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Data-Driven Relay Selection for Physical-Layer Security: A Decision Tree Approach

XIAOWEI WANG, (Member, IEEE), AND FENG LIU, (Member, IEEE)
College of Information Engineering, Shanghai Maritime University, Shanghai 201306, China

Corresponding author: Xiaowei Wang (xwwang@shmtu.edu.cn)

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ABSTRACT Conventional optimization-driven secure relay selection relies on maximization algorithm and accurate channel state information (CSI) of both legitimate and eavesdropper channels. Particularly, estimating and collecting accurate eavesdropper CSI is a difficult task. In this paper, we exploit the benefits of machine learning in solving secure relay selection problem from a data-driven perspective. We convert secure relay selection to a multiclass-classification problem and solve it by a decision-tree-based scheme, which is composed of three phases - preparing training data, building decision tree and predicting relay selection. To meet decision tree's requirement that input features must take discrete values, a feature extraction method is proposed to generate discrete input by quantizing the accurate CSI of legitimate and eavesdropper channels. By this means, the decision-tree-based relay selection only requires quantized CSI feedback which takes substantially fewer bits in predicting phase. For the purpose of optimizing quantization parameters and enhancing decision tree prediction, we further derive three splitting criteria, i.e. information gain, information gain ratio and Gini index. Simulation results show that if the quantization parameters are set properly, the proposed decision-tree-based scheme can achieve satisfactory performance in terms of average secrecy rate while reducing computational complexity and feedback amount.

INDEX TERMS Physical-layer security, relay selection, machine learning, decision tree, splitting criterion.

I. INTRODUCTION

Machine learning is an effective artificial intelligence technology which predicts the result of a task based on large amount of data. Machine learning has been widely investigated in the field of data mining, natural language processing, image processing, etc. Recently, research efforts have been devoted to using machine learning in next-generation wireless networks [1]–[9], covering channel estimation, information dissemination and network optimization. In [1], antenna selection of multiple-input-multiple-output (MIMO) systems, which is a conventional problem in wireless communications, was interpreted to multiclass-classification problem and solved by k-nearest neighbors (k-NN) and support vector machine (SVM) algorithms. More recently, authors in [2] considered antenna selection in wireless wiretap channels and proposed two machine-learning-based schemes: SVM-based scheme and naive-Bayes-based scheme.

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In recent years, physical-layer techniques for securing wireless transmissions against eavesdropping has been drawing great attention, including, resource allocation [10], [11], signal design [12], [13], etc. If active eavesdroppers exist [14], [15], more sophisticated techniques need to be designed. Relay technique, which has led to numerous theories and optimization methods, is also an effective tool enhancing physical-layer security. Relay selection for security was first investigated by Krikidis *et al.* in [16], which showed that relay selection tries to maximize the ratio of signal-to-noise ratio (SNR) of legitimate channel to SNR of eavesdropper channel. Then, researches on various relay protocols and selection requirements emerged [17]–[21]. Existing relay selection policies for physical-layer security all belong to optimization-driven schemes which strongly rely on maximization (or minimization) algorithms and accurate channel state information (CSI) feedback. Therefore, the cost of optimization computation and resource consumption of accurate CSI feedback cannot be neglected. Particularly, it is often difficult to acquire the accurate CSI of eavesdroppers, so that designing efficient feedback strategy is also of importance [22], [23]. As long as optimization-driven selection schemes are adopted, these weak points cannot be overcome. This evokes our attempt to exploit brand new relay selection methods beyond conventional optimization theories.

Inspired by recent developments of machine learning and the bottleneck of conventional optimization-driven algorithms, we reconsider relay selection problem from data-driven perspective and propose a machine-learning-based relay selection scheme. Among the learning algorithms, decision tree has advantages of low computational complexity, discrete input and one-time initialization. [4] was our first attempt to solve relay selection by a supervised learning algorithm - decision tree learning. Massive samples of relay CSI were collected to generate training data, based on which a decision tree was constructed. The decision tree was then used to predict the best relay. The computation cost and communication overhead of the decision-tree-based scheme are remarkably reduced while communication performance is comparable to the optimal selection policy.

In this paper, we design a decision-tree-based relay selection scheme for physical-layer security in dualhop wireless networks. To predict selection results with a decision tree, we first model relay selection as a multiclass-classification problem, where each class label represents the index of a candidate relay and the output label represents the index of the selected relay. Different from conventional optimization-driven selection schemes which calculate maximization (or minimization) problems with accurate instantaneous CSI, data-driven selection scheme constructs a decision tree with large amount of sample data. The proposed scheme is composed of three phases - preparing training data, building decision tree and predicting relay selection. Decision tree requires the input features to be finite discrete values, so we design an extraction method which generates discrete features by quantizing continuous CSI of legitimate and eavesdropper channels. Using this quantization method, training data is generated from a large number of CSI samples. For each dualhop transmission, the scheme only requires quantized CSI feedback to predict selection results. To achieve high spectrum efficiency, quantization parameters should be set judiciously. Because splitting criteria play a key role in building an efficient decision tree, we derive splitting criteria of the input features and examine the quantization parameters maximizing the splitting criteria. The proposed decision-tree-based secure relay selection also has advantages in computation cost, communication overhead and feedback CSI requirement. Compared with our preliminary work in [4], this work is different in the following aspects.

(1) *Feature generating method*: In [4], a binary quantization method was proposed to generate one-bit features. In this paper, we propose a multi-level quantization method which divides the CSI region into multiple segments and generates a feature set with multiple discrete values.
(2) *Derivation of splitting criteria*: As a result of the multi-level quantization method, the derivation of splitting criteria should cover all possible values of input features. Moreover, features representing legitimate CSI and eavesdropper CSI lead to different calculations.
(3) *Parameter optimization*: In [4], splitting criteria are determined by only one parameter, i.e. quantization threshold, and are concave functions of the threshold. In this paper, multi-level quantization needs two parameters to define the quantization. Thus, analyzing the optimal values of the two parameters is intriguing.

The rest of this paper is organized as follows. In Section II, system model is introduced and conventional optimization-driven selection schemes are described. Section III elaborates the decision-tree-based relay selection algorithm. In Section IV, three splitting criteria of input features are derived. Simulation results are presented in Section V, followed by conclusions in Section VI.

II. SYSTEM MODEL AND OPTIMIZATION-DRIVEN RELAY SELECTION

A. SYSTEM MODEL

Consider a dualhop network with one source (S), one destination (D), K decode-and-forward (DF) relays and a passive eavesdropper (E). The transmission from S to D is completed in two time slots aided by one of the relays. We assume coverage extension scenario where D is beyond the transmission range of S. The eavesdropper is located near D and is also beyond the coverage of S.

The wireless channel between each pair of nodes is assumed to experience independent and identically distributed (i.i.d.) Rayleigh fading. Large-scale fading is not considered in the system model. Suppose that the fading environment is not changing over time and the CSI is correctly estimated. The noise at each receiver is modeled as complex Gaussian random variable with zero mean and variance σ^2. For convenience, the K relays are denoted by $\mathcal{R} = \{r_k | k = 1, 2, \ldots, K\}$. Let h_{Sk} denote the complex channel coefficient from S to r_k, and let h_{kD} and h_{kE} denote coefficients from r_k to D and E. If r_k is selected, the secrecy rate of the dualhop transmission is [24]

$$\begin{aligned} R_k^S &= \frac{1}{2}\left[\min\{R_{Sk}, R_{kD}\} - R_{kE}\right]^+ \\ &= \frac{1}{2}\Bigg[\min\left\{\log_2\left(1+\frac{Pg_{Sk}}{\sigma^2}\right), \log_2\left(1+\frac{Pg_{kD}}{\sigma^2}\right)\right\} \\ &\quad - \log_2\left(1+\frac{Pg_{kE}}{\sigma^2}\right)\Bigg]^+, \end{aligned} \tag{1}$$

where R_{Sk}, R_{kD} and R_{kE} represent the information rates of r_k, D and E. Moreover, $[x]^+ = \max\{x, 0\}$, $g_{Sk} = |h_{Sk}|^2$, $g_{kD} = |h_{kD}|^2$ and $g_{kE} = |h_{kE}|^2$. Thus, g_{Sk}, g_{kD} and g_{kE} are exponential distributed random variables with parameter λ_D for legitimate channels and λ_E for eavesdropper channels. To improve the readability of this paper, nomenclature is listed in Table 1.

TABLE 1. Nomenclature.

h_{ij}	complex channel coefficient from i to j
g_{ij}	channel gain from i to j
g_k	equivalent channel gain via relay k
g_{ij}^q	quantized channel coefficient from i to j
R_{ij}	rate from i to j
R_k^S	instantaneous secrecy rate via relay k
$\overline{R_S}$	average secrecy rate of the dualhop transmission
σ^2	noise power
F_k	the kth input feature
x_m^k	the kth element of the mth input sample
y_m	output of the mth training sample
T_D, N_D	quantization parameters of legitimate channel
T_E, N_E	quantization parameters of eavesdropper channel
$[g_D^l(n), g_D^u(n)]$	the nth segment of quantized legitimate channel
$[g_E^l(n), g_E^u(n)]$	the nth segment of quantized eavesdropper channel

B. OPTIMAL SELECTION

In conventional optimization-driven relay selection, a central controller collects g_{Sk}, g_{kD} and g_{kE} of all relays, and selects the relay maximizing R_k^S. This problem is to find from the cluster the index of the relay which yields maximum secrecy rate, as expressed by

$$\begin{aligned} k^* &= \arg \max_{1\le k\le K} R_k^S \\ &= \arg \max_{1\le k\le K} \min\{R_{Sk} - R_{kE}, R_{kD} - R_{kE}\} \\ &= \arg \max_{1\le k\le K} \min\left\{\frac{\sigma^2 + Pg_{Sk}}{\sigma^2 + Pg_{kE}}, \frac{\sigma^2 + Pg_{kD}}{\sigma^2 + Pg_{kE}}\right\}. \end{aligned} \tag{2}$$

To evaluate the communication performance of different relay selection schemes, average secrecy rate is computed as performance metric, which is given by

$$\overline{R_S} = \lim_{T\to\infty} \frac{1}{T} \sum_{t=1}^{T} R_{k^*}^S(2t). \tag{3}$$

C. SUBOPTIMAL SELECTION

Optimal selection scheme requires full CSI of both legitimate and eavesdropper channel from all hops. Suboptimal selection schemes only take into account the CSI of a particular group of channels, ignoring the other channels with the purpose of simplifying calculation or reducing cost. One way to design suboptimal selection schemes is to consider only legitimate channel or eavesdropper channel [18], [25]. Another way to design suboptimal selection is to consider only one hop of the dualhop transmission [26]. These types of suboptimal selections are often referred to as partial selection.

Here, we give the following two partial selection schemes: the scheme that only considers legitimate CSI (Partial-D) and the scheme that only considers eavesdropper CSI (Partial-E). Partial-D is described by

$$\begin{aligned} k^* &= \arg \max_{1\le k\le K} \frac{1}{2}\min\{R_{Sk}, R_{kD}\} \\ &= \arg \max_{1\le k\le K} \min\left\{1 + \frac{Pg_{Sk}}{\sigma^2}, 1 + \frac{Pg_{kD}}{\sigma^2}\right\} \\ &= \arg \max_{1\le k\le K} \min\left\{g_{Sk}, g_{kD}\right\}, \end{aligned} \tag{4}$$

and Partial-E is described by

$$\begin{aligned} k^* &= \arg \min_{1\le k\le K} R_{kE} \\ &= \arg \min_{1\le k\le K} \frac{1}{2}\log_2\left(1 + \frac{Pg_{kE}}{\sigma^2}\right) \\ &= \arg \min_{1\le k\le K} g_{kE}. \end{aligned} \tag{5}$$

These two partial selection schemes are simpler to implement and cost fewer resources, but compromise communication performance compared with optimal selection. Partial-D and Partial-E are proposed as comparison to the decision-tree-based selection.

D. MULTICLASS-CLASSIFICATION PROBLEM

In machine learning, classification is the problem of deciding which class a sample belongs to. If each sample is labeled with single class and the class set contains multiple labels, this problem becomes multiclass classification. Let $\mathcal{X}$ denote the input space and all elements in $\mathcal{X}$ are i.i.d. Let $\mathcal{Y}$ denote the output space where the classes are marked with numbers. The learner receives a set of labeled samples $S = \big((x_1, y_1), \ldots, (x_m, y_m)\big) \in (\mathcal{X} \times \mathcal{Y})^m$, and trains a classifier which defines the target labeling function $f : \mathcal{X} \to \mathcal{Y}$.

To be solved by machine learning methods, relay selection problem needs to be converted to multiclass classification problem. To be specific, elements of $\mathcal{X}$ are drawn from g_{Sk}, g_{kD} and g_{kE}. The classes are labeled by the indices of candidate relays, i.e. $\mathcal{Y} = \{1, \ldots, K\}$. A decision tree is trained to simulate the labeling function $f : \mathcal{X} \to \mathcal{Y}$.

III. DECISION-TREE-BASED RELAY SELECTION

To solve the multiclass-classification problem converted from relay selection problem, we adopt decision tree learning and build a classification tree. The entire relay selection scheme is composed of three phases: preparing training data, building decision tree and predicting relay selection. The first two phases are regarded as initialization and conducted before S transmits the first bit. After tree building is completed, no update or modification is needed to the decision tree. At the beginning of each dualhop transmission, the central controller collects CSI from all relays and uses the stored decision tree to compute selection result. System model and the decision-tree-based scheme are briefly illustrated in Fig. 1. Next, we elaborate the details of the decision-tree-based scheme.

A. PREPARING TRAINING DATA

Training data demanded by decision tree is generated from CSI of the legitimate and eavesdropper channel, i.e. g_{Sk}, g_{kD} and g_{kE}, and is denoted by $D = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_M, y_M)\}$. $(\mathbf{x}_m, y_m)$ is the mth sample consisting of input $\mathbf{x}_m$ and output y_m. M should be sufficiently large in order to train an accurate tree. y_m represents the index of optimal relay and is calculated by the optimization-driven relay selection algorithm specified in (2) using the mth

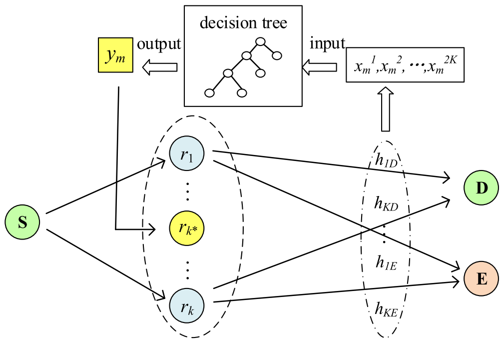

FIGURE 1. System model of the decision-tree-based secure relay selection.

CSI samples. Input data is the values of $2K$ features describing the quality of all legitimate and eavesdropper channels. The features are denoted by $\mathcal{F} = [F_1, F_2, \ldots, F_{2K}]$. $\mathbf{x}_m$ is the input vector containing $2K$ values, and is given by

$$\mathbf{x}_m = [x_m^1, x_m^2, \ldots, x_m^{2K}], \tag{6}$$

where x_m^k is the value of the kth feature.

The procedure of training data preparing is completed in the following steps.

1.1 Sensing fading characteristics. calculating splitting criterion and set up new quantization parameters.

1.2 Estimate and feedback g_{Sk}, g_{kD} and g_{kE} for all k to the central controller. Generate input features. Compute $\mathbf{x}_m = [x_m^1, x_m^2, \ldots, x_m^{2K}]$ from g_{Sk}, g_{kD} and g_{kE}.

The input features required by decision tree are discrete values describing the object to be classified. Therefore, we need to transform g_{Sk}, g_{kD} and g_{kE} to a set of values which are taken from finite discrete domain and can well characterize the relays. $x_m^1, x_m^2, \ldots, x_m^K$ are generated from g_k which is given by $g_k = \min\{g_{Sk}, g_{kD}\}, 1 \le k \le K$. The entire CSI region is divided into $N_D + 1$ segments by $S_1, S_2, \ldots, S_{N_D}$, $0 < S_1 < S_2 < \ldots < S_{N_D}$. To clearly show the relations between quantization parameters and prediction performance, we consider uniform quantization. We set an upperbound T_D for g_k, and then evenly divide the $[0, T_D]$ into N_D segments. Then, the entire CSI region is divided into $N_D + 1$ segments, each of which is denoted by $[g_D^l(n), g_D^u(n)]$ with

$$g_D^l(n) = \begin{cases} \frac{(n-1)T_D}{N_D}, & 1 \le n \le N_D \\ T_D, & n = N_D + 1 \end{cases} \tag{7}$$

and

$$g_D^u(n) = \begin{cases} \frac{nT_D}{N_D}, & 1 \le n \le N_D \\ \infty, & n = N_D + 1. \end{cases} \tag{8}$$

Then, the value of x_m^k is an integer that lies between 1 and $N_D + 1$. To be specific, for $1 \le k \le K$,

$$x_m^k = \begin{cases} n, & g_D^l(n) < g_k < g_D^u(n) \\ N_D + 1, & g_k > g_D^l(N_D + 1). \end{cases} \tag{9}$$

$x_m^{K+1}, \ldots, x_m^{2K}$ represent channel features of the eavesdropper and are generated from g_{kE} following the same procedure as the first K features. An upperbound T_E is set to g_{kE} and $[0, T_E]$ is divided evenly into N_E segments. The entire CSI region is divided into $N_E + 1$ segments, each of which is denoted by $[g_E^l(n), g_E^u(n)]$ with

$$g_E^l(n) = \begin{cases} \frac{(n-1)T_E}{N_E}, & 1 \le n \le N_E \\ T_E, & n = N_E + 1 \end{cases} \tag{10}$$

and

$$g_E^u(n) = \begin{cases} \frac{nT_E}{N_E}, & 1 \le n \le N_E \\ \infty, & n = N_E + 1. \end{cases} \tag{11}$$

For $K + 1 \le k \le 2K$, the kth feature is calculated as

$$x_m^k = \begin{cases} n, & g_E^l(n) < g_{(k-K)E} < g_E^u(n) \\ N_E + 1, & g_{(k-K)E} > g_E^l(N_E + 1). \end{cases} \tag{12}$$

The insight of the feature extraction method is to quantize g_k and g_{kE}, and assign the quantization results to input features. Quantization parameters for legitimate channels and eavesdropper channels can be set independently by different parameters.

1.3 Central controller calculates (2) with g_{Sk}, g_{kD} and g_{kE}, and form $(\mathbf{x}_m, y_m)$, assigns k^* to y_m and forms $(\mathbf{x}_m, y_m)$.

1.4 Repeat 1.1-1.3 for another $M - 1$ times to form a training data set containing totally M samples.

Collecting and preparing M samples of training data are completed offline before the transmissions are started. Once the decision tree is built, no training data are required as long as the network topology keeps stable.

B. BUILDING DECISION TREE

After training data is prepared, the decision tree is built by selecting the *best* feature and splitting the data set into subsets based on feature value test. This process is repeated on each subset until stopping criterion is satisfied. Indices of all candidate relays are represented by the leaf nodes. Before we describe the building procedure, it is necessary to introduce the terminology of decision tree.

- *Splitting criterion*: The metric of evaluating a feature is called splitting criterion. It measures the decreased impurity after the current data set is split by a feature. Information gain, information gain ratio and Gini index are commonly adopted splitting criteria.
- *Stopping criterion*: Stopping criterion is the condition under which the current data set cannot be further split and the building of the current branch should stop. It is often defined that the number of samples in current data set is smaller than a threshold, or splitting criterion of current feature is smaller than a threshold, or no feature is left to choose.
- *Multi-branch tree*: As observed from feature extraction method , each feature has more than two possible values if $N_D, N_E \ge 2$, which means that the decision tree is a multi-branch tree and each interior node is split

into multiple branches. Multi-branch tree can also be converted to binary tree.

The decision tree building of the proposed scheme directly adopts the most widely-accepted decision tree algorithms. The details depend on the selection of splitting criterion, the selection between binary tree and multi-branch tree, etc. ID3 [27] and C4.5 [28] are two well-known multi-branch decision tree algorithms. ID3 adopts information gain as splitting criterion while C4.5 adopts information gain ratio. CART (Classification And Regression Tree) [29] is another widely used decision tree algorithm. It adopts Gini index as splitting criterion and is designed by binary tree. Here, we only briefly describe the steps of building phase.

2.1 Input sample data, set up parameters and stopping criterion.
2.2 Build a decision tree with sample data. From the root node, each node represents a test to one of the features which is selected for having the best splitting criterion. Then, the current data set is split according to the value of this feature.
2.3 Split subset of each branch according to the best feature in the remaining feature set. Build the decision tree recursively until stopping criterion is satisfied.

It is worth mentioning that the decision tree is converged if one of the stopping criteria is satisfied. The training data is generated from perfect CSI of all legitimate and eavesdropper channels. Thus, the decision tree is regarded to converge to optimal point. We only need to build the decision tree in the initialization phase of the dualhop transmission. After tree construction is completed, it is used to predict the best relay in each transmission, and requires no renewal.

C. PREDICTING RELAY SELECTION

In each prediction, input features are generated from instantaneous CSI of legitimate and eavesdropper channels. As shown in feature extraction method, the values in $\mathbf{x}_m$ are assigned by the quantization results of g_{Sk}, g_{kD} and g_{kE}. Therefore, the central controller only needs to estimate and collect the quantized CSI of legitimate and eavesdropper channels.

3.1 Collect quantized CSI from all legitimate and eavesdroppers channels, and generate $\mathbf{x}_m$.

Let g^q_{Sk}, g^q_{kD} and g^q_{kE} denote the quantization results of g_{Sk}, g_{kD} and g_{kE}, the first two of which are generated by the quantization method (9) and the third one is generated by (12). Thus, $g^q_{Sk}, g^q_{kD} \in [1, 2, \ldots, N_D + 1]$ and $g^q_{kE} \in [1, 2, \ldots, N_E + 1]$. Transmitting them requires $\log_2(N_D + 1)$ bits and $\log_2(N_E + 1)$ bits, respectively. At the beginning of each odd time slot, g^q_{Sk}, g^q_{kD} and g^q_{kE} are collected by the central controller. Then, $\mathbf{x}_m$ is generated by

$$x^k_m = \begin{cases} \min\{g^q_{Sk}, g^q_{kD}\}, & 1 \le k \le K \\ g^q_{(k-K)E}, & K+1 \le k \le 2K. \end{cases} \tag{13}$$

In each dualhop transmission, the feedback amount is reduced compared with the optimal selection scheme. Accurate instantaneous eavesdropper CSI is no longer required.

After input data is generated, it is input into the root node and tested by the rule that the current node defines. A leaf nodes will be reached following each branch representing test result. Relay selection prediction is elaborated as follows.

3.2 Input $\mathbf{x}_m$ into the decision tree, test feature values from root to leaf. From root node, we examine the feature of $\mathbf{x}_m$ that current node is testing and follow the right branch to the next node until a leaf node is reached.
3.3 Assign the leaf label to k^*. The central controller broadcasts the selection result to all nodes. The selected relay is ready to work.

Before next prediction starts, the network first senses the fading environment. If fading characteristics have not changed, only Step 3, i.e. relay prediction, is repeated. Else, new data will be collected and a new tree will be built. All three steps will be repeated. The entire algorithm is summarized as follows.

Algorithm 1 Decision-Tree-Based Relay Selection

Step 1. Prepare training data.
1.1. Sensing fading characteristics. Calculate splitting criterion and set up new quantization parameters.
1.2. Estimate and feedback g_{Sk}, g_{kD} and g_{kE} for all k to the central controller. Compute $\mathbf{x}_m = [x^1_m, x^2_m, \ldots, x^{2K}_m]$ using (9) and (12).
1.3. Solve problem (2) using g_{Sk}, g_{kD} and g_{kE}, calculate k^* and assign it to y_m. Form $(\mathbf{x}_m, y_m)$.
1.4. Repeat 1.1-1.3 for $M - 1$ times. Form training data D.

Step 2. Build decision tree.
2.1. Input training sample, define stopping criterion and set up parameters.
2.2. From the root node, split data set according to the feature with best splitting criterion.
2.3. Split subset of each branch according the best feature in the remaining feature set. Build the decision tree recursively until stopping criterion is satisfied.

Step 3. Predict relay selection
3.1. Collect g^q_{Sk}, g^q_{kD} and g^q_{kE} from all K relays, and generate $\mathbf{x}_m$.
3.2. Input $\mathbf{x}_m$ into the decision tree and test feature values from root to leaf.
3.3. Assign the leaf label to k^*.

Sense fading characteristics.
if fading has not changed
  repeat **Step** 3;
else
  repeat **Step** 1-**Step** 3;
end if

D. CLOUD-ASSISTED STRUCTURE

The decision-tree-based scheme requires large amount of training data, which is generated or collected in different ways. In the considered network, training data can be collected by CSI estimation and feedback. If fading environment is changing fast, training data collection and tree building are repeated frequently, which leads to high overhead and long delay. Therefore, we consider to adopt the cloud-assisted structure proposed by [30] to save transmission overhead. Huge amount of historical data is collected and stored in cloud servers. Based on the data from same fading environment, the cloud server computes a number of different decision trees and stores them in the cloud. When it is uneconomical or impossible to collect CSI by real measurement, the dualhop network only estimates the fading characteristics and asks the cloud for the decision tree that best fits the current fading. The best tree will be used to predict relay selection.

The cloud-assisted structure provides a new way of generating training data, especially when fading environment is changing frequently. To efficiently use this structure, there are still many open issues to be solved, such as which features to be collected, how to compare the fading features with stored learning models, how to store and transmit learning model appropriately, etc.

IV. ANALYSIS OF SPLITTING CRITERIA

The input features are generated from continuous CSI and determined by quantization parameters, i.e. T_D, T_E and N_D, N_E. These parameters also affect the features' splitting criteria, which play a key role in building decision tree and enhancing prediction accuracy. Wisely setting up these parameters can promote the performance of decision-tree-based relay selection. Moreover, investigating the relation between quantization parameters and communication performance can help revealing the laws of relay selection.

In this section, we derive three commonly used splitting criteria, namely information gain, information gain ratio and Gini index. These splitting criteria describe the impurity of a data split. Large information gain means that this feature splits the current data set more efficiently. Information gain favors features with a large number of distinct values. Then, information gain ratio is defined as the ratio of information gain to intrinsic entropy to solve the weakness of information gain. Gini index measures the probability that a sample is incorrectly classified and takes value from 0 to 1. In the literature, it is not obvious which of the splitting criteria will produce the optimal decision tree for a given data set. Among all existing splitting criteria, no one is consistently superior to the others. As a result, it is necessary to derive these splitting criteria and analyze their relations with quantization parameters.

The optimal selection policy specified in (2) provides little insight and has to be simplified in order to derive the expressions of splitting criteria. Thus, approximation to (2) is made as

$$\begin{aligned} k^* &= \arg\max_{1\le k\le K} R_k^S \\ &\approx \arg\max_{1\le k\le K} \min\left\{\frac{g_{Sk}}{g_{kE}}, \frac{g_{kD}}{g_{kE}}\right\} \\ &\approx \arg\max_{1\le k\le K} \frac{\min\{g_{Sk}, g_{kD}\}}{g_{kE}}. \end{aligned} \tag{14}$$

For the convenience of derivation, we let $\gamma_k = \frac{\min\{g_{Sk}, g_{kD}\}}{g_{kE}}$.

A. INFORMATION GAIN

Information gain, which is adopted by ID3 algorithm, represents the entropy change after data set is split by a feature. To build a more efficient decision tree, information gain of the features need to be maximized. The information gain of the kth feature F_k is given by

$$\mathrm{IG}(D, F_k) = H(D) - H(D|F_k). \tag{15}$$

Here, $H(D)$ is the entropy of the classification and given by

$$H(D) = -\sum_{i=1}^{K} \Pr(y_m = i)\log_2 \Pr(y_m = i) = \log_2 K. \tag{16}$$

$H(D|F_k)$ is the average entropy after the split caused by F_k. In the remaining part, we focus on the derivation of $H(D|F_k)$.

Since all wireless links experience i.i.d. Rayleigh fading, the first K features representing legitimate channels share identical information gain, and the other K features representing eavesdropper channels also share identical information gain. This means that information gain of the first K features can be maximized simultaneously. This conclusion also applies to the other K features and to other two splitting criteria. Next, we derive the expressions of information gain for the two cases.

1) $1 \le K \le K$

The first K features are extracted from g_k, and quantized by T_D, N_D. The entropy after splitting is calculated as

$$\begin{aligned} H(D|F_k) &= \sum_{n=1}^{N_D+1} \Pr(x_m^k = n) H_n(T_D, N_D) \\ &= \sum_{n=1}^{N_D+1} \Pr\left(g_D^l(n) < g_k < g_D^u(n)\right) H_n(T_D, N_D), \end{aligned} \tag{17}$$

where

$$\begin{aligned} &H_n(T_D, N_D) \\ &\quad = -\sum_{i=1}^{K} \Pr(y_m = i|x_m^k = n)\log_2 \Pr(y_m = i|x_m^k = n). \end{aligned} \tag{18}$$

In order to facilitate the derivation of $\Pr(y_m = i|x_m^k = n)$, let $\gamma_M = \max_{i\ne k} \gamma_i$ and its probability density function (PDF) is given by $f_M(z) = \frac{(K-1)\lambda_E(2\lambda_D)^{K-1}z^{K-2}}{(\lambda_E+2\lambda_D z)^K}$. When $i = k$,

$$\begin{aligned}
&\Pr(y_m = i|x_m^k = n) \\
&= \Pr\left(\frac{g_k}{g_{kE}} > \gamma_M | g_D^l(n) < g_k < g_D^u(n)\right) \\
&= \int_0^\infty \int_{g_D^l(n)}^{g_D^u(n)} \int_0^{\frac{x}{z}} f_X(x) f_Y(y) f_M(z) dxdydz \\
&= \int_0^\infty f_M(z)\Bigg((e^{-2g_D^l(n)\lambda_D} - e^{-2g_D^u(n)\lambda_D}) - \frac{2\lambda_D z}{\lambda_E + 2\lambda_D z} \\
&\quad \times (e^{-g_D^l(n)(\lambda_E+2\lambda_D z)/z} - e^{-g_D^u(n)(\lambda_E+2\lambda_D z)/z})\Bigg)dz = q(n).
\end{aligned} \tag{19}$$

When $i \neq k$,

$$\begin{aligned}
\Pr(y_m = i|x_m^k = n) &= \Pr(\gamma_M = \gamma_i, \gamma_M > \gamma_k | x_m^k = n) \\
&= \frac{1 - q(n)}{K - 1}.
\end{aligned} \tag{20}$$

Calculating the summation in (18), we obtain

$$H_n(T_D, N_D) = -q(n)\log_2 q(n) - (1 - q(n))\log_2 \frac{1 - q(n)}{K - 1}. \tag{21}$$

Combining all probabilities derived above, we can obtain the expression of information gain for $k = 1, \ldots, K$.

2) $K + 1 \leq K \leq 2K$

$x_m^{K+1}, \ldots, x_m^{2K}$ are extracted from g_{kE} and determined by T_E, N_E. The entropy after splitting is calculated as

$$\begin{aligned}
&H(D|F_k) \\
&= \sum_{n=1}^{N_E+1} \Pr(x_m^k = n) H_n(T_E, N_E) \\
&= \sum_{n=1}^{N_E+1} \Pr\left(g_E^l(n) < g_{(k-K)E} < g_E^u(n)\right) H_n(T_E, N_E),
\end{aligned} \tag{22}$$

where

$$\begin{aligned}
&H_n(T_E, N_E) \\
&= -\sum_{i=1}^{K} \Pr(y_m = i|x_m^k = n)\log_2 \Pr(y_m = i|x_m^k = n).
\end{aligned} \tag{23}$$

When $i = k - K$,

$$\begin{aligned}
&\Pr(y_m = i|x_m^k = n) \\
&= \Pr\left(\frac{g_{k-K}}{g_{(k-K)E}} > \gamma_M | g_E^l(n) < g_{kE} < g_E^u(n)\right) \\
&= \int_0^\infty \int_{g_E^l(n)}^{g_E^u(n)} \int_{yz}^{\infty} f_X(x) f_Y(y) f_M(z) dxdydz \\
&= \int_0^\infty f_M(z) \frac{\lambda_E}{\lambda_E + 2\lambda_D z} \\
&\quad \times \left(e^{-g_E^l(n)(\lambda_E+2\lambda_D z)} - e^{-g_E^u(n)(\lambda_E+2\lambda_D z)}\right)dz = p(n).
\end{aligned} \tag{24}$$

When $i \neq k - K$,

$$\begin{aligned}
\Pr(y_m = i|x_m^k = n) &= \Pr(\gamma_M = \gamma_i, \gamma_M > \gamma_k | x_m^k = n) \\
&= \frac{1 - p(n)}{K - 1}.
\end{aligned} \tag{25}$$

Substituting above results into (23), the entropy of the nth selection result is expressed as

$$\begin{aligned}
&H_n(T_E, N_E) \\
&= -p(n)\log_2 p(n) - (1 - p(n))\log_2 \frac{1 - p(n)}{K - 1}.
\end{aligned} \tag{26}$$

Combining all probabilities derived above, we can obtain the expression of information gain for $k = K + 1, \ldots, 2K$.

B. INFORMATION GAIN RATIO

Information gain ratio is a splitting criterion defined as the ratio of information gain to the intrinsic information gain. It is proposed to reduce information gain's bias towards multi-valued features by taking into account the number of branches. Information gain ratio of F_k is calculated by

$$\mathrm{IGR}(D, F_k) = \frac{\mathrm{IG}(D, F_k)}{H_{F_k}(D)}. \tag{27}$$

$H_{F_k}(D)$ denotes the intrinsic entropy of F_k and is expressed by

$$H_{F_k}(D) = -\sum_{n=1}^{N_D+1} \Pr(x_m^k = n)\log_2 \Pr(x_m^k = n), \tag{28}$$

for $1 \leq k \leq K$ and

$$H_{F_k}(D) = -\sum_{n=1}^{N_E+1} \Pr(x_m^k = n)\log_2 \Pr(x_m^k = n), \tag{29}$$

for $K + 1 \leq k \leq 2K$. Combining the results of information gain and intrinsic entropy, information gain ration can be obtained.

C. GINI INDEX

For the convenience of comparing the splitting criteria, Gini index is defined as the change of Gini impurity. As a result, it will be maximized to optimize the performance of the proposed scheme. Assume that feature F_k is considered, Gini index is given by

$$\mathrm{GINI}(D, F_k) = \mathrm{Gini}(D) - \mathrm{Gini}(D|F_k). \tag{30}$$

$\mathrm{Gini}(D)$ denotes the impurity of sample data and is irrelevant to quantization parameters. Then, we focus on the derivation of $\mathrm{Gini}(D|F_k)$, which represents average Gini if F_k is considered.

1) $1 \leq K \leq K$

$\mathrm{Gini}(D|F_k)$ is calculated as

$$\mathrm{Gini}(D|F_k) = \sum_{n=1}^{N_D+1} \Pr(x_m^k = n)\mathrm{Gini}(n). \tag{31}$$

$\mathrm{Gini}(n)$ is the Gini of branch $x_m^k = n$ and is expressed as

$$\begin{aligned}\mathrm{Gini}(n) &= 1 - \Big(\Pr(y_m = k|x_m^k = n)\Big)^2 \\ &\quad - \sum_{j\neq k}\Big(\Pr(y_m = j|x_m^k = n)\Big)^2 \\ &= 1 - q(n)^2 - \frac{(1-q(n))^2}{K-1}. \end{aligned} \tag{32}$$

Substituting above results into (31), the Gini index of feature F_k is expressed as

$$\begin{aligned}\mathrm{Gini}(D|F_k) = \sum_{n=1}^{N_D+1}&\left(e^{-\frac{2(n-1)T_D\lambda_D}{N_D}} - e^{-\frac{2nT_D\lambda_D}{N_D}}\right) \\ &\times\left(1 - q(n)^2 - \frac{(1-q(n))^2}{K-1}\right). \end{aligned} \tag{33}$$

2) $K+1 < K < 2K$

In this case, we calculate that

$$\mathrm{Gini}(D|F_k) = \sum_{n=1}^{N_E+1}\Pr(x_m^k = n)\mathrm{Gini}(n), \tag{34}$$

where $\mathrm{Gini}(n)$ is the Gini of branch $x_m^k = n$ and is expressed as

$$\begin{aligned}\mathrm{Gini}(n) &= 1 - \Big(\Pr(y_m = k|x_m^k = n)\Big)^2 \\ &\quad - \sum_{j\neq k}\Big(\Pr(y_m = j|x_m^k = n)\Big)^2 \\ &= 1 - p(n)^2 - \frac{(1-p(n))^2}{K-1}. \end{aligned} \tag{35}$$

Substituting above result into (34), we obtain the following expression

$$\begin{aligned}\mathrm{Gini}(D|F_k) = \sum_{n=1}^{N_E+1}&\left(e^{-\frac{(n-1)T_E\lambda_E}{N_E}} - e^{-\frac{nT_E\lambda_E}{N_E}}\right) \\ &\times\left(1 - p(n)^2 - \frac{(1-p(n))^2}{K-1}\right). \end{aligned} \tag{36}$$

V. PERFORMANCE EVALUATION

A. NUMERICAL RESULTS

We provide experiments for the proposed decision-tree-based relay selection scheme. 5×10^3 CSI samples that follow Rayleigh fading are generated to construct training samples. We use classregtree function from MATLAB Statistics and Machine Learning Toolbox to build the CART tree based on training samples. More 5×10^3 Rayleigh distributed samples are generated to test the decision tree. Average secrecy rate over all testing sample output is considered as performance metric to evaluate the proposed decision-tree-based scheme. Comparison schemes are optimal selection given in (2), Partial-D in (4), Partial-E in (5) and random selection. We first demonstrate numerical results of splitting criteria,

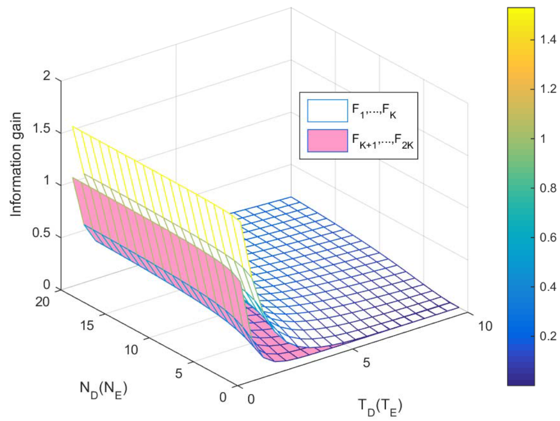

FIGURE 2. Information gain of input features.

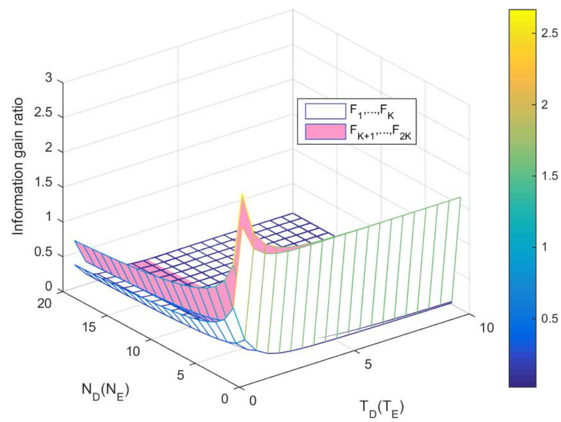

FIGURE 3. Information gain ratio of input features.

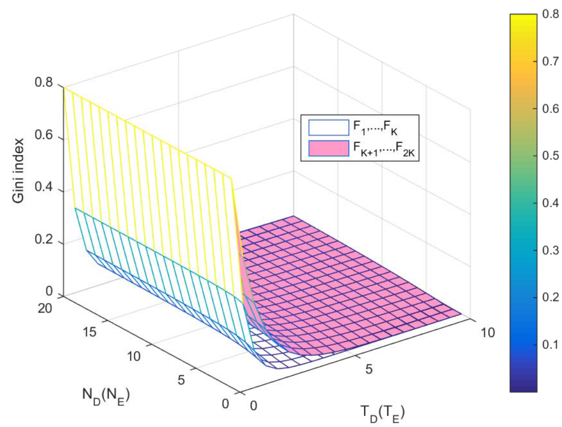

FIGURE 4. Gini index of input features.

i.e. information gain, information gain ratio and Gini index, with respect to quantization parameters. Then, we show how the performance of the proposed decision-tree-based scheme changes with quantization parameters.

In Fig. 2, Fig. 3 and Fig. 4, numerical results of splitting criteria are depicted by three-dimensional colored mesh with respect to quantization parameters. The range of T_D and T_E is from 0 to 10, and the range of N_D and N_E is from 1 to

20. These figures will show the intrinsic relation between splitting criteria and quantization parameters. Fig. 2 shows information gains of the two sets of features representing legitimate channels and eavesdropper channels. Information gain is regarded as a function of $T_D(T_E)$ and $N_D(N_E)$, which is depicted three-dimensionally. We first observe that information gain of both feature sets is decreasing with $T_D(T_E)$ when $N_D(N_E)$ is fixed. The reason lies in that large $T_D(T_E)$ yields longer segments and thus lowers accuracy of quantization. It can be concluded that the length of each segment plays an important role in the decision-tree-based scheme. Thus, we infer that information gain is also increasing with $N_D(N_E)$. However, the two surfs show no obvious rise along $N_D(N_E)$ axis, except for large $T_D(T_E)$ region. This suggests that when the length of each segment is small enough, it is no longer a significant factor that enhances the performance of the decision-tree-based scheme.

Information gain ratios of the $2K$ features are depicted in Fig. 3. It is clearly observed that both of the two surfs have a peak point at $(T_E, N_E) = (0.5, 1)$, the point closest to the origin. The reason lies in that information gain ratio favors partitions with fewer distinct values. Fig. 4 shows Gini indices of the two feature sets with respect to quantization parameters. We can easily observe that Gini indices of both feature sets are decreasing with $T_D(T_E)$. The change of the two surfs along $N_D(N_E)$ axis is inconspicuous when $T_D(T_E)$ is small. As $T_D(T_E)$ grows larger, Gini indices of the two feature sets drop slightly with the decreasing of $N_D(N_E)$. Note that Gini index changes with quantization parameters in the similar pattern to information gain. However, information gain ratio shows evident bias towards quantization with two levels. Obviously, information gain and Gini index are more appropriate to the relay selection problem. Consequently, we adopt CART algorithm to build the decision tree in simulation experiments as CART uses Gini index as splitting criterion.

In our simulation experiments, average secrecy rate over the sample data is computed instead of the average secrecy rate defined in (3) owing to the ergodicity of Rayleigh fading channels. In practical wireless networks, CSI of legitimate channels can be precisely estimated, but to obtain full CSI of eavesdropper channels is a difficult task. Therefore, we fix the parameters of legitimate channels and depict average secrecy rate with respect to T_E and N_E in Fig. 5 and Fig. 6, respectively. Average secrecy rates of optimal selection, Partial-D, Partial-E and random selection are depicted as comparison. System parameters are $K = 5$, $T_D = 5$, $N_D = 20$, $\lambda_D = \lambda_E = 1$.

Fig. 5 shows how average secrecy rate is affected by T_E when $N_E = 2, 8, 15$. We observe that when $T_E < 0.5$, increasing T_E raises $\overline{R}_S$ for $N_E = 8, 15$. This is because too small T_E cannot cover enough CSI samples. When $T_E > 0.5$, all curves drop with the growing of T_E, among which the curve with $N_E = 2$ drops with largest slope, the curve with $N_E = 15$ only drops slightly with smallest slope and the $N_E = 8$ curve lies between the other two. It is concluded

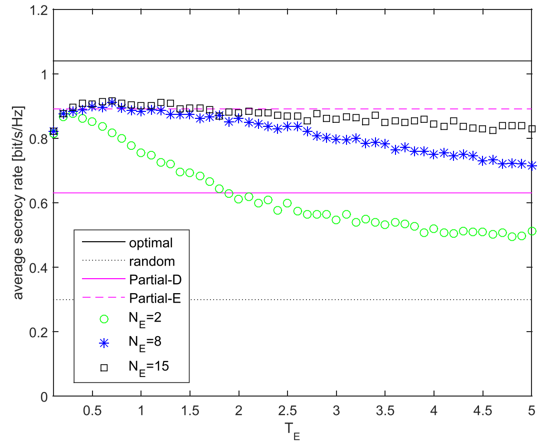

FIGURE 5. **Average secrecy rate vs. T_E when N_E =2, 8, 15.**

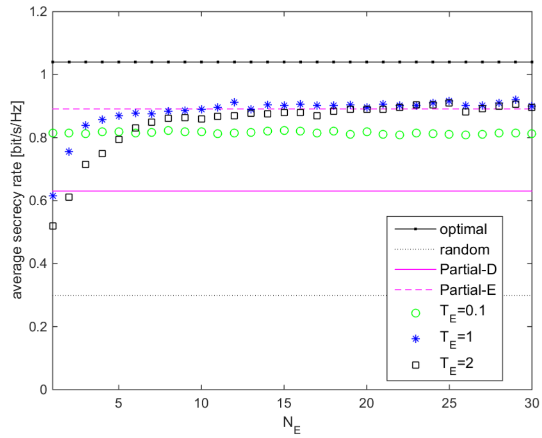

FIGURE 6. **Average secrecy rate vs. N_E when T_E =0.1, 1, 2.**

that growing T_E leads to larger quantization segments and thus lower selection accuracy. If N_E is large enough, quantization segments can maintain a small length, and selection accuracy is guaranteed. Then, we compare the decision-tree-based scheme with benchmark schemes. If T_E and N_E are set properly, $\overline{R}_S$ of the decision-tree-based scheme can achieve a value close to optimal selection. Moreover, even if T_E and N_E are not set optimally, $\overline{R}_S$ of the decision-tree-based scheme can still remarkably exceed random selection. $\overline{R}_S$ for $N_E = 8$ and $N_E = 15$ always outperform Partial-D, which only outperforms the curve with $N_E = 2$ in high T_E region. Although Partial-E is superior to Partial-D, it is still inferior to the decision-tree-based scheme if T_E and N_E are properly configured.

Fig. 6 shows how $\overline{R}_S$ changes with N_E when T_E is fixed to 0.1, 1 and 2. The first observation is that when $T_E = 0.1$, $\overline{R}_S$ shows nearly zero fluctuation with N_E due to the severely incomplete sample set covered by T_E. When $T_E = 1$ or 2, as N_E keeps growing, $\overline{R}_S$ first rises with N_E and then stays around a certain value. This is also attributed to the length change of quantization segments, which can hardly influence selection accuracy when exceeding a certain threshold. We also notice that although the converged $\overline{R}_S$ for $T_E = 0.1$

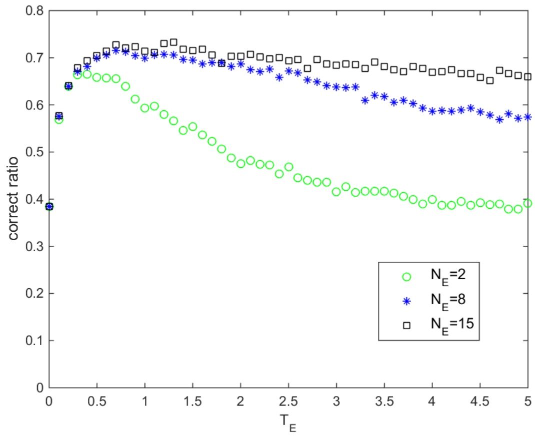

FIGURE 7. Correct ratio vs. T_E when N_E =2, 8, 15.

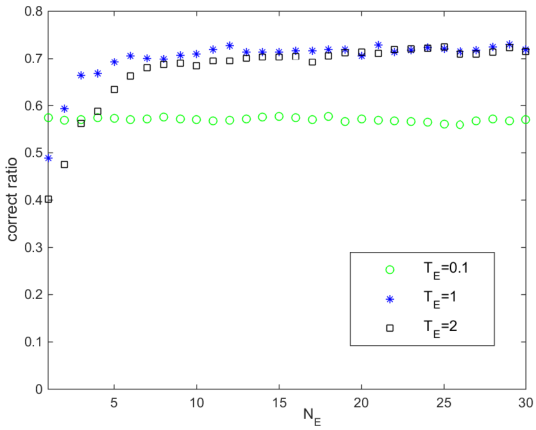

FIGURE 8. Correct ratio vs. N_E when T_E =0.1, 1, 2.

is lower than $T_E = 1$ and 2, $\overline{R}_S$ for $T_E = 0.1$ is higher than the curves with larger T_E if N_E is smaller than a threshold. This suggests that the length of quantization segments plays a more important role in the proposed decision-tree-based scheme. Comparing decision-tree-based selection with benchmark schemes, we can draw similar conclusions to Fig. 5. It is worth mentioning that $\overline{R}_S$ for $T_E = 1$ and $T_E = 2$ are higher than Partial-E if N_E is sufficiently large.

Accuracy is one of the metrics evaluating the performance of a decision tree. It is defined as correct ratio, the ratio of the number of correctly predicted samples to the total number of samples. In the simulation experiments, we calculate correct ratio of the decision-tree-based selection as a function of T_E and N_E. Fig. 7 depicts correct ratio versus T_E when $N_E = 2, 8, 15$ and Fig. 8 depicts correct ratio versus N_E when $T_E = 0.1, 1, 2$. Both figures show that correct ratio can reach 70% if T_E and N_E are set optimally. The curves of correct ratio look similar to average secrecy rate. This means that communication metrics such as average rate can also evaluate the performance of decision-tree-based selection.

In Fig. 9, the decision-tree-based scheme is compared with SVM and k-NN. Relay selection problem is solved by SVM and k-NN with both accurate and quantized CSI.

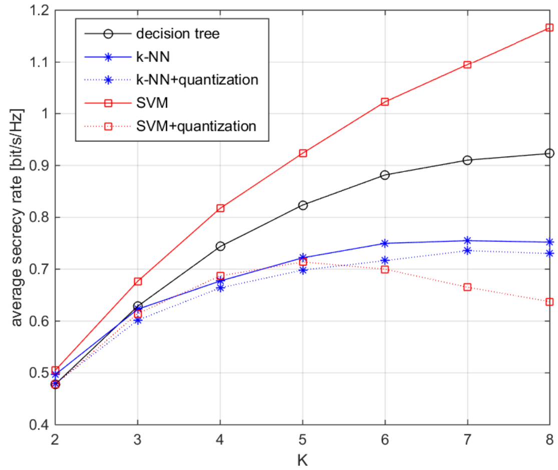

FIGURE 9. Average secrecy rate comparison with SVM and k-NN.

Average secrecy rates with respect to K are depicted. It is observed that when quantized CSI is used, decision tree is superior to SVM and k-NN for any K. Even if accurate CSI is used, decision tree still outperforms k-NN as long as $K > 2$.

Summing up all observations described above, we draw the following conclusions. (1) The proposed decision-tree-based scheme achieves satisfactory performance in terms of average secrecy rate if the learning parameters are set properly. (2) The length of quantization segments, i.e. $\frac{T_E}{N_E}$, plays the key role in deciding relay selection accuracy unless $\frac{T_E}{N_E}$ is sufficiently small when the performance boost vanishes. Therefore, T_E should be large enough to cover sufficient CSI samples. (3) Increasing N_E is definitely beneficial to enhancing $\overline{R}_S$, but also raises the difficulty of estimating eavesdropper channel. How to decide the value of N_E relies on performance requirement and system's ability to obtain eavesdropper CSI. Generally, in order to achieve high average rate, N_D/N_E and T_D/T_E should be set large simultaneously. However, large N costs more feedback bits and large T requires higher hardware quality. If resources are limited, tradeoff between performance and cost should be taken into account.

B. COST ANALYSIS

1) COMPUTATIONAL COMPLEXITY

Computational complexity of optimization-driven relay selection schemes is $O(K)$, the complexity of maximization algorithm. As comparison, the computational complexity of SVM and k-NN is $O(K^2)$ and $O(K)$, respectively.

The complexity of decision-tree-based prediction depends on the tree depth whose upperbound is K. Consequently, the average time complexity of prediction is lower than $O(K)$. We take balanced decision tree as an example, whose complexity is $O(\log_2 K)$. Preparing data and building decision tree are only performed in the initialization part before the dualhop transmissions start. Preparing each sample includes generating M samples of $\mathbf{x}_m$ and calculating y_m. Therefore, the complexity of preparing training data is $O(KM)$.

TABLE 2. Cost Comparison of relay selection schemes.

	optimal	Partial-D	Partial-E	random	decision tree
complexity	$O(K)$	$O(K)$	$O(K)$	$O(1)$	$O(\log_2 K)$
feedback amount (bits)	$48K$	$32K$	$16K$	0	$K\log_2(N_D+1)^2(N_E+1)$
eavesdropper CSI	accurate	none	accurate	none	quantized

Building decision tree includes selecting the best feature from $2K$ features and splitting the M samples into two subsets. Thus, the complexity of building a tree is $O(KM\log_2 M)$.

The decision tree needs no renewal in each dualhop transmission provided that fading environment stays stable. If one time slot is 0.5ms, the source transmits 1000 times per second. As transmissions continue, the decision-tree-based scheme shows its superiority to the optimization-driven scheme.

2) FEEDBACK AMOUNT

In optimization-driven scheme, g_{Sk}, g_{kD} and g_{kE} takes $3K$ real values. In practical systems, 16 bits are usually used to transmit one continuous real value. Thus, the feedback amount is $48K$ bits for each selection. In decision-tree-based prediction, g^q_{Sk}, g^q_{kD} and g^q_{kE} are estimated and fed back to the central controller. Total feedback amount is $K\log_2(N_D+1)^2(N_E+1)$ bits, which is much lower than $48K$ for practical values of N_D and N_E.

In decision-tree-based scheme, training data contains M samples of $(\mathbf{x}_m, y_m)$, leading to $3K\times M$ real values, i.e. $48KM$ bits. In prediction phase, if one time slot is 0.5 ms, S transmits for 1000 times per second. For $N_D = N_E = 15$, the feedback amount of is $12K$ bits per second, economizing $36K10^3$ bits per second compared with optimal selection. M is the order of 10^3, so it takes only several seconds to compensate the delay caused by training data collection.

3) CSI ACCURACY

In secure relay selection design, acquiring eavesdropper's CSI is a difficult task. Optimization-driven schemes require accurate eavesdropper CSI while decision-tree-based scheme only requires quantized eavesdropper CSI. The costs of decision-tree-based selection and comparison schemes are compared in Table 2.

VI. CONCLUSIONS AND DISCUSSIONS

In this paper, we propose a decision-tree-based relay selection scheme for secure dualhop wireless networks. Input features are generated by quantization of legitimate and eavesdropper CSI. To analyze the influence of quantization parameters, we derive three splitting criteria - information gain, information gain ratio and Gini index. We evaluate the performance of the decision-tree-based scheme via simulation, and compare it with optimal selection and other comparison schemes. Simulation results show that if quantization parameters are set properly, the decision-tree-based scheme achieves comparable average secrecy rate to optimal selection results. Cost analysis reveals that the decision-tree-based scheme has advantages in lower computational complexity, smaller feedback amount and lower eavesdropper CSI requirement.

In this paper, we have assumed that all channels in the dualhop network experience i.i.d. Rayleigh fading, based on which expressions of splitting criteria are derived and simulation results are presented. The proposed scheme can be extended to other channel models, such as non-i.i.d. fading, imperfect CSI, etc. The key issue is how to design quantization parameters for new channel models.

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XIAOWEI WANG (Member, IEEE) received the B.S. degree in communication engineering from Jiangsu University, Zhenjiang, China, the M.S. degree in control theory and engineering from Shanghai University, China, and the Ph.D. degree in communication and information systems from Shanghai Jiao Tong University, China. From June 2014 to June 2017, she was a Postdoctoral Fellow with the Department of Automation, Shanghai University. She is currently working with the College of Information Engineering, Shanghai Maritime University, Shanghai, China. Her research interests are in the fields of communication theory, wireless networks, and physical-layer security.

FENG LIU (Member, IEEE) received the B.E. and M.E. degrees in electronic and communication engineering from the Harbin Institute of Technology, Harbin, China, in 1999 and 2001, respectively, and the Ph.D. degree in electronic engineering from Shanghai Jiao Tong University, Shanghai, China, in 2009. From 2009 to 2010, he was a Postdoctoral Researcher with The Chinese University of Hong Kong, Hong Kong. He has been a Software Engineer at Huawei Technology, Beijing, China, since 2001, and has been an Algorithm Engineer in Shanghai, since 2008. Since 2011, he has been with the College of Information Engineering, Shanghai Maritime University, Shanghai, where he is currently an Associate Professor with the Department of Electronic Engineering. His research interests include MIMO systems, wireless communications, and network information theory.