State Estimation And Demand Forecasting For Operational Planning In Distributed Network Management System

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Abstract: In recent days, the distributed network system faces more number of problem by the intervention of significantly installed and embedded PV cells. Demand response capability of the node (distributed transformer) which is integrated with the Photovoltaic (PV) cells makes the distributed energy network to reduce the energy consumption from the traditional EB. NARX (Non-linear Auto-Regressive eXogenous) model play a good role in forecasting the demand efficiently when compared to Least Mean Square (LMS) approach. Periodical analysis of network status alerts the distributed network operator (DNO) about the network issues. Constraint management done at every level to restore the network when it attempts to exceed its allowable limit. Maintaining the network against the negative load shows its strength in the distribution network system. ISSDA (Irish Social Science Data Archive) dataset is used to forecast the demand. The overall methodology constantly uses the smart meter data, recorded supervisory control and PV generation data at each node.

Index Terms: Distributed management system, ISSDA, NARX, Load forecasting, MAPE.

1. INTRODUCTION

Traditionally, the energy has been supplied to the locality from the EB. Recently, the researchers showing much interest to reduce this traditional way of supply to some extent and to increase the utilization level of renewable energy resources. Nowadays, energy network have been seeing much more integration of Distributed Energy Resources (DERs) such as embedded PV cells, electric vehicles, micro grids & devices with storage capability. This integration might lead to various problems such as power flow, network fault, negative load, congestion and voltage variations. This has led the researchers to focus on distributed management system such as demand forecasting & operational planning to distribute the energy in such a way that distributedly generated energy are considered as primary source of energy and EB energy as secondary source of energy [1]-[3].Conventional power stations, such as coal-fired, gas and nuclear powered plants are centralized and often require electricity to be transmitted over long distances. It requires more transmission cost and it leads to power loss. More number of problems associated with traditional system, such as Greenhouse gas emissions, Mining destruction, Generation of million tons of waste, Emission of harmful substances. The traditional load is shifting towards more flexibility due to utilization of distributed energy resources (DERs).This paper discusses the application of AMI data for demand forecasting and to predict the network status in order to make the efficient operational planning to distribute the energy generated from the significantly installed DER. And it avoids the problem which affects the network in the distributed network. So this paper presents the novel approach to this problem, suggesting the NARX (Non-linear Auto Regressive Exogenous) model for forecasting the demand in the distributed network using the historical data collected from SCADA or from any smart meter which records the hourly consumption of data. Also, it shows how the NARX model plays better in demand forecasting than the LMS model which has been mostly used in the literature. Periodically, the network status is forecasted to predict the status such as normal, excess, insecure & emergency. The upcoming section of this paper is structured as follows: section II gives a brief explanation about the literature and reviews the current state of the art. Section III presents the methodology to make the operational plan in the distributed energy network. Finally, the Section IV & V analyzes the result and draws a conclusion.

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2 LITERATURE REVIEW

Involvements of DER in the distributed network have led the researchers to observe the network for any flaws and to make sure the operator aware of it. The more number of studies have proposed to optimize the energy management in the distribution network [4]-[6]. In [7]-[10], the authors have proposed the use of LV smart meter to estimate the state of the network. In [11]-[19], the author used the load estimation techniques since there was a lack of real number of data in the network. NN approach had been used for load estimation since it can be adapted or it has the retraining ability in [20]. In another paper [21], load estimation was done by using machine learning technique and it provides a closed loop information flow. Deterministic & statistical model of load used in [22],[23] to assess the impact level of voltage regulation in the distributed network. In [24],[25], the author defined the network status by the phasor voltages, it greatly helps to evaluate the control actions which had been taken at each & every node affecting the overall grid performance. Low voltage problem was reduced by controlling the reactive power devices in [26],[27].

3 RESEARCH METHOD

This entire section describes the proposed methodology for state estimation and demand forecasting in the distributed network. This approach focuses on developing the system that is suitable for transmitting the generated (renewable) energy in the weakly meshed network structure. The flowchart representation of the entire work flow is shown in Fig.1. Each step is described in detail in the subsection below.

3.1 Network Model
The methodology described in this paper are demonstrated using an existing distributed network which is the test network from the SmartHG EU project [28].The two years of continuous recording of energy consumption and the production generation at each and every substation is required as input to the test network.

3.2 Demand Forecasting
The forecasting of demand at each node requires energy generation and energy consumption details. The more number of techniques have been adopted for short-term load forecasting including NAÏVE, ARX, NN .In this paper, two approaches (LMS, NARX) were used to forecast the demand at each and every node. The Non-linear Auto-Regressive eXogenous (NARX) requires PV output, time related variables, historical demand variables to forecast the demand. The NARX model is structured as follows,

$$z_{t+1} = F\,(y_t, y_{t-1}, \ldots, y_{t-di}, z_t, z_{t-1}, \ldots, z_{t-do})$$

Where, the output signals are regressed. The input signals are y_t , y_{t-1} , ... and z_t , z_{t-1} , ... , z_{t-do} are previous load measurement values. The net demand is also calculated by another approach in order to detect which technique is better in demand forecasting. The demand forecasting performance in each case is expressed as the average Mean Absolute Percentage Error ($MAPE_{ave}$).

$$MAPE_{AVE} = \frac{1}{T_n}\sum_{t=1}^{T_n}\left|\frac{A_t - F_t}{A_t}\right|$$

Where, T_n is the total number of time steps in the recorded data at node n, A_t and F_t are the actual and forecasted demands recorded at each time step t.

Fig.1. *Overall outline of the proposed work*

3.3 Status of the work
Forecasted power and the network configuration are the two important thing to estimate the future states of the network. The status of each node is estimated using the WLS (Weighted Least Square) approach and it provides the most likely state of the node. In this network operation, the overall status of the network is described in one of the three categories(e.g: Normal, Emergency, Excess).

1. NORMAL: If the energy generating node (EnergyDG) is supplying more or less equal energy to the demanded node(EnergyDemand).
2. EXCESS: If the energy supplied to that node is predicted as surplus when comparing with the energy requirement of that node.
3. EMERGENCY: If the energy supply of particular node does not meeting its minimum requirement.(i.e. the node could not be able to withstand with that less energy).
4. INSECURE: If the demand of particular node could not be able to manage the requirement with that generated energy but it can sustain to some extent.

3.4 Constraint Management
The maximum energy flow is identified in the network to handle the generated energy in the efficient manner. In order to compute the maximum energy flow in the network, dinitz's algorithm is used. It is a most popular strong polynomial algorithm used to compute the different possible power flow path. From the different possible power flow, the OPF is determined that should satisfy the constraints. Each OPF is checked for voltage, line thermal and load adjustment factor constraints.

$$V_{min,n} <= V_{max,n}$$
$$S_k <= S_{max,k}$$

Since the majority of the network system operated in a radial manner, there has been a much interest in active energy distribution. With the gradual introduction of the DER in the existing network infrastructure, the severity of the network problem also getting increase in the recent days. The capability of providing 'demand response' facility leads to negative load problem. Bi-directional flow of energy in the Distributed system might lead to negative load since the existing traditional system only focuses on unidirectional flow of energy. So the continual monitoring of the network structure is required in the proposing system. Once it is detected, the negative load problem is fixed by enabling the breaker. And then the breaker status is updated at each and every table.

4 RESEARCH METHOD
This section covers the overall results obtained throughout the project and the outputs are discussed detailed manner. We used the smart energy data from the Irish Smart Energy Trial in our tests. The dataset was released by Electric Ireland and Sustainable Energy Authority of Ireland (SEAI) in March 2012. Customers who participated in the trial had a smart meter installed in their homes and agreed to take part in the research. The smart meter data along with the recorded supervisory control for PV energy is used to forecast the demand in the distribution network.

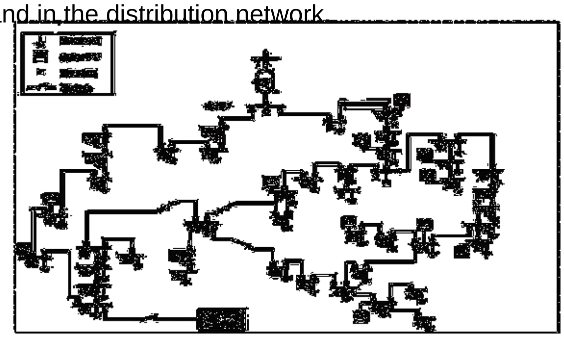

Fig.2. *DATASET FROM ISSDA*

The network comprises of a 48-bus, 10kV system with a weakly-meshed structure.12 of the substations have significant PV installed in the LV networks, and PV production is recorded separately to by the smart metering system.

Fig.3. NETWORK MODEL

The NARX & LMS model is used to forecast the net demand at each node. The performance of the NARX model is better when comparing with the LMS model. The performance is measured by the MAPE. For example, the node 4's five data is taken for consideration among the twelve energy generating node. It is analyzed with both the model by using the equation

2.1. MAPE is calculated for both the model.

NODE	Actual	Forecasted (NARX)	Forecasted (LMS)	LMS	NARX
4	0.137	0.143	0.143	0.044	0.044
4	0.138	0.139	0.135	0.022	0.007
4	0.138	0.121	0.131	0.051	0.123
4	0.138	0.14	0.12	0.130	0.014
4	0.148	0.147	0.135	0.088	0.007
Error (MAPE%)				6.691	3.910

Table.1*.Comparision of error rate in both approaches using MAPE calculation*

MAPE CALCULATION is as follows,
Node=4
Actual energy consumption (1^{st} 30 minutes)(A_1)=0.137
Actual energy consumption (2^{nd} 30 minutes)(A_2)=0.138
Actual energy consumption (3^{rd} 30 minutes)(A_3)=0.138
Actual energy consumption (4^{th} 30 minutes)(A_4)=0.138
Actual energy consumption (5^{th} 30 minutes)(A_5)=0.147

And the forecasted energy in the corresponding time period by LMS approach,

(F_1) = 0.143
(F_1) = 0.139
(F_1) = 0.121
(F_1) = 0.14
(F_1) = 0.147

$$MAPE_1 = \frac{1}{T_5}\sum_{t=1}^{T_5}\left|\frac{A_1 - F_1}{A_1}\right|$$

$$= \frac{1}{5}\sum_{t=1}^{5}\left|\frac{0137 - 0.143}{0.137}\right| \ldots$$

$$= \frac{0.044+0.022+0.051+0.130+0.088}{5}$$

$MAPE_{ave}$ = 6.691

Similarly by using NARX approach,

$$MAPE_1 = \frac{1}{T_5}\sum_{t=1}^{T_5}\left|\frac{A_1 - F_1}{A_1}\right|$$

$$= \frac{1}{5}\sum_{t=1}^{5}\left|\frac{0137 - 0.143}{0.137}\right| \ldots$$

$$= \frac{0.044+0.007+0.123+0.014+0.003}{5}$$

$MAPE_{ave}$ = 3.910

From the calculated MAPE result, we could be able to figure out that NARX approach is far more better than LMS approach.
The Overall consolidated value for the remaining nodes is calculated and tabulated below,

NODE	ERROR IN MAPE%	
	LMS	NARX
4	3.91	6.691
6	9.536	5.513
11	2.78	1.005
12	6.274	2.28
14	4.887	2.646
17	5.008	2.052
24	5.213	2.824
26	4.916	3.324
32	2.85	1.531
33	5.159	2.132
46	13.07	10.013

Table. 2*. MAPE Calculation*

5 CONCLUSION

This paper presented an methodology to eradicate the problem associated with the integration of DG (Distributed generators) such as PV cells, windmill into the existing infrastructure. This encompasses forecasting the demand with the historical consumption of AMI data using NARX and LMS approach. It is calculated and proved that NARX plays a better role in the demand estimation than LMS. The main contributions of this paper are to handle the negative load and fluctuation problem in the distributed network. The status of each node is predicted by using weighted least squares that provides the maximum likelihood nature of each & every node.

These can be used to improve situational awareness & reduce network operator workload by automating a number of tasks involved in the distributed network management system.

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