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Deep learning based active loss estimation in power grid with N-1 reactive support contingencies

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ABSTRACT

The efficient and optimal operation of power systems is critically dependent on accurate estimation and reduction of network losses. Traditional techniques such as Gauss-Seidel (GS) and Newton-Raphson (NR) are widely used to compute power system operating conditions and associated power losses. However, these methods are inherently iterative and computationally intensive, which limits their suitability for real-time applications in modern power system operations. In practical power systems, contingencies such as the tripping of generators, synchronous condensers, or capacitor banks can significantly affect the reactive power balance of the system which in turn affect the voltage profile of the grid. This paper presents a data-driven approach for real-time estimation of active power losses under different reactive power support contingency scenarios. An Artificial Neural Network (ANN) model is developed and benchmarked against other regression-based methods. The ANN model demonstrates superior performance in terms of accuracy and generalization under all operating scenarios. The proposed ANN estimator is implemented using Python libraries in conjunction with the Panda Power simulation environment. The effectiveness of the proposed approach is validated using the IEEE 14-bus test system. Simulation results demonstrate that proposed ANN-based loss estimator provides superior prediction accuracy, faster response and better generalization capability as compared to traditional methods, making it a promising and robust tool in predicting power system losses.

Keywords: Artificial intelligence; power system; active power loss

INTRODUCTION

Active power loss, usually measured in megawatts (MWs), is a crucial aspect of any electrical power system. All real-world power systems operating under various conditions have unavoidable losses. These are categorized as technical and non-technical losses of the system(Ibrahim et al. 2017). The technical losses in the power system depend on its inherent characteristics of the power network(Aoun et al. 2024). These losses can be attributed to copper loss in the windings and iron losses in the core and other parts of the machine. Iron losses are further categorized into hysteresis and eddy current losses (da Silva et al. 2024). Hysteresis loss occurs because of the alignment of magnetic domains inside the ferromagnetic core. Eddy current losses occur owing to circulating currents in the equipment core (Zhao et al. 2021). Both eddy current and hysteresis losses are frequency dependent, whereas copper losses are load dependent (Lu et al. 2018).

Copper losses in transformers, motors, and transmission lines account for a major portion of the technical losses in power systems (Kothari & Nagrath, 2008). These losses vary with the system operating conditions owing to the variation in the connected load, which follows a specific operating profile during the year. A healthy voltage profile must be maintained across the network to serve the connected load (Shakerighadi et al. 2019). Therefore, it is also important to consider the operating conditions of the network from the perspective of the reactive sources connected to the system. Reactive sources together create a reactive power pool in the system, and their ON/OFF status can significantly affect the system losses owing to variations in the system voltage profile(Pati & Choudhury 2023). These sources mainly include synchronous

generators, synchronous motors, and shunt capacitor banks. Transmission lines can generate or absorb reactive power depending on the loading condition compared to Surge Impedance Loading (SIL) (Lubośny et al. 2015). Generally, transmission lines operate under heavily loaded conditions and are therefore not considered as sources of reactive power in this study.

A significant amount of active power loss occurs in the transmission lines due to the resistance and high current through the long transmission channel. This power loss is represented by Equation (1). Figure 1 shows a transmission line section connected between the sending and receiving ends of the buses.

$$P_{line\ loss} = 3*(I_{line})^2 \times R_{line} \quad (1)$$

Where,
I_{line} = line current (A),
R_{line} = resistance per phase (Ohms)

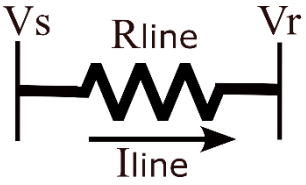


FIGURE 1. Transmission line in power system

Cumulative loss in the transmission system can be calculated using Equation (2).

$$P_T = \sum_{i=1}^{n} (P_{line\ loss})_i \quad (2)$$

Where,

$P_{line\ loss}$ = active loss in transmission line (MW)
P_T = total active loss in the system (MW)

The estimation of power loss has been an important research topic, and many analytical methods have been proposed, developed, and tested. These include the Gauss–Siedel (GS), Newton–Raphson (NR), decoupled load flow (DLF), and fast decoupled load flow (FDLF) (Akram & Ann, 2015; Hussain et al. 2024; Stott & Alsac 1974). These conventional methods are iterative and computationally inefficient for the real-time loss estimation of power networks (Bonini Neto et al. 2025; Teng, 2002). Power system always operates under varying conditions owing to load variations. In extreme cases, power systems may face a contingency situation due to unexpected or unplanned loss of a single component of the system (Pandžić et al. 2024). This may include tripping of transmission lines, generators, large shunt capacitors banks or reactor banks and heavy loads. Traditional methods become less effective for large and complex systems. This condition is referred as the N-1 contingency situation. Their findings concluded that data-driven methods are becoming essential for real-time loss estimation and smart grid applications, especially in systems with high uncertainty and renewable integration (Makanju et al. 2024). The dynamics of the power system change significantly when power system is subjected to the occurrence of any of the aforementioned contingencies (Khattak et al. 2022). This situation causes noticeable variations in the active power loss of the network, as the current is redistributed through the remaining network in parallel branches(Badrudeen et al. 2024).

Technological developments have increased the use of modern tools for estimating the power losses. With the recent development of artificial intelligence (AI) based tools such as machine learning (ML) and deep learning (DL) techniques, researchers have suggested different approaches for estimating power system losses (Amole et al. 2025; Khattak et al. 2022). Artificial neural networks (ANN) are tools that show promising progress in identifying complex patterns and making predictions for both regression and classification problems (Bre et al. 2018; Khashei & Bijari, 2010).

Neural Networks are inspired by the operation of human brain (Theotokis, 2025). The human brain is composed of several billion neurons interconnected through complex neural pathways. These pathways are used for communication between the neurons (Basheer & Hajmeer, 2000). The training of ANNs involves tuning several hyper-parameters, such as the number of neurons, activation functions, optimizers, and the number of hidden layers (Seidi et al. 2025). The ANN model requires significant times for model training. However, once trained, they provide instantaneous output at a given input (Abiodun et al. 2018). Figure 2 shows a simplified structure of a generic ANN.

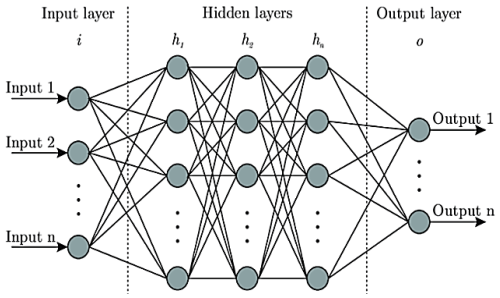


FIGURE 2. ANN architecture (Bre et al. 2018)

In earlier research, ANN based loss estimation model was implemented by (Sidhu & Ao 1995). The active and

reactive powers of the generators and loads, as well as the voltage magnitudes and angles at each bus, were used as ANN training parameters. The system loss was considered as the target.

TABLE 1. Summary of power system loss estimation using AI techniques

No.	Reference	Technique	Bus System Used	All Q-Source contingencies considered
1	(Rejc & Pantos, 2011)	Fuzzy logic	Slovenian grid	X
4	(Tulensalo et al. 2020)	LSTM	Finland grid	X
3	(Neto et al. 2023)	ANN	IEEE 14 and 30	X
4	(Shaikh et al. 2023)	ANN	IEEE 14	X
5	(da Silva et al. 2024)	Multilayer perceptron	IEEE 14, 30 and 57	X
6	(Liu et al. 2024)	ANN	IEEE 14, 30, 57, 118	X
7	(Pandžić et al. 2024)	ANN	Croatian grid	X
8	(Shaikh, Noor, et al. 2025)	FFNN and LSTM	IEEE 14	X

They displayed promising predictions using an ANN with three hidden layers. A similar study was also presented by (Ata & Gunay, 1998). They prepared an appropriate dataset using load-flow studies by operating the generators and connecting load between the maximum and minimum limits. For topological variations, they did not consider any reactive support contingency except for two randomly selected transmission lines. With the acquired dataset, an appropriate shallow ANN model was trained and tested in comparison with the actual load flow results.

Fuzzy theory provides an efficient relationship between inaccurate and unreliable data points, hence enabling calculations to be executed when accurate data are not available(Aleksić, 2024). The results show that the effective use of limited data is possible for loss estimation using the fuzzy theory. In another paper, (Dashtaki & Haghifam, 2013) argued that owing to the lack of metering equipment in the network, a proper database is not available to calculate the system's technical losses through load flow analysis. To overcome this, they proposed a method of categorizing the same equipment, such as feeders, into a single category. Then, the fraction of data of a single feeder can be applied to the same general category for further estimation. This clustering method estimates the losses of a low-voltage network with error margins of less than 10%.

The issues with different methods for obtaining a system's total technical losses such as load flow analysis, energy balance approaches, feeder segmentation, reference feeder models, and measurement-based estimation methods were highlighted in (Ibrahim et al. 2017). These issues include the unavailability of load data at each point, the inability to install meters at many locations in complex networks, and the different characteristics of same-category equipment. They addressed this

issue by establishing a reference feeder (RF) based on the peak demand. By establishing these RFs, they showed that the total system loss could be estimated

monthly with appreciable precision. In a recent paper(Shaikh, Uddin, et al. 2025), the authors

used Australian feeder profile to generate load patterns in IEEE 14 bus system, depicting a more realistic approach. They prepared a dataset spanning over 5 years span using NR load flow. They also incorporated topological variations of the network such as synchronous motors and shunt capacitor bank tripping. They did not consider the tripping of synchronous generators which is a primary source of reactive support in the system. This is one of the major limitations found in the article. Different AI models were developed and compared. The results show that the ANN model outperformed other regression models in estimating the active loss of power system. Table 1 provides a summary of the latest research on estimating active loss using AI methods.

Considering the research summary, it is evident that there is a need to develop a loss estimator that can accurately and robustly predict system loss under various operating scenarios of the power system. The proposed estimator estimates the power system loss under normal and all reactive support contingency conditions except for the slack bus generator using an efficient ANN model. This study paper also presents a performance comparison of deeply structured ANN with other regression models such as the K-neighbors regressor, gradient bosting regressor, light gradient boosting machine, AdaBoost regression, ridge regression and shallow ANN in estimating the power system active loss.

The remaining sections of the paper describe the methodology adopted for developing the loss estimator,

dataset preparation, model training, and performance evaluation of the proposed model in comparison with other models.

METHODOLOGY

POWER SYSTEM MODELING

In this study, the IEEE 14 bus system from the Pandapower library is used. It comprises of a slack bus, one synchronous generator at bus 2, fifteen transmission lines, five transformers and synchronous condensers at bus 3,6 and 8, 11 load buses, a shunt capacitor bank at bus 9. Figure 3 shows the entire single line diagram (SLD) of the IEEE 14 bus test system used in this study.

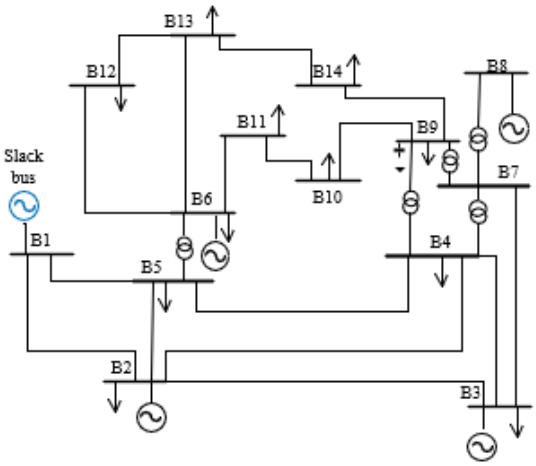


FIGURE 3. IEEE 14 bus system

DATASET PREPARATION

The effectiveness of the desired AI model depends heavily on the availability of high-quality datasets. Any type of biased data can lead to unfair model development and fail to achieve generalization. In the literature, two approaches have been used to prepare datasets. One approach is to use real-time logged data, or simulated data through any software. Because of the unavailability of real-time data, the method used in this research is based on simulations that are carried out using the Panda Power tool for power system load flow.

Load flow analysis using the NR algorithm has been iterated for different operating scenarios using scenario generator with considering the normal base case and contingency conditions comprising all reactive power generation sources in the network. Three-year load profiles for each bus of the system have been synthesized and used for each operating topology condition of the system. Normal operating scenario of the system is marked as topology number 0, synchronous generator tripping at Bus 2 is provided identity as topology number 1, similarly other operating topologies with tripping of synchronous motors and shunt capacitor banks are also provided with unique identity.

The total number of samples generated through this process is expressed by Equation (3).

$$Ns = Nt \times Ny \times Hy \tag{3}$$

Where;
Ns = Total number of samples
Nt = Number of operating topologies
Ny = Number of years
Hy = Number of hours in a year

MODEL TRAINING

Model training is crucial for designing an active loss estimator. The dataset is normalized and pre-processed, which includes the addition of 1% Gaussian Noise to the metered data. This is done to mimic real-world operations by including the metering and communication channel errors in the obtained data. For model development, the dataset was split into training, testing, and validation subsets in the ratio of 70%-15%-15% respectively.

Different strategies are available for tuning an AI model such as random search, grid search and hit and trial methods. In this experiment, grid search algorithm has been implemented to determine the best ANN model. This algorithm works by attempting all possible permutations in the given ranges of hyperparameters. These hyperparameters include hidden layers, the number of neurons in hidden layers, activation functions, epochs, optimizers, learning rates, batch sizes, and weight initialization strategies to ensure both accuracy and generalization. It is programmed to save the performance parameters of the best model that can achieve the lowest training and validation losses on the given dataset. After generating multiple candidate models through the grid search process, their performance is evaluated based on different evaluation parameters, including the R2 score and Mean Squared Error (MSE).

An ANN model with an R2 score close to 1 and a Mean Squared Error (MSE) close to zero is selected for the final implementation to ensure high predictive accuracy. To further validate the chosen model, its learning curves and convergence behavior is analyzed, confirming stable training without overfitting. The entire methodology,

including dataset preparation and model training, is illustrated in Figure 4.

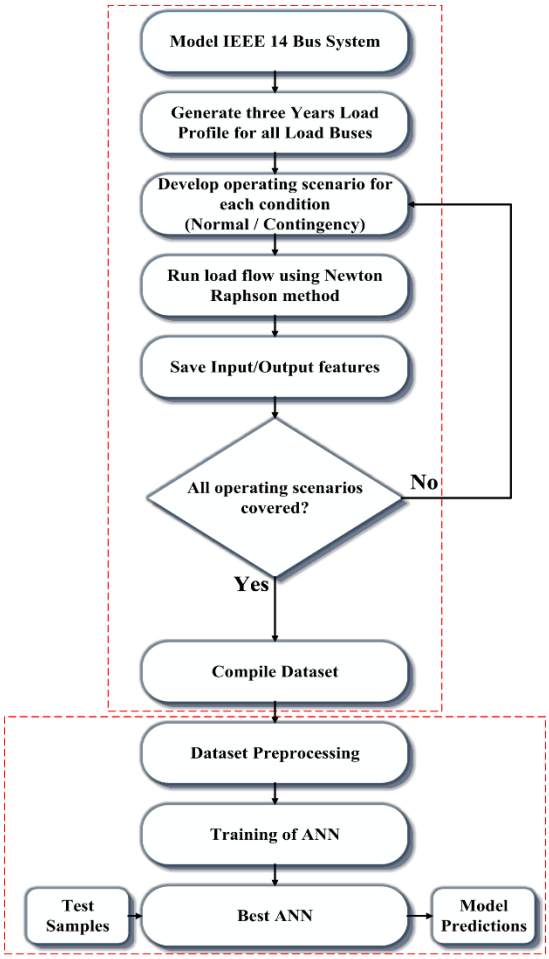


FIGURE 4. Working methodology

It is evident from the figure that the scenario generator plays a vital role in developing all operating scenarios of the test system. Only converged load flow cases are used for the dataset preparation. After obtaining the best ANN model, random operating scenarios have been provided as test samples to evaluate the model performance.

EXPERIMENTAL RESULTS

LOAD PROFILE GENERATION

To create the dataset, the normalized hourly load profile of the Australian feeder in p. u. (Willingham, 2024) is used. A scaled version of the normalized profile is used to synthesize the PQ load profile for each bus in the network for the dataset development. The normalized load profile for one year in p. u. is shown in Figure 5. The used profile span over three variations and helps in obtaining better variations and helps in obtaining better generalization of the AI model obtaining better generalization of the AI model.

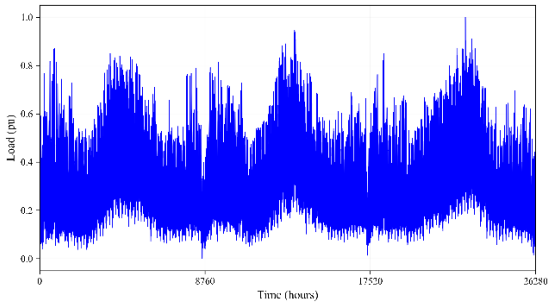


FIGURE 5. Normalized load profile

DATASET DEVELOPMENT

Load flow simulations have been performed for generations of the dataset. The dataset comprises of 23 input features with active and reactive loading values at 11 load buses in the IEEE 14 bus network and 6 different operating topologies represented by integer numbers (0 to 5). The output is set as the total active loss of the power system ($P_{SYS\text{-}LOSS}$). The details of the inputs and outputs of the dataset are presented in Table 2. Features have been selected because they have direct impact on the power system loss. Active and reactive loads cause variation in the system voltages, affecting the active loss in the power system. Topological variations are also crucial to include and power system can face contingency situation due to any malfunction or uncontrolled event. Topology representation details are as follows:

Topology 0: Normal operating condition
Topology 1: Generator at bus 2 tripped
Topology 2: Condenser at bus 3 tripped
Topology 3: Condenser at bus 6 tripped
Topology 4 Condenser at bus 8 tripped
Topology 5: Shunt capacitor bank at bus 9 tripped

The dataset comprised $3 \times 8760 \times 6 = 157716$ samples. A large dataset enables the ANN model to achieve generalization. After several hours of training, the optimum ANN model obtained by hyper-parameter tuning has a deep structure represented as i/p-256-192-128-64-32-o/p. Rectified Linear Unit (ReLU) and linear combiner activation functions were used for the hidden and output layers, respectively. The best ANN model achieved an MSE of 0.00007 and an R2 score of 0.9999. The learning curve of best model on training data as well as on the validation data i s shown in Figure 6.

TABLE 2. Input output features details

Domain	Input Output Features	Features Count
Dataset Output	$P_{SYS\text{-}LOSS}$	1
Dataset Inputs	P_{LOADS}: P_{L1}, $P_{L2,}$ …P_{L11}	11
	Q_{LOADS}: Q_{L1}, Q_{L2}, …QL_{11}	11
	Topology number (0-5)	1

TABLE 3. ANN's predictions on random test samples

Test Data Sample Index	Actual Value P Loss (MW)	Computational time using LF (ms)	Predicted Value P Loss (MW)	Computational time using ANN (ms)
141128	1.09536	55.11	1.09535	6.95
31221	1.77855	54.87	1.77747	7.00
84136	2.09419	53.09	2.09384	8.19
88060	1.95603	52.13	1.95673	6.04
12104	2.06683	53.98	2.06691	7.18
147588	7.05869	52.85	7.05859	5.60
66000	2.75938	54.83	2.75995	5.49

TABLE 4. Performance of different regression models

Model	Mean Squared Error (MSE)	Mean Absolute Error (MAE)	R2 Score
K Neighbours Regressor	0.0002	0.0006	0.9999
Gradient Boosting Regressor	0.001	0.0221	0.9996
Light Gradient Boosting Machine	0.0042	0.0107	0.9983
AdaBoost Regressor	0.1397	0.3148	0.9444
Ridge Regression	0.3655	0.4471	0.8546
Shallow ANN	0.000146	0.003	0.9999

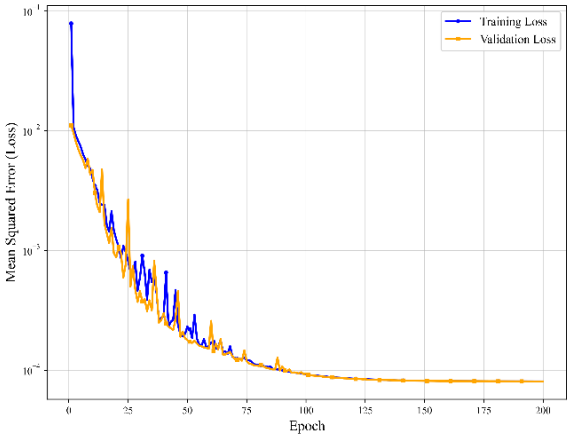


FIGURE 6. Model loss pattern

Randomly selected 7 test samples were provided as test inputs to the best ANN model, and the predictions are presented in Table 3. It is evident from the predictions that the predictions of the ANN model are close to the actual values obtained from load flow analysis, indicating that the ANN model captured the patterns of input data and adjusted itself for precise predictions of system loss as output.

COMPARISON WITH OTHER MODELS

To further test the performance of the developed ANN-based loss estimator, several other regression models, such as the K-neighbors regressor, gradient boosting regressor, light gradient boosting machine, Adaboost regression, and ridge regression, have tested, and the performance of the five best performers among all the regressors is shown in Table 4. The performance comparison of various regression models highlights notable differences in predictive accuracy. Among them, the Artificial Neural Network (ANN) deep structured model outperformed the others with the lowest Mean Squared Error of 0.00007 and a high R^2 score of 0.9999, indicating exceptional predictive capability and minimal deviation from actual values. Overall, the ANN model sets the benchmark in this evaluation, followed closely by the K-Neighbors and Gradient Boosting Regressors.

CONCLUSION

In this study, an active loss estimator for a power system is successfully developed using an ANN under reactive support-contingency conditions in the power system. We found that the performance of the deep structured ANN based loss estimator in predicting the active losses of transmission systems on the IEEE 14 bus system was superior to that of other regression models. Our proposed model successfully eliminates the need for a separate loss estimator in the case of topology variations owing to power system contingencies. This research clearly demonstrates the potential of AI tools, especially ANNs, in learning complex trends from large datasets. Our further research will be directed toward including other possible contingencies in the network, along with testing on larger power networks, to address the scalability of the proposed model.

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DECLARATION OF COMPETING INTEREST

None.

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