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VERTEX SEARCH BASED ENERGY-EFFICIENT OPTIMAL RESOURCE ALLOCATION IN COGNITIVE RADIO AD HOC NETWORKS

Abdullah H.M.A., Kumar A.V.S. **Vertex Search based Energy-efficient Optimal Resource Allocation in Cognitive Radio Ad Hoc Networks.**

Abstract. Cognitive Radio Ad Hoc Networks (CRAHN) is the infrastructure-less network model of Cognitive radios developed in an ad hoc manner. Regulating resource allocation in CRAHN is considered to be an energy constrained problem. Many researches have been carried out for allocating spectrum in an efficient way using various protocols. In this paper, the Spectrum-Map-Empowered Opportunistic Routing (SMOR) model has been utilized as the fundamental model for routing and an energy efficient optimal spectrum allocation solution is provided. In the proposed model, the previously modified SMOR model is enhanced for the main objective of energy efficient and optimal resource allocation using Vertex search algorithm with a gradient-based approximation. Initially, the resource allocation problem is modelled into a non-convex optimization problem. The power allocation, data rate adaptation, channel allocation, and user scheduling policies are optimized for maximization of the energy efficiency during data transmission. The proposed Vortex search algorithm resolves this optimization problem by determining the training interval for the channel estimation and power consumption. The experimental results prove that the proposed Vertex search based modified SMOR (VS-M-SMOR) model provides efficient routing with energy efficient optimal resource allocation.

Keywords: Resource allocation, Spectrum sharing, SMOR, Vertex search, energy efficiency, user scheduling.

1. Introduction. Rapidly rising energy costs and progressively inflexible natural models have prompted a rising pattern of tending to "energy efficiency" part of wireless communication technologies [1]. In an ordinary wireless cell network, the radio access part represents up to more than 70 percent of the aggregate energy utilization [2]. In this way, expanding the energy efficiency of radio networks is imperative to address the difficulties raised by the levels of popularity of activity and energy utilization. *Cognitive radio* technology can assume a critical part in enhancing energy efficiency in radio networks [3]. The subjective capacities have an extensive variety of properties, including spectrum sensing [4], spectrum sharing [5] and versatile transmission [6, 7], which are advantageous to enhance the tradeoff among energy efficiency, spectrum efficiency, transfer speed, and deployment efficiency in wireless networks [8, 9]. CRAHN have been developed to provide better performance than normal cognitive radio networks.

Despite the fact that the Primary Users (PUs) still have needed access to the spectrum, the Secondary Users (SUs) are permitted to have limited access subject to an obliged corruption on the PUs' execution [10, 11]. In this new worldview of correspondence, the key outline difficulties of a subjective radio network are accordingly to ensure the insurance of the PUs from intemperate obstruction initiated by the SUs and to meet some Quality-of-Service (QoS) prerequisites for the SUs [12, 13]. Then again, spectrum pooling is an opportunistic spectrum access that empowers the community to the officially authorized frequency bands [14, 15]. The fundamental thought is to combine ghastly ranges from various spectrum proprietors into a typical pool, from which the SUs may incidentally lease unearthly assets amid sit still times of the PUs. In actuality, the authorized system should not be changed, though the SUs access unused assets. In subjective radio settings where the PU exercises on the radio spectrum are exceedingly powerful and the genuine open door for the SU access is little, the issue of how we can viably share the briefly accessible frequency bands among the SUs is of special relevance.

In [16], SMOR routing protocol has been introduced for improving the opportunistic routing performance. This model has provided efficient routing with minimal delay; however due to some limitations the model has been modified in [17] with the inclusion of different approximations and Sparsity-based distributed spectrum map as SDS-M-SMOR. There were fewer hybrid models [18, 19] developed in recent past aimed at improving different aspects of SMOR. However in order further improve the user experience, the optimal channel selections, improved security through relay selection and encryption has also been included in the successive improved models of SMOR. Yet the major focus has always been on the energy reduction for spectrum allocation, for which this paper presents a novel energy efficient optimal resource allocation scheme for SMOR. The proposed model utilizes the energy efficiency concept along with the features of SMOR, M-SMOR, SDS-M-SMOR, OCJ-SMOR, and SCJB-M-SMOR. It converts the resource allocation problem as non-convex optimization and employed the vertex search optimization to resolve it. This model is named as VS-M-SMOR and has been explained and evaluated in the following sections. The remainder of this article is organized as: Section 2 describes some of the related research works. Section 3 presents the system model and section 4 explains the proposed methodology. It is evaluated and the results are provided in section 5 while section 6 makes a conclusion about this research model.

2. Related Works. In [20], Qian et al have proposed a power control mechanism to maximize the energy efficiency of the secondary users along with a guarantee of the QoS parameters. The feasibility condition of the power consumption problem is derived and both centralized and distributed solutions are provided. This approach improved the energy conservation considerably for the spectrum allocation; however, it considers only one cognitive radio which doubts its efficiency of power control for multiple cognitive radios.

Gao et al [21] proposed a framework distributed energy efficient spectrum access for CRAHNs. A multidimensional constrained optimization problem is formulated by minimizing the energy consumption per bit over the entire available subcarrier set for each individual user while satisfying its QoS constraints and power limit. Then a two-step solution is proposed by decoupling it into the unconstrained problem. However, in this model, the lack of consideration for detection errors degrades the performance. Sanchez et al [22] proposed two strategies Rate-Efficient Power Control to maximize the secondary capacity, and Energy-Efficient Power Control to minimize the secondary energy consumption. These strategies adjust the secondary user transmit power with the current transmission probability for improved performance.

Ngo et al [23] proposed two distributed resource allocation mechanisms with the spectrum sharing constraints. This design formulation aims at optimizing the energy efficiency of the power allocation strategy. The devised schemes also take into account the issue of controlling the shares of spectral holes by enforcing lower and upper limits on the number of sub-channels that individual SUs may occupy. This method improves the energy efficient spectrum allocation to the secondary users. Ding et al [24] also proposed a distributed resource allocation scheme with higher energy efficiency using decode-and-forward (DF) and amplify-and-forward (AF), based on convex optimization and arithmetic-geometric mean approximation techniques. This approach utilized a practical medium access control protocol for dynamic spectrum allocation. It maximizes the network throughput through local controls, but the major issue with this technique is the lack of congestion control model.

In [25], the authors proposed a cooperative transmission method for the energy efficient spectrum allocation process. This method uses a heuristic algorithm to solve the resource allocation problem based on the utility-spectrum ratio. The results are provided in a satisfying way however the relay selection problem has not been resolved considerably. In [26], the authors developed a provably convergent distributed algorithm that yields a locally optimal solution for the spectrum allocation problem. An alternative centralized algorithm was also developed for network duality and power control. These approaches provide efficient power control, however, the interference alignment is not precluded. In [27], the authors proposed a cross-layer opportunistic spectrum access and dynamic routing algorithm called ROSA (ROuting and Spectrum Allocation algorithm). ROSA dynamically allocates spectrum resources to maximize the capacity of links without generating harmful interference to other users. However, the problem with the techniques in literature is that they do not consider the power requirements of the secondary users in a dynamic manner.

3. System Model. Consider a downlink CRAHN comprised of a network of PUs, and a network of SUs with single transmitter Tx and K receivers Rx. The network is presumed that the wireless policies are cognitive and proficient of sensing the environment and adjusting their parameters. A sample of the system model is shown in Figure 1.

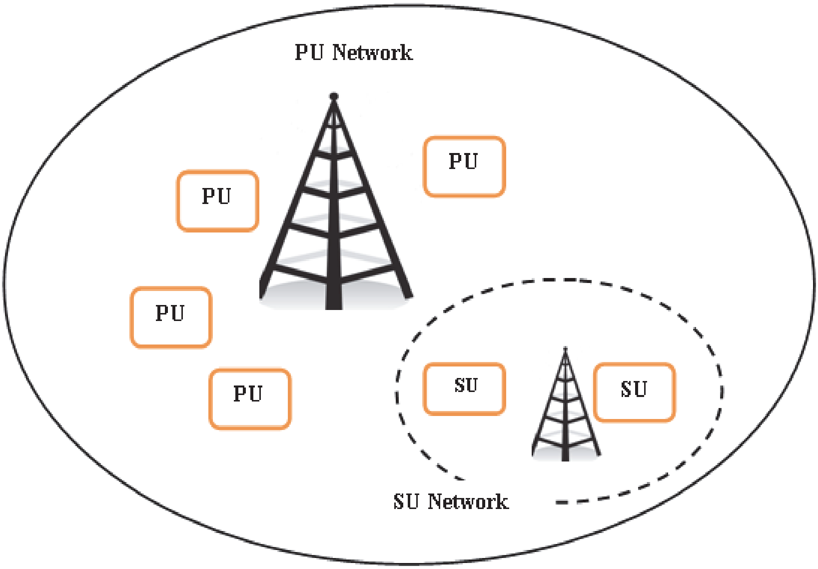

Fig. 1. System Model

In this paper, M PU nodes and N SU nodes with Q orthogonal channels are considered. The transmission energy at i-th PU is denoted by p_i^P and the transmission power at the *j-th* SU is specified by p_j^S while it is presumed that the SU transmitter/receiver pairs are inside the communication range of each other. The communication among the SU or PU pairs can practice intrusion from transmissions stemming from other PUs or SUs that are consuming the same channel and are in the sensing range of the receivers. Given the channel and transmission power as the network resources, the aim is to allot these resources such that the intrusion that SUs origin to the PUs will be decreased and SUs be capable to interconnect to each other. The aim of the PU network is to fulfill its QoS necessities with the minimum energy consumption while the SU nodes should evade accumulation intrusion to the PU nodes while trying to find a spectrum hole for their own communications.

4. Vertex Search Optimization Based Modified SMOR Routing Model. In the proposed method, the resource allocation problem is modelled into a non-convex optimization problem. It is resolved using vertex search optimization with gradient approximations. The channel between the Tx and Rx is given as h_k and the channel estimation error is given as e_k [28]. At the beginning of each transmission block, Tx receives training signals from Rx for estimating channel states over a training interval T_t. Based on the received signals, the channel with minimum mean square error is estimated and denoted as $\bar{\bar{h}}_k$. With $\bar{\bar{h}}_k$, the achievable sum rate is given as

$$R\left(T_t, s, p_d\right) = \sum_{k=1}^{K} s_k \frac{T - KT_t}{T} \log\left(1 + \frac{p_d \,|\, \bar{\bar{h}}_k \,|^2}{\sigma_n^2 + p_d \sigma_e^2}\right). \quad (1)$$

Here p_d is the channel training transmission power and p_T is the data transmission power, s is the scheduling status and r is the relay status. The term $\frac{T - KT_t}{T}$ illustrates the loss of time for data transmission caused by the time T_t for channel training σ_n^2 is the additive noise power and $p_d \sigma_e^2$ is the self-interference power.

The net energy dissipation is given as

$$E\left(T_t, s, p_d\right) = P_S + \frac{KT_t}{T} p_T + \frac{T - KT_t}{T} p_d - EH\left(T_t, s, p_d\right). \quad (2)$$

Here P_S is the constant energy consumption in circuits, $\frac{KT_t}{T} p_T$ is the power consumed for estimating the channels, $\frac{T - KT_t}{T} p_d$ is the power consumed for estimating the transmitting data and $EH\left(T_t, s, p_d\right)$ is the harvested energy at the Rx.

The energy efficiency of the entire CRAHN is the achievable rate per unit energy which is represented as

$$E_E = \frac{R(T_t, s, p_d)}{E(T_t, s, p_d)} \quad (3)$$

The optimal resource allocation can be achieved by modelling the E_E into optimization problem as follows:

$$\max_{T_t, s, p_d} \frac{R(T_t, s, p_d)}{E(T_t, s, p_d)} \quad (4)$$

Such that $s_k r_k \geq s_k r_{min}$ $r_k \geq s_k r_{min}$ and $0 \leq p_d \leq p_{max}$. These constraints ensure the scheduled data rate as minimum, amount of energy harvested is larger than energy dissipated and ensures that only one Rx schedules for one ID. Thus effective non-convex optimization problem is formulated.

In order to resolve this problem, vertex search (VS) with gradient approximation is introduced. The VS algorithm is a reasonably new global optimization method initially proposed by Berat Dogan and Tamer O lmez [29]. It is an effective meta-heuristic technique which gives a decent harmony between the exploration and exploitation. But VS is easy to trap into the local optimum and neglects to discover global optimum. Therefore, it can't generally manage the optimization problem effectively. To control the individuals all the more proficiently moving towards to the feasible region, the pre-assessed method can be utilized to recognize the obscure area for conceivable moves. Subsequently, an enhanced VS utilizing gradient-based approximation is proposed. The gradient-based approximation is specifically following up on focuses. In the wake of setting a point as the inside, the gradient course of this point is ascertained and an arbitrary search in the negative gradient bearing of the fact of the matter is finished. In the event that a superior point is found in this procedure, at that point, the inside will be refreshed. VS-G utilizes gradient matrix to decide the heading of search and the gradient-based approximation is utilized as an indicator to discover the route towards the feasible region.

In the two-dimensional optimization problem, the initial solution is computed as

$$u_0 = \frac{upper\,limit + lower\,limit}{2}. \quad (5)$$

Here upper limit and lower limit are dx1 vectors that define the bound constraints of the problem in d-dimension space. Then a number of neighbour solutions are randomly generated using Gaussian distribution as

$$p\left(z|u,\Sigma\right)=\frac{1}{\sqrt{(2\pi)^{d}\ |\Sigma\ |}}exp\left\{-\frac{1}{2}(z-u)^{T}\sum(z-u)\right\} \tag{6}$$

Here d represents the dimension, z is the $d\times 1$ vector of a random variable, u denotes $(d \times 1)$ vector of the sample mean and Σ is covariance matrix. Then the solutions that are beyond the boundary limits are neglected and a bounded solution is chosen. If the selected minimum solution is better than the best solution found so far, then this solution is allocated to be the new best solution. Likewise, a number of candidate solutions are randomly generated along the negative gradient direction in the specified d-dimension as:

$$A=C-(D.L). \tag{7}$$

Here A is the $d \times 1$ vector which represents a candidate solution, C is the center solution so far, D is the gradient direction computed by finite difference method [30], L is the step length calculated as $L=rand.(upper\, limit-lower\, limit)$. In this method, the search can be adjusted using

$$a_t=a_0-\frac{t}{MaxItr}. \tag{8}$$

Here a denotes sampling step values [0, 1]; t is the time and $MaxItr$ is the maximum iterations.

Based on this approach, the non-convex optimization problem is resolved as

$$\max_{s,p_d} f\left(T_t,s,p_d\right)=R\left(T_t,s,p_d\right)-x[E\left(T_t,s,p_d\right)+E_{vs}]. \tag{9}$$

Here x is the maximum energy efficiency and $f\left(.\right)$ is the objective function while E_{vs} denotes the energy consumed for performing the VS optimization algorithm. Thus the optimal resource allocation solution is achieved. The overall process of the proposed methodology is given in the following algorithm.

```
Begin
    For T_t = 1:T
        Initialize x, s, p_d, ε
        Repeat
        Set x = R(T_t, s, p_d) / E(T_t, s, p_d)
    End for
     Repeat
    Update s, p_d
    Update K until Convergence of s, p_d
    Use VS-G
    Initialize solutions u_0
    t=0
    Repeat
    Generate candidate solutions A
    Generate C
    Select Ci
    Adjust search using a_t
    Repeat
    For Itr=Itr+1
        Select center solution u_j
        For solution u_j
          If u_i > u_j
            Replace solution u_j
          Else
            Keep center solution u_j
        End for
    End for
    max_{s, p_d} f(T_t, s, p_d)
End
```

Listing 1. Algorithm: VS-M-SMOR

The above algorithm clearly explains the overall procedure of VS-M-SMOR. Initially, the parameters are set for VS followed by the limit setting. Then the search operation is performed and the newer results are updated continuously. The search solutions are generated based on the energy efficient resource allocation is approximated. Finally, the center solution is obtained after many iterations and it is dynamically updated.

5. Performance Evaluation. The performance of the proposed energy efficient optimal resource allocation based routing model of VS-M-SMOR is evaluated using MATLAB. The simulation environment is set as in [16] and the comparisons are made vice versa for large and small scale CRAHNs. As the proposed model is used for both the scalable networks, the model is utilized as VS-M-SMOR-1 and VS-M-SMOR-2 as in [16, 17]. The performance of these models is compared with their corresponding SMOR, M-SMOR, SDS-M-SMOR, OCS-M-SMOR [31] and SCJB-M-SMOR which are the modified models of original SMOR. The evaluations are made in terms of end-to-end delay (EED), Bit Error Rate (BER), Throughput, path loss ratio, Peak Signal-to-Noise Ratio (PSNR) and Mean Square Error (MSE), transmitted power and power consumption.

Figure 2 shows the EED comparison of regular CRAHN while Figure 3 shows EED of large-scale CRAHN comparing SMOR, M-SMOR, SDS-SMOR, OCS-M-SMOR, SCJB-M-SMOR and the proposed VS-M-SMOR. VS-M-SMOR shows a lower delay in all level of the offered load with an average of 16% reduced delay than other models because of the combination of optimal relay selection and optimal resource allocation. The other models show comparatively higher delay due to the limited spectrum availability and inability to allocate resources with better energy efficiency.

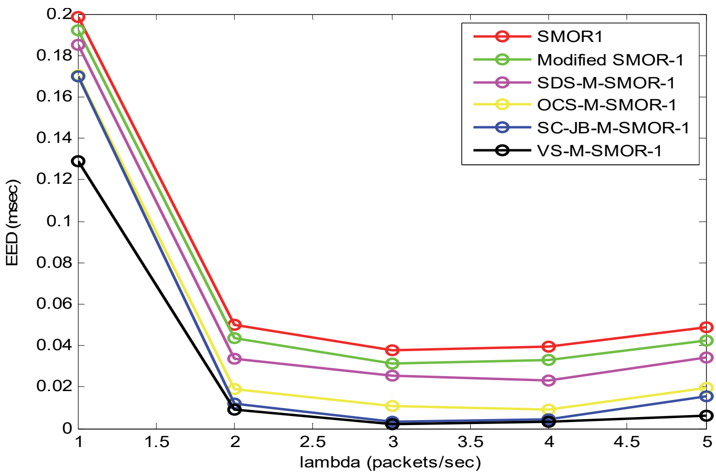

Fig. 2. End to end delay of Regular CRAHN

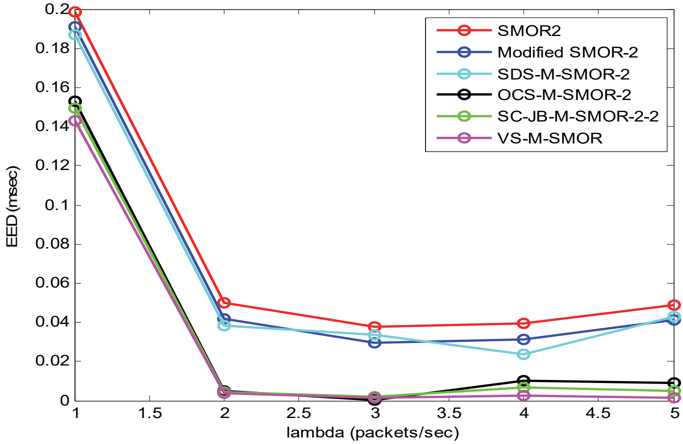

Fig. 3. End to end delay of large-scale CRAHN

Figure 4 shows the BER of regular CRAHN while Figure 5 shows BER of large-scale CRAHN comparing SMOR, M-SMOR, SDS-SMOR, OCS-M-SMOR, SCJB-M-SMOR and the proposed VS-M-SMOR. VS-M-SMOR shows lower error rate with 9 to 11% decrease on average while other models have comparatively higher BER. This can be attributed to the efficient spectrum allocation in the proposed model along with the better selection of the channel and relay for improved opportunistic routing.

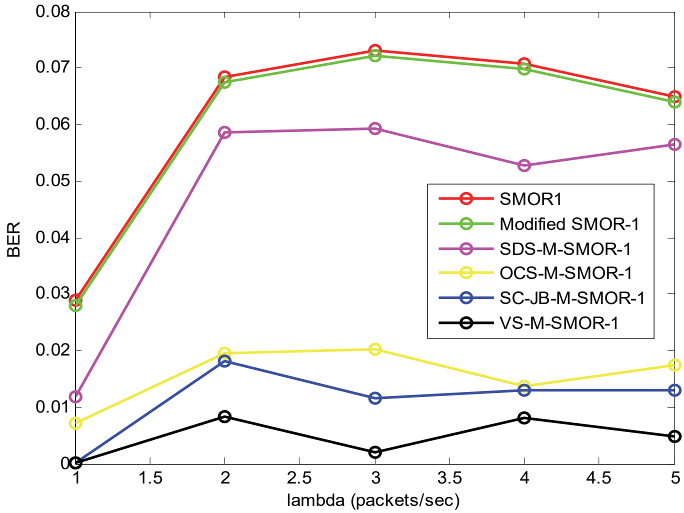

Fig. 4. BER for Regular CRAHN

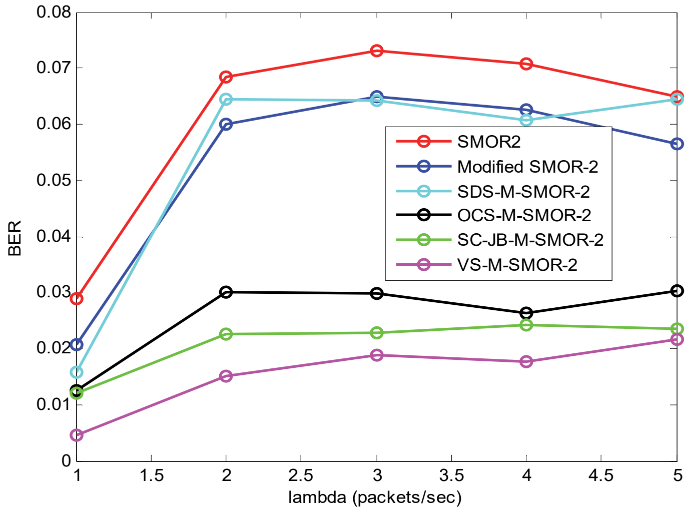

Fig. 5. BER for large-scale CRAHN

Figure 6 shows the throughput of regular CRAHN while Figure 7 shows throughput of large-scale CRAHN comparing SMOR, M-SMOR, SDS-SMOR, OCS-M-SMOR, SCJB-M-SMOR and the proposed VS-M-SMOR.

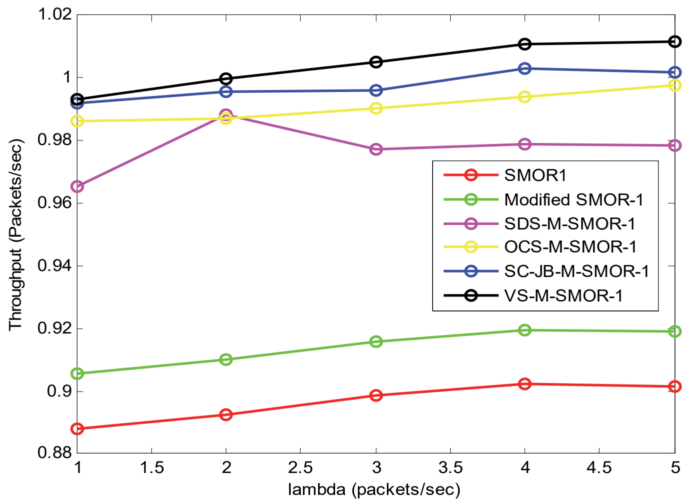

Fig. 6. Throughput for Regular CRAHN

It is seen that the VS-M-SMOR-1 and VS-M-SMOR-2 have higher throughput values of 10% increase on average because of the ability to utilize the whole resources of the multi-channels with energy efficient spectrum allocation to the users. The selection of optimal resource allocation solution largely influences this positive change in performance.

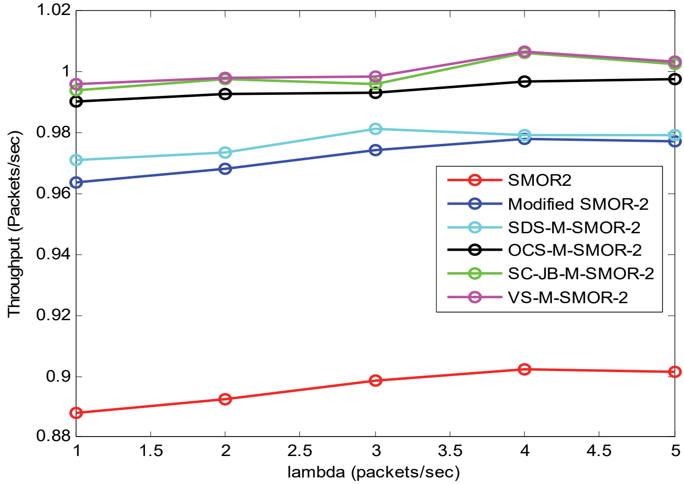

Fig. 7. Throughput for Large-scale CRAHN

Figure 8 shows the path loss ratio of regular CRAHN while Figure 9 shows path loss ratio of large-scale CRAHN comparing SMOR, M-SMOR, SDS-SMOR, OCS-M-SMOR, SCJB-M-SMOR and the proposed VS-M-SMOR. From this evaluation, it is proved that the proposed model of VS-M-SMOR is significantly efficient than the existing models in both the cases.

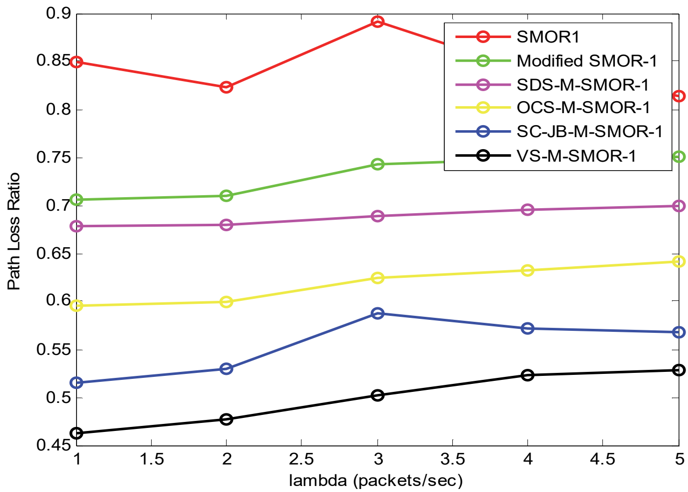

Fig. 8. Path Loss Ratio for Regular CRAHN

The optimal spectrum allocation reduces the loss with an average of 15% decrease in path loss ratio while the relay selection improves the packet delivery. Thus the proposed model satisfies all the QoS requirements for effective routing.

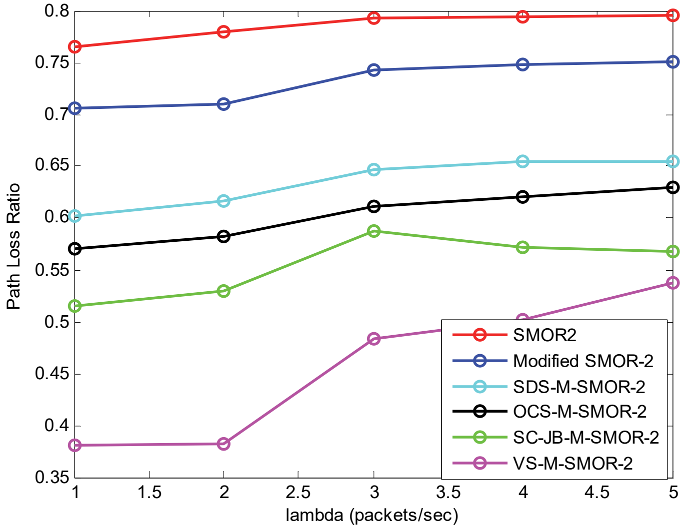

Fig. 9. Path Loss Ratio for Large-scale CRAHN

Figure 10 shows the PSNR of regular CRAHN while Figure 11 shows PSNR of large-scale CRAHN comparing SMOR, M-SMOR, SDS-SMOR, OCS-M-SMOR, SCJB-M-SMOR and the proposed VS-M-SMOR.

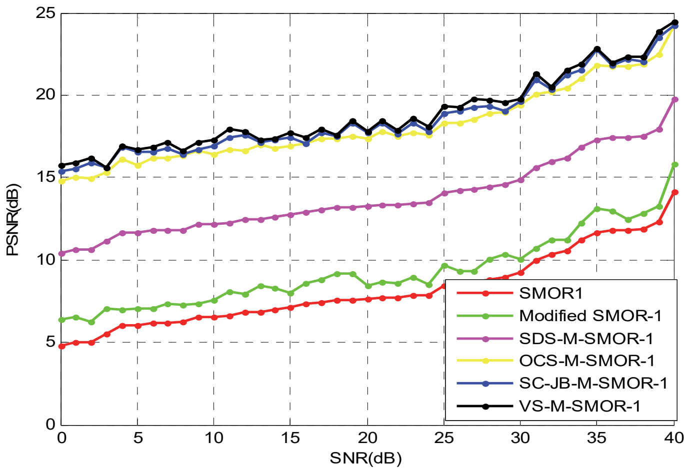

Fig. 10. PSNR for regular CRAHN

VS-M-SMOR has higher PSNR ratio on average 4% increase due to the fact the error rate is reduced considerably by selecting an efficient channel and better spectrum allocation for secondary users in opportunistic routing.

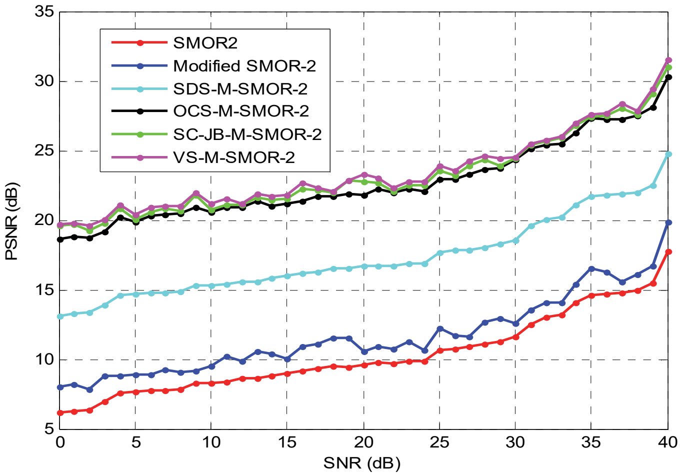

Fig. 11. PSNR for Large-scale CRAHN

The same can be applied to MSE comparison in Figure 12 and 13. VS-M-SMOR has an average of 12% decreased MSE than other models. It notably has better performance and can be stated as the best version of modified SMOR model.

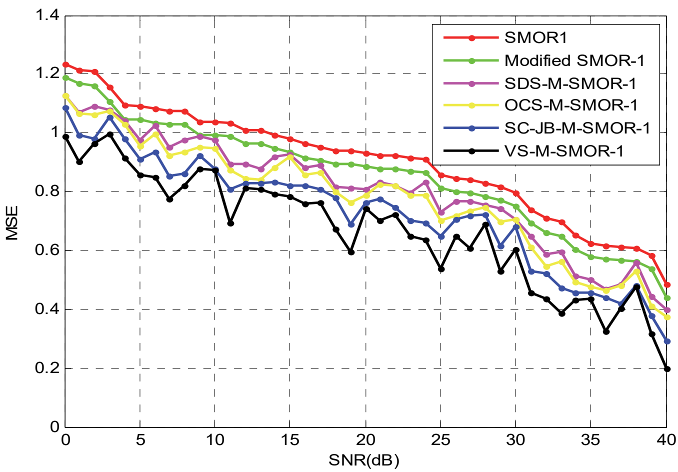

Fig. 12. MSE for regular CRAHN

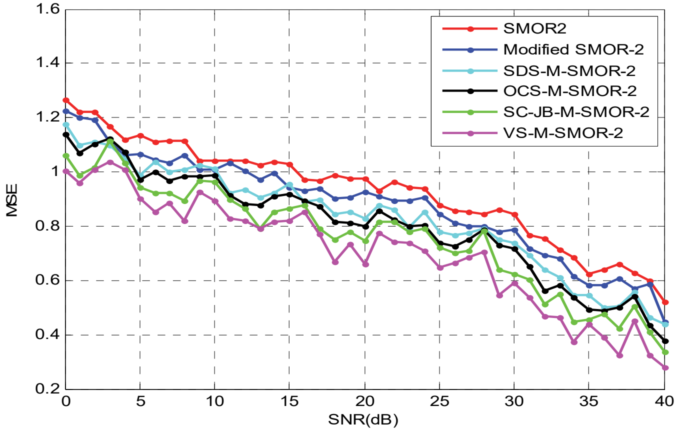

Fig. 13. MSE for Large-scale CRAHN

Figure 14 shows the transmitted power comparison of the proposed VS-M-SMOR and existing SMOR and Modified SMOR models. It can be seen that the proposed model has considerable 6% of lower transmission power on average than the SMOR model. Though at times the Modified SMOR has less power than VS-M-SMOR it can be attributed that the proposed model also improves the security of routing compared to M-SMOR as it includes all the best features of SDS-SMOR, OCS-M-SMOR, and SCJB-M-SMOR.

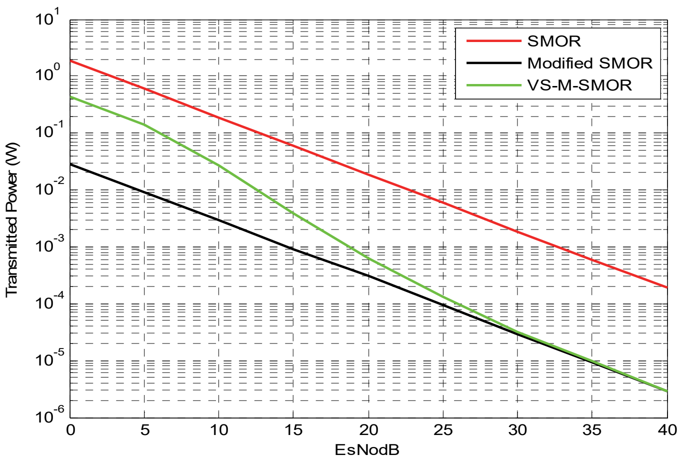

Fig. 14. Transmitted power

Similar reasons can be attributed for the improvement in power conservation of the routing models using the proposed approach. Figure 15 shows the power consumption comparison of the proposed VS-M-SMOR and existing SMOR and Modified SMOR models. The proposed model has 7% of less overall power consumption on average than the other models due to the optimal spectrum allocation.

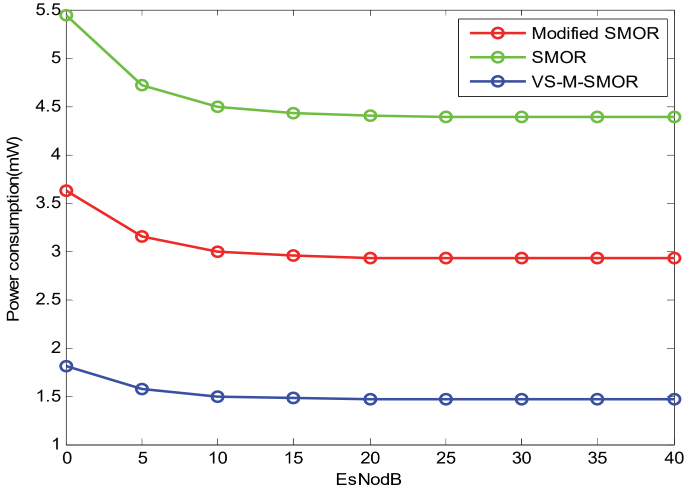

Fig. 15. Overall Power consumption

Hence from the performance comparison results, it can be verified that the proposed VS-M-SMOR model has better performance efficiency compared to the other models of SMOR.

6. Conclusion. Many improved versions of SMOR routing models have been developed in previous researches for the purpose of reducing delay in routing, reducing packet loss in transmission, improving optimal channel selection, improving security and secrecy. This paper focused on developing a modified SMOR model that includes all the above features and also enhances the energy efficiency in the resource allocation optimally. For this purpose, a novel routing strategy is introduced by using Vertex search with gradient approximation for the optimal resource allocation problem. Thus developed VS-M-SMOR model has been explained and has been evaluated for performance comparison. The results indicate that the proposed model outperforms the SMOR and other modified SMOR models with better performance results. VS-M-SMOR has an average of 16% less delay, 9-11% less error rate, 10% higher throughput, 15% lesser path loss, 4% higher PSNR, 12% lesser MSE, and 6-7% lesser power consumption with higher security. In future, more advanced techniques for security and optimal resource allocation can be utilized for improving the performance of opportunistic routing in CRAHNs.

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ЭНЕРГОЭФФЕКТИВНОЕ ОПТИМАЛЬНОЕ РАСПРЕДЕЛЕНИЕ РЕСУРСОВ В КОГНИТИВНЫХ РАДИО- AD-HOC-СЕТЯХ НА ОСНОВЕ ВЕРШИННОГО ПОИСКА

Абдулла Х.М.А, Кумар А.В.С. **Энергоэффективное оптимальное распределение ресурсов в когнитивных радио- ad-hoc-сетях на основе вершинного поиска.**
Аннотация. Когнитивная радио-ad-hoc-сеть (CRAHN) — это безынфраструктурная сетевая модель когнитивного радио, разработанная для ситуативного применения. Регулирование распределения ресурсов в CRAHN может быть рассмотрено как проблема ограничения энергии. Эффективному распределению спектра с использованием различных протоколов посвящено множество исследований. В этой работе модель Spectrum-Map-Empowered Opportunistic Routing (SMOR) была использована в качестве фундаментальной модели маршрутизации данны. Представлено решение по энергоэффективному оптимальному распределению спектра. Улучшена ранее модифицированная модель SMOR для энергоэффективного и оптимального распределения ресурсов с использованием алгоритма вершинного поиска с аппроксимацией на основе градиента. Изначально проблема распределения ресурсов была смоделирована как проблема невыпуклой оптимизации. Распределение мощности, адаптация скорости передачи данных, распределение каналов и политика пользовательского планирования оптимизированы для максимизации энергоэффективности во время передачи данных. Предлагаемый алгоритм вершинного поиска решает проблему оптимизации путем определения интервала обучения для определения канала и распределения энергии. Экспериментальные результаты подтверждают, что предлагаемая модифицированная модель SMOR(VS-M-SMOR), основанная на вершинном поиске, обеспечивает оптимальное распределение ресурсов.

Ключевые слова: распределение ресурсов, распределение спектра, SMOR, вершинный поиск, энергоэффективность, пользовательское планирование.

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