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Non-stationary Sparse System Identification over Adaptive Sensor Networks with Diffusion and Incremental Strategies

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Abstract—**in this paper we studied the performance of several distributed adaptive algorithms for non-stationary sparse system identification. Non-stationarity is a feature that is introduced to adaptive networks recently and makes the performance of them degraded. We analyzed the performance of both incremental and diffusion cooperation strategies in this newly presented case. The performance analyses are carried out with the steady-state mean square deviation (MSD) criterion of adaptive algorithms. Some sparsity aware algorithms are considered in this paper which tested in non-stationary systems for the first time. It is presented that for incremental cooperation, the performance of incremental least means square/forth (ILMS/F) algorithm surpasses all other algorithms as non-stationarity grows and for diffusion cooperation, the performance of adapt-then-combine (ATC) diffusion prevails reweighted zero attracting (RZA) ATC diffusion algorithm in non-stationary system identification. We hope that this work will inspire researchers to look for other advanced algorithms against systems that are both non-stationary and sparse.**

Keywords-Adaptive networks, , incremental least mean square, non-stationary condition, sparse system identification, diffusion.

I. INTRODUCTION

Practical uses of wireless adaptive sensor networks are so widespread and long lasting that made them a hot topic of research. Environmental monitoring, object surveillance and tracking, wireless channel control and so many other applications are proof of the importance of this flourishing technology. Analyzing the performance of these networks under different environmental and systematic conditions is the key element of many recently published papers [1 & 3]. Adaptive networks usually work with two distributed cooperation strategies namely incremental and diffusion. In diffusion strategy all nodes can communicate with each other, while in incremental method each node can only share data with its immediate neighboring nodes in a Hamiltonian cycle.

Recently numerous powerful adaptive algorithms are proposed for different applications [10-14]. Most of these algorithms are designed to be robust in sparse systems that are known with their long impulse responses and a few non-zero taps [6]. Sparse system identification is a topic that not only challenged adaptive algorithms but also crept into the topic of adaptive sensor networks. In a few papers [2,4 & 15], the sparse system identification is mentioned with sensor networks and some algorithms such as incremental reweighted zero attracting LMS (IRZA-LMS) and adapt then combine (ATC) diffusion reweighted zero attracting LMS (RZA-ATC diffusion) are presented for this task. Also in [4] diffusion normalized least mean forth (LMF) algorithm is addressed for this task. It is shown that when we want to estimate a very long weight vector with a high value of sparsity, it takes a longer time for the distributed adaptive algorithm to converge. Also it is preferable for an algorithm to have reasonable results for both highly sparse and non-sparse system identification.

Also recently the performance of adaptive networks under non-stationary conditions became an important branch of research. In several papers [3, 9, 18], the performance of distributed LMS algorithm and its variants are considered in estimating a non-stationary unknown weight vector. It is claimed in these papers that when we want to track a non-stationary vector, the performance of network degrades according to the non-stationarity of weight vector that is, when the system changes rapidly, the tracking of its behavior gets harder and in some cases impossible. The sparsity of the system may change after some time and give the algorithm the time to converge, but in non-stationary case, the vector changes at each iteration. If these changes are small enough, we can expect the convergence of network, in other cases we must look for other solutions. But there are problems where we need to identify an unknown system which is both sparse and non-stationary. Such problems arise in, for example, wireless channel estimation.

Unfortunately, while there has been a struggle for presenting more sparsity aware algorithms, up until now there has been no effort in producing algorithms that are specially designed for non-stationary systems. We tested several newly proposed algorithms in order to find a suitable one for non-stationary case and it turned out that the combined least mean square/forth (LMS/F) algorithm of [5] works slightly better than others for incremental cooperation.

Our contribution in this paper is that we combined both non-stationary and sparse system identification and analyzed the performance of some adaptive distributed algorithms over networks. As we mentioned, such complicated conditions may occur in the tasks like sparse channel estimation [16] or sparse echo and noise cancellation. It means that most of the channels that we are interested in estimating are fading channels that are modeled with non-stationary systems. Due to the complexity of the proposed condition and the multiplicity of analyzed algorithms, we only considered cyclic or incremental mode of cooperation between sensor nodes, namely incremental LMS or ILMS algorithm, and postponed analyzing diffusion mode for our future works. Also we must remind that in [10] a sparse non-stationary system is mentioned but in that system only the sparsity of weight vector changed in time and for different phases of simulation. The rest of this paper is organized as follows:

In part II we briefly review incremental and diffusion LMS algorithms for stationary systems. In part III we review some distributed algorithms with incremental cooperation then we introduce a new algorithm that can handle both non-stationarity and sparsity in systems. In part IV we describe sparse diffusion algorithms. In part V we analyze the computational complexity of the presented algorithms and in part VI we present our simulation results for non-stationary sparse system identification. Finally, in part VII we present our conclusion and future scope.

Notation: We used boldface letters for vector variables. Also we used the notation $\mathbb{E}[.]$ to denote expectation operation and notation $(.)^*$ to denote complex conjugation for vectors.

II. SYSTEM EXPLANATION

Consider a network with N active nodes as in Fig. 1 that is deployed to estimate an unknown weight vector $\boldsymbol{w}^o$ with M entries. In stationary case, this vector is considered constant for all observations, but in non-stationary case the unknown weight vector changes with time and adaptive distributed algorithm must track it. In non-stationary case instead of a weight vector with constant values, the desired unknown vector can change according to Random-walk model:

$$\boldsymbol{w}^o(i+1) = \boldsymbol{w}^o(i) + \boldsymbol{\eta}(i) \tag{1}$$

where $\boldsymbol{\eta}(i)$ is a zero mean random sequence with covariance matrix R_η . Along with non-stationarity condition we assume that the weight vector is sparse. It means that majority of its coeficients are zero and the rest are produced according to non-stationary model. Detailed explanations of the production of weight vector is explained in simulation part.

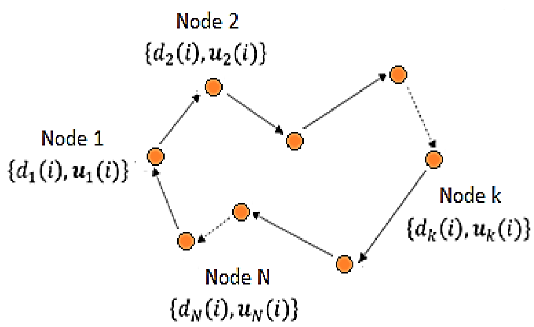

Fig. 1. Distributed sensor network with incremental cooperation

In our network we assume that each node k in time index i has access to local observations of desired output $d_k(i)$ and regressor vector $\boldsymbol{u}_k(i)$. In incremental strategy each node has only communication with its immidiate neighbors while in diffusion strategy the connections are more. here we review the simple incremental LMS and diffusion LMS algorithms.

A. Incremental cooperation

Simple ILMS algorithm starts with the assumption that there is a linear relation between desired output and algorithm inputs as follows:

$$d_k(i) = \boldsymbol{u}_k(i)\boldsymbol{w}^o(i) + v(i)$$
(2)

in this equation $\boldsymbol{w}^o(i)$ is the unknown non-stationary weight vector and $v(i)$ is white Gaussian noise sample. If we take $\boldsymbol{\psi}_k(i)$ as the local estimate of $\boldsymbol{w}^o(i)$ in node k, we have the following calculations for each iteration i repeat:

$$\boldsymbol{\psi}_0(i+1) = \boldsymbol{w}(i)$$
$$e_k(i) = d_k(i) - \boldsymbol{u}_k(i)\boldsymbol{\psi}_{k-1}(i+1)$$
$$\boldsymbol{\psi}_k(i+1) = \boldsymbol{\psi}_{k-1}(i+1) + \mu_k \boldsymbol{u}_k^T(i) e_k(i)$$
(3)
$$\boldsymbol{w}(i+1) = \boldsymbol{\psi}_N(i+1)$$

in this relation μ_k is the step size. For all the algorithms that follows and for ILMS algorithm too, we evaluate the performance with Mean Square Deviation (MSD) criteria that for each node is defined as:

$$MSD_k \triangleq \mathbb{E}\left\|\widetilde{\boldsymbol{\psi}}_{k-1}(\infty)\right\|_I^2$$
(4)

where

$$\widetilde{\boldsymbol{\psi}}_k(i) \triangleq \boldsymbol{w}^o(i) - \boldsymbol{\psi}_k(i)$$
(5)

and $\|x\|_\Sigma^2$ operator means $x^*\Sigma x$ for column vector x.

B. Diffusion cooperation

In diffusion strategy as we mentioned the nodes exchange their data with other than their neighboring nodes. The combination policy is governed by the determination of combination weights namely $a_{l,k}$. A network with diffusion cooperation is presented in Fig. 2. The simple ATC diffusion LMS algorithm can then be given as [17]:

For each iteration i repeat:

$$\boldsymbol{\psi}_k(i) = \boldsymbol{w}_k(i-1) + \mu_k \boldsymbol{u}_k^*(i)[d_k(i) - \boldsymbol{u}_k(i)\boldsymbol{w}_k(i-1)] \quad (6)$$

$$\boldsymbol{w}_k(i) = \sum_{l\in\mathcal{N}_k} a_{l,k}\boldsymbol{\psi}_l(i)$$
(7)

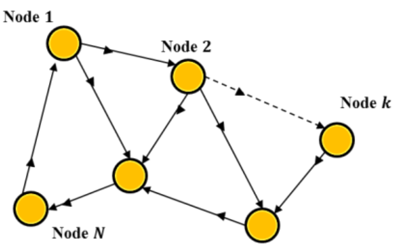

Fig. 2. Distributed sensor network with diffusion cooperation

III. SPAPRSE SYSTEM IDENTIFICATION WITH INCREMENTAL STRATEGY

In this part we will present some of the tested distributed algorithms with incremental cooperation in sparse system identification. Some of these algorithms are tested in distributed networks for the first time and others are never tested in non-stationary system tracking. All in all, four distributed sparsity-aware adaptive algorithms are tested in this part and their performances are compared to ILMS algorithm in non-stationary case. It is obvious that to find an algorithm that is robust to both sparsity and non-stationarity we must compare all algorithms in the same situations.

To the best of our knowledge only three distributed incremental algorithms are tested in sparse system identification and none of them are tested in non-stationary systems. RZA ATC diffusion and IRZA-LMS algorithms are mentioned in [15] and [2] and a normalized version of diffusion least mean forth (LMF) algorithm is used in [4]. Here we will review some incremental versions of these algorithms and also introduce LMS/F algorithm to distributed processing.

A. IRZA-LMS algorithm

The main distributed algorithms that are introduced for sparse system identification are IZA-LMS and IRZA-LMS algorithms. The later algorithm is concluded to be more robust in comparison and here we will explain it. Again for each iteration we have:

$$\boldsymbol{\psi}_0(i+1) = \boldsymbol{w}(i)$$
$$e_k(i) = d_k(i) - \boldsymbol{u}_k(i)\boldsymbol{\psi}_{k-1}(i+1)$$
$$\boldsymbol{\psi}_k(i+1) = \boldsymbol{\psi}_{k-1}(i+1) + \mu_k \boldsymbol{u}_k^T(i) e_k(i) - \rho\frac{sgn(\boldsymbol{\psi}_{k-1}(i+1))}{1+\varepsilon|\boldsymbol{\psi}_{k-1}(i+1)|}$$
(8)
$$\boldsymbol{w}(i+1) = \boldsymbol{\psi}_N(i+1)$$

As we can see only local weight vector update equation is changed in comparison with simple ILMS algorithm and in this equation a penalty term is added to previous one. In this penalty term that helps to estimate only those equations that are non-zero, both ρ and ε are positive controlling parameters.

B. ILMS/F algorithm

The LMS/F algorithm is designed with respect to least mean square and forth criterion and the updating relation of this algorithm is [5]:

$$\boldsymbol{w}(i+1) = \boldsymbol{w}(i) + \mu\boldsymbol{u}^T(i)\frac{e^3(i)}{e^2(i)+\lambda}$$
(9)

where λ is a positive threshold which controls the convergence speed and stability of the LMS/F algorithm. The optimum value of λ can be calculated according to the method proposed in [5]. The distributed version of this algorithm with incremental mode of cooperation (ILMS/F) is as follows:

For each iteration repeat:

$$\boldsymbol{\psi}_0(i+1) = \boldsymbol{w}(i)$$
$$e_k(i) = d_k(i) - \boldsymbol{u}_k(i)\boldsymbol{\psi}_{k-1}(i+1)$$
$$\boldsymbol{\psi}_k(i+1) = \boldsymbol{\psi}_{k-1}(i+1) + \mu_k \boldsymbol{u}_k^T(i)\frac{e_k^3(i)}{e_k^2(i)+\lambda}$$
(10)
$$\boldsymbol{w}(i+1) = \boldsymbol{\psi}_N(i+1)$$

C. Incremental Sparse normalized algorithms

In some papers the normalized versions of algorithms described above are used [14]. These types of algorithms are achieved via the normalization of input vector to its norm. with this technique the algorithm becomes robust to the variations of input vector. For example, to achieve the normalized version of ILMS algorithm in (3) we have:

$$\boldsymbol{\psi}_k(i+1) = \boldsymbol{\psi}_{k-1}(i+1) + \mu_k \frac{\boldsymbol{u}_k^T(i)}{\|\boldsymbol{u}_k(i)\|^2} e_k(i) \quad (11)$$

IV. SPAPRSE SYSTEM IDENTIFICATION WITH DIFFUSION STRATEGY

Now consider the equation (2) again. We assume that the unknown vector $\boldsymbol{w}^o(i)$ is still non-stationary and sparse but here we want to estimate it via diffusion cooperation starategy. The simple diffusion LMS algorithm is not designed for sparse or non-stationary system identification and for adapt then combine (ATC) scheme it is given in (6) and (7).

In order to over come sparsity, in [15] a sparsity aware algorithm namely ATC-sparse diffusion (ATC-SD) was proposed. This algorithm is presented by considering the following cost function [15]:

$$J_{\boldsymbol{w}}(\boldsymbol{w}) = \sum_{k=1}^{M} \mathbb{E}\left|d_k(i) - \boldsymbol{u}_{k,i}\boldsymbol{w}\right|^2 + \rho f(\boldsymbol{w}) \quad (12)$$

where $\mathbb{E}(.)$ is the expectation operator and $f(w)$ is a regularization term weighted by parameter $\rho > 0$. The ATC-SD algorithm is then given by:

$$\boldsymbol{\psi}_k(i) = \boldsymbol{w}_k(i-1) + \mu_k \sum_{l\epsilon N_k} c_{l,k}\boldsymbol{u}_l^*(i)[d_l(i) - \boldsymbol{u}_l(i)\boldsymbol{w}_k(i-1)] - \mu_k\rho\partial f(\boldsymbol{w}_k(i-1)) \quad (13)$$

$$\boldsymbol{w}_k(i) = \sum_{l\epsilon N_k} a_{l,k}\boldsymbol{\psi}_l(i) \quad (14)$$

For RZA ATC diffusion algorithm the $f(w)$ function is given by [15]:

$$f(w) = \sum_{m=1}^{M} \log(1 + \varepsilon|w_m|) \quad (15)$$

Finally the sub gradient term $\partial f(\boldsymbol{w})$ can be written as:

$$\partial f(w) = \varepsilon \frac{sign(w)}{1+\varepsilon|w|} \quad (16)$$

In this paper for the first time we examine the performance of RZA ATC diffusion algorithm in the identification of a non-stationary system.

V. COMPUTATIONAL COMPLEXITY

In this paper we presented several adaptive algorithms and their cooperative (distributed) versions for system identification task. Here we analyze and compare the computational complexity of these algorithms. The computational complexities of distributed versions of employed algorithms are directly dependent to that of non-cooperative algorithms. Therefore, we only compare the complexity of these non-cooperative algorithms in TABLE 1. One can easily deduce that if the non-cooperative version of an algorithm is more complex than others, then its distributed version is also more complex. Also as we used real valued data in our simulations and the complexities of algorithms are given for this case.

TABLE 1. The real computational complexity of presented non-cooperative adaptive algorithms

algorithms	Additions	Multiplications	Divisions
LMS	2M	2M+1	-
NLMS	3M	3M+1	1
ZA-LMS	M+3K	M+3K+1	-
RZA-LMS	M+4K	M+4K+1	M
LMS/F	2M+1	2M+4	1

In this Table M is the length of weight vector and K (not to be confused with the sensor index k) is the number of non-zero elements of the weight vector. As we can see the complexity of LMS/F algorithm is only a little higher than LMS and lower than other presented algorithms.

The only remaining item here would be comparing the complexity of incremental and diffusion cooperation strategies. Diffusion strategy is more complex than incremental strategy both in Computations per node and transmission per node. For incremental strategy we need $O(M)$ (order of M) computations per node and $O(M)$ scalar transmissions per node [18]. While for diffusion algorithm we need $O(3M)$ computations and transmissions per node [15]. It means that as the number of tap weights goes high, the feasibility of diffusion algorithm declines and it is better to use incremental cooperation strategy. All in all, incremental LMS/F algorithm is more desirable with respect to computational complexity.

VI. SIMULATION RESULTS

To run our simulations we consider a network with 20 nodes ($N = 20$). The value of step-size for all incremental algorithms is 0.0045 except for Normalized ILMS algorithm in which we have $\mu = 0.05$. The noise variance for all nodes is chosen to be equal and $\sigma_v^2 = 0.01$. For our simulations, we assumed perfect communication links between nodes and the study of non-stationary sparse system identification over networks with noisy links or fading conditions can be a new topic of research. In order to compare the performances of incremental algorithms that are mentioned in previous parts we follow two scenarios. In both of them as it is customary in sparse system identification literature, we consider a 16-tap FIR system. But for the first scenario we assume a stationary system and for the second one a non-stationary system is designed. In part *C.* of our simulations we consider non-stationary sparse system identification with diffusion strategies.

A. Stationary Sparse system

We run this simulation for 1800 iterations. For the first 600 iterations, only one tap, chosen at random, is non-zero. For the next 600 iterations, all the odd indexed taps are set to 1. For the last 600 iterations, the odd indexed taps remain 1 while the remaining taps are set to -1. As a result, the sparsity of the unknown system varies during the estimation process [2].

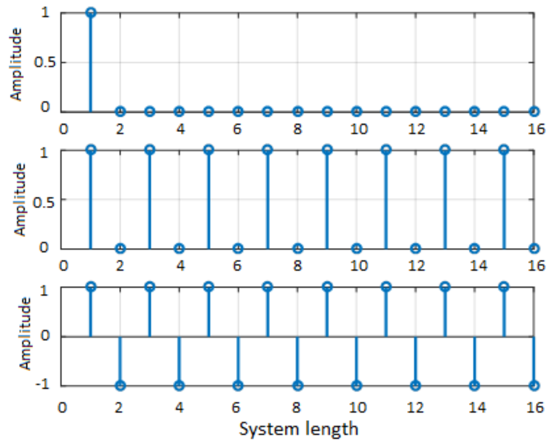

Fig. 3. Stationary sparse system taps

The taps of this system is depicted in Fig. 3. To compare the performance we run the simulation for 4 separate algorithms and presented MSD results in Fig.4. The results are averaged over 50 experiments.

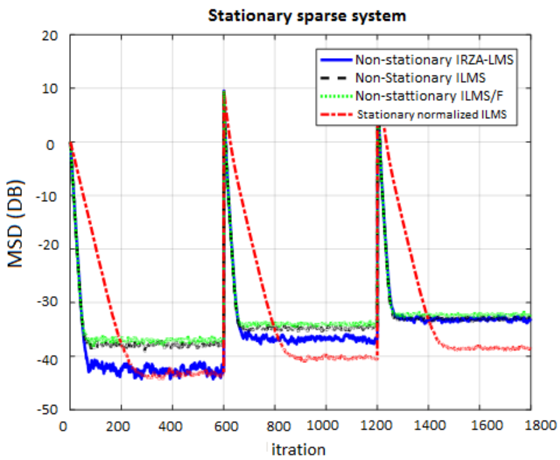

Fig. 4. Performance of incremental algorithms in stationary system identification with varying sparsity.

In this simulation the sparsity for the first 600 iterations is $\frac{1}{16}$ and as we can see the performance of IRZA-LMS is better than others because this algorithm is specially designed for highly sparse systems. The performance of ILMS and ILMS/F are almost the same and are better for final 600 iterations where the system is non-sparse. Also the performance of normalized ILMS is good but this algorithm converges slower than others. We can speed up the convergence of Normalized algorithms by increasing step-size but this will accordingly increase steady-state error.

B. Non-stationary sparse system

Now we must consider the conditions in which our paper proposes a novelty. As mentioned before we assume that our unknown weight vector is non-stationary and changing with time. It means that for each iteration we have a slightly different weight vector. Also our weight vector is assumed to be sparse. It means that only a few entries of it are non-zero.

Following the procedure in [9, 18] we produce the non-zero elements of non-stationary weight vector as follows:

$$\boldsymbol{w}_i^o = \frac{1}{2}\left[a_{1,i}, a_{2,i}, a_{3,i}, a_{4,i}\right]^T \qquad (17)$$

where $a_{k,i} = \left[cos\left(\omega i + \frac{(k-1)\pi}{2}\right), sin\left(\omega i + \frac{(k-1)\pi}{2}\right)\right]$ for $k = 1,2,3,4$ and $\omega = \frac{\pi}{3000}$. As we can see in this case the weight vector has a length of 8 (or $M = 8$) and it is not sparse. In order to make it sparse we can zero pad this vector to reach the desired length. It is important to mention that this 'time changing' model is just for simulation purposes and in order to derive theoretical results, this non-stationarity must agree with Random-walk model. Also in order to produce longer vectors we can repeat the vector with 8 entries, for example in a vector with 16 entries we repeat (17) only 2 times. We can produce this time varying vector in advanced and fed it to algorithm at each iteration or we can change weight vector iteratively.

Again a 16-tap system is considered in this simulation and we have 1800 iterations. For the first 600 iterations only one tap has value and it is calculated from (17). For the second 600 iterations only odd taps are drawn from (17) and for the final 600 iterations all the taps are calculated according to (17), in this situation the system is not sparse but it is completely non-stationary. We can see the results of this simulation in Fig. 5.:

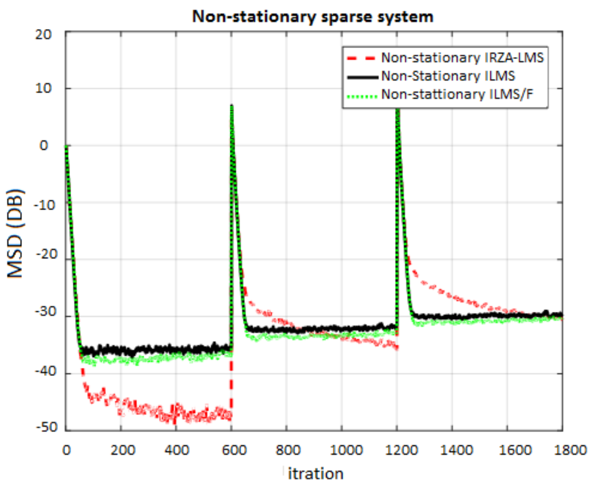

Fig. 5. Performance of incremental algorithms in non-stationary system identification with varying sparsity.

Non-stationarity imposes an intrinsic error increase to the system performance and it is because of the fluctuations of weights around changing optimum vector. As the normalized ILMS algorithm did not performed well in non-stationary case we omitted it from our simulations of this part.

It is obvious that as the non-stationarity grows, the performance of IRZA-LMS algorithm degrades, because this algorithm is specially designed for sparse systems. On the other hand, the performance of ILMS/F algorithm is better for strongly non-stationary systems and clearly outperform both fixed other algorithms in final 600 iterations.

C. Diffusion strategy performance

In this part we analyze the performance of a network with diffusion cooperation strategy in non-stationary sparse system identification. Like previous simulations we consider a network with 20 nodes that have communication with each other and combine their data with uniform combination weights [17]. The simulations are for 300 iterations and the curve for each algorithm is achieved by averaging 20 simulations. The variance of inputs are slightly higher than that of incremental algorithms, therefor we can expect a better performance for diffusion cooperation.

Only two algorithms namely simple ATC diffusion and RZA ATC diffusion are compared in this simulation. For RZA ATC algorithm the parameters are set to be: $\mu = 0.05$, $\rho = 5 \times 10^{-4}$ and $\varepsilon = 10$. We did not consider the stationary simulation in this part because similar results are given in [15]. Here we only consider a combined non-stationary and sparse system. We ran six simulations for this case, three for ATC diffusion and three for RZA ATC diffusion algorithm. Again we assume the system has 16 taps that change with time according to (17) but in the first two simulations only one entry of weight vector is not zero, in the second two simulations 8 entries are non-zero, and in the third two simulations all entries are non-zero and system is completely non-stationary and non-sparse. The results of these six simulations are gathered in Fig. 6. As we expected the performance degradation of non-stationarity is higher than sparsity.

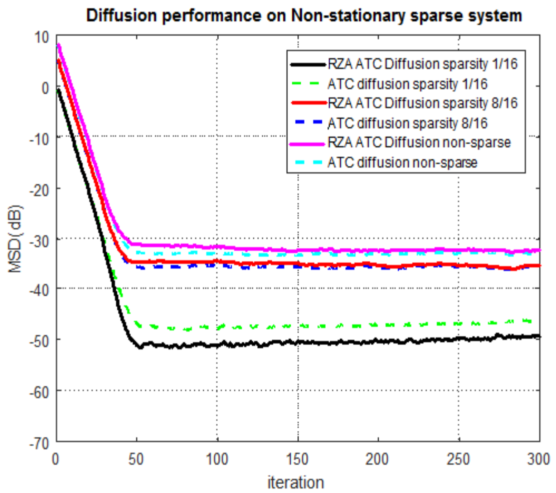

Fig. 6. Performance of diffusion algorithms in non-stationary system identification with varying sparsity.

As we can see in Fig. 6. When the sparsity ratio is $\frac{1}{16}$ the performance of RZA ATC algorithms is better than simple ATC because RZA ATC is specially designed for sparse system identification. But, as the sparsity ratio rises, and the system become non-sparse and non-stationary, the performance of simple ATC prevails RZA ATC algorithm. These results showed again that although RZA algorithms are highly recommended for sparse systems, they are not a good choice for non-stationary system identification. Further investigations must be made to find more reliable algorithms for non-stationary systems.

VII. CONCLUSION AND FUTURE SCOPE

In this paper we studied the performance of several sparsity-aware distributed algorithms in adaptive networks. The performances are carried out for the first time in identifying a non-stationary sparse system. For our simulations, three scenarios were taken into consideration, in the first scenario a 16-tap stationary system is modeled with varying sparsity and it is shown that the performance of normalized ILMS algorithm is better in the sense of steady-state error but its convergence speed is low. For the second scenario we considered a time varying non-stationary system with 16 taps and changed sparsity for our simulations. In this simulation, the ILMS/F algorithm performed slightly better for identifying a completely non-stationary and non-sparse system. In the third scenario the performance of non-stationary sparse system identification was considered with diffusion cooperation strategies. It was presented that RZA ATC diffusion algorithm has a better performance when the system is highly sparse.

From these simulations we can conclude that for highly sparse systems reweighted zero attracting algorithms are recommended while for completely non-stationary systems, ILMS/F algorithm and ATC diffusion algorithms are more preferable. We can combine these algorithms to achieve an algorithm which is robust to sparsity and non-stationarity.

In future works we will examine other newly proposed algorithms in non-stationary sparse system identification with distributed networks. P-norm like adaptive algorithms seems to be good choices for this topic and also all tested algorithms in incremental strategy can be applied to diffusion cooperation strategy and benefit from its features.

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