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PREDICTING THE DEMAND FOR SPECTRUM ALLOCATION THROUGH AUCTIONS (PREPRINT)

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14. ABSTRACT

The projected rare resource spectrum generates high profits if utilized efficiently. The current static allocation lead the spectrum to underutilized with fixed income. Predicting the user requirement for spectrum and auctioning the spectrum helps to better serve the customers and at the same time increases the income. In this research we use the automated collaborative filtering model for predicting the customer requirement and then allocate the spectrum through auctions (bidding for spectrum in open market). Genetic algorithm is used for optimization of the spectrum bidding problem and concluded that the spectrum will be used efficiently while generating more revenue by bidding for spectrum in the market.

15. SUBJECT TERMS

genetic algorithm, automated collaborative filtering, cognitive radio, channels, auctions

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Predicting the Demand for Spectrum Allocation Through Auctions

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Abstract – **The projected rare resource spectrum generates high profits if utilized efficiently. The current static allocation lead the spectrum to underutilized with fixed income. Predicting the user requirement for spectrum and auctioning the spectrum helps to better serve the customers and at the same time increases the income. In this research we use the automated collaborative filtering model for predicting the customer requirement and then allocate the spectrum through auctions (bidding for spectrum in open market). Genetic algorithm is used for optimization of the spectrum bidding problem and concluded that the spectrum will be used efficiently while generating more revenue by bidding for spectrum in the market.**

Keywords - Genetic Algorithm; automated collaborative filtering cognitive radio;channels; auctions;

I. INTRODUCTION

Historical spectrum allocation regulations insist the static assignment and long term leasing of spectrum. Over time, the static assignment led to under utilization and extreme demand for spectrum. To eliminate such under utilization of spectrum and fulfill the customer demands for spectrum, a new approach is required. As part of new approach it is required to predict the customer needs. The customer needs will be predicted using automated collaborative filtering (ACF) and allocated through auction. The spectrum trading, which uses pricing based incentives includes the functions sell, lease, and predict the user needs.

The auctions are attractive for both sellers to improve their financial returns and buyers to meet their demands. To perform these auctions, we require efficient resource allocation methods and auction algorithms. The resources must be monitored continuously by a special agent at each base station to meet the demands of the customers. The agent name is cognitive radio, which understands the radio parameters, customer demands, stores the customer history, and bid for resources to meet customer needs.

Dynamic spectrum allocation (DSA) using cognitive radios and DSA by auction and bidding are immediate answers to manage spectrum efficiently. Huang, et al [1] discussed the price driven power control to minimize the interference, where all buyers use the same spectrum band. Ileri [2] used the optimal channel allocation with iterative bidding to maximize the expected revenue. A hybrid model proposed to minimize the complexity by using simple auctions during peak period with a reserved price while applying a uniform price to all buyers during off-peak is proposed by Ryan, et al [3].

Hong and Wassel's [4, 5] results show that for dynamic channel allocation using the game theory approach for broadband fixed channel allocation, genetic algorithm [6] will be a better choice for optimum allocation of resources. The performance of genetic algorithms (GA) for resource allocation was studied by Reddy [7, 8] and concluded that genetic algorithms perform better in optimum resource allocation but take more computations. Reddy concluded that GAs produce better results in optimum power allocation and concluded that a GA approach is a viable and better for optimization problems. The proposed problem is a matter of optimum resource allocation, where the resource is the spectrum.

II. AUTOMATED COLLABORATIVE FILTERING FOR SPECTRUM ALLOCATION

Automated collaborated Filtering (ACF) is a recommendation of a product based on word of mouth [9, 10]. In ACF, if user A's ratings of a channel (or channels) matches with another user B's ratings then it is possible to predict the ratings of a new channel for A, if B's rating for that channel is available. In other words, let us assume that if users X, Y, and Z have common interest in the channels C1, C2, and C3, then if X, Y did high rate of channel C4, then we can recommend the C4 for Z. That is, we can predict that Z bids for high for that channel since C4 is close interest of Z. The approximate bid of a k^{th} bidder can be calculated by storing the bids of current bidders on the spectrum. For example, if there are N bidders and $b_1, b_2, . ., b_N$ are the bids of all N bidders. Let B is the sum of all bids, then k^{th} bidder's share is calculated as shown below:
Let b_k be bid of the k^{th} bidder and sum of the N bids is

$$B = \sum_{k=1}^{N} b_k \qquad \text{---- (1)}$$

The k^{th} bidder share of the spectrum = $\dfrac{b_k}{B}$ ----- (2)

Similarly the user interest on a product (spectrum) will be calculated.

A common way of implementing the ACF systems is by using the mean squared difference formula [11], defined as below:

Let U and J are two persons interested in a product called spectrum. Let U_f and J_f are the ratings of U and J on a feature *f* of the product. Let S, the set of features of the spectrum both U and J are rated and f ε S. The difference between two persons U and J in terms of their interests on a product is given by [11]:

$$\delta_{U,J} = \frac{1}{|S|}\sum_{f \in S}(U_f - J_f)^2 \qquad \text{---- (3)}$$

ACF recommendations are two types, namely invasive and non-invasive based on the user preferences [12, 13]. An invasive approach requires explicit user feedback, where the preferences can vary between 0 and 1. In non-invasive approach, the preferences are interactive and Boolean values. In non-invasive rating 0 means user not rated and 1 means rated. Therefore in non-invasive cases, it requires more data for any decision.

In ACF systems all user recommendations will be taken into account, even they are entered at different times. More recommendations give good strength for recommendation and recommendations solely depends upon the data.

III. SPECTRUM BIDDING MODEL

The efficient spectrum allocation can be achieved through complete coordination of reconfigurable base stations. Cognitive radio plays a role for real time spectrum sharing and can be achieved by pooling the frequencies of different radio access technologies owned by different operators. The pool of spectrum can be accessed by any of the radio access technology (RAT) by maintaining inter and intra co-channel reusable distance constraints (without violating the set constraints). The reusable channel distance between two base stations is measured through spatial reusable distance. The eligible channel of available channels is selected by satisfying the rules of the reusable distance. The reusable channel is important for automated collaborative filtering before a user bids in auctions.

The dynamic spectrum allocation through ACF and auctions (DSATAA) improves the usage of spectrum by adjusting the parameters of allocation in time and space. The ACF model helps the better selection of channel and quick selection of user interested channel. In this article a GA approach was used for resource bidding model that maximizes the spectrum utilization through DSA while increasing the revenue.

The bidding prices are never uniform in any profitable business. If a customer is willing to pay a higher price for the product, then the customer will win the bid. If the difference of interest between any two customers (see equation 3) is very little (means that both customers are interested on the same spectrum) then there is a chance of higher bid by these two customers on a particular spectrum (when the spectrum is available for bid). For better bidding, the market clearing algorithms were useful and studied extensively by Sandholm and Suri [14]. The seller predicts higher price on a particular spectrum and the customers willing to pay based on the recommendation on that product.

The product recommendation in the current problem depends upon customer interest and the impact of interference, where the product is the spectrum with M channels. The best channels among the available channels have higher prices. The prediction of customer interest will be detected using ACF model and then the bidding price will be fixed. The recommendation is based upon the signal of non-associated access points, which disrupt communications. Unlike product recommendations based on ratings by two customers, the spectrum recommendation is based upon the interference constraint. If a k^{th} user pays price p_k for spectrum frequency f_k then bidding for spectrum (auction clearing problem) is expressed as a non-linear optimization problem with minimum interference [15]:

$$f_k . p_k(f_k) \qquad \text{----- (4)}$$

subject to $f_k \leq 1$.

If the bidder share is $\frac{b_k}{B}$, the equation (4) becomes:

$\frac{b_k}{B} \times p_k(f_k)$ .The term $p_k(f_k)$ is the unit price of the spectrum f_k , $f_k \in F_k$, and $F_k = \sum_k f_k$

The best price is obtained by maximizing $\frac{b_k}{B} \times p_k(f_k)$:

$$Maximize \sum_{k \in bidders} \frac{b_k}{B} . p_k(f_k) \qquad \text{------ (5)}$$

The spectrum assign policy follows the spectrum usage policy. The policy is:

Assume that there are three base stations A, B, and C where they are neighbors and spectrum assigned to neighboring base stations should not be same. i.e.

$$F_A \cap F_B \cap F_C = 0 \qquad \text{----- (6)}$$

If a channel is assigned to a user (s_k^A =1), the channel is not available to other users, where each base station has the channel frequency as:

$$F_k = \{s_1^A, s_2^A, .. s_M^A\} \qquad \text{----- (7)}$$

The best bidding price will be setup if the seller know the closely interested customers bidding for the spectrum. The closely related customers are obtained by using the mean squared difference formula given in equation (3). The bidding process takes new shape when the system creates a database of users and user interests. Using the closely related customers stored in database we can increase or decrease the unit bidding cost of the specified spectrum. The closely interested bidding customer case is dealt separately.

Maximization of the bid depends upon $p_k(f_k)$. Equation (5) is a non-linear integer programming problem, since interference constraints involve integers. i.e. s_k^A = 0 or 1. The optimal solution can be obtained by using genetic algorithms.

IV. APPROACH

The static allocation and uniform pricing of the spectrum generates constant revenue and inefficient use of the spectrum. FCC reports [16] show that more than 70% of the spectrum is underutilized, which is due to static allocation of the spectrum. Due to static allocation of the spectrum, the licensed users or primary users use the specified channels. During the peak time, spectrum is not available to a normal user (secondary user). ACF model helps to predict the type of spectrum requirement for a particular user. Dynamic spectrum allocation and auction policy will help secondary users to use the spectrum efficiently and at the same time increase revenue. Efficient utilization of spectrum and auctioning policy should not interrupt the quality of service (QoS) or increase the interference.

There are many approaches to deal with this problem. An intelligent agent called cognitive radio (CR) is created at each base station to keep track of the current state of the spectrum, store history of spectrum utilization, track the users (customers), predict the needs of users, and bid for spectrum. That is, the cognitive radio works at the base station for secondary users and provides the extra revenue for the manager. Because the process involves the quality of service, the CR must take care of the interference.

Prediction through ACF: Using the equation (3) the difference between interests of any two persons will be determined. If these persons present in the bid, the bidding process takes different direction and seller gets high value. So there is a need to maintain the ACF database with dynamic updates of user interests, which helps for profits in bidding. Sorabh [15] discussed the piecewise linear price demand (PLPD) using the linear equation for price sensitivity. The formula allows the bidders to express the preferences privately by eliminating complex bid signaling. But ACF further simplifies the bidding because it predicts various user needs and helps in auction clearing.

Auction Clearing Algorithms (ACA): The ACA's are NP-hard. If a channel frequency in a cell allocated to any bidder, none of the neighboring cells of same frequency should not be allocated due to interference. So it is required to have a maximal independent set of conflict graph of frequencies to allocate the same frequency. If a large number of bidders are involved it becomes a more complex linear programming problem and requires large amount of time. One of the possible solutions to solve such problem is genetic approach [6]. The genetic algorithm approach helps to solve the problem of allocation of the spectrum to the appropriate user and higher bid. The trials and success rate is provided to the genetic algorithm to find the fitness of channels and select the appropriate channel for the future request. In other words, CR uses the genetic algorithm to process and find the best channel ordered list for the best bidding.

The best price on bidding will be obtained by maximizing the value in equation (5). To solve the equation (5) we need the following input:

- number of users
- channel numbers assigned to users
- channel rating
- bid value

The values for the input are taken randomly and calculated the price of the spectrum. The bid values are selected depending upon the channel rating received from users. An example of the calculations for bid price is given in Table 1 below:

Table 1: Spectrum bidding with 'n' channels and k users.

User #	Channel #	Channel Rating	Bid-value	(bi/B)*A
1	**1**	**0.5**	**0.5**	0.5/5*0.625=0.0625
2	**2**	**0.4**	**0.5**	0.5/5*0.625=0.0625
1	**4**	**0.6**	**0.7**	0.7/5*0.625=0.0875
4	**3**	**0.8**	**0.9**	0.9/5*0.625=0.1125
3	**5**	**0.2**	**0.3**	0.3/5*0.625=0.0375
2	**8**	**0.5**	**0.5**	0.5/5*0.625=0.0625
1	**7**	**0.8**	**0.9**	0.9/5*0.625=0.1125
2	**6**	**0.6**	**0.7**	0.7/5*0.625=0.0875
			5	0.5/5*0.625=0.0625
			A=5/8=0.625	Sum=1.25

Channel rating	**bid-value**
0 to 0.3	0.3
0.31 to 0.5	0.5
0.51 to 0.7	0.7
0.71 to 0.99	0.9

We solved the spectrum auction policy by using MATLAB language. The output is then assigned as fitness function to 'gatool' (MATLAB genetic algorithm tool) and observed the convergence. The simulations are discussed in section VI.

V. WHAT IS GENETIC ALGORITHM

Genetic algorithms (GA) are a particular class of evolutionary algorithms used in computing to find exact or approximate solution. Genetic algorithms are inspired by evolutionary biology such as inheritance, mutation, selection, and crossover. In computations the abstract representations of candidate solutions are chromosomes and set of chromosomes formed as population. Traditionally the chromosomes are randomly generated as binary strings of 0s and 1s, but other encodings are also possible. In each generation the fitness of individual (chromosome) in population is evaluated and multiple individuals are stochastically selected from the current population based on their fitness. The new population is formed using mutation, crossover and selection operators and fitness of the individual chromosome. The algorithm terminates as maximum number of generations are reached or satisfactory fitness level has been reached for the population.

A typical genetic algorithm requires a genetic representation of the solution domain and a fitness function to evaluate the solution domain. The fitness of the solution is the sum of values of all objects in the knapsack if the representation is valid or 0 otherwise. Once we have the genetic representation and the fitness function defined, GA proceeds to initialize a population of solutions randomly, and then improve it through repetitive application of mutation, crossover, inversion, and selection operators.

The chromosomes are homogeneous in length to facilitate crossover operation. Tree-like representations are explored in genetic programming and graph-form representations are explored in Evolutionary programming. The operations are explained below:

Initialization: The individual population (chromosome) is generated randomly. The size of the population depends upon the nature of the problem.

Selection: Selection eliminates the poorer performing individuals by promoting the better performing individuals. Depending upon the problem, a certain percentage of new population will be added to lead better solution. The less fit population are normally ignored to bread for next generation. This helps keep the diversity of the population large, preventing premature convergence on poor solutions. Popular and well-studied selection methods include roulette wheel selection and tournament selection.

Reproduction: Generate new population from the current population using crossover and mutation operators. To produce new population, take a pair of randomly selected chromosomes (parents) and generate the children using crossover and mutation operators. The children share the many of the characteristics of its parents. The process continues until a new population of solutions of appropriate size is generated. These processes ultimately result in the next generation population of chromosomes that is different from the initial generation.

Termination: The common termination condition is number of generations. Other termination conditions may include that a solution is found that satisfies minimum criteria or budget constraints on computations.

VI. RESULTS AND CONTRIBUTIONS

The equation (5), bidding for spectrum was solved using MATLAB program and MATLAB *gatool* in parallel. The data for user entrance in the system for channel use, channel numbers (without duplication), and channel rating by users were developed randomly through MATLAB programming. Figure 1 is drawn for 500 channels, 10 users, and 100 different iterations. For each one of the iteration the bidding value is calculated and the lowest bidding is observed after 70 iterations.

Next the bidding value is input to the MATLAB *gatool* and executed for 600 generations as shown in Figure 2. The crossover is set for heuristic with population of 30 and mutation Gaussian and with appropriate stopping criteria. The heuristic selection of crossover converges quickly compared to scattered or two point (see Figure 4). Initially we used the crossover, mutation, and scaling function values were used as the default values. In the second step, the parameter values of population were changed to 30, crossover function as heuristic, mutation as Gaussian, and selection function as Stochastic Uniform. The execution was selected for 600 generations for better bidding values (Figure 4 and Figure 5). The function was tested with 4 to 200 users and with variation of 20 to 50 channels. The maximum number of generations observed was set to 600. The example graphs generated through *gatool* were provided in Figure 4 and Figure 5. The best fit value is better when more users are trying to bid for spectrum (top part of the Figure 4 and Figure 5).

Figure 3 (4 to 20 bidders) and Figure 6 (4 to 50 bidders) are tested with MATLAB program with 50 channels. It is observed that if number of bidders is less, more channels are available for bidding and if the bidding range is smaller then more users are bidding for spectrum. The reason for decreasing of profit depends upon the number of channels for bidding and bidding rate. Therefore, we can conclude that as the number of channels open for bidding increases the profit decreases because profits based on number of open channels and bidding rate, which is natural in the market.

Figure 7 shows the market value for fixing the number of channels 50 for bidding. The figure 7 concludes that the profit decrease as few number of channels are available for bidding.

The figure 3, Figure 6, and Figure 7 conclude that open bidding for spectrum or bidding for spectrum through dynamic allocation generates more revenue compared to static allocation of spectrum. Figure 1 show that if no one requires the spectrum (or no one bids for spectrum), we do not distinguish between dynamic allocation and static allocation of spectrum. Figure 4 and Figure 5 (Lower part) show the convergence of the equation (5) using *gatool* for 50 channels and 600 generations. The best fitness shows the decreasing value or market generated value as we fix the number of channels for static allocation from 1 to 50. Figure 2 (right top of the figure) further concludes that the average distance between any two individuals of the population close to 0 (zero) quickly at generation 1, means the system converges at an earliest time. That is, when the system generates the best population and the profit will be optimum from that point. Figure 1 also shows the fitness scaling of expected number of children versus the raw scores at each generation. It concludes that number of channels and bidders make difference for profit in the auctions.

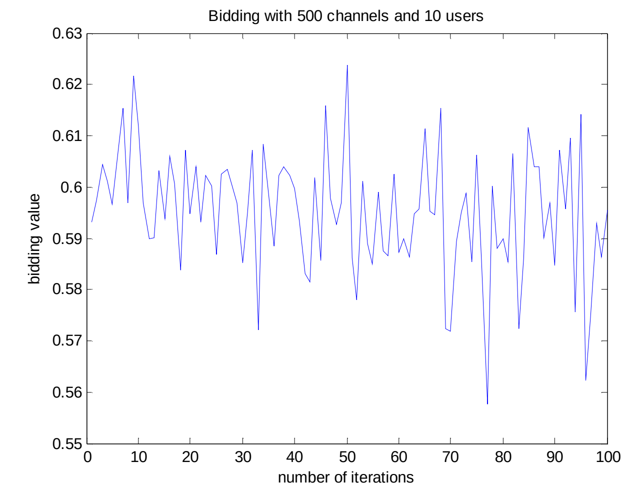

Figure 1: Bidding 500 channels and 10 users fixed with 100 different iterations

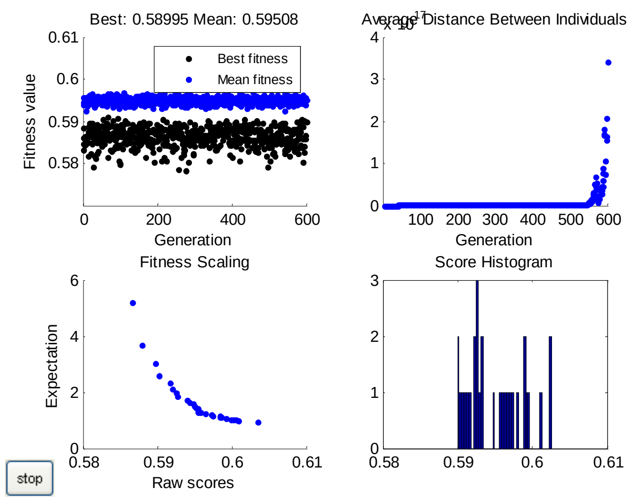

Figure 2: Convergence with crossover as heuristic search

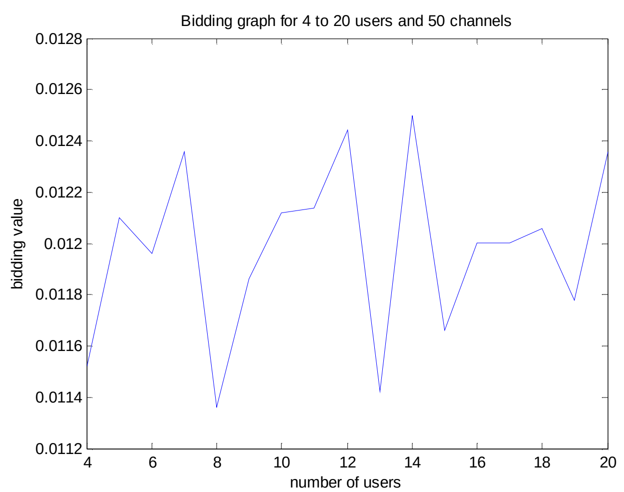

Figure 3: Bidding mean value for 4 to 20 users and 50 channels

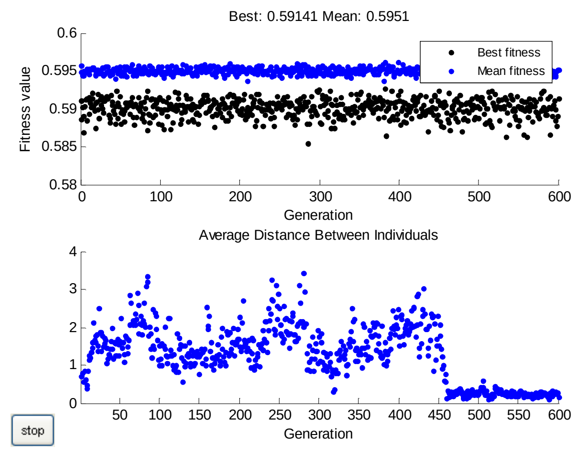

Figure 4: users varying 4 to 200 the graph converges after 450 generations

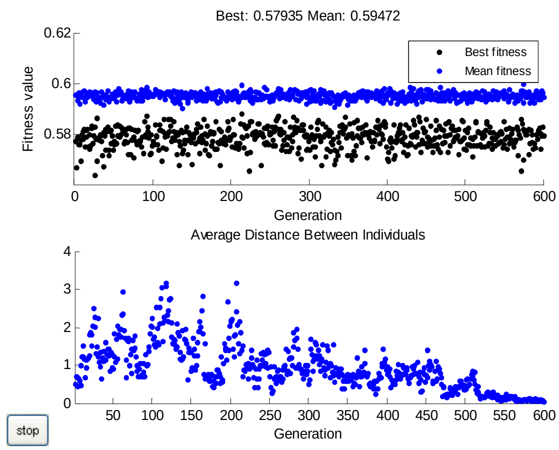

Figure 5: users varying 4 to 20 the graph converges after 550 generations

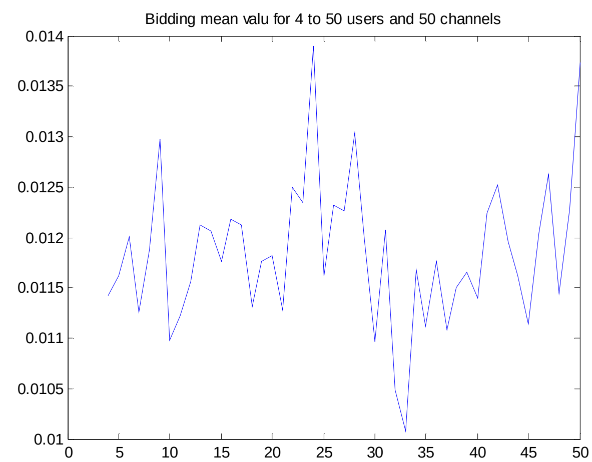

Figure 6: Bidding mean value for 4 to 50 users and 50 channels

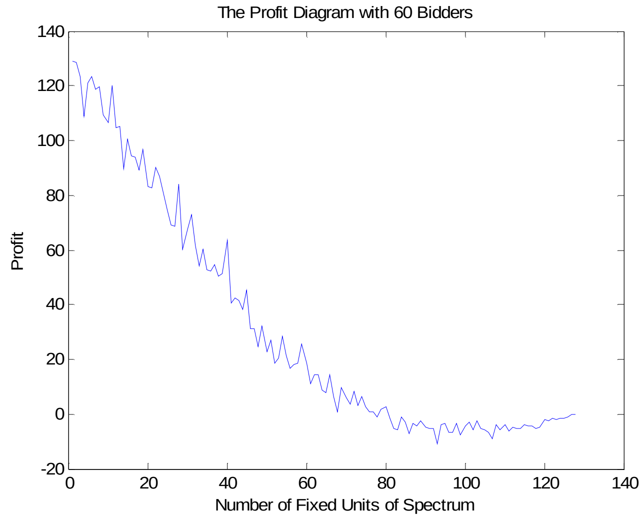

Figure 7: Market Value By Fixing the Channels 60 Bidder

VII. CONCLUSIONS

The current research discusses the properties of three modules contributed for optimum utilization of wireless communications facility. First, cognitive radio is the best tool to sit at the base station and keep track of the channel allocation, optimum power utilization, and use the auction facility for best bidders. Second, the automated collaborative filtering facility helps to provide the data of user recommended channels which leads to predict the channel (s) for higher bid. Third, the MATLAB *gatool* to optimize the resource allocation and calculate the best fit for allocation of channels (spectrum).

The genetic algorithms for optimization was used by many authors [7, 8], but the ACF model for predicting demand for spectrum is proposed first time in (wireless communications) the proposed research and the results are satisfactory. In continuation of this research we include ACF and game theory for better bidding process. Many times ACF works closely with game theory for predicting the channel gain and utilization. With the introduction of current results, many researchers will use the ACF and game theory combination for better results.

In conclusion, the results through MATLAB ‘gatool’ and MATLAB program conclude that less static allocation generates more revenue and efficient utilization of spectrum. Also, using ACF approach we can predict the channel in demand and recommend for higher bidding.

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