DIFFUSION LMS STRATEGY OVER WIRELESS SENSOR NETWORK

A THESIS SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE DEGREE OF

MASTER OF TECHNOLOGY
IN
SIGNAL AND IMAGE PROCESSING

BY

YOGENDRA PRASAD (212EC6386)

Under the Guidance of

Prof.UPENDRA KUMAR SAHOO

DEPARTMENT OF ELECTRONICS AND COMMUNICATION ENGINEERING
NATIONAL INSTITUTE OF TECHNOLOGY
ROURKELA

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Dedicated to…,

My parents and my younger brother

ABSTRACT

The mess with distributed detection, where nodes arranged in certain topology are obliged to decideamong two speculations focused around accessible estimations.We look for completely appropriated and versatile usage, where all nodes make singular constant-choices by putting crosswise over with their quick neighbours just, and no combination focus is vital. The proffered distributed detection algorithms are based on a concept of extension of strategies that are employed for diffusion mechanism in a distributed network topology. After a large-scale systematic plan or arrangement for attaining some particular object or putting a particular idea into effect detection using diffusion LMS are fascinating in the context of sensor networksbecause of their versatility, enhanced strength to node and connection disappointment as contrasted with unified frameworks and their capability to convey vitality and correspondence assets. The proposed algorithms are inherently adaptive and can track changes in the element speculation.We examine the operation of the suggested algorithms in terms of their chances of detection and false alarm, and provide simulation results comparing with other cooperation schemes, including centralized processing and the case where there is no cooperation. In the context of digital signal processing and communication, the role of adaptive filters is very vital. In day to daywork where practical requirement is necessary,the computational complexities is the most considerable parameter in context of an adaptive filter. As it tells us about reliability of any system, agility to real time environment least mean squares (LMS) algorithm is generally utilized in light of its low computational multifaceted nature (O(N)) and easier in implementation.

DEPT. OF ELECTRONICS AND COMMUNICATION ENGINEERING

NATIONAL INSTITUTE OF TECHNOLOGY, ROURKELA

ROURKELA – 769008, ODISHA, INDIA

Declaration

I certify that

a) The work contained in the thesis is original and has been done by myself under the general supervision of my supervisor.

b) The work has not been submitted to any other Institute for any degree or diploma.

c) I have followed the guidelines provided by the Institute in writing the thesis.

d) Whenever I have used materials (data, theoretical analysis, and text) from other sources, I have given due credit to them by citing them in the text of the thesis and giving their details in the references.

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Yogendra prasad

25th May 2014

CERTIFICATE

This is to certify that thesis entitled"DIFFUSION LMS STRATEGY OVER WIRELESS SENSOR NETWORKS"submitted by Mr. YOGENDRA PRASAD in partial fulfillment of the requirements for the award of Master of Technology Degree in Electronics & communication Engineering with specialization in "Communication and Signal Processing" at the National Institute of Technology, Rourkela (Deemed University) is an authentic work carried out by him under my supervision and guidance.

To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University / Institute for the award of any Degree or Diploma.

Date:

Prof. U. K. SAHOO
Department Of Electronics and Communication Engg.
National Institute of Technology
Rourkela-769008

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YOGENDRA PRASAD

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ABBREVIATIONS

LMS	Least Mean Square
RLS	Recursive Least Square
MSE	Mean Square Error
MSD	Mean Square Deviation
EMSE	Excess Mean Square Error
WSN	Wireless Sensor Networks
ATC	Adapt Then Combine
CTA	Combine Then Adapt

CHAPTER-1

INTRODUCTION

1.1. MOTIVATION:

Distributed networks sensors,linking PCs, actuators and cell phones will form the chief support of future datacommunication and control networks. Applications will range from sensor networks to high degree of accuracy in the field of agriculture, environmentmonitoring, disaster relief management, smartspaces, target localization, as well as medical applications. In all the above stated cases, the distribution of the nodes in the study provides a spatial diversity, which should be worked alongside the temporal dimension in order to increase the robustness of the ongoing tasks and improve the probability of signal and event detection. Distributed processing deals with the extraction of information from data amalgamated at nodes that are spread over a geographic region.For instance, each node in a web of nodes could collect noisy observations related to a certain parameter of interest.The guests would then interact with each other in a certain manner, as ordered by the network topology, in society to come at an approximation of the parameter. The aim is to arrive at an estimate that is every bit as accurate as the one that would be obtained if each client had access to the information across the integral web.Evidently, the strength of any distributed implementation will depend on the modalities of cooperation that are admitted among the guests.

In an incremental method of cooperation, information flows in a sequential manner from one node to the next node.This modality of procedure requires a cyclic form of collaboration among the guests, and it tends to take the least quantity of communications and power.

In diffusion mechanism, each node communicates with all its neighbours as dictated by the network topology. The quantity of communication in this instance is higher than in an incremental solution.However, the nodes have access to more data from their neighbours.The communications in the dissemination, implementation can be diluted by letting each guest to communicate entirely with a subset of its neighbours.In this modality of cooperation, the selection of which subset of neighbours to communicate with can be randomized according to some performance criterion.

Distributed detection schemes have been considered before in the writing. The supposed non-centralized detection scheme requires conveying the estimations to a central processing centre for handling or accepts that the system is completely associated. Detection schemes focused around normal agreement have additionally been proposed, which evade the utilization of a combination focus, also where each node in the system settles on a singular choice.

1.2 PROBLEM STATEMENT :

In conventional agreement-based plans, all nodes get a set of estimations, and in this manner run an iterative calculation to achieve agreement. These calculations utilize two time scales: one scale to take the estimations and an alternate scale to run the accord cycles between estimations. Dissemination plans are diverse as in new estimations are consolidated into the calculation on the fly as they get to be accessible. In doing along these lines, dissemination plans bless systems with taking in and following capabilities as the resulting dialog will demonstrate. Detection schemes have been proposed formerly in the connection of dispersed estimation, counting diffusion least-mean squares (LMS),diffusion recursive slightest squares (RLS), and diffusion Kalman filtering[1].

Algorithms focused around agreement that utilize a solitary time-scale were additionally proposed in the connection of dispersed estimation. Case in point, the work utilized here utilization node pecking order to perform the estimation, an agreement-sort emphasis that recognizes quantization commotion and nonlinear perception models. These circulated estimation calculations are unique in relation to diffusion methodologies and have been differentiated and contrasted and diffusion plots prior in the writing reviewed. The idea of running agreement implies, where a solitary time-scale is needed, and has been connected to the issue of circulated identification. Subsequently, we will utilize the effects for correlation within our work. One critical contrast between diffusion and consensus is that the last endeavours to attain agreement around nodes, while diffusion looks to improve cost capacities and does not require the nodes to meet to the same state esteem. Rather, diffusion methods permit nodes to merge towards the sought result with least mean-square error limits. By evacuating the necessity of definite agreement, diffusion plans give more adaptability in selecting the synthesis weights, prompting enhanced execution.

The location calculations proposed in this work use the diffusion LMS calculations to figure a parameter gauge, and at that point handle this appraisal to perform the theory test. Notwithstanding, different types of diffusion techniques could be utilized, and we centreon LMS here to pass on the primary plans.This article gives a diagram of compelling dissemination systems for adjustment and adapting over systems that copy some of these valuable properties. The systems depend on basic guidelines including neighbourhood adjustment and meeting and can convey upgraded system execution. The presentation is in the setting of versatile systems, which comprise of taking in operators that are interfaced together through static or element topologies. The operators cooperate with one another through in-system transforming to understand estimation, deduction, or enhancement undertakings in a completely dispersed way. The persistent imparting furthermore dissemination of data over the system empowers the operators to react progressively to streaming information, to respond to floats in the measurable properties of the information, and to modify the system topology when fundamental. Such versatile systems are appropriate to perform decentralized data transforming assignments. They are additionally appropriate to model types of complex conduct displayed by organic and social or investment systems.

The literature here clarifies a percentage of the difficulties for adjustment furthermore adapting over systems, depicts methods that can address these difficulties, and clarifies how and when participation over systems beats non-cooperative methods. The article recognizes provisions in appropriated sensing, interruption location, target restriction, online machine taking in, fisheducating, and disseminated optimization. The issue of dispersed estimation, where a set of hubs is obliged to on the whole gauge some parameter of enthusiasm from loud estimations. The issue is helpful in a few connections including remote and sensor systems,where adaptability, heartiness, and low power utilization are alluring characteristics.

Detection schemes have been indicated to give great execution, heartiness to node and connection disappointment, what's more is agreeable to conveyed executions. In this work we concentrate on dispersion-based versatile results of the LMS sort. We rouse and propose new forms of the dispersion LMS calculation that outflank past results. We give execution and merging dissection of the proposed calculations, together with re-enactment outcomes contrasting and existing procedures. We additionally examine improvement plans to outline the dispersion LMS weights.

1.3.THESIS OBJECTIVE:

Our thesis objective is to estimate an optimal value over a particular geographic area under consideration. For fulfilment of this objective sensors spread over a particular geographical area collect data generated by underlying some unknown distribution and then achieve to the desired estimation by cooperation strategies. The chucklesome thing is that the nodes do not have any idea in what order they are connected or in other words who are their neighbours, but still their objective is to converge to a common optimal value. In achieving to this common goal there will be a collaborative decision making among the nodes.

To endow a network with adaptation capabilities:

•Individual nodes are able to calculate data independently and are adaptive.

• Individual nodes share local information among themselves.

• The network responds in real-time to excitations.

•The nodes will cooperate among themselves in such a manner that instead of relying on the output ofindividual node, each and every node in the vicinity of node under consideration will calculate results independently and then the output of that node under consideration will produce results based on the output of other nodes[10].

1.4. THESIS LAYOUT:

In the following chapter-2 we will know about the background and scope of this project. Chapter-3 deals with the mathematical formulation of the data model where we will know about the minimization techniques, recursive algorithm and how this diffusion process is employed in distributed sensors spread over a particular geographical area. Chapter-4 explains about the simulation results and discussion over the results we obtained and then in further chapters we will be concluding our work in addition with the future scope of this project, if any.

CHAPTER-2

BACKGROUND AND SCOPE OFTHISPROJECT

The elements that comes about when versatile nodes are permitted to communicate with each other. Through collaboration, some fascinating conduct happens that is not watched when the nodes work autonomously. For case, if one versatile operator has more terrible execution than an alternate autonomous versatile operator, can both operators chip in with one another in such a way, to the point that the execution of both executors makes strides? Imagine a scenario in which *N* operators are collaborating with each other? Can all executors enhance their execution with respect to the non-helpful case actually when some of them are noisier than others? Does collaboration need to be performed in a brought together way or is conveyed collaboration sufficient to attain this objective? Beginning with two versatile nodes, we determine systematic interpretations for the mean-square execution of the nodes under a few conditions on the estimation information.

Persuaded by the conduct of biotic systems, we concentrate on circulated choice-production over systems where operators are subject to information emerging from two separate models. The executors don't know already which model records for their information what's more the information of their neighbours. The target of the system is for all executors to achieve concession to one model and to gauge and track this basic model helpfully. The assignment of arriving at understanding over a system of operators subjected to diverse models is more testing than prior takes a shot at deduction under a solitary information model. The trouble is because of different reasons. To begin with, customary (diffusion and consensus) procedures will join to an inclined result. We along these lines require a system to make up for the inclination. Second, every operator now needs to recognize which display each of its neighbours is gathering information from (this is known as the watched model) and which demonstrate the system is advancing to (this is known as the craved model). As it was, also to the taking in and adjustment process for following, the executors should be furnished with a grouping plan to recognize between the watched and craved models. The operators likewise need to be blessed with a choice procedure to concur around themselves on a typical (wanted) model to track. Also, the arrangement plan and the choice-production methodology will need to be actualized in a completely circulated way and in continuous, nearby the adjustment process[2].

Driven by a wide compass of anticipated provisions, decentralizedestimation of signs focused around perceptions procured by spatially disseminated sensors has pulled in much consideration as of late. Sending of impromptu remote sensor systems (WSNs) focused around single-bounce interchanges is imagined to perform different versatile indicator transforming undertakings, including conveyed commotion scratch-off, force range estimation, restriction, field observing, and target following. Not the same as WSN topologies that incorporate a combination focus (FC), specially appointed ones need to depend on in-system preparing. The nonattendance of a focal preparing unit prompts neighbourhood sensor evaluations to inevitably agree to a typical worldwide assessment while completely abusing spatial relationships to augment estimation execution. A few huge commitments have developed the field of accord based conveyed estimation. Accomplishing agreement crosswise over executors was recognized in vehicle coordination, and also in appropriated example averaging of sensor perceptions. A general appropriated estimation skeleton was advanced in. In the previously stated plans, sensors gain information just once and afterward mainly trade messages to achieve agreement. Developments for diffusion following of the example normal of time-differing signs could be discovered all around. Consecutive in-time fuse of sensor perceptions to improve the estimation methodology was acknowledged in the setting of straight minimum squares parameter estimation. The space–time dissemination calculation of obliges information of the information model and expensive trades of networks among neighbours, while the necessity for lessening step-sizes renders itbe unequipped for following time-differing signs. Circulated kalman shifting methodologies have been additionally reported, however they are relevant when the state and perception models are known. In numerous requisitions, then again, sensors need to perform estimation in an always showing signs of change environment without having accessible a (measurable) model for the underlying techniques of investment. This spurs the improvement of dispersed versatile estimation plans. The main such approach presented a successive plan whereby LMS-sort versatile separating for every sensor permits the system to record for time varieties in the sign facts. For more general estimators, a comparable stochastic incremental inclination plummet calculation was created which subsumes as an exceptional case. The incremental LMS plans may beat an unified usage of LMS as far as meeting rate and consistent state slip, while involving a generally low correspondence overhead. These characteristics make them engaging, particularly for little size WSNs. In any case, such plans inalienably oblige a Hamiltonian burn through which sign evaluations are consecutively coursed from sensor to sensor. In the inevitability of a sensor disappointment, determination of another cycle is a NP-hard issue, in this manner testing the appropriateness of incremental plans in medium- to huge size WSNs. Maintaining a strategic distance from the need of such a cycle and expanding the level of cooperation among neighbours, the term diffusion LMS offers an enhanced option at the cost of expanding correspondence cost[4].

We communicate with the physical world through our sense organs and mind. What's more, we make instruments to enlarge our capacities. With the development in processing, correspondence, and microelectronic mechanical framework innovations, we are getting closer to the physical world and checking and overseeing it. A sensor system is a vigorous, disseminated framework, comprising of many physically implanted, unattended, and frequently, untethered gadgets. Since the WSNs is dispersed over a physical space, circulated indicator preparing calculations are more suitable to concentrate data from the information gathered at different hubs. On the off chance that the obliged requisitions, and the sensor structural engineering permits more nearby handling, then it would be more vitality productive, contrasted with correspondence broad incorporated preparing.

WSNs embody an expansive number of little sensing self-fuelled sensor hubs circulated in a geological area, which accumulate data or distinguish uncommon occasions and impart in a remote manner. Sensing, preparing and correspondence are three key components whose fusion in one small gadget offers ascent to an endless number of remote sensing provisions. Due to their few prevalent requisitions, proficient outline and usage of WSNs have turned into a range of momentum examination. The nodes in a WSN work with little and restricted battery control and typically non-renewable asset. Since correspondence among hubs expends the greater part of the vitality, it is imperative to plan the system with less correspondence among the hubs to gauge the obliged parameter vector. Nonetheless, late developments in low power-extensive scale joining (VLSI), implanted registering, correspondence fittings, and when all is said in done, the union of figuring and correspondences, lead to the development and usage of this rising innovation .There are numerous assorted requisitions of WSNs . In military, WSNs might be utilized for order, control, correspondence, sagacity, reconnaissance, observation, focusing on framework and so forth. WSNs can screen patients and help impair quiet in medicinal services. WSNs can additionally enhance the execution of businesses in ranges, for example, stock administration, item quality checking, fiasco observing and so on. Despite the fact that WSNs give unlimited open doors, however in the meantime posture considerable difficulties. Some of these difficulties are correct estimation of source position known as source limitation, vitality minimization, deficiency tolerant and so on. To beat these difficulties, the sensor systems ought to have circulated handling ability. In an unified framework, a portion of the sensor hubs need to impart over long separations which prompt more vitality consumption. Thus, it is alluring to process generally however much data as could be expected with a specific end goal to minimize the aggregate number of bits transmitted. The sensor hubs are thickly sent, and are inclined to disappointments. The topology of a sensor system changes regularly.

Therefore, not at all like customary systems, where the centre is on boosting channel throughput or minimizing hub arrangement, the significant attention in a sensor system is to expand the framework lifetime and the framework vigor.

CHAPTER-3

MATHEMATICAL FORMULATION OF DATA MODEL

3.1. DATA MODELLING

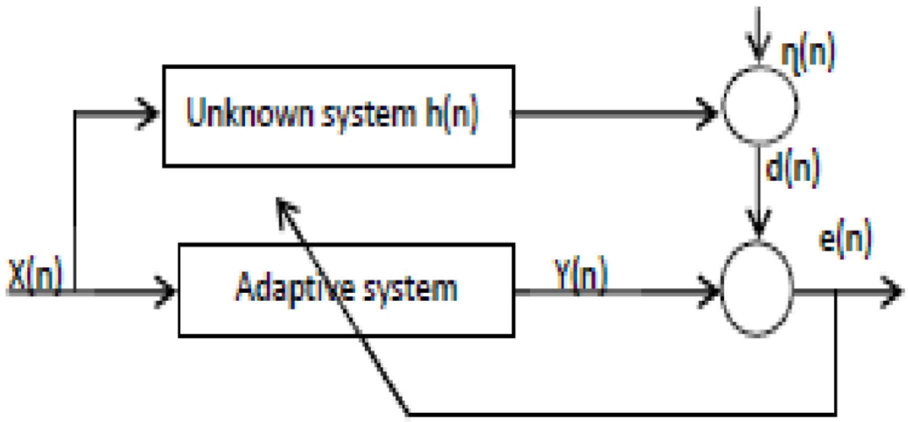


FIGURE 3.1.1 GENERAL ADAPTIVE DATA MODEL

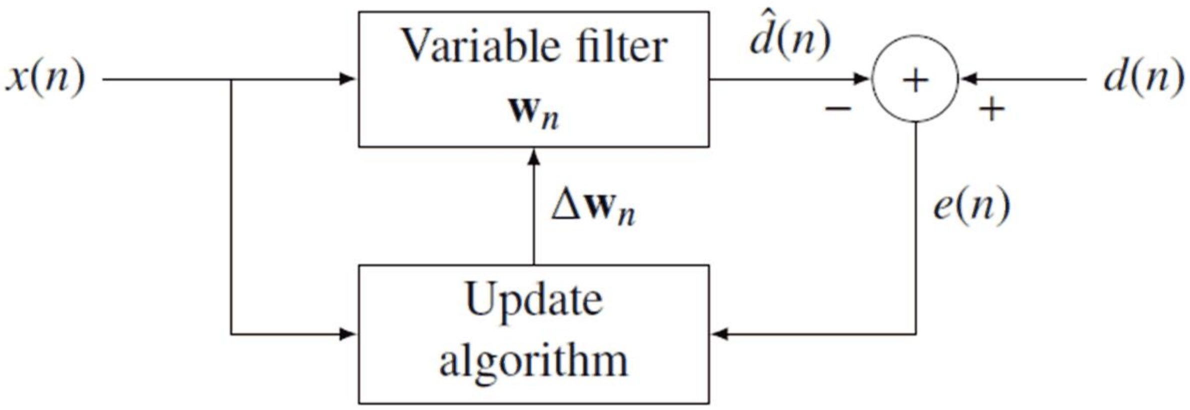


FIGURE 3.2.1 ADAPTIVE FILTER

The figure above is a pictorial representation of a general adaptive filter. The x(n) is our applied input signal, h(n) is transfer function or in more general are the filter weights for our case, d(n) is our desired response , y(n) is the response of the unknown system for which we are trying to find a solution as closest as possible to our known system and that solution we will be calling as minimal solution. In order to achieve our goal i.e. to obtain a minimal solution some recursive algorithm will be employed to the unknown system. There are number of recursive algorithms like least mean squares(LMS), recursive least squares(RLS), normalized least mean squares(NLMS), Block LMS, steepest descent etc. which are employed to get the minimal solution depending on the distribute network parameters, requirements and constraints. For our purpose we have employed here LMS algorithm[3].

3.2. GLOBALOPTIMIZATION

Wewill findlinear estimator $\boldsymbol{w^0}$ that will minimize the following global cost function

$$\boldsymbol{J^{glob}}(\mathbf{w}) \triangleq \sum_1^N E\left|d_k(i) - u_{k,i}w\right| \text{^}\, 2 \tag{3.1.1}$$

Where, E denotes the expectation operator.The bothprocesses$\boldsymbol{d_k}(\boldsymbol{i})$and $\boldsymbol{u_{k,i}}$are considered to be jointly wide sense stationary, therefore optimal solution is given by

$$\boldsymbol{w^0} = \left(\sum_1^N R_{u,k}\right)\left(\sum_1^N R_{u,k}\right)^{-1} \tag{3.1.2}$$

Where, $R_{u,k} > 0$ and therefore is assumed to be positive-definite.

3.3. LOCALOPTIMIZATION

Let us consider N×N matrix C such that each entry ispositive and real. The nominated entries are assumed to be $c_{l,k}$ such that$\{c_{l,k}\}$ = 0, if *l* is not in the neighborhood of node *k*. When node *k*has entry just to information from its neighbors , it can then try to minimize the cost function given below[15]:

$$\boldsymbol{J_K^{loc}}(\boldsymbol{w}) = \sum_1^N c_{l,k} E\left|d_k(i) - u_{k,i}w\right| \text{^}\, 2 \tag{3.2.1}$$

Now therefore here the local optimal solution is

$$\boldsymbol{w_K^{loc}} = \left(\sum_1^N c_{l,k} R_{u,l}\right)\left(\sum_1^N c_{l,k} R_{du,l}\right)^{-1} \tag{3.2.2}$$

The $\boldsymbol{w_K^{loc}}$we get is the local estimatewhich usesonly covariance of input data

$(R_{u,l}, R_{du,l})$ within the neighborhood of node k. this process employed here is indifference to the global optimization which uses the covariance of the input data$(R_{u,l}, R_{du,l})$ across the entire network .

Let us introduce a variable term

$$\text{Ʈ}_k \triangleq \sum_{l \ni N_k} c_{l,k} R_{du,l} \qquad (3.2.3)$$

Now we can rewrite equation(2.1) in terms of $\boldsymbol{w_K^{loc}}$ as

$$\boldsymbol{J_K^{loc}(w)}=\| \boldsymbol{w}\text{-}\boldsymbol{w_K^{loc}} \|_{\text{Ʈ}_k}^{2} + \text{mmse} \qquad (3.2.4)$$

Where, symbol $\|\boldsymbol{b}\|_{\Sigma}^{2}$represents a weighted norm and mmse is independent of $\boldsymbol{w_K^{loc}}$**.** By using the above equation (3.2.4), the equation (3.1.1) can be rewritten as

$$\boldsymbol{J^{glob}(w)}=\sum_{l=1}^{N} \boldsymbol{J_K^{loc}(w)} = \boldsymbol{J_K^{loc}(w)}+\sum_{l \neq k}^{N} \boldsymbol{J_l^{loc}(w)} \qquad (3.2.5)$$

Finally we can conclude here from the above discussion that by using the above stated equations i.e. (3.2.1) to (3.2.5)

$$\boldsymbol{J^{glob'}(w)}=\sum_{l \ni N_k} c_{l,k}\, E\left|d_l(i) - u_{l,i} w\right|\hat{}2+\sum_{l \neq k}^{N} \| w - w_l^{loc} \|_{\text{Ʈ}_l}^{2} \qquad (3.2.6)$$

The equation above what we have derived is the method of finding global cost with the help of local estimates across the total network topology.

3.3.STEEPEST DESCENT GLOBAL SOLUTION

This conventional method gives us an iterative solution to minimize the global cost function as given in equation (3.1.2). the solution yields an iterative approach as stated below[15]:

$$w_i = w_{i-1} - \mu\, [\nabla_w \boldsymbol{J^{glob}}(w_{i-1})]^{*} \qquad (3.3.1)$$

Where, μ>0 is step size parameter and w_i is an estimate of $\boldsymbol{w^0}$at ith instant and $\nabla_w \boldsymbol{J^{glob}}$denotes the complex gradient of J^{glob}(w) with respect to w.

$$[\nabla_w \boldsymbol{J^{glob}}]^{*} = \sum_1^N R_{u,k} w \text{-} \sum_1^N R_{d.u,k} \qquad (3.3.2)$$

Substituting the above equation(3.3.2) into equation(3.3.1) leads us to steepest descent iteration

$$w_i = w_{i-1} + \mu[\sum_1^N R_{u,k} w - \sum_1^N R_{d.u,k}] \tag{3.3.3}$$

The above equation () can be approximated into LMS type as such as follows:

$R_{u,k} \approx u_{k,i}{}^* u_{k,i}$

$R_{d,u,k} \approx d_{k,i} u_{k,i}{}^*$

Replacing the equation() by the above approximations will give us final global LMS recursion as

$$w_i = w_{i-1} + \mu(\sum_1^N u_{k,i}{}^* d_{k,i} - \sum_1^N u_{k,i}{}^* u_{k,i} w_{i-1}) \tag{3.3.4}$$

We can easily interpret from the above equation that it cannot be employed for the distributed Network because it requires data from all N nodes $\{d_{k,i}, u_{k,i}\}$. So this will work basically for a centralized network in which a central fusion will calculate the output based on the data across the entire network so in next section we will be leading towards distribution techniques.

3.4. MSEMINIMIZATION

Consequently allude to the equal worldwide expense assessed by above neighborhood expense capacity minimizing cost at each Node k still requires the nodes to have admittance to worldwide data, to be specific the nearby gauges at alternate nodes of the system. Along these lines, every node can continue to minimize an altered expense of the structure[16]:

$$\boldsymbol{J_K^{dist}}(\mathbf{w}) = \sum_1^N c_{l,k} E\left|d_k(i) - u_{k,i} w\right|\hat{}\ 2 + \sum_{l \epsilon N_k} b_{l,k} \|w - \psi_l\|\hat{}\ 2 \tag{3.4.1}$$

The basic idea behind formulation of this equation is that we are trying to minimizing the cost function by implementing the idea of distributed algorithm.Before starting the discussion here we will first try to substitute the covariance matrix Ʈl by a new form which will be like a diagonal matrix

Ʈl= $v_{l,k} I_M$ (3.4.2)

Where, $v_{l,k}$ belongs to the set of positive coefficients or zero. The coefficient value will be assigned zero whenever the particular node will not be in the vicinity of that particular node under consideration.

In order of getting a recursion for our calculation at any node we can use equation (3.4.1). at that instant the estimate at that particular mode will be denoted as $w_{k,i}$.

$w_{k,i}$=$w_{k,i-1}$+ $\mu_k \sum_{l\epsilon N_k} c_{l,k}(R_{du,l} - R_{u,l}w_{k,i-1})$+$v_k \sum_{l\epsilon N_k} b_{l,k}(\psi_l - w_{k,i-1})$ (3.4.3)

For any positive value of $\{\mu_k, v_k\}$ but it should be less than 1.

Where,

ψ_l →An intermediate approximate available at Node *l*

$\psi_{l,i}$ → An intermediate approximate available at Node *l* and at time *i*.

We willtry to now put back an intermediate estimate instead of$\psi_l$that will

be available at node *l* at time instant*i* namely $\psi_{l,i}$ .Our motive is now toput back$\psi_{k,i}$ instead of$w_{k,i-1}$ because such replacement will lead us to a better solutionsince $\psi_{k,i}$instinctively contains more relevant messagein comparison to $w_{k,i-1}$. This approach guide us to:

$\psi_{k,i}$= $w_{k,i-1}$ + $\mu \sum_{l\epsilon N_k} c_{l,k}\left(R_{du,l} - R_{u,l}w_{k,i-1}\right)$ (3,4.4)

$w_{k,i} = \sum_{l\epsilon N_k} a_{l,k}\, \psi_{l,i}$(3.4.5)

Where,

μ → step size

$c_{l,k} = a_{l,k}$=0 if $l \epsilon N_k$

3.5. DIFFUSION LMS

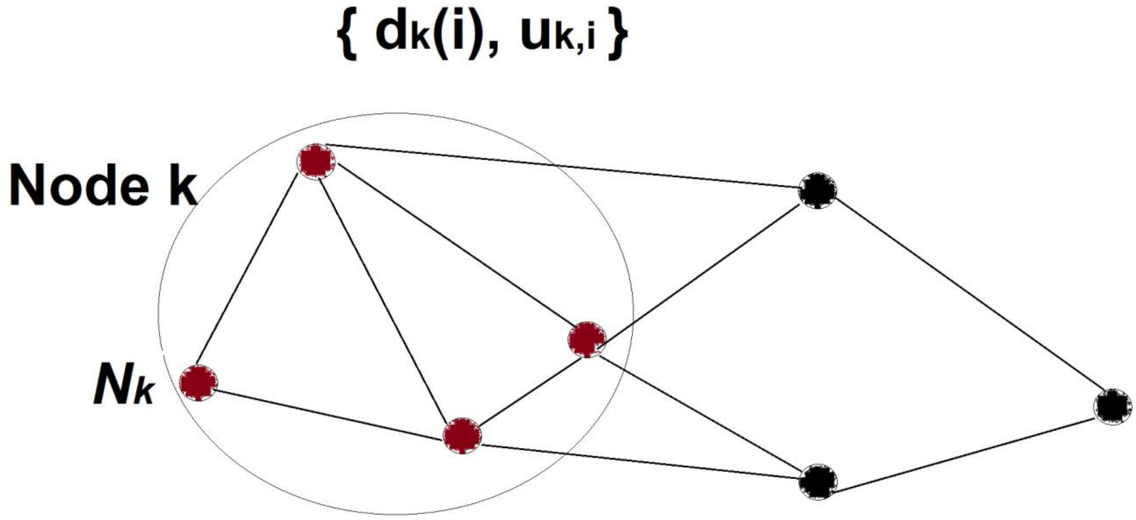


FIGURE3.5.1 DIFFUSION NETWORK TOPOLOGY

With the help of instantaneous estimations obtained we will develop the methodology of combining and adapting the nodes. Depending on this methodology we will have two diffusion schemes:

- ATC(ADAPT THEN COMBINE) DIFFUSION LMS:

$$\psi_{k,i} = w_{k,i-1} + \mu_k \sum_{l \epsilon N_k} c_{l,k} u_{l,k}^{*} \left(d_l(i) - u_{l,i} w_{k,i-1}\right) \tag{3.5.1}$$

$$w_{k,i} = \sum_{l \epsilon N_k} a_{l,k}\, \psi_{l,i} \tag{3.5.2}$$

- CTA(COMBINE THEN ADAPT) DIFFUSION LMS:

$$\psi_{k,i-1} = \sum_{l \epsilon N_k} a_{l,k}\, w_{l,i-1} \tag{3.5.3}$$

$$w_{k,i} = \psi_{k,i-1} + \mu_k \sum_{l \epsilon N_k} c_{l,k} u_{l,k}{}^{*}\left(d_l(i) - u_{l,i}\psi_{k,i-1}\right) \tag{3.5.4}$$

The equations (3.5.1) and (3.5.2) show the incremental and diffusion processes or steps respectively. For incremental step we are applying a recursive LMS algorithm. Similarly equations (3.5.3) and (3.5.4) show diffusion and incremental steps respectively.

The experiments and simulation results given by researchers explains that adapt then combine diffusion scheme is superior to the combine than adapt diffusion scheme. When both schemes were employed same weights and the diffusion matrix was constrained to certain conditions necessary for the comparison between the ATC and CTA diffusion methods, it was concluded that in every iteration ATC algorithm uses the data that are two hops away while in every iteration the CTA algorithm uses the data that are one hop away[15].

CHAPTER-4

SIMULATION RESULTS AND DISCUSSION

The simulation conditions of regressor input, noise power profile are taken as given below. The experiment is simulated for 50 independent experiments to obtain the result. The network structure of 20 nodes is shown below

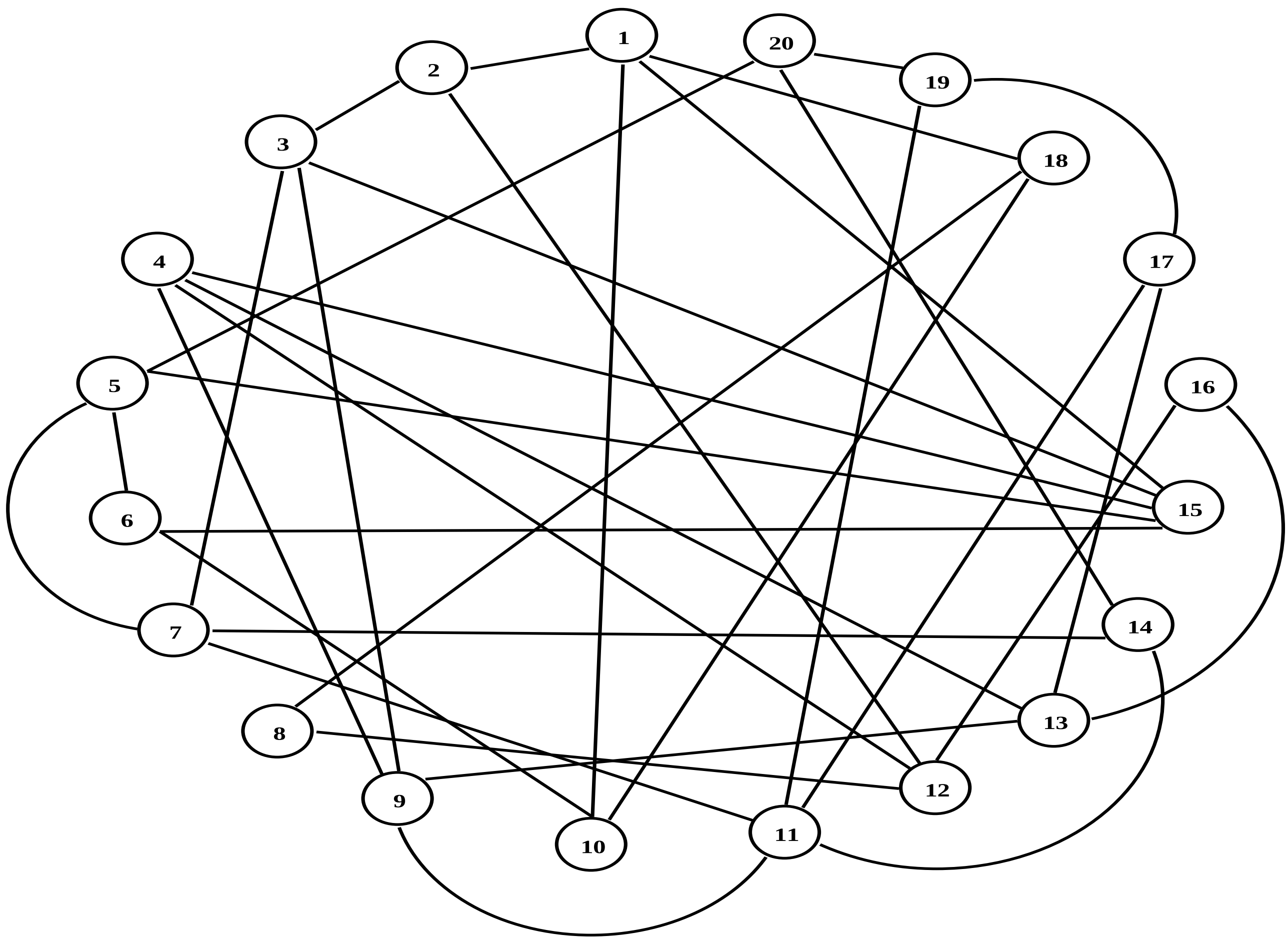


FIGURE 4.1 NODE STRUCTURE

Depending on the above node structure the value of the coefficients $c_{l,k}\ a_{l,k}$ will be decided which will be further explained in below section. Depending on the value of coefficients we will call them as uniform or laplacian or maximum degree or mertropolis or relative degree or relative degree variance.

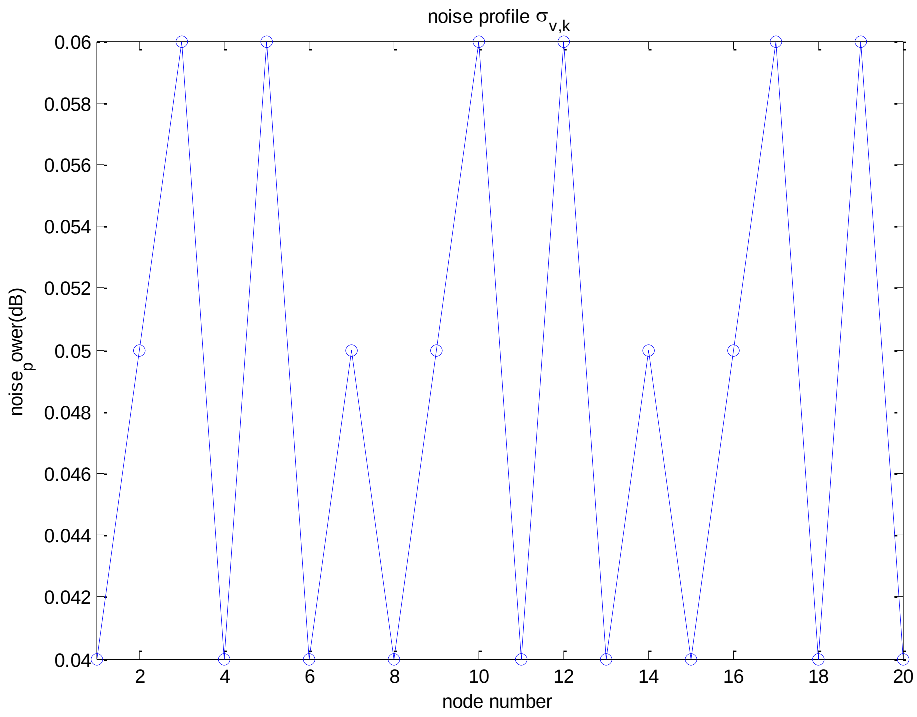


FIGURE 4.2; NOISE VARIANCE

In order to explain the performance of the distributed adaptive network, the noise power profile for input nodes have been selected as illustrated in the above figure. The above figure shows how the signal to noise power vary for each particular node in the network topology.

Based on the algorithm as explained in equations (3.4.1) and (3.4.2), the adapt then combine mechanism have been followed here for getting the simulation results.

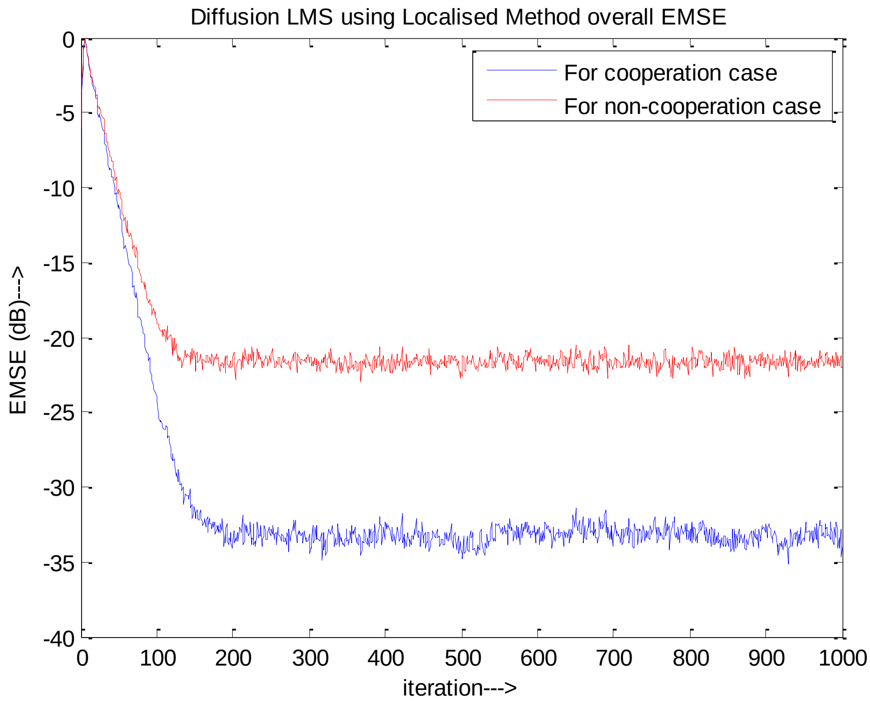


FIGURE4.2;EMSE FOR DIFFUSION STRATEGY

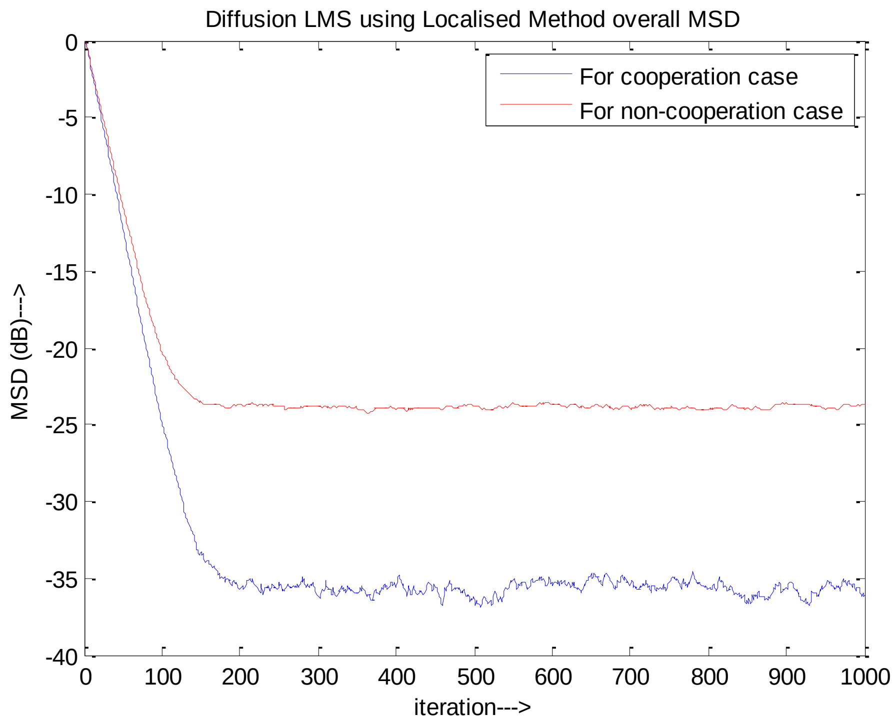


FIGURE 4.3;MSD FOR DIFFUSION STRATEGY

For getting the simulation results the step size value has been taken 0.05 and the outputs of each and every node have been averaged for 1000 times. What we can observe from the graph is till 150 iterations transient state prevails but after that steady state is achieved but we have taken iterations upto 1000 so as to ensure that further there is no more fluctuations or transient state.

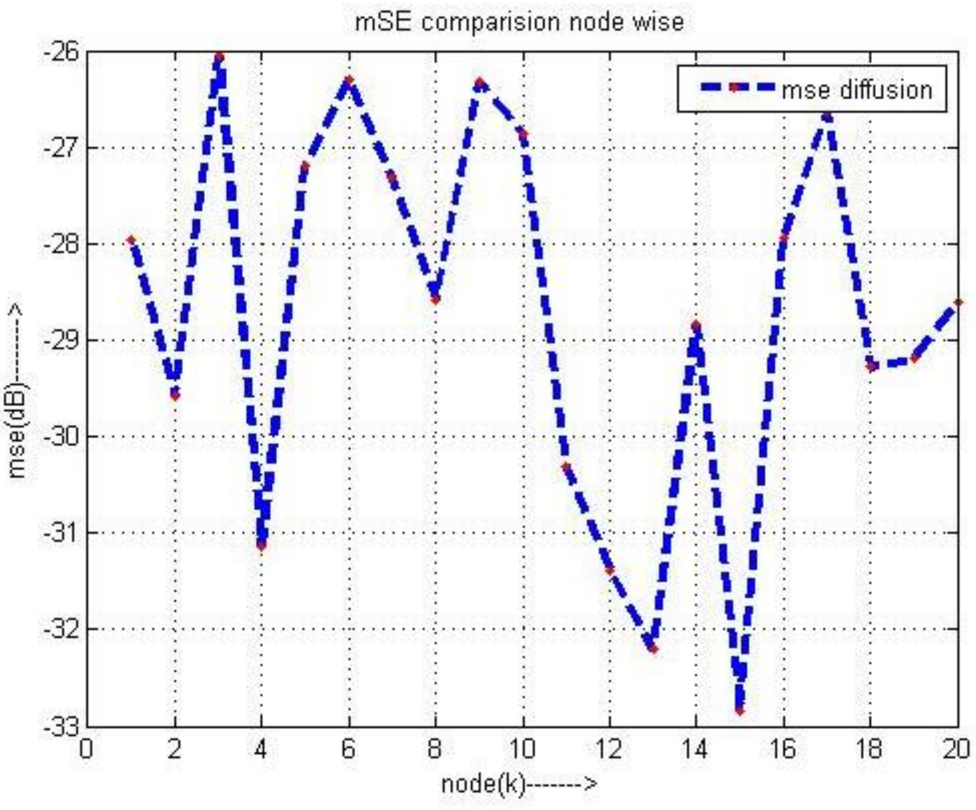


FIGURE 4.4; MSE COMPARISON NODEWISE

The above plot gives us a detailed examination of the nodes when plot for mse has attained a steady state value. When the above values of mse(dB) are averaged for given no. of iterations the plot will be similar to the figure 4.2 as plotted above for mean square error(mse) v/s no. of iterations.

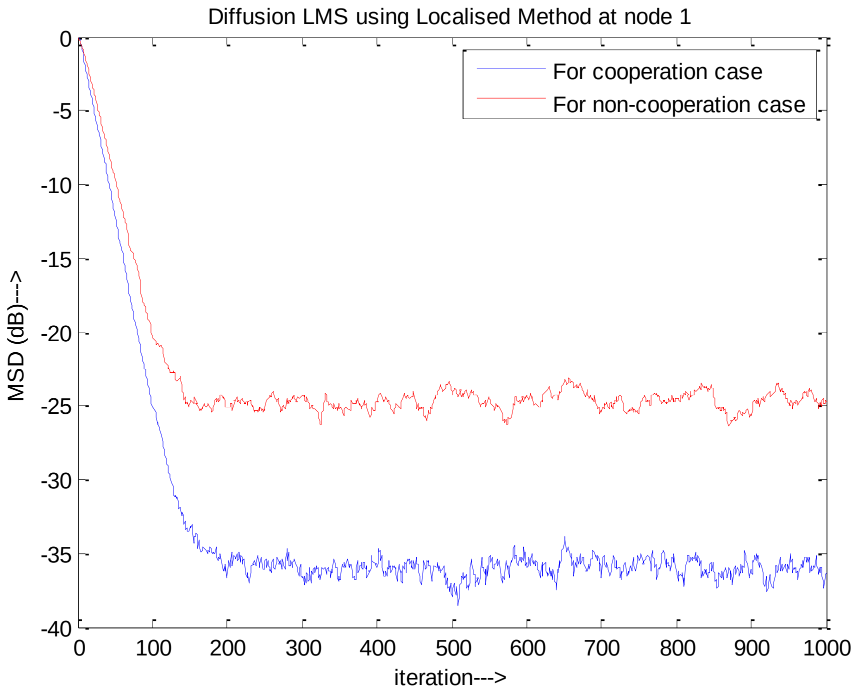


FIGURE 4.5; MSE AT NODE1

RULES TO DESIGN DATA PROCESSING MATRIX $c_{l,k}, a_{l,k}$

Rule	Weights $a_{l,k}, c_{l,k}$ $for\ l \in \aleph_k$
Metropolis	$\begin{cases} 1/max\{n_k, n_l\} & for\ l \neq k \\ 1 - \sum_{m \in \aleph_k} c_{m,k} & for\ l = k \end{cases}$
Relative Degree	$n_l / \sum_{m \in \aleph_k} n_m \qquad for\ l \in \aleph_k$
No Cooperation	$\begin{cases} 0 & if\ l \neq k \\ 1 & if\ l = k \end{cases}$

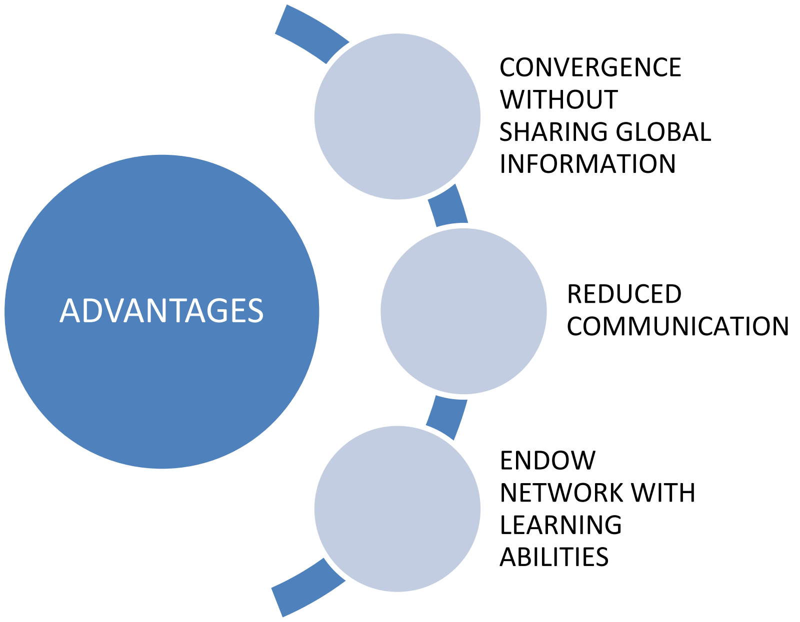
C is a $N \times N$ matrix such that its l^{th} row and k^{th} elements is $c_{l,k}$. The coefficients $c_{l,k}$ such that

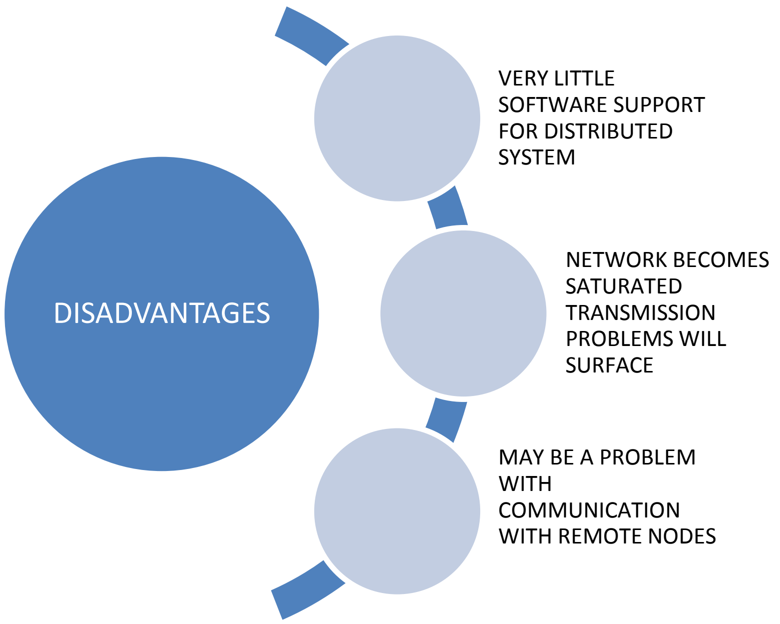
$$\mathbb{1}^{\boldsymbol{T}}\boldsymbol{C} = \mathbb{1}^{\boldsymbol{T}} \quad \text{and} \quad \boldsymbol{C}\,\mathbb{1} = \mathbb{1}$$

CHAPTER-5

CONCLUSION

From the simulation results obtained, a very common form of LMS algorithm has been implemented. In addition to this formulation, we also implemented adapt then combine and combine then adapt versions of diffusion LMS algorithm. Transient state, steady state analysis, mean square error, mean square deviation, noise variance analysis were presented and matched well with simulation results. The convergence of LMS algorithm was also examined methodically and in detail so that vital information can be interpreted from it. The option for choosing weight optimization problem has also been presented which proved a better plan unlike in the case of global steepest descent optimization techniques.It has been found that adapt then combine version outperforms the combine then adapt version of diffusion LMS, moreover it can be concluded that diffusion scheme which employed cooperative estimation strategies are more stable thanincremental networks because stability of diffusion networks are independent of combination weights and also they are more robust to node and link failure because they do not require nodes to be connected in a circular path as in incremental strategies.


ADVANTAGES
CONVERGENCE WITHOUT SHARING GLOBAL INFORMATION
REDUCED COMMUNICATION
ENDOW NETWORK WITH LEARNING ABILITIES


DISADVANTAGES
VERY LITTLE SOFTWARE SUPPORT FOR DISTRIBUTED SYSTEM
NETWORK BECOMES SATURATED TRANSMISSION PROBLEMS WILL SURFACE
MAY BE A PROBLEM WITH COMMUNICATION WITH REMOTE NODES

CHAPTER – 6

FUTURE WORK

For future work of this project there has been an idea that the metropololis or weighting matrices or the coefficients i.e $\{ c_{l,k}, a_{l,k}\}$ as introduced in chapter 3 equation(3.3.3) can be made adaptive indifferent to a particular value which has been taken here for this project. This adaptability will help us to improve our performance because if they will become adaptive in nature then if any node or link failure will occur it will help us to recover easily from that diabolical problem as coefficients being adaptive in nature will adjust themselves in such a way that the failed or noisy node weighted coefficients will be negligible.

CHAPTER-7

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