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Optimization of Spectrum Sensing for Cognitive Sensor Network using Differential Evolution Approach in Smart Environment

P.C. Ng
InfiniteQL Sdn. Bhd,
46300 Petaling Jaya, Malaysia
ngpaichet@infiniteql.com

***Abstract* — The spectrum congestion due to the static spectrum allocation scheme in wireless communication had been an issue for decade. Despite the rapid growth of wireless communications, the emerging of Internet of Things to transform everyday objects into smart objects which are capable to communicate with each other wirelessly in a smart environment have/had further increase the spectrum demand. In this paper, cognitive sensor network had been proposed to handle the loophole in the spectrum intelligently via spectrum sensing. In order to achieve a reliable spectrum sensing, an optimization scheme with fast convergence speed has been employed to optimize the sensing performance. The parameters of differential evolution have been set for solving the optimization problem in spectrum sensing for cognitive sensor network. The spectrum sensing formulation in cognitive sensor network has been modeled in MATLAB, and the optimization has been simulated using the differential evolution algorithm. The simulation result has shown that optimization using differential evolution approach has significantly increased the sensing performance which is an essential criterion for CSN which comply of many smart sensors that connect to each other wirelessly.**

Keywords* — *Cognitive Sensor Netowork(CSN), Differential Evolution(DE), Internet of Things(IoT), smart environment, spectrum sensing

I. INTRODUCTION

The internet has been evolved from internet of information toward the internet of things (IoT). Such evolution has further increase the spectrum load to handle the internet traffic which already in a very congested situation that yet to be solved. According to Cisco Canada, there will be estimated 50 billion devices connected to the internet by 2020 [1] which mean that about 40 Zettabytes of information will be running around the internet wirelessly. The concept behind IoT is to turn the everyday objects such as LED light tube, ceiling fan, air conditioner, kettle and water heater around us as shown in Figure 1 to become the smart objects which are aware of its environment through tracking, monitoring and are able to communicate their sensing data wirelessly over the internet with/without human intervention. Every smart objects are consider as a node that connect to each other through the gateway generally the access point to the cloud for further processing. To ensure a wider coverage, every node is design to connect to each other node in a distribute manner so that the sensing information can hop from one node to the other node until it reach the gateway successfully. The smart computing enables the sensing information to talk to each other intelligently without human intervention. On the other side, human can retrieve the sensing information that is available on the cloud and control it through their handheld tablet, smart phone or computers that are connected to the internet. The IoT seems capable for bringing us to a prominent digital world, and hence a smart environment. However, as mentioned earlier, the current spectrum is very congested with current internet traffic load due to its static spectrum allocation scheme. The spectrum situation will get even worst with the exponential increase demand for transmission from the smart objects.

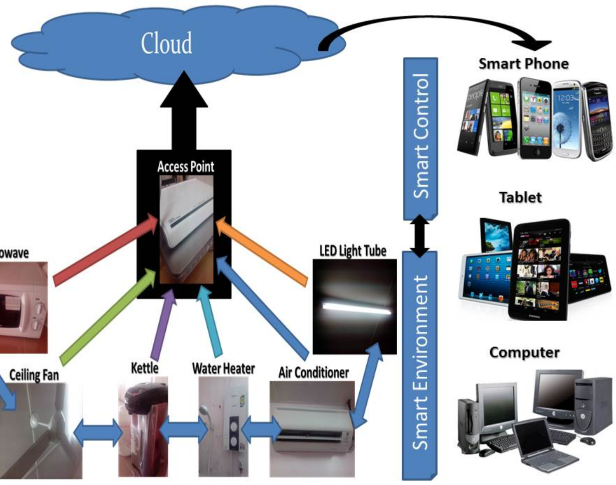

Fig. 1. The Internet of Everyday Things with its smart environment

Despite of the congested spectrum that we face in today wireless community, there are still some spectrum that are underutilize especially those spectrum allocated for the licensee usage. After a study on 2002 by FCC which show that most of the allocated spectrum in US is under-utilized [2], on 2003 FCC had identifies that cognitive radio as the potential candidate for implementing opportunistic spectrum sharing [3]. Now US is the first country in the world to allow the unlicensed user to use the TV white space, which are the licensed spectrum allocate for TV industry. Hence we can see that the global development of cognitive radio in the near future could be the key solution for spectrum congestion issue. For the case of smart environment, cognitive sensor radio (CSN) has provide us a bright solution by integrate the human artificial intelligent feature in searching for a spectrum loophole within the given licensed spectrum. The capability of CSN to detect and sense the characteristics of the given spectrum enable the secondary users(SU) [4], which are the unlicensed users to use the licensed spectrum freely without causing the interference to the authorized primary user(PU) [4], which is the licensed user who had pay to use the allocated spectrum. In order for CSN to work perfectly, the SU, which also known as CR user need to have a strong sensing ability that is aware of its environment and can adapt to the change of environment spontaneously. A powerful spectrum sensing scheme is essential to enable the CSN to sense the idle spectrum and vacate the spectrum immediately when the PU has been detected in order not to cause any interference to the PU. Differential evolution (DE) [5] has been employ to assist the spectrum sensing to achieve an optimal sensing performance. DE, since its first invention, has been become a very popular optimization tool to help to solve many engineering issue. Here, DE will be used to solve the optimization problem in spectrum sensing for CSN. We will look into the detail of DE algorithms in section II, section III will discuss the mathematical model of the spectrum sensing for CSN, the MATLAB simulation results will be discuss in section IV, finally a conclusion will be drawn in section V.

II. DIFFERENTIAL EVOLUTION

The differential evolution algorithms, which was propsed by Kenneth Price and Rainer Storn [6], had revolved into a powerful optimization algorithms and it had been successfully applied to many diverse real life applications. The simplicity to code with only few control parameters involved [7] and effectiveness in solving numerous types of optimization problems including multi-objective, multi-modal, dynamic and constrained optimization problems had make DE to become one of the popular optimization tool.

A. The basic formulation of DE

DE is belonging to the group of evolutionary algorithms that operates in the same computational steps as employed by a standard evolutionary algorithm [7] [8]. Similarly, DE is a population based optimization tools that attacks the given problem by sampling the objective function at multiple and random chosen points. The simplicity and parallelizable characteristics of DE [7] [8] make it simple to use where only 4 basic strategies involved, which are initialization, mutation, crossover and selection. The detail flowchart for DE algorithm is depicted in Figure 2.

B. Initialization

The ever first approach in DE is to initialize the population before sending the target vector to the mutation strategy. The parameters that govern the systems performance will be represented in a vector as shown in Equation 1 and Equation 2 shows the objective function by passing the vector to them.

$$\vec{X}_r = [x_1, x_2, x_3, \dots, x_D]^T \qquad (1)$$

$$f(x) = f(x_0, x_1, \dots, x_{D-1}) \qquad (2)$$

Where $\vec{X}_r$ is the sample vector within the initialize population with r the number of sample vector and D is is the dimension of the given objective function. For our CSN spectrum sensing function, the different size of population will be chosen with a fixed dimension of 20 will be set before passing the function for mutation process. With the D dimensional problem given, DE will search and looking for a global minimum value within the given initialize population bound.

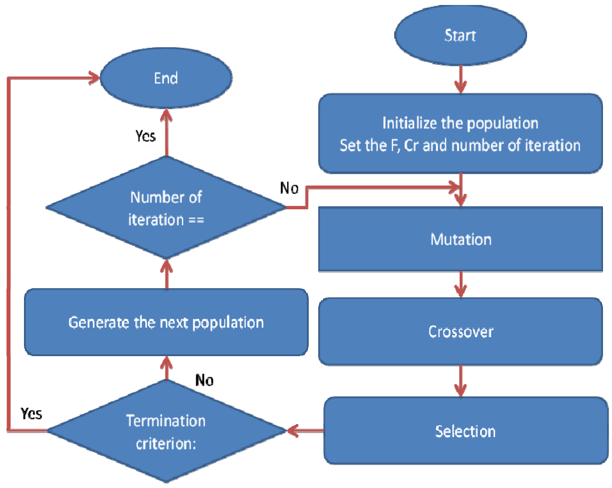

Fig. 2. The general flowchart of DE algorithm

C. Mutation

Three vectors within the given bound of population will be selected randomly and pass to mutation operation which will produce an unexpected modification in the vector features with some random and casual elements. A mutant vector will be produce by subtracting any two random vectors from the given three vectors; the resulting difference value will be scaled by a scalar number F before adding to the third vector as shown in the Equation 3.

$$\overrightarrow{v_{\iota,G}} = \overrightarrow{X_{r_1^i,G}} + F \cdot (\overrightarrow{X_{r_2^i,G}} - \overrightarrow{X_{r_3^i,G}}) \qquad (3)$$

Where G is the number of generation and F is the scale factor. The resultant $\overrightarrow{v_{\iota,G}}$ is known as the mutant vector.

D. Crossover

Crossover plays an important role to increase the diversity of the population. The resultant mutant vector from the above mutation process will exchanges its component with the target vector from the current population in order to form a trial vector [7]. There are generally two kinds of crossover methods namely exponential and binomial. In the case of CSN spectrum sensing function, the binomial crossover will be used. The binomial crossover is executed on each of the D variables by comparing the component vector in the current population whenever a randomly produced number among 0 and 1 is less than or equal to the predefined crossover value. The Equation 4 shows the resultant trial vector after the crossover process.

$$u_{j,i,G} = \begin{cases} v_{j,i,G} & if\ (rand_{i,j}\,[0,1] \le Cr\ or\ j = j_{rand} \\ x_{j,i,G} & otherwise \end{cases} \qquad (4)$$

Where $u_{j,i,G}$ the resultant trial is vector and Cr is the crossover value.

E. Selection

Selection is a process to compare the two vectors which are the final trial vector and the best vector from the current generation. The vector that give the best value over the other will be chosen and pass to the next generation for comparison. This iteration process will continue on until the desired optimization value is reach or the termination requirements are met. In the case of CSN spectrum sensing function, the ultimate optimal value to be reach is 1, however, the iteration will terminate automatically when it reach 1000 even though not yet reach the optimal value. The Equation 5 shows the selection process.

$$\begin{aligned}\overrightarrow{X_{\iota,G+1}} &= \overrightarrow{U_{\iota,G}}\ if\ f(\overrightarrow{U_{\iota,G}}) \le f(\overrightarrow{X_{\iota,G}}) \\ &= \overrightarrow{X_{\iota,G}}\ if\ f(\overrightarrow{U_{\iota,G}}) > f(\overrightarrow{X_{\iota,G}})\end{aligned} \tag{5}$$

where $f(\vec{X})$ is the objective function to be minimized. Hence, if the new trial vector produces an equal or lesser value of the given objective function [7], it will substitutes the resultant target vector in the next generation; else the target vector is retained in the population.

III. Spectrum Sensing Formulation

Spectrum sensing is one of the major elements in the cognitive radio. By definition, spectrum sensing mean to sense and study the condition of the spectrum to see whether the spectrum is in use or is being vacant [4]. The CR sensing Design can be divided into two layer which is MAC sensing layer and PHY sensing layer. MAC sensing layer is responsible for access strategy while PHY sensing provide the spectrum sensor. What we are interested here is the role of energy detector in the PHY sensing layer. The energy detector will measure the energy received on a primary band during an observation interval and declares a spectrum hole or white space if the measured energy is less than a properly set threshold. We can formulate the energy detector using the binary hypothesis test as shown in Equation 6 and 7:

With *H_0:* The spectrum is empty and there is no PU signal

H_1: The spectrum is occupied, there is PU signal

$$H_0: Y_i[n] = W_i[n] \tag{6}$$

$$H_1: Y_i[n] = g_i[n]S[n] + W_i[n] \tag{7}$$

Where $W_i[n]$: Noise, $S[n]$: PU signal, $Y_i[n]$: Measured signal with *i* number of samples

Let assume the PU signal is normally distributed with Gaussian random process and zero mean and variance and with an additive white Gaussian noise (AWGN) channel as a channel to be sensed, we have Equation 8

$$W_i[n] = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{n}{\sigma}\right)^2\right] \tag{8}$$

Hence, the probability density functions of a_0 is detected is given by Equation 9:

$$Y_i[n|a_0] = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{y-a_0}{\sigma}\right)^2\right] \tag{9}$$

Whilst the probability density functions of a_1 is detected is given by Equation 10:

$$Y_i[n|a_1] = \frac{1}{\sigma\sqrt{2\pi}} exp\left[-\frac{1}{2}\left(\frac{y-a_1}{\sigma}\right)^2\right] \tag{10}$$

The probability of detection can be obtained by integrated the received signal with the threshold value, γ. For a optimum threshold detector, we have Equation 11

$$\gamma_{opt} = \frac{(a_0+a_1)}{2} \tag{11}$$

Let set $u = \frac{(y-a_0)}{\sigma}$, so we get $du = \frac{dy}{\sigma}$, with $y = \frac{(a_0+a_1)}{2}$, $u = \frac{(a_1-a_0)}{2\sigma}$, then the probability of false alarm can be obtained as in Equation 12

$$P_f = \int_{\frac{(a_1-a_0)}{2\sigma}}^{\infty} \frac{1}{\sqrt{2\pi}} exp\left[-\frac{1}{2}(u)^2\right] du\ = Q\left(\frac{(a_1-a_0)}{2\sigma}\right) \tag{12}$$

The energy content at the SU are then estimated as in Equation 13:

$$Z = \sum_{i=1}^{m} \omega_i Z_i = \bar{\omega}^T \bar{Z} \tag{13}$$

Where $\bar{Z} = [Z_1, Z_2, Z_3, \ldots.]^T$ and $\bar{\omega} = [\omega_1, \omega_2, \omega_3, \ldots.]^T$, with $\omega_i \ge 0$. With such, the probability of detection can be formulated as in Equation 14:

$$P_d = \left(\frac{Q^{-1}(\overline{P_f})\sqrt{\bar{\omega}^T \Sigma_{H_0} \bar{\omega}} - \bar{\omega}^T\theta}{\sqrt{\bar{\omega}^T \Sigma_{H_i} \bar{\omega}}}\right) \tag{14}$$

IV. Simulation Result and Discussion

The crossover value had been set at 0.95 and the scaled factor at 0.5. The various size of population from 5 to 150 with an increment of 5 each time as shown from Figure 3 to Figure 7, was tested to determine the best population size to be sampled at the initialized process in order to achieve a better optimization result. The simulation shows that the population with size 30 outperforms the rest for the given spectrum sensing function in CSN as shown in Figure 7. As in Figure 6, we can observe that the CSN reach above 0.93 with the population size of 45. In Figure 4, we can observed that as the population size continue to increase, the spectrum sensing function can reach a much more higher optimal value as compare to the previous two graphs. With size of population equals to 70, the optimal value can reach 0.94 and above. It's stable to maintain the detection optimal value at 0.9 and above.

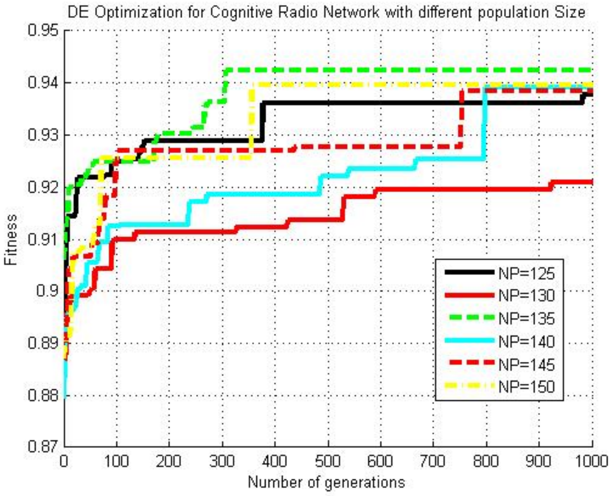

Fig. 3. DE Optimization for CSN with population size from 125 to 150

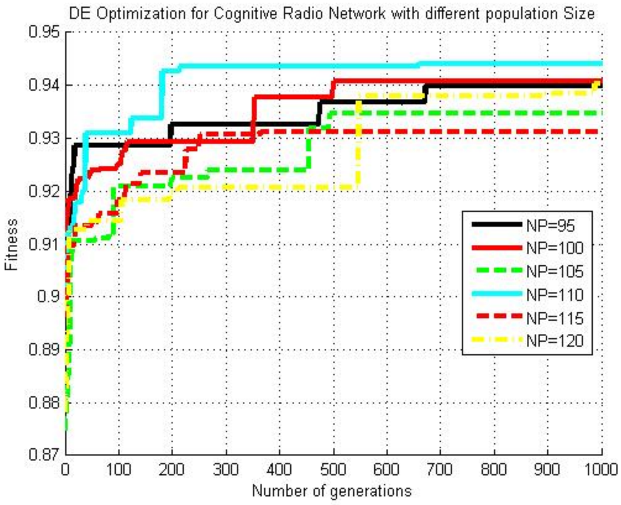

Fig. 4. DE Optimization for CSN with population size from 95 to 120

From all the 5 figures, we can see that by setting the size of populations 20 and above, we can reach the optimal sensing value 0.9 above which is a very satisfying condition to ensure the CSN operate in a stable condition. Overall, the simulation result had proved that DE can help the spectrum sensing function in CSN to achieve a better optimization result and hence increase its sensing performance. The result is promising as the spectrum sensing is an important element in CSN for it to determine whether the spectrum is empty or not for further transmission. And the DE can help the spectrum sensing function to detect the incoming PU signal quickly so that the SU can immediately leave the spectrum. This feature can help the SU to use the licensed spectrum freely by minimizing the interference that it may cause to the PU.

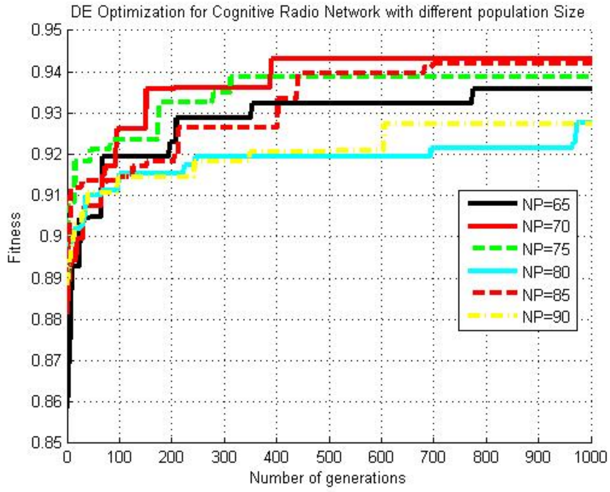

Fig. 5. DE Optimization for CSN with population size from 65 to 90

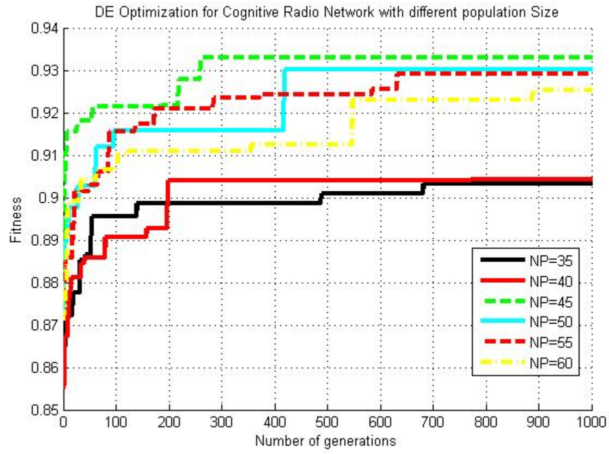

Fig. 6. DE Optimization for CSN with population size from 35 to 60

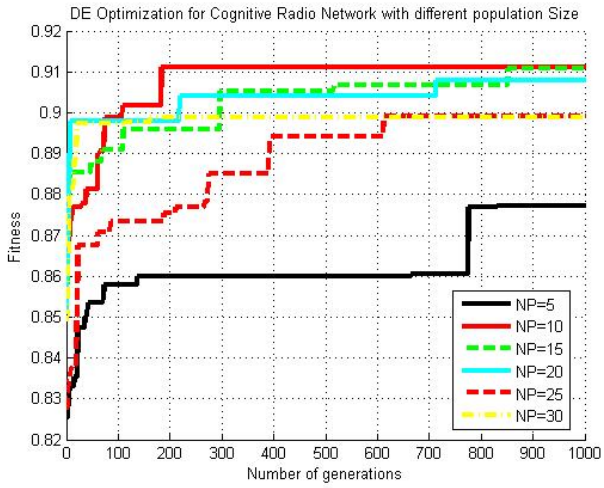

Fig. 7. DE Optimization for CSN with population size from 5 to 30

V. Conclusion

It is clear that the smart environment that complies of various smart objects which are connected wirelessly to the cloud will dominate the world in the near future. The typical wireless sensor network can consist of at least 10 sensing nodes to 100 sensing nodes within a small area which will contribute to heavy traffic load to the wireless channel. Most of the smart sensor nodes are connected and communicate to each other using Zigbee, Bluetooth or WiFi communications. All this communication protocols are using the 2.4GHz spectrum that is currently used for most of the data communication over the internet. The 2.4GHz spectrum had been over congested with the current traffic and the big data contribute by the smart sensor network will be a burden for this spectrum to handle. Cognitive sensor network with add on optimization tool to increase the spectrum sensing capabilities can help to ease the spectrum load. DE has proved himself as one of the popular optimization tools for solving the global optimization problem ever since its first invention. To achieve a better sensing performance for the given spectrum sensing in CSN for smart environment, DE has been employed and has show satisfy optimize result by assisting the spectrum sensing to increase its sensing capability within a short period of time. The fast convergence speed achieve by using DE can help to reduce the interference problem where the SU can sense the incoming PU signal very quickly so it allows SU to have the enough time to leave the spectrum before the arrival of PU signal. As the technology continue to growth and the smart objects increase day by day, the internet traffic load has increase to a point that the current available spectrum is incapable to handle. With the employment of CSN, the issue of spectrum congestion can be solved significantly. Furthermore, with the assistance of DE optimization in spectrum sensing, the issue of interference can be reducing. Hence, we can conclude that the cognitive sensor network is a key enable for us to transform our analogy world to digital world, an ordinary environment to smart environment.

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