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Energy-Efficient Cooperative Spectrum Sensing Strategy for Cognitive Wireless Sensor Networks Based on Particle Swarm Optimization

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ABSTRACT Cognitive wireless sensor networks (CWSNs) can use the idle authorized frequency band to solve the problem of spectrum resource shortage in traditional wireless sensor network. By employing spectrum hole in the authorized frequency band, the spectrum sensing technology can degrade the coexistent interference and enhance the performance of whole sensor network. Due to the characteristics of limited battery energy and low processing capacity with sensor nodes, it is necessary to enhance the energy efficiency while improving spectrum sensing performance. In this paper, a cooperative spectrum sensing strategy for CWSNs based on particle swarm optimization is proposed. Firstly, the system throughput and energy consumption are quantitatively analyzed, and the mathematical model related to energy efficiency is established. Secondly, the particle swarm optimization (PSO) algorithm is used to obtain the optimal selected nodes set under the limited conditions of false alarm probability and detection probability. To avoid local optimization in the process of problem solving, Cauchy mutation method is introduced to optimize the parameter selection of fitness function. The experimental results illustrate that our proposed method can improve the throughput of the system while ensuring the sensing performance, and achieve the energy efficiency effectively.

INDEX TERMS Energy-efficiency, cognitive wireless sensor networks, cooperative spectrum sensing, particle swarm optimization.

I. INTRODUCTION

As the most potential solution to overcome the spectrum resource shortage, cognitive radio technology has attracted a lot of attention. In cognitive radio networks, spectrum resources are allocated to the primary users (PUs), and the secondary users (SUs) have to access the spectrum opportunistically by detecting the PU's signal correctly and avoiding interference to the authorized user's communication [1], [2]. The effectiveness and reliability of spectrum detection has become a key issue in cognitive radio networks. The performance of channel detection is affected by many factors, such as the uncertainty of noise, multipath fading, shadow fading and the uncertainty of signal receiver [3]. In order to overcome those unfavorable factors, cooperative spectrum sensing (CSS) is introduced and regarded as an effective measure to improve the detection accuracy and sensing performance by exploiting the spatial diversity of multiple sensing nodes [4]. By taking advantage of dense sensor nodes and obtaining more accurate signal measurements, CWSNs also can organize multiple nodes to obtain better detection performance and overcome the problem of hidden terminal [5], [38]. However, CSS will generate more energy consumption and sensing overhead. On the one hand, more sensor nodes participating in CSS will result in additional energy consumption. In addition, the reporting time slot of sensing results in the data frame will be greatly extended, which will influences the throughput and energy efficiency of the system.

From the perspective of system sensing performance, plenty of cooperating SUs can provide the diversity with more signal measurements and thus obtain better detection performance [6], [39]. However, the energy consumption also shows a linear increase with the number of cooperative nodes. Especially for power constrained sensor nodes, plenty of energy consumption will be includes mainly in terms of the authorized user's signal detection and sensing data reporting [7]. In addition, in correlated log normal shadow

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channel, the correlation between sensing nodes will seriously affect the detection results of the cooperative nodes set. The correlation between adjacent nodes will cause the redundancy of the sensing results owing to the less useful information, and the increase of the number of cooperative SUs does not enhance the detection accuracy significantly [8]. Therefore, the issues about the sensor nodes selection to meet the performance constraints of the system on false alarm probability and missing detection probability should be investigated.

The remainder of the paper is organized as follows. In Section II, the related works are reviewed and the major contributions of our paper are summarized. In Section III, the system model is described and the problem of energy efficiency is discussed. The proposed optimization algorithm is presented in Section IV. In Section V, the simulations results and analysis are provided. The conclusions are presented in Section VI.

II. RELATED WORK

In order to enhance the throughput or spectrum utilization, SUs often operate with high transmission power, which leads to the reduction of energy efficiency. Therefore, many studies not only examine spectrum sensing in terms of throughput and spectrum utilization, but also study MAC protocol in CWSN from the perspective of energy efficiency. In [9], the tradeoff between detection accuracy and energy efficiency is considered, and the optimal MAC frame structure is designed to improve the energy efficiency. In [10], an energy-efficient spectrum access scheme and optimal sensing order are designed, in which SUs sequentially senses the channel until determining the licensed channel for data transmission. In [11], the transmission time and power for SUs for sensing multiple channels are determined to ensure the energy efficiency under the condition of the existence of the interference to PU. In [12], it is assumed that PU does not return and occupy the channel during the process of SU's transmission, and the transmission time can be defined as a function of sensing time. Then, the sensing time slot and transmission time slot are jointly optimized to enhance the energy efficiency of the system. In [13], the optimization problem of sensing time and transmission duration are discussed and a sub-optimal algorithm is proposed to achieve the maximization of the network energy efficiency of the whole system and satisfy constraint conditions of limited interference to the authorized signal.

Some researches focus on the specific topology or coordination among SUs, for instance, clustered-based collaborative spectrum sensing. By grouping neighboring nodes logically, spectrum-aware clustering is regarded as one of the most promising schemes to address the energy consumption problem. Focusing on increasing energy efficiency and prolonging the network lifespan, a cluster head selection algorithm base on fuzzy c-means (FCM) clustering is proposed according to several factors, which takes advantage of sensor node's spatial diversity and residual energy to organize the clusters [14]. In [15], a novel cluster-based CSS mechanism is proposed for CWSNs, which schedules the sensor nodes into awake or sleep modes for energy saving. To improve the detection probability, a weighted CSS scheme is proposed to assign different weights according to the signal-to-noise ratio of SUs [16]. However, due to lack of consideration of energy efficiency, it results in high energy consumption of the system when a large number of SUs cooperate in spectrum sensing. According to the local sensing data and the intra-cluster fusion decisions, the intra-cluster and inter-cluster rules are combined for CSS to reduce the number of reports from the cluster member nodes [17]. In [18], an iterative algorithm is introduced to determine the optimal number of cooperative SUs, sensing and transmission time, so as to obtain the maximization of the energy efficiency.

Most of the approaches presented choose all SUs to participate in cooperative sensing. However, in the actual environment, due to the influence of geographical location and node's distribution, there may be great differences in local sensing performance of each SU. Some studies have considered various node selection schemes to reduce the overhead and energy consumption during the process of spectrum sensing. In [19], the selection of cooperative sensor nodes is formulated as binary knapsack problem, and a dynamic programming method is employed to resolve the minimization of the energy consumption. In [20], a joint sensing nodes and decision node selection method is introduced, which adopts the convex optimization framework. Due to the NP-complete property, the problem of sensor selection is handled by mapping the assignment index from an integer to a real number field. To reduce energy consumption and sensing overhead, a selection probability scheme is proposed, which exploits the historical observations from adjacent sensor nodes and excludes the nodes with low strength of the received signals [21]. In [22], an energy-efficient CSS is proposed to acquire the minimization of the energy consumption among the distributed sensor nodes under the constraints of global detection probability and false alarm probability.

Due to the hardware limitation and energy constraint of sensor nodes in CWSNs, it is important to make a trade-off between detection accuracy and energy efficiency [23]. The sensing performance will be enhanced with the number of SUs, meanwhile the energy consumption in the transmission phase also increases. Therefore, it is very of significant to study how to find the optimal number of cooperative sensor nodes to minimize energy consumption and provide reliable detection results and transmission quality. Generally, the major contributions of our paper can be summarized as follows:

i) The system throughput and energy consumption are quantitatively analyzed, and the mathematical model related to energy efficiency is established.
ii) The PSO algorithm is used to solve the problem, which makes the cooperative sensor nodes be selected optimally under the limited conditions of global false alarm probability and detection probability.

iii) To avoid local optimization in the process of problem solving, Cauchy mutation method is introduced to optimize the parameter selection of fitness function.

III. SYSTEM MODEL

A. COOPERATIVE SPECTRUM SENSING

There are N sensor nodes deployed in a CWSN with a specific fusion center (FC). The cognitive sensor node can sense the licensed channel periodically and conduct local decisions on the existence of the primary user according to its own observations. To avoid any interference to primary users, secondary users should keep silent during detection process. The local decisions of all sensing nodes will be sent to FC continuously in the time slot based on TDMA scheme. Comparatively, the hard decision method needs to transmit one-bit decision to the FC, which can save more energy consumption than soft fusion. Thereupon, the FC employs hard decision fusion instead of soft fusion to make the final decision.

Assuming each node is independent in the sensing process and makes local decisions by employing energy detection method. For a given received signal, the detection of the primary user can be formulated as a statistical problem [25], and H_1 and H_0 denotes the hypothesis that the PU exists or does not exist respectively. Therefore, the received signal by i-th sensor node can be expressed by

$$x_i(k) = \begin{cases} u_i(k), & H_0 \\ h_i(k)s(k) + u_i(k), & H_1 \end{cases} \tag{1}$$

where $s(k)$ represents the primary user's signal, and the noise sample $u_i(k)$ can be assumed to be a cyclic symmetric Gaussian random vector with zero mean and variance σ_n^2. Besides, $h_i(k)$ is the channel gain between the i-th sensor node and the primary user with the mean value 0 and the variance δ_i.

For its simplicity, the energy detection method will be employed for signal's detection. For the i-th node, its energy statistics can be simply expressed as $E_i = \frac{1}{M}\sum_{k=1}^{M} |x_i(m)|^2$. If the test statistics of the sensing node is greater than the energy threshold, the presence of the primary user signal will be made. Otherwise, the decision of the licensed channel will be idle. According to the above decision rules and given threshold η, the false alarm probability and detection probability can be given by

$$p_{f,i} = Q\left(\left(\frac{\eta}{\sigma_n^2} - 1\right)\sqrt{M}\right) \tag{2}$$

$$p_{d,i} = Q\left(\left(\frac{\eta}{\sigma_n^2} - \gamma_i - 1\right)\sqrt{\frac{M}{1+2\gamma_i}}\right) \tag{3}$$

where γ_i represents the received signal-to-noise ratio of the PU's signal at i-th sensing node. Besides, $Q(\cdot)$ is a Gaussian tail function and is defined as: $Q(t) = \frac{1}{\sqrt{2\pi}}\int_t^{\infty}\exp\left(-\frac{x^2}{2}\right)dx$.

Since multipath fading and shadow fading will impact on the degradation of sensing performance of a single node, the CSS can overcome this phenomenon. By using OR combination rule, the global detection probability and false alarm probability can be given by

$$P_d = 1 - \prod_{i=1}^{N}\left(1 - p_{d,i}\right) \tag{4}$$

$$P_f = 1 - \prod_{i=1}^{N}\left(1 - p_{f,i}\right) \tag{5}$$

Although CSS has obvious advantages in PU's signal detection, the sensing performance is still affected by many factors such as related shadows. Some researches show that with the increase of the number of sensing nodes in the fixed area, the performance of the sensor network will decline due to the stronger correlation between adjacent users, especially in the correlated lognormal shadow [26]. In addition, cooperative sensing has a great impact on resource consumption, such as bandwidth consumption of control channel and transmission energy consumption of sensing reports. The energy consumption usually increases linearly with the number of nodes participating in the cooperation [27]. Therefore, it is more advantageous to select some uncorrelated cognitive sensor nodes to incorporate during the sensing process under certain constraints of sensing accuracy. On the one hand, it can improve the robustness of decision results. On the other hand, it can help to reduce the cost of collaborative awareness.

To enhance the energy-efficiency during the process of CSS, sensing nodes should be selective to participate in spectrum sensing while maintaining the performance constraints. Therefore, the global detection probability and false alarm probability will be written as

$$\tilde{P}_d = 1 - \prod_{i=1}^{N}\left(1 - \rho_i p_{d,i}\right) \tag{6}$$

$$\tilde{P}_f = 1 - \prod_{i=1}^{N}\left(1 - \rho_i p_{f,i}\right) \tag{7}$$

where ρ_i denotes the assignment index with the value 0 or 1. Among them, 0 represents that the corresponding sensor node is selected for spectrum sensing, and 1 indicates that the sensor is not involved in cooperation.

B. ENERGY EFFICIENCY ANALYSIS

Next, the energy efficiency of the system is analyzed mathematically. In order to discover and utilize the idle authorized channel in time and reduce the interference to the primary user, the SUs usually adopt the periodic frame structure as shown in Fig. 1. The frame length of cognitive user can be fixed to T, including spectrum sensing time, spectrum and data transmission time. The spectrum sensing time can be divided into two parts: local sensing and decision result reporting. The time intervals assigned are T_s and KT_r respectively, where $K = \sum_{i=1}^{N}\rho_i$ denotes the number of SUs participating in cooperative sensing. In order to ensure certain detection accuracy, the local sensing time is usually composed of M sensing time slots. In the data transmission stage, cognitive sensor nodes decide whether to send data frames

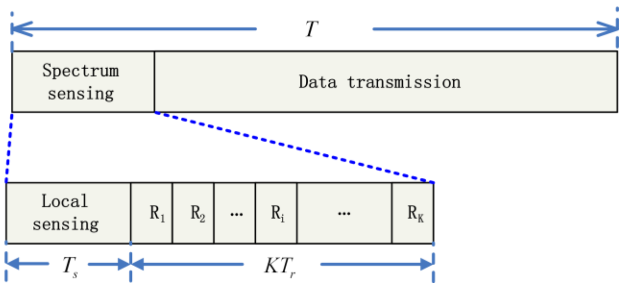

FIGURE 1. The frame structure for CWSNs with spectrum sensing.

according to the spectrum sensing results, i. e., if the channel is decided to be busy, the sensor nodes will not send the data, and vice versa.

When the FC decides that the PU exists, the SUs will silently wait for the start of the next frame for the next round. If the primary user channel is idle, the FC allocates the channel to the sensor nodes for data transmission. In CWSNs, the throughput of the system can be composed of the PU's throughput and the throughput from all sensor nodes. When the Bayesian risk is constant and the interference rate is below the threshold, the throughput per unit time of SUs in the channel can be expressed as follows:

$$\begin{cases} \Psi_{s,0}\left(T,K\right) = C_s\left(\dfrac{T-T_s-KT_r}{T}\right)\left(1-\tilde{P}_f\right)P(H_0) \\ \Psi_{s,1}\left(T,K\right) = C_s\left(\dfrac{T-T_s-KT_r}{T}\right)\left(1-\tilde{P}_d\right)P(H_1) \end{cases} \tag{8}$$

where C_s denotes the channel capacity that can be utilized under the transmitted signal power of the secondary user. Besides, $P(H_0)$ and $P(H_1)$ represent the probability that the primary user does not exist in the authorized channel and the probability that the PU exists, respectively.

Hence, the PU's throughput per unit time can be calculated by

$$\begin{cases} \Psi_{P,0}\left(T,K\right) = C_P\tilde{P}_dP(H_1) \\ \Psi_{P,1}\left(T,K\right) = C_P\left(1-\tilde{P}_d\right)P(H_1) \end{cases} \tag{9}$$

where C_P denotes the channel capacity that can be utilized under the transmitted signal power of the PU.

When the FC makes the prediction errors in channel estimation according to the reports from the SUs, the PU and the SUs may transmit data in the channel at the same time. It will cause interference between them and be almost impossible to complete normal communication. Evidently, the throughput generated by the system in the case of self interference can be ignored. Since the detection probability of the system is known, based on the sensing time and the number of sensing nodes, we can obtain the energy detection threshold of each SU. Therefore, the average throughput of network can be expressed as follows:

$$\Psi\left(T,K,\phi\right)=\Psi_{P,0}\left(T,K\right)\left(1-\phi\right)+\phi\Psi_{s,0}\left(T,K\right) \tag{10}$$

Suppose that E_s is the power of the SU for sensing the channel, E_r is the power when the SU reports the sensing result to the FC through the control channel, E_{Ts} is the power generated by the SU occupying the PU's channel for data transmission, and E_{Tp} is the power generated by the PU for data transmission in the licensed channel. Then, the energy consumption will be discussed in the following four cases:

Case 1: The PU does not transmit data in the channel, and the SUs detect that the PU is idle. Within a frame length, the energy consumption of the network can be calculated by

$$\Xi_{0,0}\left(T,K\right)=K\left(T_sE_s+T_rE_r\right)+\left(T-T_s-KT_r\right)E_{Ts} \tag{11}$$

with the probability $p\left(H_0|H_0\right)=p\left(H_0\right)\left(1-\tilde{P}_f\right)$.

Case 2: The PU is idle but a false alarm occurs. The SUs detect that the PU is busy and the FC make a false spectrum decision. In this case, the energy consumption of the network can be calculated by

$$\Xi_{1,0}\left(T,K\right) = KT_sE_s + KT_rE_r \tag{12}$$

with the probability $p\left(H_1|H_0\right)=p\left(H_0\right)\tilde{P}_f$

Case 3: The PU transmits data in the channel, but the sensing results from sensor nodes indicate that the PU is absent. In this case, both PU and the SUs will dissipate the energy consumption, which can be expressed by

$$\Xi_{0,1}\left(T,K\right)=KT_sE_s+KT_rE_r+\left(T-T_s-KT_r\right)E_{Ts}+TE_{Tp} \tag{13}$$

with the probability $p\left(H_0|H_1\right)=p\left(H_1\right)\left(1-\tilde{P}_d\right)$

Case 4: The SUs can successfully detect the PU's signal, and FC will notify all sensor nodes not to occupy the licensed channel. In this case, the energy consumption of the network can be calculated by

$$\Xi_{1,1}\left(T,K\right) = KT_sE_s + KT_rE_r + TE_{Tp} \tag{14}$$

with the probability $p\left(H_1|H_1\right)=p\left(H_1\right)\tilde{P}_d$

Therefore, we can obtain the average energy consumption per frame as

$$\Xi\left(T,K\right) = \sum\nolimits_{i\in\{0,1\},j\in\{0,1\}} \Xi_{i,j}\left(T,K\right)P\left(H_i|H_j\right) \tag{15}$$

The energy efficiency can be expressed as follows:

$$EE = T \times \frac{\Psi\left(T,K,\phi\right)}{\Xi\left(T,K\right)} \tag{16}$$

The FC needs to determine the sensing duration which can maximize energy efficiency and the number of sensor nodes participating in CSS. Hence, the optimization problem can be formulated as

$$\begin{aligned} &\max\nolimits_{\tau\geq 0,L<N}\ \{EE\} \\ &s.t.\ \tilde{P}_d \geq \alpha,\quad \tilde{P}_f \leq \beta \\ &KT_r + T_s \leq T. \end{aligned} \tag{17}$$

Since $\tilde{P}_f$ is not dependent on the γ_i and using Eq. (7), the upper limit for the number of sensing nodes is obtained as:

$$K \leq \left\lfloor \frac{\ln\left(1-\beta\right)}{\ln\left(1-Q\left(\left(\frac{\eta}{\sigma_n^2}-1\right)\sqrt{\frac{M}{1+2\gamma_i}}\right)\right)} \right\rfloor \tag{18}$$

Therefore, the above optimization problem can be stated as follows:

$$\begin{aligned}&\max_{\tau\geq 0,L<N}\ \{EE\};\\&s.t.\ \prod_{i=1}^{N}\left(1-\rho_i p_{d,i}\right)\leq 1-\alpha,\\&\sum_{i=1}^{N}\rho_i=\left\lfloor\frac{\ln\left(1-\alpha\right)}{\ln\left(1-Q\left(\left(\frac{\eta}{\sigma_n^2}-1\right)\sqrt{\frac{M}{1+2\gamma_i}}\right)\right)}\right\rfloor\\&KT_r+T_s\leq T.\end{aligned}\tag{19}$$

IV. PROPOSED METHOD

PSO is an intelligent algorithm which imitates the behavior of birds, which was jointly proposed by Kennedy and Eberhart [28] in 1995. Due to its simplicity and easy implementation, we apply it for above optimization problem for sensor node's selection. By initializing a random group of particles, each particle represents a feasible solution to the problem. To seek the optimal solution, each particle moves in the direction to its historical best position and the global best position [29].

The PSO model includes a D-dimensional search space and m particle nodes. The whole particle swarm is represented by $X=\{x_1,x_2,\cdots,x_m\}$, and $x_i=(x_{i1},x_{i2},\cdots,x_{id})$ denotes the D-dimensional position vector of the i-th particle. According to the actual optimization problem, the fitness function is specified as the energy efficiency. The current fitness value will be calculated, and then compared with the current particle position and determine whether the particle's position is optimal or not. $v_i=(v_{i1},v_{i2},\cdots,v_{id})$ represents the velocity of i-th particle. Besides, $p_i=(p_{i1},p_{i2},\cdots,p_{id})$ indicates the current best position, and $p_g=\left(p_{g1},p_{g2},\cdots,p_{gd}\right)$ shows the best position by the whole swarm. At iteration t, the particle swarm will update the speed and position according to the following rule:

$$\begin{cases}v_{id}\left(t+1\right)=wv_{id}\left(t\right)+c_1r_1\left(p_{id}\left(t\right)-x_{id}\left(t\right)\right)\\\qquad\qquad+c_2r_2\left(p_{gd}\left(t\right)-x_{id}\left(t\right)\right)\\x_{id}\left(t+1\right)=x_{id}\left(t\right)+v_{id}\left(t+1\right)\end{cases}\tag{20}$$

where t is the number of iterations. r_1 and r_2 is a random number to maintain the diversity of the population. As acceleration factors, c_1 and c_2 represent the ability of particles, who learn from themselves or groups and approach to the optimal position. The inertia weight w is used to measure the influence of local or global optimal ability in particle swarm optimization.

The standard particle swarm optimization algorithm is easy to fall into local optimization and slow convergence speed [32]. By applying the appropriate weighting factor for updating the position, it can reduce the blindness of the search process, and the computational efficiency can be effectively improved [33]. Consequently, Cauchy mutation will be introduced to accelerate the convergence of standard PSO algorithm.

The probability density function of one-dimensional Cauchy distribution is defined as

$$f\left(x\right)=\frac{\theta}{\pi\left(x^2+\theta\right)}\tag{21}$$

where θ is the coefficient and $\theta>0$, and the distribution function of one-dimensional Cauchy distribution is

$$F\left(x\right)=\frac{1}{\pi}\left(\arctan x+\frac{\pi}{2}\right)\tag{22}$$

when $\theta=1$, the above function obeys the standard Cauchy distribution. In order to improve the convergence speed of PSO and make the fitness value jump out of the local optimum quickly, the variable Cauchy mutation factor is employed. In the early and middle period of the PSO algorithm, the large value of θ will be generated to avoid falling into local optimum. While in the later stage of the optimization resolution, the value of θ should be small to improve the convergence speed. Thus, the Cauchy variation factor can be defined as:

$$\lambda=\frac{t_{\max}-t}{t}\times\hat{V}_j\tag{23}$$

where $\hat{V}_j$ denotes the average velocity of swarm.

After introducing Cauchy variation factor, the position and velocity of the i-th particle can be updated by

$$\begin{cases}v_{id}\left(t+1\right)=v_{id}\left(t+1\right)+\lambda C\left(0,1\right)\\x_{id}\left(t+1\right)=x_{id}\left(t\right)+v_{id}\left(t+1\right)\end{cases}\tag{24}$$

where $C\left(0,1\right)$ is the random number generated by the standard Cauchy distribution function.

Furthermore, during the search process, the smaller inertia weight can make the PSO gain faster convergence speed. But out of the range of global position, the global optimal solution may not be obtained [30], [31]. The larger inertia weight can make the PSO not fall into the local optimum, but the convergence speed is slow. In the early stage, it should be paid more attention not to fall into the local optimum. But in the later stage, the particles are already near the global optimal position, so the particle convergence speed should be more important. According to the above analysis, the inertia weight should be reduced linearly with time and can be updated by

$$w=w_{\max}-\frac{w_{\max}-w_{\min}}{t_{\max}}\times t\tag{25}$$

where $w_{\max}$ is the initial weight value and $w_{\min}$ is the final weight value.

The algorithm is described as follows:

V. PERFORMANCE EVALUATION

In this section, we conduct the experiments to evaluate the performance of the proposed strategy for CWSNs, and compare with Counting-based Selection [36], CogLEACH [37] and Joint selection [38] schemes in terms of average throughput and energy efficiency. In our simulation environment, the cognitive sensor nodes change from 10 to 100 in quantity, and the values of the parameters used are listed as: $E_s=0.01$W, $E_r=0.05$W, $E_{Tp}=5$W, $E_{Ts}=2.5$W, $M=50$,

Input: PU, Number of sensor nodes N, $t_{\max}$.
Output: Selected sensing nodes.
1. Initialize particles $x_i \in X$ as described in Section IV
2. While $t < t_{\max}$
3. For $i = 1$ to N do
4. Calculate the fitness value of x_i;
5. If $EE(x_i) > pbest_i$ then
6. x_i will be replaced by $pbest_i$;
7. End if
8. If $EE(x_i) > gbest$ then
9. $gbest$ will be replaced by x_i;
10. End if
11. The velocity of particle x_i is updated according to Eq. (24);
12. The position of particle x_i is updated according to Eq. (24);
13. End for
14. For $j = 1$ to N do
15. Obtain the value of $\hat{V}_j$;
16. Update the Cauchy variation factor according to Eq. (23);
17. End for
18. End while
19. Working out the optimal selected sensing nodes.
20. End

$\sigma^2 = 1$, $\gamma = -20$dB, $\alpha = 0.9$, $\beta = 0.1$, $t_{\max} = 100$, $w_{\max} = 0.9$ and $w_{\min} = 0.3$.

Figure 2 shows the curve of the global false alarm probability with the increase of the number of cooperative sensing nodes, and Fig. 3 shows the curve of the sensing performance gain. The sensing performance gain is defined as $\Delta Pf_j = P_f(j-1) - P_f(j)$, which indicates the sensing performance gain caused by adding the j-th cooperative node to the cooperative sensing node set, and $P_f(j)$ is the false alarm probability of j cooperative nodes. Since the cognitive sensor nodes are randomly distributed in the coverage of the network, the simulation results are obtained by executing 1000 times. It can be seen that with the increase of cooperative sensor nodes, the false alarm probability shows an obvious downward trend. When the number of cooperative nodes increases to a certain extent, the sensing performance gain is gradually contracted and tends to zero. It also demonstrates that there is an asymptotic performance lower bound for CSS.

From the experimental results in Fig. 3, it can be found that when the number of cooperative nodes is greater than 30, the sensing performance gain is close to zero. From the perspective of system performance, large number of cooperative sensing nodes can obtain better sensing performance. However, with the increase of the number of cooperative nodes, the energy consumption and the traffic increase approximately linearly. Therefore, it is necessary to make a trade-off between energy efficiency and detection performance in accordance with the selection of the number of cooperative sensing nodes.

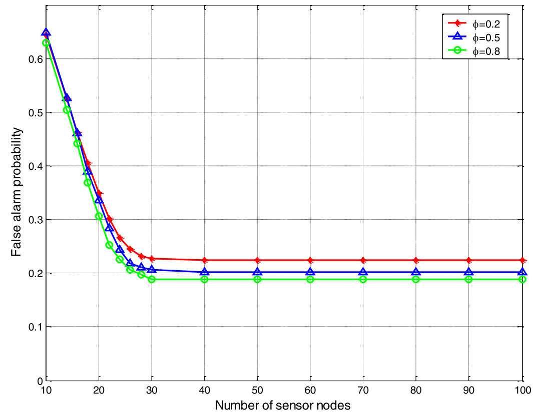

FIGURE 2. False alarm probability with different sensor nodes.

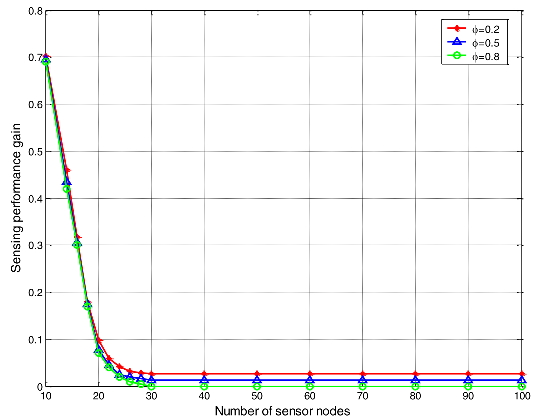

FIGURE 3. Sensing performance gain with different sensor nodes.

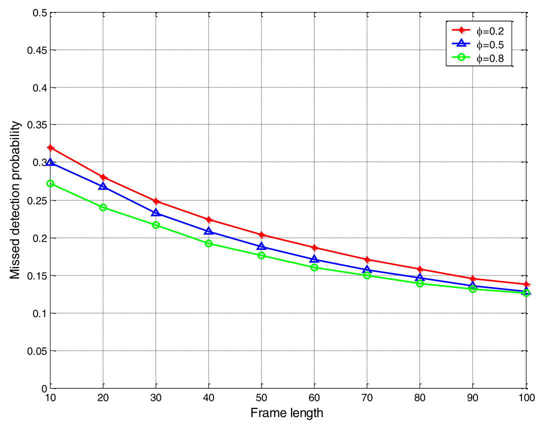

FIGURE 4. Missed detection probability with different sensor nodes.

Figure 4 shows the missed detection probability with different sensor nodes. It demonstrates that with the increase of the number of nodes, the number of selected cooperative sensing nodes increases accordingly as well as improving the sensing performance. Compared with the false alarm probability, the missed detection probability can be maintained at a relatively low level even when the node density is small. The reason is that the optimization algorithm can meet the requirements of sensing performance and select the appropriate set of sensing nodes. However, it should be noted that

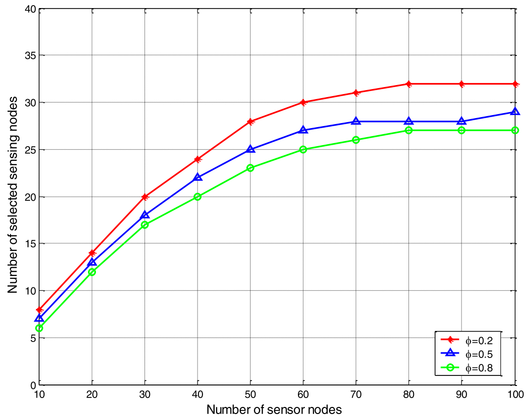

FIGURE 5. Number of selected sensing nodes with different sensor nodes.

the better sensing performance will increase the requirement of algorithm computation and increase the number of iterations. In addition, too many cooperative nodes may increase the energy consumption for the sake of the improvement of sensing performance, which is not conducive to ensuring the energy efficiency of the whole system.

Fig. 5 shows the number of selected cooperative nodes with different sensor nodes. From the experimental results, we can observe that the number of sensing nodes selected by optimization algorithm under the constraints increases with the increase of node's density, but the obvious growth rate slowly slows down. The reason is that the relative distance between the cooperative sensing nodes decreases with the increase of node's density, and the sensing performance gain is also relatively small even if too many sensor nodes participate in cooperation. It means that the relative distance between cooperative sensing nodes can impact on the correlation between cooperative sensing nodes, which is conducive to the improvement of sensing performance of cooperative sensing node.

Fig. 6 shows the total error probability with different sensor nodes. The total error probability is defined as the sum of missed detection probability and false alarm probability [39, 40]. By utilizing particle swarm optimization, our proposed method can select the optimal sensor nodes to meet target detection probability and false alarm probability. It effectively guarantees the sensing data of all cooperative nodes being combined at the FC. Due to the SUs whose sensing data is subjected to error, the total error probability in CogLEACH is degraded with large number of sensor nodes. In joint selection scheme, the SUs will be selected for cooperation depending on the sensing measurement is error-free or not, in which the error probability is reduced effectively.

The comparison of the average throughput of our proposed method with traditional schemes is shown in Fig. 7. From the results, it can be observed that when the density of sensor nodes is too high, the more cooperative sensing nodes participate. Although more accurate sensing results can be obtained, it will lead to the decline of throughput contrarily. Moreover, more nodes participating in cooperative sensing will cause more energy consumption in sensing and sensing

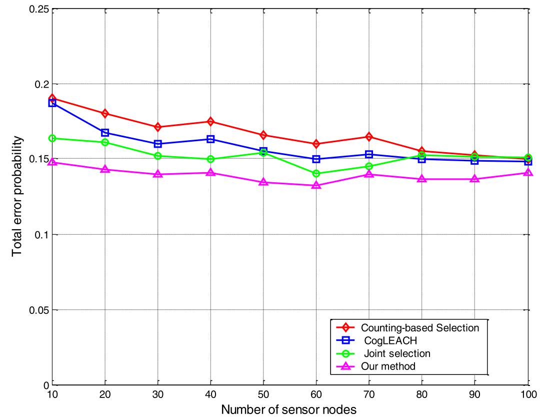

FIGURE 6. Total error probability with different sensor nodes.

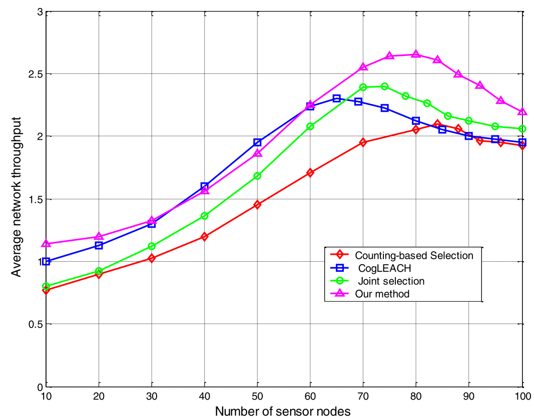

FIGURE 7. Average network throughput with different sensor nodes.

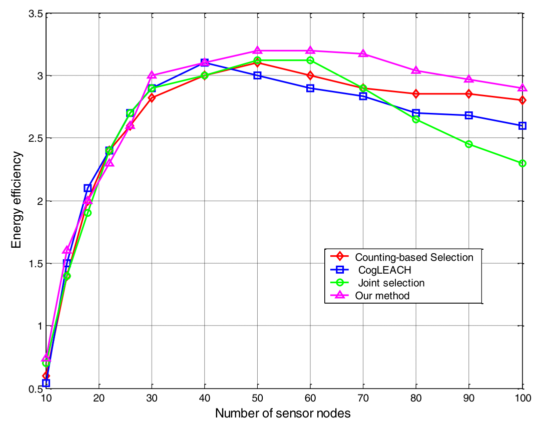

FIGURE 8. Energy efficiency with different sensor nodes.

results reporting. Therefore, by selecting the appropriate cooperative sensing nodes, the optimal ratio of the network throughput to the energy consumption can be achieved.

Fig 8 shows the efficiency of our proposed methods compared with traditional scheme. It can be observed that with increasing number of sensor node, the energy efficiency increases rapidly especially when the node density is small. It also clearly shows that efficiency of our proposed method is higher than other schemes when the number of sensor nodes exceeds 50. Due to increasing number of cooperative nodes, large amount of energy will be consumed and contrarily the throughput will be decreased due to sensing errors. Our proposed method only chooses limited number of sensor nodes can degrade the coexistent interference and enhance the performance of whole sensor network.

VI. CONCLUSION

In this paper, a cooperative spectrum sensing strategy for cognitive wireless sensor networks based on particle swarm optimization is proposed to achieve energy-efficient transmission. Firstly, the system throughput and energy consumption are quantitatively analyzed, and the mathematical model related to energy efficiency is established. Secondly, the particle swarm optimization algorithm is used to solve the problem, which makes the cooperative sensor nodes be selected optimally under the limited conditions of global detection probability and false alarm probability. To avoid local optimization in the process of problem solving, Cauchy mutation method is introduced to optimize the parameter selection of fitness function. The experimental results show that the algorithm can improve the throughput of the system while ensuring the sensing performance, and achieve the energy efficiency effectively.

In the future work, we will further improve the network energy efficiency by optimizing the frame length, and also consider the multicast throughput for multi-channel wireless sensor networks.

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