Based on net real power generation, as presented [4] is;

$$\begin{cases} P_k = \sum P_m + P_{loss}^{(T_k)}, k \in T_k \cap ns \; and \; m \in T_k \cap nb \\ P_{Loss}^{(Tk)} - transaction\ loss\ of\ T_k; \end{cases} \qquad (1)$$

The power injections are translated into complex injected currents as;

$$I_i = \frac{S_i^*}{V_i^*} = \frac{P_i - jQ_i}{V_i e^{-j\theta_i}}, i \in ns \quad or \quad I_i = \frac{-S_i^*}{V_i^*} = \frac{-P_i + jQ_i}{V_i e^{-j\theta_i}}, i \in nb \qquad (2)$$

Complex branch current components imposed by individual transaction can be calculated as;

$$I_{branch(ij)}^{Tk} = y_{ij} \times \left\{ \frac{P_k - jQ_k}{V_k e^{-j\theta_k}} \left(Z_{ik} - Z_{jk} \right) + \sum_{m \in Tk \cap nb} \frac{-P_m + jQ_m}{V_m e^{-j\theta_m}} \left(Z_{im} - Z_{jm} \right) \right\} \qquad (3)$$

Real and reactive losses $P_{Loss}^{(Tk)}$ and $Q_{Loss}^{(Tk)}$ incurred by T_k can be calculated by,

$$\begin{aligned} P_{Loss}^{(Tk)} &= \sum_{ij \in nl} P_{Loss(ij)}^{(Tk)} = \sum_{ij \in nl} Re \left\{ I_{branch(ij)}^{(Tk)} \times (V_i^* - V_j^*) \right\} \\ Q_{Loss}^{(Tk)} &= \sum_{ij \in nl} Q_{Loss(ij)}^{(Tk)} = - \sum_{ij \in nl} Im \left\{ I_{branch(ij)}^{(Tk)} \times (V_i^* - V_j^*) \right\} \end{aligned} \qquad (4)$$

The real power flow components (denoted by $P_{branch(ij)}^{(Tk)}$) in branch (ij) contributed by a transaction T_k can be expressed as;

$$P_{branch(ij)}^{(Tk)} = Re \left\{ I_{branch(ij)}^{(Tk)} \times V_i^* \right\} \qquad (5)$$

Finally, the actual real power flow in branch between bus i and j can be represented in terms of transaction pairs as;

$$P_{branch(ij)} = \sum_{k=1}^{nt} P_{branch(ij)}^{(Tk)} \qquad (6)$$

The proposed usage allocation technique is applicable for all general networks.

3.0 Proposed ANN in Pool and Bilateral Trade

The structure of the proposed neural network for each power system model is discussed. The input samples for training is assembled using the daily load curve and performing load flow analysis for every hour of load demand. Similarly the target vector for the training is obtained from the Graph method [5,6]. Input data (D) for developed ANN contains independent variables such as real power generation ($P_{g1}, P_{g2}, P_{g3}, P_{g6}$ and P_{g8}), real power demand (P_4, P_5, P_7, P_9 to P_{14}), bus voltage magnitude (V_4, V_5, V_7, V_9 to V_{14}), real power for line flows (P_{line1} to $P_{line20}$and the target/output parameter, (T) contains generator contribution to all line flows which corresponds to 20 output neurons. Five simultaneous bilateral transactions are obtained by allowing five generators to transact directly with five bundled consumer groups.

The number of hidden neurons is selected through empirical to find the optimum number of neurons for a predefined minimum of mean square error and compromise with the lowest number of epochs in each training process. By considering the nonlinear characteristic of input (D) and noting that the target values are either positive or negative, the suitable transfer function to be used in the hidden layer is a tan-sigmoid function. Non linear activation functions allow the network to learn nonlinear relationships between input and output vectors. Levenberg-Marquardt algorithm has been used for training the network. After the input and target for training data is created, next step is to divide the data (D and T) up into training, validation and test subsets. In this case 14 samples (60%) of data are used for the training and 5 samples (20%) of each data for validation and testing.

The regression analysis under bilateral trade for the trained network that referred to contribution of generator at bus 2 to line flow (P_{2-4}) as shown in Figure 1.

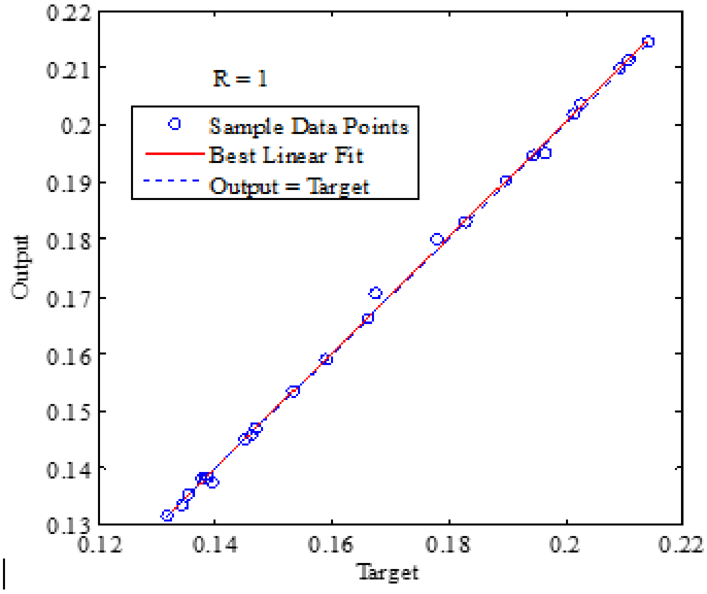

Figure 1. Regression analysis for the network output and the corresponding target under bilateral trade

4.0 Simulation Results

A number of simulations have been carried out to demonstrate the accuracy of the developed ANN. The case scenario under pool trade is that, for each hour the real and reactive power at each load is assumed to decrement by 10% from hour 1 to 24, from the nominal trained pattern. Figure 2 shows the line usage allocation result for generator located at bus 2 calculated by the ANN along with the result obtained through to Graph method for line flows $P_{6-11}, P_{6-12}, P_{9-10}, P_{9-14}, P_{10-11}, P_{12-13}$, and P_{13-14} within 24 hours.

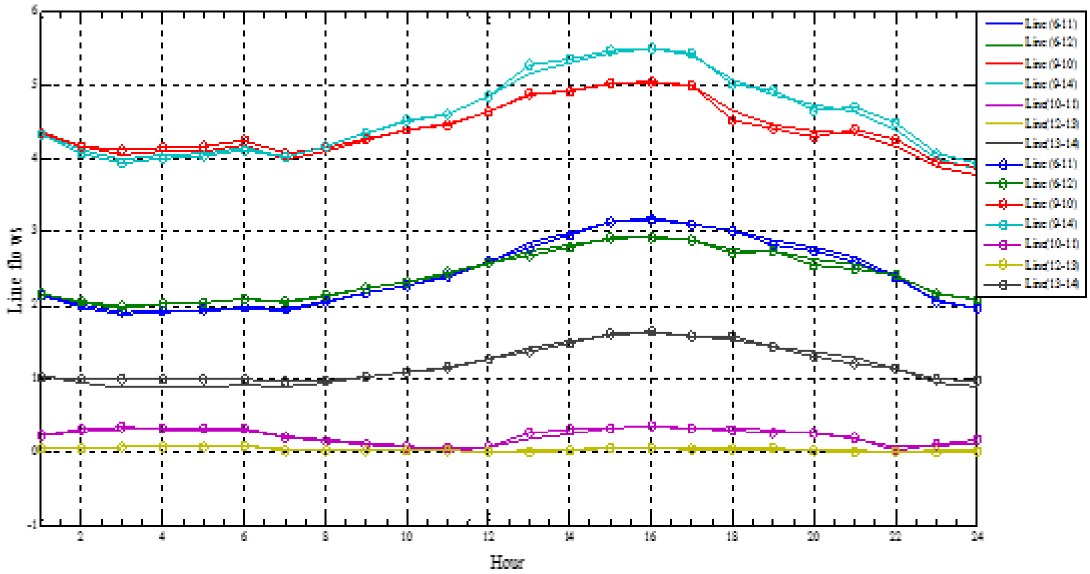

Figure 2. Line usage allocation result for generator 2 within 24 hours

Results obtained from ANN are indicated with lines having circles and the solid lines represent the output of the graph method. From Figure 2, it can be observed that the developed ANN can allocate line usage to generator involved in pool trade with very good accuracy, at almost 97%.

The modified IEEE 14-bus system on hour 9 is used which represents load demand and generation involved in bilateral trades. The final allocation of real power to line flows using proposed ANN on this hour is presented in Table 1.

Table 1: Analysis of Line Usage Allocation on Hour 9 by the ANN for the Bilateral Trade Model

Line flows From-To		Actual flow (MW)	ANN Output (Transaction Pairs) T1 (MW)	T2 (MW)	T3 (MW)	T4 (MW)	T5 (MW)	Total Flow (MW)
1	2	114.820	126.700	-7.900	-3.450	0.166	-0.260	115.200
1	5	78.871	66.200	7.917	3.707	-0.14	1.012	78.690
2	3	21.808	26.510	6.641	-11.300	0.147	-0.310	21.630
2	4	70.429	54.250	13.950	1.834	0.333	-0.220	70.140
2	5	62.234	42.550	13.380	6.057	-0.300	0.471	62.150
3	4	49.943	26.860	6.819	16.510	0.149	-0.450	49.880
4	5	-35.17	-50.000	-2.980	16.790	-2.790	3.897	-35.100
4	7	56.368	44.950	16.780	0.587	2.086	-8.330	56.070
4	9	35.682	25.780	6.285	0.341	1.183	1.931	35.520
5	6	73.076	55.740	18.13	-0.910	-3.27	3.267	72.940
6	11	24.281	5.616	-2.690	-0.580	18.41	3.394	24.150
6	12	24.926	10.790	14.060	-0.070	0.578	-0.340	25.000
6	13	48.853	40.590	7.448	-0.290	2.122	-1.030	48.83
7	8	-39.920	0	0	0	0	-39.900	-39.900
7	9	78.625	47.570	-0.110	0.620	2.301	28.300	78.680
9	10	31.751	-5.670	2.677	0.589	6.322	27.910	31.820
9	14	32.407	29.670	3.628	0.384	-2.670	1.476	32.480
10	11	0.8265	-5.580	2.669	0.572	6.279	-3.120	0.807
12	13	-0.189	10.170	-10.500	-0.070	0.520	-0.350	-0.320
13	14	11.536	14.280	-3.450	-0.360	2.579	-1.470	11.570

The total line flows from the proposed method are evaluated by summing each of decouple line flows due to transaction pairs. This result obtained by the ANN output can be compared with that obtained using other method like Circuit method.

5.0 Conclusion

Transmission usage allocation for pool and simultaneous bilateral trades based on ANN has been proposed. The developed ANN adopts line usage allocation outputs determined by each conventional method respectively as a teacher to train the neural networks. The proposed ANN based method provides the results in a faster with very good accuracy. Accordingly, the proposed method has been successfully tested and demonstrated on the modified IEEE 14-bus system.

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Review on Optimal Siting of Electric Vehicle Charging Infrastructure

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Abstract— **Concerns about the need for clean energy and the need to reduce green-house gases have led researchers and engineers to explore adoption of electric vehicle technology. Electric vehicles hold a promising future due to their efficiency, low maintenance cost and zero carbon emission. Unfortunately, due to metric range drawbacks associated with electric vehicles, large scale adoption of electric vehicles still remains relatively low. To solve this issue of range anxiety, optimal placement and sizing methods of electric vehicle infrastructure is essential. This paper presents a review of optimal siting of electric vehicle charging infrastructure. It discusses impacts of electric vehicle charging loads on the distribution network and how large scale electric vehicle penetration would affect the grid. Further, the benefits of electric vehicles on the distribution network as well as the integration of renewable energy resources are presented.**

Keywords- Electric Vehicles, Charging Infrastructure, Charging Stations, Optimal Location, renewable energy integration.

I. INTRODUCTION

With rising concerns over environmental pollution as well as diminishing oil reserves, research into electric vehicles (EVs) is becoming increasingly popular [1], [2]. EVs also have the added advantage of being easy to maintain, efficient and are cost effective in the long run [1]. Even though during the manufacturing stage of EVs, greenhouse gases are produced, their carbon footprint is much lower than (only about 40%) internal combustion engines (ICEs) [2]-[4]. These reasons make EVs an ideal and realistic alternative to ICE vehicles in the near future. As promising as EVs may seem, they have some major obstacles to overcome such as high initial cost, limited driving range and limited charging infrastructure [1], [2], [5] – [7].

Driver range anxiety is the concern the driver has about running out of power before reaching desired destination [8]. Several factors that affect the range of EVs include temperature, battery charge, terrain, travelling speed, etc. [8]. Limited driving range may likely discourage potential consumers from adopting EVs [9]. In order to tackle such problems (and many more), charging infrastructure is critical to the development and full-scale deployment of EVs. These charging infrastructure include battery charging stations and battery exchange stations.

For EVs to be a viable option, it is important to have an adequate amount of optimally distributed and sized charging stations. Given the electric or transport network of a particular area, optimal placement and sizing of electric vehicle (EV) infrastructure is a multi-objective multi-constraint problem [2]. The most common objectives are maximizing the covered demand or service coverage of EV charging stations and minimizing costs (initial investments, operating costs, maintenance costs) [2], [10]. With respect to the electric grid, significant challenges will arise as a result of increased installation of charging infrastructure. Power loss, voltage profile and system reliability are all factors that must be taken into consideration for successful planning of EV infrastructure [10]. Therefore, optimal siting of EV charge infrastructure becomes essential to the success of EV deployment.

Optimal siting of charging infrastructure has been reported in literature and various methods used [1], [2], [7] – [10]. This paper reviews some of the works previously reported on optimal siting of EV infrastructure.

II. OPTIMAL SITING OF EV CHARGING INFRASTRUCTURE

The deployment of EV Charging infrastructure is vital to the development of EVs. These charging infrastructure must contend with growing population, change in market trends and other factors that directly affect EV adoption.
The EV infrastructure location problem has been widely discussed in literature [1], [2], [8]-[20]. Optimal siting of charging infrastructure is usually a minimization of the cost, maximizing coverage of charging stations or a combination of both [2].
From the literature reviewed, optimal location of EV charging infrastructure is generally modeled by considering the transportation network, the electricity distribution network or a hybrid of both [20].

A. Optimal Siting of Charging Infrastructure Using Transportation Network Based Model

Optimal siting of charging infrastructure using transportation network can be further divided into: flow-based demand model and point-based demand model. In this approach optimal siting is focused on the transport network alone.

i. Flow-based demand model

Flow-demand models try to maximize the vehicle flows along certain paths. Flow Capturing Location Model (FCLM), Flow Capturing Refueling Model (FCRM) and Maximal Covering Location Model (MCLM) are path-based approaches for optimal placement of charging station problem. Dimitrios Efthymiou et al. [2] presented a Genetic Algorithm (GA) approach. Origin destination (OD) data from conventional vehicles was analyzed with necessary assumptions made.

A tool developed in *R* and based on the GA was used to identify optimal locations for charging stations in the city of Thessaloniki, Greece. The downside of this method is that the OD data used was from conventional ICE's and not EVs. Also the tool used was an open source program which may face certain difficulties in the face of computational complexities. In [21], Ren et al. established a location model to minimize total social cost using GA to solve the quantity and location of charging stations. The paper details grey decision-making scheme to calculate quantity and location of charging stations. Unlike earlier studies the paper considered both quantity and optimal placement of charging stations. Unfortunately, the proposed method is such that when carrying out index evaluation scoring for a site selection scheme, its result depends on the subjectivity of the expert. Barış Yıldız et al. [22] proposed an urban model for recharging infrastructure design problem (RIDP) with stochastic recharging demands, capacitated facilities and deviation tolerances. These problems were solved by formulating a two stage stochastic programming formulation. In the first stage, an efficient branch-and-cut algorithm to solve large RIDP instances was obtained. In the second stage a novel characterization for the feasible solutions of the capacitated flow capturing problem was derived.

ii. Point-based demand model

Points are nodes in transportation networks and are intersections of geographic zones. A point is modeled as a node-based facility location problem where facilities are placed at nodes based on the demand at nodes. It has the advantage of low data requirements as only the population and road network data is necessary.

Zheng & Peeta [8] studied the EV routing and optimal charging station location problems. In the optimal charging station location problem (CSLP) each OD pair was defined within a feasible range and EVs recharged a limited number of times. This was modeled as a mixed integer mixed commodity problem which involves many binary variables making it difficult to solve. The authors developed a novel algorithm based on Benders decomposition which was able to determine the exact solution. Traffic congestion was not taken into consideration which will likely be a big factor in the shortest path problem. Similarly, Brandstätter et al. [23] modeled the problem as a time-dependent integer linear program where a heuristic algorithm was developed to solve it given stochastic demand forecast. Computational studies carried out on the set of graph grid-based tests analyzed the influence of different parameters on the overall performance. The study focused on car-sharing systems for optimal CSLP. However the model assumes that the potential location for charging station is at maximum capacity (i.e. max number of charging stations) and that cars should be fully charged before a trip. For a faster convergence, Hu et al. [24] proposed a hybrid heuristic algorithm based on Genetic Algorithm (GA) and Binary Particle Swarm Optimization (BPSO) for the optimal CSLP. The model was derived by forecasting future data of EV quantities using a unique Nonlinear Autoregressive Neural Network. Results presented show that GA-BPSO converges faster and reaches better objective value than traditional GA [24]. This is because BPSO has a better random search ability which gives the GA-BPSO greater diversity, meaning it is less likely to fall into a local minimum or maximum. Through the hybridization, GA also helps with the slow convergence of the BPSO.

B. Optimal Siting of Charging Infrastructure Using Distribution Network-Based Model

To reduce the adverse effect on the power grid, optimal placement of EV charging infrastructure is necessary [20]. Some issues like voltage stability, reliability and power losses are addressed while selecting the optimal locations of EV charging infrastructure with respect to the distribution network [20]. Here only the electric distribution network is considered.

Shinde and Swarup [25] presented a locational marginal pricing-based approach to solve the charging station location problem. The location marginal pricing was calculated at different load buses and based on that optimal placement was done using a Non-Dominated Sorting Genetic Algorithm (NSGA) and Multi-Objective Particle Swarm Optimization. When compared to random placement of charging infrastructure the two optimization techniques saved charging costs [25]. In [10], Mohsenzadeh et al. presented a Genetic Algorithm solution to the EV infrastructure placing and sizing optimization problem. The problem was viewed from the perspective of the electric distribution network where changes in system reliability, power loss, voltage drop, and costs associated with the installation of EV infrastructure were considered. The EV charging infrastructure, namely parking lots, were considered as distributed generation sources due to their potential for electricity exchange. The optimal placing and sizing of parking lots include different levels of charging stations. Using the proposed method, the results show improvements in the power loss levels, voltage profile, system reliability and costs even though increase in EVs causes financial and technical challenges in the electric distribution network.

C. Optimal Siting of Charging Infrastructure Using Transportation And Distribution Networks-Based Models

A Geographic Information System (GIS) based multi-objective Particle Swarm Optimization (PSO) technique was used in [26]. PSO was applied to analyze the relationship between upfront and operating costs and service coverage of the charging stations. Taken into account were charging infrastructure influence on the loads of power grid as well as the conveniences of the charging station. Here, the GIS was used to overlay the traffic system and electric power grid together to find EV charging infrastructure sites. Wang et al. [27] presented a traffic constrained multi-objective planning of EV charging stations using a novel method. The IEEE 33 bus radial network representing the model electric distribution network and a 25 node road network were superimposed together. Similarly, the authors in [28]-[31] all presented optimal allocation of charging stations using a superimposed distribution and road network. They all either used IEEE's test network or real electric grid in a locality to model the distribution network.

III. IMPACT OF EV CHARGING STATION LOADS ON THE ELECTRIC DISTRIBUTION NETWORK

In the future it is expected that there will be high penetration of EVs due to the concerted effort by governments around the world to reduce greenhouse gases (GHGs) [17]. The transportation sector plays a key role here as it is the second highest contributor to GHGs [17]. The increase in number of EVs, while solving some challenges, pose a whole new set of problems especially as it concerns the electric power grid. An increase in EV charging station loads will lead to rise in peak demand, power loss, voltage instability, transformer life reduction and power quality problems (due to harmonics, voltage sag and unbalance) [32] – [50].

In addition, EV charging effects on the electric grid depend on the state of charge (SOC) and capacity of the battery, load profiles of existing feeders and charging modes of the EV. This makes operation and planning of electric grid more complex with the rise in EV penetration [5]. The EV charging parameters are usually modeled using stochastic methods to capture the uncertainties.

A. Voltage Instability

Voltage instability may cause very low voltage in an electric grid as a result of excess power demand by the loads, which is beyond the grid's capability. A stable electric distribution network is essential for steady and reliable power supply. Power outages may be caused as a result of voltage instability due to excessive power demand. EVs have nonlinear load characteristics and may draw large amounts of current in a short amount of time [17]. Studies have shown that different load profiles of EVs have an effect on the voltage stability [17], [32], [33]. This makes studying the effects that EVs have on voltage stability ever more important. Several methods have been suggested to tackle the issue of instability [34], [35]. Rajakaruna et al. [34] proposed a voltage control method via tap transformer to reduce instability. Mitra et al. [35] proposed a wide area control method to dampen out the oscillations in EVs while charging and discharging to mitigate voltage stability.

B. Increase in Peak Demand:

An increase in EV penetration may lead to a corresponding increase in the grid peak demand if there is uncontrolled charging [36], [37]. In [36] McCarthy et al. determined that a substantial amount of EV loads must be shifted to off-peak hours for demand to be stable assuming generation is not increased. The problem of increase in peak demand can be resolved without necessarily increasing generation by using smart charging and time of use (TOU) tariff plan [38], [39].

C. Harmonics:

The nonlinear nature of EVs leads to high frequency components of voltage and current which are integer multiples of a reference frequency. These high frequency components are undesirable and are known as harmonics [17]. Harmonics has many negative effects, these include [17], [40]:

i. Distortion of component waveforms leading to poor power quality.
ii. It can cause stress in distribution network equipment (e.g. cables and fuses).
iii. Can lead to current flow in neutral wire.

The total amount of voltage or current harmonics can be expressed as total voltage harmonics distortion (THD_v) and total current harmonics distortion (THD_i), given in (1) and (2).

$$THD_v = \frac{\sqrt{\sum_{h=2}^{H} V_h^2}}{V_1} \times 100\% \qquad (1)$$

$$THD_i = \frac{\sqrt{\sum_{h=2}^{H} I_h^2}}{I_1} \times 100\% \qquad (2)$$

Where, H is the highest harmonic number, h is the harmonic order number, V_h is the RMS voltage, I_h is the RMS current, V_1 is the RMS value of the fundamental frequency voltage, I_1 is the RMS value of the fundamental frequency current.

Boynuegri et al. [41] proposed various operating modes to eliminate power quality problem in a smart grid-compatible system. The results showed a significant improvement in voltage quality and a reduction in the total harmonic distortion.

D. Voltage Unbalance

Voltage unbalance or voltage imbalance is a power quality problem that only affects three-phase systems. Voltage unbalance happens when the magnitudes of the line or phase voltages are different, the phase angles are different (from a balanced system) or both [42]. Voltage unbalance is caused by unequal loads in the distribution lines. IEEE defines voltage unbalance as the phase voltage unbalance rate (PVUR) given in (3).

$$\%PVUR = \frac{max\,voltage\ deviation\ from\ avg.line\ voltage}{avg.phase\ voltage} \times 100\% \qquad (3)$$

However the true definition of voltage unbalance (VU) is given as the ratio of negative sequence voltage component (V-) to the positive sequence voltage component (V+) shown in (4).

$$VU = \frac{V_-}{V_+} \times 100\% \qquad (4)$$

Shahnia et al. [43] showed tl [illegible] jor impact at the end of the feeder. Li et al. [44] also showed that with more than 50% EV penetration voltage starts to reduce at the end of the feeder. They also suggested a smart charging plan to mitigate the effect of voltage unbalance [44].

E. *Voltage Sag:*

Voltage sag or voltage dip is a reduction in the RMS voltage value for a short duration (half a cycle to one minute) of time caused by starting of electrical machines, overload and short circuit. Tie et al. [45] and Lee et al. [46] showed the effect of EV penetration on voltage sag limit. Tie et al. [45] showed that up to 60% EV penetration can be achieved if proper charge control strategies are used. Without any charge control strategies, only 10% EV penetration would be acceptable without exceeding the voltage sag limit.

F. *Power Loss*

Power loss is the loss of electrical power supply. Large EV penetration into the electric grid can cause huge power losses. Power loss (P_{LOSS}) in a distribution network feeder is given in (5).

$$P_{LOSS} = \sum_n^N I^2 R_n \qquad (5)$$

Where N is the total number of feeders in a system, I is the current and R_n is the resistance across feeder n. The extra power loss (P_{LE}) caused by EVs can be mathematically expressed as given in (6).

$$P_{LE} = P_{LEV} - P_{LO} \qquad (6)$$

Where P_{LEV} is the total power lost when EVs are connected to the electric grid and P_{LO} is the total power lost when the EVs are not connected to the electric grid. Fernandez et al. [47] showed that power loss to the electric grid could be as high as 40% if 60% of the EVs in UK were connected at the same time. Without coordinated charging schemes the loss could grow even more.

G. *Overloading of Transformers*

Overloading of transformers occur when its voltage or current ratings have been exceeded. Transformer overloading causes excess heat which affects the insulation of the transformer leading to reduction of transformer life [48]. Although in areas with low ambient temperature, studies show transformer loading has little effect on its aging [48].

Integration of EVs to the electric grid may increase overloading of transformers. Therefore, proper transformer selection, network planning and load management are necessary to mitigate the negative effects of EVs. Some smart metering schemes have been suggested to increase transformer lifespan [49], [50].

IV. BENEFITS OF ELECTRIC VEHICLES ON THE ELECTRIC DISTRIBUTION NETWORK

A. *Vehicle-to-Grid (V2G) Technology*

V2G is a service where EVs can provide power back to the electric grid. Power flow can either be unidirectional or bidirectional. For bidirectional power flow extra equipment are needed to supply power to the grid from the EV as well as other protection issues related to grid connections. This technology can increase reliability and potentially reduce peak demand when necessary [51]. EV users can gain financially from the V2G technology by selling some of their stored power to the grid. Arita et al. [52] and Sasaki et al. [54] showed the impact of V2G in limiting voltage fluctuations and improving power quality in the electric grid. In related studies [54]-[56], the authors noted that the V2G technology can provide voltage support to minimize the use of voltage regulators, reduce distribution line loss and voltage drop. Constant charging and discharging can have adverse negative effects on the battery life. It is therefore important that intelligent charging systems are employed to reduce this effect [51].

Prasomthong et al. [57] presented optimal placement of V2G enabled charging station in a radial distribution network and considered the net benefit of the V2G model. Khalkhali et al. [58] proposed an optimal placement method for a V2G enabled charging station in electric grid. The results showed an improvement in the voltage profile and reduction in active power loss.

B. Smart Grid

Smart Grid technology incorporates communications with decision making to make the electric grid 'intelligent'. This technology paves the way for many solutions to the problems of EV integration into the electric grid. Reliable power supply, advanced control methods, better integration of renewable energy resources, V2G and coordinated charging schemes are all advantages of smart grids.

V. INTEGRATION OF EV CHARGING INFRASTRUCTURE WITH RENEWABLE ENERGY RESOURCES

Integration of EVs and renewable energy is a promising area due to the need to add distributed generation to reduce excess stress on the electric grid. Parking lots, rooftops, public buildings are all potential sites for either Photovoltaic (PV) panel or wind turbine placement. EVs parked under these structures can conveniently charge using these sources while EV users carry out other activities. Though, there are other forms of renewable energy resources, this work focuses on wind and solar PV.

A. Wind Energy

A number of studies present the impact that EVs have on the electric grids integration with wind energy. Fernandez et al. [47] showed that V2G technology can increase the penetration of wind energy by up to 59%. Similarly, Turton et al. [59] derived a model that forecasts impact of integration of EVs with a V2G enabled grid. Their findings show that there is increased renewable energy capacity as a result of the EVs storage and discharge capability in the V2G scheme. Borba et al. [60] modeled the electric grid in a 20-year span and assumed a huge increase in wind energy generation. The exact size of the hybrid EVs that could be powered by the excess wind energy was then calculated. They estimated that 1.6 million cars will be able to be powered during the optimal seasonal conditions (from January to June). Bellekom et al. in [61] studied the combined and separate effect of EVs and wind energy. The study showed that 4 GW of wind energy can be added without EV penetration, and 10GW with 1 million EVs. Ekman et al. [62] discussed the relationship between energy produced and consumed, and EV charging load patterns. EVs with smart charging capabilities were shown to reduce excess wind generation and could decrease the backup capacity required. All these studies show that EVs are likely to play a big role in increasing the wind energy penetration by capturing energy that would have been wasted.

B. Solar Photovoltaic

EVs and solar PV integration has been widely discussed in literature [63]-[66]. Dallinger and Wietschel [63] considered both solar PV and wind energy with 50% capacity by 2030 in Germany. The results show that EVs can absorb about 50% of excess solar PV and wind energy yearly. The author in [64] proposed installing solar panels on parking lot rooftops. Using New Jersey as a case study, their findings showed that during summer, given the solar irradiation, module efficiency and parking space, most driving needs would be met. This was not the same case for winter where average energy production dropped drastically. The paper however did not mention the economic viability of such systems. Gibson et al. in [65] and Zhang et al. in [67] discussed the feasibility of EV battery charging using solar PV. Using on-site generated energy, many losses associated with electric grid were avoided. These losses include, transmission losses and DC-to-AC conversion losses. The study proves the viability of the method. The authors in [67] proposed a method in which solar PV is integrated with EVs and heat pumps in Japan. Their finding showed that with a 30GW solar capacity installed, that would take the overall production excess to about 10 TWh annually. 5 million EVs and heat pump would absorb all the excess energy. Only about 30% of excess energy would be absorbed if 1 million EVs and heat pumps were added to the grid. These studies show that integration of solar energy with EVs would assist in capturing excess energy.

VI. CONCLUSION

This paper presents a general overview of EV charging infrastructure and impacts of EV on the distribution grid. Low emission and high efficiency among others are considered as some of the major benefits of EVs. Despite these benefits, driver anxiety, costs, increase in demand of EVs and by extension new technical challenges to the electric distribution networks are some of the major impacts. For this reason it is important for EV charging infrastructure to be optimally placed and sized. Optimal siting based on the transport network, distribution network or a combination of both were discussed. Then, the impact of EV charging loads on the electric grid were discussed with various papers proposing solutions to the challenge. The benefits of EVs to the grid were presented, notably V2G technology was one of the major benefit that could be derived from this method. It is still clear that V2G technology is an area for future studies as it makes EVs an asset as opposed to just an ordinary load. Finally, the integration of solar PV and wind energy has huge potentials for EVs to absorb excess energy. The integration of these renewable energy resources also helps lift some of the burden from the electric grid.

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Nigerian Power Grid: Model development, validation and standardization for R&D

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Abstract

The Nigerian power grid is characterized by uncertainties ranging from unbalanced load to generation rationing, radial topology, voltage instability, and incessant grid collapse. These uncertainties and their causes require rigorous and time-consuming investigative studies. To adequately studied any phenomena of interest in power systems, due to the complex and physical nature of power systems interconnection and associated control equipment, software-based model development and validation approach are paramount, particularly for research and development (R & D). A significant task in the power system's model development is the validation of the developed models with the actual field measurement. In this paper, some selected publications on the models of the Nigerian power grid were reviewed, and are found to be inconsistent in terms of number of buses modelled, load, and generation profile. Also, the models are often not benchmarked for either static or dynamic simulation studies. Therefore, this paper draws the attention of the various stakeholders in the Nigerian power sector, to as a matter of urgency pay attention to the accurate model development, validation, and benchmarking of the Nigerian power grid for R & D; recommendations were equally proffered in the conclusion section.

Introduction

Due to the improvements in technology and the need for sustainable power delivery, modern power systems have evolved from the conventional and centralised controlled grid structures to a highly interconnected networks. The transition presents new challenges in terms of accurate models of either: the technological change in generating technologies, load growth pattern and models used in simulation studies, and on the other hand the use of Flexible Alternating Current Transmission Systems (FACTS) devices to achieve highly complex and precision control. Furthermore, structural change in power systems operations through the microgrid operations or Islanding operation have made power systems modelling a critical task. The modern power systems, therefore, witness drastic transformation in terms of technology improvement, sophistication and dynamism of power electronics converters, smart grid as well as distributed generation penetration mainly due to support schemes for renewable "———[1][4]. The large size, dimensionality, and risk level involved in physical power grid infrastructure, the prerogative of the unbundled companies (GenCos, TransCos and DisCos) on various aspects of their planning and operations constitute the factors in planning and operations of power grid [5]. Moreover, technology-based solutions such as FACTS control operations often within the transmission network adds to the factors responsible for power grid sectioning in planning and operation studies. The key to adequate planning, operations, the reliable, and economic performance of large power systems rely to a great extent on the integrity, readiness, availability, and access to the power systems' data in all form. The data of the different power grid component enables the development of computer-based models. Hence, computer-based models of power grids are adopted for research and development. The geographical terrain, poor policies, and lack of information management systems make the data acquisition and in extension model development and validation of the Nigerian power grid almost impossible. Long transmission paths, radial grid nature, loose interconnection, and uneven generation to load profiles produce poor power quality, dynamic interactions/oscillations, and many systems collapse far below recommended best practices ———[6][9].

Power systems simulation studies can be classified into two major categories: steady-state (static) and dynamic simulations. The static simulation also referred to power flow or load flow analysis involves the computation of the power systems equilibrium, assuming constant parameter. The simulation assumes a snapshot thereby neglecting the dynamism of faults and other components used for control operation. On the other hand, dynamic system simulation is the computation of power systems response over time; it covers different time scales and is genrally time consuming compared to static simulation [10]. The various simulation studies performed in power systems can be grouped as either static or dynamic simulation and depicted in Figure 1.

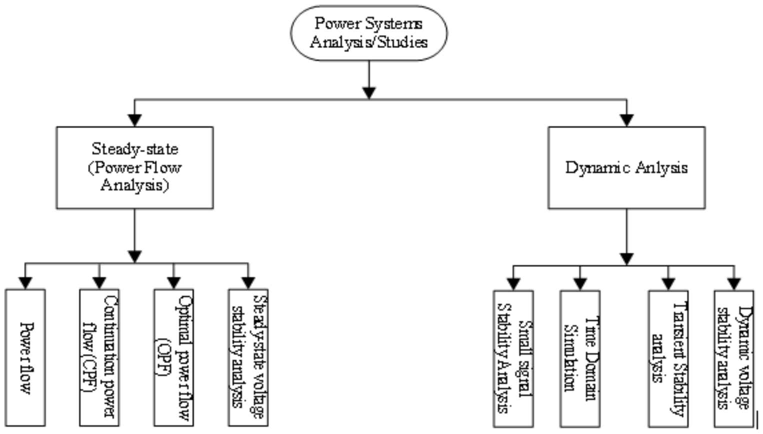


Figure 1: Power systems analysis classification

The major work in power grid modelling and simulation lies in the models' ability to adequately capture the phenomena of interest, either in a steady-state or dynamic state. The foundation of power grids analysis is often hidden in assumptions and methods as well as in model improvement that has resulted from years of experiences and cleverness. In power grid models, there is often a need to strike a balance between techniques and models mixed with power engineering on the one hand and the sophistication of power grids' control system which requires extensive theories on the other hand. The middle ground ensures that theoretically, sound engineering solution models are achieved [11]. All power grid studies (operating limits, planning studies for assessment of new generation and load growth, performance assessments of protection schemes) depend on the mathematical model representations of the various power grids' components: generation, transmission, and load.

However, from the various literature ——[12][16], researchers use significantly different models of the Nigerian 330 kV power grid. Moreover, evidence of the comparison of the performance of these models against actual measured power system data is yet to be reported. As the power grid expands as well as the occurrences of observed phenomena, there is the need for routine model validation such that the model represents significant observed phenomena on the power grid [17]. The techniques for the analysis of power systems have been transformed drastically by the superior computing abilities of the digital world. Various commercial and open sourced research-based software tools are available for the analysis and validation of multiple power systems models [18], [19].

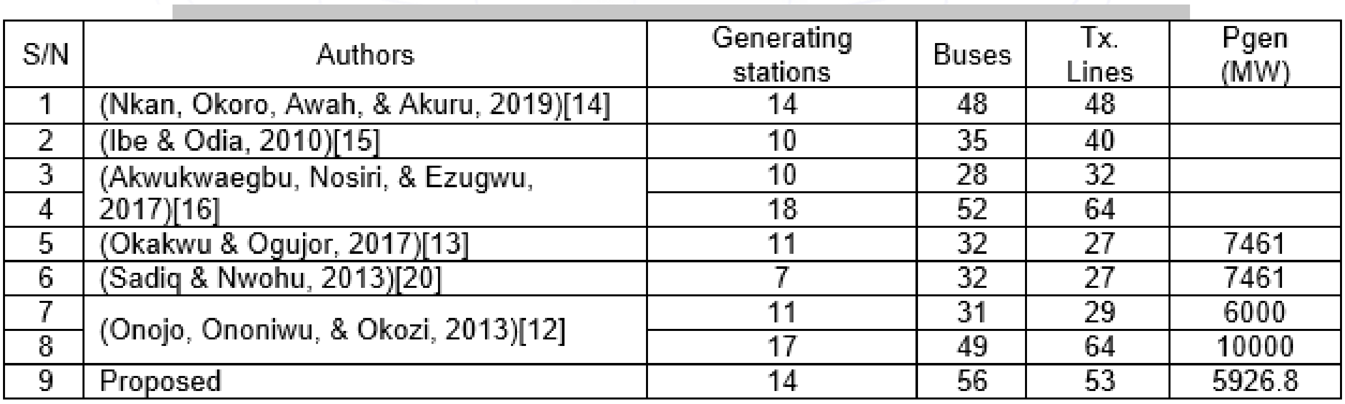
This paper draws the attention of the various stakeholders (in the Nigerian power sector) to the importance of modelling, validation and benchmarking of the Nigerian power grid at a different level for research and development (R&D); thereby ensuring grid security, reliability, quality of supply, safety and economical operation.

Related works on Nigerian power grid models

The Nigerian power grid is majorly a mix of hydro and gas-fired (thermal) generation plant. According to the statistics of the model in [9], the Nigerian grid consists of 5, 523.8km of 330 kV transmission lines and thirty-two (32) 330/132kV substations with installed transformation capacity totalling 7, 688 MVA (which amount to 6, 534.8 MW). The average available capacity on 330/132kV is 7, 364MVA that is about 95.8% of installed capacity. The transmission voltages are 132 kV and 330 kV while 33 kV and 11 kV are nominal distribution voltages.

Statistically, the reviewed literature ———[14][16], [20] claimed to have obtained the network parameters from official sources, yet the models differ considerably as summarized by Table 1. The critical question, however, is how accurate are the data and the genuineness of these data to represent the actual parameters of the network?

Table 1: A tabular summary of different models of the Nigeria 330kV power grid



S/N	Authors	Generating stations	Buses	Tx. Lines	Pgen (MW)
1	(Nkan, Okoro, Awah, & Akuru, 2019)[14]	14	48	48	
2	(Ibe & Odia, 2010)[15]	10	35	40	
3	(Akwukwaegbu, Nosiri, & Ezugwu, 2017)[16]	10	28	32	
4		18	52	64	
5	(Okakwu & Ogujor, 2017)[13]	11	32	27	7461
6	(Sadiq & Nwohu, 2013)[20]	7	32	27	7461
7	(Onojo, Ononiwu, & Okozi, 2013)[12]	11	31	29	6000
8		17	49	64	10000
9	Proposed	14	56	53	5926.8

Generally for large interconnections (like the Nigerian power grid), to study some phenomena of interest, researchers often use reduced model as against the complete detailed mode. The justification for adopting the reduced models include: (i) the necessity of comprehensive models of the far-off section eases with the increase of the electrical distance from the event to be studied; (ii) practical restrictions of the model environment and those of computational resources; (iii) the guidelines and policy on information sharing amongst areas (of large interconnections) owned by different utilities; and (iv) limited resources (such as PMUs) deployed to monitor the system for the purpose of validation [21], [22]. Consequently, those parts of the interconnections remotely located and sufficiently distant from the event of interest are often represented using reduced-size models known as "equivalents".

Similar to power systems analysis, techniques for obtaining reduced model equivalents are broadly divided into static and dyanamic; the choice of either model is based on the phenomena of interest. Some of the model reduction techniques for static analysis includes: Dimo's (REI) method, Kron reduction, Ward reduction, and Zhukov's method [21], [22].

To study the various events which affects the performance of the Nigerian grid, and the radial topology of the grid characterized by long transmission lines (electrical distance of some portions of the grid) as well as limited measurement resources, reduced equivalent models of the grid for different events are important. At present, there exist no equivalent model of the Nigerian grid which provide adequate and comprehensive model, (of the electrical network, power generation, and other control equipment) for at least static studies. In [23], only a portion of the Nigerian grid was used as case study, however, the other sections of the grid were not adequately represented. Hence there is the need for several of such equivalent models validated and benchmarked for R&D. In the reduced equivalent model, the portion of interest are retained while the external areas, buses and portion are represented by an equivalent as depicted in Figure 2.

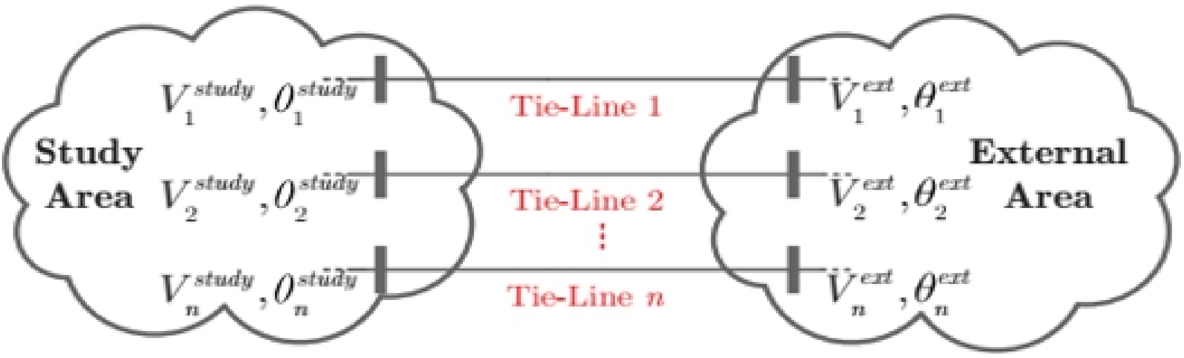


Figure 2: Power system schematic showing study area and external area, for reduction (Source:[24])

Model Development

Power systems' model development and validation form the foundation of all power systems studies. The approach to the development of entire power systems model is such that generators, transformers, loads and other associated components' models are individually obtained. The components' models rely majorly on physical and operational description and the data from the inherent characteristics of each component. Furthermore, the extent of components model representation depends on the phenomena of interest, which classified the model as either in steady-state (power flow) or dynamic simulation. Following the August 14, 2003 blackout in the north-eastern United States and eastern Canada, the recommendation by the U.S. Canada Power System Outage Task Force and NERC, identifies model validation and benchmarking to replicate the system's condition. The validated model permits rigorous investigative studies on the causes of the outage as well as mitigation measure; which resulted to several months of work to develop the power flow model used to study the outage [17].

Generally, steady-state models of the transmission section represent only the positive sequence quantities (in addition to negative and zero sequence for unbalanced short circuit studies), while remote parts of a large interconnections can be represented using the equivalent reduced-size models. The formulation of the model equation of an m-bus power systems network is considered as a set of nonlinear equations [25] given by equation (1).

$$\begin{aligned} \dot{x} &= f(x, y) \\ 0 &= g(x, y) \end{aligned} \qquad (1)$$

Where $y(y \in \square^m)$ are the algebraic variables, voltage amplitudes V and phases θ at the network buses and all other algebraic variables such as generator field voltages, AVR reference voltages, etc. $x(x \in \square^n)$ are the state variables, $g(g \in \square^m)$ are the algebraic equations and $f(f \in \square^m)$ are the differential equations.

In the traditional formulation of the steady-state AC power flow model, the power balance equation is considered under real and reactive components expressed in equations (2) and (3), expressed as functions of the voltage angles θ and magnitudes ${}_mV$ and generator injections ${}_gP$ and ${}_gQ$, where the load injections are assumed constant. The solution of the steady-state or power flow model of the equation (1) involves solving for the set of voltages and flows in a network corresponding to a specified pattern of load and generation [19].

$$g_P(\theta,V_m,P_g) = P_{bus}(\theta,V_m) + P_d - C_g P_g = 0 \quad (2)$$

$$g_Q(\theta,V_m,Q_g) = Q_{bus}(\theta,V_m) + Q_d - C_g Q_g = 0 \quad (3)$$

For each active component, the dynamics of the components need adequate representation. For stability studies, the phenomena of interest usually are time constants dependents and range from a few tens of milliseconds to many seconds. Therefore, the dynamic models denote the performance of power plants and their controls, certain components of loads, power electronic transmission devices (i.e., FACTS and HVDC), and, for some studies, on-load tap changers, PLC controls on shunt devices, remedial action schemes, and other similar control devices. Each component in the steady-state model needs to be matched with their corresponding dynamics models.

As a typical example, Figure 3 depicts the steady-state model of Nigerian 330 kV network for static studies such as load flow, continuation power flow and optimal power flow; which neglects the dynamics of the generator and its associated component —[20].

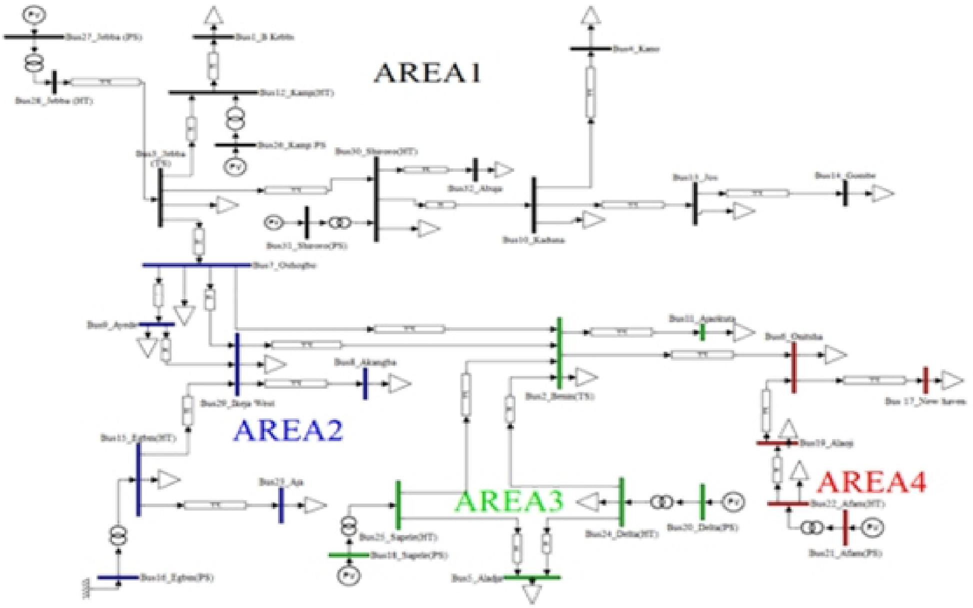


Figure 3: Steady-state model of Nigerian 330 kV power grid (Source: —[20])

For dynamic studies, each of the active components' nonlinearity and dynamic models of the generator, AVR, turbine governors and all other circuit dynamics are modelled as depicted in Figure 4.

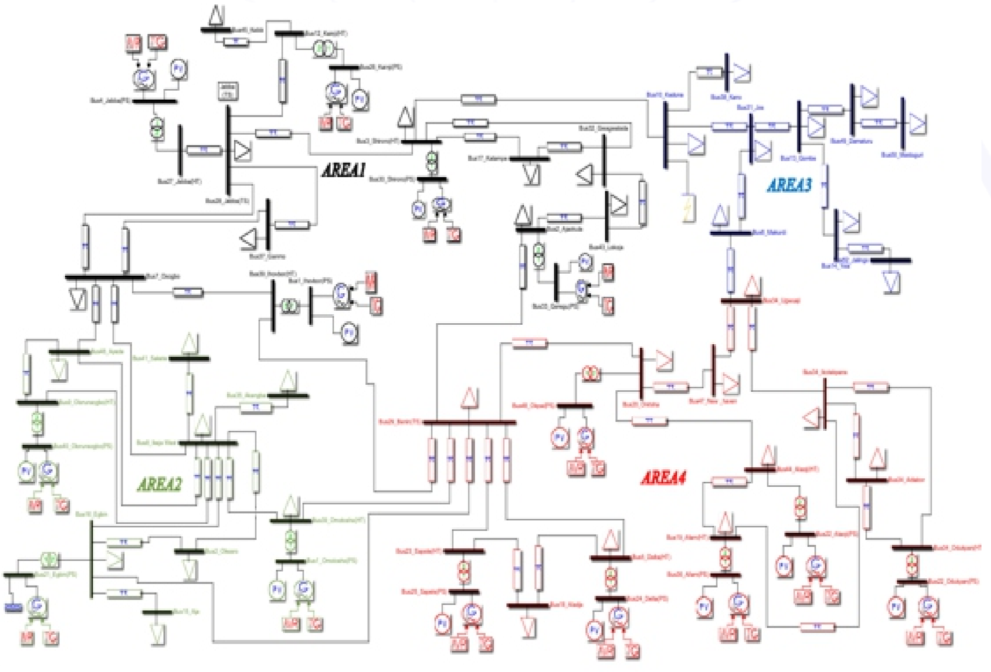


Figure 4: A modified dynamic model of Nigerian 330 kV power grid

Model Validation

The accuracy of each model depends on the extent of validation through comparison with actual field measurement. Periodic model validation is required to ensure its accuracy, keep up to date with the changes, provide a means of planning and expansion, as well as for research and development. The analysis of disturbances present opportunities for model validation as well as identification of improvements necessary in the existing model; hence, power grid planning and operating decisions are obtained from approximate results from the simulation.

The simulations of power systems depend on the adequacy of the model to predict the performance of the grid during phenomena of interest. Therefore, the accuracy and integrity of dynamic components model, as well as their corresponding data, must be up to date. For reliable and economic operations of power systems, realistic models are necessary, which is neither optimistic or pessimistic. Power systems performance prediction requires that all aspects of the performance of the system are model correctly. The power systems performance model requires an understanding of the system's behaviours and the assumptions made during model development. Complete system behaviour is obtained from observations, measurement and analysis, which allows for model validation [17]. A typical need for the Nigerian power grid model development and validation is the incessant power grid collapse —[26][28]. The frequency of the grid collapse reported in ——[26], [28][31] is far below the grid reliability requirement. In the first quarter of 2019, four (4) grid collapses occurred [31]. It is worthy of note here that simulation studies are yet to be conducted on the causes and the necessary mitigation measures of the incessant grid collapse.

A typical illustration of the importance of model development and validation is the 1996 western interconnection outages. Initial attempt to reproduce the event in simulation did not match the actual observation and recordings as depicted in Figure 5.

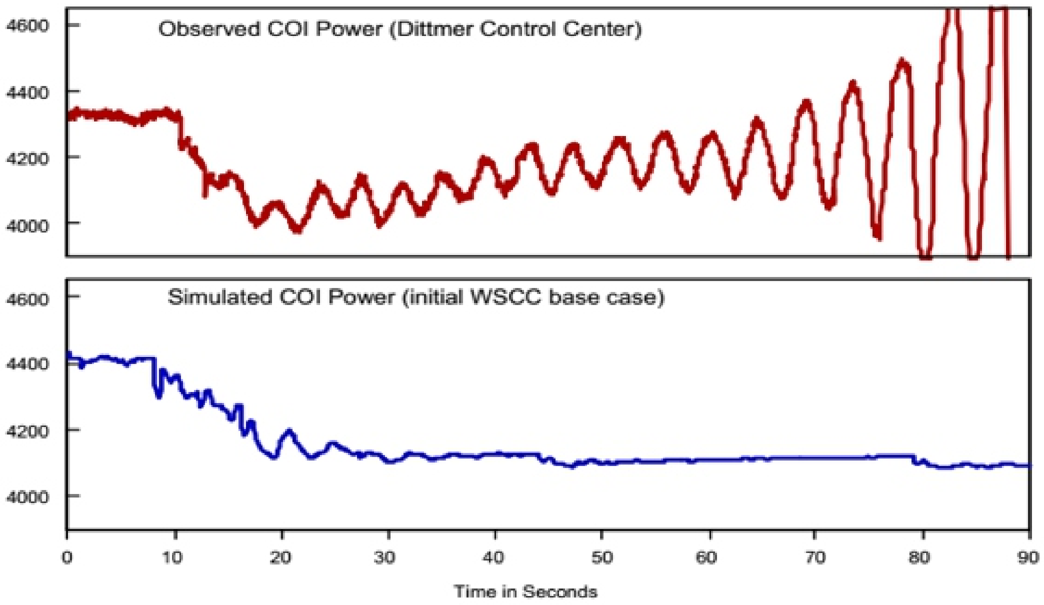


Figure 5: Comparison of observed and simulation results from 1996 WSCC outage (Source: [17])

To effectively implements and simulate different components and the entire power systems model, various software tools/packages are have been developed. The software tools are categorized as either commercial such as NEPLAN, PSCAD, and PSS/E or open sourced such as EMTP, ETAP, MATPOWER, Power World Simulator (PWS), PSAT, and PST. Each of these has been deployed for power systems model implementation, simulations, and validation. The choice of any of the software tools depends on the needs of the events to be studied, availability and adequacy of various component models and the capacity in terms of the maximum number of buses that each software can handle.

Generally, a model of interest that needs validation are Operational cases, Planning cases, Models for the components that make up the cases, and data constants associated with the component models. Power system model validation is carried out both at the component model or system-wide model validation. Figure 6 depicts a flow chart for a typical system-wide model validation process.

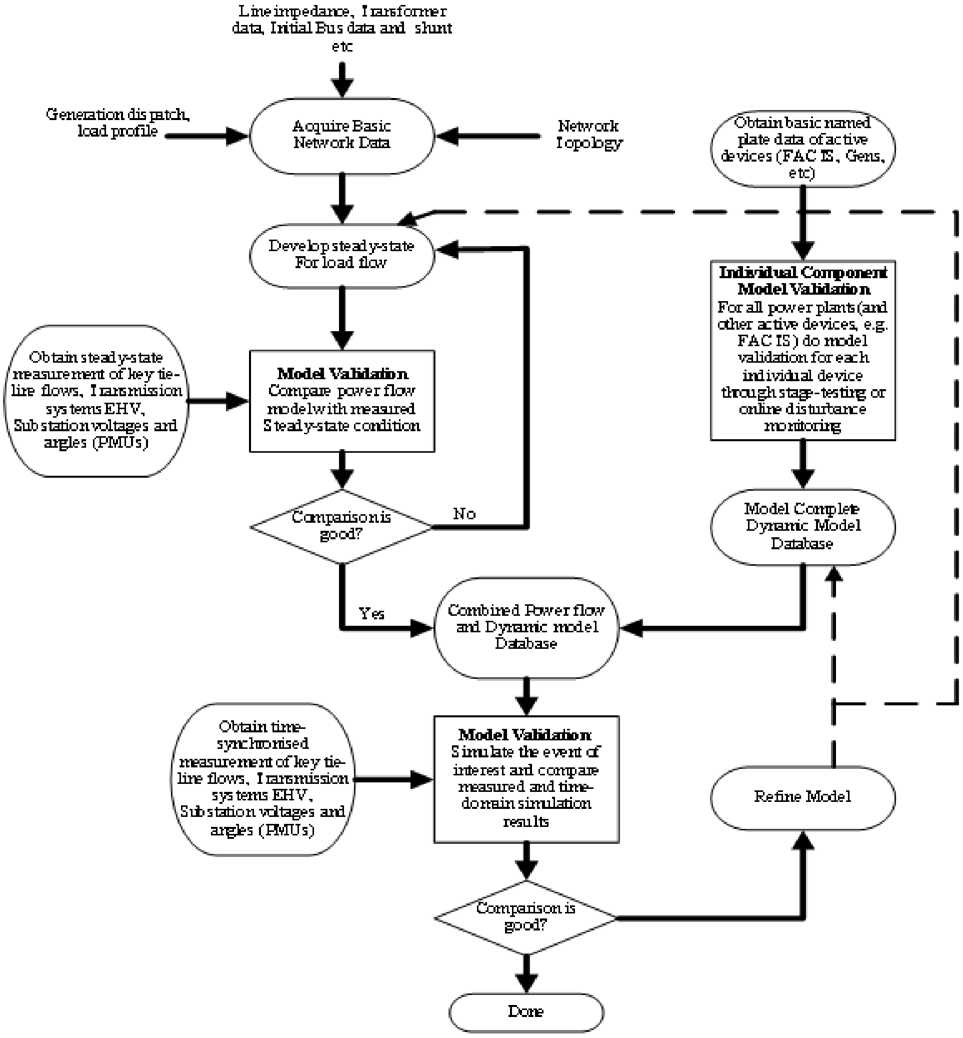


Figure 6: Model development and Validation Process (Source: [17])

Standardization

Depending on the phenomena of interest or the events that need to be studied, parts of large interconnections remote from locations of interest have often represented an equivalent. Therefore, for R&D, and in addition to the events being studied, different system-wide models of the Nigerian power grid is required for both power flow and dynamic studies. For instance, to study various grid collapses caused by generation or line outages in the Nigeria grid, an equivalent system-wide model is required, and upon successful completion, the developed model needs to be benchmarked for future similar events or against new mitigation technologies or methods.

Dynamic simulation of a modified Nigerian grid system

The dynamic model of Figure 4, was simulated under three-phase to ground severe fault at 40 s. The fault simulation is at Kaduna bus 1, throughout 200 ms. Upon clearing the fault, the post-contingencies performance of the dynamic model under voltage profile, generator rotor angle, and frequency responses were examined with and without FACTS devices, particularly SSSC and STATCOM [32]. Figures 7 to 9 depict the voltage profile, all generator rotor angles, and frequency responses under the simulated faults with and without FACTS devices.

As depicted in Figure 7, the voltage profile of the dynamic model under the said fault improves significantly with the FACTS devices. Also, Figure 8 shows that the behaviour of all the generators nose-dived from the start of the simulation without fault; however, with the introduction of SSSC and STATCOM, the system response was normalized.