

A Hybrid Approach for Enhancing Line Parameter Estimation in Power Systems

Markos Asprou and Christos G. Panayiotou
KIOS Research and Innovation Center of Excellence and
Department of Electrical and Computer Engineering
University of Cyprus
Nicosia, Cyprus
Email: {asprou.markos, christosp}@ucy.ac.cy

Andreas Stavrou
Transmission System Owner
Electricity Authority of Cyprus
Nicosia, Cyprus
Email: astavrou@eac.com.cy

Abstract—Accurate modeling of power systems is crucial for various control center applications. One of the key components in a power system model is the transmission lines. The line model includes parameters such as series impedance and shunt admittance, which are typically assumed to be time-invariant. However, these parameters vary based on the ambient and operating conditions of the system. Therefore, it is essential for the different monitoring and protection applications of the power system to have an accurate visualization of the line parameter variance throughout the day. In this context, this paper develops a hybrid line parameter estimation scheme that makes use of the available Phasor Measurement Unit (PMUs) measurements and Neural Network (NN) estimations to calculate the series line parameters of the transmission lines. The developed scheme was tested in the IEEE 14-bus system under realistic ambient and operating conditions, showcasing its practical applicability and enhanced accuracy.

Keywords—Neural network, parameter estimation, phasor measurement units, transmission lines.

I. INTRODUCTION

Power systems are operated in their limits today due to the ever-increasing electricity demand and the high penetration of renewable energy resources. In this volatile environment, power system operators aim to maintain the power system operation within the operational limits for avoiding disturbances that could lead in brownouts or even blackouts. In this attempt, monitoring and protection tools either in the control centre or in the field should fulfill all the functional requirements (i.e., accuracy, time responsiveness, reliability) for enabling the operator to mitigate any contingencies timely and effectively [1].

Many of these tools rely heavily in the model of the power system. In particular, monitoring tools such as the state estimation and power flow consider the connectivity of the system, the generation and demand status, and the line parameters of the network (i.e., resistance and reactance) [2]. The distance protection relays consider the line parameters of the transmission line for identifying a fault within their protection zones [3]. Further, contingency analysis performed in the control center for identifying any imminent contingency according to the current operation and the short-term forecasts also relies on a detailed power system model including transmission line parameters and power network configuration. It is therefore of paramount importance to

model accurately the power system network considering variable operating and ambient conditions.

Although, the operating conditions of the power system in these applications can be updated and represented fairly accurate through the measurements received in the control center, the power system model and especially the parameters that characterize the transmission lines are considered time invariant [2]. Usually, the transmission lines are represented as a pi-model including series and shunt lumped parameters. These parameters are calculated based on the structure of the transmission line, the conductor medium, the phase configuration and the manufacturer data sheet [3]. Once the line parameters are calculated, they remain unchanged in the power system model except if a line is upgraded or its structure changes significantly.

In reality, the parameters of the transmission lines are affected by environmental factors (i.e., temperature and soil resistivity) [4] or modeling inaccuracies (parallel lines coupling). Further, due to the connection of two different types of lines (e.g., overhead line connected with an underground cable for a few meters) it may be difficult to know the exact values of transmission line parameters. Human factor could be also a possible cause for outdated transmission line parameter databases since several changes in the network configuration might not be reported correctly in the control center or transmission line length could be inaccurately calculated. Some case studies report that the error between the actual and the stored values of the line parameters can be up to 30% [5]. Such a considerable error can degrade the accuracy of the monitoring applications that run in the control center, limiting the situational awareness of the power system operators. Furthermore, errors in the line parameters can also affect the reliability of the distance protection schemes since the line parameters are used as settings in the relays. In essence, the error in the stored line parameters and ignoring their time variability could compromise the integrity of the transmission grid.

Several works in the literature deal with the detection of parameters of certain lines that are erroneous. Such methods are usually involve the estimation problem in the loop, while the identification procedure of the erroneous parameters is usually based on the “largest normalized residuals” test that is calculated using the Weighted Least Squares (WLS) state estimator results [6]. The use of Lagrangian multipliers for identifying lines with erroneous parameters is proposed in [7] while, PMUs are strategically deployed in [8] for enabling the accurate identification of erroneous parameters in critical k-tuple parameters. Such type of methodologies ignores the time variability of the line parameters throughout the day due to environmental conditions, while they also consider that only a portion of the line parameters mismatch with the parameters

This work is supported in part by the Republic of Cyprus and the Cyprus Research and Innovation Foundation under grant agreement ENTERPRISES/ENERGY/1123/15 (GridEye), through the European Union's NextGenerationEU initiative and the Recovery and Resilience Plan of Cyprus (Cyprus - Tomorrow); in part by the European Union's Horizon Europe Research and Innovation Programme under grant agreement No 101172819 (CABLEGNOSIS); and in part by the European Union's Horizon 2020 research and innovation programme under grant agreement No 739551 (KIOS CoE - TEAMING) and from the Republic of Cyprus through the Deputy Ministry of Research, Innovation and Digital Policy.

of the power system model. Further, due to the consideration of time invariance, the methodologies used measurements from multiple time instances while, their accuracy depends on the measurement redundancy of the power system [9].

After identifying the erroneous branches, their incorrect parameters should be estimated to update the database with accurate values. In [10], the transmission line parameters are determined using only SCADA measurements. This work discusses critical issues that impact the calculation of line parameters, such as corona loss, line unbalance, and measurement error. The calculation of frequency-dependent transmission line parameters for use in electromechanical simulations is proposed in [11].

A more precise calculation of the transmission line parameters can be achieved by using synchronized current and voltage phasor measurements provided by PMUs. However, this approach necessitates installing PMUs at both ends of a transmission line [12]. Although the deployment of PMUs is increased in the last years due to their unique characteristics that offer to the monitoring, protection and control of power systems, not all the lines are monitored by two PMUs. Consequently, a methodology requiring only one PMU at one end of the line and voltage and current magnitude measurements at the other end is proposed in [13]. In [14], a methodology that combines identification and estimation of the erroneous line parameters in lines that are monitored by one PMU is proposed. In all the methods, the parameters are considered constant, ignoring their variability due to the temperature and other environmental conditions.

The high reporting rate of the PMUs and the GPS time stamped voltage and current phasor measurements can contribute to monitor the time and seasonal variance of the line parameters. The periodic information about the line parameters variance can help the operators update the power system model, enhancing the accuracy of several model-based applications that are hosted to the control center and can also change periodically the relay settings dedicated for line protection. Ideally, for having an accurate representation of the line parameter variance, the transmission lines should be monitored by two PMUs (one at each line end), however this is not the case for most of the power systems.

In the recent years there is an increased tendency in applying machine learning based techniques in power system applications. Neural Networks (NN) find application in estimating power system dynamics [15] such as frequency fluctuations and state estimation [16]. In this paper, NN is used to provide PMU related quantities for transmission lines that are not monitored by PMUs. Time stamped PMU measurements from the one end of the transmission lines are used as input to the trained NN, while voltage and current phasor measurements are provided by the NN in the PMU unobservable end of the line. PMU and NN-based measurements are then used for calculating the transmission line parameter in consecutive time intervals throughout the day, capturing the variations of the line parameters due to the temperature and other environmental and loading conditions.

In this context, the contribution of this paper is the development of an effective hybrid approach for estimating the transmission line parameter variations in cases that the lines are not observed by two PMUs. The approach has been applied to realistic conditions with variable line parameters in the IEEE-14 bus system, showing its effectiveness and

accuracy in estimating the daily variation of the parameters in lines that are observed by PMUs only at the one end.

II. HYBRID APPROACH FOR TRANSMISSION LINE PARAMETERS ESTIMATION

Transmission lines are typically represented using an equivalent pi model in most power system control center applications, such as state estimators, power flow analysis, and transient stability analysis. This model, depicted in Fig. 1, is characterized by four parameters: series conductance (g_{sr}), series susceptance (b_{sr}), shunt conductance (g_{sh}), and shunt susceptance (b_{sh}). It should be noted that the shunt conductance is negligible and is usually omitted from the pi model. With synchronized current and voltage phasors available from both ends of the line via PMUs, the series admittance y_{sr} , which includes both the series conductance and susceptance and the shunt admittance y_{sh} can be calculated as,

$$y_{sr} = \frac{\tilde{I}_s \tilde{V}_r + \tilde{I}_r \tilde{V}_s}{\tilde{V}_s^2 + \tilde{V}_r^2} \quad (1)$$

$$y_{sh} = \frac{\tilde{I}_s - \tilde{I}_r}{\tilde{V}_s + \tilde{V}_r} \quad (2)$$

where \tilde{V}_s and \tilde{V}_r are the voltage phasors of buses s and r respectively while \tilde{I}_s is the current phasor that flows from bus s and \tilde{I}_r is the current phasor that arrives to bus r as shown in Fig. 1.

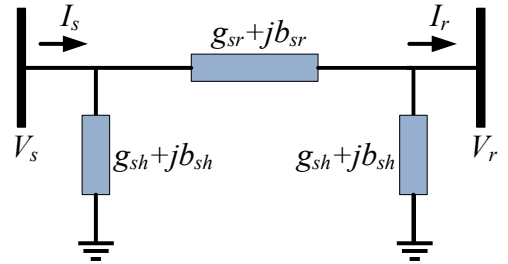


Fig. 1: Transmission line pi-model

Through the series admittance, the series impedance be calculated as,

$$\tilde{Z}_{sr} = \frac{1}{y_{sr}} = R_{sr} + jX_{sr} \quad (3)$$

where R_{sr} and X_{sr} are the series resistance and reactance of the transmission line. Further the magnitude of the impedance, which is important setting in the distance protection relays can be obtained as,

$$|\tilde{Z}_{sr}| = \sqrt{R_{sr}^2 + X_{sr}^2} \quad (4)$$

In the case that the transmission lines are monitored by only one PMU, the measurements from the other end of the line are not available and consequently the line parameters cannot be calculated. In this work, a hybrid approach is used that considers the PMU measurements from the one end of the line while NN-based estimated measurements are used from the other end of the line. The concept of the proposed approach is shown in Fig. 2.

In the proposed concept, the PMU reports the measurements to the control center where a Phasor Data Concentrator (PDC) collects the measurements from all the PMUs of the system. The PMU measurements with the same time stamp are aligned together to create a set of

measurements with the same time stamp. In the proposed hybrid approach the PMU measurements from the one end of the transmission line are extracted from the PDC to be used as input to the trained NN, which provides the voltage and current phasors for the other end of the transmission line.

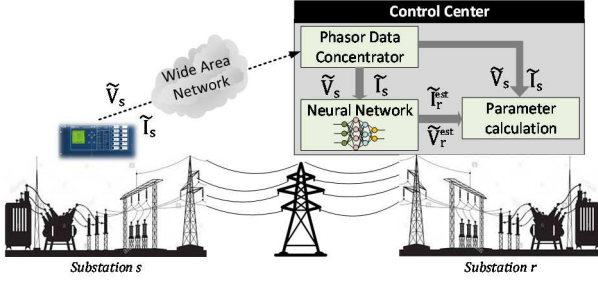


Fig. 2: Concept of the hybrid approach for parameter estimation

The NN is trained for each PMU in the system, considering as input the voltage phasor measurement of the PMU bus (bus that the PMU is installed) as well as all the current phasor measurements that flow through the transmission lines connected to the PMU bus and their other end is not observed by a PMU.

In order to better explain the proposed hybrid approach for parameter estimation, the IEEE 14 bus system shown in Fig. 3 is assumed that is fully observable by 3 PMUs installed at buses 2, 6, and 9 [17]. Without loss of generality, the PMUs have enough channels to measure all the current phasors flowing from the transmission lines that are connected to the PMU bus. Although a linear state estimation can be executed in such PMU configuration and estimate all the states of the system, the states will be estimated according to the model of the power system using the time invariant parameters of the power system model. In this sense, any variations of the line parameters due to the environmental and loading conditions are not reflected to the estimated states.

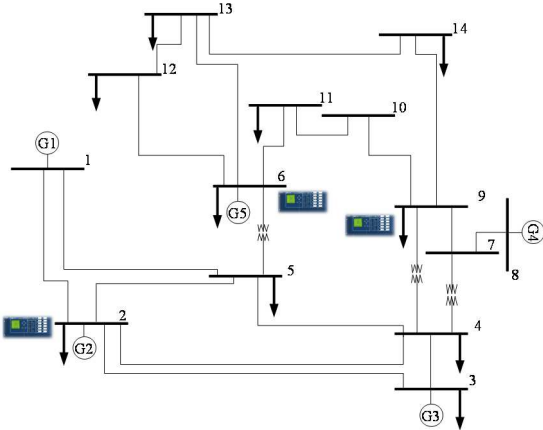


Fig. 3: IEEE 14 bus system with 3 installed PMUs

In the case of the proposed hybrid approach for parameter estimation, three NNs (one for each PMU) are going to be trained for the lines that their one end is monitored by PMUs. The general function showing input-output relation of the NN that is dedicated for the PMU bus i is,

$$\mathbf{y}_i = f(\mathbf{x}_i; \mathbf{v}_i) \quad (5)$$

where, \mathbf{x}_i is the vector containing the PMU measurements of the i^{th} PMU (voltage and current phasor measurements), \mathbf{v}_i are the parameters of the NN as obtained by the training

process of NN (using as input the measurements from the i^{th} PMU bus), and \mathbf{y}_i is the estimated voltage and current phasor measurements for the other end of the line that is unobservable by a PMU.

For instance, considering the case of PMU at bus 6, three transmission lines are connected to the PMU bus that connect buses 11, 12, and 13 to bus 6. For all the three lines, only the quantities from the one end are measured namely the voltage phasor of bus 6 and the current phasors flowing through transmission lines (6-11, 6-12, and 6-13). Consequently, the inputs for the NN assigned to bus 6 will be,

$$\mathbf{x}_6 = [V_6 \ \theta_6 \ I_{6-11} \ a_{6-11} \ I_{6-12} \ a_{6-12} \ I_{6-13} \ a_{6-13}] \quad (6)$$

where V and θ is the voltage magnitude and voltage angle of the PMU bus, while I and a are the current magnitude and angle of the currents flowing through the lines connected to the PMU bus. The output of the NN in bus 6 is formulated as,

$$\mathbf{y}_6 = [V_{est} \ \theta_{est} \ I_{est} \ a_{est}] \quad (7)$$

where V_{est} and θ_{est} are the vectors containing the estimated voltage magnitudes and angles respectively of the buses that are connected to bus 6 (PMU bus) and are formulated as,

$$\mathbf{V}_{est} = [V_{11} \ V_{12} \ V_{13}]; \ \theta_{est} = [\theta_{11} \ \theta_{12} \ \theta_{13}] \quad (8)$$

while I_{est} and a_{est} are the vectors containing the currents at the unobservable end of the lines connected to the PMU bus 6 and are formulated as,

$$\begin{aligned} \mathbf{I}_{est} &= [I_{6-11} \ I_{6-12} \ I_{6-13}]; \\ \mathbf{a}_{est} &= [\theta_{6-11} \ \theta_{6-12} \ \theta_{6-13}] \end{aligned} \quad (9)$$

Consequently, having the unobserved quantities provided by the trained NN using the reporting measurements for the PMU at bus 6 the line parameters of the lines 6-11, 6-12, and 6-13, can be estimated in consecutive time intervals using (1) and (2).

A. Neural network structure and training approach

An important part in the proposed approach is the accuracy of the NN to provide reliable estimations of the quantities required for the calculation of the line parameters. In this work, a simple rather effective structure of a NN is used. In particular, as shown in Fig. 4, a two-layer feed-forward network with sigmoid hidden neurons and linear output neurons is employed. The MATLAB tool [18] *nftool* is used in this work for training the NN. All the NNs that were assigned to the PMU buses of the IEEE 14-bus system were trained with Bayesian regularization backpropagation algorithm and they include 10 neurons in the hidden layer, while in the output layer the number of neurons varies according to the size of the NN output (depending on the number of lines connected to the PMU bus).

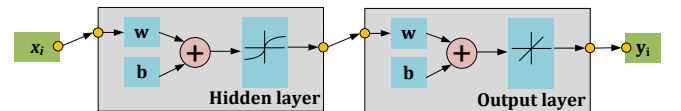


Fig. 4: Neural network structure

The training data were obtained from DigSilent software (using Quasi simulation) after running 3 days with different loading conditions light, medium, and high loading conditions. In total 4320 data were used for the training of the NNs having 70% of the data for training and 30% for testing.

The base case total load shown in Fig. 5 was derived from the Cyprus power system, and it was scaled down by 70% and 50% to represent the two other loading conditions (the base case is considered as the high loading conditions). The total load at each time instant was randomly allocated to the loads of the system, to represent more realistic conditions.

Further, in the simulation environment the series resistance and reactance of the transmission lines vary according to the temperature shown in Fig. 6 as [19],

$$R(T) = R(T_o)[1 + \alpha(T - T_o)] \quad (10)$$

$$X(T) = X(T_o)[1 + \beta(T - T_o)] \quad (11)$$

where T_o is the reference temperature, 20 °C; T is the ambient temperature; $R(T)$, $X(T)$ are the resistance and reactance of the line at temperature T respectively; $R(T_o)$, $X(T_o)$ is the resistance and reactance of the line at temperature T_o respectively; α , β are the temperature coefficients of the resistance and reactance respectively and they are equal to 0.00393 (assuming an aluminium conductor). It should be noted that the $R(T_o)$, $X(T_o)$ are the parameters of the IEEE-14 bus network and vary throughout the day.

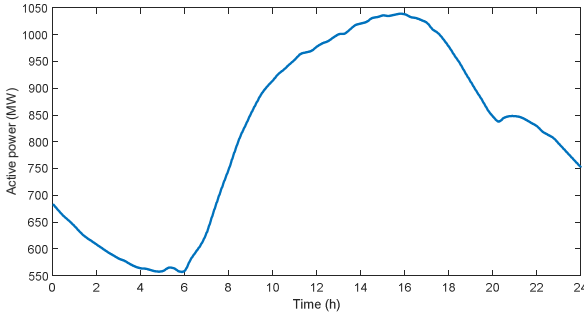


Fig. 5: Total load for the IEEE-14 bus system

During the training procedure the variables (v_i) are obtained for each NN, while the average training time of the NNs is less than 5 minutes, since it is a quite shallow NN. It should be noted that the training of the NN as well as the structure, number of neurons, and the training function can be optimized according to the dataset, however this is not the scope of this paper, since the objective of this work is to showcase the applicability of the machine-learning approaches to the line parameter estimation problem.

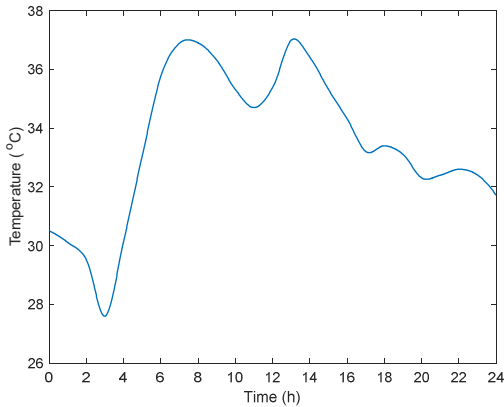


Fig. 6: Daily temperature variation

III. SIMULATION RESULTS

The proposed hybrid line parameter estimation approach was tested and validated to the IEEE 14-bus system. The PMU

configuration of Fig. 3 is assumed, thus 3 different NNs were trained. In order to test the methodology a dataset for a whole day was created (in DigSilent as the training datasets) considering that the loading conditions are 30% lower from the base case loading condition shown in Fig. 5 (thus these loading conditions were not seen by the NNs in the training session). Further, PMU noise was injected to the ideal PMU measurements that were used as inputs to the NNs. It was assumed that the measurement noise has a Gaussian distribution with standard deviation according to the manufacturers data sheets error, as explained thoroughly in [19]. The metric accuracy that is used in this work is the Mean Absolute Percentage Error (MAPE) for the series impedance magnitude (a compact value including both resistance and reactance) and is calculated as,

$$MAPE(|\tilde{Z}|) = \frac{1}{N} \sum_{t=1}^N \frac{||\tilde{Z}_{est,t}| - |\tilde{Z}_{act,t}||}{|\tilde{Z}_{act,t}|} \times 100 \quad (12)$$

where, $|\tilde{Z}_{est,t}|$ and $|\tilde{Z}_{act,t}|$ is the estimated and actual series impedance magnitude respectively at time t for the lines observed by one PMU. It should be noted that the estimated line parameters are updated every minute therefore N in (12) is equal to 1440 time instants (for a whole day). Although the analysis of the results in this paper is concentrated on the series impedance estimation, the methodology can be also applied to the estimation of the shunt admittance of a line without any limitation to the accuracy (using (2)).

Table 1 tabulates the MAPE of the impedance magnitude for all the lines observed by one PMU at the IEEE 14-bus system. Actually, the MAPE is calculated for two cases, in the first case the estimated impedance from the proposed hybrid approach is used in (12) (denoted as *MAPE Proposed*), while in the second case the MAPE was calculated considering constant values for the line impedances in 20 °C ($R(T_o)$, $X(T_o)$), denoted as *MAPE Constant*. Furthermore, the improvement of the MAPE by subtracting the *MAPE Constant* from the *MAPE Proposed* is also shown.

Table 1: MAPE of the impedance magnitude

Line (bus#-bus#)	MAPE Proposed	MAPE Constant	MAPE improvement
1-2	0.314	2.503	2.378
2-3	0.507	4.422	4.307
2-4	0.466	2.554	2.372
2-5	0.475	2.345	2.142
6-10	0.913	6.843	6.710
6-11	0.993	10.742	9.749
6-12	0.920	8.357	7.437
7-9	1.503	6.894	6.676
9-10	2.387	1.285	-0.573
9-14	2.177	7.007	6.696

As indicated in Table 1, the proposed hybrid approach that utilizes PMU measurements from the one side of the transmission line and NN measurements at the other end of the line performed excellent in all the cases. Actually, the larger MAPE (2.387%) is attributed in the line that connects buses 9 and 10, while for 7 out of 10 cases the MAPE of the proposed approach is below 1%. In comparison to the case that the line parameters are considered time invariant the MAPE of the proposed approach is 9 out of 10 times smaller with a larger MAPE improvement of 9.749 % in the case of line 6-11. In only one case (line 9-10) the MAPE of the proposed approach is larger by 0.573% than the case of time invariant line parameters. This is due to the very small values of the parameters (R and X) for line 9-10 that essentially do not vary much throughout the day (so they are close to their values for the line impedances in 20 °C).

The Absolute Percentage Error (APE) of both the proposed and the constant approach for each time instant of the whole day is shown in Fig. 7 for line 9-14. As it is evident, the APE of the proposed approach is always smaller in comparison with the APE if constant line parameters are assumed. This indicates the importance of having real time information about the line variations throughout the day.

Further, to visualize how the estimated impedance magnitude can capture the variations throughout the whole day, Fig. 8 indicates the estimated and the actual impedance magnitude throughout one day. As it is shown through the proposed approach, the line parameters can be estimated reliably and accurately for the whole day.

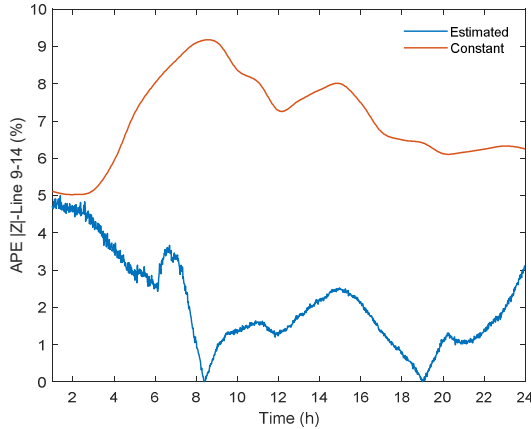


Fig. 7: APE for impedance magnitude of line 9-14

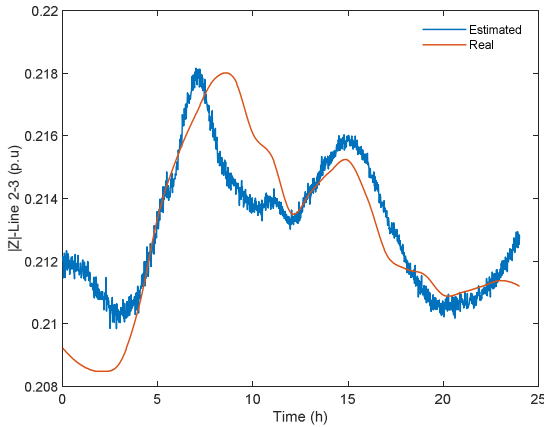


Fig. 8: Estimated and real values of impedance magnitude of line 2-3

IV. CONCLUSIONS

This paper presents a hybrid approach for estimating in real time the parameters of the transmission lines that are monitored by one PMU. The proposed approach is hybrid in the sense that pure PMU measurements are used for the one end of the line while estimated phasor measurements provided by dedicated NNs are used for the unobservable end of the lines. The NNs that were used for this approach are quite shallow and very fast to be trained, providing a flexible and easily applicable approach for the line parameter monitoring. The results indicate the accuracy and reliability of the proposed approach in monitoring the variations of the line parameters in real time. Such approach can certainly enhance applications related to monitoring (i.e., state estimation) and protection (distance relays) that are based on the accurate knowledge of the line parameters of the system. As a part of the future work, the methodology will be applied to a real

power system evaluating its impact under different loading conditions, temperature and soil resistivities. Further, a comparison of the state estimation accuracy when variable and constant parameters are used will be also performed.

REFERENCES

- [1] M. Kezunovic, S. Meliopoulos, V. Venkatasubramanian and V. Vittal, Application of Time-Synchronized Measurements in Power System Transmission Networks, Springer International Publishing, 2014.
- [2] A. Abur and A. G. Exposito, Power system state estimation: Theory and implementation, New York: Basel, 2004.
- [3] D. Glover, M. Sarma and T. Overbye, Power system analysis and design, Stamford: Cengage Learning, 2012.
- [4] M. Bockarjova and G. Andersson, "Transmission line conductor temperature impact on state estimator accuracy," in *IEEE PowerTech*, Lausanne, Jul. 2007.
- [5] K. J. Kusic and D. L. Garrison, "Measurement of transmission line parameters from SCADA data," in *IEEE PES Power System Conference and Exposition*, New York, USA, Oct. 2004.
- [6] M. R. M. Castillo, J. B. A. London, N. G. Bretas, S. Lefebvre, J. Prevost and B. Lambert, "Offline detection, identification, and correction of branch parameter errors based on several measurement snapshots," *IEEE Transactions on Power Systems*, vol. 26, no. 2, pp. 870-877, May 2011.
- [7] J. Zhu and A. Abur, "Identification of network parameter errors," *IEEE Transactions on Power Systems*, vol. 21, no. 2, pp. 586-592, May 2006.
- [8] L. Zhang and A. Abur, "Strategic placement of phasor measurements for parameter error identification," *IEEE Transactions on Power Systems*, vol. 28, no. 1, pp. 393-400, Feb. 2013.
- [9] L. Zhang and A. Abur, "Identifying parameter errors via multiple measurement scans," *IEEE Transactions on Power Systems*, vol. 28, no. 4, pp. 3916-3923, Nov. 2013.
- [10] Y. Wang and W. Xu, "Online tracking of transmission-line parameters using SCADA data," *IEEE Transactions on Power Delivery*, vol. 31, no. 2, pp. 674-682, Apr. 2016.
- [11] S. Kurokawa, J. Pissolato, M. C. Tavares, C. M. Portela and A. J. Prado, "A new procedure to derive transmission-line parameters: Applications and restrictions," *IEEE Transactions on Power Delivery*, vol. 21, no. 1, pp. 492-498, Jan. 2006.
- [12] Y. Du and Y. Liao, "On-line estimation of transmission line parameters, temperature and sag using PMU measurements," *Electric Power Systems Research*, vol. 93, pp. 39-45, Dec. 2012.
- [13] S. Mousavi-seyedi, F. Aminifar and S. Afsharnia, "Parameter estimation of multiterminal transmission lines using joint PMU and SCADA data," *IEEE Transactions on Power Delivery*, vol. 30, no. 3, pp. 1077-1085, Jun. 2015.
- [14] M. Asprou and E. Kyriakides, "Identification and Estimation of Erroneous Transmission Line Parameters Using PMU Measurements," *IEEE Transactions on Power Delivery*, vol. 32, no. 6, pp. 2510-2519, Dec. 2017.
- [15] J. Stiasny, G. S. Misyris and S. Chatzivasileiadis, "Physics-Informed Neural Networks for Non-linear System Identification for Power System Dynamics," in *2021 IEEE Madrid PowerTech*, Madrid, Spain, Jul. 2021.
- [16] G. Tian, Y. Gu, D. Shi, J. Fu, Z. Yu and Q. Zhou, "Neural-network-based Power System State Estimation with Extended Observability," *Journal of Modern Power Systems and Clean Energy*, vol. 9, no. 5, pp. 1043-1053, Sept. 2021.
- [17] S. Chakrabarti, E. Kyriakides and D. Eliades, "Placement of Synchronized Measurements for Power System Observability," *IEEE Transactions on Power Delivery*, vol. 24, no. 1, pp. 12-19, Jan. 2009.
- [18] MATLAB, "Nftool," Mathworks, 2024. [Online]. Available: <https://www.mathworks.com/help/deeplearning/ref/nftool.html>. [Accessed 15 May 2024].
- [19] M. Asprou, E. Kyriakides and M. Albu, "Uncertainty Bounds of Transmission Line Parameters Estimated From Synchronized Measurements," *IEEE Transactions on Instrumentation and Measurement*, vol. 68, no. 8, pp. 2808-2818, Aug. 2019.