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Energy Aware Channel Allocation with Spectrum Sensing in Pilot Contamination Analysis for Cognitive Radio Networks

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Abstract

Cognitive radio (CR) is an innovative and contemporary technology that has been making an effort to overcome the problems of bandwidth reduction by rising the usage of mobile cellular bandwidth connections. The reallocation and distribution of channels is a fundamental characteristic of cellular mobile networks (CMN) to exploit the consumption of CMS. Meanwhile, throughput maximization might lead to higher power utilization, the spectrum sensing system must tackle the energy throughput tradeoff. The spectrum sensing time should be defined by the residual battery energy of secondary user (SU). In that context, energy effective algorithm for spectrum sensing should be developed for meeting the energy constraint of CRN. This study designs a new quantum particle swarm optimization-based energy aware spectrum sensing scheme (QPSO-EASSS) for CRNs. Here, the presented QPSO-EASSS technique dynamically estimates the sensing time depending upon the battery energy level of SUs and the transmission power can be computed based on the battery energy level and PU signal of the SUs. In addition, in this work, the QPSO-EASSS technique applies the QPSO algorithm for throughput maximization with energy constraints in the CRN. The detailed set of experimentations take place and reported the improvements of the QPSO-EASSS technique compared to existing models.

Keywords- Cognitive radio network; Spectrum sensing; Energy aware; Metaheuristics: PSO algorithm

1. Introduction

The utilization of wireless devices is expanding step by step. Clients likewise maintain that remote gadgets should be associated with web with high information rate. Giving various frequencies to every one of the devices is extremely challenging. The effective utilization of accessible restricted radio spectrum is a vital issue. Cognitive radio innovation is one of the procedures to deal with the proficient utilization of the accessible spectrum. In cognitive radio networks, unlicensed clients can utilize the authorized band spectrum when it is free [1]. The pernicious client (MU) is disturbing the spectrum sensing system which goes after the essential sign discovery and influences the precision of the sensing result [2]. The degree of mindfulness about the discernment radio world is one of the primary variables impacting the legitimate activity of a CRN. Exact ID of PUs is a huge issue that could expand the nature of both the PU and SU networks' execution and QoS. Channel sensor methods have generally been ordinarily used to screen the radio assets accessible. In current circumstances, the PU signal data probably won't be open and, if accessible data, matched separating for highlight identification calculations will permit explicit SS unit yield for every PU sign to be distinguished in CR situation. One more significant sensing calculation in CR applications is the energy finder (ED) strategy, which differentiates the two boundaries. ED execution for spectrum sensing has been surveyed for blurring (remote) and non-blurring (wired) channels [3]. To conquer both the spectrum consumption of various groups and the debasement in complete spectrum use, the cognitive radio (CR) framework has been recommended as an expected reaction to the IoT interest in identifying and getting to radio spectrum by utilizing the unused bits of the spectrum to increment spectrum band use. Fig. 1 demonstrates the overview of spectrum sensing in CRN.

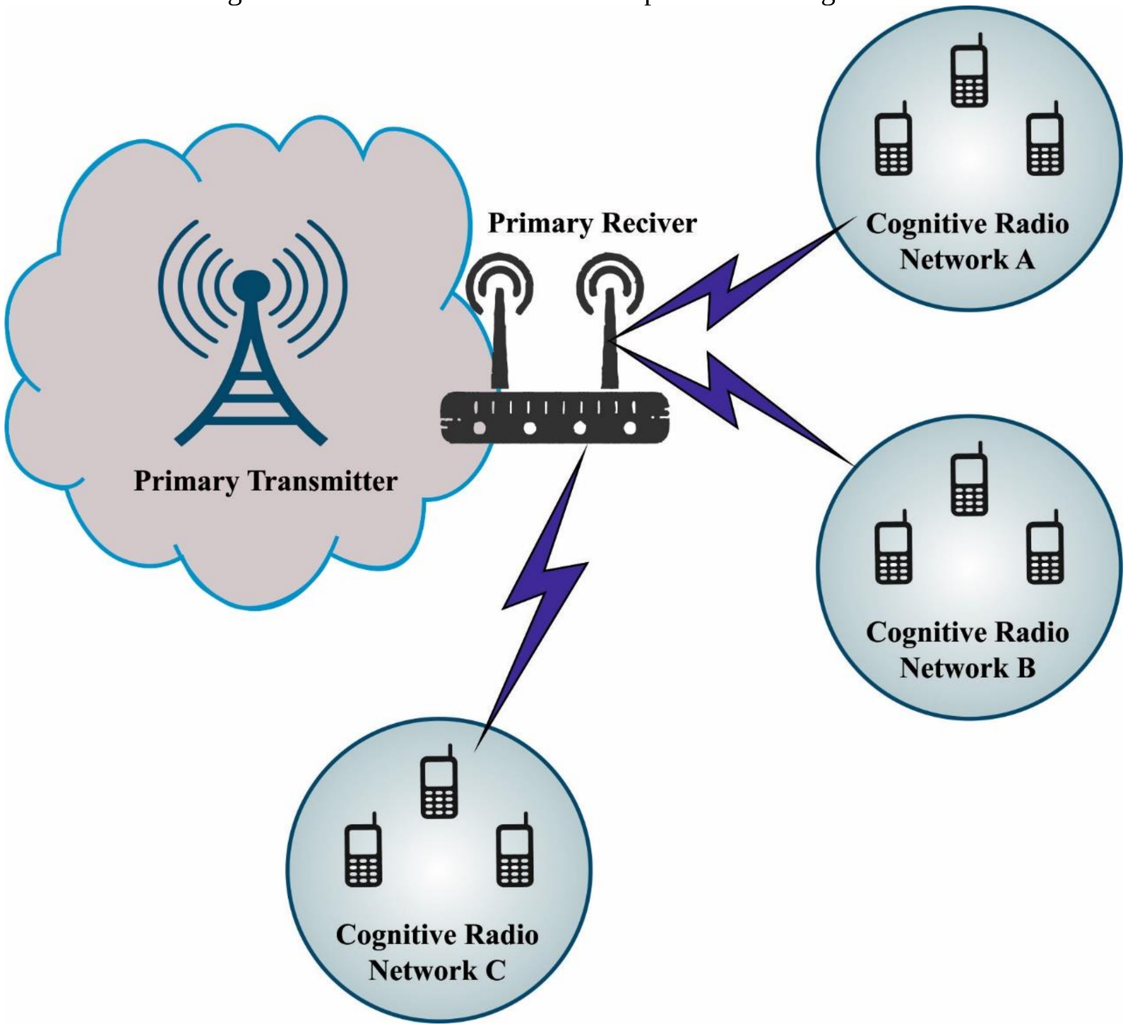

Fig. 1. *Spectrum sensing in CRN*

This expects to mutually lessen energy costs and manage the issue of supplanting batteries, promising a cognitive radio framework with less expensive and more helpful energy supply [4]. In the RF energy gathering based conspire, spectrum sensing and information transmission exercises of the SU can happen with sufficient reaped RF energy (a peculiarity alluded to as energy causality). The framework is anyway a stochastic cycle in. terms of the auxiliary client energy state after some time. The energy level toward the start of each edge relies upon the lingering energy and the move made in the past casing [5]. The RF energy appearance is additionally discontinuous and irregular, while the size of the electrical energy got from the gathered RF may not generally be adequate to augment throughput. It is subsequently basic that the CRN is energy effective as far as adjusting the energy utilization during sensing and transmission exercises with how much energy is gathered. In the regular cognitive radio networks (which can, in any case, be alluded to as unconstrained energy partners), a sensing-throughput compromise exists, which relies on the sensing time and sensing precision.

To stay away from impedance and moderate the actuated execution debasement cognitive radio arrangements have been as of late visualized with regards to remote sensor networks: the fundamental thought custom-made by these plans is to permit sensor gadgets to screen the accessible recurrence groups and deftly select for their transmissions unused bits of spectrum (additionally called blank areas or spectrum openings) [6]. Two distinct methods can be executed for this reason. A first methodology targets taking advantage of spectrum openings in the recurrence space through recurrence dexterity: whenever impedance is identified on a specific channel, hubs change their radio to an alternate one and restore joins with their neighbors. An alternate arrangement rather is to exploit blank areas in the time space getting to the medium during intra-parcel inactive periods, while meddling gadgets are not sending. The two methodologies require sensor hubs to recognize appropriate spectrum openings through spectrum sensing [7]. These outcomes in broad use of the radio unit address the significant wellspring of energy utilization for low-power remote bits and consequently present critical energy above. To meet power requirements of sensor networks and empower the reception of obstruction evasion plans given dynamic spectrum access energy effective calculations for spectrum sensing have consequently to be planned.

CR hubs have difficult spectrum sensing capacities to detect the empty, allowed band called blank areas [8]. Void areas don't screw with music, simply white Gaussian clamor. Auxiliary CR hubs permit sharp utilization of these void areas without rivaling fundamental clients in the network. Assuming that the level of exactness is high, gadget activity will be ideal since the probability of erroneous spectrum task will be tiny and impacts between the PU and SUs will stay away. High energy financial plans will bring about precise sensing results however then again, contributing a lot to this undertaking probably won't be worth it on the off chance that meddling signs are irregular or are seen with extremely high power and are hence simple to identify [9]. Moreover, to accomplish the most elevated energy effectiveness, the sensing energy financial plan ought to be dimensioned representing the size of communicated bundles. The deficiency of long parcels brought about by sensing mistakes brings about exorbitant retransmissions and must be abstained from by accomplishing sensing results as solid as could be expected; while communicating more limited bundles all things being equal, lower energy spending plans could start sensing errors however bring about lower by and large energy utilization [10]. It ought to be noticed that this issue is of outrageous interest for remote sensor networks: sensor parcels can be as little as two or three several bytes accordingly choosing the perfect proportion of energy that must be committed to spectrum sensing could fundamentally further develop energy proficiency.

This study designs a new quantum particle swarm optimization based energy aware spectrum sensing scheme (QPSO-EASSS) for CRNs. Here, the presented QPSO-EASSS technique dynamically estimates the sensing time depending upon the battery energy level of SUs, and the transmission power can be computed based on the battery energy level and PU signal of the SUs. In addition, in this work, the QPSO-EASSS technique applies the QPSO algorithm for throughput maximization with energy constraints in the CRN. The detailed set of experimentations take place and reported the improvements of the QPSO-EASSS technique compared to existing models.

2. Literature Review

Joon and Tomar [11] present Energy aware Q-learning AODV (EAQ-AODV) routing. The projected EAQ-AODV practices Q-learning grounded reward system to select CH and AODV allowed routing protocol related to diverse structures like Communication Range, Residual Energy, Number of Hops, Licensed Channel, Trust Factor, and Common Channel for establishing the directing path. KN et al. [12] announce a new method to allocate resources and sharing related to cooperative node selection and cooperative game theory will ensure exploited payoff. The projected technique enhances overhead power utilization and source application. Additionally, power utilization and resource allocation problems changed into optimized issues. A backtracking search process was implied for the calculation complexity and to find the best answer for source operation.

Thareja and Sharma [13] contemporary methods were devised for enhancing the network representation, i.e., packet delivery, network time, energy reduction having a new spectrum sensed method. For managing the subject of vigor operation, the writer presents inter- and intra-cluster transmission methods having a clustering technique. Further, the author modern a subsequent transition probability-related method for spectrum sensing. Wang et al. [14] suggest a new spectrum-aware cluster method relate to weighted cluster metrics for gaining the optimum gathering through cracking an optimized method. The novel weighted clustering metric, concurrently assessing temporal-spatial association, residual energy and confidence level, was used to select CHs and supporter member nodes. After, the CHs sensing range in its place of very associate nodes importantly decreases the energy feasting of spectrum detection as well as surges the chance of data communication.

In [15], an energy-aware vigorous MAC (ER-MAC) etiquette to prolong network lifespan in CRSNs was modelled where the network time was augmented through reduction of accidents as well as altering detection interval. Besides, amount of transmissions was minimized by exploiting extra dependable stations. Zhong et al. [16] suggest an energy aware coded OR in CR-SIoT after dissimilar kinds of flows viewpoint that equally contemplates energy efficacy and community feature to design coded OR. In this method, the novelists use an innovative route metric and an auction method to select candidates and utilize network coding for the data program among designated bulges in CR-SIoT. In accumulation, the writers prove the contender selection issue was NP-hard and suggest a game-theoretic method for allocating channels which were related to interference graphs.

3. The Proposed Model

This study designed a novel QPSO-EASSS technique for energy aware spectrum sensing in the CRNs. Here, the presented QPSO-EASSS technique dynamically estimates the sensing time depending upon the battery energy level of SUs and the transmission power can be computed based on the PU signal and battery energy level of the SUs. In addition, in this work, the QPSO-EASSS technique applies the QPSO algorithm for throughput maximization with energy constraints in the CRN. PSO is an evolutionary computation technique that originated from the study of predation behaviors of birds [17]. The study presents equal particles for stimulating the bird. The particles have position and speed attributes. Position signifies the direction of movement and Speed characterizes the speed of movement. All the particles individually search for the optimum solution in the problem, recorded as the existing individual extreme values which share that value with another particle in the entire particle swarming and find the optimum value as the existing global optimum solution of the entire particle swarming. Each particle in the particle swarming alters the position and speed based on the existing value and the recent global optimum solution shared through the entire particle swarming.

Assume a population $G = (G_1, G_2, \dots, G_M)$ comprised of M particles in a N dimension vector where $i\text{-}th$ particles are characterized by a N dimension search space $G_i = (g_{i1}, g_{i2}, \dots, g_{iN})$ that denotes the location of $i\text{-}th$ particles in the N dimension vector and a possible solution to the problem. The fitness values respective to the location of all the particles G_i is evaluated based on the decision criteria. The velocity of $i\text{-}th$ particles is $V_i = (v_{i1}, v_{i2}, \dots, v_{iN})$, individual values are $P_i =$

$(p_{i1}, p_{i2}, \ldots, p_{iN})$, and the population values are $P_i = (p_{i1}, p_{i2}, \ldots, p_{iN})$. In all the iterations, particle updates the position and speed via individual and group extremes as follows,

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - g_{id}^{k}\right) + c_1 r_2 \left(p_{gd}^{k} - g_{id}^{k}\right), g_{id}^{k+1} = g_{id}^{k} + v_{id}^{k+1}, \qquad (1)$$

In Eq. (1), ω indicates inertia weight; $d = 1,2, \ldots, N$; $i = 1,2, \ldots, M$, k represents the existing amount of iterations; v_{id}^{k} denotes the velocity of particles; c_1, c_2 indicates a non-negative constant, named the acceleration factor, r_1, r_2 shows the arbitrary value within[0,1]. Fig. 2 depicts the movement of PSO and QPSO.

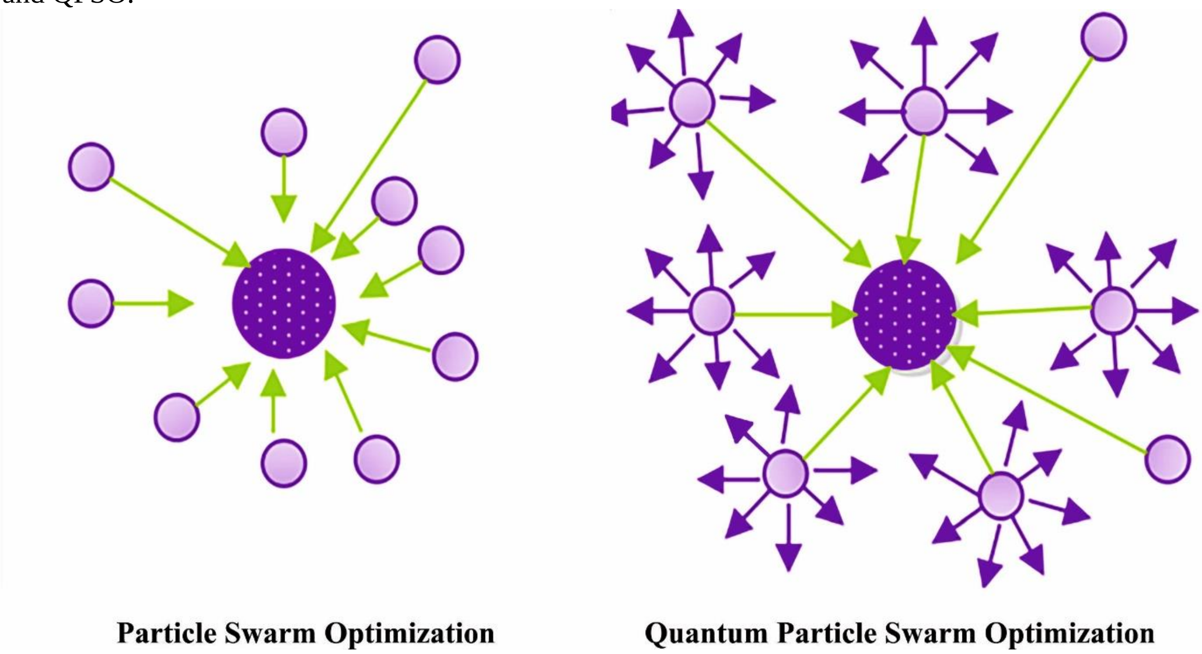

Fig. 2. *Movement of PSO and QPSO*

In the QPSO algorithm, a quantum space depending on the quantum theory is an indefinite search technique that could find a better improvement that is not nearby the optimum solution of the $i\text{-}th$ particles from the initial iteration to the existing amount of iterations and the existing optimum solution. Verified by benchmark function, the performance of algorithms is superior to the standard PSO technique in each aspect.

In this work, the population size is fixed to M, during the evolution, the particle adds or subtracts to a specific probability for updating the location of all the particles and generated a novel population as follows:

$$p = a * pbest(i,:) + (1 - a) * gbest, \qquad (2)$$

$$mbest = \frac{sum(pbest)}{popNum}, \qquad (3)$$

$$b = 1 - \frac{step}{\text{Max}\, step} * 0.5, \qquad (4)$$

$$pop(i,:) = p + b * abs(mbest - p) * \log\left(\frac{1}{u}\right) * \left(1 - 2 * (u \geq 0.5)\right), \qquad (5)$$

From the expression, a and u indicates arbitrary values within [0,1], $step$ denotes the existing iteration count, $Maxstep$ represents the maximal iteration count, $popNum$ indicates the population size, $mbest$ shows the average value of past extreme values of contemporary PSO, b indicates the expansion and contraction coefficients that linearly reduced in the convergence procedure of QPSO, $pbest$ $(i,:)$ indicates the past extreme values of the $i\text{-}th$ particles, $gbest$ represents the global extreme values of PSO, and $step$ indicates the existing evolutional generation, sum characterizes a function that sum each component, abs refers to finding the absolute values and log signifies natural logarithm.

The energy level (Eg) of SU at $t + l$ time is represented in the following [18]:

$$Eg_r(t+1) = Eg_r(t) - eg^{con}(t) \leq B, \qquad (6)$$

Whereas $eg^{con}(t)$ indicates the energy consumed at t time, and B represents battery ability of the SU. Then, indicate the transmission power of i^{th} nodes as Q^i_{tx}. The transmission and interference range of the i^{th} nodes are correspondingly quantified as S^i_{tx} and S^i_{if},. The lessened power occurrence as Q^j_{rx} at j^{th} receiver could be estimated as follows,

$$Q^j_n = \alpha . Q^i_{tx}\{d^j\}^{-\beta} \qquad (7)$$

Where

d^i-the fixed distance amongst the j^{th} receivers and i^{th} nodes

B -the proponent factors of path loss

α -the function of frequency f^I selected using the i^{th} transmission node

c-the speed of light

Consider Min_P and Max_P as minimal and maximal bounds for Q_{tx} broadcast energy

Consider EPU_r as a power of the received PU signals and $EPU_{\max}$ indicates the maximal limits for EPU_r where $Eg_{\max}$and $Eg_{\min}$ indicates the minimal and maximal bounds of Eg_r

Next, the circumstance to select the broadcast level of power has been shown below:

$$\begin{aligned} TPL &= MinP, when\ EPUr > EPU_{\max}\ or\ Eg_r < Eg_{\min} \\ &= MaxP, when\ EPUr < EPU_{\max}\ or\ Eg_r > Eg_{\max} \end{aligned} \qquad (8)$$

The objective is to choose the TPL of SU based on the discovered PU signals and Eg_r in the SU battery.

The superior the PU level is, the inferior the transmission energy of SU is. In difference, the bigger the SU residual energy, the larger the SU transmission energy. This is because the bigger the recognized power because innovative probability of the PU existence, and thus, the transmission energy must be selected for lessening the PU intervention. Once the SU level is smaller, the transmission energy should be smaller to increase the energy efficiency of the model.

The spectrum sensing interval (SI) is appropriately attuned according to the residual energy (Eg) of SU.

Hence the major constraints to adjusting the sensing intervals are

$$\begin{aligned} SI &= SI + \Delta i, if\ Eg > Eg >= Eg_{ax} \\ & SI - \Delta i, if\ Eg < Eg < Eg_{min} \end{aligned} \qquad (9)$$

When the Eg_r is higher, the sensing range is somewhat improved using the factor Δi. Alternatively, when the Eg_r is lesser, it must be minimized using similar factors.

Every user of CR gathers N sample in periodic sensing and transmission time frame of Tf; when Ts indicates the specimen period, next $Tf = N \cdot Ts$. The frame involves sensing time ρ which has n detection value exploited to sense PU. The next part of the frame is information transmission time of $(Tf - \rho)$ with (N-n) instance, where $1 \leq n \leq N$.

Therefore, the predictable throughput of i^{th} SU is evaluated as follows

$$TH_n(\rho) = \frac{T_f - p}{T_f}\left(1 - Q_{f,i}\right) \qquad (10)$$

4. Result Analysis

In this section, a detailed result analysis of the QPSO-EASSS model is given. Table 1 and Fig. 3 represent a normalized throughput (NTHR) assessment of the QPSO-EASSS model. On 50 CR users, although the EEISS and SAI offered NTHR of 22.45Mbps and 18.38Mbps, the QPSO-EASSS model accomplished higher NTHR of 28.48Mbps. At the same time, on 250 CR users, although the EEISS and SAI presented NTHR of 40.04Mbps and 28.97Mbps, the QPSO-EASSS method established higher NTHR of 45.74Mbps.

Table 1 *NTHR analysis of QPSO-EASSS system with varying CR users*

Normalized Throughput (Mbps)			
No. of CR Users	**QPSO-EASSS**	**EEISS**	**SAI**
50	28.48	22.45	18.38
100	35.48	27.99	20.66
150	41.50	33.85	22.62
200	43.29	36.78	24.25
250	45.74	40.04	28.97

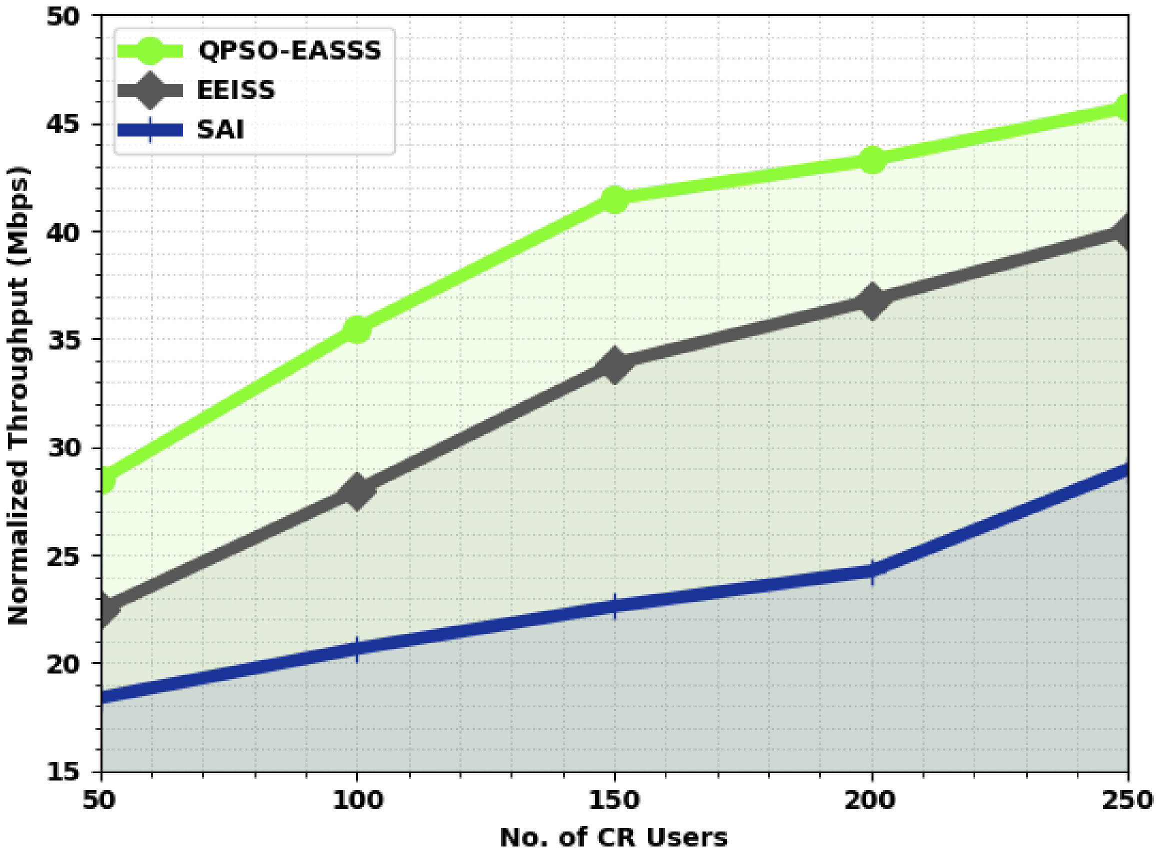

Fig. 3. *NTHR analysis of QPSO-EASSS system with varying CR users*

Table 2 and Fig. 4 signify average residual energy (ARE) valuation of the QPSO-EASSS method. On 50 CR users, although the EEISS and SAI presented ARE of 9.21J and 8.80J, the QPSO-EASSS technique exhibited higher ARE of 9.61J. At the same time, on 250 CR users, although the EEISS and SAI offered ARE of 8.25J and 7.46J, the QPSO-EASSS approach exemplified higher ARE of 8.83.

Table 2 *ARE analysis of QPSO-EASSS system with varying CR users*

Average Residual Energy (J)			
No. of CR Users	**QPSO-EASSS**	**EEISS**	**SAI**
50	9.61	9.21	8.80
100	9.58	9.18	8.74
150	9.21	8.66	7.67
200	9.02	8.52	7.60
250	8.83	8.25	7.46

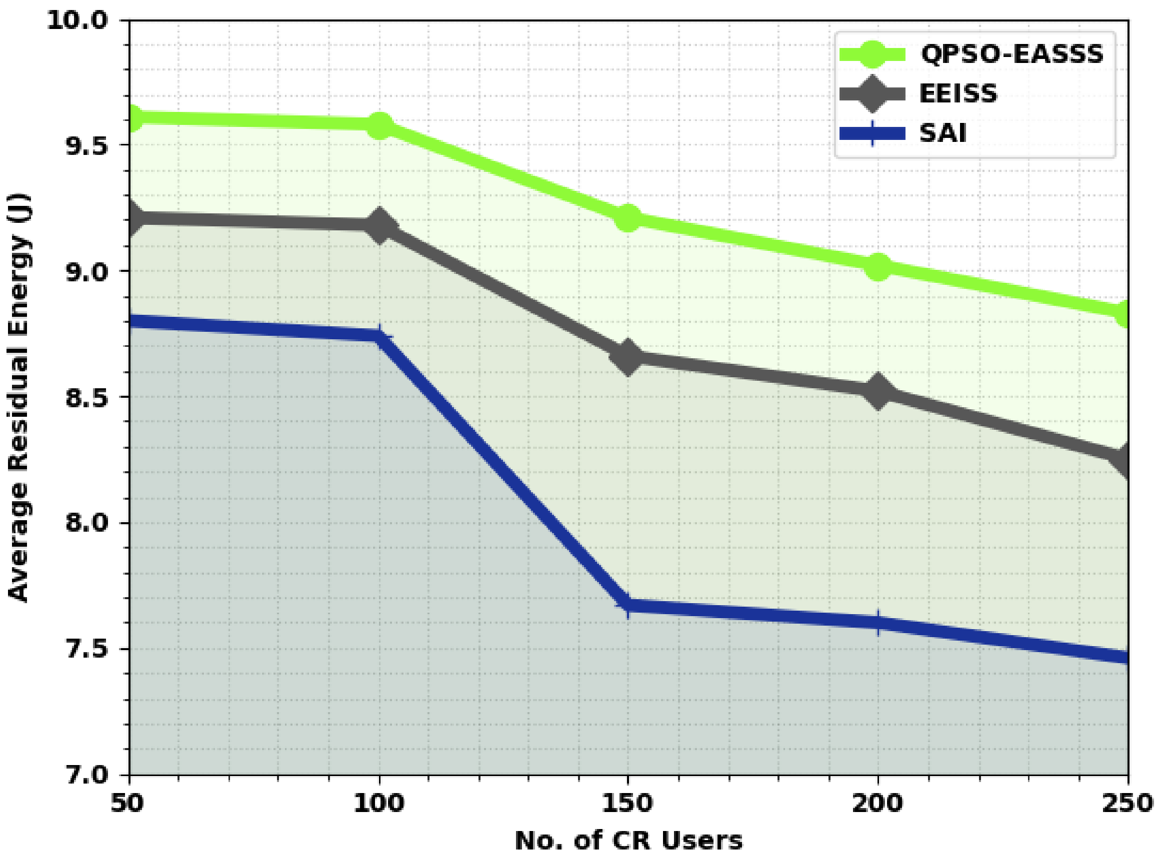

Fig. 4. *ARE analysis of QPSO-EASSS system with varying CR users*

Table 3 and Fig. 5 denote a probability of detection (POD) assessment of the QPSO-EASSS method. On 50 CR users, although the EEISS and SAI rendered POD of 76.05% and 71.46%, the QPSO-EASSS algorithm accomplished higher POD of 87.86%. Simultaneously, on 250 CR users, although the EEISS and SAI offered POD of 89.17% and 85.23%, the QPSO-EASSS method exhibited higher POD of 95.73%.

Table 3 *POD analysis of QPSO-EASSS system with varying CR users*

Probability of Detection (%)			
No. of CR Users	**QPSO-EASSS**	**EEISS**	**SAI**
50	87.86	76.05	71.46
100	92.78	80.97	71.46
150	93.76	83.92	75.72
200	94.74	87.86	80.31
250	95.73	89.17	85.23

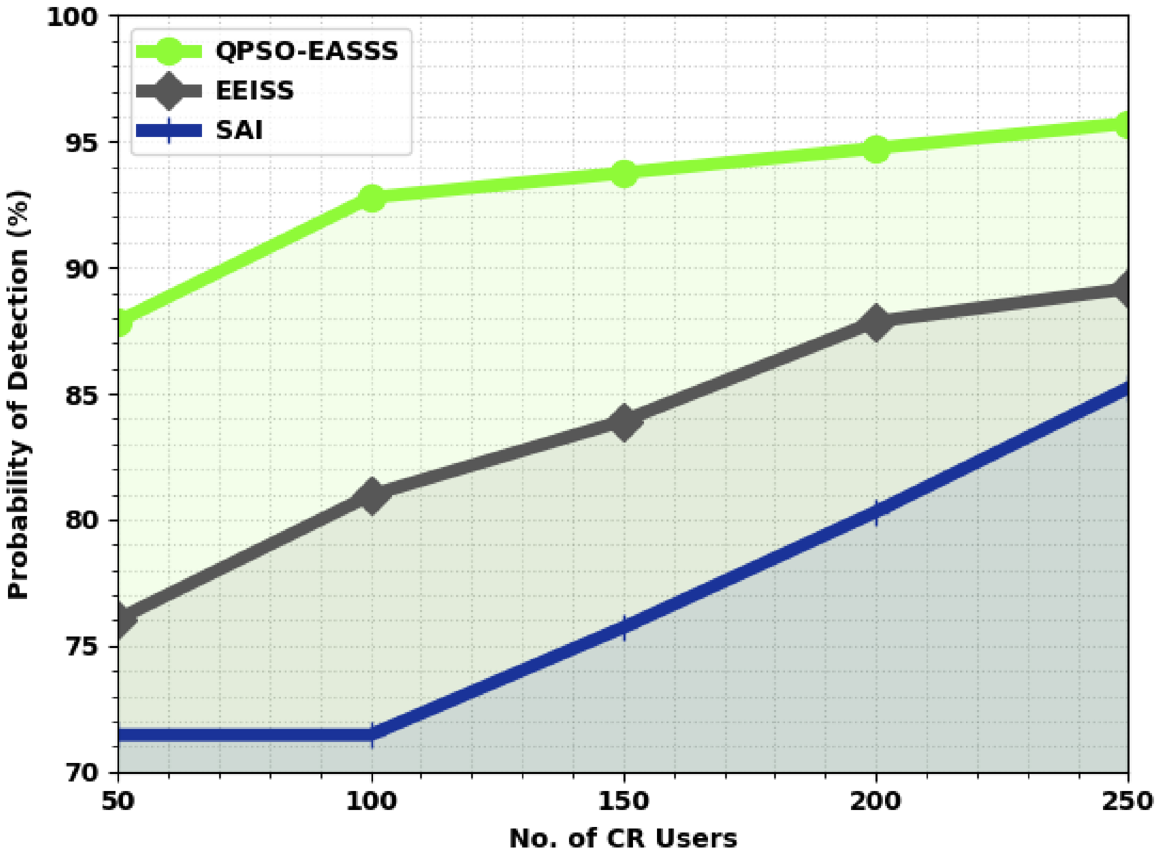

Fig. 5. *POD analysis of QPSO-EASSS system with varying CR users*

A detailed AECON assessment of the QPSO-EASSS model under numerous CR users is portrayed in Table 4 and Fig. 6. The results exhibited that the SAI model has failed to show proficient results with minimal values of AECON. Followed by, the EEISS model has reached reasonable outcome with closer AECON values. But the QPSO-EASSS model has shown effectual outcomes with minimal AECON values.

Table 4 *AECON analysis of QPSO-EASSS system with varying CR users*

Average Energy Consumption (%)			
No. of CR Users	**QPSO-EASSS**	**EEISS**	**SAI**
50	16.68	29.14	39.30
100	25.53	36.35	50.12
150	31.11	47.17	55.36
200	35.04	48.48	69.45
250	41.59	53.07	72.08

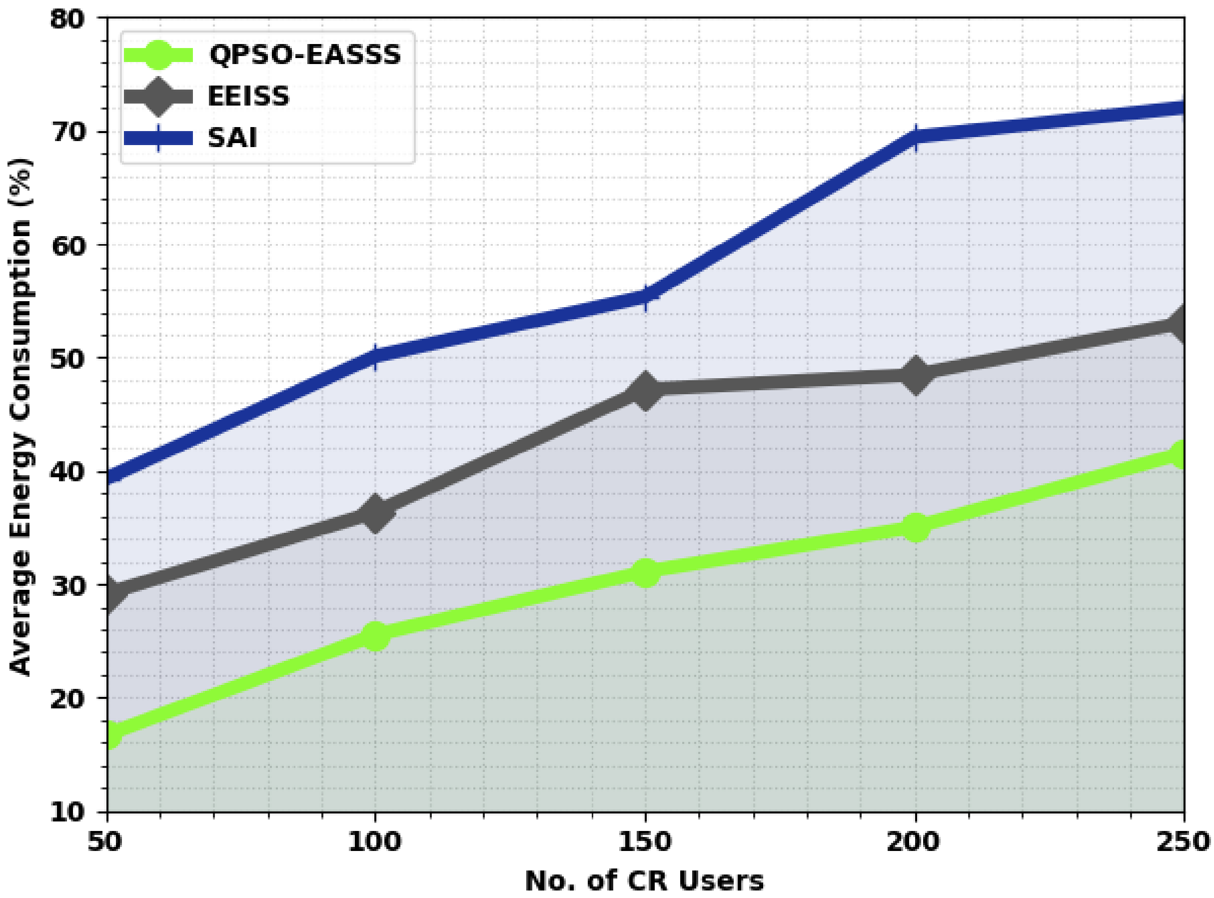

Fig. 6. *AECON analysis of QPSO-EASSS system with varying CR users*

A comprehensive ADEL assessment of the QPSO-EASSS method under numerous CR users is depicted in Table 5 and Fig. 7. The results displayed the SAI approach has failed to show proficient results with minimal values of ADEL. Then, the EEISS approach reached reasonable outcome with closer ADEL values. But the QPSO-EASSS technique has displayed effectual outcomes with minimal ADEL values.

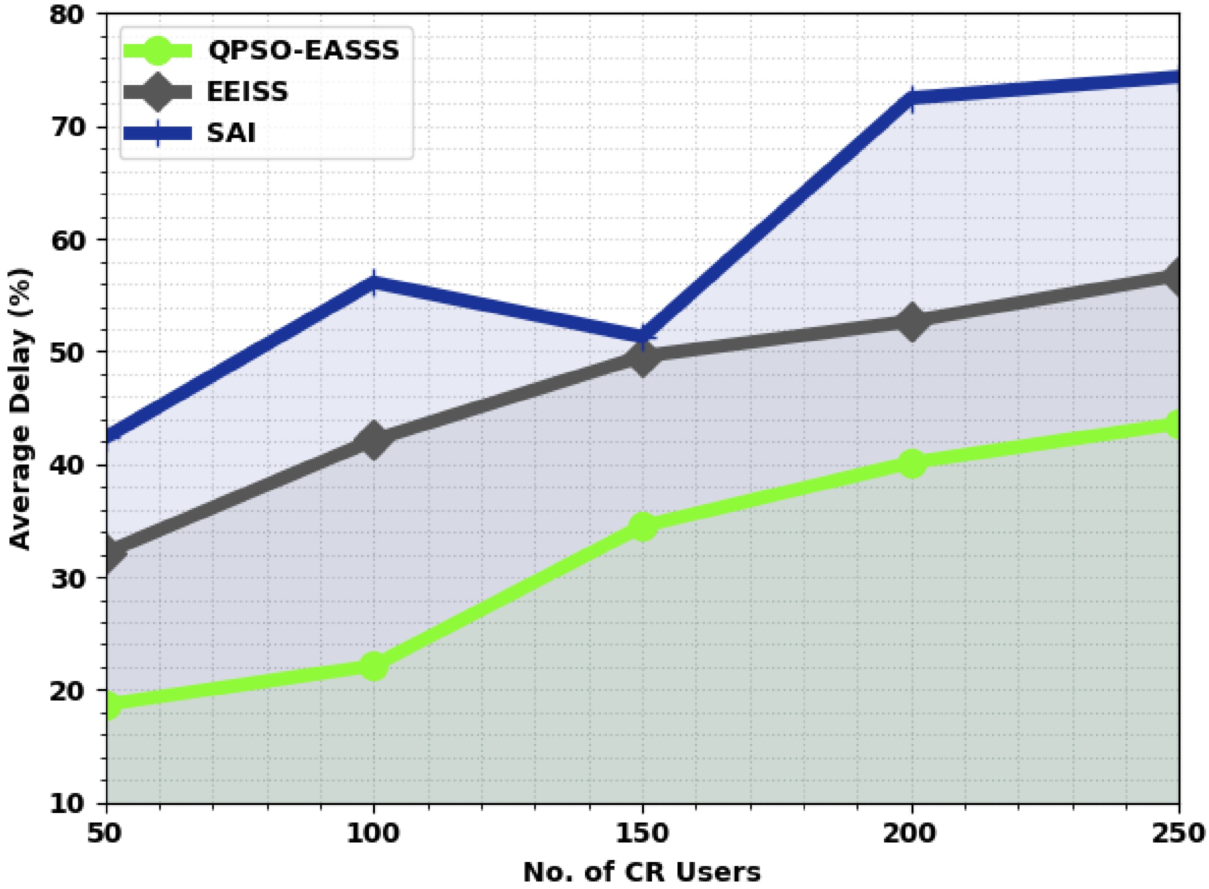

Fig. 7. *ADEL analysis of QPSO-EASSS system with varying CR users*

Table 5 *ADEL analysis of QPSO-EASSS system with varying CR users*

Average Delay (%)			
No. of CR Users	**QPSO-EASSS**	**EEISS**	**SAI**
50	18.68	32.14	42.35
100	22.13	42.15	56.14
150	34.51	49.57	51.32
200	40.14	52.68	72.49
250	43.62	56.77	74.38

5. Conclusion

This study designed a novel QPSO-EASSS technique for energy aware spectrum sensing in the CRNs. Here, the presented QPSO-EASSS technique dynamically estimates the sensing time depending upon the battery energy level of SUs, and the transmission power can be computed based on the battery energy level and PU signal of the SUs. In addition, in this work, the QPSO-EASSS technique applies the QPSO algorithm for throughput maximization with energy constraints in the

CRN. The detailed set of experimentations take place and reported the improvements of the QPSO-EASSS technique compared to existing models. Hence, the QPSO-EASSS technique can be exploited for real time spectral sensing in the CRNs.

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