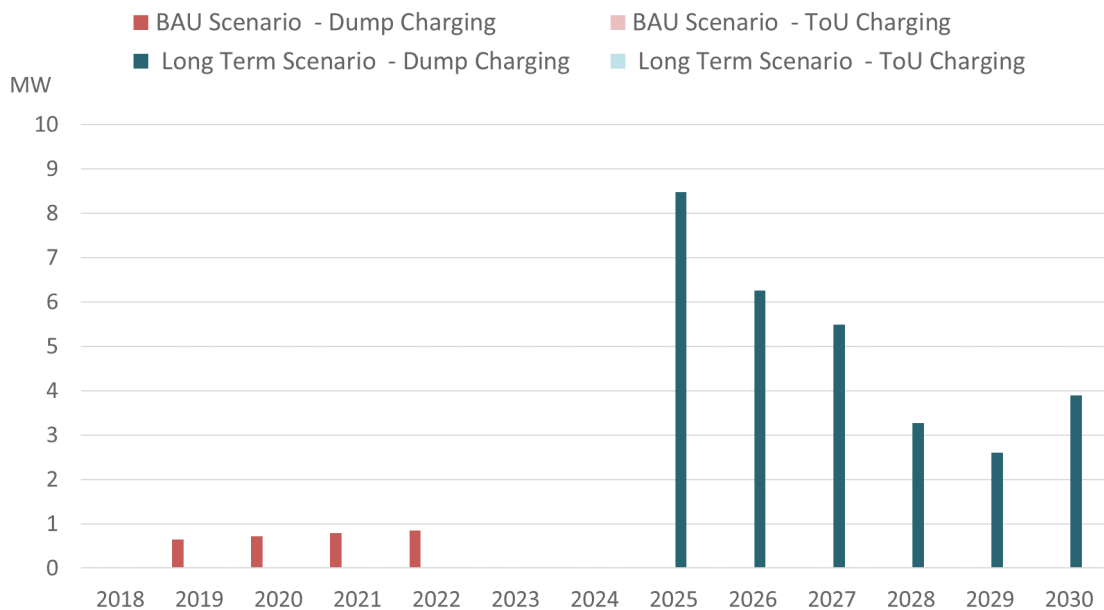


Figure 10: Additional Upward Regulating Reserve requirement of different scenarios.

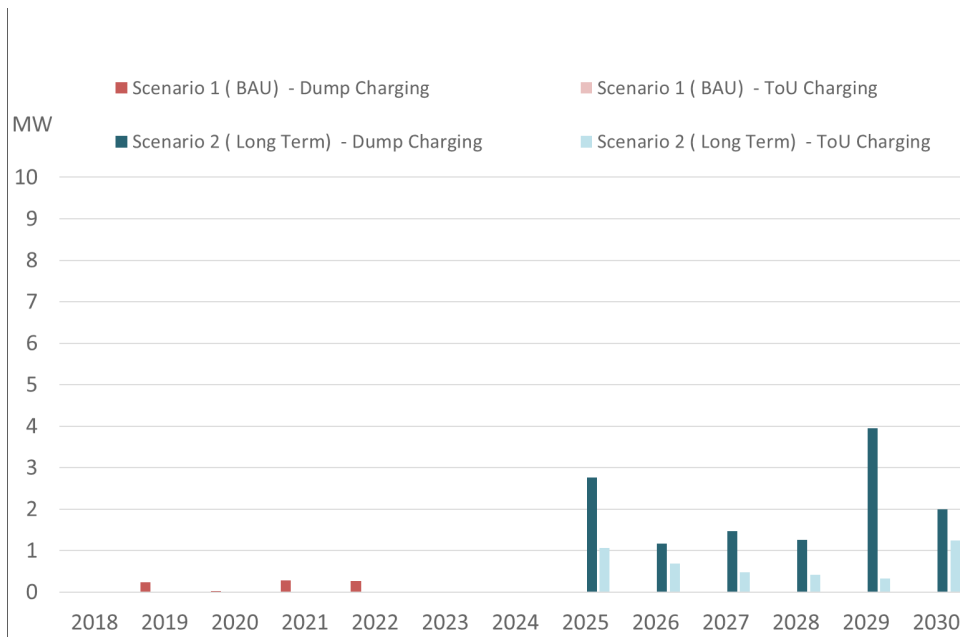


Figure 11: Additional Downward Regulating Reserve requirement of different scenarios.

Table 1: Incremental Reserve requirement of Different scenarios and charging schemes.

Incremental Upward Reserve requirement (MW)														
Scenario		2018	2019	2020	2021	2022	2023	2024	2025	2026	2027	2028	2029	2030
BAU	Dump	0	1	1	1	1								
	ToU	0	0	0	0	0								
Long Term	Dump								8	6	5	3	3	4
	ToU								0	0	0	0	0	0
Incremental Downward Reserve requirement (MW)														
BAU	Dump	0	0	0	0	0								
	ToU	0	0	0	0	0								
Long Term	Dump								3	1	1	1	4	2
	ToU								1	1	0	0	0	1

According to the Figures 9 and 10, the impact of EV charging load on the regulating reserve requirement in the BaU scenario is negligible given its low EV penetration level in the market. In the Long term scenario with higher EV penetration level the EV charging load slightly increases the upward regulating reserve requirement by about 3 – 8 MW when charging takes place at peak hours under the dump charge scenario. An increment of this scale under long term scenario will not be a heavy burden on power plants which provide regulating reserves for the system. However, this implies that further increase in EV penetration level with dump charging schemes is more likely to have a notable impact on regulating reserves. Further according to Figure 5, a steeper rise of the EV charging load is present in the ToU charging scheme. Even though the impact of ToU charging scheme on total regulating reserve is not significant in BaU and Long Term scenarios discussed in this paper, it can be envisaged that the presences of a steeper ramp during the off peak period

due to ToU EV charging can potentially raise the ramping needs of the future system.

CONCLUSION AND FUTURE WORK

This paper focuses on estimating the incremental regulating reserve requirement in 10 minute time frame considering the load variability and different EV uptakes and charging regimes. Country’s Load profile has its own characteristics driven by consumption patterns and as a reason variation in 10 minute time scales do not exhibit a complete Gaussian characteristics. Therefore, the exceedance level based percentiles were used to estimate the regulating reserve needs.

Results of the EV integration scenario analysis show that the dump charging scheme has a greater impact on the regulating reserve requirement than the ToU charging scheme as it overlaps with the usual evening peak demand. EV penetration level similar to the long term scenario with dump charging can be accommodated to the system

without additional measures for regulating reserves as the increments in reserves due to EV is in the range of 3 – 8 MW. However, with further uptake in EV in the market beyond the long term scenario's projection, it is essential to place a greater attention on the regulating reserves and system ramping needs under different charging schemes.

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