International Journal of Engineering & Technology, 7 (1.2) (2018) 141-150

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET

Research paper

Levenberg-marquardt algorithm to identify the fault analysis for industrial applications

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Abstract

The data are collected and forwarding it to the goal is a significant function of a sensor network. For some applications, it is additionally imperative to admit the fault signal to the collected data. To monitor the industrial environment through a wireless sensor network (WSNs), present a neural network based Levenberg-Marquardt (LM) Algorithm for detecting the fault using the gradient value and mean square error of the signal. The data are collected and presented by the magnetic flux sensor and MEMS acoustic sensor. The simulation model is developed in MATLAB/Simulink.

1. Introduction

Wireless industrial networks are rising as a new propagation of communication base for industrial operation monitoring and control. Equated to traditional operation control frameworks, industrial networks have possible to save costs, increase flexibility and reliability. A distributed adaptive algorithms established on the conjugate gradient (CG) technique for distributed networks. Both incremental and diffusion adaptive results are altogether considered. The distributed conventional CG (CCG) and altered CG (MCG) algorithms have an enhanced execution as far as mean square error as a contrasted and Least-mean square (LMS) based algorithms and execution that is near recursive least-squares (RLS) algorithms. The subsequent algorithms are cooperative, distributed and ready to react progressively to changes in the environment [1].

Wireless underground sensor networks empower numerous applications, for example, mine and tunnel tragedy prevention, earthquake prediction and landslide detecting, upstream oil monitoring, intelligent producing and irrigation among numerous others. Most applications are area subordinate, so they need exact sensor positions. Be that as it may, traditional localization arrangement based on the spread properties of electromagnetic waves doesn't work well in underground conditions. Here, presents a magnetic induction (MI) based area that effectively and accurately locates arbitrarily sent sensors in underground conditions by utilizing the multi-path fading free nature in MI signals. In particular, the MI-based localization structure is first aimed based on underground MI channel system with additive white Gaussian noise, the assigned error work, and semi definite programming relaxation. Next, the paper aims a two-stage positioning mechanism for acquiring quick and accurate area outputs by: first, building the fast-initial positioning through a flipping direction increased Lagrangian technique for rough sensor areas inside a short duration time, and after that proposing fine-grained positioning for executing powerful scan for ideal area estimations by means of the conjugate gradient algorithm. Simulation affirms that our results yield exact sensor areas with both low and high noise and uncovers the major effect of underground environments on the limitation execution [2].

Model-driven data acquisition is one of the methodologies used to save sensor node energy in wireless sensor networks (WSNs), which inhibits information transmission by running one synchronized prediction technique at the sink node and sensor, and just when the predicted value varies a long way from the genuine value should the sensor node transmit the detected information to the sink node. Here, we present a novel online model-driven data acquisition strategy which runs two forecast models on the sensor node at the same time. In particular, one model is modified online utilizing stochastic gradient descent (SGD) learning algorithm once sensor information is accessible, and the other is utilized to predict sensor value and updated with the previous one when it is the ideal opportunity for model re-training. The shared working of these two frameworks, together with the SGD learning algorithm, clears two main issues of existing techniques: information transmission during off-line model re-preparing and high asset necessity for framework update. Broad experiments are executed to confirm the advantages of our technique more than two existing strategies given more than 20000 information records from three informational collections. The investigation comes about show that up to 96% of information transmission decreased by our technique while remaining user characterized information accuracy, which exceeds the compared strategies regarding energy use and information accuracy [3].

The real-time and in-situ supervising capacity in oil supplies is highly wanted to build the present recuperation factor of natural gas and crude oil. To this end, the Wireless sensor systems (WSNs) are imagined to be sent inside oil supplies to gather and report the chemical and physical data continuously. None of them being wireless communications and networking systems can aid WSNs in oil supplies because of the difficult environment and the small size device. To address the issue, this paper suggests another independent micro wireless sensor network system is based on the Magnetic Induction (MI) strategy, which can modify the real-time and in-situ monitoring in oil supplies. Rigorous analytical methods

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are produced to describe the oil supplies channel for both energy transfer and MI communications, which affirm the feasibility of the aimed independent sensor network system. To improve the framework reliability and efficiency, high-permeability proppants are infused in the hydraulic fracture to increment mutual induction; when the tri-directional MI coil antenna is planned to accomplish omnidirectional region. The theoretical methods and numerical outcomes are approved by the broadly utilized limited component simulation software COMSOL Multiphysics [4].

Dispersed inference/estimation in Bayesian structure with regards to sensor networks has lately received much consideration because of its wide applicability. The variational Bayesian (VB) algorithm is a strategy for approximating intractable integrals emerging in Bayesian induction. A two novel conveyed VB algorithm for basic Bayesian induction issue, which can be connected to an exceptionally broad class of conjugate-exponential models. In the main approach, the worldwide natural parameters at every node are streamlined utilizing a stochastic natural gradient that uses the Riemannian geometry of the estimated space, trailed by a data diffusion step for collaboration with the neighbors. In the second strategy, an obliged optimization formulation for disseminated estimation is set up in natural parameter space and worked out by alternating direction method of multipliers (ADMM). A utilization of the dispersed inference/estimation of a Bayesian Gaussian mixture method is then displayed, to assess the effectiveness of the aimed algorithms. Simulations on both real datasets and synthetic exhibit that the aimed algorithms have brilliant execution, which is nearly in the same class as the relating centralized VB algorithm depending on all information accessible in a fusion center [5].

The issue of robust transmission of detected information through an immense field of little and vulnerable sensors towards sink nodes. It presents a routing algorithm called P-GRAB depending on a probabilistic gradient broadcasting structure. The aim is to enhance the GRAB algorithm by representing the energy consumption and the capability of the node for making impedance in the forwarding decision of the algorithm. It is the forwarding phase of P-GRAB that varies from GRAB: once a node has the correct cost for broadcasting a packet, it chooses to forward it with a given probability calculating on its left energy level and its impedance potential. The simulation shows that P-GRAB algorithm by furnishing comparative robustness however with less forwarding packets and inertness for packet delivery [6].

Development of technology and step by step progress in telecommunication, wireless sensors, wireless communication, and different technologies has prompted improvement of such miniaturized sensors which can be embedded in or on the human body. This creative and invigorating area of research is Wireless Body Area Network (WBAN). Low power utilization and dependable data transmission are a necessity in medical systems utilizing WBAN. Here, first research efficient routing algorithm for WBAN and it is changed to add energy factor as for routing gradient, energy mindful looked transmission. Energy Efficient Tree Routing (EETR) algorithm is projected for WBAN and it is equated with Ad-hoc On-Demand Distance Vector Routing (AODVR) algorithm. This algorithm can mutually address the problem of low-power consumption and end-to-end delay for dependable information transmission by changing current algorithm so that nodes can robustly select routing paths by limiting the power level for transmission. Significant experiments are led utilizing OMNET++4.5 as an environment to guarantee the effective execution of aimed EETR algorithm by calculating some elements like power utilization and Packet Reception Ratio (PRR). The experimental output examination demonstrates that EETR algorithm is helpful than the AODVR algorithm for energy-saving health monitoring utilizing WBANs. Specifically, tree-based multi-hop tree topology and single hop tree topology is contrasted and with the help of broad analyses directed [7].

Wireless Sensor Networks (WSNs) is an accumulation of an extensive number of sensor nodes with detecting, computation, and wireless communication abilities. Dead end issue is one of the difficulties that happen in greedy forwarding. At the point when the message is forward to a node that has no neighbors nearer to a goal than itself, it makes avid forwarding to fail at that node. An energy efficient algorithm is known as GRADE (Gradient Algorithm for Dead End) to take care of this issue. GRADE splits network charts into a functional subgraph utilizing only data about prompt neighbors, and given these sub graphs, every node is given the message forwarding direction. It does not require planarization of the basic graphs and produce loop-free paths. Exploratory comes about demonstrate that GRADE gives path length close to near most path, low energy consumption, and ideal control overhead than different procedures [8].

Distributed adaptive algorithms given the conjugate gradient (CG) technique and the diffusion procedure for parameter estimation over sensor networks. A sparsity-aware conventional is developed, and altered distributed CG algorithms are utilizing l_1 and log-sum penalization capacities. The introduced sparsity-aware diffusion distributed CG algorithms have an enhanced execution as far as mean square deviation (MSD) and convergence rate as contrasted with the consensus least-mean-square (Diffusion-LMS) algorithm, the diffusion CG algorithms and a nearby execution to the diffusion distributed recursive least squares (Diffusion-RLS) algorithm. Numerical outcomes demonstrate that the introduced algorithms are reliable and can be connected in a few scenarios [9].

Localization is an important application for wireless sensor networks as the positioning of the sensors node are basic to both system operations and most application level undertakings. Various methods for location of sensor nodes that make utilization of the Received Signal Strength Indicator (RSSI) have been introduced in light of the straightforwardness and minimal effort of usage. However, a large portion of the examination up to this point has viewed the RSSI technology as unacceptable for accurate localization due to the constrained accuracy inherent to the current running methods. These methods make the presumption that the antenna radiation design is omnidirectional to modify the complexity of the algorithms. In this investigation, an exact and effective localization technique that makes utilization of an enhanced RSSI distance estimation method by adding the antenna radiation design and also nodes introductions are exhibited. Numerical models for the estimation of distance, cost capacity, and gradient of the cost function, which can be utilized as a distributed localization algorithm, are produced. An examination additionally presents sensor data fusion methods, joining accelerometer information, RSSI, antenna radiation design and node orientation to decrease the calculation complexity during the monitoring phase. The introduced algorithm is executed in Matlab. Simulation outputs demonstrate that the introduced method increases the exact value of existing techniques utilizing RSSI by up to 59% [10].

Communication, intelligent sensing and processing are contributing the improvement of Wireless Sensor Networks (WSNs) and its practical application. Artificial Neural Network (ANN) is by and large widely used to create localization systems in WSN. A comparative examination of some conjugate gradient based Feedforward Artificial Neural Network (FFANNs) for creating localization system in Wireless Sensor Networks (WSNs). Localization is the procedure by which the sensor node in the system can recognize their location in the general network. Localisation in WSN assumes a vital part in executing a myriad of utilization, such as agriculture management, disaster management, healthcare management and environment management. Artificial neural network based localization system is picking up significance because of the quicker speed of convergence and least amount of computation. The examination of conjugate gradient backpropagation with Fletcher-Reeves update, conjugate gradient backpropagation with Powell-Beale restarts, one-step secant, conjugate gradient backpropagation with Polak-Ribiere and scaled conjugate gradient backpropagation training algorithms. In the perfect simulation, a comprehensive assessment of these training algorithms is acted. The aimed method effectively shows that conjugate gradient FFANNs based sensor bits can be intended for creating cost-effective localization system [11].

A distributed and formula-based bilateration algorithm that can be utilized to give sign set of locations. In this plan, every node utilizes distance estimates to anchors to figure out a set of circle-circle intersection (CCI) issues, explained through a simple geometric formulation. The leading CCIs are prepared to pick that cluster together and afterward take the average to deliver an initial node location. The algorithm is looked at as far as exactness and computational complexity with a Least-Squares localization algorithm, in light of the Levenberg-Marquardt approach. The outputs in precision versus computational execution demonstrate that the bilateration algorithm is aggressive contrasted with the optimization localization algorithms [12].

New advances in the innovation of wireless electronic devices have influenced conceivable to construct ad-hoc Wireless Sensor Networks (WSNs) utilizing cheap nodes comprising of low-power processors, an unassuming amount of money, and basic wireless transceivers. In recent years, numerous novel applications have been imagined for distributed WSNs in the area of observing, communication, and control. One of the key modifying and irreplaceable services in WSNs location (i.e., positioning) given that the accessibility of nodes location may present the essential support for different protocols (e.g., routing) and applications (e.g., home ground monitoring). In the described context, the present commitment reports our current research progresses along two principle: I) at first, present a comparative analysis of different optimization algorithms that can be utilized for atomic location estimation, which admit: Conjugate Gradient, Triangulation, Non-Linear Least Squares, Steepest Descent, and an enhanced version of the Steepest Descent (ESD) is presented, and II) a statistical portrayal of location errors, by demonstrating that the distribution of error positions can be very much approximated by the group of Pearson distributions. Specifically, demonstrate that i) the ESD algorithm might be competitive with alternate algorithms regarding estimation precision and numerical complexity, and ii) the information of location error distribution might be efficiently utilized to speed-up the determination of iterative-based positioning algorithms by voiding they require of simulating the entire location discovery algorithm and permitting simulation only at the atomic level [13].

A distributed conjugate gradient (CG) algorithm for conveyed parameter estimation and spectrum estimation over wireless sensor networks. Specifically, distributed conventional CG (CCG) and altered CG (MCG) algorithms are created with incremental and dispersion adaptive cooperation procedures. The distributed CCG and MCG algorithms have an enhanced execution regarding mean square errors contrasted with the least-mean square-based algorithms and execution that is near to recursive least-squares algorithms. In an examination of distributed estimation procedures or existing centralized, key features of the aimed algorithms are i) more exact assessments and faster convergence speed can be acquired and ii) the pattern of preconditioners for CG algorithms, which can enhance the execution of the aimed CG algorithms, is displayed. Simulations demonstrated the execution of the aimed CG algorithms against previously described methods for distributed spectrum estimation and distributed parameter estimation applications [14].

A new direction is present to apply a lightweight synchronization serve for wireless sensor nodes. In the end, gradient descent synchronization (GraDes) is present, a new multi-hop time synchronization protocol established on gradient descent algorithm. The details are about the usage of GraDes is scalable, it has processing overhead and identical memory, better convergence time, and practically identical synchronization execution as contrasted with the current lightweight solutions [15].

Extended Johnson algorithm approximately gives 33.33 % better response time than the other algorithms. The Throughput is 13.33 % better than the other algorithms. Also Latency time increase, almost stabilize with higher node capacity. The algorithm results in efficient utilization of network resources with high throughput in shortest paths identification in a sparse weighted, dense and directed graph [16].

2. Inferences from survey

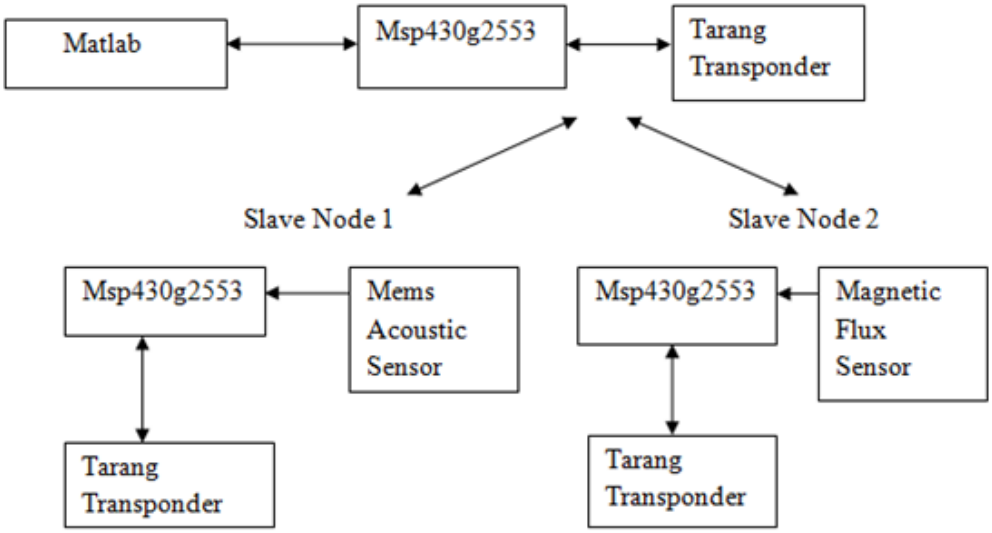
The current analysis proposes a Levenberg-Marquardt algorithmic methodology to detect the machine function in industrial environment by using Magnetic Flux sensor and MEMS Acoustic Sensor. The current analyze Levenberg-Marquardt in Neural network are proposed to produce more accurate results for the industrial environment. Consequently, MATLAB/Simulink is used to simulate a wireless sensor network (WSN) which can deploy for monitoring the machine in industrial environments.

3. Methodology

The section draws the design of the proposed industrial machine monitoring infrastructure, as shown in the figure.1, modernized according to hierarchical architecture, a sensor used in WSN. The hierarchical architecture can be divided into Msp430g2553, Tarang Transponder, MEMS Acoustic Sensor and Magnetic Flux Sensor, according to the different functions performed by them. The sensors are placed on the machine to monitoring information. In order to reduce the cost from firmware, implementation and maintenance linear perspectives and meanwhile to increase the system tractability and accessibility to support industrial application setting along with different design necessity and limitations, WSNs, which have been demonstrated as the promised technologies to introduce a low cost, low power and flexible information acquisition system, are utilized to form the monitoring environmental infrastructure.

MEMS Acoustic sensor is utilized to monitor civil infrastructure such as machine noise. Acoustic sensor transient ultrasonic wave released from the machine while running. Acoustic sensors consist of transducers and demonstrate an increase in sensitivity using characterization measurements. A theoretical method of noise sources in our MEMS device that forecast noise levels coherent with determined noise levels. MEMS sensor constructed to date detect displacements normal to the contact surface.

Magnetic flux sensor is constructed to test a device, through which the complex permeability of a magnetic flux circuit can be determined. The magnetic flux sensor measuring the external magnetic field has been planned in concordance with each case of the machine (harmonics rang, power, type or the frame) and located to determine the field elements which includes the searched information. The utilized machines permit one to form a fault by short-circuiting coils and a test bench with rotor broking bar is also utilized. The machine can run under load or no load conditions.



4. Levenberg-marquardt (LM) algorithm

The neural network comprising of three layers has been applied utilizing the Matlab software. The last structure chose (demonstrated in figure 2) comprises a 10-1 structure having 1 input layer hubs, 10 hubs in the hidden layer and 1 hubs in the output layer, prepared to utilize the Levenberg-Marquardt algorithm. The data sources are the single moment of the MSE estimations of the signals got from the hubs, while the output stage the relating X and Y directions of the hubs.

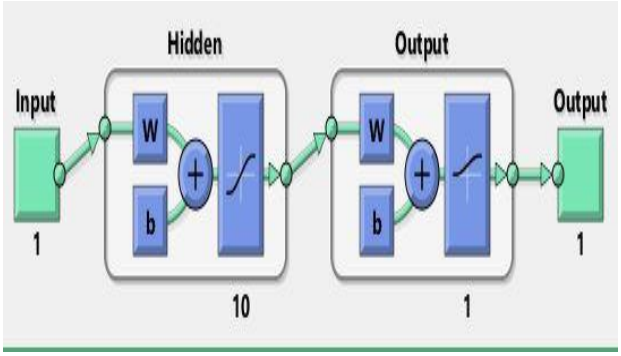


Fig. 2: The Proposed Neural Network Having 1 Input and 1 Output.

The LM algorithm is the most broadly utilized optimization algorithm. The outgo simple gradient descent and another conjugate gradient technique in the arrangement of a wide variety of issues. The LM algorithm is an iterative method that finds the base of a multivariate capacity that is shown as the sum of squares of nonlinear real esteemed capacities. The LM is quick and has stable convergence. In the neural-networks field, this algorithm is utilized for training networks and to detect the machine faults in the industrial environment. The LM algorithm describes the blend between the Gauss-Newton iteration and vanilla gradient descent.
The issue for which the LM algorithm gives a result is called Nonlinear Minimum Mean Squares error. This involves that the function to be minimized is the pursuing special form:

$$f(x) = \frac{1}{2}\sum_{j=1}^{m} r_j^2(x)$$

Where the vector is $x = (x_1, x_2, \cdots\cdots\cdots, x_n)$ and each r_j is a function from $\Re^n$ to$\Re$. The r_j are denoted as residuals and it is adopted that $m \geq n$.
To make subjects easier, f is denoted as a residual vector r: $\Re^n \rightarrow \Re^m$ determined as

$$r(x) = \left(r_1(x), r_2(x), \ldots\ldots\ldots, r_m(x)\right)$$

At present, f can be rewritten as $f(x) = \frac{1}{2}\|r(x)\|^2$. The differential of f can be written utilizing the Jacobian matrix J of r with respect to x determined as $J(x) = \frac{\partial r_j}{\partial x_i}, 1 \leq j \leq m, 1 \leq i \leq n$.
Give us initially a chance to consider the linear event where every r_i function is linear. Here, the Jacobian is consistent, and we can stage r as a hyperplane through space, with the goal that f is presented by the quadratic $f(x) = \frac{1}{2}\|Jx + r(0)\|^2$. We additionally get $\nabla f(x) = J^T(Jx + r)$ and $\nabla^2 f(x) = J^T J$. Illuminating for the minimum by setting $\nabla f(x) = 0$, we acquire $x_{min} = -(J^T J)^{-1} J^T r$, which is the answer to the arrangement of normal equations.
Bringing back to the general, non-linear case is

$$\nabla f(x) = \sum_{j=1}^{m} r_j(x)\nabla r_j(x) = J(x)^T r(x) \quad (1)$$

$$\nabla^2 f(x) = J(x)^T J(x) + \sum_{j=1}^{m} r_j(x)\nabla^2 r_j(x) \quad (2)$$

The typical property of mean-squares error is that shows the Jacobian matrix J; we can acquire the Hessian $\left(\nabla^2 f(x)\right)$ for free if it was possible to be close the $r_j s$ by linear functions $(\nabla^2 r_j(x) are\ little)$ or the residuals ($(r_j(x))$ are little. The Hessian in this event simply becomes

$$\nabla^2 f(x) = J(x)^T J(x) \quad (3)$$

This is like as the linear event.
The usual approximation utilized here is one of near-linearity of the r_is near the result so that $\nabla^2 r_j(x)$ are little. It is also significant to note that (3) is only truth if the residuals are little. The Large residual issue cannot be cleared utilizing the quadratic approximation, and accordingly, the function of the algorithms demonstrated in this document in poor in such events.
The most intuitive and the simplest technique is vanilla gradient descent to determine minima in a function. The parameter updating is executed by adding at each step the negative of the scaled gradient, i.e.

$$x_{i+1} = x_i - \lambda\nabla f \quad (4)$$

Simple gradient descent suffers from different converge issues. Generally, we would like to take huge steps down the gradient at areas where the gradient is little (the slope is delicate) and alternately, make small steps when the gradient is extensive, so as not to shake out of the minimum. With the above refresh conditions, we do opposite to the conditions. Another problem is that the bend of the error surface may not be equal in all the directions. For case, if there is a narrow and long valley in the error surface, the

elements of the gradient in the direction that dots along the base of the valley is little while the elements along the valley dividers are huge. This outcome in motion more towards the dividers despite the fact that we need to move a long distance along the base and a little distance along the dividers.

This position can be enhanced by utilizing curvature and also gradient data, specifically second derivatives. One approach to do this is to utilize Newton's strategy to solve the condition$\nabla f(x) = 0$. Elaborating the gradient of f utilizing a Taylor series around the present statex_0, we get

$$\nabla f(x) = \nabla f(x_0) + (x - x_0)^T \nabla^2 f(x_0) + \text{higher order terms of } (x - x_0) \quad (5)$$

If we ignore the higher order terms (presuming f to be quadratic aroundx_0) and determine for the minimum x by placing the left-hand side of (5) to 0, we get the modify rule for Newton's strategy

$$x_{i+1} = x_i - \left(\nabla^2 f(x_i)\right)^{-1} \nabla f(x_i) \quad (6)$$

Where x_0 has been substituted by x_i and x byx_{i+1}.

Since Newton's strategy verifiably utilizes a quadratic premise on f (emerging from the disregard of higher order terms in a Taylor series expansion of f), the Hessian require not to be assessed exactly. Rather the estimation of (3) can be utilized. The most important advantage of this method is rapid convergence. The rate of convergence is sensible to the beginning location (or more precisely, the linearity around the beginning location).

It can be seen that basic gradient descent and Gauss-Newton iteration are integral in the focal points they give. Levenberg aimed an algorithm based on this notice, whose refresh rule is a blend of the previously mentioned algorithm an is given as

$$x_{i+1} = x_i - (H + \lambda I)^{-1} \nabla f(x_i) \quad (7)$$

Where H is the Hessian matrix assessed atx_i. This refresh condition is utilized as follows. If the error goes down after a refresh, it suggests that our quadratic assumption on f(x) is working and we lessen λ (normally by a factor of 10) to diminish the impact of gradient descent. Then again, if the error goes up, we might want to take after the gradient more thus λ is expanded by a similar factor. The Levenberg algorithm is given as:

1) Do a refresh as coordinated by the rule above.
2) Analyse the error at the fresh parameter vector.
3) If the error has raised as an update the output, at that point withdraw the step (i.e., reset the weights to their past values) and increment λ by a factor of 10 or some such critical factor. At that point go to (1) and attempt an update once more.
4) If the error has reduced as an update the output, at that point admit the step (i.e., keep the weights at their new values) and reduction λ by a factor of 10 or so.

The above algorithm has the drawback that if the value of λ is high, the computed Hessian matrix is not utilized at all. We can determine some favorable position out of the second derivative even in such cases by scaling every element of the gradient as per the curvature. This should be the outcome in larger development along the direction where the gradient is smaller, so the great "error valley" issue does not happen anymore. This significant knowledge was given by Marquardt. He supplanted the identity matrix in (7) with the diagonal of the Hessian ensuing about the Levenberg-Marquardt update condition.

$$x_{i+1} = x_i - (H + \lambda \text{diag}[H])^{-1} \nabla f(x_i) \quad (8)$$

Since the Hessian is relative to the curvature of f, (8) infers a large step toward the path with low curvature (i.e., a flat terrain) and a small step toward the path with high curvature (i.e., a steep grade). It is to be noticed that while the LM strategy is not the slightest bit ideal however only a heuristic, it works amazingly well in practice. The main defect is its requirement for matrix inversion as a feature of the update. Despite the fact that the converse is typically executed utilizing clever Pseudo-inverse strategies, for example, singular value decomposition, the cost of the refresh becomes prohibitive after the product size increments to a couple of thousand parameters. For modestly sized models (of a couple of hundred parameters) be that as it may, this strategy is considerably faster than say, vanilla gradient descent.

5. Result and discussion

To assess the measurement accuracy of the aimed WSNs LM neural network, a laboratory of the training set, validation set, test set, and the MSE value. Here, the signals are named as a low signal, medium signal, high signal and transient signal, and then the other levels of signal are collected and compared with low signal. The training set is utilized to find the optimal solution of the neural networks involves calculating the set of parameters, which reduce the error. The error function is the addition between the target value and the network output. The validation set is utilized to tune the classified parameters in the case, and it's mainly used to validate the hidden units. The test set is utilized only to measure the function of a fully-trained classifier. The test is to calculate the error rate after choosing the final model. An epoch is an amount of the number of times all of the training vectors are utilized once to update the weights. The MSE is a mean square error, which is the difference between the test value estimated by the model and the actual test value. A histogram is a frequency distribution demonstrates that how the different values of data in a set occur. The output charts maximum looks like a bar chart, but there will be a significant difference among them.

The calculated output graphs are mentioned in the figure below. As we mentioned before the LM algorithm is more guaranteed to present the optimum solution. To get MSE histogram, the different signal is examined in training, validation, and testing. The optimal solution of the different signal has been demonstrated in table 1 and table 2. In table 1, the errors are calculated concerning the MSE and the gradient value of the different signal. At high speed, the MSE value will be high in the range of $7.56e^{-07}$ then the machine is identified as a fault. In a transient signal, the gradient values are in the range of $4.32e^{-08}$ then the machine is identified as a fault. In table 2, the analysis of regression values are mentioned, and at high speed, the machine fault is identified as the overall regression value is 0.75805. The LM neural network is selected due to its best trade-off among the accuracy and the detection of a fault.

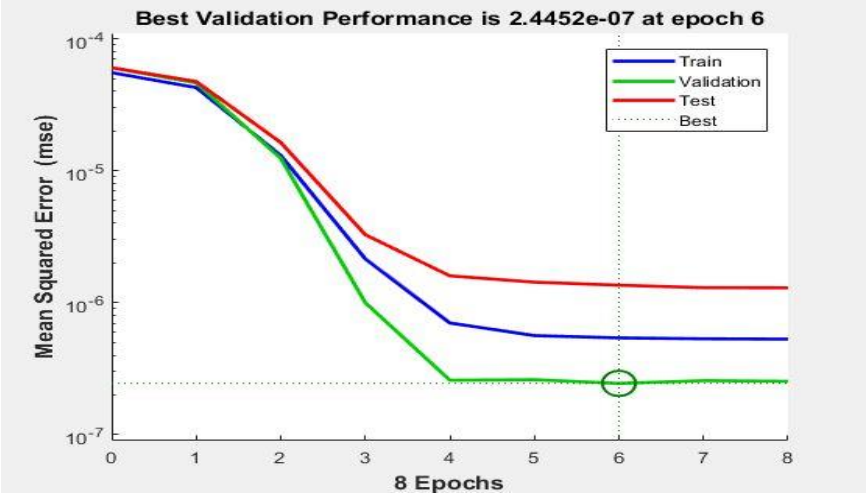


Fig. 3: The Graphs between the MSE and Epochs at the Medium Signal.

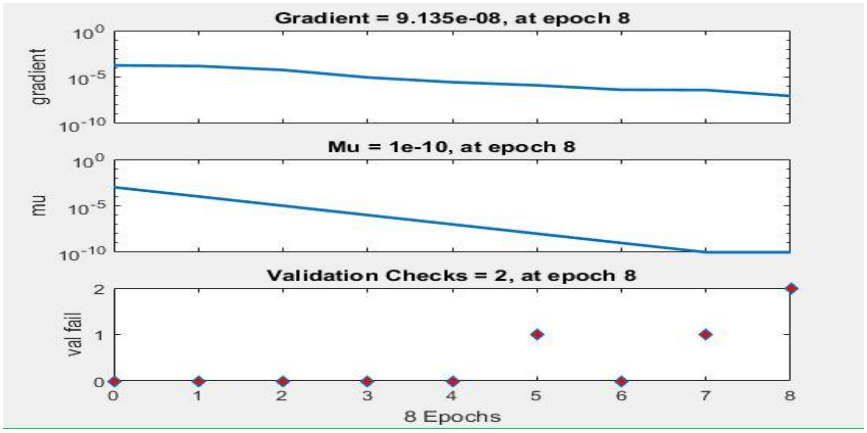


Fig. 4: The Graphs between the Gradient, Mu, Validation and Epochs at Medium signal.

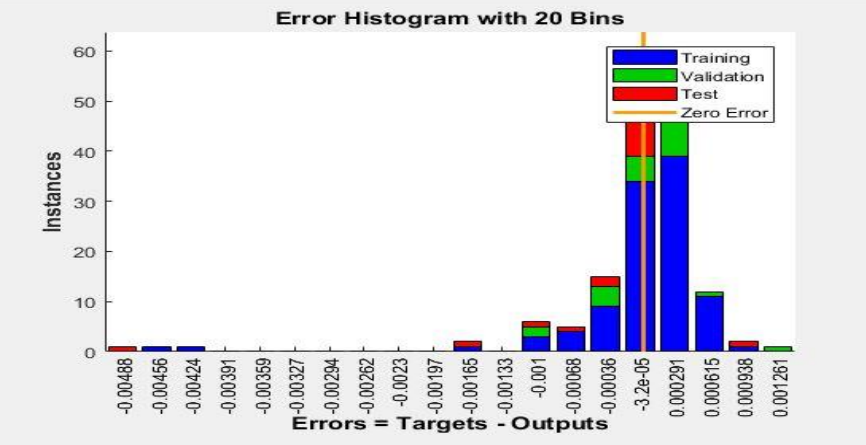


Fig. 5: The Histogram Analysis of the Medium Signal.

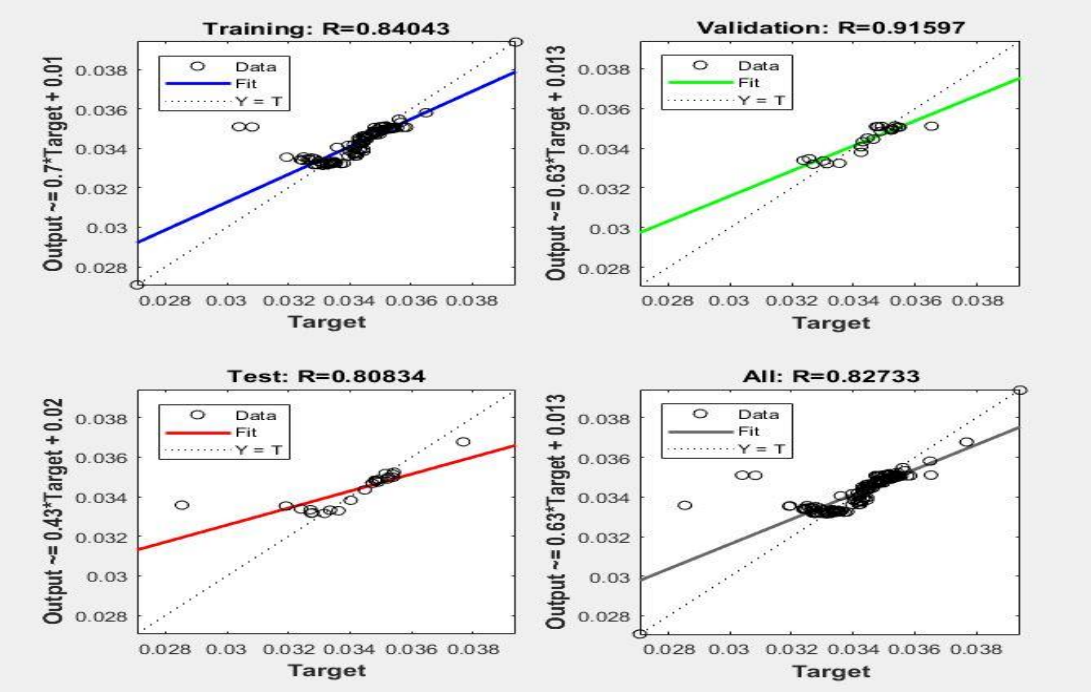


Fig. 6: The Regression Analysis of the Medium Signal.

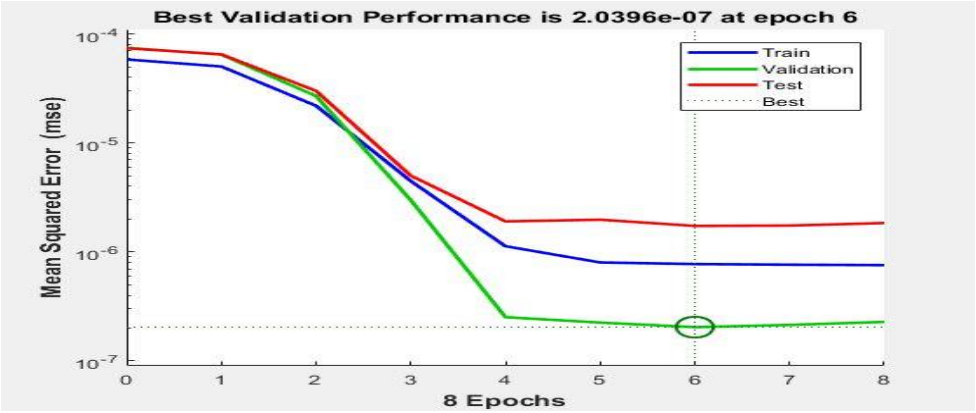


Fig. 7: The Graphs between the MSE and Epochs at the High Signal.

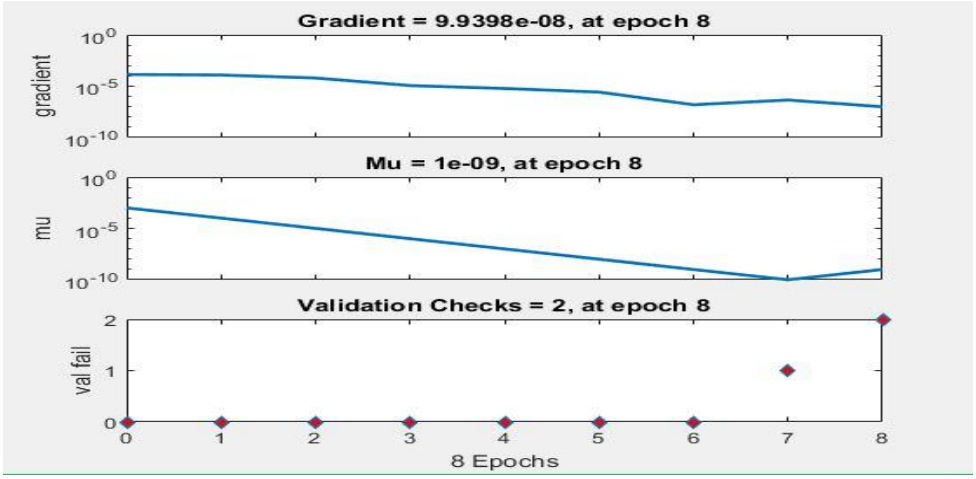


Fig. 8: The Graphs between the Gradient, Mu, Validation, and Epochs at High Signal.

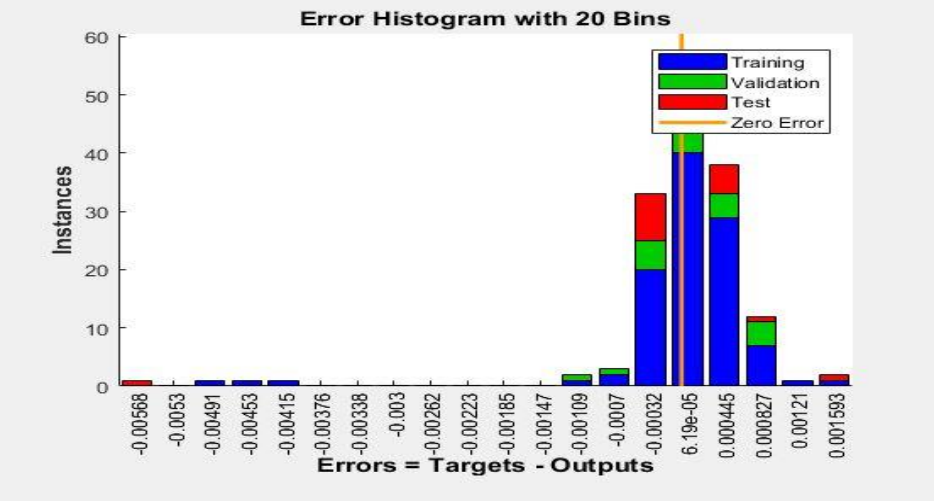


Fig. 9: The Histogram Analysis of the High Signal.

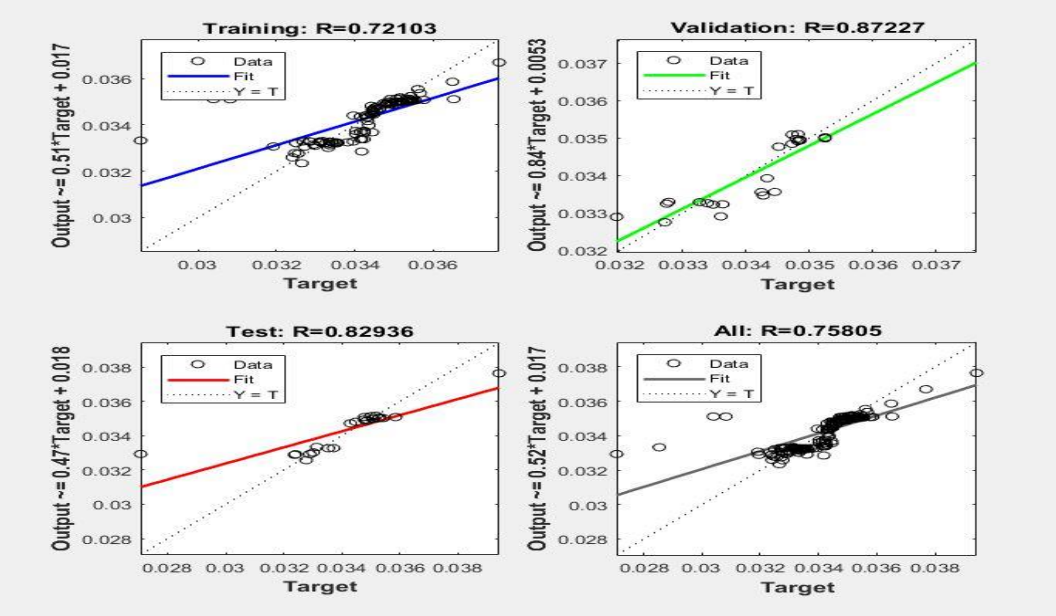


Fig. 10: The Regression Analysis of the High Signal.

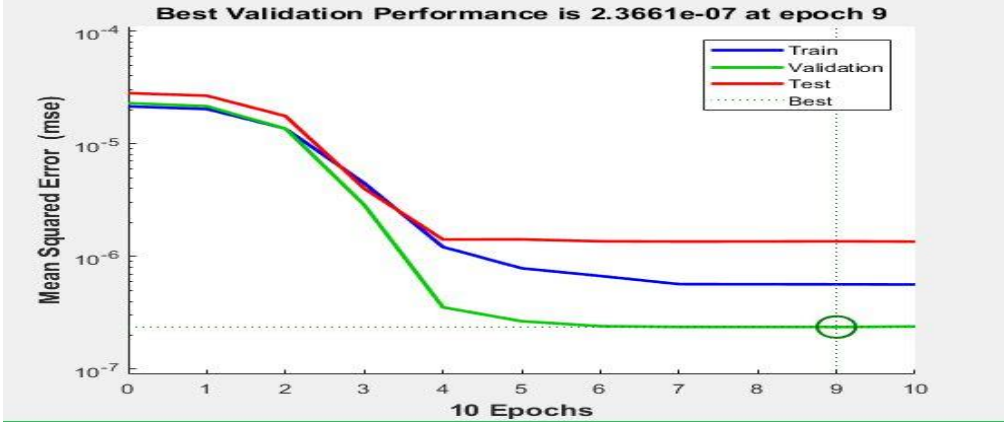


Fig. 11: The Graphs between the MSE and Epochs at the Transient Signal.

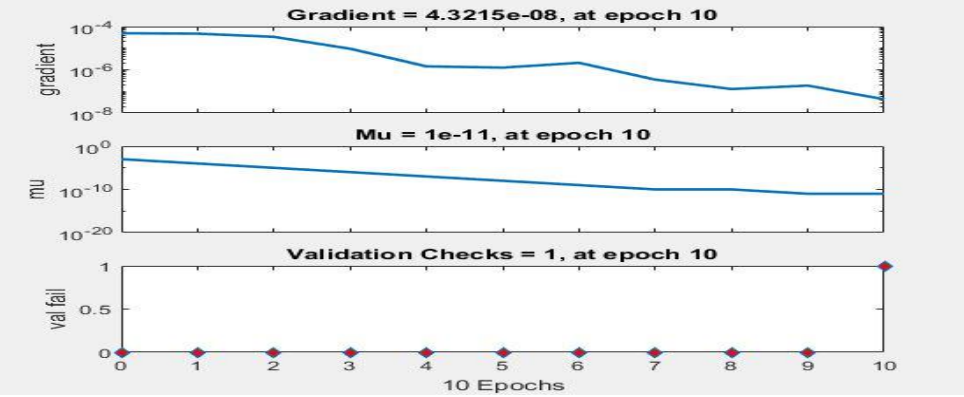


Fig. 12: The Graphs between the Gradient, Mu, Validation, and Epochs at Transient Signal

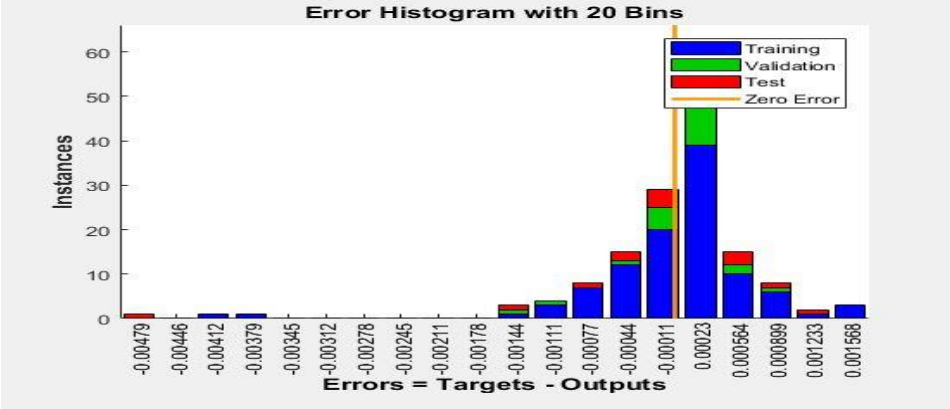


Fig. 13: The Histogram Analysis of the Transient Signal.

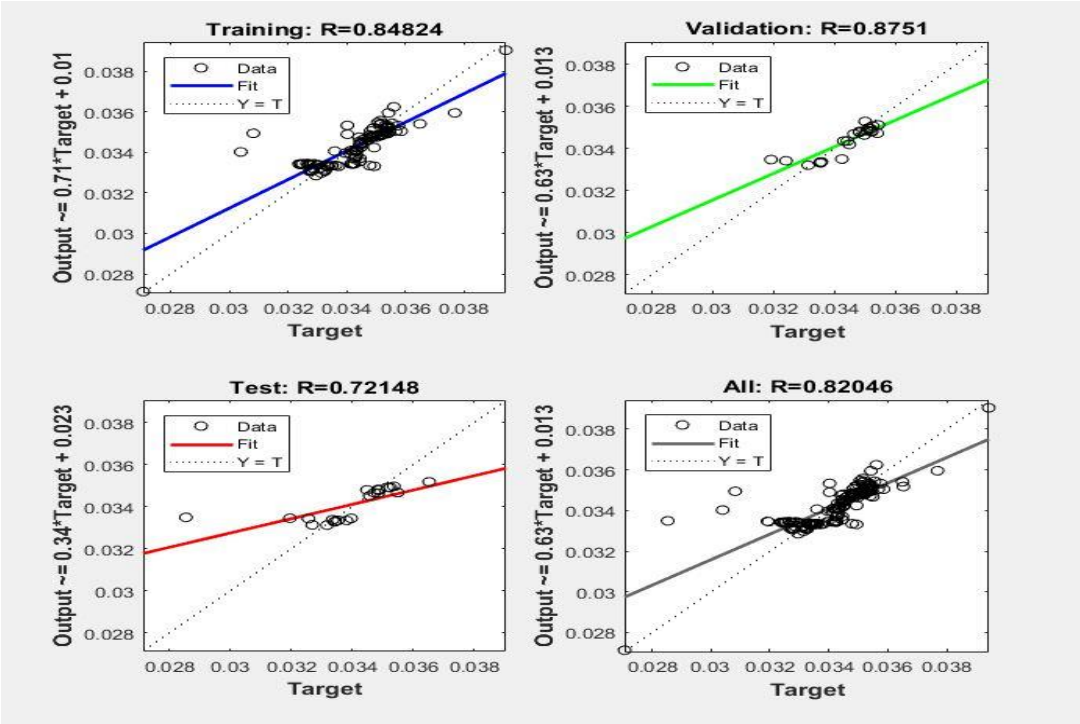


Fig. 10: The Regression Analysis of the Transient Signal.

Table 1: The Analysis of the Different Signal Levels

S.No	Comparison of different speed levels	Training Algorithm	Epoch	Performance MSE	Gradient	Mu	Validation checks
1	High speed vs. low speed	Levenberg-Marquardt	8 iteration	$7.56e^{-07}$	$9.94e^{-08}$	$1.00e^{-09}$	2
2	Medium speed vs. low speed	Levenberg- Marquardt	8 iteration	$5.30e^{-07}$	$9.14e^{-08}$	$1.00e^{-10}$	2
3	Transient vs. low speed	Levenberg- Marquardt	10 iteration	$5.64e^{-07}$	$4.32e^{-08}$	$1.00e^{-11}$	1

Table 2: The Regression Analysis of the Different Signals

S.No	Different Signal levels	Training	Validation	Test	Overall
1	Medium	0.84043	0.91597	0.80834	0.82733
2	High	0.72103	0.87227	0.82936	0.75805
3	Transient	0.84824	0.8751	0.72148	0.82046

6. Conclusion

The major advantage of utilizing neural network is that it does not need more information of the noise distribution and the environment as the MSE estimations are highly unstable and change under the environmental noise. This paper introduces a detection of machine fault for WSN utilizing the neural network and achieved an MSE values on the unknown test data. For applications where online based preparing will be required, the utilization of LM algorithm is suggested. The results demonstrate that the proposed strategy can enhance the accuracy and energy consumption. With such less complexity, LM technique is suitable for distributed schemes of WSNs.

References

[1] S. Xu and R. C. De Lamare, "Distributed Conjugate Gradient Strategies for Distributed Estimation Over Sensor Networks," Signal Process. Def. (SSPD 2012), pp. 1–5, 2012.

[2] S. Lin, A. A. Alshehri, and P. Wang, "Magnetic Induction-Based Localization in Randomly-Deployed Wireless Underground Sensor networks," Accept. Publ. IEEE IOT J.

[3] Y. Chen, Z. Wang, Z. Zhao, D. Li, and L. Cui, "Online Model-Driven Data Acquisition for Wireless Sensor Networks," 2015 IEEE Wirel. Commun. Netw. Conf., pp. 1572–1577, 2015.

[4] H. Guo and Z. Sun, "Channel and Energy Modeling for Self-Contained Wireless Sensor Networks in Oil Reservoirs," IEEE Trans. Wirel. Commun., vol. 13, no. 4, pp. 2258–2269, 2014. https://doi.org/10.1109/TWC.2013.031314.130835.

[5] J. Hua and C. Li, "Distributed Variational Bayesian Algorithms over Sensor networks," IEEE Trans. SIGNAL Process, vol. 64, no. 3, pp. 783–798, 2016. https://doi.org/10.1109/TSP.2015.2493979.

[6] K. Jaffr and C. Comaniciu, "A Probabilistic Interference and Energy Aware Gradient Broadcasting Algorithm for Wireless Sensor Networks," Wirel. Pervasive Comput. 2008. ISWPC 2008. 3rd Int. Symp., pp. 1–5, 2008.

[7] P. Juneja, "Tree Based Energy Efficient Routing Scheme for Body Area Network," 2015 Int. Conf. Adv. Comput. Eng. Appl. IMS Eng. Coll. Ghaziabad, India Tree, pp. 940–947, 2015. https://doi.org/10.1109/ICACEA.2015.7164841.

[8] S. H. Manjula et al., "Network Lifetime Maximizing Gradient Algorithm for Dead End in Wireless Sensor Networks," TENCON 2008 - 2008 IEEE Reg. 10 Conf., pp. 1–6, 2008. https://doi.org/10.1109/TENCON.2008.4766601.

[9] T. G. Miller, S. Xu, and R. C. De Lamare, "Sparsity-Aware Distributed Conjugate Gradient Algorithms for Parameter Estimation over Sensor Networks," 2015 49th Asilomar Conf. Signals, Syst. Comput., no. 2, pp. 1556–1560, 2015. https://doi.org/10.1109/ACSSC.2015.7421407.

[10] M. K. Mwila and K. Djouani, "An Efficient Approach to Node Localisation and Tracking in Wireless Sensor Networks," 2014 IEEE Glob. Commun. Conf., pp. 492–497, 2014. https://doi.org/10.1109/GLOCOM.2014.7036856.

[11] A. Payal, C. S. Rai, and B. V. R. Reddy, "Artificial Neural Networks for Developing Localization Framework in Wireless Sensor Networks," 2014 Int. Conf. Data Min. Intell. Comput., pp. 1–6, 2014.

[12] J. Cota-ruiz, J. Rosiles, E. Sifuentes, and P. Rivas-perea, "A Low-Complexity Geometric Bilateration Method for Localization in Wireless Sensor Networks and Its Comparison with Least-Squares Methods," Sensors 2012, pp. 839–862, 2012. https://doi.org/10.3390/s120100839.

[13] S. Tennina, M. Di Renzo, F. Santucci, and F. Graziosi, "On the Distribution of Positioning Errors in Wireless Sensor Networks : A Simulative Comparison of Optimization Algorithms," 2008 IEEE Wirel. Commun. Netw. Conf., pp. 2075–2080, 2008. https://doi.org/10.1109/WCNC.2008.368.

[14] S. Xu, R. C. De Lamare, and H. V. Poor, "Distributed estimation over sensor networks based on distributed conjugate gradient strategies," IET Signal Process, pp. 291–301, 2015.

[15] K. S. Yıldırım, "Gradient Descent Algorithm Inspired Adaptive Time Synchronization in Wireless Sensor Networks," IEEE SENSORS JOURNAL, VOL. 16, NO. 13, JULY 1, 2016, vol. 16, no. 13, pp. 5463–5470, 2016.

[16] M.Bindhu, Ramesh.G.P, and Introduction, "Algorithm Analysis for Load Balancing and Congestion Control in Software DefinedNetworking,"Journal of Innovative Technology and Education Vol. 3, 2016, no. 1, pp 51 - 59.