Spectrum Cost Optimization for Cognitive Radio Transmission over TV White Spaces using Artificial Neural Networks

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***Abstract*—In this paper, the use of TV White Spaces (TVWS) by small cognitive radio wireless network operators (SCWNOs) is considered in order to support the growing demands for IoT applications in smart grid and smart cities. In order to support the wide range of services and applications that are being offered by SCWNOS, spectrum leasing could be considered as an alternative solution to achieve improved Quality of Service (QoS). We consider a situation whereby in order to satisfy the QoS requirements, SCWNOs can decide to lease a certain part of the TVWS spectrum that is referred to as high priority TVWS channel (HPC) for a certain period and pay a fee depending on the duration of HPC spectrum usage. We develop an Artificial Neural Networks (ANN) based online algorithm to determine the optimal transmission decision per time slot that would minimise the overall HPC leasing cost of the SCWNOs while satisfying the QoS constraints. The simulations results shows that our proposed ANN based online algorithms outperforms the Lyaponuv based online algorithm while its performance is very close to the optimal offline solution with 99% accuracy.**

I. Introduction

The rapid increase in the number of machine type devices and internet of things (IoT) applications would result in an enormous demand for wireless spectrum [1]. Cognitive radio (CR) provides a means of opportunistically exploiting unused frequency channels for communication by an unlicensed or secondary user when the licensed or primary user is absent [2]. However, exploiting the licensed frequency spectrum might not be sufficient to handle the enormous demands that would be placed on the network due to anticipated massive deployment of IoT devices in 5G networks [3]. Recently, the TV white space (TVWS) have become available as a result of the migration of TV broadcasting from analog to digital transmission [4], [5]. This TVWS spectrum can be exploited using CR technology to facilitate IoT applications such as smart grid, smart health, and smart cities.

The free utilization of the TVWS for CR transmission would bring about the establishment of many new cognitive radio networks (CRNs) as well as other virtual wireless networks (VWN) that would support machine-to-machine communications (M2M). The operators of these kind of networks can be refereed to as small cognitive radio wireless network operators (SCWNO) [6]. Competition is bound to arise between conventional mobile network operators and the SCWNOs for the utilization of the available TVWS since it does not require any spectrum leasing fee. This has given rise to some proposals [5] requesting that certain channels within the TVWS be designated as high priority channels (HPCs) which interested SCWNOs can lease temporarily for a fee in order to support the varying QoS demands of various IoT applications and services.

The major challenge that confronts SCWNOs is to minimize the HPC leasing cost while satisfying the various QoS requirements of IoT applications. Opportunities abound, owing to the varying QoS requirements of IoT applications, which SCWNOs can take advantage of, in order to minimize the HPC leasing cost [7]. For example, data packets of delay tolerant IoT applications can be queued pending when free TVWS spectrum becomes available before they are transmitted. In addition, the size of data packets for certain applications can be reduced before transmission by exploiting certain redundancies in data measurements (e.g. smart meter readings) which would result in reduced quality of data transmission but lesser HPC leasing cost.

Depending on the information that can be obtained regarding channel availability and spectrum leasing, the optimization of HPC spectrum leasing cost for CRNs can be classified into offline and online solutions. Offline solutions are developed when there is non-causal information about the channel availability as well as spectrum leasing cost. However, its is not feasible to apply such developed offline solutions in an online setting as it will produce sub-optimal results. Online solutions are developed when there is causal information about the channel availability and spectrum leasing cost and can be solved using dynamic programming techniques. However, the development of an online algorithm to learn the optimal policy for spectrum leasing cost often suffer from the curse of dimensionality when the dimensions of the system becomes very large and such solutions cannot adapt when probabilities change. Both offline and online solutions maps a given state of a system e.g. channel condition and HPC leasing cost to a specific transmission decision e.g. either to transmit/not transmit or transmit full/reduced size. Therefore, an optimal offline transmission decision policy also contains the information regarding the mapping of a given input or state of the system to the required output or transmission decision. Thus, using the optimal offline solution, the mapping of the system state to the optimal transmission decision that will minimize the overall HPC leasing cost can be learnt, which can be exploited to design an online solution with near optimal performance even for networks with very large dimensions.

In [6], we developed an optimal offline solution for minimizing the overall HPC leasing cost of SCWNOs with strict constraints on transmission delay and data quality. The work in [6] was extended by developing a Lyaponuv based online algorithm [8] for minimizing the overall HPC leasing cost of SCWNOs. The outcome of the simulation indicated that the proposed online algorithm produced results that are very close to the optimal lower bound offline solution, however, very relaxed constraint regarding the transmission delay and the quality of data were considered. As stated earlier, due to the impracticability of applying the offline to online setting, the difficulty of generalising the solutions of the online algorithms as well as the "curse of dimensionality" challenges, we propose an Artificial neural networks (ANN) based online algorithm for minimizing the HPC leasing cost of SCWNOs.

The ANN is able to learn the mapping between the state of the system and the optimal transmission decision in order to minimize the overall HPC leasing cost. The motivation for using ANN is because of its excellent generalization ability and its increasing application for the optimization of the performance of wireless communication networks [9]–[14]. The data we used to train our ANN is obtained from the optimal offline solution. The ANN model obtained is then applied to obtain the optimal transmission decision in an online setting when the channel state and HPC leasing cost are feed into it as inputs. Simulation results shows that the performance of our ANN based online algorithm for minimizing HPC leasing cost is very close to the optimal offline solution with strict constraints and outperforms the Lyapunovs based online solution with relaxed constraints.

The remaining parts of the paper is organized as follows. The system model and problem formulation is presented in Section II. Section III details the proposed ANN based online algorithm, in Section IV the simulation results are presented while Section V concludes the the paper.

II. System model and problem formulation

We consider a discrete time system with equal duration time slots. We assume a CR node has N data packets which are required to be transmitted in $D \geq N$ time slots. We also assume that CR node can reduce the size of $A \leq N$ data packets without compromising the overall data quality. Radio spectrum availability is random and we assume that CR node cannot transmit more than one data packet (either full size or reduced size) in any given time slot. Let $h(t)$ denotes the random state of harvested radio spectrum in time slot t. We assume $s(t) \in \{0, 1, 2\}$ has three states where: state 0 correspond to non-availability of harvested spectrum, state 1 corresponds to availability of harvested spectrum for reduced size packet transmission, and state 2 corresponds to the availability of harvested spectrum for full size packet transmission.

In order to guarantee the transmission of N data packets in D time slots, CR node can also lease radio spectrum from licensed spectrum owners. However, spectrum leasing incurs cost and we assume spectrum leasing cost are also time varying. Let, $c^f(t)$ and $c^r(t)$ respectively denote the spectrum costs for the transmission of full size and reduced size data units. We also assume $c^r(t) < c^f(t)$. The objective of CR node is to minimize the transmission cost of N data packets in D time slots with at most A packets of reduced size.

In order to formulate the optimization problem, we introduce four binary decision variables in each time slot t. Let, $\mathcal{A} = [d_h^f(t), d_h^r(t), d_l^f(t), d_l^r(t)]$ respectively denote the binary decision variables associated with the transmission/non-transmission of a full size or a reduced size data packet on harvested and leased spectrum. Note that subscript h indicates spectrum harvesting and l indicates spectrum leasing, while the superscript f indicates full size packet transmission and r indicates reduced size packet transmission. We assume causal information availability on $s(t)$, $c^f(t)$ and $c^r(t)$ and formulate the following cost minimization problem:

$$\min_{\mathcal{A}} \mathcal{C} = \mathbb{E}\left[\sum_{t=1}^{D} \left(d_l^f(t)c^f(t) + d_l^r(t)c^r(t)\right) 1_{\{s(t)<2\}}\right] \quad (1)$$

subject to the following constraints,

$$\sum_{t=1}^{D} d_h^f(t) + d_h^r(t) + d_l^f(t) + d_l^r(t) = N \quad (2)$$

$$\sum_{t=1}^{D} d_h^r(t) + d_l^r(t) \leq A \quad (3)$$

$$d_h^f(t) + d_h^r(t) + d_l^f(t) + d_l^r(t) \leq 1, \quad \forall t \quad (4)$$

$$d_h^f(t) \in \{0,1\}, d_h^r(t) \in \{0,1\}, d_l^f(t) \in \{0,1\}, d_l^r(t) \in \{0,1\}, \forall t \quad (5)$$

$$s(t) \in \{0, 1, 2\}, \forall t \quad (6)$$

where, (2) provides strict guarantee on the transmission of N packets in D time slots, (3) is required to maintain data quality, (4) ensures that a maximum of only one decision variable can become 1 in any time slot t, (5) is due to binary nature of decision variables, and (6) indicates the state of harvested spectrum in time slot t. It should be noted that $1_{\{s(t)<2\}}$ in the objective function is an indicator function that is 1 if $s(t) < 2$ indicating that harvested spectrum is not sufficient for the transmission of full size packet in time slot t.

In general dynamic programming may be used to solve this problem. However, dynamic programming requires more stringent system modeling assumptions, knowledge of spectrum availability and leasing cost probabilities, cannot adapt when probabilities change, and the computation of value function suffers from curse of dimensionality in large dimensional systems. In [6], an offline solution is developed for this optimization problem under the assumptions of non-causal information on spectrum availability and leasing costs in all D time slots. The performance of the online heuristic presented in the same paper is far from the optimal offline solution. In this paper, we propose an ANN based online solution. ANN learns the optimal online solution by using optimal offline solution.

III. Intelligent online solution

We propose an ANN based online algorithm to learn the optimal transmission decision policy per time slot that would result in the overall minimization of the HPC leasing cost of SCWNOs. In order to facilitate the proposed algorithm, first, the optimal offline solution in [6] is exploited, such that it is run with the given input values $(A, s(t), c^f(t), c^r(t))$ and the output ($\mathcal{A}$) is produced accordingly. Therefore, in order to train the proposed ANN model, a data set, which is composed of inputs (features) and the outputs (labels), is created by running it for different inputs. ANN has already being used in wireless communication network optimization [9]–[12] due to its abilities in dealing with large dimensions and ease of implementation. Moreover, it outclasses the statistical methods in regression problems, as it does not require any prior knowledge about the underlying distribution in the data [2]. On the other hand, the current case is treated as a classification problem, where the elements in $\mathcal{A}$ constitute the classes, and ANN provides a suitable solution due to its proven performance in solving the classification problems [15].

The developed ANN model is a feed-forward fully-connected neural network comprising input, hidden, and an output layers. The input layer comprises 3 neurons with each neuron corresponding to a feature. Therefore, the features of the proposed ANN model are the channel state, $s(t)$, the HPC leasing cost for full size transmission, $c^f(t)$ and reduced size transmission, $c^r(t)$ respectively. The input is then processed by the hidden layers in order to produce the output which is the optimal transmission decision per time slot that would result in the overall minimization of the HPC leasing cost. The output layer consists of 5 neurons, each representing a decision in $\mathcal{A} = [d^n(t), d_h^f(t), d_h^r(t), d_l^f(t), d_l^r(t)]$, where the additional $d^n(t)$ variable indicates no transmission, as a class.

The ANN model is able to learn the optimal mapping from the input vector, $s(t), c^f(t), c^r(t)$ to the transmission decision vector $\mathcal{A}$ by properly adjusting the weights and biases associated with the neurons in the network. This can be achieved by minimizing a loss function over a training set. The training process specifically involves minimizing the average error over the whole training data set. The loss function that is used to train the proposed ANN model is sparse categorical cross entropy (SCCE) and it can be expressed as:

$$\text{SCCE} = -\frac{1}{N}\sum_{s\in S}\sum_{c\in C} 1_{s\in c}\log p(s\in c), \tag{7}$$

where s denotes the number of sample points in the training data set and c is the class that each sample point belongs to. The training is achieved through a step by step minimization of the SCCE in (7), by the process of backpropagation.

IV. Simulation results

We model the availability of TVWS channel and HPC spectrum leasing cost as time varying quantities. Three channel states, $s(t) \in \{0, 1, 2\}$, are considered and they include: state 0 corresponds to non-availability of harvested spectrum, state 1 corresponds to availability of harvested spectrum for reduced size packet transmission, and state 2 corresponds to the availability of harvested spectrum for full size packet transmission. The channel states are generated as uniformly distributed integer random variables. The reduced size data transmission is assumed to be half of the size of full size data transmission. The HPC spectrum leasing cost for full sized data transmission, $c^f(t)$, is also generated as uniformly distributed random variable between $[0.5, 5]$$ cents. The leasing cost for half data size transmission, $c^r(t)$, is assumed to be half the leasing cost for full data transmission.

The ANN model consists of an input layer with 3 neurons, 2 hidden layers with 128 neurons in each, and an output layer with 5 neurons. The activation function used for mapping the input layer to the first and second hidden layer is the rectified linear unit (ReLu) while the softmax function is used to map the second hidden layer to the output layer, since a binary decision is required from each neuron in the output layer. The SCCE loss function is used to train the ANN model by utilizing the Adam backpropagation optimizer [16]. The data set used to train the model comprising the channel state, $s(t)$, HPC full data size, $c^f(t)$, and reduced data size spectrum leasing cost, $c^r(t)$ as well as the optimal transmission decision for each time slot, $\mathcal{A}$ was obtained from the offline algorithm. The offline algorithm was run two times in order to obtain a separate data set for model training and another data set for model testing. The ANN training was performed using the machine learning library known as TensorFlow Keras library. The training data set was first divided in batches, each comprising 32 sample points, after which each batch was fed into the ANN model in order to reduce the computational cost involved in model training as well as prevent over-fitting problem. The training process was performed over 30 epochs.

We compare the performance of the proposed ANN based online solution with the optimal offline algorithm in [6] and the Lyapunov based online solution developed in [8]. The performance of the proposed ANN based online algorithm is shown in Fig. 1 where we plot the accumulated HPC spectrum leasing cost of our proposed ANN based online algorithm, Lyaponuv based online algorithm and the optimal offline algorithm for different values of V, where V is a parameter for Lyapunov algorithm that is used to indicate the trade-off in delay, quality, and performance.

From Fig. 1, it can be observed that with smaller V values, the accumulated cost becomes very high. However, as the the values of V increases, the accumulated cost gradually reduces

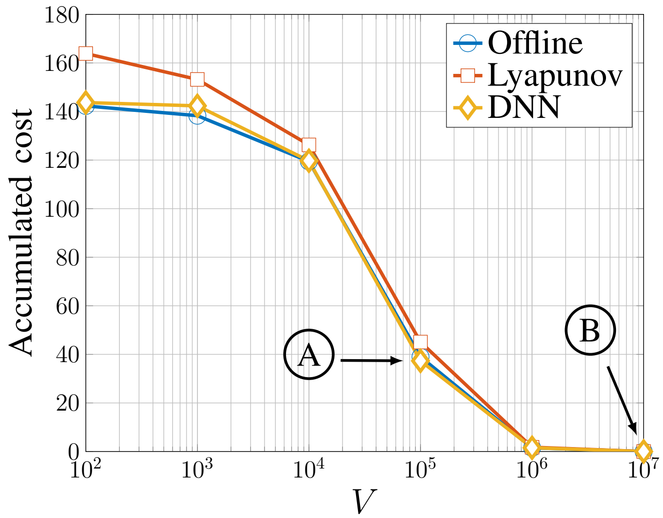

Figure 1. Accumulated cost values against different values of V for offline, Lyapunov, and ANN-based algorithms. Results for ANN-based algorithm is the averages of 10 runs.

until it reaches zero when the values of V becomes very large as depicted by point (B) in Fig. 1. Very large values of V could mean large queue length, or large delay tolerance, hence the data is been queued pending when free channel would be available before they would be transmitted at zero cost. The overall performance of the ANN based algorithms shows that it outperforms the Lyaponuv based online algorithm and its performance is very close to the optimal offline lower bound solution due to its high prediction accuracy (up to 99%).

Due to some prediction errors, our algorithm seems to be giving a lesser accumulated cost than the optimal offline solution at certain V values as depicted by point (A) in Fig. 1. Nonetheless, as it is impossible to outperform the offline solution without violating the constraints, it should be noted that due to prediction errors, our algorithm violates the strict constraints of the optimal offline solution on some few occasions, leading to sub-optimal solution with less HPC costs. Moreover, the prediction inaccuracies tend to increase with increasing values of V. However, the overall performance of the proposed ANN framework is satisfactory, since the above-mentioned problems arising from inaccurate predictions are quite limited.

V. Conclusion

In this paper, an ANN based online algorithm for obtaining the optimal spectrum leasing cost for cognitive radio transmission over TVWS is proposed. The offline algorithm for this problem produces the optimal lower bound solution but would yield sub-optimal solutions when applied online. We exploit the results of the offline solution to train our ANN based online solution in order to obtain an optimal transmission decision policy that would minimize the overall HPC spectrum leasing cost. The results of the simulations show that the ANN based online solutions produces very good performance that is comparable to the optimal offline solution with accuracy up to about 99%.

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