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Fault Detection in Smart Grid Networks by Optimizing the Sensor Network for Distributed Decision Guided by Machine Learning

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***Abstract:** A smart grid network allows the existence of distributed power generation units. These units generate power through renewable or non-renewable means and supply it through the distribution networks. A major problem with these distributed power generation units is that they introduce harmonic components and affect power flow, creating high impedance faults (HIF) in the distribution network. HIF detection is difficult because the associated current has a low amplitude, rendering overcurrent safety devices ineffective. Wireless communication is one of the solutions for fault detection and feeder reconfiguration. This proposed work has an effective sensor network employed to determine and localize the HIF faults in the distribution network supporting distribution generation units. Fast Independent Component features are clustered in each area, and a SVM classifier is constructed to recognize faults. The learnt knowledge represented in SVM is converted to decision rules and disseminated into the sensor network nodes for effective distributed detection and localization of faults. Due to distributed detection, faults can be localized in less time. This improves the accuracy of fault detection as well as improves the network performance.*

***Keywords:** Smart Grid, Sensor Network, High Impedance Faults, Support Vector Machine Classifier*

I. INTRODUCTION

With increased focus on the addition of renewable energy capacity to conventional power grid systems, many small distributed generation (DG) units are being further affixed to distribution networks. The majority of these DG units are unaffiliated with the distribution system operator (DSO). DG units aim to generate power, obtain maximum profit and keep the cost of interconnection to the distribution network low. A DSO must maintain stability, high reliability, and sufficient power quality in the network. While adding DG to the distribution units provides many benefits, like overcoming power shortages, reducing transmission losses by locating generation units close to consumption, etc., it also introduces high impendence faults (HIF) in the distribution network. These mistakes are dangerous as Electric arcs can be created by electrified cables, which can damage the cable and consequently lead to fire and explosions. It is challenging to detect HIF as the current involved is of low amplitude and it prevents over current protection devices from operating. Differentiating the faults due to consumer features or by operations of systems like It's difficult to switch capacitor banks and turn on transformers. Detection of HIF involves current waveform analysis and adaptive threshold. Conventional power grid infrastructures do not have this infrastructure to detect HIF. A smart grid integrates sensor networks into conventional power grid networks for monitoring and control of power grid components. A smart grid sensor network is a promising solution for the detection and localization of various faults in power grid networks. Sensor nodes can collect various current and voltage waveforms and send the data to the centralised analysis system via multi-hop communication. At the centralised system, waveform features can be extracted and passed to machine learning systems for detection and localization of faults. But transferring current or voltage waveform data continuously over sensor networks increases the communication overhead and can introduce congestion and faults in the sensor networks. Waveform analysis is a complex operation which cannot be implemented in sensor nodes as it will drive up the sensor node cost. In this work, an effective sensor network integrated with unsupervised learning is employed to determine and localise the HIF faults in the distribution network supporting distribution generation units. Due to distributed detection, faults can be localised in less time with network overhead.

II. RELATED WORK

Baqui et al. [1] proposed a technique combining wavelet transform and an artificial neural network (ANN) for the detection of HIFs in electrical distribution feeders. In the time domain, current signals are decomposed with a discrete wavelet transform to extract features. These features are used to design a multi-layer perception neural network to classify different faults. Bretas et al. [2] suggested a failure detection and location scheme for HIF. It is capable of offering particular fault region estimators for each linear, low impedance, and non-linear excessive impedance fault.

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The fault detection is based on a harmonic phase angle difference. Third harmonics were found to be more significant and are the main source of details about HIF. Fourier features extracted from third harmonics were classified using neural networks to classify the faults. The method needed continuous data regarding current and voltage acquired from local potential and current transformers. Bretas et al. [3] presented a method for the detection of HIF in distributed systems with distributed generation. Local measured voltage and current phase components are processed using wavelet transforms to extract coefficients. A neural network is trained to classify the coefficients of faults. Costa et al. [4] presented a set-up for real-time detection of transients induced by the HIF. A maximal overlap DWT transform is used to wavelet coefficient energy features from the current signals. Thresholding is done on the wavelet coefficient energy to detect HIV distortions. Etemadi et al. [5] proposed an HIV detection method based on the non-linear behaviour of current waveforms. Features are extracted from the current waveform using wavelet multi-resolution signal decomposition. For features extracted, they are provided to an adaptive neural fuzzy interference structure for identification and stratification. Wavelet decomposition was done using the mother wavelet (rbio3.3). Ibrahim et al. [6] proposed a real-time algorithmic rule for detecting high-voltage transmission lines. algorithmic technique is projected to add all the values of the generated signal, having a high frequency over one cycle and shifting one sample. The tactic is to be ready to notice HIF at intervals solely [*fr1] a cycle from the moment of fault prevalence. Lucas et al. [7] submitted a technique for HIF detection using wavelet and adaptive neural networks. Most discriminative features for fault detection are selected from discrete wavelet transform coefficients. Energy-related features in the wavelet transform coefficients were found to have a higher correlation to HIF faults. An adaptive neural network is trained with HIF features to classify the faults. Santos et al. [8] proposed a transient-based algorithm for HIF detection in distribution networks. Voltage waveforms are decomposed into high and low-frequency voltage components using discrete wavelet transforms to identify the area where disturbance has occurred. The algorithm is able to significantly reduce the search field of the high-impedance fault and reliably distinguish it from other disturbances. Sedighi et al. [9] proposed a HIF detection system using a genetic algorithm. Current waveform signals are decomposed using a wavelet transform and features are extracted. Feature dimension reduction is done using a genetic algorithm. To detect HIF faults in power distribution systems, Silva et al [10] proposed an incremental learning algorithm. Temporal styles of electrical current data are identified by the usage of wavelets blended with neural networks.

Different wavelets like Haar, Symlet, Daubechie, Coiflet, and Biorthogonal were experimented with. An evolving neural network was used with these features to recognise HIF faults. Torres et al. proposed a prototype for depicting HIF faults in distribution networks. It is a nonlinear resistance model that characterises the high impedance path in the course of HIF faults. The performance of the model was tested against several electrical variables, and the model was found to predict the HIF faults. Lucas et al. [12] proposed a combined system with a wavelet transform based feature extraction method and advanced neural networks to detect HIF faults in time-varying distributed generation systems. The energy coefficients of the Symlet-2 wavelet combined with an online learning-based neural network were found to have detected HIF faults with 99% accuracy. Ekici et al. [13] compared various regression models to determine the location of the fault on hybrid power systems. Distinctive features are extracted from current waveforms using a discrete wavelet transform. Authors experimented with different models of linear regression, regression trees, ensembles of trees, support vector regression, and Gaussian process regression. Among all the models, Gaussian process regression is found to have higher prediction accuracy. Bueno et al. [14] proposed a fuzzy logic system to detect HIF faults. To detect any anomaly, an oscillography examination of three-phase currents uprooted from distribution networks based on amplitude is performed. Once an anomaly is detected, envelope features are extracted from the signals and classified using fuzzy logic detection to detect the type of anomaly. Admasie et al. [15] proposed an intelligent islanding detection method in distribution networks. Intrinsic mode function features are extracted from voltage waveforms and classified using a grey wolf optimised artificial neural network. Voltage waveforms are preprocessed using variation model decomposition. Energy and standard deviation features are extracted from preprocessed signals using the Hilbert transform. Wei et al. [16] proposed an efficient heuristics algorithm for the detection of faults in high-voltage transmission lines. The diagnosis problem on the drawback is developed as an associated improvement during this project: the parameters concerned within the fault diagnosis drawback, like the fault location, and therefore the undetermined parameters like ground resistance and area unit, are taken under consideration as improvement parameters; the deviation of the parts of the particular and scheduled waveform is taken with the intention of improvement. Then, as per the characteristics of the developed improvement, the harmony search improvement is finished to spot the fault. Shukla et al. [17] employed an ensemble of tree, least square, and Adaline algorithms for the detection of faults in transmission lines. DAC offset and the fundamental component of the current signal are used as features to detect faults. To detect faults in high voltage transmission lines, Almeidaa et al. [18] combined independent component analysis (ICA) with travelling wave theory (TW) and support vector machine. The proposed model is capable of pinpointing flaws with pinpoint accuracy. Nabamita et al. [19] used S-transform along with a neural network for the detection of faulty phases on overhead transmission lines. An S-transform is applied to the voltage signals to generate an S-matrix. The frequency components of the S-matrix are provided to the neural network to classify the faults. Arifa et al. [24] suggested a wireless sensor-based smart grid that uses a cognitively driven load management technique for efficient decision-making and communication among sensor nodes.

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The Fuzzy Long Sort Term Memory (FLSTM-CSOA) is used to obtain the shortest possible data transmission delay (FLSTM-CSOA). As a result, a cognitively driven load management technique is being used to improve the throughput and latency of the WSN-based smart grid. As a result, this strategy fails to detect malicious assaults and network malfunctions, which have an impact on the entire SG communication network. [25] Yang et al. For successful data transfer, the grid-based Routing and Charging (IGRC) Algorithm was introduced. In IGRC, multiple ring division of WSN is used to measure energy consumption. The IGRC technique reduces design complexity and improves the performance of WSN-based smart grid networks. In a WSN-based smart grid, IGRC provides the best transmission path with the best transmission time while reducing the number of dead nodes, which leads to faults. However, providing a proper smart grid network to identify a failure in a transmission line during data transmission is not an efficient way.

III. RESEARCH GAP

A smart grid integrates sensor networks with conventional power grids for monitoring and control. HIF fault detection necessitates complex wavelet transform and machine learning models, which cannot be run on resource-constrained sensor nodes. It can be alleviated by shifting the detection process to centralised systems and requiring sensors to send only current and voltage data. But this creates a lot of overhead in the sensor network and affects the rest of the operations of the smart grid. Thus, there is a need for breaking the complex detection process into simplified rules and distributing them to the sensor nodes to ensure distributed detection of HIF faults.

IV. PROPOSED SOLUTION

The proposed solution for HIF fault detection using sensor networks involves three stages.

A. Pre-learning stage
B. Learning stage
C. Post-learning stage

A. Pre-learning stage

The sensor nodes are in a pre-learning stage till they are disseminated with decision rules for detection of HIF. In the pre-learning stage, sensor nodes observe the current signals at a sampling rate and send the current signals via multi-hop transmission to the centralised station. Sending the current signals continuously consumes more bandwidth and can create congestion in the network. To reduce it, compressive sensing is applied to the current signals. Compressive sensing is a technique used for compressing and recovering signals that have sparse representation in certain bases [20]. The non-sparse current signal is transformed into a wavelet basis and a hard threshold is put in to restore in-significant coefficients with a value of 0. A Gaussian-sensing matrix is built and it is multiplied with the spare vector coefficients so that the resulting volume of data is comparatively lower than the original current signal. This reduced the amount of data transmitted from the sensor node to the collection center. At the collection center, reconstruction is done to get the original current signal.

Compressed sensing is based on the idea that most actual signals are sparse in some bases, making it unnecessary to investigate all coefficients. Considerable samples allow for restoration, offering the most thorough analysis of resources. The network's bandwidth consumption and congestion are reduced as a result of the transmission of a reduced set of coefficients.
Say the current signal is to produce the sparse vector of wavelet coefficients, $\acute{\emptyset}$, the current signal is reflected on a wavelet basis, as shown in (1).

$$s \cong \varphi\acute{\emptyset} \qquad (1)$$

The acquired signal (due to compressive sensing) is defined as (2)

$$y = \emptyset s = \emptyset\varphi\acute{\emptyset} \qquad (2)$$

φ is the wavelet basis of dimension $N \times N$, $\emptyset$ is the sensing matrix of dimension $M \times N$. y is the compressed sensed signal of dimension M is sent from sensor node to the collection center. The value of M is very less compared to N. At the collection center, to rebuild the signal s of length N from the y of dimension M , l_2 norm minimization is applied. l_2 norm minimization is defined as in (3)

$$\|s\|_2 = (\sum_{i=1}^{N} s^p)^{1/2} \qquad (3)$$

The algorithm for compressive sensing at the sensor node has the following steps.

1. Apply discrete cosine transform on current signal collected over a period T.
2. Perform hard threshold to make non-significant coefficients as 0 and create sparsity.
3. Multiply the sparse vector of coefficients with Gaussian matrix known between sensor node and collection center.

The algorithm for reconstruction at collection center has following steps

1. Apply l_2 minimization.
2. Do inverse DCT on result of l_2 minimization coefficients.

B. Learning stage

At the collection center, after the current signal is reconstructed, features are extracted from it using the Symlet wavelet transform [21]. A two-level decomposition is done on the current signal to get the detailed coefficients. System behaviour under fault conditions has a higher correlation with the signature or energy of specific detail coefficients.
The current asymmetry in the presence of HIF distortions and its equivalent representation in Symlet 2 detail coefficients is As illustrated in Figure 1,

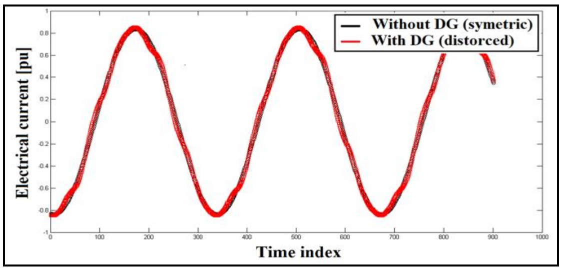

Figure 1 Current distortion

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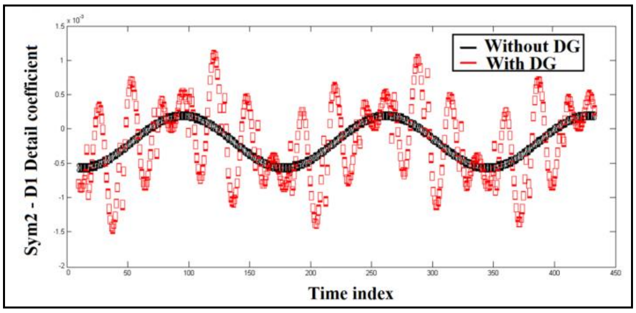

Figure 2 Current distortion represented in Symlet2 Detail coefficients

The energy of the detail coefficients is calculated as (4)

$$E = \sum_{i=1}^{T} x_i^2 \qquad (4)$$

x is the amplitude of the data in the time window, and T is the number of samples in the time window. The energy of the detail coefficients is a reliable indicator of fault detection. The energy of the first and second wavelet detail coefficients acquired from current signals is adopted as a feature for HIF detection in this work.

The first and subsequent wavelet detail coefficients' energy is calculated using each node for a certain duration of L, and these energy vectors are clustered using K-means clustering into 2 clusters. The clusters are labelled manually, thereby creating the training data set of faults and no-fault classes. A support vector machine (SVM) classifier is constructed from this dataset.

Given a set of training samples $D = \{(x_1, y_1), (x_2, y_2), \dots (x_n, y_n)\}$ and $y_i \in (-1, +1)$, the objective of SVM is to detect a division hyperplane from the sample space according to training sample D. The hyperplane can be modeled as shown in (5).

$$w^T x + b = 0 \qquad (5)$$

w= $(w_1, w_2, \dots w_d\}$ is the normal vector that influences the path of the hyperplane and b is the distance between coordinate origin and the hyperplane. The hyperplane distance from point x in sample space is represented as (6).

$$r = \frac{|w^T x + b|}{||w||} \qquad (6)$$

The plane classifies the training samples subjecting to following constraints:

$$w^T x_i + b \geq +1, y_i = +1$$
$$w^T x_i + b \leq +1, y_i = -1$$

For (x_i, y_i) in the training sample D,

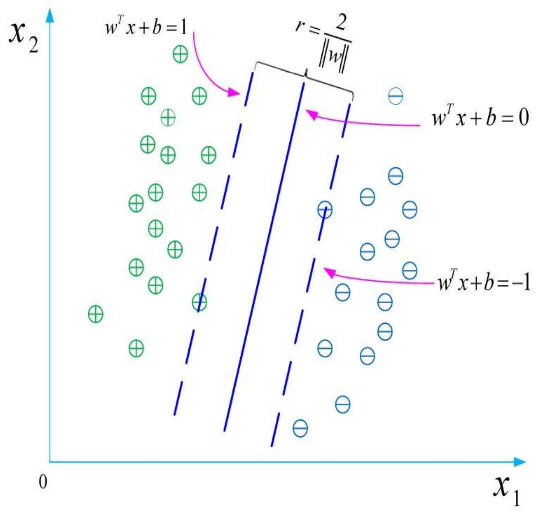

Figure 3: Data classification using SVM

the training dataset near to the hyperplane are referred to as support vectors in Figure 3. The gross of distances of two types of heterogeneous support vectors to the hyperplane is given in (7).

$$r = \frac{2}{||w||} \qquad (7)$$

The support vector machine is constructed from the training sample. D can classify the energy vectors derived from the first and second wavelet detail coefficients of the current signal as fault or not-fault cases.

Though SVMs are state-of-the-art models in data mining, they are incomprehensible black box models considering the non-linearity. Extracting rules from SVM models gives us the comprehensibility and convenience to execute the rules for classification without the necessity of maintaining the models in bulk storage.

The SVM model trained for detecting faults from the energy vectors is converted to decision rules using a pedagogical rule extraction algorithm (Yang et al. 2011).

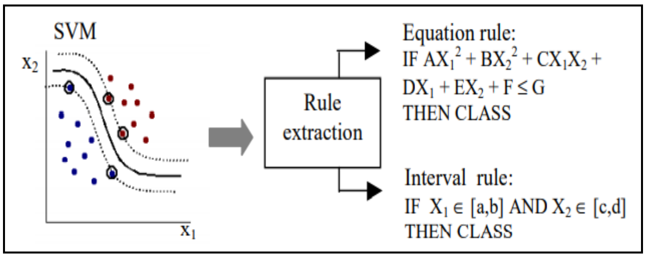

Figure 4: Block diagram of SVM to Decision rule conversion.

The decision rules extracted from SVM are disseminated to the sensor nodes in broadcast mode.

C. Post-learning stage

A sensor node enters post-learning stage, when it is disseminated with rules for detection of faults.

In the post-learning stage, sensor node collects current signal data and executes Symlet 2 wavelet transform to get the level 1 and level 2 detail coefficients. Energy feature vector is extracted from the level 1 and level 2 coefficients.

The decision rules stored at the sensor node are executed with the energy feature vector as input to get the output class as faulty or not faulty.

On detection of faults, sensor node creates a alarm packet send it via multi-hop using geographic shortest path routing to the control station.

Control station can send response packet to sensing node to cut-off the feed line from the power generator to prevent the grid from HIF faults cascading and affecting multiple locations in the grid.

V. NOVELTY IN PROPOSED SOLUTION

Following are the novelties in the proposed solution

1. Detection of HIF fault is distributed, avoiding the load on the sensor network.
2. The learning is very adaptive to the HIF variations in different part of network.

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3. The solution reduces the overall computational requirements needed at sensor node by distribution of resource intensive operations to centralized sink and low computational operation at the sensor node.

VI. RESULTS

The effectiveness of the proposed solution is measured in two modes

A. Fault detection effectiveness

B. Network performance improvement

A. Fault Detection Effectiveness

The IEEE 13 bus test feeder is used to replicate a HIF in a normal power distribution system [23]. The feeder scheme is depicted in Figure 4. In this work, the transformer between buses 650 and 632 is not considered during this work. This component encompasses an advanced prototype, and its existence within the feeder doesn't impact the survey applied during this research. IEEE thirteen bus examine the feeder could be a small, heavily loaded feeder with 4053 kVA apparent power and a power factor of 0.85. The feeder is almost a 1.5-kilometer extension from bus 650 to 680. Many different line configurations are possible. There are three-, bi-, and mono-phase segments, as well as various other tower arrangements that can be used on completely different line segments. Primarily, the load is spot connected, but distributed load is additionally thought of within the section between buses 632 and 671..

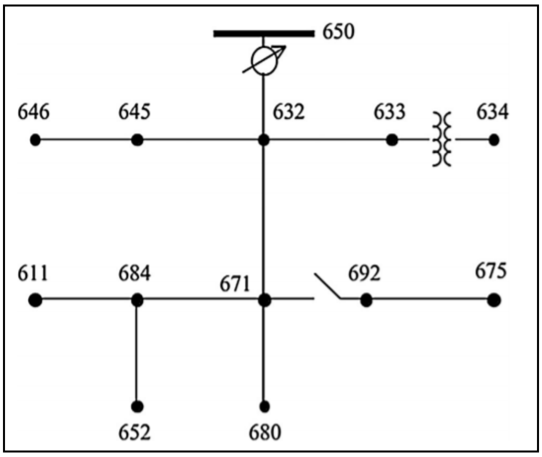

Figure 5: IEEE 34 node test feeder model

The fault detection effectiveness is measured in terms of

1. True positive rate
2. True negative rate
3. False positive rate
4. False negative rate
5. Misclassified rate

The performance is compared against SECoS approach with Sym4 wavelet proposed by Silva et al [10]. The results as given in table 1.

Table1: Comparison of proposed Algorithm with SECoS

Parameter	Proposed	SECoS
True positive rate (%)	99.56	93.75
True negative rate(%)	83.97	52.09
False positive rate(%)	1.06	6.25
False negative rate (%)	16.50	47.91
Misclassified rate (%)	9.80	47.25

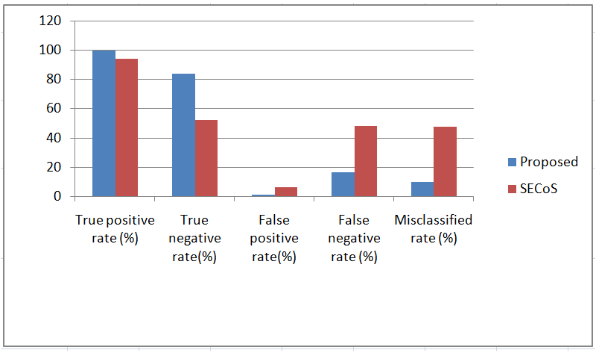

Figure 6: Performance of Fault detection using proposed algorithm

The proposed solution is able to detect fault with 5.81% more accuracy compared to SECoS. The clustering of samples collected at different points, and SVM based classification has given better performance in proposed solution compared to SECoS.

B. Network Performance Improvement

The network performance due to distributed fault detection is enabled due to decision rule dissemination in the proposed solution and is measured by simulation in NS2. The simulation is conducted against the following configuration, which is tabulated in table 2.

Table2: Simulation Parameters

Parameter	Values
Number of nodes	50 to 250
Communication range	150 m
Area of simulation	900*900
Sink position	At right top
Simulation time	100 seconds
Sensing rate	20 Hz

The performance is compared against centralized fault detection. The performance is compared in terms of

1. Network overhead
2. Delay in detection
3. Network overhead over time

The network overhead is calculated for a variety of node counts, and the results are shown in figure 7.

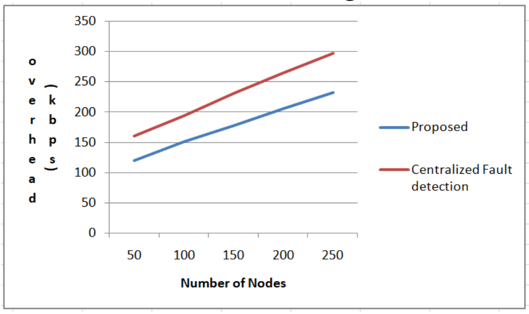

Figure 7: Network Overhead Vs Number of nodes

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As the number of nodes rises, the overhead also surges due to the addition in the number of packets exchanged, but on average, the network overhead in the suggested solution is 29.34% lessened in contrast to centralised fault detection. The reduction in the number of packets transmitted due to localised fault decisions at nodes has minimised the overhead in the intended solution.

The average delay in detection of faults is calculated for a distinct number of nodes, and the calculated solution is given in figure 8.

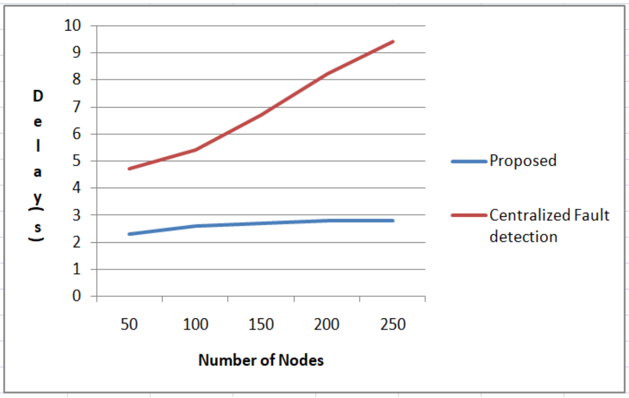

Figure 8: Delay for transmission

The delay is almost constant in the intended results, in contrast with the linear increase in the centralised fault detection. The linear increase is due to packet exchange to a centralised sink and fault detection at the sink. The delay in the proposed solution is on average 2.6 times lower compared to centralised fault detection.

The network overhead is measured over the period of simulation time and the result is given in Figure 9.

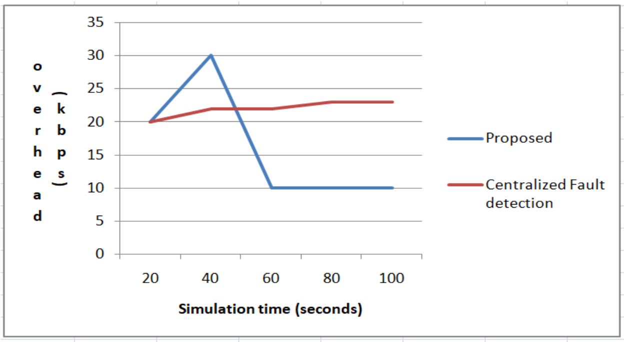

Figure 9: Network Overhead Vs simulation time

The network overhead is initially high in the proposed solution till the decision rule dissemination stage and thereafter it reduces almost 100% compared to centralised fault detection.

VII. CONCLUSION

In this work, efficient sensor network-based HIF fault detection in a smart grid with distributed generation units is proposed. The proposed solution is adaptive to HIF variations in the different regions of the network. Learning made at a centralised station is converted to simplified decision rules and disseminated to the sensor nodes for HIF detection. Through simulations, it is found that the proposed method has lower network overhead (29.34%) and lower fault detection time (2.6 times lower) compared to centralised detection of faults. Also, the accuracy of fault detection is 5.81% more compared to the existing solution of SECoS.

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