Optimization and Learning in Energy Efficient Resource Allocation for Cognitive Radio Networks

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***Abstract*—The recent surge in real-time traffic has led to serious energy efficiency concerns in cognitive radio networks (CRNs). Network infrastructure such as base stations (BSs) host different service classes of traffic with stringent quality-of-service (QoS) requirements that need to be satisfied. Thus, maintaining the desired QoS in an energy efficient manner requires a good trade-off between QoS and energy saving. To deal with this problem, this paper proposes a deep learning-based computational-resource-aware energy consumption technique. The proposed scheme uses an exploration technique of the systems' state-space and traffic load prediction to come up with a better trade-off between QoS and energy saving. The simulation results show that the proposed exploration technique performs 9% better than the traditional random tree technique even when the provisioning priority shifts away from energy saving towards QoS, i.e., $\alpha \geq 0.5$.**

Keywords*—CRNs, Energy efficiency, Resource allocation, Bipartite matching, Resource percentage threshold, Power consumption, Energy saving.

I. Introduction and Background

Due to the increase in data rate requirements, the rate of change of network traffic in future communication networks brings new challenges in terms of network energy consumption [1]. The stringent QoS requirements of multimedia and other real-time mission critical applications hosted by wireless networks has resulted in huge energy consumption [2]. As a result, concerns regarding energy consumption in terms of network operational costs have escalated. Thus, designers are faced with the pervasive problem of maximizing user QoS satisfaction while simultaneously minimizing the energy consumption of the networks' computational equipment(s). However, upholding QoS requirements by increasing power has substantial effects on energy consumption, while reducing power degrades QoS performance [3]. Therefore, quantifying the trade-off between energy consumption and QoS have become the key parameters that require a balanced optimization.

Research contributions have proposed the installation of new energy-efficient hardware to reduce network operation costs [4]. However, this does not seem to fully solve the problem since it is a costly exercise that has consequences of invariably over or under-provisioning network resources with respect to traffic demands [5]. Thus, more energy-efficient resource management schemes, capable of controlling the amount of network resources required at a certain time, can be an effective solution. There are numerous studies to allocate resources reasonably by considering QoS requirements for SUs that consider the energy problem that use partially observable Markov decision processes [6], retry policies [7], queueing theory [8], [9]; etc.

From the above literature, it is evident that a possible solution in QoS provisioning relies heavily on various factors such as the degree of cooperation between PUs and SUs and the reliability of spectrum sensing. However, an energy saving solution relies on the decision making inside the computational equipment(s) of the BS. To circumvent this issue, QoS and Energy Efficiency solutions have been proposed from the energy saving. As a result, an energy saving technique known as the EARTH model which switches BS operation between ON/OFF mode based on the traffic load [10]. Even though this technique offers energy efficient operation by reducing overall network power consumption, it has some drawbacks. When a BS is switched ON/OFF, there is a switching cost incurred in terms of state transitioning time and the energy required to do so. The energy consumed during this process is a significant amount and cannot be ignored [11]. Another technique referred to as green cellular networking incorporates hybrid energy supply through the use of grid power supply and energy harvested from solar and wind. The BS can selectively switch between these power sources in order to reduce network operation energy costs. As it eases the stress on high energy consumption it also reduces the escalating concerns caused by carbon dioxide emissions [12], [13]. The last technique involves network traffic prediction where predictive analytics are applied through meta-heuristics [14], [15] and deep architectures (i.e, deep learning) [16], [17]. This technique applies data analytics, which entails the extraction of network traffic patterns and the analysis of trends, to predict future network traffic behavior for energy efficient resource allocation. This seems to be a better approach and makes energy energy saving solutions possible without resources being under or over-provisioned.

Therefore, quantifying the trade-off between energy consumption and QoS provisioning through the application of deep architectures has shown significant benefits in energy saving. In this paper, we are motivated by an interesting contribution in [18], where a computational resource-aware energy consumption model was proposed to capture the total energy consumption of a virtual BS. However, our approach differs from [18] through the use of a separation principle that helps decouple the design of resource allocation, energy consumption, and service QoS provisioning makes the problem manageable. The contributions of this paper are summarized as follows:

- Distributed power allocation and dynamic resource allocation based on SU resource reservation is derived using a channel reservation scheme. Resource reservation solved using geometric programming (GP) and resource allocation is conducted using a weighted bipartite matching technique where multi-objective oriented bipartite graphs facilitate resource allocation through regenerative bipartite graph concepts.

- The amount of consumed resources is obtained and treated as the BS load efficiency and a weighted cost function that weighs the servers' computational power consumption and traffic load is defined. The weighted cost function is treated as a Lyapunov candidate [19] and solved using an online management technique where the BS processor is treated as a hybrid switching system. Control actions are obtained such that the weighted cost function is associated with reaching a best state and maintaining it.
- Finally, the control actions are applied as inputs to a stacked autoencoder (SAE). Using this formulation, the relevant parameters of the operating environment are estimated and used by the system to predict the future behavior over a finite horizon. The predicted future behavior of specified QoS requirements is optimized by selecting the best control inputs to apply to the system to make decisions on either QoS provisioning or energy saving provisioning as is necessary.

The rest of this paper is organized as follows: The resource allocation system model is presented in Section **II**. The mathematical description of the model is presented in Section **III**. The solution of energy efficient resource allocation together with the prediction model are given in Section **IV**. In Section **V**, the simulation results are presented and Section **VI** then concludes the paper.

II. Proposed System Model

Considered here is a single-cell CRN where several SUs are non-uniformly distributed in the primary network where they coexist with two PUs and a BS, as shown in Fig. 1. We consider an instance where the BS is serving K SUs over J shared resource blocks (RBs). The BS is assumed to use the OpenFlow software defined networking (SDN) standard defined in [13]. Using this SDN standard it can monitor network information and subsequently decide on best configurations to be applied in the entire CRN. It is assumed that the BS can predict its future traffic and energy consumption right after the current time slot to provide QoS to its covered users.

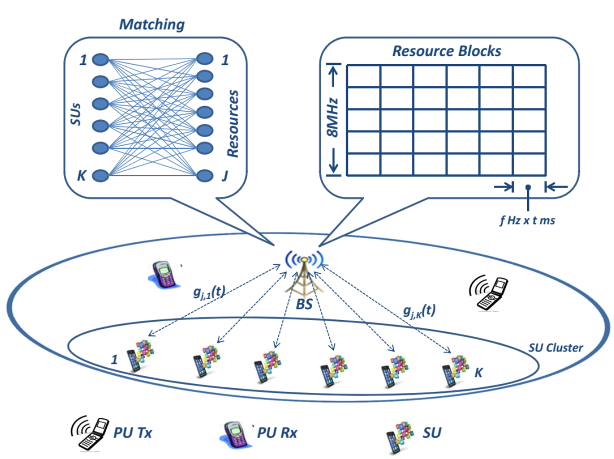

Fig. 1: Resource allocation characterized as a weighted bipartite matching problem.

III. Problem Formulation

A. Spectrum Efficiency Analysis

Let $P_{j,k}$ be the SU transmission power, whose value is adjusted based on PU activities. Thus, the spectral efficiency of SU k accessing RB j is given as

$$R_{j,k} = \xi \cdot \log_2(1+\gamma_{j,k}), \qquad \gamma_{j,k} = \frac{P_{j,k} g_{j,k}}{\sigma^2 + \mathcal{I}_k}, \tag{1}$$

where ξ is the system bandwidth, $\gamma_{j,k}$ is the signal-to-interference-plus-noise ratio (SINR), $g_{j,k} = \beta_{j,k} d_{j,k}^{-\beta} h_{j,k}$ represents the channel gain at location of SU k, where $\beta_{j,k}$ is the path-loss coefficient, $d_{j,k}$ is the distance from the SU to the BS, $h_{j,k}$ is the fading coefficient, and β is the path-loss exponent [20]. $\mathcal{I}_k$ denotes the interference caused other simultaneous transmissions, and σ^2 designates the noise spectral density. Therefore, the UL rates achieved by all SUs can be obtained using

$$R_{j,k} = \frac{\xi \varsigma^{th}}{\lambda} \log_2\left(1+\gamma_{j,k}\right), \tag{2}$$

where $\frac{\xi \varsigma^{th}}{\lambda}$ is the fraction of resources reserved for SUs. The terms ξ and ς are respectively the system bandwidth and the resource percentage threshold for SUs, computed as

$$\xi = \log(1+\gamma) - \varsigma \log \gamma, \qquad \varsigma = \frac{\gamma}{1+\gamma}, \tag{3}$$

and λ is the total number of SUs currently served.

B. The Optimization Problem

To maximize SU capacity based on the number of PUs currently being served, dynamic resource reservation is covered by (2) and (3). The resource allocation optimization problem is formulated as

$$\mathbf{P1} = \arg\max_{\mathbf{P}} \sum_{j=1}^{J} \sum_{k=1}^{K} R_{j,k}, \qquad \text{subject to} \tag{4}$$

$$\mathbf{C1}: \sum_{j=1}^{J} P_{j,k} \leq P_{max}, \tag{5}$$

$$\mathbf{C2}: \left\{ \sum_{j=1}^{J} P_{j,k} |g_{j,k}|^2 > \mathcal{I}_{th} \right\} \leq \delta, \tag{6}$$

where $\mathbf{P}$ is the set of all $P_{j,k}$, (5) imposes a constraint that the UL transmission power must be lower than maximum allowed power P_{max}, and (6) restricts the collision probability to PU transmissions not exceed δ.

C. Traffic Load and Power Consumption

The total BS energy consumption is obtained from a combination of the power consumed by its components, given as

$$P(\upsilon,\rho,t)=\upsilon(t)P_{on}(t)+P_{tx}(t)+P_{server}(\rho,t), \quad (7)$$

where $\upsilon(t) \in \{\varepsilon, 1\}$, $\varepsilon \neq 0$ denotes BS switching status (1 for active mode and ε for power saving mode), and $\rho(t)=\lambda(t)/\mu(t)$ is the server utilization factor at time slot t. The terms $\lambda(t)$ and $\mu(t)$ denote the arrival and processing rates of the data streams, respectively. $P_{on}(t)$ is the load-independent power consumption, $P_{tx}(t)$ represents the BS load-dependent total transmission power, and $P_{server}(\rho,t)$ is the load-dependent computational energy consumption of the server; defined as $P_{server}(\rho,t) = P_{idle}(t)+\rho(t)P_{comp}(t)$. Here, $P_{idle}(t)$ is the server's load-independent operational component, $P_{comp}(.)$ is the maximum amount of energy consumed by the computational components of the server scaled with respect to the current load $\rho(t)$. We thus define a weighted cost function as

$$J(\upsilon,\rho,t) \triangleq (1-\alpha)P(\upsilon(t),\rho(t),t)+\alpha(\varphi(t)-\rho(t))^2, \quad (8)$$

where $\alpha \in [0,1]$, is the optimization weight, the quadratic term $(\varphi(t)-\rho(t))^2$ accounts for the QoS cost, where $\varphi(t)=\ell(t)/\ell_{max}$ is the approximation of the normalized BS load at time slot t, where $\ell(t)$ is the offered load and ℓ_{max} is maximum load that the BS queue can hold, [21]. The final optimization problem is defined as

$$\mathbf{P}^{**}: \min_{\upsilon,\rho} J(\upsilon,\rho,t), \quad (9)$$

subject to:

$$\begin{aligned} &C1^*: 0 \leq \rho(t) \leq 1,\\ &C2^*: \upsilon(t) \in \{\varepsilon,1\},\\ &C3^*: I(t) \geq b, \end{aligned} \quad (10)$$

where $\mathbf{C1}^*$ specifies the server utilization factor bounds, $\mathbf{C2}^*$ specifies the BS operation status, and $\mathbf{C3}^*$ enforces resource reservation by forcing the required number of channels $I(t)$ to be always greater than or equal to a minimum number $b \geq 1$ to make sure the BS has space for processing mission critical applications.

IV. Proposed Solution Formulation

To solve (4), the BS checks its admission control condition by increasing the number of SUs by 1 to obtain an admission condition. The new admission condition is then compared with an admission bandwidth threshold, ξ^{su}, $\xi_{new} \geq \xi^{su}$. This leads to an admission constraint ϕ, given as

$$\phi = \left\{ \begin{array}{ll} 1, & \xi_{new} \geq \xi^{su} \\ 0, & \text{Otherwise,} \end{array} \right\} \quad (11)$$

where $\xi_{new}=\frac{\xi\varsigma^{th}}{\lambda+1}$. Then, the total number of SUs attempting to connect to the BS can be given by

$$\lambda = \frac{\xi\varsigma^{th}}{\xi_{new}} - 1 = \xi\varsigma^{th}(\xi^{su})^{-1}. \quad (12)$$

So, if $0 \leq \frac{\xi\varsigma^{th}}{\xi_{new}} - 1 \leq \xi\varsigma^{th}(\xi^{su})^{-1}$, it means the BS is under-loaded, thus the admission probability equals 1. If $\frac{\xi\varsigma^{th}}{\xi_{new}} - 1 > \xi\varsigma^{th}(\xi^{su})^{-1}$, the BS is overloaded and new connection requests are rejected.

To obtain the resource consumption efficiency, multi-dimensional resource allocation is done bipartite matching. Assume a single bipartite graph where SUs form a set $\mathcal{K}$ on one side and RBs form a set $\mathcal{J}$ on the opposite side, and $\mathcal{K} \leq \mathcal{J}$. The result is a graph data structure where the two sets $\mathcal{K}=\{1,2,\cdots,K\}$ and $\mathcal{J}=\{1,2,\cdots,J\}$ are two independent sets constructed using SUs and RBs. This results is supported by the Hall's theorem in [22] where a weight is added to an edge that connects SUs to the number of RBs allocated to them. To conclude the solution, the number of RBs consumed by each SU is represented as

$$r_k = \sum_{j\in J} a_{kj} b_{iu_k}, \qquad b_{iu_k} = \frac{b_{min}}{b_{max}}, \quad (13)$$

where $\{a_{kj} \in [0,1] | j=1,\cdots,J\}$ is a binary variable indicating the usage of the $j \in J$ RBs by each SU k. The term b_{iu_k} is the number of consumed RBs, where b_{min} is the minimum required long-term rate which represents the rate QoS class. Then, the resource consumption efficiency can be given as

$$\rho(t) = \frac{R_{jk}(t)}{r_k(t)}. \quad (14)$$

Using this value, and the values associated with the parameters including the maximum BS capacity $\varphi(t)$, the energy consumption cost function $J(\upsilon,\rho,t)$ in (9) can now be solved. To solve $J(\upsilon,\rho,t)$, we employ an online management technique where the cost function is treated as a Lyapunov candidate, discussed in [19]. Here, the BS processor is treated as a hybrid switching system where $J(\upsilon,\rho,t)$ is associated with a search of an optimum operating state, which when reached is maintained until parameters are updated. The control actions that drive the SAE in the next time-slot $t+1$ are $\varrho(t) \triangleq (\upsilon(t),\rho(t))$. Thus, the system state vector which contains the inputs to the SAE at time-slot t is denoted by $x(t)=(\varrho(t),\varphi(t))$. The procedure exhaustively explores the system operating states within a prediction horizon T as outlined in **Algorithm 1**:

A. Algorithm Discussion

The terms $x(t)$ and $\hat{x}(t)$ denote the actual and estimated states of the system, respectively; $u(t)$ and $\hat{u}(t)$ represents the actual and estimated system control parameters. $\mathcal{S}_t$ and $\mathcal{S}_{t+1}$ are the representation of the systems' state-space, at time-slot t and $t+1$, respectively. Our approach utilizes an exploration technique from reinforcement learning. It assigns the current value of $\ell(t)$ into a system state $x(t)=[\varsigma(t),u(t)]$ as the input vector that drives the system behavior at time t. The system evolution is described in terms of a discrete-time state-space equation, adopted from [23]. By initializing the cost function $J(x,t)$ to zero; a breadth-first search begins by building a tree of all future states up to the prediction depth T. The cost is accumulated as the search travels through the tree, accounting for predictions and past outputs. The set of states reached in every prediction depth $t+n$ become the state space $\mathcal{S}(t+n)$. For every prediction depth $t+n$, the search continues from the set of states $\mathcal{S}(t+n-1)$ reached at the previous step $t+n-1$, exploring all possibilities of obtaining the next system state; updating the accumulated cost as the result of the previous

Algorithm 1: Proposed algorithm to exhaustively evaluate operating states within the prediction horizon T.

Input: b_{iu_k}, T, $x(t)$

Output: $\hat{u}(t)$, $\hat{x}(t)$

Initialize all inputs: $\mathcal{S}_t = x(t)$, $J(x(t)) = 0$
For $t = 1 : T$ **do**
  Predict environment parameters for $t+1$
  $s_{t+1} \neq \emptyset$
  For $x \in \mathcal{S}_t$ **do**
    For $u \in U$ **do**
      Estimate state for $t+1$, $\hat{x} = \phi(x, u)$
      $J(\hat{x}) = \min_{u(.)} J(x(t), u(.))$
      $\mathcal{S}_{t+1} = \mathcal{S}_{t+1} \cup \{\hat{x}\}$
    End For
  End For
  $t = t + 1$
Find $x_{min} \in \mathcal{S}_T$ with minimum cost $J(x)$
$\hat{u}(t) =$ initial input leading from $x(t)$ to x_{min}
Return $\hat{u}(t)$, $\hat{x}(t)$

accumulated cost, plus the cost associated with the current time step $t+n$. When this exploration has finished, the action at time t that leads to the best final accumulated cost, at time $t+T$, is selected at the optimal operating value.

V. Simulation Results and Discussion

Using the state vector, the SAE is trained for the QoS and energy saving using traffic flow as an input data set obtained from a traffic flow simulator obtained from [24]. The data set is aggregated into time-slots $t = 1$ second and arrival patterns are extracted. The data set is then split into 30% for training and 70% for testing. To validate our main findings, we show some selected numerical results where we consider a cell radius of 300 meters, carrier frequency of 2.1GHz and a system bandwidth of 8MHz (South African standard for CRs), the number of RBs is 100. P_{tx} is 46dBm [40W], P_{on} is 40.25dBm [10.6W], P_{idle} is 50dBm [100W], and P_{server} is 56.74dBm [472.3W].

Fig. 2, presents a resource allocation performance comparison between two variants of dynamic resource percentage threshold (varied with GP alone, GP + Bipartite). Here, it can be observed that the achievable capacity for SUs decreases, but by combining dynamic resource percentage threshold with bipartite matching achieves better performance through the GP solution.

Table I presents root mean square error (RMSE) convergence performance of the training and validation process of the SAE. The SAE was trained using 110 epochs, each epoch consisting of 2,000 individual training trials, with a batch size of 1. As seen from Table Is, a better performance loss of 0.10 (i.e., 10%) is obtained, which is a good performance considering the size of the data. Fig. 3 shows the BS load pattern prediction results based on the SAE DNN architecture for a time horizon of $T = 90$ seconds. Throughout the prediction horizon, there is an upward and downward trend and no obvious seasonality can be observed. This is because the data was aggregated into shorter time scales in order to exposed the microscopic behavior of modern day network

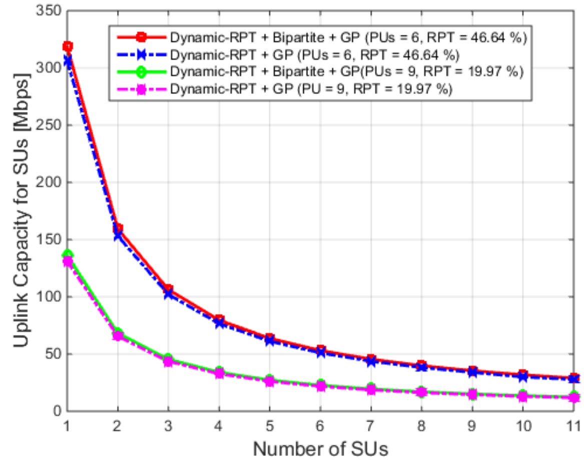

Fig. 2: UL achievable capacity per SU.

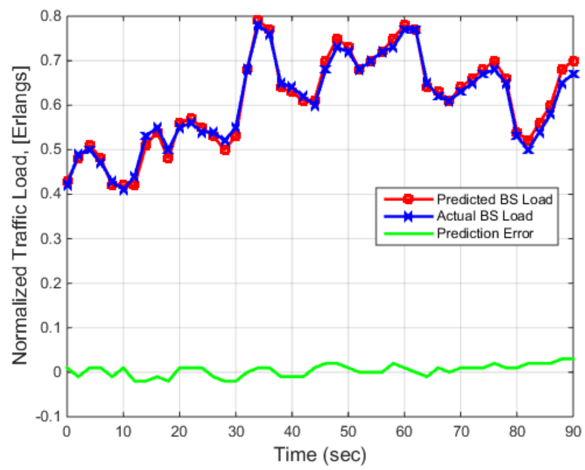

Fig. 3: BS load prediction using an SAE DNN architecture.

traffic. Fig. 4 shows the evolution of the mean energy saving with respect to the optimization weight α. A drop in the energy saving is observed when $\alpha \geq 0.5$, i.e., as $\alpha \to 1$, the QoS is prioritized over BS energy consumption. The exploration technique performs 9% better than the random tree in saving energy even when provision priority shift to QoS at $\alpha \geq 0.5$.

VI. Conclusion

This paper envisioned a computational-resource-aware energy consumption technique using deep learning. The predicted future behavior of QoS requirements is optimized by selecting the best control actions to apply to the system in the trade-off between QoS and energy saving. An exploration technique is proposed to perform the trade-off between energy saving and QoS. The simulation results show that the proposed exploration technique performs 9% better than the traditional random tree technique even when the provisioning priority shifts away from energy saving towards QoS, i.e., $\alpha \geq 0.5$. This shows that

Stacked Autoencoder (SAE)											
Training Epoch	10	20	30	40	50	60	70	80	90	100	110
Training Loss	0.3115	0.2819	0.2284	0.1711	0.1493	0.1185	0.1110	0.1084	0.1065	0.1000	0.1000
Validation Loss	0.2805	0.2529	0.2054	0.1505	0.1399	0.1176	0.1109	0.1082	0.1065	0.1000	0.1000

TABLE I: This table shows the training and validation results for the MLP SAE DNN.

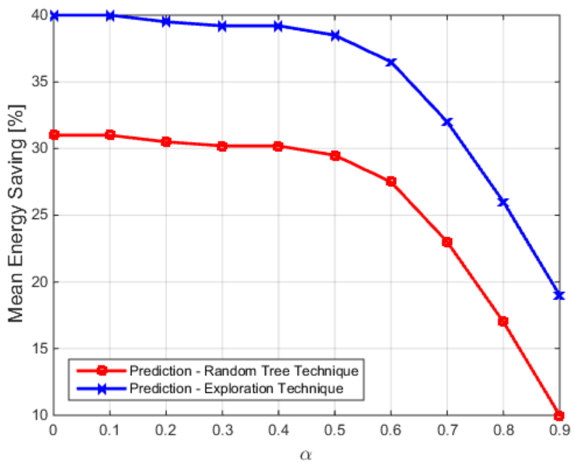

Fig. 4: Mean energy saving as a function of α.

the adoption of predictive analytics can be useful in providing energy efficiency solutions.

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