# Multiobjective Evolutionary Algorithm for Hybrid Cooperative Spectrum Sensing in Cognitive Radio Networks

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***Abstract*** **- In cognitive radio networks (CRNs), cooperative spectrum sensing can be used by means of hard decision fusion (HDF) or soft decision fusion (SDF) techniques. SDF-based CRNs show better detection performance than HDF-based CRNs whereas HDF-based CRNs require lesser relay overhead than SDF-based CRNs. Thus, there is an obvious contradiction between two main objectives, namely detection performance and communication overhead in CRNs. This paper presents an extended architecture for cooperative spectrum sensing in CRNs that is realized by means of hybridizing SDF and HDF schemes in a cluster based deployment so as to balance between the detection performance and communication overhead under different operational scenarios. The proposed hybrid SDF-HDF architecture employs a multi-objective evolutionary algorithm (MOEA) to optimize the performance metrics of CRNs. Computer simulations show that the proposed MOEA is able to achieve optimized solutions under different CRN's operational scenarios.**

***Keywords - cognitive radio, spectrum sensing, data fusion, evolutionary algorithms.***

## I. INTRODUCTION

In cognitive radio networks (CRNs), the cooperative spectrum sensing (CSS) is proposed to overcome the hidden terminal problem where local sensing by a single SU might fail to detect an active primary user (PU) as a result on an existing obstacle shadowing the transmission of the PU-BS. Due to the hidden terminal problem and detection uncertainty [1], cooperative spectrum sensing (CSS) is widely used as a key concept to improve PU detectability [2][3]. CSS can be realized by means of centralized [4][5] or distributed [6][7] architectures. Distributed sensing has an advantage in the sense that it does not require a backbone infrastructure. However, the concept of distributed cooperation where multiple cognitive radio (CR) terminals have to communicate among themselves might not be an attractive solution when the main CR goals and functionalities are taken into account due to the increased cooperation overhead during the detection cycle. To reduce the cooperation overhead, there have been studies proposed where CR users might only share their 1-bit sensing decisions among themselves [6]. However, this approach has been proven to be inferior to soft/data fusion schemes [4][5]. Also, distributed sensing performs poorly in shadowing environments and scenarios of hidden node problem [8] Thus, centralized sensing can be considered as a good candidate that suits network-wide optimization though it requires infrastructural deployments [9].

To obtain awareness on PU activities, all CR users who are classified as secondary users (SUs) perform spectrum sensing locally and then relay either their sensing decisions to their corresponding centralized SU-BS at which these decisions or data will be combined by using a hard decision fusion (HDF) scheme or a soft data fusion (SDF) scheme, respectively, implemented at a fusion center (FC). The FC makes a global decision on the existence of PU and SU-BS will then instruct its corresponding SUs whether or not to use the sensed band based on that decision. This collaboration among SUs assures reliable detection of PU, thus reduces potential interference to it. The cooperation between multiple SUs is also justified by being a means to have spatial diversity and mitigate degradation of detection performance due to potential poor quality of SU-BS links.

In the literature, many research works have been carried out to study the detection performance of cooperative sensing [10][11][12]. However, these studies were less focused on elaborating the resultant traffic overhead due to the relaying activities between the collaborated SUs and their central base station. This paper handles this contradiction between the detection performance and overhead requirements through hybrid SDF-HDF cluster based CRN architecture. The HDF-based schemes show low overhead communication while their PU detection performance is moderate. On the other hand, SDF-based schemes exhibit high PU detection performance but they do suffer from increased overhead. SDF-based CRNs show better PU detection performance than HDF-based CRNs since the measurements data carry more informative content than the 1-bit decisions of the HDF-based CRNs upon fusion. On the other hand, the HDF-based CRN requires lesser data to be reported from SUs to FC than SDF-based CRNs and therefore has a reduced traffic overhead. In this paper, the proposed hybrid SDF-HDF cluster-based CRN can be used to compromise between detection performance and traffic overhead. The proposed architecture employs a multi-objective evolutionary algorithm (MOEA) based on a genetic algorithm (GA) to optimize the performance metrics of CRNs.

## II. HYBRID SDF-HDF CRN SYSTEM MODEL

The proposed deployment of hybrid SDF-HDF CRN is depicted in Fig. 1. The hybridization between SDF and HDF schemes is realized by grouping the existing SUs within the vicinity of a central BS into multiple clusters. The sensing measurements from the SUs of each cluster are relayed to their corresponding cluster header (CH) where an SDF scheme is performed. Then, the individual sensing decisions made at the CHs are forwarded to the central BS at which a HDF scheme is conducted to construct a global decision on PU availability. Clustering the existing SUs provides means of frequency reuse among CRN clusters and thus spectral resources can be efficiently utilized. Fig. 1 shows the proposed CRN system model where each *M* SUs are grouped into a cluster governed by a CH and the *N* CHs of the *N* clusters report their decisions to a common BS. The use of a weighting vector in the linear SDF brings up the advantage of eliminating the need for finding optimal thresholds for the individual SU nodes and abstracting all into a single global threshold. A well-dedicated algorithm to choose the CH of each cluster can be found in [13]. It is assumed that the instantaneous channel state information (CSI) of the reporting channel is available at each CH. In Fig. 1, three main links can be distinguished; the primary user-secondary user (PU-SU) link, the secondary user-cluster header (SU-CH) link, and the cluster header-fusion center (CH-BS) link.

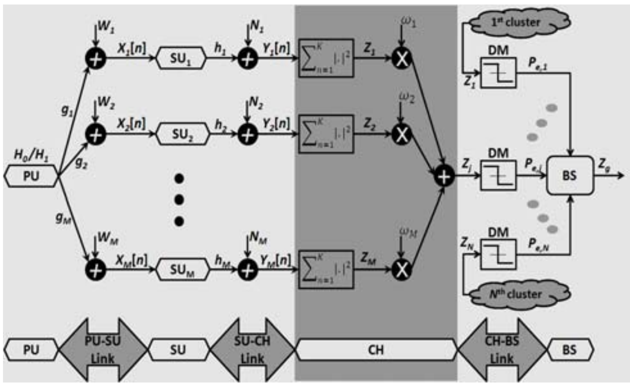


Figure 1. Detailed system model of the proposed hybrid SDF-HDF cluster-based cooperative spectrum sensing.

## III. PERFORMANCE METRICS AND PARAMETERS

In this section, several performance metrics and their related parameters that characterize the overall quantitative performance of the proposed hybrid SDF-HDF CSS-based CRN are proposed. These proposed objectives are put in normalized forms so that no objective of high scores overwhelms others of low scores.

### *A. PU Detection Probability*

The probability of detecting the PU is one of the main metrics of cooperative spectrum sensing in CRNs. As shown in Fig. 1, an SDF scheme is employed at the CH stage whereas a HDF scheme is used at the BS. Thus, the probability of detection at the $j^{th}$ CH, $Q_{d,j}$ is expressed as

$$Q_{d,j} = Q\left(\frac{Q^{-1}(\bar{Q}_f)\sqrt{\vec{\omega}^T \sum_{H0} \vec{\omega}} - \vec{\omega}^T \vec{\theta}}{\sqrt{\vec{\omega}^T \sum_{H_1} \vec{\omega}}}\right) \tag{1}$$

where $\theta_i = K\, P_{Ri}\, |g_i|^2 |h_i|^2\, \sigma_S^2$ , $\vec{\theta} = [\theta_1, \theta_2, ..., \theta_M]^T$ , and $\vec{\omega} = [\omega_1, \omega_2, ..., \omega_M]^T$ .
$H_o$ and $H_1$ refer to the two potential hypotheses of the PU being absent or present, respectively.

In the CH-BS link, all CHs communicate with the central BS through a dedicated control channel in an orthogonal manner. The individual clusters' decisions are forwarded from the *N* CHs to the BS at which a final global decision is made based on a HDF OR-rule. The HDF is used to reduce the reporting traffic overhead from the *M* SUs to the BS. In our proposed system model, it is assumed that the reporting channel of each CH-BS link is a binary symmetric channel (BSC) with a probability of reporting error, $P_{e,}$[14]. Therefore, the overall probability of detection, $Q_d$, of the hybrid SDF-HDF cluster based CRN is given by

$$POD = Q_d = 1 - \prod_{j=1}^{N} \left[(1-Q_{d,j})\left(1-P_{e,j}\right) + Q_{d,j}P_{e,j}\right] \tag{2}$$

The objective of this metric is to maximize POD.

### *B. Relay Probability of Error*

In the proposed model shown in Figure 5.1, any $i^{th}$ SU relays its sensing measurements to the $j^{th}$ CH. For simplicity, it is assumed that all SUs within a given cluster use an *M*-ary QAM scheme with the same modulation index, $M_d$, when relaying their measurements to their corresponding CH. Thus, the relay probability of error, denoted by BER, is expressed as [15]

$$BER = \frac{2*\left(1-\sqrt{M_d}\right)}{\log_2 \sqrt{M_d}} Q\left(\sqrt{\frac{3\log_2 \sqrt{M_d}}{(M_d - 1)} \frac{2*E_b}{N_0}}\right) \tag{3}$$

where $E_b/N_0$ is bit energy per noise power spectral density. The objective of this metric is to minimize BER.

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### C. Control Channel Bandwidth

The bandwidth of the control channel is an important design metric since the spectral resources is the main concern that has led to the emergence of CR technology. Assume that the SUs relay their measurements to their corresponding CH using orthogonal frequency division multiple access (OFDMA) manner with $L_n$ subcarriers. For simplicity, it is assumed that the number of subcarriers used by each SU is the same. The normalized control channel bandwidth (CCB) is then written as

$$CCB = \frac{(2T_s B)u L_n \sum_{j=1}^{N} M_j \Big/ \left(\log_2 M_d\right) T_r F_{reuse}}{CCB_{\max}} \tag{4}$$

where $T_s$ is the sensing time duration, $B$ is the sensed bandwidth, $u$ is the number of quantization bits per sample, $M_j$ is the number of SUs into the $j^{th}$ cluster, $M_d$ is the $M$-ary modulation index, $T_r$ is the relay time, $F_{reuse}$ is the frequency reuse factor and $CCB_{max}$ is the maximum available control channel bandwidth. The objective of this metric is to minimize CCB.

### D. CRN Throughput

The CRN throughput is proportional to the available time of SU opportunistic data transmission out of the total frame time duration. The normalized CRN throughput (THR) for a given frame time duration can be modified by from [16] as follows

$$THR = \frac{\left(\frac{T_f - (T_s + T_r)}{T_f}\right)\left(1 - Q_f\right)}{THR_{\max}} \tag{5}$$

where $THR_{max}$ is the maximum achievable throughput of the CRN. The sensing time period is assumed to be the same for all SUs. This is because varying the sensing time among SUs may result in synchronization issues that complicate the periodic sensing activity of the CRN. The objective of this metric is to maximize THR.

### E. Total Power Consumption

The power consumption should be minimized to allow long connectivity especially when limited power resources are available. The total power consumption of SUs in the network is due to the total transmission power used to relay the sensing measurements from the SU transmitters all the way to the central BS through the corresponding FC. The normalized total power consumption (TPC) during the relay of sensing measurements can then be expressed as

$$TPC = \frac{\sum_{j=1}^{N} \sum_{i=1}^{M_j} P_{r\,j,i}}{TPC_{\max}} \tag{6}$$

where $P_{r\_j,i}$ is the transmit power of the $i^{th}$ SU in the $j^{th}$ cluster and $TPC_{max}$ is maximum power consumption. The objective of this metric is to minimize TPC.

### F. Signal to interference and noise ratio

As the number of SUs per cluster increases, the mutual interference caused by the transmission of nearby SUs becomes a serious matter. In this metric, it is assumed that the interference effect at the receiver of a certain SU is limited to the SUs who exist within the same cluster only and not to be influenced by the transmission of SUs of neighbouring clusters. The normalized signal to interference and noise power (SINR) can be expressed as

$$SINR = \frac{1}{SINR_{\max}} \sum_{j=1}^{N} \sum_{i=1}^{Mj} \frac{P_{r\,j,i}}{N_{j,i} + \sum_{k=1,k\neq i}^{M_j} P_{r\,j,k}} \tag{7}$$

where $SINR_{max}$ is the maximum possible score of SINR. The objective of this metric is to minimize SINR.

### G. Quantization fidelity of sensing measurements

The collected samples of the sensing measurements at the SU receivers are quantized to a certain number of levels to reduce the amount of traffic overhead upon relaying the sensing measurements to the corresponding CHs. The number of quantization levels, and thus the number of quantization bits per sample ($u$), has to be carefully selected. This is because using too many quantization levels results in bandwidth expansion whereas reducing the number of quantization levels will degrade the signal fidelity. The fidelity can be simply thought of how much the quantized samples resemble their original signal [15]. The normalized quantization fidelity (CFD) can be written as

$$CFD = \frac{2^{2u}}{CFD_{\max}} \tag{8}$$

where $CFD_{max}$ is the maximum possible fidelity. The objective of this metric is to maximize CFD.

## IV. DEPENDENCY RELATIONSHIPS OF PERFORMANCE METRICS

The performance metrics formulated in Equations (2) to (8) describe multiple objectives of the CRN that need to be jointly optimized. By inspecting the mentioned equations of the performance metrics, several dependent parameters can be distinguished. These parameters and their used symbols and descriptions are tabulated in Table 1. Each of these

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parameters may control more than one single performance metric as shown in Fig. 2.

TABLE I. SUMMARY OF DEPENDENT DESIGN PARAMETERS OF THE PROPOSED METRICS

| Parameter Name | Symbol | Description |
|---|---|---|
| Modulation index | $M_d$ | Modulation index used to relay the measurements. |
| Sensing time | $T_s$ | Time duration taken to perform spectrum sensing. |
| Probability of false alarm | $Q_f$ | The CRN-wise probability of false alarm. |
| Relay power | $P_r$ | Amount of power required to relay the measurements. |
| Number of SUs per cluster | $M$ | Number of SUs in each cluster. |
| No of bits per sample | $u$ | Number of quantization bits per sample. |
| Total relay time | $T_r$ | Total relay time from SU to BS through CH. |

Fig. 2 depicts the dependency relationships between the performance metrics and their corresponding parameters. By performing simple inspections for the performance metrics expressed in Equations (2) to (8), it can be observed that the same parameter may influence a given performance metric differently.

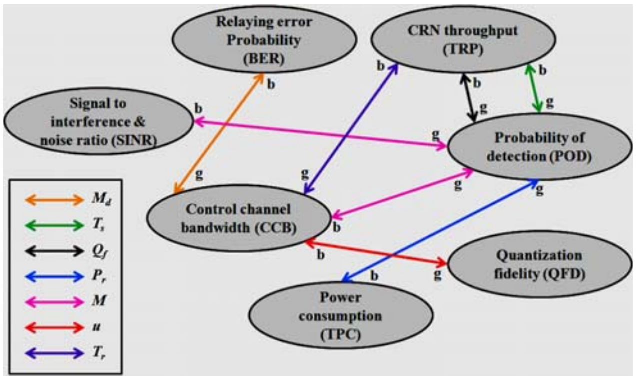


Figure 2. Objective-parameter dependency relationships and their conflicting behavior.

This means that increase a certain parameter may improve a certain performance metric but at the same time, it may degrade another. The proposed performance metrics are shown in ellipses shaded in gray whereas the corresponding parameters are listed in the legend. These parameters use arrows of different colors connecting the performance metrics they are related to. On these arrows, (g) and (b) are labelled to indicate good and bad effect on the connected metrics as the related parameter increases, respectively. For instance, increasing the $M_d$ has a good effect on control channel bandwidth whereas it has a bad effect on the relay probability of error as can be observed by inspecting Equations (4) and (3), respectively. Also, increasing the sensing time $T_s$ improves the detection probability of PU (good effect) but at the same time it reduces the CRN throughput (bad effect) since remaining time for transmission is then decreased. The later effects can be confirmed by inspecting Equations (2) and (5), respectively. The same goes for all other parameters and their related performance metrics.

It is clear that the proposed objectives demonstrate a conflicting behavior which requires an intelligent system that is able to search for sub-optimal parameters at which a balanced compromise among these conflicting objectives can be achieved.

## V. FORMULATION OF OPTIMIZATION PROBLEM

The intended objectives of the performance metrics expressed mathematically in Equations (2) to (8) are now defined as shown in Table II. All objective functions are formed as maximization problems. The original minimization problems of CCB, TPC, and BER are complemented into equivalent maximization problems. The design parameters (decision variables) that control each objective are also listed. These objectives are classified into four main classes according to their functionality. The forth class combines quality parameters of the relay process from the SUs to the BS through corresponding CHs. These multiple objective functions shown in Table II are aggregated into one multi-objective.

TABLE II. THE PROPOSED OBJECTIVE FUNCTIONS AND THEIR RELATED PARAMETERS

| $f_i$ | Objective | Abbr. | Parameters | Class |
|---|---|---|---|---|
| $f_1$ | PU detection Probability | POD | $f(T_s, Q_f, P_r, M)$ | 1 |
| $f_2$ | CRN Throughput | TRP | $f(T_s, Q_f, T_r)$ | 2 |
| $f_3$ | Control Channel Bandwidth | 1 - CCB | $f(M_d, T_s, M, u, T_r)$ | 3 |
| $f_4$ | Total Power Consumption | 1 - TPC | $f(P_r)$ | 4 |
| $f_5$ | Quantization fidelity of measurements | QFD | $f(u)$ | |
| $f_6$ | Signal to interference and noise ratio | SINR | $f(M)$ | |
| $f_7$ | Relay probability of error | 1 - BER | $f(M_d)$ | |

The aggregation of seven objectives is realized using the weighted-sum utility function as follows:

$$
\begin{aligned}
f_{multi-objective} &= \sum_{i=1}^{C} w_i f_i \\
&= w_1 f_1 + w_2 f_2 + w_3 f_3 + w_4 f_4'
\end{aligned}
\quad (9)
$$

where $f_4' = (f_4 + f_5 + f_6 + f_7)/4$ , $C$ is the number of objective classes (i.e. $C$ = 4) and $w_i$ is the weighting coefficient of the $i^{th}$ class.

The aggregation procedure realized using the weighted-sum or linear logarithmic utility functions provides a unique feature that can benefit the cognition requirement of CRN as well as the CR systems. This cognition allows the optimization process to be steered towards a specific objective according to the operational requirements and/or user demands. The rational priority of each objective in comparison to other objectives is set by assigning a distinct weighting coefficient as shown in Equation (9). In this research work, six operational modes of the CRN have been defined by adjusting the weighting coefficients of the individual functions that constitute the overall multi-objective function as shown in Table III. In this table, the objective which is receiving more emphasis is arbitrarily allocated 70% whereas other objectives would share the other remaining 30%. The rational distribution of the weighting coefficients of the multi-objective function is to be set externally by a network administrator or internally based on channel conditions and operational requirements.

TABLE III. PROPOSED OPERATIONAL MODES AND THEIR CORRESPONDING WEIGHTING COEFFICIENTS

| Operational Mode | Weighting coefficients | | | |
|---|---|---|---|---|
| | $w_1$ | $w_2$ | $w_3$ | $w_4$ |
| High licensee protection mode | 0.7 | 0.1 | 0.1 | 0.1 |
| Multimedia mode | 0.1 | 0.7 | 0.1 | 0.1 |
| Low bandwidth mode | 0.1 | 0.1 | 0.7 | 0.1 |
| High quality mode | 0.1 | 0.1 | 0.1 | 0.7 |
| Balanced mode | 0.25 | 0.25 | 0.25 | 0.25 |
| Customized mode | $c_1$ | $c_2$ | $c_3$ | $c_4$ |

## VI. MULTI-OBJECTIVE EVOLUTIONARY ALGORITHM (MOEA)

The proposed MOEA-assisted SDF-HDF cluster based cooperative spectrum sensing is developed to optimize the multi-objective function stated in Equation 9. The design parameters shown in Fig. 3 and described in Table 1 are encoded into the chromosomes of the proposed MOGA hybrid SDF-HDF cluster based optimization system. The chromosome is comprised of 7 decision variables and it has a length of 38 bits in total as shown in Fig. 4. This chromosome length results in a search space of $2^{38}$ potential solutions. The selection of number of bits to represent a certain decision variable depends on the discrete range of values for that variable. Binary GA is developed due to the discrete nature of the optimization problem and to reduce the search space of potential solutions.

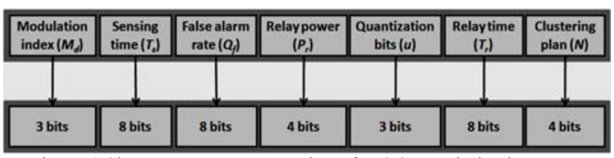

Figure 4 Chromosome representation of MOGA optimization system

The proposed algorithm is initialized by generating a population of potential solutions $P(t)$. Then, GA evolutionary operations are carried out to continuously update this population and produce solutions of better quality. A self-explanatory description of MOEA algorithm is stated in Table IV.

TABLE IV. PROPOSED SDF-HDF CLUSTER-BASED MOEA

| Steps | Details of the Algorithm |
|---|---|
| *Step 1* | Set $t$ = 0 and randomly generate a population $P(t)$ of *pops* chromosomes each of which is of $\sum_{i=1}^{NOV} vbits_i$ bits long, where *NOV* is the total number of decision variables and $vbits_i$ is the number of bits to represent the $i^{th}$ decision variable. |
| *Step 2* | Decode each chromosome in the random population into its corresponding numerical values of $M_d$, $T_s$, $Q_f$, $P_r$, $M$, $u$ and $T_r$ which denote the operational parameters in Table 1. |
| *Step 3* | Compute the fitness score of every decoded chromosome using Equation (9, rank their corresponding chromosomes based on their fitness scores and identify the best $\lfloor pops * elite \rfloor$ chromosomes, where *elite* is a parameter determines a fraction of *pops*, i.e. $elite \in [0,1)$, and $\lfloor . \rfloor$ denotes floor operation. |
| *Step 4* | Update $t$ = $t$ +1 and reproduce $\lceil pops * (1 - elite) \rceil$ new chromosomes (candidate solutions) through genetic algorithm operations; selection, crossover, and mutation, where $\lceil . \rceil$ denotes ceiling operation. |
| *Step 5* | Construct new population $P(t)$ by concatenating the newly $\lceil pops*(1-elite) \rceil$ reproduced chromosomes with the best $\lfloor pops*elite \rfloor$ found in $P(t$ - 1). |
| *Step 6* | Decode the chromosomes of the new population $P(t)$ as in Step 2. |
| *Step 7* | Evaluate the fitness score of each candidate solution as in Step 3. |
| *Step 8* | If $t$ equals to a predefined number of generations (iterations), *ngene*, the algorithm is terminated; otherwise go to Step 4. |

## VII. SIMULATION RESULTS

In this research work, a graphical user interface simulation model (GUISM) has been developed in order to realize a friendly interactive tool user interface that helps the user to choose the operational mode of the MOEA optimization system, select the aggregation approach and utility functions, setting the range of decision variables, and setting the genetic algorithm parameters. The GUISM is used to show the convergence performance of the proposed hybrid SDF-HDF cluster based CRN. The system is initialized by selecting the utility function to be used for aggregation of objectives and the channel condition as well as the operational mode. Also, the range of each decision variable and the GA parameters are supplied. The GUISM is set to 100 existing SUs, total number of generations of 600, and total frame duration of 100 microseconds. The system is then run to observe the graph of fitness versus number of generations. The optimal parameters panel show the obtainable parameters after terminating the evolutionary processes of the system. Figure 5 show the settings as well as the obtained results under the high quality mode taken arbitrarily. The convergence performance is shown on the upper fitness versus generation's graph.

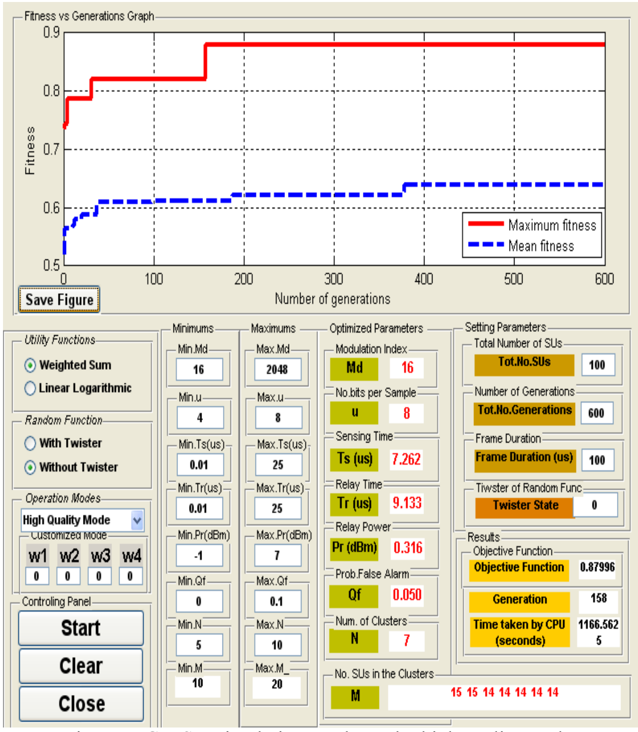


Figure 5. GUISM simulation results under high quality mode

It is noticed that the obtainable sub-optimal solution is obtained after 158 generations scoring a maximum fitness of about 0.88 (or 88%). The obtainable parameters are modulation index $M_d$ = 16, $u$ = 8 quantization bits per sample, sensing time $T_s$ = 7.262 microseconds, relay time $T_r$ = 9.133 microseconds, relay power $P_r$ = 0.316 dBm, false alarm rate $Q_f$ = 0.05, and number of clusters $N$ = 7 of about equal number of SUs. Under the chosen high quality operational mode, the optimization process is steered towards prioritizing the forth class of objectives in Table 2 that is to minimize the power consumption, maximize the quantization fidelity, minimizing the signal to interference and noise ratio, and minimizing the relay error rate. However, the dependent parameters of these conflicting objectives may conflict among each other as well as with objectives of other classes. For example, increasing the number of quantization levels results in increasing the quantization bits which improves the quantization fidelity but it causes increment on the control channel bandwidth. Also minimizing the power consumption can be achieved by reducing the transmission power of the SUs when relaying their sensing measurements to their corresponding CH. However, reducing the transmission power has the bad effect of degrading the CRN-wise probability of detection as has been shown in Figure 2. Therefore, the obtainable parameters are not expected to be the optimal parameters at their extreme values that solely maximize the class of objectives with the highest priority. Instead, the obtainable solutions are only sub-optimal values that can realize compromises between the conflicting intra and inter classes of objectives. By inspecting the values of obtainable parameters, the lowest modulation index of 16 is chosen since high relay quality is demanded. The highest number of quantization bits of 8 is also used to improve the quantization fidelity. A low sub-optimal transmission power of 0.316 dBm is acceptable to reduce the power consumption. The other parameters are selected to attain a balanced compromises based on the weighting coefficients assigned to the respective objectives.

## VIII. CONCLUSION

This paper presents a hybrid SDF-HDF based CSS for CRNs. Several performance metrics are proposed to construct the overall multi-objective fitness function of the whole network from the SUs all the way to the central FC/BS through corresponding CHs. The CRN design parameters are then identified and the single objective functions are aggregated into one overall multi-objective function after being weighted using appropriate weighting coefficients. The CRN operational modes associated with the distinct settings of the weighting coefficients are also identified. A MOEA optimization system with an interactive interface called GUISM is then developed to optimize the CRN design parameters so that the overall MOF function is maximized. The obtainable design parameters under various operational modes prove the effectiveness of the proposed MOEA algorithm for the presented hybrid SDF-HDF CSS.

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