Data-Driven Based Relay Selection and Cooperative Beamforming for Non-Regenerative Multi-Antenna Relay Networks

JIE LUO, SAI ZHAO, ZHAO YANG, (Member, IEEE), GAOFEI HUANG, (Member, IEEE), AND DONG TANG, (Member, IEEE)
School of Electronics and Communication Engineering, Guangzhou University, Guangzhou 510006, Guangdong, China
Corresponding author: Sai Zhao (e-mail: zhaosai@gzhu.edu.cn).

This work was supported in part by the National Natural Science Foundation of China under Grant 61902084, Grant 61872098, and Grant 61872102, in part by the Featured Innovation Project of Guangdong Education Department under Grant 2018KTSCX174 and in part by the Innovation Research for the Postgraduates of Guangzhou University under Grant 2020GDJC-M02.

ABSTRACT In this paper, an attempt to exploit the benefits of data-driven methods in solving joint relay selection and beamforming for non-regenerative relay networks has been made. The common relay selection and beamforming optimization problem aiming to maximize the receiver’s achievable rate under the constraint of relay transmit power is intrinsically hard since the mixed discrete and continuous variables. The direct map from channel state information to select a relay with optimized beamforming weights via data-driven methods often fails to yield good results. To overcome this difficulty, we propose a two-stage algorithm based on data-driven method. Firstly, we convert relay selection to a multi-class classification problem, and a Support Vector Machine (SVM) based data-driven scheme is suggested to determine the best relay. After the relay is selected, we utilize a closed-form solution to obtain the corresponding relay beamforming weights. Since the number of relays is often more than two, the sample imbalance problem exists in the classification problem, considered in our proposed data-driven scheme. The core idea of SVM based classification method is equivalent to training the optimal parameters of the SVM classifier through a large number of offline sample data. In this way, the computation of relay selection can be transferred to offline SVM training. Simulation results demonstrate that the performance of the proposed method is close to that of the global optimal relay selection scheme. Moreover, our proposed scheme has much lower complexities than the international optimal relay selection scheme, especially when the number of relays is large.

INDEX TERMS Non-regenerative, relay selection, beamforming, Support Vector Machine (SVM), sample imbalance.

I. INTRODUCTION

MACHINE Learning (ML) has been broadly accepted as an effective Artificial Intelligence (AI) technique for supporting a variety of tasks, for classification and decision-making. Recently, machine learning in wireless communication has also attracted people’s attention [1]–[3]. [1] using K-Nearest Neighbor (K-NN) and Support Vector Machine (SVM) algorithm to solve the antenna selection problem is the first attempt to machine learning application in communication. Data-driven based antenna selection schemes have been investigated in point-to-point systems [4]. Data-driven based joint beamforming, and antenna selection scheme is studied in [5] in which a favorable tradeoff of system performance and computation complexity has been observed. For relay systems, the Transmission Antenna Selection (TAS) scheme is investigated based on data-driven algorithms for entrusted relay networks [6], [7]. Some studies have applied Q-learning to solve the relay selection problem. For example, [8] proposed a relay selection algorithm based on Q-learning for cooperative wireless network, which adopts Markov decision process modeling and uses...
an iterative method to approximate the optimal solution. Source nodes with learning ability can determine the best relay to participate in collaborative communication based on previously observed system performance status and quality functions describing rewards. However, the relay selection scheme based on Q-learning can only deal with the problem in a small state space, and all nodes are equipped with a single antenna.

Wireless Sensor Networks (WSN) have been extensively used in military, political, and medical fields [9]. However, in some applications, due to the large number and small scale of sensor nodes deployed in some applications, the system throughput of the nodes is insufficient, and the energy is deficient [10]–[14]. Collaborative communication technology is seen as a key technology to improve and prolong the network life cycle and improve the performance of sensor networks [15], [16]. It utilizes broadcast characteristics of wireless systems to improve the data rate of the system and expand the coverage of nodes by deploying relay nodes in wireless sensor networks. Cooperative relay is a key technology used in current wireless systems and applications such as Long-Term Evolution (LTE), LTE-Advanced cellular systems [17], [18], and Wireless Local Area Network (WLAN), to improve quality of service, coverage, and resource utilization efficiency. In multi-relay networks, relay selection can not only simplify signaling, save energy costs, but also maintain most of the system performance. Relay selection is the main technology to keep the most of system capacity improvement in multi-relay networks and at the same time reduce energy and signaling [19]–[24]. However, relay selection is an NP-hard problem, and the hardness is carried over to joint relay selection and relay beamforming problem [25]–[28]. In [27], the optimal local design of joint cooperative beamforming and relay selection scheme is considered, by approaching the binary constraints by continuous box constraints, iterative-based d.c. (difference of two convex functions/sets) programming is employed to find the approximation solutions. In [28], the optimal global design of joint optimization of relay selection and cooperative beamforming is investigated.

The optimal global design is built on exhaustive search; in each step of the thorough search, a semidefinite programming (SDP) problem is solved. Both iterative-based algorithm and exhaustive-search-based algorithms involve high computation complexity, especially when the number of relays is large. In particular wireless networks where the computation ability and energy storage of nodes is bounded, i.e., wireless sensor networks and the Internet of Things (IoT) networks, algorithms with high computation complexity algorithm is prohibitive. At present, there have been studies on finding low complexity multiple relay selection schemes based on various methods [29], [30]. However, as far as we know, there is no literature investigating the data-driven based relays selection and beamforming scheme in multi-antenna multi-relay networks, which have the advantages of low complexity and high performance.

This paper uses a data-driven method to design a joint relay selection and beamforming scheme, aiming at maximizing the achievable rate under the individual relay power constraints and the relay selection constraints and supposed to reduce the online computation burden of multi-antenna multi-relay network and at the same time maintain high performance. We propose a two-stage scheme based on data-driven method. Firstly, we convert relay selection to a multi-class classification problem, and SVM based data-driven scheme is suggested to determine the best relay. After the relay is selected, we utilize a closed-form solution to obtain the corresponding relay beamforming weights. Since the number of relays is often more than two, the sample imbalance problem exists in the classification problem, which is considered in our proposed data-driven classification scheme. To implement data-driven method, the multi-class classification training systems are constructed accordingly. By feeding massive sample data into the training system, the parameters of the multi-class classifier are optimized. Once the multi-class classifiers are tuned in the training stage, only simple computations are necessary for real-time implementation.

The remainder of this paper is organized as follows. In Section II, we introduce the system model. In Section III, we propose a data-driven joint relay selection and cooperative beamforming scheme, and obtain an improved support vector machine algorithm and a low complexity cooperative beamforming matrix under sample imbalance. In Section IV, the performance is evaluated, including simulation results and complexity analysis. Finally, the paper is summarized in Section V.

Notations: Lower and upper case boldface letters represent a column vector $a$ and a matrix $A$, respectively. $A^T$, $A^*$, $A^\dagger$, $|A|$, and $\text{tr}(A)$ denote the transpose, conjugate, conjugate transpose, Forbinius norm, and trace of the matrix $A$, respectively. $\otimes$ denotes Kronecker product, $\text{vec}(A)$ denotes to stack the columns of a matrix $A$ into a single vector $a$, $A \succeq 0$ means that $A$ is positive semidefinite, $\text{diag}(A)$ denotes the diagonal elements of the matrix $A$, $|a|$ denotes the absolute value of vector $a$.

II. SYSTEM MODEL
Consider a multi-antenna multi-relay network, as shown in Fig. 1, which consists of one source, one destination, and $K$ relays. The source and the destination are equipped with a single antenna, and each relay is equipped with $M$ antennas. We assume that the direct link between the source and destination is sufficiently weak to be ignored. This occurs when the direct link is blocked due to long-distance path loss or obstacles. Let $h_k \in \mathbb{C}^{M \times 1}$ and $g_k \in \mathbb{C}^{1 \times M}$ denote the channel vectors from the source to the $k$th relay and from the $k$th relay to the destination, respectively, where $k \in K = \{1, 2, ..., K\}$. The network operates in the time-division duplex mode, and the transmission of information is divided into two phases. In the first phase, the source
transmits the symbol $s \in \mathbb{C}^{1 \times 1}$ to the relays. Thus, the received signal at the $k$th relay, $k \in \mathcal{K}$, is expressed as

$$y_k = \sqrt{P}h_k s + n_k,$$

(1)

where $P$ denotes the transmit power of the source and $n_k \sim \mathcal{CN}(0, \sigma_k^2)$ denotes the additive Gaussian noise vector at the $k$th relay. In the second phase, select a relay and multiply the received signals through an adequately designed beamforming matrix, then forward the product to the destination. The transmitted signal from the $k$th relay, $k \in \mathcal{K}$, is

$$x_k = \Delta_k W_k y_k,$$

(2)

where $W_k \in \mathbb{C}^{M \times M}$ denotes the beamforming matrix at the $k$th relay and $\Delta_k \in \{0, 1\}$ denotes the relay selection indicator. Specifically, $\Delta_k = 1$ means that the $k$th relay is selected to forward signal, and $\Delta_k = 0$ means that the $k$th relay is not selected. The number of selected relays is constrained to be $\kappa$, $0 \leq \kappa \leq K$ in this work, i.e.,

$$\sum_{k \in \mathcal{K}} \Delta_k = \kappa.$$

(3)

For simplicity, we assume $\kappa = 1$ in the following. The received signal at the destination, denoted as $y$, is given by

$$y = \sum_{k \in \mathcal{K}} g_k^\dagger x_k + n_d = \left( \sum_{k \in \mathcal{K}} \sqrt{P} g_k^\dagger \Delta_k W_k h_k \right) s + \sum_{k \in \mathcal{K}} \left( g_k^\dagger \Delta_k W_k n_k \right) + n_d,$$

(4)

where $n_d \sim \mathcal{CN}(0, \sigma_d^2)$ denotes the additive Gaussian noises at the destination. Thus, the signal-to-noise ratio (SNR) at the destination is

$$\gamma = \frac{\sum_{k \in \mathcal{K}} P |g_k^\dagger \Delta_k W_k h_k|^2}{\sum_{k \in \mathcal{K}} \sigma_k^2 |g_k^\dagger \Delta_k W_k|^2 + \sigma_d^2}.$$

(5)

We aim to maximize the achievable rate of multi-relay network subject to transmit power constraint and relay selection constraint. The optimization problem is formulated as follows

$$\max_{\{W_k, \Delta_k\}} \frac{1}{2} \log_2 (1 + \gamma)$$

$$s.t. \sum_{k \in \mathcal{K}} \left( P |\Delta_k W_k h_k|^2 + \sigma_k^2 |\Delta_k W_k|^2 \right) \leq P_r,$$

$$\Delta_k \in \{0, 1\}, (3), \quad k \in \mathcal{K},$$

(6)

where $P_r$ denotes the total transmit power constraint at all the relays $^1$.

### III. DATA-DRIVEN-BASED JOINT RELAY SELECTION AND COOPERATIVE BEAMFORMING

In this section, a two-stage approach is proposed for efficiently selecting the optimal relay as well as deriving the relevant beamforming matrix that achieves the maximum achievable rate design goal. A SVM-based relay selection method is designed to map the channel vector to the optimal relay. Since the number of relays is often more than two, the sample imbalance problem exists in the multi-class classification problems. The issue of sample imbalance often causes deviation to the expected classification effect, and we propose an improved SVM-based classification algorithm to solve this problem. Once the optimal relay is selected, a generalized rayleigh quotient-based algorithm is utilized to derive the closed-form optimal cooperative beamforming weights for the selected relay. The aim is to leverage the computational efficiency with data-driven method in order to obtain a fast real-time joint relay selection and beamforming scheme.

#### A. DATA-DRIVEN RELAY SELECTION

In this section, we detail our proposed data-driven relay selection scheme. Since there are multiple relays in the relay networks, we first set up a multi-class classification model. By extracting features from the Channel State Informations (CSIs), we apply the SVM approach to construct the classification model and predict the class label that the current channel belongs to. The belonged class represents an ideal relay index to select that may optimize the achievable rate of the current channel. The construction of the classification model needs a sufficiently large training data set and can be completed offline.

1) Training Set Preparation

We first generate $L$ channel samples for training. Each sample can be represented as $(\{h_k\}_{k=1}^K, \{g_k\}_{k=1}^K)$. The channel realization $h_k$ and $g_k$ randomly generate according to Rayleigh fading characteristics. Then, covariance matrices $\{\mathbf{A}_{hk}\}_{k=1}^K$ and $\{\mathbf{A}_{gk}\}_{k=1}^K$ are constructed, where $\mathbf{A}_{hk} = \mathbf{h}_k \mathbf{h}_k^\dagger$ and $\mathbf{A}_{gk} = \mathbf{g}_k \mathbf{g}_k^\dagger$.

$^1$The constraint on the total power of the selected relay is reasonable because the channels of the unselected relays are mute by the corresponding selection variables $\Delta_k, k \in \mathcal{K}$, and the power on the unselected relays will be zero.
be formulated as
\[
\min_{w, b, \xi} \frac{1}{2} ||w||^2 + C \sum_{i=1}^{L} \xi_i
\]
\[
s.t. \quad y_i(w^T \phi(t_i) + b) \geq 1 - \xi_i, i = 1, \ldots, L.
\]
\[
\xi_i \geq 0, i = 1, \ldots, L.
\]
(8)
where \( \phi \) is the mapping function, \( b \) is the threshold, \( C \) is the penalty constant, \( \xi \) is the value of error caused by misclassification for sample \( t_i \).

Considering sample imbalance in our classification problem, we choose \( C_+ \) as penalty constant for positive samples and \( C_- \) as penalty constant for negative samples, respectively. The problem (8) can be reformulated as
\[
\min_{w, b, \xi} \frac{1}{2} ||w||^2 + C_+ \sum_{i|y_i=+1} \xi_i + C_- \sum_{i|y_i=-1} \xi_i
\]
\[
s.t. \quad y_i(w^T \phi(t_i) + b) \geq 1 - \xi_i, i = 1, \ldots, L.
\]
\[
\xi_i \geq 0, i = 1, \ldots, L.
\]
(9)
In order to ensure the accuracy of hyperplane separation in imbalanced datasets, we choose a more significant penalty constant for positive samples and a more minor penalty constant for negative samples. To be specific, we use the reciprocal of the positive and negative sample numbers as \( C_+ \) and \( C_- \), respectively. To solve the problem (9), we construct the dual problem of problem (9) as below
\[
\max_{a_+, a_-} \sum_{i=1}^{L} a_i - \frac{1}{2} \sum_{i=1}^{L} \sum_{j=1}^{L} a_i a_j y_i y_j K(t_i, t_j)
\]
\[
s.t. \quad 0 \leq a_i \leq C_+, y_i = +1,
\]
\[
0 \leq a_i \leq C_-, y_i = -1,
\]
\[
\sum_{i=1}^{L} a_i y_i = 0, i = 1, \ldots, L.
\]
(10)
where \( a_i \) and \( a_j \) are Lagrange multipliers and \( K(t_i, t_j) \) is the kernel function. \( a_i \) and \( a_j \) can be solved by Sequential Minimal Optimization (SMO) algorithm with the fast and reliable convergence as in [2]. \( K(t_i, t_j) \) is chosen to be radial basis kernel function according to TABLE I, which shows the accuracy comparison of several kernel functions based on the classification test made on the training samples. The radial basis kernel function is \( K(x_i, x_j) = e^{-||x_i - x_j||^2/(2\sigma^2)} \), with \( \sigma \) being the design parameter. Cross-validation is a common method to decide the value of parameter \( \sigma \), but it needs to train the model many times, which leads to high

---

2 Since we take the maximum reachable rate of formula (6) as the KPI of the classifiers, and the power gains of the channels \( h_k \) and \( g_k \) are the major factors that determine the KPI. On the other side of the diagonal elements in \( A_{hk} \) and \( A_{gk} \), which are the squared amplitude of the elements of \( h_k \) and \( g_k \) are the power gains of the channels \( h_k \) and \( g_k \). Therefore, we take the diagonal elements in \( A_{hk} \) and \( A_{gk} \) as the features. Compared to just taking the amplitude of the elements of \( h_k \) and \( g_k \) as features, our selection of features is more directly connected to the KPI hence more effective.
complexity. In this paper, we propose a new method to optimize the parameter \( \sigma \) according to the sample distance. Thus, problem (10) can be transformed as

\[
\min_{\sigma} \sum_{i=1}^{L} \sum_{j=1}^{L} y_i y_j K(t_i, t_j) = \min_{\sigma} \sum_{i=1}^{L} \sum_{j=1}^{L} y_i y_j e^{\sigma D_{ij}},
\]

where \( D_{ij} = \| t_i - t_j \|^2 \), \( \alpha = -1/(2\sigma^2) \) and \( y_i y_j \in \{+1, -1\} \). By using Mclaughlin expansion, the problem (11) can be represented as

\[
\min_{\sigma} \sum_{i=1}^{L} \sum_{j=1}^{L} y_i y_j e^{\sigma D_{ij}} = \min_{\sigma} \sum_{i=1}^{L} \sum_{j=1}^{L} y_i y_j (1 + \alpha D_{ij} + \frac{1}{2} \alpha^2 D_{ij}^2).
\]

Then, we can get the optimal value, \( \alpha^* = -1/D_{ij} \). When \( \{a_i\} \) are the support vectors,\( w \) and design parameter \( \sigma \) are determined, the \( n^{th} \) classifier can be presented as

\[
f_n(\bar{x}_j) = \sum_{i \in S} a_i y_i \phi(t_i)^T \phi(\bar{x}_j) + b
\]

where \( \bar{x}_j \) is a new feature vector needed to be classified, \( t_i \) is a support vector, \( S \) is the set of support vectors. If \( f_n(\bar{x}_j) > 0 \), the optimal relay is \( n^{th} \) relay.

3) Training Stage

For each normalized feature vector \( t_i \), \( i \in \{1, 2, ..., L\} \), we have its corresponding class label \( r_i \), \( i \in \{1, 2, ..., L\} \). By using \( L \) tuples \( \{t_i, r_i\} \) as input, SVM classifier tries to find the optimal weights of the hyperplane parameter parameters \( w \) and design parameter \( \sigma \). Once the training optimization of SVM classifier is done, we can make a prediction of relay selection for a new input of channel realizations.\(^3\)

4) Testing Stage

In the testing stage, the channel realization is generated following the same distribution as the training stage. Then, the diagonal elements of covariance matrices \( A_{kh} \) and \( A_{gk} \), \( k \in K \) are obtained as input data and fed to the SVM classifier. The selected relay tags can be predicted by trained support vector machines. Afterwards, the corresponding relay beamforming matrix that attains the maximum achievable rate is deduced, which details in the following subsection.

\(^3\)The training of the SVM classifiers is performed offline. In the training stage, a sufficient number of CSIs are processed so as to obtain the effective SVM classifiers. The trained SVM classifiers then are applied on the online scenario and make the decision of the best relay with just simple computations. Therefore, the online computational complexity of our proposed SVM scheme wouldn’t cause significant delays or system overhead.

**Algorithm 1 Data-driven relay selection algorithm.**

**Phase 1. Prepare training data**

1: Estimate all \( h_k \), \( g_k \), \( A_{kh} \) and \( A_{gk} \), \( k \in K = \{1, 2, ..., K\} \). Calculate \( t_i, i \in \{1, 2, ..., L\} \) using (7);

2: Solve the problem (19) using \( h_k \), \( g_k \), \( A_{kh} \) and \( A_{gk} \), calculate \( k^* \) and label it with \( r \in \mathbb{C}^{3 \times L} \);

3: Repeat 1-2 for \( K \) times;

**Phase 2. Predict relay selection**

1: Input training sample \( \{t_i, r_i\} \), find the optimal values of the hyperplane parameter parameters \( w \) and design parameter \( \sigma \); Build SVM classifier;

2: In the established SVM classifier, the new feature vector \( \bar{t}_j \) is input, and the predictive relay is output;

3: Assign the relay label to \( k^* \);

4: return \( k^* \);

**B. LOW COMPLEXITY COOPERATIVE BEAMFORMING**

First, we assume that the selected relay is the \( k^* \)th relay, \( k \in K \), to the \( l \)th testing channel realization. Then, the optimization problem (6) can be rewritten as

\[
\max_{z_k} \frac{1}{2} \log_2 \left( 1 + \frac{P|z_k^H w_k h_k|^2}{\|z_k^H w_k h_k\|^2 + \sigma_k^2} \right)
\]

s.t. \( P \|w_k h_k\|^2 \leq P_r \). (14)

The optimization problem (14) is still non-convex and difficult to solve. Using the equality \( \text{tr}(A_1 A_2) = \text{vec}(A_1)^T \text{vec}(A_2) \) and vec \((A_1 A_2 A_3) = (A_1^T \otimes A_1) \text{vec}(A_2) \), where \( A_1, A_2, \) and \( A_3 \) are arbitrary matrices with compatible dimensions [35], [36]. Problem (14) can be equivalently reformulated as

\[
\max_{z_k} \frac{1}{2} \log_2 \left( 1 + \frac{P z_k^H a a^H z_k}{\sigma_k^2 z_k^H B B z_k + \sigma_d^2} \right)
\]

s.t. \( P z_k^H C C^T z_k + \sigma_k^2 z_k \leq P_r \), (15)

where \( z_k = \text{vec}(w_k) \), \( a = h_k^H \otimes g_k \), \( B = I \otimes g_k \), and \( C = h_k^H \otimes I \).

Letting \( D_1 = P a a^H \in \mathbb{C}^{M^2 \times M^2} \), \( D_2 = \sigma_k^2 B B^H \in \mathbb{C}^{M^2 \times M^2} \), and \( D_3 = P C C^T + \sigma_k^2 I \in \mathbb{C}^{M^2 \times M^2} \), problem (15) can be further rewritten as

\[
\max_{z_k} \frac{1}{2} \log_2 \left( 1 + \frac{z_k^H D_1 z_k}{z_k^H D_2 z_k + \sigma_d^2} \right)
\]

s.t. \( z_k^H D_3 z_k \leq P_r \). (16)

For problem (16), the optimal relay beamforming vector \( z_k \) should satisfy that the transmit power constraint is active [32], i.e., \( z_k^H D_3 z_k = P_r \). Under this condition, problem (16) can be equivalently transformed into

\[
\max_{z_k} \frac{z_k^H D_1 z_k}{z_k^H (D_2 + \sigma_d^2 P_r^{-1} D_3) z_k}
\]

s.t. \( z_k^H D_3 z_k = P_r \). (17)
It is noted that the function \( \log_{\beta}(\cdot) \) is omitted in (17) since the logarithm is a monotonically increasing function, which has no effect on the optimization problem.

**Theorem 1:** The optimal solution, denoted as \( z_k^* \), is
\[
z_k^* = \beta T^{-1} a,
\]
where \( T = D_2 + \sigma_q^2 P_r^{-1} D_3 \) and \( \beta = P_r^{\frac{1}{2}} \left( ||D_3^\frac{1}{2} T^{-1} a|| \right)^{-1} \). Thus, the optimal value of objective function (17) is \( R_k^* = \lambda_{\text{max}}(T^{-1} D_1) \). In order to evaluate the performance of our system, we adopt the maximum achievable rate as the performance metric. As per the rules of the conventional relay selection scheme, the index of the selected relay is expressed as
\[
k^* = \arg\max_{1 \leq k \leq K} R_k^*.
\]

**Proof:** Problem (17) is the maximization of a generalized Rayleigh quotient [35] whose optimal solution is \( \beta q \), where \( q \) is the unit-norm eigenvector of the matrix\(^4 \)
\[
\frac{D_1}{D_2 + \sigma_q^2 P_r^{-1} D_3}
\]
corresponding to its largest eigenvalue and
\[
\beta = \sqrt{\frac{P_r}{q^\dagger D_3 q}}.
\]

Since \( D_1 = P a a^\dagger \) is rank-one, \( q = \frac{a}{(D_2 + \sigma_q^2 P_r^{-1} D_3)^{\frac{1}{2}}} \) and substituting the solution of \( q \) into \( \beta \), we have \( \beta = P_r^{\frac{1}{2}} \left( ||D_3^\frac{1}{2} T^{-1} a|| \right)^{-1} \).

**IV. PERFORMANCE EVALUATION**

\(^4\)The rank of \( D_3 \) is full, the matrix \( D_2 + \sigma_q^2 P_r^{-1} D_3 \) is invertible.
the “Exhaustive Search” scheme obtains the highest average achievable sum rate. The “Data-driven method with SVM (improved method)” scheme performs obviously better than the “Data-driven method with SVM (original method)” scheme under different values of transmit power at the relays, which verifies that the process for the imbalance nature of the samples is effective. Moreover, the performance gap between the “Data-driven method with SVM (improved method)” scheme and the “Exhaustive Search” scheme is narrow.

In Fig.3, we present the average achievable rate comparison of the “Data-driven method with SVM (original method)” scheme, the “Data-driven method with ANN” scheme, the “Exhaustive Search” scheme, and the “Random Selection” scheme. It is seen from Fig.3, the performance of the “Data-driven method with SVM (original method)” scheme is better than the “Data-driven method with ANN” scheme.

B. COMPLEXITY ANALYSIS

In this section, we analyze the complexity of the exhaustive search scheme, the random selection scheme, the proposed improved SVM scheme, the original SVM scheme and the ANN scheme, respectively. Among them, the computational complexity of the SVM schemes, and the ANN scheme is obtained in the test stage. The complexity of the SVM algorithm [38] is represented by \( O(pn_{sv}) \), and the complexity of the ANN algorithm is represented by \( O(pn_{11} + n_{1}n_{2} + \ldots) \), where \( p \) denotes the dimension of the feature, \( n_{sv} \) denotes the number of support vectors, and \( n_{l2} \) denotes the number of neurons in layer \( i \). According to the actual simulation experiment, a three-layer neural network is designed, and the number of neurons in the second layer (hidden layer) is \( n_{l2} \). The complexity of the optimal beamforming is composed of two parts according to (18), the first part is the complexity of \( T \) inverse matrix, and the second part is the complexity of multiplying three matrices \( (\beta, T^{-1}, a) \). The complexity of \( T \) inverse matrix is \( O(M^6) \), and the complexity of multiplying three matrices is \( O(M^6 + M^4) \), so the complexity of the optimal beamforming is \( O(M^6 + M^4) + O(M^6) \), namely, \( O(M^6 + M^4) \).

Therefore, the complexity of the exhaustive search scheme is \( KO(M^6 + M^4) \). The complexity of our improved SVM scheme is \( O(K^2M) + O(M^6 + M^4) \), the complexity of original SVM scheme is \( O(K^2M) + O(M^6 + M^4) \), the complexity of ANN scheme is \( O(K^2M + 2Kn_{l2}) + O(M^6 + M^4) \), and the complexity of random selection scheme is \( O(M^6 + M^4) \), as shown in Table II.

It can be observed from Table II that the complexity of the exhaustive search scheme is the worst, and the complexity of the improved SVM scheme is a little better than that of the ANN scheme. Since the support vectors and categories of the SVM classifiers have not changed, the complexity of our proposed improved SVM scheme is the same as that of the original SVM scheme according to the calculation rules.

### Table II. Complexity Comparison for Different Relay Selection Schemes

| Schemes            | Complexity                                      |
|--------------------|-------------------------------------------------|
| Exhaustive Search  | \( KO(M^6 + M^4) \)                             |
| Random Selection   | \( O(M^6 + M^4) \)                             |
| SVM(improved method)| \( O(K^2M) + O(M^6 + M^4) \)                   |
| SVM(original method)| \( O(K^2M) + O(M^6 + M^4) \)                   |
| ANN                | \( O(K^2M + 2Kn_{l2}) + O(M^6 + M^4) \)        |

V. CONCLUSIONS

In this paper, we propose a joint relay selection and beamforming scheme in multi-antenna multi-relay networks based on the data-driven method. Considering the sample imbalance problem in classification, we propose an improved SVM scheme for relay selection and derive the closed-form beamforming matrix for the selected relay. Simulation results demonstrate that the performance of our proposed SVM scheme approaches that of the global optimal relay selection scheme. Moreover, the proposed SVM scheme has much lower computational complexity than the global optimal relay selection scheme, especially when the number of relays is large. More work remains to be carried out. In future work, we will continue to study multi-relay selection schemes in multi-relay networks.

REFERENCES

[1] J. Joung, “Machine Learning-Based Antenna Selection in Wireless Communications,” IEEE Communication Letters, vol. 20, no. 11, pp. 2241-2244, 2016.
[2] Y. Long, Z. Chen, J. Fang, and C. Tellambura, “Data-driven-based analog beam selection for hybrid beamforming under mm-Wave channels,” IEEE J. Sel. Topics Signal Process., vol. 12, no. 2, pp. 340–352, May 2018.
[3] M. Y. Manesh, A. Olfa, “Sigmoid Function Detector in the Presence of Heavy-Tailed Noise for Multiple Antenna Cognitive Radio Networks,” IEEE ICC2017, Paris, France, pp. 21-25, 2017.
[4] D. He, C. Liu, T. Q. S. Quek, and H. Wang, “Transmit Antenna Selection in MIMO Wiretap Channels: A Machine Learning Approach,” IEEE Wireless Communication Letters, vol. 7, no. 4, pp. 634-637, 2018.
[5] M. S. Ibrahim, A. S. Zamzam, X. Fu, and N. Sidiropoulos, “Learning-Based Antenna Selection for Multicasting,” in 2018 IEEE 19th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), pp. 1-5, 2018.
[6] R. G. Yao, Y. X. Zhang, S. Y. Wang, N. Qi, N. I. Miridakis, and T. A. Tsiftsis, “Deep Neural Network Assisted Approach for Antenna Selection in Untrusted Relay Networks,” IEEE Wireless Communications Letters, vol. 8, no. 6, pp. 1644-1647, 2019.
[7] R. G. Yao, Y. X. Zhang, N. Qi, T. A. Tsiftsis, and Y. S. Liu, “Machine Learning-Based Antenna Selection in Untrusted Relay Networks,” in 2019 2nd International Conference on Artificial Intelligence and Big Data (ICABD 2019), pp. 329-334, 2019.
[8] J. Awais and S. Kim, “Relay selection Algorithm for wireless cooperative networks: a learning-based approach,” IET Communications, vol. 11, no. 7, pp. 1061-1066, 2017.
[9] Y. Xiao et al., “A survey of key management schemes in wireless sensor networks,” Comput. Commun., vol. 30, nos. 11–12, pp. 2314–2341, Sep. 2007.
[10] T. Meekawy, R. G Yao, N. Qi, and Y. Lu, “Secure Relay Selection for Two Way Amplify-and-Forward Untrusted Relaying Networks,” IEEE Transactions on Vehicular Technology, vol. 67, no. 12, pp. 11979-11987, 2018.
[11] J. Huang, Q. Li, Q. Zhang, G. Zhang, and J. Qin, “Relay beamforming for amplify-and-forward multi-antenna relay networks with energy harvesting.
constraint,” IEEE Signal Processing Letters, vol. 21, no. 4, pp. 454-458, 2014.
[12] Y. Zhao, R. S. Adve, and T. J. Lim, “Improving amplify-and-forward relay networks: Optimal power allocation versus selection,” IEEE Transactions on Wireless Communications, vol. 6, no. 8, pp. 3114-3123, 2007.
[13] Q. Li, Q. Zhang, and J. Qin, “Beamforming in non-regenerative two-way multi-antenna relay networks for simultaneous wireless information and power transfer,” IEEE Transactions on Wireless Communications, vol. 13, no. 10, pp. 5500-5520, 2014.
[14] M. S. Gilan, M. Y. Manesh, B. Maham, “Optimized Target Packet Error Rate for a New Cross-Layer Scheme in AF Relay Selection System,” IEEE Communications Letters, vol. 8, no. 11, pp. 865-867, 2004.
[15] X. Du, Y., Xiao., M. Guizani, and H.-H. Chen, “Transactions papers a routing-driven elliptic curve cryptography based key management scheme for heterogeneous sensor networks,” IEEE Trans. Wireless Communications, vol. 8, no. 3, pp. 1223-1229, Mar. 2009.
[16] M. S. Gilan, A. Olfa, “On the Performance of Space-Time Coding and Threshold-based Selection Relaying in Cooperative Networks with Multiple Antenna Relays,” Transactions on Emerging Telecommunications Technologies, vol. 29, no. 9, 2018.
[17] Evolved Universal Terrestrial Radio Access (E-UTRA), Physical Channels and Modulation, document 3GPP TS 36.211 V8.2.0. Rel-8, Mar. 2008.
[18] A. Ibrahim, A. Sadek, W. Su, and K. Liu, “Relay selection in multi-node cooperative communications: when to cooperate and whom to cooperate with?” IEEE Transactions on Wireless Communications, vol. 7, no. 7, pp. 2814-2827, 2008.
[19] M. S. Gilan, B. Maham, “A New Cross-Layer Approach for MIMO Amplify and Forward Relay System,” 2018 IEEE International Black Sea Conference on Communications and Networking, Batumi, Georgia, 2018.
[20] M. S. Gilan, A. Olfa, “New Beamforming and Distributed Space-Time Coding with Selection Relaying over Nakagami-m Fading Channels,” Transactions on Emerging Telecommunications Technologies, vol. 29, no. 9, 2018.
[21] Q. Li, L. Yang, “Beamforming for Cooperative Secure Transmission in Cognitive Two-Way Relay Networks,” IEEE Transactions on Information Forensics and Security, vol. 15, pp. 130-143, 2020.
[22] Q. Li, L. Yang, “Robust Optimization for Energy Efficiency in MIMO Two-Way Relay Networks with SWIPT,” IEEE Systems Journal, vol. 14, no. 1, pp. 196-207, 2020.
[23] Q., L. Yang, “Artificial Noise Aided Secure Precoding for MIMO Untrusted Two-Way Relay Systems with Perfect and Imperfect Channel State Information,” IEEE Transactions on Information Forensics and Security, vol. 13, no. 10, pp. 2628-2638, 2018.
[24] Y. Jing and H. Jafarkhani, “Single and multiple relay selection schemes and their achievable diversity orders,” IEEE Transactions on Wireless Communications, vol. 8, no. 3, pp. 1414-1423, 2009.
[25] J. Kim, A. Ikhlief, and R. Schober, “Combined Relay Selection and Cooperative Beamforming for Physical Layer Security,” Journal of Communication and Network, vol. 14, no. 4, pp. 4440-4453, 2012.
[26] T. Tao, and Andreas Czyliwk, “Beamforming design and relay selection for multiple MIMO AF relay systems with limited feedback,” 2013 IEEE 77th Vehicular Technology Conference (VTC Spring), pp. 1-5, 2013.
[27] E. Che, H. D. Tuan, and H. H. Nguyen, “Joint optimization of cooperative beamforming and relay assignment in multi-user wireless relay networks,” IEEE Transactions on Wireless Communications, vol. 13, no. 10, pp. 5481-5495, 2014.
[28] Q. Li, Q. Zhang, R. Feng, L. Luo, and J. Qin, “Optimal relay selection and beamforming in MIMO cognitive multi-relay networks,” IEEE Communications Letters, vol. 17, no. 6, 1188-1191, 2013.
[29] Zhong. Yang, M. Dong, “Low-Complexity Cooperative Relay Beamforming for Multi-Cluster Relay Interference Networks,” 2016 IEEE 17th International Workshop on Signal Processing Advances in Wireless Communications (SPAWC), 2016.
[30] Xiaowei. Wang, “Decision-Tree-Based Relay Selection in Dualhop Wireless Communications,” IEEE Transactions on Vehicular Technology, vol. 68, no. 6, pp. 6212-6216, 2019.
[31] V. Cherkassky, “The nature of statistical learning theory,” IEEE Transactions on Neural Networks, vol. 8, no. 1564-1564, 1997.
[32] S. Zhao, Q. Li, Q. Zhang, and J. Qin, “Optimal Secure Relay Beamforming for Non-Regenerative Multi-Relay Networks with Energy Harvesting Constraint,” Springer: Wireless Personal Communications, vol. 85, no. 4, pp. 2355-2365, 2015.
[33] C. Hsu, C. Chang, and C. Lin, “A practical guide to support vector classification,” Technical report, Department of Computer Science and Information Engineering, National Taiwan University, 2003.
[34] H. Li, Y. X. Zhang, “An algorithm of soft fault diagnosis for analog circuit based on the optimized SVM by GA,” 2009 9th International Conference on Electronic Measurement, 2009.
[35] R. Horn, and C. Johnson, Matrix Analysis, Cambridge, U.K.: Cambridge Univ. Press, 1985.
[36] S. Boyd, and L. Vandenberghe, Convex Optimization, Cambridge, U.K.: Cambridge Univ. Press, 2004.
[37] M. Z Chen, U. Challita, W. Saad; C. C Yin, M. Debbah, “Artificial Neural Networks-Based Machine Learning for Wireless Networks: A Tutorial,” IEEE Communications Surveys and Tutorials, vol. 21, no. 4, pp. 3039-3071, 2019.
[38] Christopher J. C. Burges, “A Tutorial on Support Vector Machines for Pattern Recognition,” Data Mining and Knowledge Discovery 2(2):121-167, 1998.