Prediction of Power Measurements Using Adaptive Filters

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***Abstract*—With the advent of smart grid concept, Internet of Things (IoT) and the deployment of smart meters, the cyber-attack threats on power networks have increased due to the use of communication systems that can be accessed by adversaries. Attackers will have the ability to manipulate the outcomes of smart meters which in turn influence the core application of Energy Management System (EMS): State Estimation (SE). Bad data analytic tools may fail to detect some attacks into measurements. Meanwhile, Machine Learning (ML) solutions have been proposed for detecting False Data Injection (FDI) attacks. However, there is a lack of ML time-series solutions presented in the state-of-the-art that is yet to be less complex. In signal processing, time-series solutions does not only consider the signal, but also the statistics of the signal over time. Therefore, in this paper, a machine learning for time-series solutions is presented as an application to model the measurements of the power grid that are used in SE. The presented model takes into account adaptive linear and non-linear filters: Finite Impulse Response (FIR), and Infinite Impulse Response (IIR). The presented models are implemented and performed on the IEEE-118 bus system. The results indicate the advantage of applying those filters over the state-of-the-art machine learning solutions.**

***Index Terms*—false data injection, gamma filter, smart grid**

I. Introduction

The implementation of Smart Grid on the power grid is enhancing considerably because of the smart meters, control analysis, and other technical components that's been added to it [1], [2]. This change has increased the smart grid's dependency on communication systems. Thus, the power network has become susceptible to cyber attacks [3], [4]. If the power network got attacked, the operators of the system can receive inaccurate data that result a blackout [5], [6]. There has been numerous cases that showed the severity of these attacks. For example, there was a cyber-attack in Ukraine that impacted 225,000 customers with a blackout [7] and a cyber attack that happened in Iran in [8] with the digital weapon Stuxnet. Such cases increased researchers interest in cyber-physical security for the power grid, which also includes machine learning-based solutions.

Real-time monitoring is an essential tool for securing the operation of the grid. Most utilities rely on State Estimation (SE) as real-time monitoring tool to monitor the state of the grid [9]. The ultimate goal of SE is to estimate the voltages at each bus through the process of the measurements set collected from the grid. Bad data analytic process these measurement as well as the outcomes of SE such as residuals in order to remove incorrect measurements or correct any detected errors [10]. Errors could be due to cyber-attacks on the grid or Gross Errors (statistically large errors). Most research is emphasizing on False Data Injection (FDI) attacks which is an attack on the measurements data from the physics-based solution point of view [11]–[18].

Another approach of bad data analysis, which is more recent in power systems, is in the field of Machine Learning (ML) and Artificial Intelligence (AI) research: such as deep learning, deep belief networks, and clustering approaches [19]–[21]. In addition, there are bad data analysis methods that integrate physics-based solutions with data driven solutions [22], [23]. The advantage is to embed the temporal characteristic of real-time data into the solution. However, because of the sudden changes in the power system states, the prediction process of these solutions are not able to acquire an adequate accuracy. Moreover, aforementioned not many ML solutions consider time series solution. The work in [24], [25] proposed ML time-series solution where recurrent nonlinear autoregressive exogenous neural network (RNARXNN) is used. Such model could be complex due to the large number of parameters to be tuned. It could also take more time to train and increase the computational complexity of the model given an application in real-time. The power system operation is a dynamic operation because it involves data that is being processed through time. The measurements of the power system typically include voltage magnitudes, real and reactive power flows, and real and reactive power injections [26]. Depending on the load conditions and noise level, the measurements changes over time which in turn changes their statistics. Hence, the machine learning model needs to adapt to these changes in order to improve the prediction's accuracy.

In this paper, a simple time-series solution is presented to overcome the aforementioned drawbacks of the ML solutions. In particular, two type of filters are considered in this work for measurements' prediction: Finite Impulse Response (FIR), and Infinite Impulse Response (IIR). The former filter is a representative of the class of linear filters, while the latter belongs to the class of non-linear filters. The advantage of these filters is the ability to mitigate the effects of noise on

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the signal, which in turn provides an accurate estimation of the measurement. The prediction of the measurements can then be used in detecting FDI. Therefore, the contribution of this work is two folds:

1) Applying time-series filters that takes into account the signal's statistics in order to provide an accurate prediction of measurements
2) Mitigating the effect of noise on measurements' prediction

The remainder of the paper is organized as follows. Section II provides background information on filters from signal processing point of view. Section III presents the application framework of linear and non-linear models in power network data. A case study based on the IEEE 118-bus is shown in Section IV. Finally, Section V presents conclusions.

II. Background

In signal processing, a temporal signal is considered stationary if its statistics are not changing through time [27]. In other words, two samples are only correlated by their time difference. There are multiples of models that can be used to predict stationary signals like the Least Mean Squared (LMS) [28], Normalized Least Mean Squared (NLMS) [29], and Affine Projection Algorithms (APA) [30], which are linear models. One way of knowing if the signal is stationary or not is through the use of auto-correlation. Auto-correlation shows the degree of similarity between a given signal and a lagged version of itself over time intervals [31]. For a signal $x(t)$, the auto-correlation can be represented as follows:

$$r(l) = \frac{\sum_{t=1}^{N-l}(x_t - \bar{x})(x_{t-l} - \bar{x})}{\sum_{t=1}^{N}(x_t - \bar{x})^2} \tag{1}$$

where l is the lag value, $\bar{x}$ is the mean of the signal, and t is the time sample. Therefore, when $l = 0$, then $r(0)$ is the auto-correlation of the signal with itself. However, when $l = 1$, then $r(1)$ is the auto-correlation of the signal $x(t)$ with a lagged version of itself by 1 sample. This method has the ability to demonstrate if the signal repeats itself after number of lags, which identifies if the signal is stationary or not. In this work, auto-correlation is used to classify stationary signals. In particular, if the correlation value $r(l)$ is close to 1 or -1 for a substantial number of lagged values, the signal is characterized as stationary. On the other hand, if the correlation value $r(l)$ is close to zero for a substantial number of lagged values, the signal is characterized as non-stationary.

The signals that are identified as non-stationary are non-linear signals, which are the ones that are difficult to be predicted by linear models. Therefore, non-linear models provide accurate prediction such as: Kernel Least Mean Square [32], Infinite Impulse Response - Gamma Filter (IIR-Gamma) [33], or Time Delayed Neural Network (TDNN) [34]. The presented solution in this work includes linear (Normalized Least Mean Square - FIR filter) and non-linear (IIR-Gamma filter) models that will be discussed in the following section.

III. Proposed Framework

The goal of this work is providing a time-series solution to predict a measurement data. Depending on the characteristics of the data, temporal signals' statistics could change over time. The solution for addressing this concern is either using linear or non-linear filters. In the following subsections, the two types of filters are illustrated.

A. FIR Filter

The NLMS uses the FIR filter, which is a linear filter, to process the data and build a machine learning model. Fig. 1 depicts the FIR filter [33].

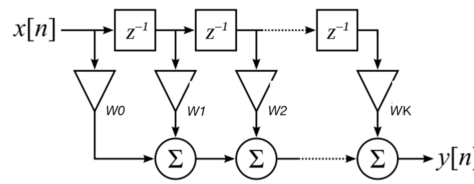

Fig. 1. FIR Filter Diagram [33]

As illustrated in Fig. 1, in FIR filter, a window of K points is selected. The feed-forward of this filter would be mathematically written as follows:

$$y(n) = w_0x(n) + w_1x(n-1) + ... + w_Nx(n-K) \tag{2}$$

where w_0, w_1, ..., w_n are the weights, x is the input signal, $y(n)$ is the output of the filter, and n is the time/sample. The number of weights determines the filter order or dimension, (window size). The delay operator z^{-1} delays the input signal by one sample in time where z is a complex number that can be written as $z = Ae^{j\phi}$.

The cost function J is the prediction mismatch as follows:

$$J = \sum_{n=0}^{T}(d(n) - y(n))^2 \tag{3}$$

where $d(n)$ is the desired true signal, and $y(n)$ is the output of the FIR filter. The weights are updated through the following mechanism:

$$w(n+1) = w(n) + \frac{\eta}{\delta + ||x(n)||^2} * e(n) * x(n) \tag{4}$$

where $e(n) = d(n) - y(n)$ is the error, $||x(n)||^2$ is the l_2-norm to normalize the $x(n)$ value, η is the learning rate that can vary between $[10^{-3}, 10^{-6}]$, and δ is any small value in ranges of $[10^{-3}, 10^{-6}]$ to avoid instability and cases where the $||x(n)||^2$ is almost equal to zero.

B. IIR-Gamma Filter

Different from the FIR filter presented in III-A, the IIR-Gamma Filter is a non-linear filter. In fact, it is more efficient than FIR and Kernel filters since the number of weights in IIR-Gamma filter is less. [33]. The FIR filter is most often used to adapt to specific signals because of the IIR-Gamma's difficulty of adjusting the parameters in it. However, IIR-Gamma filters are more suitable for signals that are characterized by a deep memory and a low number of free parameters (weights). Fig. 2 illustrates the IIR-Gamma filter.

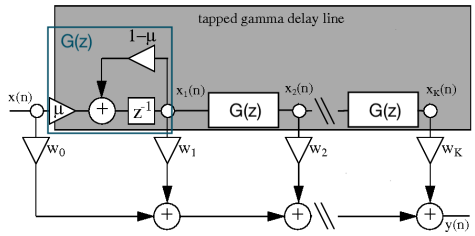

Fig. 2. IIR-GAMMA Filter Diagram [33]

As observed, a processed version of the input is used. As Fig. 2 illustrates, the previous input value is multiplied by $1-\mu$ and then added to the current input. In such, the role of μ in the IIR-Gamma filter is to use part of the previous inputs instead of the previous inputs themselves. The delay operator $G(z)$ in IIR-Gamma filter is represented as follows:

$$G(z) = \frac{\mu}{z-(1-\mu)} \tag{5}$$

For stability purposes, μ is constrained to be within the range $\mu \in (0,2)$. In order to adapt the filter, the input would be:

$$x_k(n) = (1-\mu)x_k(n-1)+\mu x_{k-1}(n-1), \forall k = 1, ..., K \tag{6}$$

where n is a time/sample or time step, and K is the filter order. The feed forward pass $y(n)$ is similar to (2) and can be found in [33]. The same MSE cost function was used for the IIR-Gamma. To update the weights, (7) was used:

$$\Delta w_k = \eta_1 \sum_{n=0}^{T} e(n)x_k(n) \tag{7}$$

Where η_1 is the learning rate that has a range of $[10^{-3}, 10^{-4}]$. The new parameter, μ, should also be updated:

$$\Delta\mu = -\eta_2 \sum_{n=0}^{T}\sum_{k=0}^{K} e(n)w_k\alpha_k(n) \tag{8}$$

where η_2 is the learning rate that has a range of $[10^{-4}, 10^{-5}]$ and $\alpha_k(n)$ is defined according to the following expression:

$$\begin{aligned}\alpha_k(n) &= (1-\mu)\alpha_k(n-1)+\mu\alpha_{k-1}(n-1) \\ &+ [x_{k-1}(n-1)-x_k(n-1)], \forall k = 1, ..., K\end{aligned} \tag{9}$$

where α starts with zero, $\alpha_0(n) = 0$. The weights do not depend on μ. However, the input x does. Since this is a gradient descent approach, the summation of the error is there. If a stochastic gradient descent was used, then we should remove the summation in order for it to be sample by sample error values. Since this filter depends on memory, it would be very sensitive to set the order of the filter. The reason is that if the order was too high, then the model will depend on data that is way too old, which might affect its prediction about the current data. Therefore, there will be some cases in which the filter order of the IIR-Gamma needs to be a small value [33].

The algorithm of conducting IIR-Gamma filter is depicted in [33]. After applying auto-correlation on all of the data, there were many measurements that showed an average correlation over multiple lags of zero as Fig. 3 illustrates, which implies non-stationary signals.

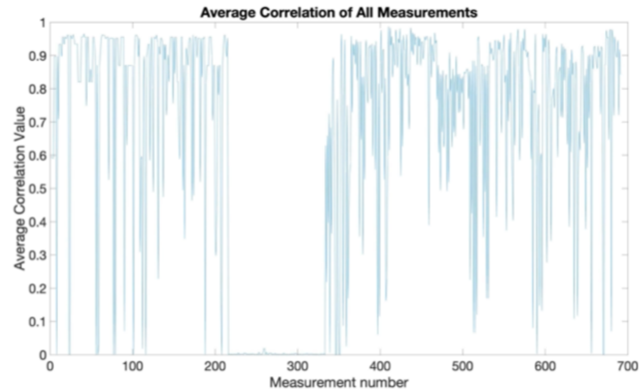

Fig. 3. Average Correlation of All Measurements

IV. Results

The time-series analysis for measurements' prediction was validated using the IEEE 118-bus system. All simulations are conducted on MATLAB using a personal computer iMac with 4GHz i7 processor. Using the MATLAB package MATPOWER [35], 21,600 samples (i.e. one day's worth) of measurement were generated with Gaussian noise based on a common daily load profile that contains temporal information of a power system's changing state. Multiple days worth of data were generated. The training data included one day worth of data and the test data was data generated for another day. The measurement set included are real and reactive power flows, real and reactive power injections, and all voltage magnitudes, resulting in 691 measurements.

Some of the signals considered in the simulation are illustrated in Fig. 4. These plots show a general view of how the generated 691 measurement signals or data look like.

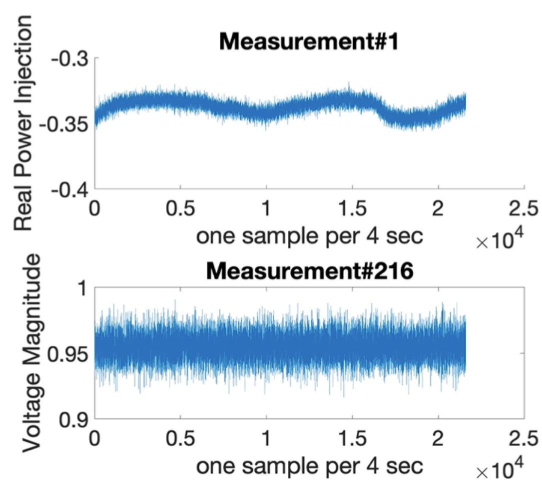

Fig. 4. Measurement Signals

After multiples of experiments, the parameters used throughout the results are: a) For FIR filter, $\eta = 0.001$ and $\delta = 0.001$, b) For IIR-Gamma, $\eta_1 = 10^{-3}$, $\eta_2 = 10^{-4}$, $\delta = 10^{-5}$, and an initialization of $\mu = 0.99$. The weight values are initialized randomly. Unlike classical machine learning techniques in which the dimension of the model is the same as the number of features in the data, in time series the dimension of the model is unknown. Hence, for the time series analysis of this paper, the order of the model is varied from 2 to 5 and applied for the two filters: NLMS and IIR-Gamma. The average value of the Mean Square Error (MSE) of the two filters is calculated and presented in TABLE I. The results indicate that as the order of the filter increase, the mismatch of the prediction increases for IIR-Gamma filter while decreases for NLMS. The NLMS started to decrease in error because increasing the order filter will have better results in prediction. However, the Avg. MSE for NLMS started to increase after order 5 because the model will start to overfit. The reason why the IIR-Gamma Avg. MSE started to increase is that the model will start to overfit even though the model order is not that high due to the minor sensitivity of the filter. Overfitting is avoided using the normalization term in the weight update equation $\frac{\eta_1}{\delta+||x||^2}$, which normalizes the current sample and acts as a regularizing term. This term was used for both filters. In all cases, though, IIR-Gamma filter provided on average a lower MSE.

691 trained models were generated. As mentioned, the models were trained on a one day worth of data. Fig. 5 illustrates how the weight values are updating through the training process for both filters of order $K = 2$. The FIR plot illustrates that the training process went on for a large number of samples and it is almost hard to decide if the training should be stopped as it was the case for the other measurements. The IIR-Gamma plot shows that there was no need to keep on training the model for more than 5000 samples because the weights have already converged, which means there is no need to train the model further. It was the same case for all of the other measurements.

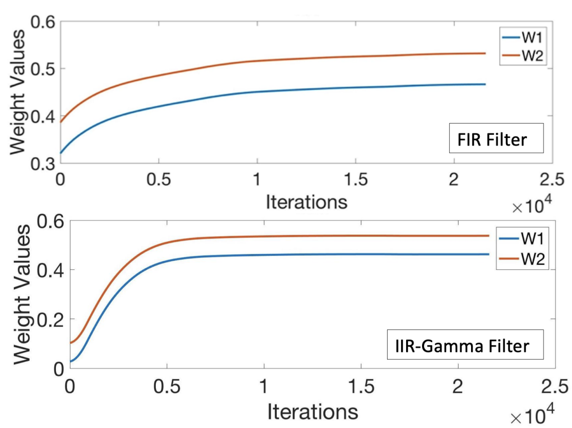

Fig. 5. Filter order $K = 2$ Weight Track Plot for one of the 691 measurements

A comparison between state-of-the-art ML solution Multiple Linear Regression Model (MLRM) [36] and the presented time-series solution in this paper is illustrated in TABLE II. As shown, the IIR-Gamma filter produced the least error. In order to observe the behavior of the presented work, the noise level in the data is increased. The statistics of the MSE are empirically calculated and presented in TABLE III. Both filters were able to produce similar results. In addition, the adaptive filter models were tested on data set for other days of the week (different load behaviour) as illustrated in TABLE IV. Similar results were obtained, indicating the robustness of the model.

TABLE I
MODEL ORDER COMPARISON

Order \ Model	**FIR-NLMS Avg. MSE**	**IIR-Gamma Avg. MSE**
$K = 2$	2.0443e-04	2.5562e-06
$K = 3$	1.8497e-04	8.1982e-05
$K = 4$	1.8267e-04	9.9069e-05
$K = 5$	1.8242e-04	1.4568e-04

TABLE II
MODEL COMPARISON

Value \ Model	**MLRM [36]**	**FIR-NLMS**	**IIR-Gamma**
Avg. MSE	0.0041	1.8872e-04	2.6118e-06
Avg. Std. MSE	0.0040	2.7306e-04	3.7582e-06

TABLE III
MODEL COMPARISON WITH MORE NOISE ADDED TO THE DATA

Value \ Model	**FIR-NLMS**	**IIR-Gamma**
Avg. MSE	2.0129e-04	2.9073e-06
Avg. Std. MSE	2.9048e-04	4.1862e-06

TABLE IV
MODEL COMPARISON TEST FOR DIFFERENT DAYS

Date	**Value \ Model**	**FIR-NLMS**	**IIR-Gamma**
01/08/2018	Avg. MSE	1.9129e-04	2.5564e-06
	Avg. Std. MSE	2.7635e-04	3.6794e-06
01/09/2018	Avg. MSE	1.8601e-04	2.3204e-06
	Avg. Std. MSE	2.6746e-04	3.3201e-06
01/10/2018	Avg. MSE	1.9490e-04	2.4348e-06
	Avg. Std. MSE	2.7843e-04	3.5005e-06
01/11/2018	Avg. MSE	1.9118e-04	2.3863e-06
	Avg. Std. MSE	2.8205e-04	3.5393e-06
01/12/2018	Avg. MSE	1.4546e-04	1.8205e-06
	Avg. Std. MSE	2.1212e-04	2.6551e-06
01/13/2018	Avg. MSE	1.5300e-04	1.9168e-06
	Avg. Std. MSE	2.2162e-04	2.7783e-06

V. CONCLUSIONS

The development of smart grid technology is increasing rapidly with a high potential of cyber attacks. The damages that cyber attacks cause are huge and it is extremely costly to fix. it is crucial to protect the smart grid from such attacks by enhancing the cyber-physical security of the grid with efficient and reliable solutions. This paper proposes a machine learning for time series solution that presented high prediction accuracy results using the FIR and IIR-Gamma adaptive filters. Test case illustrates the capability of the presented solution, as well as its easiness to real-life.

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