Improved Two Hidden Layers Extreme Learning Machines for Node Localization in Range Free Wireless Sensor Networks

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Abstract —Wireless Sensor Network (WSN) architectures are widely used in a variety of practical applications. In most cases of application, the event information transmitted by a sensor node via the network has no significance without the knowledge of its accurate geographical localization. In this paper, a method based on Machine Learning Technique (MLT) is proposed to improve node accuracy localization in WSN. We propose a Single Hidden Layer Extreme Learning Machine (SHL-ELM) and a Two Hidden Layer Extreme Learning Machine (THL-ELM) based methods for nodes localization in WSN. The suggested methods are applied in different Multi-hop WSN deployment cases. We focused on range-free localization algorithm in isotropic case and irregular environments. Simulation results demonstrate that the proposed THL-ELM algorithm greatly minimizes the average localization errors when compared to the Single Hidden Layer Extreme Learning Machine and the Distance Vector Hop (DV- Hop) algorithm.

Index Terms—Wireless sensors network, range free, localization, deep extreme learning machine.

I. INTRODUCTION

In recent years, Wireless Sensor Networks (WSNs) have grown considerably therefore attracting researchers and industrials. A WSN consists of a high number of small radio frequency sensor devices, generally characterized by limited communication capability and strict energy constraint. Each device (sensor node) acquires data from its sensing environment and communicates the obtained information through the network infrastructure. The knowledge of both, the collected information and the geographical localization of the sensor node is very important for many applications. Tracking, supervision and security IoT (Internet of Things) application can be a typical example [1]. In the literature, many research works have focused on the geographical localization problem in WSN. In recent works, a particular interest has been given to Machine Learning Techniques (MLT) application in this field. MLT such as Artificial Neural Network (ANN) [2]-[4]. Support Vector Machine (SVM) [5], [6], Deep Learning approach [7], and statistical models [8] are used in different domains for classification, density estimation or process modelling. Indeed, the machine learning technique permits to generate a parametric model in order to predict process behaviour. ANN paradigm can be effortlessly used for this modelling task. This technique was used in many research works, [9]-[12], for different localization techniques (range-based and range-free) and for different WSN topologies (isotropic and anisotropic. In the range-based techniques, usually used in the case of large scale applications, the sensor nodes localization ANN inputs (Fig. 1 and the Fig. 2) are composed of physical characteristics of the received signals such as the RSSI (Received Signal Strength Indication), ToA (Time of Arrival), the TDoA (Time Difference of Arrival) or the AoA (Angle of Arrival) [13]-[16]. In this case, the more expensive the measuring hardware is, the better the localization accuracy is. In range-free techniques, the sensor node localization is based on connectivity and minimum hop counts. This permits to avoid the use of a high number of signals and expensive measurement devices. For this technique, the positions of a limited number of nodes called Anchors must be known. The remaining nodes (with unknown position) are to be localized. These nodes are called normal nodes. Based on network connectivity information and anchors' positions, normal nodes localization could be estimated without additional hardware to measure and evaluate the distance between whole nodes. This method could be adapted to any type of isotropic wireless network and ensures acceptable accuracy. In this work we suggest novel localization algorithms based on Extreme Learning Machine (ELM). They consist of Two-Hidden-Layers (THL) ELM algorithms. The new variants of the ELM represent a new way to treat the WSN localization based on Range-Free technique. The proposed algorithms will be experimented for different scenarios in isotropic environments to show the effectiveness of the proposed method. The rest of the paper is organized as follows. In section 2, we recall a set of works treating the localization problem in WSN. Section 3 and 4 are dedicated respectively to the presentation of the single hidden layer ELM and the two hidden layer ELM applications for the localization task. Simulation results will be presented and

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analysed to compare the performance of the proposed ELM architectures in section 5. Finally, conclusions are drawn in Section 6.

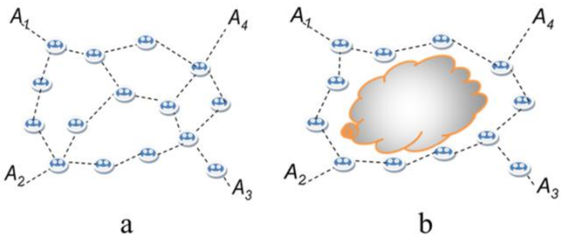

Fig. 1. (a) Isotropic WSN deployment (without obstacles), (b) Anisotropic WSN deployment (with obstacles)

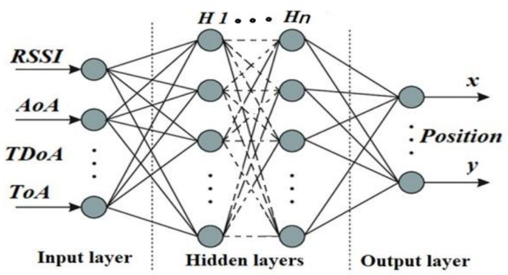

Fig. 2. Range based Deep-ANN localization modes

II. Related Work

In the last decades, based on smart computing and machine learning, some approaches have been carried out such as ANN, SVM, ELM (Extreme Learning Machine) and Deep Learning to solve the localization problem in the wireless networks. Indeed, Zheng et al. proposed an Enhanced Mass-Spring Optimization (EMSO) method to develop different range-free algorithms. These algorithms are based on single ANN or a set of ANNs with different architectures to estimate the position of the unknown normal nodes by using the neighboring anchors positions and the hop-counts information [2]. As expected, the set of ANNs localizer gave better performance than a single ANN localizer. Tran et al. proposed a range-free localization algorithm based on a modified SVM method (LSVM or Location SVM). The localization task is then treated as a classification problem where a set of clusters (sets of unknown normal nodes) is defined in order to estimate the unknown nodes positions [5]. LSVM uses the correspondence between anchors coordinates and hop count distances as a set of training data in the learning process. The case of two-dimensional spaces was treated in this paper (X, Y). The classification process (LSVM) is built following the sets of classes (X-Classes and Y-Classes), and each localized node is assigned to the pair (X-Classes, Y-Classes). In the same work, the authors proposed a modified version of mass-spring optimization to improve the location estimation with LSVM. Javadi et al. exploited the SVM and the Twin-SVM learning algorithms in WSNs for sources (normal nodes) localization. First, the authors considered that the WSN detects the region of the expected event to be localized and using the distributed learning algorithm, the centroid of the event proximity nodes is computed. The average of the nodes positions in the event region is then considered as the position of the event to be located [17], Chatterjee *et al*. proposed the exploitation of the supervised feedforward neural-network as a localization classifier in the case of a 2-D sensor net- work (X-Classes and Y-Classes). The feedforward neural network uses the multi-hop connectivity information and anchors positions of a large number of sensor nodes. This work is based on conjugate gradient algorithm for training the multilayered feedforward neural network. In this paper, it has been verified that the ANN-based localizer has better accuracy than the LSVM [18], [19]. Cottone et al. address the localization problem, exploiting knowledge acquired in different environment samples and extensible. Localization problem is transformed into learning problem solved by a statistical algorithm. Additionally, based on connectivity information, the SVM auto-tuning parameters are formulated as an optimization problem [8]. Zheng et al. exploited the Regularized Extreme Learning Machine (RELM) for the large-scale multi-hop localization problem in WSNs and proposed a Multi Scale RELM (ML-RELM). The proposed algorithm consists of three steps: acquiring data for the learning process via the equivalence between hop count and physical distances, modeling the distances between known and unknown nodes using the RELM, and the localization process is given by the Trilateration or the Multilateration procedure [4]. Many metaheuristics like GA and PSO have been applied for WSN localization problem [20], [21]. Phoemphon *et al.* presented a cooperative localization models (fuzzy weighted centroid results and ELM model) optimized by the Particle Swarm Optimization (PSO) metaheuristics for WSNs localization. The ratios of known nodes to the total known nodes and of the sensing coverage range to the maximum coverage range were used as adaptive weights for this combined process. To improve the efficiency of such hybrid model, the concept of resultant force vectors was applied via the PSO to minimize the effects of irregular deployments [20].

III. Single Hidden Layer Localization Process

Due to its simple principle, random projection concept has recently gained a lot of popularity, especially in the area of ANN. The well-known feedforward ANN method is the Extreme Learning Machine (ELM), which is based on random projection and direct calculation of the output layer. In fact, ELM process has become a popular supervised training algorithm due to its simple structure (single hidden layer and single linear output layer) and its fast computational process. Initially, proposed by Huang *et al*. the main idea of the ELM is presented by the exploitation of the Single Layer Feedforward Networks (SLFNs). It consists of generating randomly the input weights and the hidden bias, and calculating analytically the output weights using the least-square method [22]-[24]. Indeed, the ELM facilitates the SLFNs implementation and allows a significant training time reduction. Many variants of the ELM have been proposed to improve the efficiency of this learning algorithm [25], [26].

A. Single Hidden Layer ELM Structure for WSN Localization

In WSN, intuitively the minimum hop count between sensors nodes and the anchors nodes and the corresponding physical distance (geographical locations) are correlated. Using the ELM model, this correlation could be exploited for estimating the locations of the unknown nodes in the WSN .

The principle of minimum hop count is given by the process. Let us consider an anchor i and an unknown node j. Anchor i and node j could be linked using different paths (sets of intermediate nodes). The unknown node (j) receives information of the (i) anchors position (x_i,y_i) and hop count of the whole paths (starting from the anchor i). The minimum hops count is then selected and defined as $hop_{i,j}$. A table gathers the minimum hops counts between the whole anchors and unknown nodes. Table I. gives an example of Hop-count between 4 anchor nodes and 9 unknown nodes. The Fig. 3 gives the ELM structure for WSN localization in range free cases.

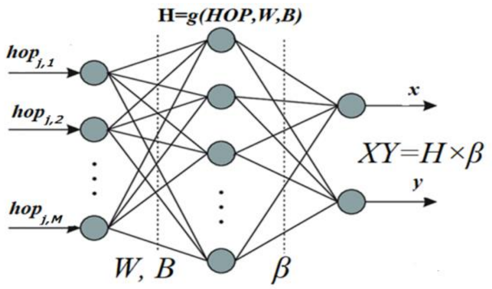

Fig. 3. The based hops single ELM localization model

TABLE I: CORRESPONDENCE BETWEEN HOP COUNT AND XY POSITION

	A_1	A_2	A_3	A_4			X	Y
N_1	1	4	3	4	ELM >>>	N_1	x_1	y_1
N_2	2	3	3	4		N_2	x_2	y_2
N_3	3	4	3	3		N_3	x_3	y_3
N_4	3	2	4	4		N_4	x_4	y_4
N_5	4	2	4	3		N_5	x_5	y_5
N_6	3	3	2	2		N_6	x_6	y_6
N_7	4	4	3	1		N_7	x_7	y_7
N_8	4	4	2	2		N_8	x_8	y_8
N_9	5	5	1	3		N_9	x_9	y_9

B. Single Hidden Layer ELM Training and Eexploitation Phases for WSN Localization

The ELM based WSN localization model will estimate the geographical location of a target node via the minimum hops counts between unknown nodes and anchors nodes. In this case, for one unknown j the ELM input vector is:

$$HOP_j = [hop_{1,j} \cdots hop_{M,j}]$$

M being the number of anchors and $hop_{i,j}$ denotes the training hops count data between anchors i and unknown node j. The ELM output denotes the location (x,y) of the unknown nodes.

Let us suppose that the number of the normal nodes is N. The x_i and y_i coordinates of these nodes are supposed to be known (training data), we can write:

$$\mathbf{H\beta} = \mathrm{XY} \tag{1}$$

with:

$$\mathbf{H} = \begin{bmatrix} g_1(HOP_1W_1 + b_1) & \cdots & g_z(HOP_1W_z + b_z) \\ \vdots & \ddots & \vdots \\ g_1(HOP_NW_1 + b_1) & \cdots & g_z(HOP_NW_z + b_z) \end{bmatrix}$$

with $\mathrm{H} \in R^{N\times z}$, $\beta \in R^{z\times 2}$ and $XY \in R^{N\times 2}$

$$HOP_j = [hop_{1,j} \cdots hop_{M,j}],$$

$$W_z = [w_{1,z} \cdots w_{M,z}]^T,$$

$$B = [b_1 \cdots b_z]^T,$$

$$\beta = \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \vdots & \vdots \\ \beta_{z,1} & \beta_{z,2} \end{bmatrix}, \text{ and } XY = \begin{bmatrix} x_1 & y_1 \\ \vdots & \vdots \\ x_N & y_N \end{bmatrix}$$

$\hat{\beta}$ is the solution of the optimization problem:

$$\underset{\boldsymbol{\beta}}{Minimize} \quad (\mathbf{H\beta} - \mathbf{XY})^2 \tag{2}$$

Using the Least Square Estimator (LSE), the solution of this optimization problem is given by:

$$\hat{\boldsymbol{\beta}} = \mathbf{H}^{\dagger}\ \mathrm{XY} \tag{3}$$

where XY is the target vector and $\mathbf{H}^{\dagger}$ is the Moore Penrose generalized inverse of matrix $\mathbf{H}$. The calculation of the MP-inverse matrix is given by:

$$\mathbf{H}^{?} = (\mathbf{H}^T\mathbf{H})^{-}\ \mathbf{H}^T \tag{4}$$

In the case of a singular matrix $\mathbf{HH^T}$, we can introduce the regularization factor C to calculate $\hat{\beta}$. The regularized pseudo-inverse of matrix H becomes:

$$\mathbf{H}^{?} = (\mathbf{H}^T\mathbf{H} + \frac{1}{C} \times Id)^{-}\ \mathbf{H}^T \tag{5}$$

where: ***Id*** represents the ($z \times z$) identity matrix.

IV. THE TWO HIDDEN LAYER ELM LOCALIZATION PROCESS

Geographical localization of unknown position nodes is performed following two steps: based on the minimum hop count between the sensor nodes and the anchors, the first step (first hidden layer) consists of estimating the distances between each unknown node and the whole anchors. The second step (second hidden layer), whose input is the estimated distances, aims to estimate the geographical localization of each unknown position node.

A. *Two Hidden Layer ELM Structure for WSN Localization*

For training phase, inputs and outputs of the first hidden layer are the supervised information HOP counts and the Euclidean distances (DIST) between unknown nodes to the anchors, respectively. Once parameters matrix of the first hidden layer β_1 is identified using ELM, then estimated distances (Dist) using the first hidden layer could be calculated. In order to identify β_2 using ELM, the estimated distances (Dist) and the XY information become the inputs and the outputs of the second hidden layer, respectively. The flowchart and the THL-ELM structure of the proposed two hidden layers ELM for localization process are given by Fig. 4, and Fig. 5, respectively.

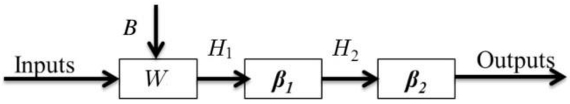

Fig. 4. The flowchart of the Two hidden layers ELM

were H_1=g(Inputs,W,B); H_2= $g(H_1, \beta_1)$; Outputs= $H_2\ \beta_2$

B. *The Two Hidden Layer ELM Interpretation*

The first hidden layer interpretation gives:

$$\mathbf{H}_1\boldsymbol{\beta}_1 = \mathrm{DIST} \tag{6}$$

where:

$$\mathbf{H}_1 = \begin{bmatrix} g_1(HOP_1W_1+b_1) & \cdots & g_z(HOP_1W_z+b_z) \\ \vdots & \ddots & \vdots \\ g_1(HOP_NW_1+b_1) & \cdots & g_z(HOP_NW_z+b_z) \end{bmatrix}$$

$$\boldsymbol{\beta}_1 = \begin{bmatrix} \beta_{1,1} & \cdots & \beta_{1,M} \\ \vdots & \ddots & \vdots \\ \beta_{z,1} & \cdots & \beta_{z,M} \end{bmatrix}, \quad \mathrm{DIST}=\begin{bmatrix} d_{1,1} & \cdots & d_{1,M} \\ \vdots & \ddots & \vdots \\ d_{N,1} & \cdots & d_{N,M} \end{bmatrix}$$

with $\mathrm{H}_1 \in R^{N\times z}$, $\widehat{\beta}_1 \in R^{z\times M}$ and $\mathrm{DIST} \in R^{N\times M}$

Then:

$$\widehat{\boldsymbol{\beta}}_1 = (\mathbf{H}_1^T\mathbf{H}_1)^{-1}\mathbf{H}_1^T \times \mathrm{DIST} \tag{7}$$

The second hidden layer interpretation gives:

$$Dist = \mathbf{H}_1 \times \widehat{\boldsymbol{\beta}}_1 \tag{8}$$

$$\begin{aligned} &\mathbf{H}_2 = g(\mathbf{H}_1, \widehat{\boldsymbol{\beta}}_1) \\ &\mathbf{H}_2\boldsymbol{\beta}_2 = \mathrm{XY} \\ &\widehat{\boldsymbol{\beta}}_2 = (\mathbf{H}_2^T\mathbf{H}_2)^{-1}\mathbf{H}_2^T \times \mathrm{XY} \end{aligned} \tag{9}$$

With:

$$\beta_2 = \begin{bmatrix} \beta_{1,1} & \beta_{1,2} \\ \vdots & \vdots \\ \beta_{M,1} & \beta_{M,2} \end{bmatrix}, \text{ and } XY = \begin{bmatrix} x_1 & y_1 \\ \vdots & \vdots \\ x_N & y_N \end{bmatrix}$$

$$Dist = \begin{bmatrix} \widehat{d}_{1,1} & \cdots & \widehat{d}_{1,M} \\ \vdots & \ddots & \vdots \\ \widehat{d}_{N,1} & \cdots & \widehat{d}_{N,M} \end{bmatrix}$$

with $\mathrm{H}_2 \in R^{N\times M}$, $\beta_2 \in R^{M\times 2}$ and $XY \in R^{N\times 2}$

Finally, during the training localization phase, we consider the static WSN here we assume that the nodes positions do not change. The two hidden layers ELM algorithm constructs a model based on the training database. The number of hidden neurons, input weights matrices and bias vectors are then defined. After that, the weights matrix between the two hidden layers and the output weights is calculated by the two hidden layer ELM localization algorithm.

V. Simulation Results and Comparaison

This section is dedicated to evaluate the performance of our proposed two hidden layer ELM algorithm. Original DV-Hop algorithm, single hidden layer ELM localization algorithm and our proposed two hidden layers are compared in the isotropic cases with the same simulation conditions. We used Matlab-R2018a for ELM implementation and simulation. We performed 100 times randomly deployment scenarios, and we calculated the average values of these scenarios. In all simulation cases, the unknown nodes are deployed in a 2-D area which surface is S=100m×100m with 50 anchors nodes and the same communication range for each node R=20m. During the localization phase, we assume that all the nodes and the anchors in the network are static. Firstly, for the learning process in isotropic case, the WSN structure considers N = 200 unknown nodes and M=60 anchor nodes. The anchors nodes are deployed following random, circle, spiral and sinusoidal deployment scenarios. The data learning set consider 25 scenarios for the 200 unknown nodes, 25×200=5000 WSN nodes. In the case of single hidden layer and two hidden layer, each layer involves 250 neurons with a sigmoidal activation function 250 hidden neurons for the ELM hidden layer and the sigmoidal activation function. Secondly, in the exploitation phase, the positions of the anchors nodes remain the same as those used in the training phase (unchanged positions of anchors). These simulations correspond to the random, circle, spiral and sinusoidal scenarios deployments.

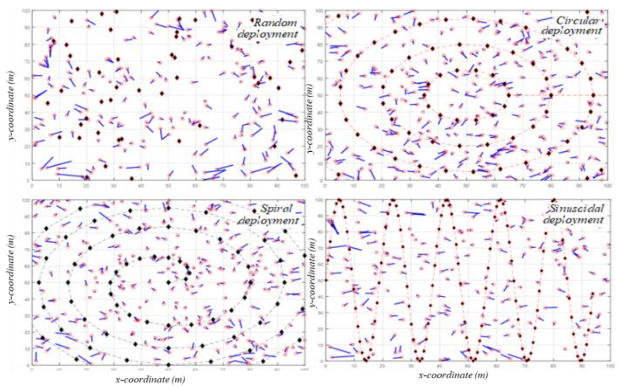

Fig. 5. Samples of localization results for Random, Circular, Spiral and Sinusoidal anchors deployment scenarios

The Fig. 5 gives the example of localization results of the unknown sensor nodes by THL-ELM algorithm for

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different anchors deployment scenarios. In this figure, symbol 'o' denotes the real location of the unknown node and blue straight line represent the localization errors between exact position and the estimated position, the black points denote the anchors nodes positions. In the following, we validate our proposed approaches SHL-ELM and THL- ELM by comparing their results with the well-known DV-hop algorithm for the isotropic case. These comparisons are conducted under the same network settings and spiral anchors deployment scenario. The metric that we use to evaluate the performance of our localization algorithms is Cumulative Distribution Function (CDF) of the Normalized Localization Error (NLE). The normalized localization error characterizes the localization accuracy and defined by the following equation.

$$NLE = \frac{1}{N \times R}\sum_{i=1}^{N}\sqrt{(x_i^{est} - x_i)^2 + (y_i^{est} - y_i)^2} \tag{10}$$

where N and R represent respectively the number of unknown nodes and the communication range fixed in our simulation (R=20m). The (x_i, y_i) are real coordinates and the (x^{est}, y^{est}) are estimated coordinates of the i'th unknown sensor node position.

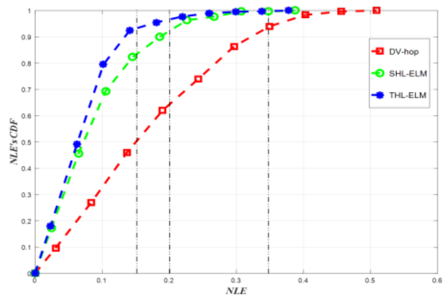

Fig. 6. CDF results for SHL-ELM, THL-ELM and the DV-hop algorithm for spiral anchors deployment.

Fig. 6 gives the NLE's CDF results achieved by our proposed localization algorithms SHL-ELM and THL-ELM and the DV-hop algorithm for spiral anchors deployment scenario. The localization results show that the accuracy due to the two proposed localization algorithms based on the ELM surpasses largely the localization results accuracy given by the original DV-hop algorithm. For instance, the THL-ELM algorithm, the SHL-ELM algorithm and the DV-hop algorithm give respectively 98%, 90% and 63% for accuracy equal to 0.2×R. This further demonstrates the accuracy of the THL-ELM model when compared to SHL-ELM and DV-hop.

Fig. 7 describes the normalized localization error (NLE) with different strategies of the anchors deployment scenarios (random, circle, sinusoidal and spiral scenarios). As it can be observed from this figure, regardless of the anchors deployment scenario, the results achieved by the ELM algorithms are better than the DV-hops results. Concerning the ELM algorithms, THL-ELM gives better results than the SHL-ELM algorithm. THL-ELM gives double precision when compared to the DV-hop algorithm in the entire anchors deployment scenario

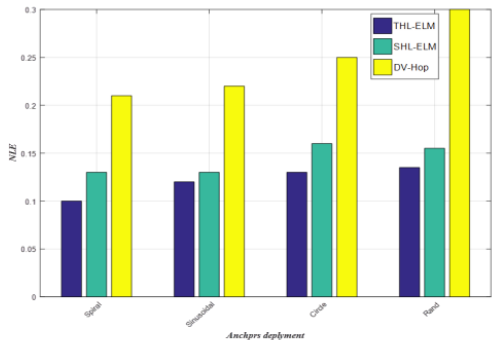

Fig. 7. Accuracy results for SHL-ELM, THL-ELM and the DV-hop algorithm for spiral anchors deployment

VI. Conclusion

In this paper, a two hidden layer (THL) algorithm based on the Extreme Learning Machine (ELM) has been proposed in order to optimize node localization accuracy in WSN. The suggested THL-ELM algorithms are based on Range Free technique in isotropic WSNs. They represent a new way to tackle the WSN localization. For the performances evaluation the Cumulative Distribution Function (CDF) of the Normalized Localization Error (NLE) has been applied. Simulation results show that for the same NLE value, THL-ELM presents better accuracy when compared to SHL-ELM and DV-hop algorithms. In addition, computation time in the case of THL-ELM and SHL- ELM algorithms is relatively low when compared to DV-hop. These advantages make THL-ELM algorithm a very promising candidate for treating the WSN localization problem in real time. The FPGA implementation of the proposed algorithms will be treated in the next work.

Conflict of Interest

The authors declare no conflict of interest.

Author Contribution

The first author wrote the machine learning technics, simulation results and wrote the paper.

All authors had approved and analyzed the final results and the final version

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