Phasor measurement unit optimization in smart grids using artificial neural network

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ABSTRACT

The wide area measurements systems (WAMS) play a vital role in the operation of smart grids. The phasor measurement units (PMU) or synchrophasors are one of the principal components under WAMS. PMU in a smart grid converts power system signals into phasor from voltage and current which enhances the observability of the power system. A variety of operations is performed by the PMUs such as adaptive relaying, instability prediction, state estimation, improved control, fault and disturbance recording, transmission and generation modeling verification, wide area protection and detection of fault location. The PMUs can improve the performance of grid operations and monitoring. Thus, PMU optimization is very necessary to achieve the desired power system observability. The performance of the PMUs can be optimized using artificial intelligence (AI) technologies. The novice method of monitoring maximum power transfer using PMUs equipped with artificial neural networks has been discussed in this paper. In this paper, a two-bus system model is developed that can be generalized to multiple bus systems. The proposed method is novel, simple, feasible, and cost effective for smart grids.

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1. INTRODUCTION

Phasor measurement unit (PMU) is a robust device used to measure the magnitude and phase angle particularly, current and voltage at a common time source for synchronization. It is the transducer that converts analog signals of three phase current or voltage into synchrophasors. PMU can be a dedicated device, or it can be integrated with a relay to measure synchronized phasor quantity viz; positive sequence current, voltage magnitude, angle, frequency in power grid and uses global positional system (GPS) to time stamp. Thus, using PMU, the measurements can be conducted at remote points in a grid at the common time [1]. PMUs are also called synchrophasors as they perform measurement at different locations at the same point of time. Synchronous measurements are essential because if demand and supply are not matched the system may lose stability [2].

Traditionally, numeric meters are used to perform measurements. The numeric meters are installed at substations and supervisory control and data acquisition (SCADA) centers for monitoring and controlling power systems. However, several challenges and issues can arise with these installations. Numeric meters do not provide accurate data for effective monitoring and control. Thus, inaccuracies can lead to incorrect decision-making and inefficiencies on the power grid. Secondly, at much lower sampling rates, numeric meters often rely on communication networks to transmit data to SCADA systems. Failures in communication links can result in data loss or delays. PMU provides data at a very high sampling rate (typically 30 to 120 samples per second), allowing for real-time monitoring of grid conditions. PMUs are found to be superior to SCADA as they have a high sampling rate. PMUs measure 50 Hz or 60 Hz AC waveforms at the rate of about 48 samples per cycle. PMU measures the phase angle and magnitude of sinusoidal waveforms with time synchronization using GPS, enabling precise comparison of measurements from different locations. PMU enables wide-area monitoring and control by providing synchronized data from multiple locations, enhancing situational awareness and state estimation accuracy in the power system.

The need for PMU is based on wide area visibility, time synchronization of data and to monitor dynamic behavior of the system in real time. There are several real time and offline applications of PMU. The offline applications are power system model verification, event analysis and reconstruction, base lining power system performance and load characterization [3]. Analysis of the effectiveness of PMU based wide area monitoring system in the Indian power grid has been clearly mentioned by Sufyan *et al.* [4], [5].

2. METHOD

PMUs provide real-time data on voltage and current phasors, which are essential for maintaining the reliability, stability, and efficiency of power distribution. However, deploying PMUs across an entire grid can be cost-prohibitive due to their high installation and maintenance costs. Therefore, optimizing the placement and utilization of PMUs is crucial to maximize their benefits while minimizing costs. The challenge lies in determining the optimal placement and configuration of PMUs within a smart grid to achieve comprehensive monitoring and fault detection with minimal redundancy and expense. Traditional optimization methods often fail to capture the complex, non-linear relationships between various grid parameters and PMU placements, leading to suboptimal solutions. To address this issue, an artificial neural network (ANN) based approach for PMU optimization in smart grids is proposed in this research. The ANN will be trained to predict the optimal placement and number of PMUs required to ensure full observability of the grid, considering network topology, load distribution, and existing infrastructure constraints. The goals are mentioned as:

i). Data collection and pre-processing: gather and pre-process data on the grid's topology, load profiles, existing PMU placements and historical fault data.
ii). Model development: develop an ANN model capable of learning the complex relationships between grid parameters and the effectiveness of PMU placements.
iii). Training and validation: train the ANN model using historical data and validate its performance using a separate dataset to ensure accuracy and generalizability.
iv). Optimization algorithm: integrate the ANN with an optimization algorithm to generate the most cost-effective PMU placement strategy that ensures complete grid observability.
v). Implementation and testing: implement the proposed ANN-based optimization strategy in a simulated smart grid environment to evaluate its effectiveness and practicality.
vi). Performance metrics: define and measure key performance indicators (KPIs) such as cost savings, grid observability, fault detection accuracy and computational efficiency.

2.1. Working of PMU

Figure 1 shows the functional block diagram of PMU [6]. Analog inputs are current signals received from the secondary of current transformers (CT) and the voltage signals received from the secondary of a potential transformer (PT). These signals are sensed by the respective CT/PT sensors and fed to anti-aliasing filter which restricts the bandwidth of signal with respect to the sampling theorem. GPS consists of a network of number of satellites (usually 24) which work in geosynchronous orbits, providing location and time at any instant which is taken as a reference time [7]. The phase lock oscillator is to divide the pulse received. To input to the microprocessor, the pulses will be separated and fed to AD converter. The analog input signals received from CT/PT sensors are translated into digital form to be acceptable by the microprocessor [8]. A phasor microprocessor is a 16-bit processor computes positive sequence phasor values (magnitude and angle) of current and voltage signals at a given synchronized pulse coming from GPS receiver.

According to Charles Steinmetz, the pure sinusoidal wave can be expressed in the form of phasor [9], [10]. The sinusoidal signal is given by the (1).

$$x(t) = X_m(\cos \omega t + \varphi) \tag{1}$$

Where, $x(t)$ is the time-based signal with respect to time t. X_m is the amplitude of the signal. The variable ω is an angular frequency in radians per second and φ is the phase angle [11] and [12]. The phasor representation of these sinusoids is given by the (2) in exponential and trigonometric form;

$$X = \frac{X_m}{\sqrt{2}} \varepsilon^{j\varphi} = \frac{X_m}{\sqrt{2}} (cos\,\varphi + j\sin\varphi) \tag{2}$$

Once the magnitude and angle are known it can be represented in form of a phasor as (3) and (4),

$$V = |V|e^{j\theta_v} = |V|\angle\,\theta_v \tag{3}$$

$$I = |I|e^{j\theta_i} = |I|\angle\theta_i \tag{4}$$

As shown in Figure 2, the dotted line represents a reference line with respect to which the lagging and leading phasor measurement is conducted. The common time reference is required for these measurements. To obtain time references, GPS is used. The satellites provide a clock pulse at the rate of one pulse per second. The PMU records about 30 samples per second [12]-[14].

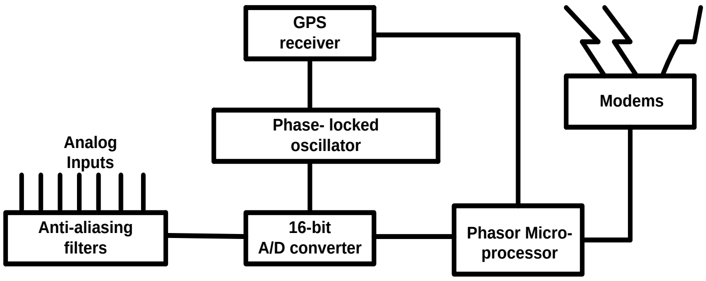

Figure 1. Functional block diagram of PMU

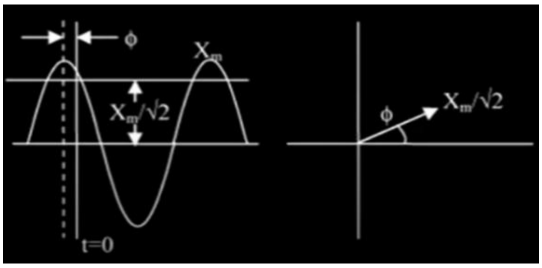

Figure 2. Waveform and phasor representation

2.2. Two bus system model

Let us consider two bus system model as shown in Figure 3 comprising two substations connected by the transmission line. The data is received at PMU1 and PMU2 at bus 1 and bus 2 respectively. Two PMUs are provided, one at each substation.

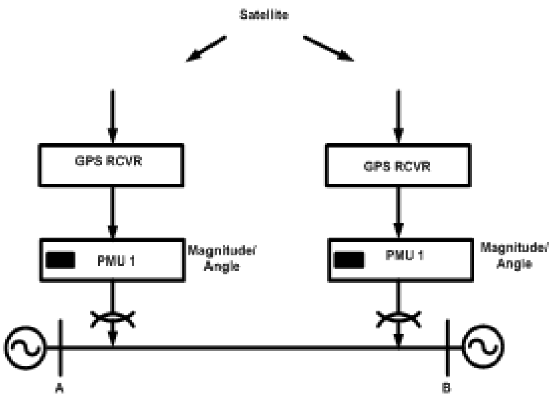

Figure 3. PMU provision at sending end and receiving end

The power flows from with common time reference provided by GPS [15]. This can be expressed in terms of power P_{12} flowing through a line having line bus1 to bus 2 is expressed as (5). Where V_1 is the voltage at sending end at bus 1 leads with respect to voltage V_2 at receiving end at bus 2. In this manner, various points on signals V_1 and V_2 can be compared at reactance X_L.

$$P_{12} = \frac{V_1 V_2 \sin(\varphi_1 - \varphi_2)}{X_L} \quad (5)$$

The data in respect of several PMUs can be viewed at one location like a control unit where entire grid is controlled. Figure 4 shows circuit representation of a two-bus system. The angle $(\varphi_1 - \varphi_2)$ is measured by providing PMUs at sending end and receiving ends. Maximum power can be delivered if the difference is π/2 radians. Therefore, the targeted output of a neural network model is set to π/2 radians [12]. The existing method of measurements is performed by numeric meters installed at substations and SCADA centers. It has been seen that the decision regarding maximum power flow cannot be predicted accurately.

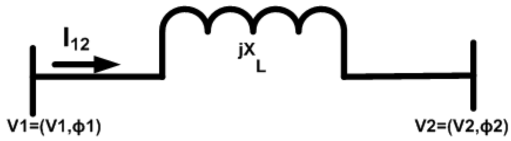

Figure 4. Circuit representation

2.3. Artificial intelligence application in power system

Before developing the ANN based PMU model, it is required to review the concepts of artificial intelligence (AI) and applications in power systems in brief. AI is the mimic representation of human behavior. It is the replacement of a human by a computer. Machine learning (ML) is the study of computer algorithms that bring out improvement using experience and data [16]. The famous products based on ML are Tesla, Google Car, and Alexa. ML is the subfield of AI that mainly focuses on the design of the system thereby allowing it to learn and make predictions based on experience which is data for the machine [17]. Observations of some experiments can also be treated as experience and used as data. Based on the black and white pixels of an image, image recognition can be done effectively using ML. Python language can be used as a back-end tool for this purpose. If the computer is given access to data, then it learns from the data itself. AI confirms whether the computer thinks like a human being or not. When the network is trained the model finds the expected output accurately with never-seen input [18]-[20].

In power systems both distribution utility and consumer have benefited in the advent of the AI based applications. Some of these applications are conducted effectively using linear regression and ANNs [21]. The proactive maintenance of substation equipment is carried out wherein the life of the equipment is predicted using AI-based residual life assessment (RLA) techniques. The load frequency control is achieved effectively using ANN. The electrical theft committed by the miscreant by tampering with the energy meter is detected using ANN [22]. Based on the ML algorithm, the source code is written. For this purpose, Python is the most accepted language, simple and easy to understand. Python is an interpreted, high level, general purpose, object oriented, platform independent; web enabled dynamically typed programming language developed by Guido Van Rossum. It comprises an extensive set of libraries and is widely used in data science, big data, ML, internet of things (IoT), cloud computing, and AI. Google, YouTube, Instagram, Dropbox, Quora, Big Torrent, Delug, Cinema 4D, and Mozilla Firefox are some of the well known, famous and globally used applications based on Python [23]-[26]. AI approaches in smart grid are well explained by Judge *et al.* [27].

2.4. The ANN based PMU model

The human brain comprises billions of nerve cells called neurons. The neurons are connected by the links called dendrites and axons. The neurons get input from the eyes, nose, touch etc. The inputs received by neurons are processed and sent forward for further activation. Thus, the network formed by neurons and dendrites is called biological neural network (BNN). The BNN works on parallel processing [23]. Based on this analogy ANNs are developed. The ANNs are massively parallel computing systems comprising of large number of processors having interconnections as inspired by the BNN [24].

Figure 5 illustrates an ANN model for theft detection. The ANN model basically comprises three layers viz; the input layer, the hidden layer, and the output layer. At the input layer, the input signals x_1 and

x_2 are received by ANN as phase angles of voltages at the sending end and receiving ends respectively. The bias signal b is given addition to input signals. It is possible to include bias at the input layer. Input x_0 having weight w_0 can be taken in the input layer such that w_0=b which is bias. These inputs are fed to a linear transfer function at a hidden layer through links formed by synoptic weights- w_0, w_1 and w_2. All inputs are modified by a weight (e.g., multiplied by weights) and then added at the output layer, giving output, y [11]. This junction is called perceptron which is like a neuron in the case of BNN. The expression for output y is expressed in the form of the (6).

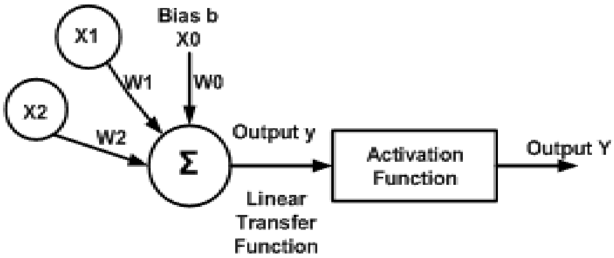

Figure 5. ANN model for theft detection

$$y= w_0x_0 + w_1x_1 + w_2x_2 = \Sigma_0{}^2 w_i x_i \quad (6)$$

In order to obtain a scalable output, the output y is further processed using an activation function. There are a number of activation functions such as sigmoid, rectified linear unit (ReLU), and hyperbolic tangent. The sigmoid function is an activation function that yields output Y between 0 to 1. The sigmoid function is expressed as (7) [25].

$$Y = \frac{1}{1+e^{-y}} \quad (7)$$

The network forming a sequence of the input layer, hidden layer and output layer is called a feed forward network. The output so obtained through a feed forward network is called as predicted output. The predicted output (Y) is compared with the targeted output (T). The deviation between predicted output and targeted output is called an error, denoted by e. In order to achieve a targeted output, ideally, the error should be obliviously zero. As such the neural network is conducted only if the error is zero or within a specified permissible limit. The error would be minimal at its gradient concerning weights. The gradient is the rate of change of error with respect to weight (de/dw). In order to determine the gradient, it is required to travel back from error to weight. This process is called as back propagation. There are different methods of back propagation such as chaining, gradient decent method and so forth [28]-[30].

The following ANN based algorithm is developed for the proposed method of theft detection. Training and test data is as shown in Table 1.

i). Creation of a neural network. The synoptic weights are initialized randomly. In Python, the random library is imported. Alternatively, the numeric Python (Numpy) library can also be imported. In the proposed method, the Numpy library is used for the generation of random numbers.
ii). The input datasets are applied to the network. In the proposed method, ten data points are applied as shown in Table 1.
iii). The other parameters of the network are set such as bias, threshold and activation function. The output is calculated using Python source code.
iv). The calculated output is compared with the targeted output. In the proposed method, the targeted output is obtained the angle at which the maximum power transfer will be there. The difference between calculated output and targeted output is called an error.
v). To minimize the error, the gradient of the error with respect to weight is determined through back propagation. For this purpose, the techniques namely Gradient Descent and chaining rule are applied in the proposed method.
vi). The steps d and e are repeated through the number of iterations till the error is reduced to the acceptable range. This phenomenon is called training of the network.
vii). Once the network is trained, it is validated by applying test inputs.

Table 1. Observations: training and test data

X1 radians	X2 radians
3.14	3.14
3.11	3.21
3.31	3.22
0.503	1.14
3.12	1.55
3.22	1.58
2.99	1.43
1.20	0.59
0.89	0.21
2.78	1.20

A Python code was developed based on the ANN model for tamper detection. The main features of the code are as follows:

a) The library Numpy is imported to execute mathematical functions, sigmoid function in particular. The weights are initialized randomly using random functions available in Numpy. Alternatively, the random function can be imported separately.
b) The datasets are formed using arrays or tuples. If the size of the data is larger, separate data files can be connected to the code at the back end. The data file can be an Excel spreadsheet or a comma separated value (CSV) file.
c) The sigmoid function and its derivative are assigned as user-defined functions. These are not in-built functions in Numpy or any other Python library.

The weights w_1, w_2 and bias are initialized randomly by Python. The output y is determined as per (1). Using the sigmoid function, the output Y is computed as shown in Figure 2. It is defined that the theft event is detected at mode 1. Therefore, if the output value is less than its threshold of 0.8, the connection is normal; otherwise, the theft event is generated by the neural network. The output Y is compared with the targeted output T. Then error e is computed as a difference of the calculated or predicted output (Y) and targeted output (T). The square of error is computed and is differentiated with respect to weights w_1 and w_2 by using the chaining rule as (8).

$$\frac{\partial e}{\partial w} = \frac{\partial e}{\partial Y}\frac{\partial Y}{\partial y}\frac{\partial y}{\partial w} \tag{8}$$

The chaining is conducted through a number of successive iterations. The convergence is said to be reached when the values of weights do not change with respect to iterative cycles. At convergence the error is minimum. As such the predictive output approaches the targeted output.

3. RESULTS AND DISCUSSION

The model has been prepared using training data and test data as shown in Table 1 and as per the set up given in Figure 3. The observations have been undergone in a detailed manner and results are obtained. The sample results obtained after giving adequate training to the network are furnished in Table 2. The tamper event was generated by connecting a link in parallel with the meter in the case of serial numbers 1, 2, 5, 8, and 10 given in Table 2. In other cases, normal status is maintained. The results furnished in Table 2 are found to be appropriate as compared with the corresponding unit consumption displayed on the check meter. The observations from the experiment also led to the following results or findings.

a) The prediction of output becomes more accurate if the quantum of the training data points is greater. The predicted and targeted outputs come close to each other in the case of many training data points.
b) The success of the neural network depends on a variety of training data. It is required to cover all conditions of normal and abnormal data. Secondly, it is required to cover different loading conditions such as partial load and full load.
c) Initially, the program execution is delayed as the neural network is not trained. Once the network gets trained, the program execution becomes faster.
d) It takes a large number of iterative cycles through a range such as 25,000 to 100,000 depending on the selection of initial values of weights to get convergence. In this context, the Python code is found to be a proper choice compared to conventional C/C++ and Java platforms. The fast convergence depends on the selection of initial values of weights.

e) The Sigmoid function is found to be a proper choice out of available activation functions as compared to the other activation functions such as Tanh, Ramp, and ReLU.
f) The back propagation is done effectively using the gradient decent method and the chaining rule, as compared to the other methods.

The results obtained from the ANN model compared with the output from the ETAP simulation. The phase difference between sending end and receiving end voltages is computed using the ANN model through a number of iterations and compared with the output obtained from ETAP simulation. The results of both methods are nearly the same as furnished in Table 2.

Table 2. Sample results from ANN and simulation models using ETAP

X1 radians	X2 radians	ANN output Y	Output from ETAP simulation
3.14	3.14	0.00 1	0
3.11	3.21	-0.0999	-0.099833417
3.31	3.22	0.088	0.089878549
0.503	1.14	-0.579	-0.578590914
3.12	1.55	0.998	1
3.22	1.58	0.945	0.94
2.99	1.43	0.998	0.99994172
1.20	0.59	0.575	0.57286746
0.89	0.21	0.624	0.628793024
2.78	1.20	0.997	0.999957646

4. CONCLUSION

The PMU provides synchronized data as required for WAMS and plays a critical role in monitoring and controlling modern power systems within smart grids. For this purpose, the PMUs are installed at various locations in the transmission network. Most of the applications presented here in this paper are currently in practice in the power sector. For instance, in Maharashtra state in India, the PMUs are provided at 21 locations covering 5 substations. The condition of maximum power transfer is met when the phase difference between the phasors of sending end and receiving end voltages is $\pi/2$ radians. The ANN is developed as phase angles of sending end and receiving end voltages as inputs, which are received from the output of PMUs and $\pi/2$ radians as targeted output. After undergoing several successive iterations, the neural network was fully trained. The ANN model based on PMUs detects maximum power transfer between the sending end and the receiving end through voltage angles. The method can be extended to multiple bus systems. Thus, the proposed method is found to be novice, accurate, cost effective, and feasible for smart grid.

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AUTHOR CONTRIBUTIONS STATEMENT

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Suchita Ingle	✓	✓			✓	✓		✓	✓	✓	✓	✓		
Haripriya Kulkarni		✓	✓	✓	✓	✓	✓			✓	✓			
Poonam Mane		✓			✓	✓	✓	✓	✓		✓	✓		
Shashikant Bakre	✓	✓	✓	✓	✓		✓	✓	✓		✓			

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

Derived data supporting the findings of this study are available from the corresponding author [Ashpana Shiralkar] on request.

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