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Frequency Estimation by the Method of Minimum Mean Squared Error and *P*-value Distributed in the Wireless Sensor Network

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The development of electronic equipment technology, followed by the advancement of electronic systems, has increased the sensitivity of signal identification. Control and monitoring is a matter that forces existing engineers to make decisions and protect systems. In this paper, the distributed least mean *p*-norm method (dLMP) has been evaluated and evaluated to estimate the distributed frequency of the signal in three incremental, consensus, and scattering strategies. In the proposed method, based on the definition of appropriate cost functions, a distributed method is used to estimate the frequency of common sinusoidal signals with a common frequency in a wireless sensor network. The results of simulation with MATLAB software showed that the proposed algorithm has better and more favorable performance compared to other methods such as single-sensor and distributed methods. In the proposed method simultaneously with the distributed frequency estimation, the domain and phase estimation with a suitable and fast convergence is possible locally. Due to this advantage compared to the distributed filter method, the proposed method is less complicated and the convergence rate is appropriate and better.

Keywords: *P*-norm, wireless sensor network, dLMP, LMP, minimum mean square error

1. INTRODUCTION

The use of the wireless sensor network to the fifty-fifth century and the Cold War time are attributed to two superpowers. It is said to have been used for the first time in the Vietnam War. But what is certain is its widespread use which goes back to the last two decades [1]. The recent advances in integrated circuit manufacturing technology in small sizes, and the development of wireless communications technology, on the other hand, have paved the way for designing wireless sensor networks. The main elements in the wireless sensor network include the sensor or sensor, the central processor, and the communications and communications sector (transmitter/receiver) [2, 3]. Wireless sensor network consists of tens to hundreds of sensors according to their application. Sensors will be placed in a standard, predefined structure, or placed in an unclear and distributed space. One of the standard structures of sensors in the network, one-to-one structure, a star structure, a mesh structure, and a tree cluster structure, which is also a kind of com-

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bination of main structures, can be mentioned [2]. Sensors detect an event or physical state through unique algorithms, and the results are sent to management centers for decision making after analyzing the environmental parameters after the conversion into an electrical signal. The management centers may include back-up systems, computer processing centers, administrative servers, or human operators that fit the design and application of the network [4]. In sum, the unique features of the wireless sensor network, which has been developed in the light of the relevant technologies, has led to the rapid development of its applications. Thus, in the present era, its widespread use in various sectors of military, security, medical engineering, transportation, industry, environment, production, transmission and distribution networks, *etc.* [4, 5].

2. RESEARCH PROBLEM

The enhancement in electronic technology has grew the sensitivity of signal identification. Significant parameters of the signal, such as amplitude, phase, and frequency, are categorized in the signal recognition process. Considering the importance of maintaining the stability of electronic and telecommunication systems, many methods have been proposed to allow accurate and accurate estimation of these parameters in various conditions and disruptive environments [1]. However, wireless sensor network has the ability to analyze environmental parameters and then send data to databases and eventually receive and respond to appropriate conditions [4]. Therefore, the capability of these networks on the one hand and the importance of estimating signal parameters, especially frequency, on the other hand, provide the basis for research and integration of these two. Signal frequency estimation and recognition algorithms can be categorized into two groups of single-sensor or non-distributed methods and multi-sensory or distributed methods. Different methods and algorithms of single-sensor are based on signal processing. Among these methods, we can use methods such as Discrete Fourier Transform (DFT) [6-8], weighted least square [9], least square error method [10], artificial intelligence techniques [11] algorithms such as recursive wavelet [12], Newton [13, 14], Kalman filter [15], phase locked loop [16] and zero crossing technique [17]. These are examples of several existing and developing methods in this area that have more applications. Different methods for estimating the distribution in the wireless sensor network are presented. In general, three common methods are the incremental method, the consensus method and the diffusion method. Among these three methods, according to the advantages of the diffusion method, this method is more widely used [18]. In this method, after updating the estimation in each sensor, with the distribution of estimates, adjacent sensor estimates are combined with each other and the final estimate is obtained. Furthermore, this method looks at the cutoff points of execution of disseminated stochastic-inclination arrangements and talks about systems that assistance bring their potential all the more completely. The introduction receives a helpful factual system and infers execution results that explain the mean-square security, combination, and unfaltering state conduct of the learning systems. The work likewise represents how appropriated preparing over diagrams offers ascend to some noteworthy objects because of the coupling impact among the operators. These objects are talked about in the unique situation of versatile systems, alongside models from an assortment of zones including disseminated detecting, interruption discovery, circulated estimation, online adjustment, organize framework hypothesis, and machine learning.

3. REVIEW THE METHODS FOR IDENTIFYING AND ESTIMATING THE SIGNAL

The precise recognition of the signal and its parameters helps to accurately and accurately measure the system. The use of this topic in the military field to detect Douppler frequency of a fighter or helicopter and equipment of the enemy through radar and other identification equipment is necessary after frequency analysis to deal with it. In the field of security and the detection of specific sound frequencies among a variety of different sounds and noise, and even in the industrial grid and smart grid, and many other applications, it is evident that the signal parameters and errors in the system will be timely estimated and timely diagnosed in the system. Several methods are presented in two single-sensor and distributed models to estimate the signal frequency with high accuracy and convergence velocity. The following is a brief summary of the important methods used in the paper.

3.1 Single-Sensor Methods (Non-distributed)

There are many methods for estimating signal parameters in single-sensor conditions, which, based on their application and importance, some of these methods are described below. The Maximum Likelihood Estimation (ML) method for estimating signal parameters by sensors is mainly one of the most popular approaches for evaluating practical estimates [19]. Another method and algorithm has been presented in recent years in the discrete Fourier transform and fast Fourier transforms. In 2012, a method to detect high-frequency frequencies using DFT sampling was presented at three points [6, 7]. In fact, this method has the ability to trace and estimate the frequency by performing the following two steps.

1. Large-scale search of the signal with N-point DFT
2. Better estimation based on the results of the first step

In total, it can be said that this method, in addition to less operations and calculations, has a higher accuracy and is better for environments with SNRs [6]. Signal processing is a promising tool for the next generation of wireless networks and electrical systems. In this context, the least-mean square (LMS) method was introduced for the first time by Holf & Widrow in 1960 and was widely used for calculations because of its simple structure and high capability [21]. The LMS algorithm has been studied by many researchers, and over the years, many improvements have been proposed. Among them is the article [10], which in 2005, based on an adaptive filter, provided a more appropriate model for the LMS method [10]. The LMS method updates the filter coefficients in a specific loop, so that the square of the error signal is minimized. That is why this method is called the least squares error method or least squares mean. In other words, it can be said that the input signal after receiving by the sensor will be in a repeating loop, in this loop, the estimated estimate is instantaneously estimated by the instantaneous moment, until the square of the error signal is minimized. This operation is calculated in each repetition by the following equation [21].

$$\omega_{k+1} = \omega k - \mu \nabla e^2(n)$$

Where μ is the step size and ω specifies the filter coefficients. In the mentioned relationship, the gradient of the signal indicates an error relative to the filter coefficient [21]. In recent years, improvements have been made to this method, such as CLMS[1] [10], ACLMS[2] [22] and MLMS[3] [23]. The methods mentioned above have the proper performance in the power network and also in presence of high noise [23]. One of the methods of frequency estimation that has been presented in recent years is the Kalman Filter method [15]. This method depends on the signal state space model. In this method, it is tracked and estimated by eliminating disturbing noise and system error as well as harmonics in the input frequency signal of the system. This method is applicable to both linear and nonlinear systems. Kalman Filter is divided into two types of Linear Kalman Filter and Extended Kalman Filter, whose extended type is most commonly used for nonlinear functions [15]. This algorithm is capable of estimating in high noise, especially in power systems [24]. Another method for estimating the frequency is the phase locked loop (PLL) algorithm. Phase locked loop is a fundamental method with many applications in electrical engineering. The main idea in this method is to produce a sinusoidal signal, which phase amplifies the main component of the input signal. More precisely, the phase locked loop method is similar to a servo system, which controls the phase of the output signal, so that the error between the output phase and the input phase is minimized [16]. Another algorithm is the zero crossing technique for estimating network parameters. The zero crossing method can be used to track the frequency in power networks, because the existence of many harmonics in a power network signal requires a suitable method for network identification and estimation. In simple and general terms, this method calculates the number of points passing through zero at a given interval of the input signal. The final estimation in this method is calculated by calculating discrete Fourier transform and analyzing the sinusoidal and cosine elements of the incoming signal during specific relationships [17]. Among other methods that can be mentioned are methods such as recursive wavelet, Newton algorithm, neural network methods, weighted least square method, and methods that are derived from the integration of several algorithms. Each of the proposed methods, according to the environmental conditions and type of input signal, and other factors, should be selected and applied.

3.2 Multi-Sensor Methods (Distributed)

In a wireless sensor network, sensors have limitations in power supply, signal processing, and communication capabilities. Signal input to sensors is often influenced by noise. Network constraints will result in the loss of sensitive and original signal data or inaccessibility and the correct estimation of signal parameters. Distributed methods should be presented in such a way as to deal with these unfavorable conditions, so that they can be better utilized in the wireless sensor network with higher precision. There are three general strategies for estimating the following: [18].

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[1] Complex LMS
[2] Augmented complex LMS
[3] Modified LMS

(1) Incremental: In this strategy, a loop in the network is considered and from the beginning of the loop, the sensor first updates its target and delivers the second sensor in the loop. As shown in Fig. 1, this works in the same way to reach the sensor in the loop. One of the disadvantages of this strategy is that, with the failure of a sensor in the loop, the estimate is error-prone [16]. In the incremental strategy, the network model and the algorithm shown in Figure 1 are used to estimate the desired parameter. In general, the algorithm of this strategy is shown in Fig. 1 [18].

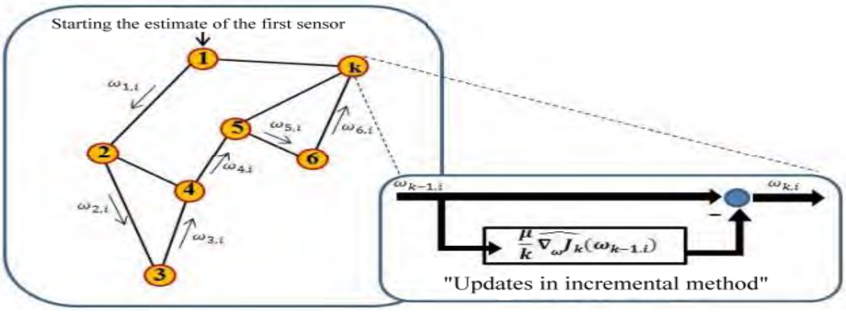

Fig. 1. Network model and update algorithm in incremental strategy [18].

In the relationship mentioned, μ, ωk, i and k are the steps of the length of the step, the estimated parameter in the instant of the sensor and the number of sensors.

(2) Consensus: In this strategy, adjacent sensors acquire an estimate of consensus. In fact, in this strategy, each sensor simultaneously estimates the parameter according to at least one cost function and also the combination of estimations obtained from neighboring sensors [19, 20].

$$\omega_{k,i} = \omega_{k-1,i} - \tfrac{\mu}{k}\widehat{\nabla_\omega J_k}(\omega_{k-1,i}) \tag{1}$$

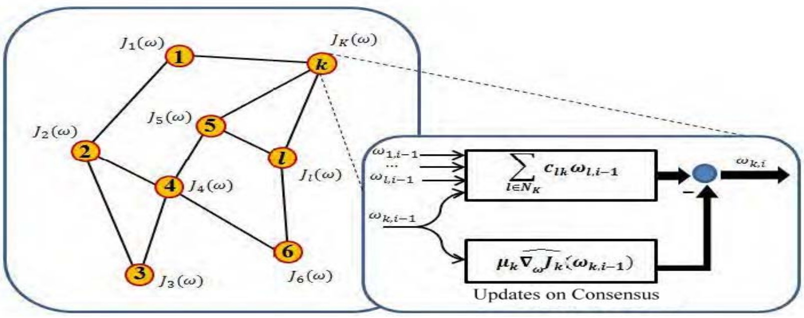

Fig. 2. Network model and update algorithm in consensus strategy [18].

As shown in Fig. 2, the update algorithm estimates the signal parameters according to the consensus strategy during the two stages of the combination and updating. Which uses the following two equations of their results at any given time for the final estimation of the parameter [21].

$$\begin{aligned}
\varphi_{k,i-1} &= \sum_{l\in N_k} c_{lk}\omega_{l,i-1} \\
\omega_{k,i} &= \varphi_{k,i-1} - \mu_k \widehat{\nabla_\omega J_k}(\omega_{k,i-1})
\end{aligned} \tag{2}$$

In the above-mentioned relations, Φk represents the coefficient of the neighborhood of the sensors and $i-1$ represents the combination obtained from the estimation of neighboring sensors at the moment $i-1$ [22, 23].

4. MINIMUM DISTRIBUTED LEAST MEAN *P*-NORM METHOD (DLMP)

In this paper, the distributed least-mean-*p*-norm (dLMP) method has been evaluated to estimate the distributed frequency of the signal in three additive, consensus, and scattering strategies. In the proposed method, based on the definition of a proper cost function, a distributed method is used to estimate the frequency of common sinusoidal signals with a common frequency in a wireless sensor network. One of the advantages of the proposed method is that it has the ability to simultaneously, in addition to estimating the distributed frequency, estimate the amplitude and phase of the sinusoidal signal locally in each sensor with accurate convergence and high velocity. The results also show that the complexity of the proposed method is less than the Notch filter-based algorithm, since it does not use the Notch filter to eliminate the central sinusoidal frequency. In the second part of this paper, we briefly refer to some of the available single-sensor and distributed methods. Then, in the third part of this paper, we will describe the proposed distributed method. In the fourth section, the results of simulation and comparison of distributed and single-sensor methods in the specific conditions are compared with the proposed method, and the conclusion is presented in the fifth section. In the proposed method, a network of sensors is considered. In that network, each sensor receives a high-noise (high-noise) sine signal as sensor input. Each sensor is in a two-way communication between itself and neighbors (the connection that sensors can exchange data for better estimation). The estimation process in this method is repeated several times and each time it is updated, the estimation of each sensor will be updated. The proposed method allows a network with the help of the collaboration of sensors in the network to identify and evaluate the parameters of the environment, especially the frequency, with precision and speed. The proposed paper method, which benefits from all three types of distributed distribution strategies and compares them, is the least-distributed algorithm (DLMP) of the distributed distributions (dLMP) [24]. This method with high speed convergence and high accuracy will have many applications in multi-sensor networks [25]. The advantage of this method is the optimal and fast convergence as well as high sensitivity to high SNRs. In addition to the distributed frequency estimation, another advantage of this method is to estimate the amplitude and phase of the sinusoidal signal locally in each sensor with accurate convergence and high speed. In this section, we first introduce the network model and the overall estimation signal model, and then the dLMP method for three distributed strategies is presented separately, based on article [16], where in [16]. the researcher manages a standout amongst the most critical issues in the control of matrix-associated converters, which is the discovery of the positive grouping major segment of the utility voltage. The examination completed. Furthermore, in this study, exact, and hearty positive grouping voltage indicator offering a decent conduct, regardless of whether uneven and contorted conditions are available in the lattice. The proposed indicator uses another "twofold synchronous reference outline PLL" (DSRF-PLL), which totally kills the current mistakes in customary synchronous reference outline PLL frameworks (SRF-PLL) while working under uneven utility voltages. In the investigation performed in this paper, the positive and negative arrangement segments of the uneven voltage vector are legitimately portrayed. At the point when this unequal vector is communicated on the DSRF, the examination of the signs on the DSRF tomahawks grants to plan a decoupling system which secludes the positive and negative succession parts. This decoupling system offers ascend to another PLL structure which recognizes the positive arrangement voltage segment rapidly and precisely. In the proposed system the sensor network consists of a number of N specific sensor nodes in a randomized geographic area. Sensors have the capability to share their information with adjacent (adjacent) sensors via existing communication channels, while each sensor has a number of adjacent and neighboring sensors. Neighborhood communication can be fully connected between sensors, or that each sensor is connected to a number of sensors only. This depends on the dimensions and conditions of the network, so in general, the number of neighbors of the sensor k can be specified. The sine signal is distributed in the distribution. Let's suppose that in the k-sensor, the signal of the discontinuity observed.

$$X_k(i) = A_k \cos(\omega_0 iT + \varphi_k) + \upsilon_k(i) \tag{3}$$

Where A_k, φ_k, $\upsilon_k(i)$ and T are equal to the amplitude, initial phase and signal noise, observed by the k-sensor and the periodicity of the signal. Then, together with the neighboring sensors and by sharing the initial estimation of each sensor with neighboring sensors, the common parameters are estimated. Based on the proposed method, we can use the following equation to estimate the frequency or any other parameter of the observed signal.

$$\omega_{i+1} = \omega_i - \mu(|e|p) \tag{4}$$

Where ω is the frequency or any other desired parameter for estimation in Fig. 3 shown the main steps of the proposed algorithm.

5. SIMULATION RESULTS

Based on the proposed method, several experiments have been conducted to evaluate the performance of this method. The proposed method is named as the minimum P-norm method of distributed error. The performed experiments are performed in two values, $p = 2$, which are commonly known as minimum error squares (LMS) and $p = 4$, usually the minimum mean quadrant error, the minimum average error cube (LMF). As noted, the proposed method for estimating the distributed frequency is presented as a common parameter between the sensors within the network. Therefore, in the simulation, the proposed method is based on similar single-sensor methods and distributed distributions such as three-point Fourier transform, maximum field appearance, minimum square error and minimum P-norm of single sensor error also distributed filtering method are analyzed and compared for distributed frequency estimation [27]. The method is also compared to three distributed strategies, simulations and comparisons. In the proposed method, the phase and domain estimation capabilities are localized, according to the description and the proven relationships in the previous sections, simultaneously with the distributed frequency estimation. The simulation carried out in the Matlab programming environment was performed using a sampling frequency of 500 ***Hz*** [28]. Each simulation experiment is 100 times repeated. The optimal signal is considered as the input signal to the network with phase, amplitude and frequency of $\pi/2$, 5, and 50 ***Hz***, respectively [29]. The sensor network designed in this simulation is modeled with five sensors, all of which are distributed structurally, in the same way [30].

In all experiments, to calculate the performance matrix, the mean squared error (MSE) frequency is used, which is defined as follows.

$$MSE = \frac{1}{K}\sum_{K=1}^{K}\frac{1}{K}(f_0 - \widehat{f}_0)^2 \tag{5}$$

In the relationship mentioned above, $K = 100$, $\hat{f}_0$ as the initial value of the frequency, and also f_0, represent the estimated frequency of the frequency. In general, two types of experiments, a comparison test with all single-sensor and distributed distribution methods (distributed Notch filter), as well as a comparison test between the proposed distributed strategies were performed. Each experiment was individually divided into two experiments with Gaussian noise and also in the presence of impulse noise. In total, four experiments in this paper have been evaluated and analyzed for the accuracy of the proposed method.

Experiment 1: in the first experiment, Gaussian noise with a noise variance of 0.1 ($\sigma^2 = 0.1$) is considered. For simulation, the sampling frequency is 500 Hz and 700 repeats for algorithms. μ for each method is considered as convergent in 700 replications. The purpose of the first experiment is to compare and evaluate the proposed method with similar single-sensor and distributed methods. In Fig. 3, the convergence diagram of the comparative methods is presented. As can be seen, the proposed method of LMP has a faster convergence than the rest of the methods.

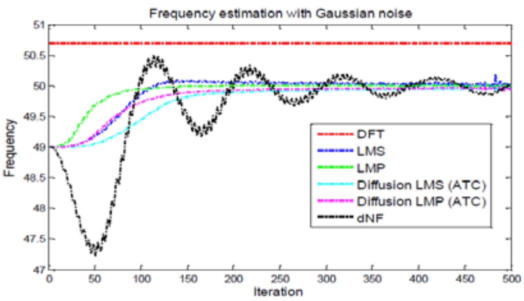

Fig. 3. Convergence diagram and estimation in Gaussian noise mode.

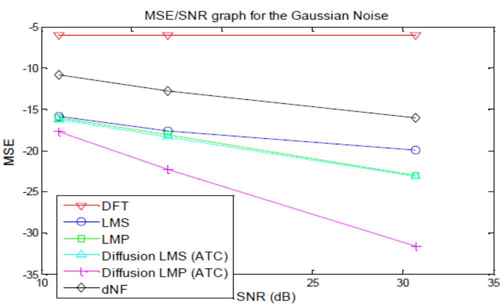

Fig. 4. MSE chart based on SNR.

In Fig. 4, the MSE (Mean square error) is shown in terms of signal to noise in each method. Different domains have been used to compute signal-to-noise ratio (SNR), which is calculated as follows.

$$SNR = 10\log_{10}\left(\frac{A^2}{2\sigma^2}\right) \tag{6}$$

Where A represents the amplitude of the signal and σ^2 of the variance of noise (σ^2 = 0.1). Simulated SNR is taken from 10dB to 30dB. As is evident from the figure, in the high-noise signal, the proposed distribution method of LMP with p = 4 is the best.

Experiment 2: In the second experiment, Bernoulli-Gaussian impact noise was considered with 10% of the impact samples. As in the previous experiment, a second test was carried out at a sampling frequency of 500 Hz and 700 repetitions. μ is intended for each method in a way that converges to 700 repetitions. In Fig. 5, the distributed frequency convergence diagram shows the method presented with single-sensed and distributed methods such as the first one. As can be seen, the proposed LMP method has a higher convergence rate than other methods.

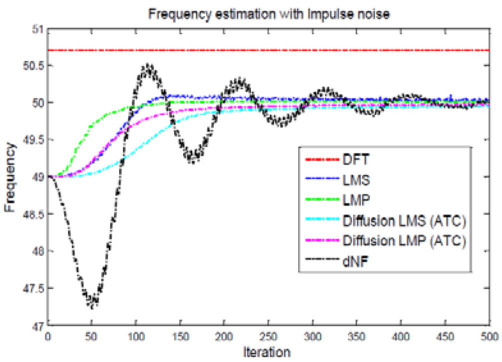

Fig. 5. Convergence diagram and frequency estimation with impulse noise.

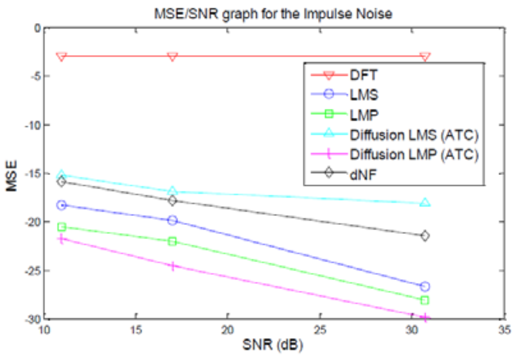

Fig. 6. MSE diagram in terms of SNR in shock mode.

In Fig. 6, the noise-to-noise error diagram is shown for each method. As can be seen from the figure, the LMP single-sensor method and distributed LMP with p = 4 have better signal-to-noise ratio than other methods.

Experiment 3: In this noise experiment Gaussian noise with a noise variance equal to 0.1 (σ^2 = 0.1). All sampling and simulation conditions are considered as the previous tests. This experiment aims to compare the proposed method with distributed strategies (incremental, consensus, and dispersion) with p = 4 and p = 2. In Fig. 7, the convergence diagram of the estimation frequency is observable. As is well known, the LMIP consensus strategy has the highest convergence rate.

In Fig. 7, the signal-to-noise error diagram shows the comparison methods in this test. As we can see, the LMP-type dispersion strategy has the least error. As shown in

Fig. 8, distributed LMP methods of the LMP type of ATC distributed type of CTA and distributed LMP type of consensus are better and better than other methods. Among these methods, with a low difference, the distributed LMP method has a better status than the two other methods in SNR > 12dB.

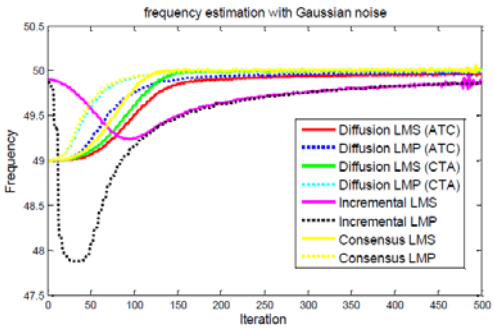

Fig. 7. The convergence and estimation diagram method in Gaussian noise mode.

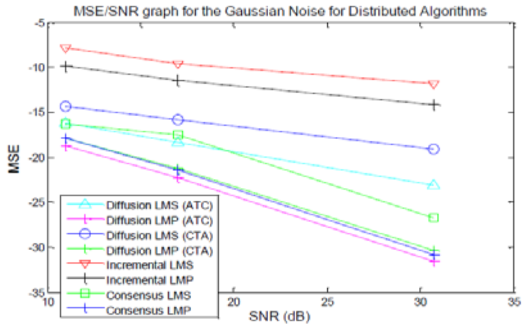

Fig. 8. MSE chart in terms of SNR distributed methods in Gaussian noise mode.

Experiment 4: In this experiment, as a second experiment, the shock noise was considered as a beryllulonics with 10% of the impact specimens. All sampling and simulation conditions are considered as previous tests. This experiment aims to compare the methods of this test, as in the third experiment, but in the presence of shock noise. Fig. 10 shows the convergence diagram of the methods. In this case, similar results are obtained with Gaussian noise, in which the consensus-type strategy of the LMIP type has the fastest convergence.

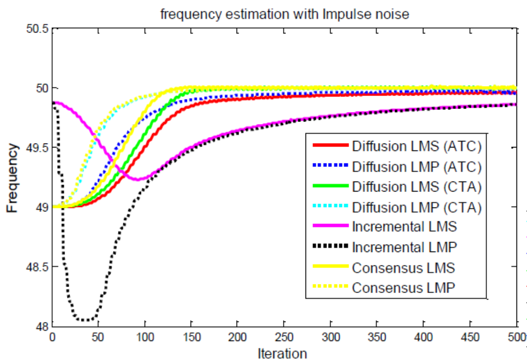

Fig. 9. Convergence diagram and estimation of distributed frequency with impulse noise.

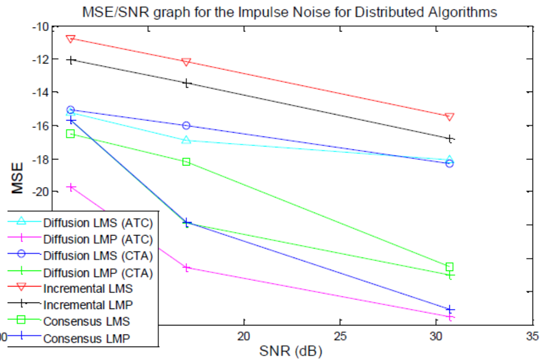

Fig. 10. MSE Chart based on SNR distributed methods in impact noise mode.

In Fig. 9, the noise-to-noise error diagram is shown in the comparison methods in this experiment under shock noise. In this case, the results are similar to the Gaussian noise state, and again, the LMP-type dispersion strategy has the least error in estimating the frequency.

As shown in Fig 10, the distributed LMP methods of the ATC type have a significantly better performance than other methods in different SNRs. This is while the distributed LMIP method of consensus type is at a distance of 30dB SNR, which is an ATC type. The overall result of the above experiments indicates the proper status of the proposed method with the dispersion strategy. So locally in a sensor, the amplitude and phase convergence diagram of the minimum 2-error mode with p = 2 and p = 4 = simultaneously with the distributed frequency estimation, in both Gaussian noise and the shock with the same and the same conditions with the tests performed, it can be seen in Figs. 11 and 12.

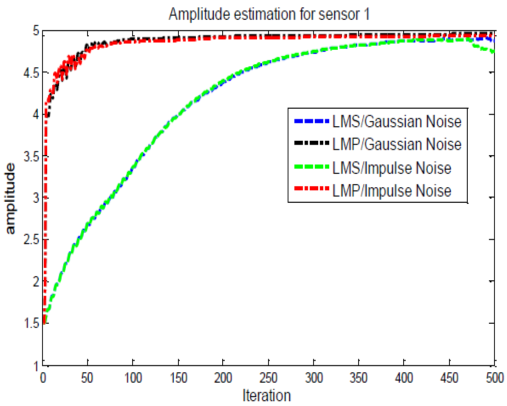

Fig. 11. Convergence diagram and estimation of the first sensor domain.

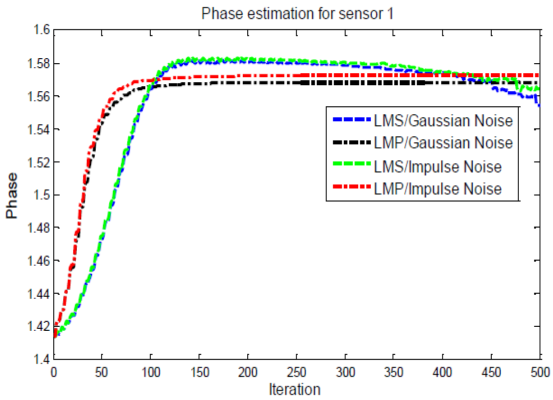

Fig. 12. Convergence diagram and estimation of the first sensor phase locally.

As shown in Figs. 12 and 13, according to the local estimation carried out simultaneously with the distributed frequency estimation method, the speed and accuracy of the convergence in the proposed method is better and more appropriate.

5. CONCLUSIONS

In this paper, a new method called the distributed error of distributed P-norm (LMP) is proposed for estimating not only the frequency but also the amplitude and phase. The simulations show that the proposed algorithm has better and more favorable performance compared to other methods, such as single-sensor and distributed methods. In the proposed method simultaneously with distributed frequency estimation, domain and phase estimation with optimal and fast convergence is possible locally. Due to this advantage compared to the distributed filter method, the proposed method has less complexity and better convergence speed, since the Notch filter has not been used in the proposed method. Therefore, in general, based on all the experiments conducted, the results of distributed strategies show the superiority of the dispersion method. According to the results, the distributed least significant p-norm method (dLMP) and its implementation with the Dispersion Strategy (ATC), is prone to research and development in various applied industries, including three-phase power networks.

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