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Enabling Relay Selection in Cooperative Networks by Supervised Machine Learning

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***Abstract*—In fifth generation (5G) networks, cooperative transmission assisted by relays is believed to be an essential element, which significantly improves the system reliability and enhances the network design flexibility. To coordinate multiple relays in cooperative networks and utilize them in an efficient manner, relay selection is required. In this paper, we enable a generic relay selection scenario by supervised machine learning techniques and propose a prototype framework for further investigation. The prototype framework is constructed by a relatively simple artificial neural network consisting of only one hidden layer and the number of neurons in the hidden layer is equal to the number of inputs/outputs. Numerical results show that any relay selection criteria that conform to a certain form can be implemented by such a simple prototype framework, which can reduce the required system complexity for performing complicated processing of relay selection by conventional algorithms. Furthermore, we also point out a number of potential research directions that are worth investigating as future work.**

Keywords*—Relay selection, supervised machine learning, artificial neural networks, cooperative networks, 5G wireless communications.

I. Introduction

At the beginning of the 21st century, point-to-point communications have show an irreversible declining tendency to support an ever increasing wireless data transmission demand [1]. With the proliferation of various smart devices in recent decade, cooperative networks and relay assisted communications that lead to multi-hop transmission scenarios have attracted many researchers' attention [2]. However, when multiple relays are involved, it is not a trivial task to coordinate among them and exploit them efficiently. Researchers have found that relay selection is one of the most powerful approaches to achieve so [3]. After performing relay selection, a transmitted signal from source will only be received and forwarded by one selected relay to destination, so as to achieve a *selection diversity gain* [4]. There exist a large number of different relay selection criteria suiting for different application scenarios [5]–[9]. Because relay nodes are spatially distributed over a two-dimensional plane, coordination among multiple relays and implementation of a certain relay selection criterion are not trivial tasks as well [10]. Traditionally, relay selection can be performed either by centralized or decentralized way [11]. By centralized way, a centralized controller, e.g. a base station (BS) is assumed to have access to all channel state information (CSI) and is connected to all relays, so as to make decision and announce the selected relay. By decentralized way, a timer-based solution is applied, which significantly raises the system complexity and results in a higher transmission delay. Albeit effective, their efficiency in practice is still questionable.

Since the arrival of the 'smart era' where most mobile devices and nodes are capable of processing and having intelligent functionality, this provides a foundation to enable relay selection in a more efficient manner based on artificial intelligence (AI) related technologies. Machine learning, as a new star for AI, has been adopted for time-variant power line communications in [12]. However, the results provided are not general and difficult to extend to other communication circumstances. Reinforcement learning, one of the most common unsupervised learning techniques has been applied to assist relay/channel selection [13]–[17]. Meanwhile, due to the state-of-the-art achievements in channel estimation, channel statistics and relevant estimated states used for relay selection are normally labeled data. This makes supervised machine learning that relies on labeled data more suited for performing relay selection in some circumstances. On the other hand, to the best of authors' knowledge, the work linking relay selection and supervised machine learning is still lacking. To bridge this gap, we in this paper enable a generic relay selection scenario by supervised machine learning techniques and propose a prototype framework for further investigation. The prototype framework is constructed by a relatively simple artificial neural network consisting of only one hidden layer and the number of neurons in the hidden layer equals to the number of inputs/outputs. We also carry out numerical simulations and numerical results have confirmed the effectiveness of the proposed prototype framework. Based on the numerical results and following discussion, we point out several potential research directions that are worth investigating as future work.

The rest of this paper is organized as follows. In Section II, we give the fundamentals of supervised machine learning and present the system model investigated in this paper. Based on these, we detail the learning algorithm in Section III. Then, we illustrate and discuss the numerical results in Section IV. Subsequently, we articulate a number of potential research directions that are worth investigating as future work in Section V. Finally, we conclude the paper in Section VI.

II. Fundamentals and System Model

A. Fundamentals of Supervised Machine Learning

In essence, machine learning provides an adaptive mechanism, which can dynamically adjust a series of system configurations by sensory information from environment. Normally,

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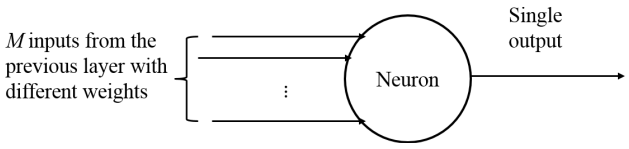

Fig. 1. Schematic of a typical neuron.

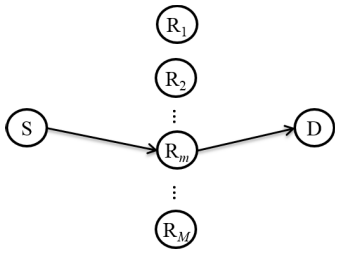

Fig. 2. System model of a cooperative network assisted by M relays. S: source, R: relay and D: destination.

machine learning is based on a structure called *artificial neural network*, which consists of a vast number of connected processors termed *neurons*. A typical neuron has multiple inputs and only a single output, which is connected by *weighted* links to other neurons in adjacent layers. The schematic of a typical neuron is shown in Fig. 1. Learning from labeled data set, neurons are capable of strengthening the 'correct' connections and weakening those 'incorrect' connections by dynamically changing the weights in a *supervised* manner. Therefore, as long as the volume of labeled data sets is large enough, a properly designed artificial neural network can converge to the optimal setting and produce satisfactory output for a given input by repeating the learning process for a large number of rounds. The neuron represents the basic processing element in artificial neural networks and the weighted link characterizes the memory of artificial neural networks.

Except from the artificial neural networks, knowledge is also the key for the performance of machine learning. As the supervised machine learning is adopted in this paper, knowledge is carried by labeled data sets. Specifically, when a labeled data set with desired output is introduced and processed by an artificial neural network through multiple layers, the real output will be compared to the desired output. Subsequently, each neuron will adjust the weights of its connections by the comparison result via a certain algorithm accordingly. Therefore, a self-adapting structure that is able to learn from labeled data sets is formed.

B. System Model

A typical two-hop cooperative network is considered in this paper, in which one source, one destination and M relays exist. To ease the following description, we denote the set of relays as $\mathcal{M}$. Assume there does not exist a direct transmission link between the source and destination and thereby signal propagation must be assisted by relays, so that two phases are required to complete one transmission. Such a system model of a cooperative network assisted by multiple relays is pictorially illustrated in Fig. 2.

To make the best use of multiple relays and achieve the selection diversity gain, relay selection is employed to select *one* out of M relays to forward the signal transmitted by source to destination[1]. As mentioned in the introductory section, there exist a variety of relay selection methods. In general, most of single relay selection methods can be classified into two categories: max-based relay selection and min-based relay selection. The max-based relay selection can be formulated by

$$\mathcal{S}(n) = \arg\max_{m\in\mathcal{M}}\{h_m(n)\}, \tag{1}$$

where $\mathcal{S}(n)$ denotes the set of the selected relay at the nth epoch and $h_m(n)$ is the selection metric, which should be maximized in order to optimize the system performance and could be end-to-end signal-to-noise ratio (SNR), capacity, channel gain etc.

Similarly, the min-based relay selection can be formulated by

$$\mathcal{S}(n) = \arg\min_{m\in\mathcal{M}}\{g_m(n)\}, \tag{2}$$

where $g_m(n)$ is the selection metric, which should be minimized in order to optimize the system performance and could be propagation distance, noise power, error rate etc.

Apart from the set $\mathcal{S}(n)$, we can also characterize the relay selection state at the nth epoch by a $M\times 1$ matrix $\mathbf{S}(n)$, where the index of the entry of '1' represents the index of the selected relay. By involving matrix, the processing and programming in the sequel can be facilitated.

Now, we have to define the structure of the artificial neural network employed in this paper to enable relay selection. First, as a prototype framework, we only consider a simplified artificial neural network having three layers, i.e. the input and output layers and a single hidden layer. In the input layer, there are M inputs for introducing M selection metrics, and similarly in the output layer, there are M outputs representing M entries of $\mathbf{S}(n)$, by which we can know which relay has been selected by the processing of the artificial neural network. The input and output layers are interfaces for information exchanging with external environment and are observable to operators/users[2]. The most difficult part is to define the hidden layer, in particular how many neurons should be deployed to achieve the predefined functionality. Unfortunately, there is still not a 'golden rule' regarding this issue applicable for all cases and scenarios. As a rule of thumb, we might choose to have a same number of neurons in the hidden layer as the number of inputs [18]. Therefore, we finally have the artificial neural network demonstrated in Fig. 3, where the weight of the link between neurons in the input and hidden layers is denoted as $u_{ij}(n)$ and the weight of the link between neurons in the hidden and output layers is denoted as $v_{jk}(n)$.

Meanwhile, to learn from the labeled data sets, we first need to explicitly define what a labeled data set refers to in this paper. To be simple, we define a labeled data set as follows.

[1]To be more specific, this is termed the single relay selection, while there also exist multi-relay selection schemes. As the latter is simply an extension of the former, we here only focus on the single-relay selection and the relevant results obtained in this paper can be easily transferred to multi-relay selection cases.

[2]It should be noted that in general the neurons in the input layer do not perform any processing and simply distribute the inputs to the neurons in the hidden layer.

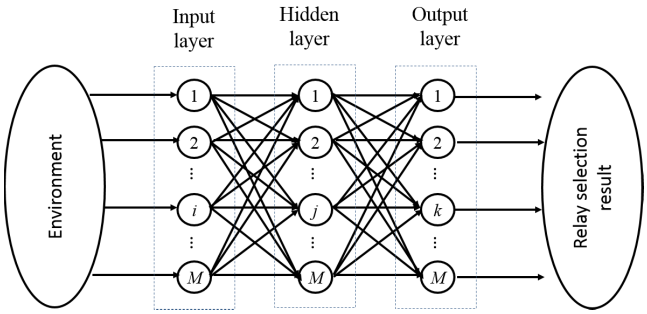

Fig. 3. Artificial neural network model adopted in this paper to enable relay selection by supervised machine learning.

Definition 1: A labeled data set consists of M selection metrics $h_m(n)$ or $g_m(n)$ pertaining to M relays for selection and a desired selection matrix $\mathbf{S}_d(n)$ corresponding to M given selection metrics.

III. Learning Algorithm

As specified in [18], we adopt the conventional four-step learning algorithm for performing supervised machine learning in this paper. These four steps are *initialization*, *activation*, *training* and *iteration*. We detail these four steps as follows.

A. Initialization

There are four sets of parameters that are required to be initialized in order to start the learning process, i.e. the weights $u_{ij}(1)$ and $v_{jk}(1)$, $\forall\, i,j,k \in \{1,2,\ldots,M\}$ and the thresholds used to activate neurons in the hidden layer and output layer $\theta_j(1)$ and $\vartheta_k(1)$. For simplicity, we employ the random initialization method in this paper and the aforementioned parameters are uniformly chosen within the range [19]

$$\Omega = \left(-\frac{2.4}{M}, \frac{2.4}{M}\right), \tag{3}$$

which is completed in a neuron-wise manner.

B. Activation

For the jth neuron in the hidden layer, the input/output relation of the nth epoch can be given by

$$y_j(n) = \text{Sigmoid}\left(\sum_{i=1}^{M} u_{ij}(n)x_i(n) - \theta_j(n)\right), \tag{4}$$

where $\text{Sigmoid}\,(x) = \frac{1}{1+\exp(-x)}$ is the sigmoid function and $x_i(n) = h_i(n)$ or $g_i(n)$ depending on the selection criterion (c.f. (1) and (2)).

Likewise, we can have the input/output relation of the nth epoch at the kth neuron in the output layer by

$$z_k(n) = \text{Sigmoid}\left(\sum_{j=1}^{M} v_{jk}(n)y_j(n) - \vartheta_k(n)\right). \tag{5}$$

The output relay selection matrix at the nth epoch is thereby organized by

$$\mathbf{S}(n) = [z_1(n), z_2(n), \ldots, z_M(n)]^T, \tag{6}$$

where $(\cdot)^T$ denotes the matrix/vector transpose operation.

We can ditto express the desired selection matrix $\mathbf{S}_d(n)$ in the same way to be

$$\mathbf{S}_d(n) = [z_{d,1}(n), z_{d,2}(n), \ldots, z_{d,M}(n)]^T. \tag{7}$$

Incidentally, the learning performance at the nth epoch can be characterized by the sum of squared errors (SSE) compared $\mathbf{S}(n)$ with $\mathbf{S}_d(n)$, which can be written as

$$\text{SSE}(n) = \left\|\mathbf{S}_d(n) - \mathbf{S}(n)\right\|_F^2, \tag{8}$$

where $\|\cdot\|_F$ denotes the Frobenius norm of the enclosed matrix/vector.

C. Training

After the activation stage, the real output selection matrix $\mathbf{S}(n)$ will be compared to the desired output selection matrix $\mathbf{S}_d(n)$, so that errors can be produced and back-propagated to update $u_{ij}(n+1)$, $v_{jk}(n+1)$, $\theta_j(n+1)$ and $\vartheta_k(n+1)$. In particular, the adaptive training mechanism on these parameters is specified infra according to the methodology provided in [18].

1) $v_{jk}(n+1)$: For the kth neuron in the output layer, we first determine the error by

$$e_k(n) = z_{d,k}(n) - z_k(n). \tag{9}$$

Then, we are able to derive the error gradient by

$$\delta_k(n) = z_k(n)(1 - z_k(n))e_k(n). \tag{10}$$

Finally, given α, a preset learning rate, the correction term can be determined by

$$\Delta v_{jk}(n) = \alpha y_j(n)\delta_k(n), \tag{11}$$

which is added to update the weight in the next epoch as

$$v_{jk}(n+1) = v_{jk}(n) + \Delta v_{jk}(n). \tag{12}$$

2) $u_{ij}(n+1)$: In a similar manner, we can determine the error gradient and correction term for the jth neuron in the hidden layer by

$$\zeta_j(n) = y_j(n)(1 - y_j(n)) \sum_{k=1}^{M} \delta_k(n)v_{jk}(n) \tag{13}$$

and

$$\Delta u_{ij}(n) = \alpha x_i(n)\zeta_j(n). \tag{14}$$

Finally, the weight of the link between the ith and the jth neurons in the input and hidden layers can be updated by

$$u_{ij}(n+1) = u_{ij}(n) + \Delta u_{ij}(n). \tag{15}$$

3) $\theta_j(n+1)$ and $\vartheta_k(n+1)$: With $\zeta_j(n)$ and $\delta_k(n)$, the correction terms for $\theta_j(n+1)$ and $\vartheta_k(n+1)$ can be written by

$$\Delta\theta_j(n) = -\alpha\zeta_j(n) \tag{16}$$

and

$$\Delta\vartheta_k(n) = -\alpha\delta_k(n). \tag{17}$$

As a consequence, the thresholds for neurons in the hidden and output layers are updated as

$$\theta_j(n+1) = \theta_j(n) + \Delta\theta_j(n) \tag{18}$$

and

$$\vartheta_k(n+1) = \vartheta_k(n) + \Delta\vartheta_k(n) \tag{19}$$

D. Iteration

After performing the activation and training process, we check the termination condition. If the condition is satisfied, we terminate the learning process and the artificial neural network is said to be *trained*. Otherwise, we go back to the activation stage and repeat the process. There are two methods to stipulate the termination condition. The first one is to define a fixed maximum number of iterations and the second one is to check whether the SSE is below a predefined threshold level. To investigate the effects of the number of iterations on the learning performance, we adopt the former in this paper as the termination condition and the maximum number of iterations is denoted by N.

IV. Numerical Results and Discussion

In this section, we apply Monte Carlo simulations to numerically verify the effectiveness of using supervised machine learning to enable relay selection in cooperative networks. We configure relevant system parameters for simulations as follows: $\alpha = 1$ and $N = 500$. Then we average the SSE over a hundred thousand trials to produce the average SER in order to show the average learning performance. The simulation results pertaining to the max-based and min-based relay selections with different $M \in \{2, 4\}$ are shown in Fig. 4 and Fig. 5, respectively. Here, we generate labeled data sets by randomly generating selection metrics by exponential distribution and determine $\mathbf{S}_d(n)$ by conventional brute-force method. From both figures, the effectiveness of the learning algorithm assisted relay selection can be confirmed. With the increase in epochs, the average SSE goes down, which indicates that on the average, selection matrix $\mathbf{S}(n)$ converges to the desired benchmark $\mathbf{S}_d(n)$. Additionally, compared to the cases with different numbers of relays, it can be found that the supervised machine learning can handle cases with a smaller number of relays better. Furthermore, comparing the numerical results in Fig. 4 and Fig. 5, we can also see that the solid lines are almost the same, whereas there is an apparent gap between the dashed lines. This is because when $M = 2$, the computational complexity for finding the maximum and minimum is the same. It is nevertheless because for $M > 2$, the inherent algorithms in artificial neural networks to produce the maximum and minimum are different.

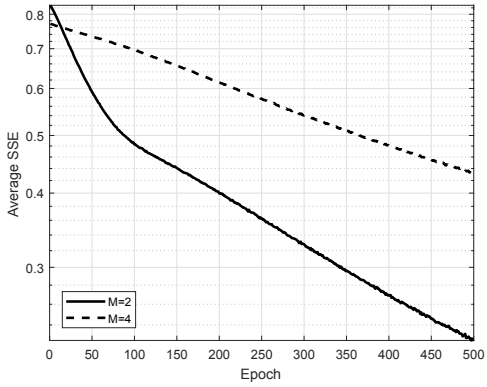

Fig. 4. Average SSE vs. epoch for the max-based relay selection with $M \in \{2, 4\}$.

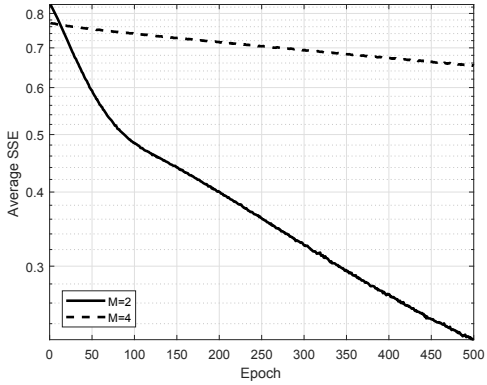

Fig. 5. Average SSE vs. epoch for the min-based relay selection with $M \in \{2, 4\}$.

V. Potential Future Research Directions

As a prototype framework proposed in this paper, before implementing in practice, there still exist a number of potential research topics that are worth investigating as future work. We introduce them in this section, which are of high importance for implementing the supervised machine learning assisted relay selection in practice.

A. Impacts of Initialization, Parameters and activation functions

In this paper, we adopt random initialization for simplicity. However, random initialization is not optimal in terms of learning efficiency for most of training algorithms, but simply a compromise due to the lack of domain knowledge [20]. Assisted by domain knowledge, we might choose another better approach to initialize the artificial neural network and set more reasonable initial values for weights and thresholds. Meanwhile, the system parameters also matter, e.g. the learning rate α and N, which could lead to a trade-off between learning efficiency and stability as well as a trade-off between learning performance and complexity, respectively. Furthermore, apart from the original sigmoid function, we can also alter the coeffcients related to sigmoid function or even utilize other activation functions to process the neural inputs. How to optimize the initialization process and these parameters as well as activation functions are of importance, but still awaiting further investigation.

B. Structure of Artificial Neural Network

It is well known that an artificial neural network is a black box for outside observation. Operators and users can only interact with an artificial neural network by the input and output layers, but have no idea what is going on in the hidden layer(s). However, the performance of supervised machine learning is highly dependent on the structure of artificial neural network, i.e. the number of layers and number of neurons in each hidden layer. Although there is still no a generalized design guideline regarding these structural issues, it is believed increasing both numbers could lead to better learning results at the cost of a higher system complexity. More research is

required to discover these structure related topics and find out a better solution to the trade-off between performance and system complexity.

C. Acceleration of Training Process

As shown in Fig. 4 and Fig. 5, despite effective, the efficiency of the proposed prototype framework still needs to be improved. In particular, the training process should be accelerated, as the training data sets and time are stringent in realistic circumstances. Some methods could be introduced to enhance the training process and lower the average SSE in a quicker way. First, we can replace the sigmoidal activation function with a hyperbolic tangent activation function. Second, a momentum term can be involved to amend the weight updating mechanism. Third, a dynamic mechanism of the learning rate can be employed to adapt the learning rate according to the SSE [18]. All these are still open issues for the prototype framework constructed in this paper.

D. Relay Selection with Channel Estimation Error

Instantaneous CSI as the input of the artificial neural network is a prerequisite to perform relay selection by supervised machine learning. On the contrary, perfect instantaneous CSI accessibility is normally impossible in practice, because of channel estimation error [21]. Therefore, to develop a realistic system based on the prototype framework, one has to investigate the effects of channel estimation error and see whether it still works well under imperfect CSI.

VI. Conclusion

In this paper, we investigated a new method to perform relay selection in cooperative networks by supervised machine learning and constructed a prototype framework. The proposed prototype framework relying on a single hidden layer is simple but effective. Numerical results generated by Monte Carlo methods showed the effectiveness of the proposed prototype framework for both max-based and min-based relay selections. Finally, in order to promote the research regarding the proposed prototype framework and build a realistic system for practical applications, we also pointed out a number of potential research directions that are worth investigating as future work

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