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Back Propagation Neural Network Based Cluster Head Identification in MIMO Sensor Networks for Intelligent Transportation Systems

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ABSTRACT Wireless Sensor Network (WSN) is an essential technology for the Internet-of-Things (IoT) and intelligence-based applications. In the case of Intelligent Transportation Systems (ITS), the WSNs play an important role in safety and efficient traffic management. Therefore, there is enormous demand for energy efficient WSNs for dynamic resource allocation in vehicles and infrastructures. This work presents a Multi-Input Multi-Output (MIMO) technique model in WSNs, which addresses the Cluster Head (CH) recognition issue for MIMO sensor networks by using Back Propagation Neural Network (BPNN). The conventional CH identification suffers from a lack of location identification due to the dynamic and real-time environment. Thus, to obtain more precise positioning accuracy, the proposed work uses BPNN combined with a distributed gradient drop technique to calculate the position of the unknown CH. This reduces the distance estimation error, and the particle swarm optimization technique is further used to obtain the optimal weight and threshold of the network. The work is validated by using mathematical analysis, simulations, and comparison with existing techniques. The proposed model shows a better performance in terms of energy consumption, error rate, and computation time.

INDEX TERMS Back propagation neural networks, intelligent transportation systems, gradient descent, MIMO, wireless sensor networks, cooperative communication.

I. INTRODUCTION

Transportation systems are one of those technological developments, which effected the human race greatly. The number of vehicles are increasing every day on the road, which is making concerns about road safety and congestion. Therefore, Intelligent Transportation System (ITS) came into the scenario to provide efficient management of traffic and innovative solutions for transportation-related problems. The ITS makes this possible by integrating both wireless communication technologies and advanced control systems [1]. The several challenges in the transportation system arise on a daily basis. To overcome that Artificial Intelligence (AI) [2] is introduced AI-based services is useful to mitigate the problems due to the complexity of mobility of progressively increasing population [3]. The technology behind these

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AI based services is mainly based on the working principle of data management by collecting them from vehicles and drivers [4], [5], which can be accomplished by WSNs. As a result, it helps to provide safety and sustainability of human lives [6], [7]. The AI application is not limited to only for this purpose, and it can be implemented for other application purposes in ITS. Among various AI techniques, Artificial Neural Network (ANN) is one of a kind that is very useful for dynamic environments and distributed systems.

Wireless Sensor Networks (WSNs) is convincing and constantly developing technology for the advancement of future internet-based systems and applications. As a result for ITS is making significant impact and providing its usefulness. The basic of WSNs is to sense data with the sensor nodes in small to large networks and gathering information to process any application [8]. The advantages of WSNs provide the cost-efficiency of the network by enabling the use of cheap wireless sensors instead of wired connections. In terms of distributed intelligence, it also has a significant role. For the ITS, the use of distributed intelligence develops efficient, diverse real-time applications for traffic safety, which are not up to the feasibility of centralized solutions. Furthermore, WSNs can work with other technologies in the ITS context, such as Vehicular Ad Hoc Networks (VANETs), instead of providing single phenomena all alone.

We know that in an ad-hoc sensor network, the application deployment is composed of numerous sensor nodes randomly scattered in the monitoring area, and its position information is unknown. With the evolution of efficient cooperative communication between these applications or clusters solves the next step towards future technologies to become green and sustainable. While cooperative communication in wireless communication has a high requirement for time synchronization, this depends very much on the location of nodes and Cluster Head (CH), so the problem of node location is significant. For any two random nodes, researchers usually use the multidimensional scale [9], [10] to find the unknown node location with a prior knowledge distance between them. However, in practice, node movement is dynamic and random, and the conditions required by the above methods will change rapidly. In [11], the author uses a convex method to locate the nodes, that is, angular constraints and model range movement. The convex result is then transformed into a linear programming problem by using Semi-Definite Programming (SDP) caused by the problem of computational efficiency. Also, the approximate distance matrix method [12] which is used to calculate the adjacent distance and the distance between each other linearly is flawed as this method has a large amount of computation that is limited by space. For this, [13], the authors have proposed SOMAP technology, which uses the pairwise distance between sensors to calculate the geodesic distance to realize node positioning. More recently, the authors in [14] proposed a hybrid technology combining geodesic distance, and machine learning technology in order to provide the solution to the problem of node location. Although the designed framework has strong robustness, the dynamic formation of clusters and the unknown location of CH have not been given much focus. Based on previous research, the author adds error correction and objective function strategy to the positioning problem in [15], but this method still has its shortcomings, that is, the position of a single node will change in each iteration process. To overcome the problem, authors in [16] illustrates a solution based on the sum of error square distance, using a minimal method to minimize the distance in order to find the unknown node location. Although the designed method is robust, it still has to deal with a large amount of computation in the process of processing.

Problem Statement and Contribution: In general, the WSNs are being used for data transmission by using the network protocol between nodes, with static or dynamic spatial placements. Therefore, it is utilized for a different types of systems for various ITS applications. In this process, it may arise certain cases, where the position of the nodes is unknown for forming a cluster without compromising the performance of the network. The energy-efficiency of the WSNs till now is only with the routing protocol of the network layer and the static node location information [17]–[22]. In cooperative communication, the nodes need to communicate with each other for collective decision-making, and we select the MIMO sensor network as the research model in this paper [23]. In a MIMO network, a transceiver in one cluster may comprise more than two nodes, wherein at least two of the nodes act as a receiver. In the case of intra-cluster communications, we establish a collaborative communication set up between all the nodes. Therefore, a plurality of CHs is present in the inter-cluster communication, and the CH of each cluster will make a decision, respectively [17]. Furthermore, the diversity of the application also requires the CH-CH communication of the physical layer. Many researchers often take the shortest distance algorithm [18], which has the disadvantage of high computing and system complexity. In this paper, we combine the BPNN with distributed gradient descent technology. The BPNN is a kind of multi-layer feed-forward network, which is based on the backward propagation of the error and the strong nonlinear mapping capability and has the capability of generalization and fault tolerance. The method reduces the number of calculation steps after each iteration of the most recent CH and reduces the calculation complexity so that the convergence of the decision in the dynamic environment is narrower and more precise. The novelty and state-of-art for this paper are to introduce the BPNN technique using a distributed gradient approach to identify the CHs. Also, we use the Particle Swarm Optimization (PSO) Algorithm to optimize the NN to obtain the optimal weight and the threshold in the BPNN. We have used PSO due to its utmost result for detecting the position of particles. The obtained optimal particle will continue to carry out the network training in the NN, and the positioning accuracy for CHs will be improved continuously. Finally, the performance of the work is validated by using the power distribution problems. In brief, the objective and the contributions of the proposed work can be written as:

- State-of-art analysis: BPNN based solution for CH recognition issue in MIMO sensor networks for ITS
  a. Use of BPNN for dynamic clustering
  b. Use of PSO to optimize the position of CH
  c. Mathematical validation and Simulations

The rest of this work is organized as follows. Section II discusses a detailed related works regarding the neural networks and MIMO sensor networks. Section III analysis the proposed work in terms of mathematical approach and Section IV illustrates the simulation results and discussions based on the proposed model. Finally, Section V elaborates the conclusion with possible extension of work.

II. RELATED WORK

The importance of WSNs for development of future internet and technology including ITS is immense. Based on WSNs architecture, it is possible to monitor urban train transportation environments [24]. As well as with analysis of the channel behavior, the interaction between users can be provided and future need can be predicted. WSNs can be utilized efficiently to provide road information in terms of traffic management [25]. For large scale ITS applications huge data can be processed collecting data through Vehicular Sensor Networks (VSNs). The authors Nie *et al.* [26] designed an analyzing framework for VSNs called Vehdoop to increase the computing capability of vehicles for efficient process of sensor data in parallel, across a large number of vehicles in a decentralized manner. The neural network based solution is also taken considered in many of the literatures for ITS. The BPNN and PSO based solution is considered with double layer architecture for the problem of convergence in case of optimization of path-loss model and improved wireless localization [27]. It was implemented by using mind evolutionary algorithm (MEA) and quantum-behaved PSO (QPSO) method. The short-term traffic flow prediction is done [28] with neural network approach. In case of trajectory control for remotely operated vehicle adaptive neural network can be used based on observer [29]. Similarly the neural network approach with radial basis function is useful for traffic volume forecasting [30] with consideration of traffic flows.

The positioning problem of cooperative communication between sensor networks plays a vital role in wireless communication systems, including optical communication [31]. Visible light communication adds new energy to existing RF communication systems. Saud *et al.* [32] proposed a protocol for VLC/RF that allows nodes to switch vertically between the two links. Many algorithms have been proposed for studying node localization. The range-based positioning algorithm [33] calculates the position of the node according to the distance or angle information between the nodes, and the positioning accuracy is high, but the disadvantage is that the node positioning process is more complicated. The network costs are high. In contrast, Niculescu *et al.* [34] proposed a positioning algorithm without ranging. During the node location process, the position of all nodes in the static node location is fixed [35]. Due to the instability of the statistical characteristics of the system, Mukherjee *et al.* [36] proposed the ED-AE method to solve the power allocation of cooperative sensing and proved the importance of the problem of active node identification. The positioning algorithm can be divided into two types: centralized and distributed [37]. More recently, some people introduced intelligent optimization algorithms in the field of positioning technology [38]. The use of intelligent computing methods to solve the problem of node location is a new idea proposed in recent years, which can be adapted to the surrounding environment. The *EM* algorithm is used by Malla *et al.* [39] to accurately identify the direction of arrival of the high correlation signal in wireless communication, and the robustness of the hybrid method is verified by introducing noise. The intelligent positioning model is established by using prior knowledge and posterior knowledge [40], and the positioning accuracy can be obtained by optimizing the model. Genetic algorithms and PSO algorithms are typical because both algorithms are easy to implement and have high positioning accuracy. Genetic algorithms and PSO technique are typical, both of which are easy to implement and have high positioning accuracy. A WSN node localization algorithm based on a Genetic Algorithm (GA) was used [41], although the algorithm is slower than the PSO. Zhang *et al.* [42] proposed a new WSN localization algorithm based on a genetic algorithm. By establishing a mathematical model with the unknown node position as a parameter, the coordinates of the unknown node are obtained, but the node positioning accuracy needs to be improved. Further an improved PSO localization algorithm proposed by Low *et al.* [43] while Li *et al.* [44] proposed a PSO positioning algorithm based on the bounding box, which effectively improved the positioning accuracy. Namin and Tinati [45] proposed a three-dimensional WSN localization method based on PSO technique, which improved the positioning accuracy compared with the original algorithm. To solve the problem of insufficient spectrum utilization, spectrum sensing plays a vital role in cognitive radio [46], which can effectively resist shadow multipath fading and the uncertainty of accepting information. The authors Kumar *et al.* [47] dedicated to the WSN energy-saving protocol based on base station technology, using CH to transmit information, the clustering technology used can achieve effective and real-time decisions in the state of incomplete intelligence. A platform for analyzing the WSN protocol is provided in [48], which significantly assists in designing more efficient protocols.

Thus, the proposed work contributes towards implementing an energy-efficient MIMO sensor networks for various IoT applications. As shown discussed, the conventional method restricts with pre-defined knowledge of sensor positioning along with substantial error rate during cooperative communication. By using BPNN and PSO, the work analysis

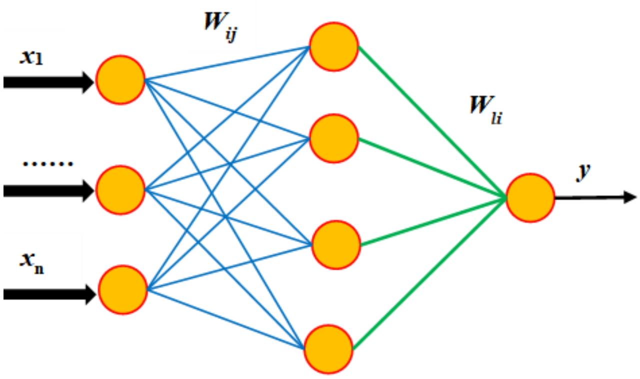

FIGURE 1. Illustration of a back propagation neural network.

and obtains the optimum position of the CH for every clusters along with efficient cooperative communication between the sensor nodes.

III. MATHEMATICAL ANALYSIS

A. BP NEURAL NETWORK FOR CLUSTERING

Deep learning, as a branch in the field of machine learning, is mainly derived from the study of the artificial neural network, which is used to imitate the mechanism of the human brain to interpret the data, and the basic structure is simply a multi-layer perceptron with a plurality of hidden layers. The NN has proven that any continuous function can be approximated to any desired accuracy, where the BPNN is a NN with error feedback. It consists of three layers of an input layer, a hidden layer, and an output layer, and the basic structure is as shown in Fig.1, wherein the activation function of the hidden layer adopts a sigmoid function. Moreover, the weight values of the hidden layer and the output layer are and, respectively.

When the output of the input layer is $\theta_j^{(1)} = x(j)$, $j = 1, 2, \ldots, n$, the hidden layer node input can be represented as:

$$\alpha_i^{(2)}(k) = \sum_{j=0}^{n-1} w_{ij}^{(2)} \theta_j^{(1)} \tag{1}$$

The input information for the hidden layer is output after the activation function:

$$\theta_i^{(2)}(k) = f_1(\alpha_i^{(2)}) \tag{2}$$

where, the activation function is $f_1\,(x) = \frac{1}{1+\exp(-x)}$.

The hidden layer information is again transmitted to the output layer, which is output after the activation function of the output layer is activated. The relevant formulas of the output layer node are as follows:

$$\alpha_i^{3}(k) = \sum_{j=0}^{n} w_{li}^{(3)} \theta_i^{(2)}(k) \tag{3}$$

$$\theta_i^{(3)}(k) = f_2(\alpha_i^{(2)}) \tag{4}$$

where $f_2(x) = (1 + f(x))/2 = e^x/(e^x + e^{(-x)})$.

At this time, the output error of the neural network is

$$E(k) = (y(k) - y'(k))^2 \tag{5}$$

B. PARTICLE SWARM OPTIMIZATION FOR OPTIMIZATION OF THE LOCATION

The PSO is considered to be one of its kind representing an ant colony algorithm in addition to fish swarm algorithm, which is used to solve the optimization problem. It uses particles called bee swarm, which can move around and explore search space, and find the optimal solution of the problem through cooperation and information sharing between particles. Let N particles be located in D-dimensional space, and the position of the first particle can be shown as $x_i = (x_{i1}, x_{i2}, \ldots, x_{iN})$, and its velocity is $v_i = (v_{i1}, v_{i2}, \ldots, v_{iN})$. The best position extremum experienced by the particle individual and population is $pb_i = (p_{i1}, p_{i2}, \ldots, p_{iN})$ and $\mathrm{gb} = (G_1, G_2, \ldots, G_D)$ respectively. These values are followed in d dimension to update the particle velocity and position. The d-dimensional velocity updating formula is as follows:

$$v_{\mathrm{id}}^{iter+1} = v_{id}^{iter} + c_1 r_1 (pb_{id}^{iter} - x_{id}^{iter}) + c_2 r_2 (\mathrm{gb}_d^{iter} - z_{id}^{iter}) \tag{6}$$

In Eq. 6, *iter* is the current number of iterations, c_1 and c_2 are acceleration constant, *r1* and *r2* are two random functions.

In a two-dimensional space, there are n sensor nodes with the same communication ability, and k nodes are deployed randomly. Considering the nodes with known location information anchor nodes, and assuming that the distance between the two anchor nodes k and s is $d_{k,s}(1 \le k \le n, k, s)$ [19]. The position information of the CH is unknown and set to (x_1, y_1). According to the gradient drop theory, the position can be expressed as follows:

$$\begin{cases} x_1 = w_{1,2}d_{1,2} + w_{1,3}d_{1,3} + \ldots + w_{1,n}d_{1,n} \\ y_1 = v_{1,2}d_{1,2} + v_{1,3}d_{1,3} + \ldots + v_{1,n}d_{1,n} \end{cases} \tag{7}$$

$$d_{k,s}^* = \sqrt{(x_k - x_1)^2 + (y_k - y_1)^2} \tag{8}$$

Here, the $d_{k,s}^*$ is the calculated distance between the two anchor nodes k and s after applying gradient descent. Thus, the obtained output can be used to calculate the optimum position of the CHs. Further, to calculate the mean square deviation error for a continuous BPNN, we can write:

$$\varepsilon = \frac{1}{2} \sum_{\substack{k,s \\ k<s}}^{n} (d_{k,s} - d_{k,s}^*)^2 \tag{9}$$

The Autocorrelation functions for the cooperative communications between the nodes can be represented as [20]:

$$R_{a_s(k),a_{s+1}(k)} = \lim_{T\to\infty} \frac{1}{T} \int_{T=0}^{T} \sum_{s=1}^{p} a_l(k)(T+\tau) * a_{s+1}(T)\mathrm{dt} \tag{10}$$

Therefore, the modified square deviation error for our proposed method can be written as:

$$\varepsilon = \frac{1}{2}\sum_{\substack{k,s\\k<s}}^{n}(R_{a_s(k)a_{s+1}(k)})^2$$
$$\varepsilon = \frac{1}{2}\sum_{\substack{k,s\\k<s}}^{n}(\lim_{T\to\infty}\frac{1}{T}\int_{T=0}^{T}\sum\nolimits_{s=1}^{p} a_s(k)(T+\tau)*a_{s+1}(T)dt)^2 \tag{11}$$

In the reverse transmission of BPNN, we use distributed gradient drop to adjust the weight and threshold of the network, and the adjustment formula of neuron is as follows:

$$w_{ji}(k+1) = w_{ji}(k) - \eta\sum_{p}\frac{\partial\varepsilon(k)}{\partial_{ji}(k)} = w_{ji}(k)+\Delta w_{ji}(k) \tag{12}$$

where, η is the learning factor. After the adjusted sample is input into BPNN, the network training is carried out again, and the new mean square error continues to be compared with the given error value, and if the value is exceeded, the reverse transmission continues until the desired effect is achieved.

The block diagram of CH identification of WSN with distributed gradient drop based on BPNN is shown in Fig. 2.

In our work, the performance of the system is analyzed, and the sensing functions for respective nodes are monitored in a static environment conditions. We also assume a negligible interference between the nearby nodes during cooperative communication. In this case, assuming that the allocation probability of a single SU node is Ps, the minimum threshold of allocation probability is P_{min}, P_j is the determined conversion probability, and φ is the interference threshold of a single SU. As per copula theory [15], the conditional autocorrelation distribution of the node (SUs) signals can be written as:

$$P_j = P_r(P_h \geq P_s, I_p > \varphi) \tag{13}$$

As shown in Eq. (13), the total estimation error ε depends on the probability transition Pr. This probability represents the magnitude of the degree of certainty. When the value is smaller, the total estimation error is smaller during PSO, and the CH identification of the system becomes more accurate.

The block diagram of CH identification of WSN with distributed gradient drop based on BPNN is shown in Fig. 2.

IV. PERFORMANCE EVALUATION AND RESULTS ANALYSIS

In The simulation experiments in this section are developed in the form of analysis and comparison. The proposed work is compared with HML [17] and DAI [4] in terms of energy-consumption and response time of CH formation. The HML algorithm is dedicated to improving the cooperative sensing capability of channel energy detection in terms of Hierarchy. The DAI algorithm can effectively control the power allocation problem in node location using multi-agent

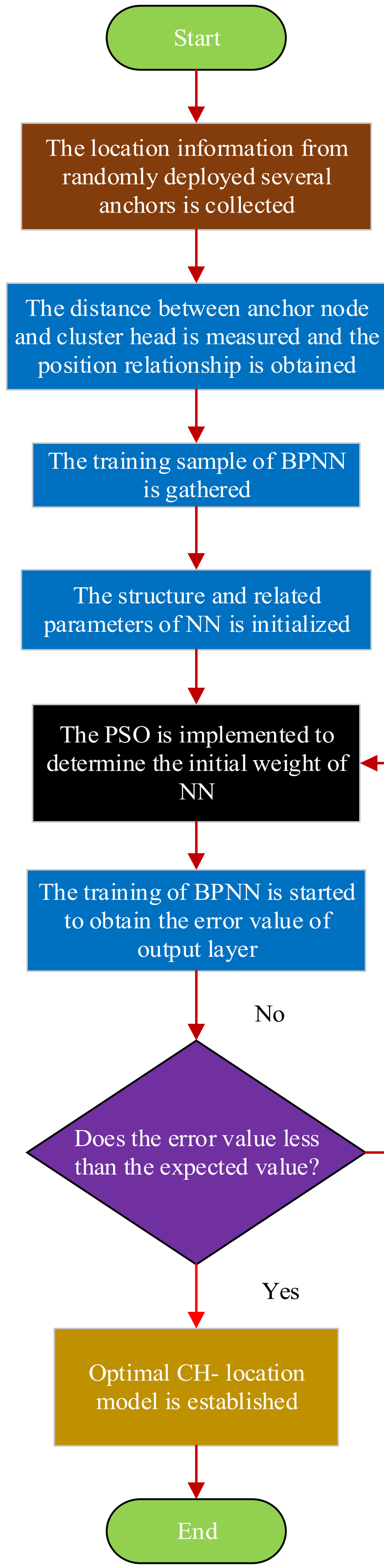

FIGURE 2. Block diagram of cluster head identification of wireless sensor network.

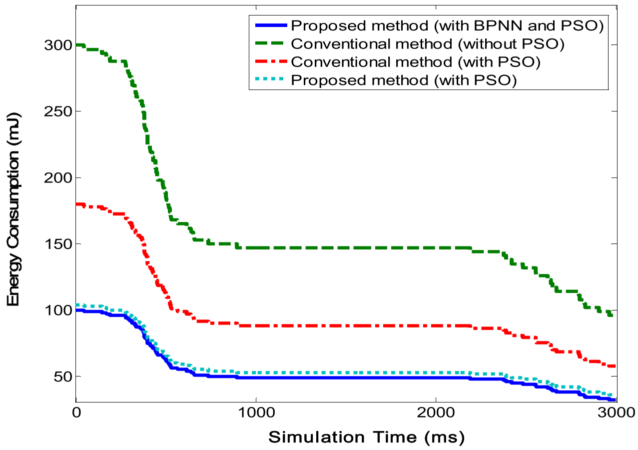

FIGURE 3. Energy consumption performance comparison with respect to simulation time comparison.

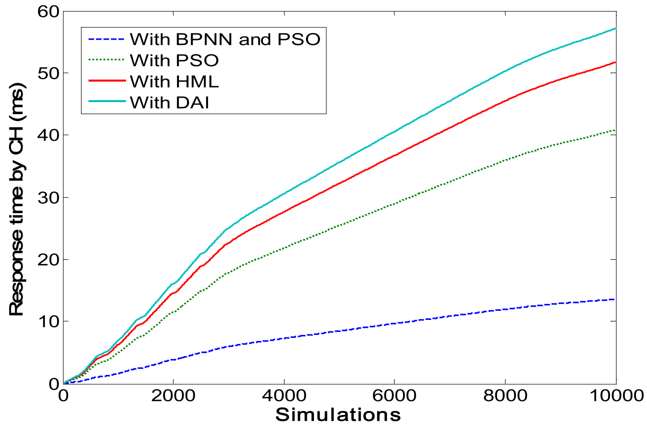

FIGURE 4. Response time performance by cluster head and its comparison with conventional methods.

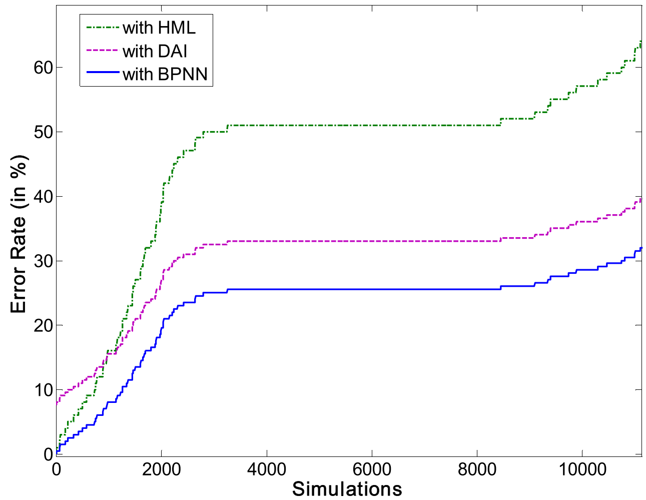

FIGURE 5. Cluster head selection error rate performance using BPNN.

distributed system. The simulations are performed by considering an area of 100mX100m and 3 layers except input and output layer is considered for BPNN. We have carried 10,000 simulations with 1000 nodes which are moving randomly. The simulations are performed with respect to the mathematical derivations for energy-efficient and optimum computations.

Fig.3 illustrates the energy consumption of the network and compared with the existing techniques. It can be clearly seen that as the number of simulation increases, the system energy consumption of all methods gradually decreases. In general, the conventional method where the nodes are placed with equal distance (using traditional PSO) uses more average energy as compared with the proposed method (BPNN and PSO). The combination of BPNN and PSO consumes less energy per simulation due to back propagation, although there is a continuous optimization for position estimation of CH. This further justifies a less computation complexity for the proposed method. Here, the dynamic PSO effectively improves the positioning accuracy and reduce the unnecessary energy loss in the system.

Fig. 4. depicts the CH response time comparison with respect to number of simulations. As shown, the DAI based approach has a poor CH response time due to its distributed approach of finding CH. In case of HML, the CH response time is also less due to a continuous hierarchical management process of selecting CH. In both the cases, the CH response time suffers high computations and thus consumes more overall energy. The hybrid approach of BPNN and PSO proves to be better solution in terms of CH response time with an optimum position accuracy for the CH.

With the energy-efficient and optimum time response, Fig. 5 illustrate the positioning accuracy of the CH. As we know that the positioning error is generally calculated from the square deviation error as mention in Eq. 11. For simulations, we have selected the error probability of the CH selection as the basis for testing the positioning accuracy of the system.

In Fig. 5 the error rate comparison is performed concerning simulations carried. The error rate in the process of HML starts from near 10 % because in HML information is gathered and cluster is formed until the last node is left, which in turn results in higher error rate in channel initially. As we can see, the BPNN performance is well as compared to the other methods due to a continuous weigh update of NN and training them. When the number of simulations reaches to a particular value, the error probability will approach a saturated state of around 30%, which is very less as compared with the other existing methods. Thus, the BPNN based approach successfully provides the lowest error rate and demonstrates its advantage as a neural network with error feedback that can approximate any objective function to the desired accuracy for CH positioning.

As shown in Fig. 6, the processing power is varied and the computation time for overall communication was being carried out. It can be clearly seen that the computation time almost gets optimized from 0.3 to 0.5 processing power (normalized to 1). The proposed method is shown in green color which is compared with the Adaptive Distributed Arti-

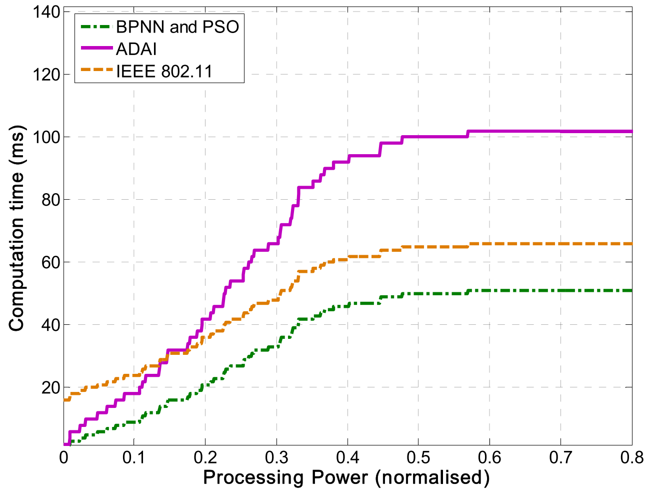

FIGURE 6. Processing power and computation performance.

ficial Intelligence (ADAI) [50] and standard protocol technique IEEE 802.11, which initially gives higher computation time due the improper distribution of loads in nodes. Although there is a difference of 10-15ms with respect to the 0.3-0.5 processing power, the method will significantly reduce the computation time for any given larger network.

V. CONCLUSION AND FUTURE WORKS

In this paper, we have addressed the location identification problem of CHs for MIMO sensor networks for ITS applications. We have used BPNN combined with distributed gradient drop method to identify CH for MIMO sensor networks, which can minimize the total estimation error. In MIMO sensor networks, the dynamic node position in the cluster is identified using the distributed gradient. In this paper, the PSO is used to improve the quality of the initial population, and the population quality of the offspring (node positions) is also improved in the iterative process, which leads to position accuracy. The model proposes an energy-efficient and high response time in comparison to the conventional methods. Thus it helps to provide efficient and reasonable resource to vehicle and infrastructures. The introduction of deep learning into the positioning problem improves the computational complexity of the processor. The work can be useful for both Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication modes. Through mathematical analysis and simulation, we justify the proposed methods as a novel technique to identify CH positions in a dynamic network in ITS. Further, the work can be extended by considering vehicle localization issues using WSNs.

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