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Published in:
2018 Innovations in Intelligent Systems and Applications (INISTA)

DOI:
10.1109/INISTA.2018.8466273

Published: 20/09/2018

Document Version
Peer reviewed version

A Fuzzy-based Throughput Prediction For Wireless Communication Systems

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***Abstract*—Ideally, Wireless Communication System (WCS) and its various services are expected to operate effectively without any restrictions be it in space, time or communication locations. However, this is not absolutely possible in real-time, simply because the WCS's environmental space called Spectrum is currently found to be limited, heavily congested and continuously dynamic in nature. To address this problem, Cognitive Radio (CR) system has been proposed as the innovative technology solution. In this paper, Fuzzy Logic (FL) based approach has been proposed, designed and implemented as an adaptive prediction algorithm for the CR. The results obtained from the simulation shows that the proposed prediction algorithm was found to be faster with reduced computational complexity and offer quality improvement to the WCSs in terms of its overall throughput prediction accuracy.**

Keywords- Fuzzy Logic System, Cognitive radio, Wireless Communication System, Prediction, Spectrum state, Simulation Modelling

I. INTRODUCTION

The massive expansion of Wireless Communication Systems (WCS) with its countless users, numerous services and applications has put challenging demands and requirements for WCS's environmental space, called spectrum. The spectrum is naturally limited and currently drifting the resource out of capacity [1]. Furthermore, as the WCS's environmental state has currently been found to be heavily congested, Cognitive Radio (CR) nodes are expected to keep up with the WCS's spectrum erratic and its unstable conditions as well as any other discrepancies in WCSs. [2]. The problem of meeting spectrum demands has not been easy, so-much that spectrum cannot be physically controlled nor can its limited space be extended.

Fundamentally, spectrum inadequacies in WCSs, such as complexity, congestion, insufficiency and uncertainty have been considered as challenges to CR systems [1] and [2]. Parameter re-configuration and its adaptation with the spectrum variation is another significant concern in CR systems. Although quite a number of research had already been conducted on spectrum sensing, dynamic management and its utilization at various level of WCSs operations, fewer works have been recorded on the parameter reconfiguration of the CR in respect to the WCSs improvement. Currently, the rate of developments in WCS in terms of its users, unlimited demand and other countless services have been found to be on the rise. Specifically various CR parameters are relevant in today's WCSs, such as energy consumption, high data-application, fast mobility and many others [3]. The need for accurate prediction techniques in WCSs is now vital, as the spectrum dynamic state continues to undergo huge deviations. Some of these predictions mechanisms have previously been proposed in various dimensions, such as multiple propagation schemes, higher frequency bands, smart antenna systems [4]. Since WCSs states are naturally frequency dependent, time-varying, and space selective, it is essential for CR to effectively determine the sufficient spectrum utilization required to satisfy these dependencies under any conditions by prediction [5].

The main objective of this paper is to design and build an adaptive prediction engine for a CR system, which can be used to predict future WCSs performances under any operating spectrum conditions. The proposed algorithm serves as a significant tool for addressing various causes of spectrum's inconsistencies and deficiencies using Fuzzy Logic (FL) based prediction mechanism. As proposed, the FL based prediction algorithm is expected to predict reasonable amount of overall throughput by dynamically adjusting selected CR's input parameters in order to use the spectrum state. Meeting-up such anticipated conditions has generally been referring to as the CR's main objective function, which mostly accounts for its user's end-to-end requirements [1]–[3].

To enhance the WCS for better performances, different desired objective functions can be adopted, such as: minimizing the bit-error rate, maximizing the battery power saving, maximize spectral efficiency, maximizing the WCS's throughput etc. and many others [2], [3]. However, for this paper, the desire for a good overall throughput has been considered as the algorithm's prediction objective function. The proposed algorithm was designed, modelled and simulated using Matlab simulation software and specifically through FL toolbox. This include: (1) Construction of a FL's Ruled Based System (RBS). (2) Developing of a robust inference system closer to that of the human ability of thinking and perception. (3) Simulation of the present WCS's situations with the proposed prediction algorithm.

The rest of this paper is organized as follows. A literature review is written in Section II. The CR system's description and design are presented in Section III. Section IV introduces the simulation methodology and the stages through which the proposed prediction engine was developed. Section V presents a performance evaluation of the proposed algorithm. Finally, conclusions derived based on the outcomes of the paper are presented in Section VI.

II. Literature Review

In the context of embracing intelligence mechanism into WCSs, a tractable information-based prediction technique was proposed in [5] to evaluate the channel utilization. In their research, the spectrum states for the communicating nodes were effectively predicted without any prior knowledge of the primary users. This was later used to measure how their proposed model performed in terms of predicting WCS's qualities channel utilization and the amount of the overall throughput available within the network. In [6] the prediction was tackled by using an Artificial Neural Network (ANN) approach. This was done by exploring the dynamic adaptation between the radio input parameters which are classified as the WCS's network basic features. The Signal to Noise Ratio (SNR) was used to represent the wireless communication surrounding environment. Their study was based on the CR input parameters characterization to evaluate the WCSs performance in real-time. Through their study, they were able to effectively monitor the unstable WCSs medium and at the same time predict accurate output performances in terms of delay, network reliability and the available overall throughput.

Hou et al. [7] established their prediction research into WCSs based on the collection of historical information. In their work, information was collected, such as the nodes status, their communication speed, the number of free channels available for nodes to operates to determine through a developed prediction system. The technique was able to predict the overall throughput available for the nodes. According to their predicting scheme, the sensing status for every varied WCS's spectrum states, both in frequency and time-based sensing modes were adequately monitored. As a result, their work was able to justify the introduction of intelligence as the most benefiting enhancing function for this present WCSs. An evolutionary algorithm based on Genetic Algorithms (GA) as the biologically inspired prediction agent has been presented in [8] and [9]. Their works addressed some identified CR fundamental challenges, such as the problem of robustness and reliability to spectrum dynamic management. However, evolutionary algorithm implementation is costly, they are computationally complex and exhibits slow convergence, which limits their usage in real time applications.

The studies presented in [10] and [11] focussed on the FL based prediction system, specifically for heterogeneous WCSs, where nodes can be allowed to communicate seamlessly without interruption to their communication services. Kammoun and Tabbane in [10] were able to present their prediction algorithm using FL predictive feature which was developed as a vertical handover decision algorithm towards improving WCS network performances. In their work, various network conditions, such as supplied bandwidth, the communication link between the nodes, the received signal strength and delay were considered to carry-out their evaluation. By this they were able to predict the amount packet loss, the end-to-end delay and available overall throughput as the WCSs improvement measuring factor. Extending the work of [10], energy initialization was considered and added as another input in [11]. The proposed study differs from these two aspects, because basic communication features of CR systems were considered as the input parameters in this paper. The proposed algorithm input-output mapping prediction generalization will be based on the CR basic features, such as data-rate, battery powered utilization, node's mobility within the network and many others basic functions.

III. Cognitive Radio System

A brief description of CR including its basic intelligence framework and various radio features used for the two input parameters are discussed in this section. CR has been conveyed as an advanced technology with intelligence capability. Primarily, CR comprises of two functional blocks, namely the Software Defined Radio (SDR) and the intelligence engine, also known as Cognitive Engine (CE). The focus of this paper based on the proposed FLS based prediction controlling model belong to the CE; as the unit (i.e.CE) is considered as the core-engine to the CR and comprises of different three intelligent engines namely, the reasoning engine, the knowledge-based engine and the learning engine [8].

A. *Cognitive Radio Input Parameters*

CR systems comprises of two categorized input parameters, namely the Environmental Parameter **(EV-P)** and Transmission parameter **(TX-P)** [12]. The EV-Ps are the WCSs environmental space (i.e. the spectrum) information available at specific state and are generally collected through the use of sensors. The TX-Ps are the basic radio features, which are mostly used to execute final decision and primarily controlled by the SDR module of the radio. These two categorized parameters are crucial elements used by the CR to optimize its desired performances. The more they are (i.e. the input parameters), the better the CR information generalization is, faster and more knowledgeable the controller becomes. However, with many parameters, the intelligence implementation becomes challenging and more complex; thereby requiring more computational processing, higher memory capacity as well as large space for data storage [6].

There is only one EV-P of interest used in this paper, which is defined and named as Floor-Noise - (F_{-Noise}) . This CR's feature accounts for every spectrum sensing related issues, comprising of every unwanted signals generated as noises, such as the conventional Signal-to-Noise-Ratio (SNR) as well as others spectrum associated challenges. The selected TX-Ps are extracted from the CRs node - SDR operating features, which are data-rate, user density and transmitting power. These selected variables for the two CR input parameters are presented in Table I and Table II respectively. These parameters are the assigned as input variables to the model. They are expected to be reconfigured for the algorithm to accomplish its desired objective function, which is the accurate prediction for the available overall throughput.

TABLE I: The Environmental Parameters (EV-P)

Parameter Name	Symbol	Description
Floor Noise	$\mathbf{F^{-Noise}}$	All un-solicited generated noise

TABLE II: The Transmission Parameters - (TX-P)

Parameter Name	Symbol	Description
Data Rate	$\mathbf{D^{r}}$	Data usage & transferring rate-Mbps
User Density	$\mathbf{U^{d}}$	The number of CR nodes
Transmission Power	$\mathbf{TX^{pwr}}$	CR transmitting power level (Watts)

IV. Proposed Prediction Engine Methodology

By perception, CR systems are expected to sense its surrounding communication space at the very beginning of its operation and this includes awareness and sensitivity of its environment. However, for the spectrum state to be effectively and efficiently managed, the medium must be properly sensed using appropriate sensing devices which are either attached directly to the CR or otherwise. Though numerous sensing devices are available, such as thermal, noise, speed, geographical or location detectors and etc [13], however, only noise and mobility sensors are considered in this work. After the sensing had been thoroughly conducted, the sensed values are determined and collected as the EV-Ps settings. And instantly, the CR discharges its embedded intelligence function to dynamically adapt all available TX-Ps values to predict the WCSs capacity obtainable under such spectrum state. Our proposed prediction engine was designed based on the FLS Type-1 basic architecture. Figure 1 presents the methodology used in developing the CR system simulation as originally proposed by Mitolas [14]. Furthermore, other required literature about FLS for detail study can be found in [15].

1) Fuzzification: This is the stage where all corresponding input parameters values are logically represented as fuzzy variables. Two things happens at this stage. Firstly selected input parameters are combined and transformed with relevant linguistic terms. The second action is to fix suitable membership functions (MFs) into these assigned [15]. MF is expressed as the degree of membership and has its values between 0 and 1. Trapezoidal, triangular, and Gaussian object-based MFs are the most commonly used MFs. Figure 2

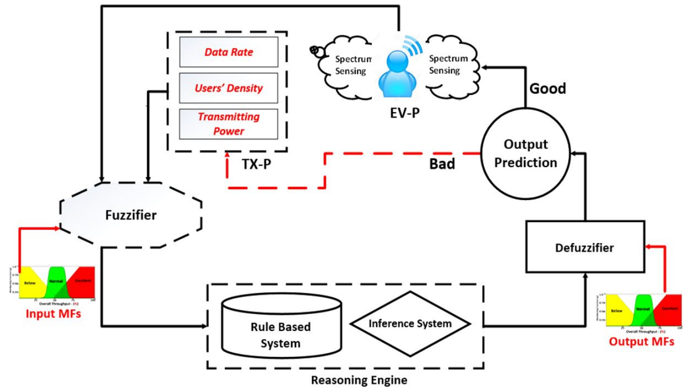
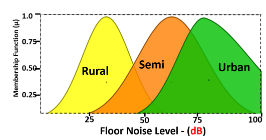
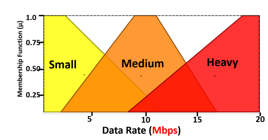


Fig. 1: The Proposed FLS Prediction Engine Framework

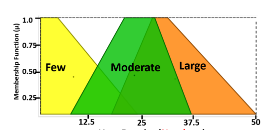
present different linguistic variables and their corresponding MFs used for fuzzification. Figure 2 shows input fuzzy sets and corresponding membership functions for all the selected input parameters' fuzzification process. Figure 2(a) has floor-noise fuzzification with linguistic terms as "Rural, Semi and Urban". Figure 2(b) depicts the data-rate fuzzification with linguistic terms as "Small, Medium and Heavy". While Figure 2(c) indicates the fuzzification input for the number of nodes or users present within the WCS with linguistic terms as "Few, Moderate and Large". Finally, transmitting power fuzzification is shown in Figure 2(d), having its linguistic terms as "Low, Average and High".



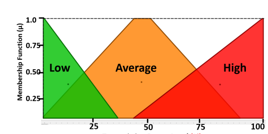
(a) Floor Noise Membership Function



(b) Data Rate Membership Function



(c) Users' Density Membership Function



(d) Transmission Membership Function

Fig. 2: Input Fuzzy Sets Membership Functions

*2) **Inference Engine**:* The Rule Based System (RBS) is very significant and considered as the engine room for the algorithm; also this is the stage and where the adaptive intelligence in the form of human reasoning are being developed by means of inferencing the rules. The "IF-THEN" rule base corresponds mapping relationship between the input fuzzy sets and output fuzzy sets. Where the "IF" is acknowledged as the antecedent and accounts for the way knowledge is being extracted from the expert. Meanwhile, "THEN" is considered as the consequent and produces the logical end-statement through

which the knowledge generalization are initiated. However, if the RBS is properly developed, then adapting the selected CR transmission parameter becomes possible and the generated rules will be used to predict better overall throughput with good percentage for such conditions.
For example, N^{th} - number of rules can be represented as:

$$\textbf{\textit{if}} \ldots (F_{Noise} = E_i) \wedge (U_d = U_i) \wedge (D_r = D_i) \wedge (Tx_{pwr} = T_i) \tag{1}$$

$$\textbf{\textit{then}} \ldots\ldots T_{put} = \Gamma_{(overall)} \tag{2}$$

Where:-

E_i = *Floor noise MFs (for rural, semi & urban) (dB)*
U_i = *Users MFs (between 0 50 nodes)*
D_i = *Data-rate MFs (0 - 11)Mbps*
T_i = *transmitting power MFS (0 100)% (Watts)*
$\Gamma_{(overall)}$ = *Overall Throughput available (0 - 100)%*

To determine the true state for all the generated rules, an expert based knowledge RBS was implemented using the Shannon channel capacity scalability on WCSs resources allocation. Theoretical expression of complex WCSs sensing states with Shannon capacity under the impact of high signal to noise ratio is formulated using Equation (3) [16].

$$S_{-capacity} = \beta * log(\frac{P^{tx}}{F^{noise} * \beta}) \tag{3}$$

Where:-

β = *Bandwidth* (Mb)
P^{tx} = *Transmitting Power* (Watts)
F^{noise} = *noise density at the receiver = all noise* (dB)

TABLE III: Sample of the Developed Rules

Rule	*Evn*	*UD*	*DR*	*TX*	$T_{(put)}$
1	Urban	Large	Small	Low	Below
2	Semi	Moderate	Medium	Average	Normal
3	Rural	Few	Heavy	High	Excellent
4	Rural	Few	Medium	Moderate	Normal
5	Rural	-	-	Strong	Excellent
6	Urban	Large	-	Low	Below
7	Rural	-	Heavy	High	Excellent
8	Semi	Few	Small	Low	Normal
9	Rural	Moderate	Heavy	High	Excellent
10	Urban	Large	-	High	Normal

Comprehensively, 81 active rules were generated by combining our four preferred input parameters with respective three MFs as defined and shown in Figure 2. Samples from the generated rules are presented in Table III.

3) ***Defuzzification:*** The output evaluation process for the basic FL system is known as the defuzzification [15]. After the inference stage, this is the stage at which the algorithm's final predicted results is determined. Through this stage, all obtained fuzzified output sets are converted back into crisp, which are generally in real numbers. Different defuzzification methods are available in FL systems development, Centroid of Area (COA) has been the most commonly used technique and has been adopted in this paper and the formula for this method is mathematically formulated with Equation 4. To present the algorithm improvement to the WCSs performance, based on the COG expression; the results obtained from the inference engine, with corresponding output MFs (μ_{out}) were later scaled between zero percentage (0%) being the lowest and one-hundred percent (100%) being the maximum predicted performance resource available in such WCSs state.

$$CrispOutput = \int \frac{\Gamma_{(overall)} * \mu_{out}(\Gamma_{(overall)})}{\mu_{out}(\Gamma_{(overall)})} . \delta\Gamma_{(overall)} \tag{4}$$

A. Proposed Prediction Engine Validation

To evaluate the model's prediction capability, several simulation investigations were conducted on the few selected CRs input parameters listed in Table II and their prediction at various dynamic spectrum states or communication domains with corresponding sensed valued of EV-Ps listed in Table I are measured and compared. Based on the FL inference engine, the defined FL-based rule based system (RBS) was used to develop the predicting mechanism. Through this, available overall throughput at such different communication domains are determined to verify the WCS's performance enhancement.

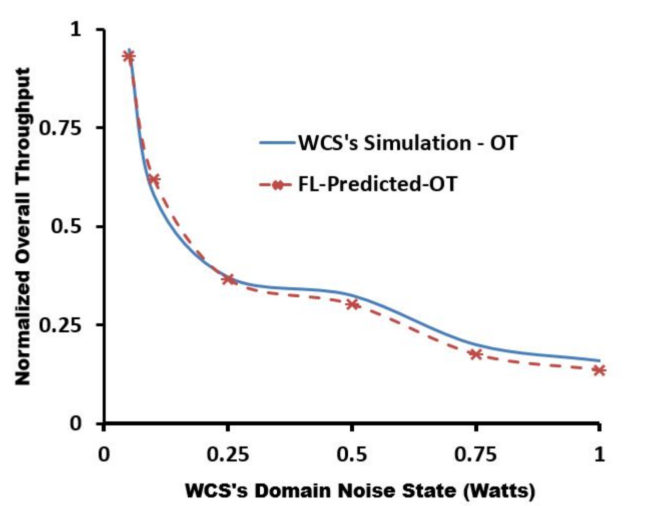


Fig. 3: The Algorithm Prediction Validation

The developed algorithm was validated by comparing the algorithm predicted results with a simulation developed WCS using Shannon channel capacity equation with the Additive White Gaussian Noise (AWGN) as the WCSs unstable environmental state in real-time. Figure 3 shows the validation performance as the results obtained between the developed prediction algorithm and the implemented WCS simulation. After the results has been compared, two error estimator functions namely the linear correlation and the Root Mean Squared Error (RMSE) were used to validate the developed prediction model. With the developed FL based prediction algorithm achieving about 96% accuracy in its prediction output and the RMSE value was 0.016258. This indicates that the developed algorithm predicted outputs are relatively closer to the simulated ideal WCS and in this regard, presenting the consistent relationship of the FL systems non-linear mapping to manage the complex and unstable WCSs medium by predicting the amount of the overall throughput available in such WCSs state.

V. Performance Analysis and Discussions

After the proposed algorithm has been designed, various predictions were carried out to determine the available overall throughput under different WCS's environmental conditions and all the obtained results from each of these simulation scenarios are discussed in this section. The performance evaluation of the proposed FL based prediction model was carried out and analysed in this section. To carry-out the various investigations, selected CR input parameter values were varied in different simulations and results obtained were highlighted and evaluated to determine the models performance in terms of its prediction accuracy.

A. Prediction Evaluation

The purpose of this performance analysis is to evaluate the developed FL based prediction generalization capabilities under different CR input parameters classification. Since it is expected from CR system to apply its intelligence functionalities with various selected TX-Ps so that its respective users or CR nodes on itself can enjoy constant communication quality. To carry out this evaluation with the developed algorithm, input values were manually selected and later simulated for the WCSs under such conditions in which two different input parameter re-configuration settings were investigated. In the first perspective, all the selected TX-Ps values were assigned with lowest values and considered as the Poorest Reconfiguration Mode (PRM), while for the second re-configuration setting, all the selected TX-Ps were respectively assigned with maximum values and referred to as the Best Reconfiguration Mode (BRM). Under this two conditions, the developed prediction engine generalization was later evaluated by using it to determine the amount of overall throughput available under the two simulation settings. With the notion, the number of users, data rate and transmission power are respectively fixed with 50 nodes, 5Mb and 30dB as maximum values, while the minimum values assigned for each corresponding parameters are 5dB for the transmission power, 0mbps data-rate and 5 node for the users.

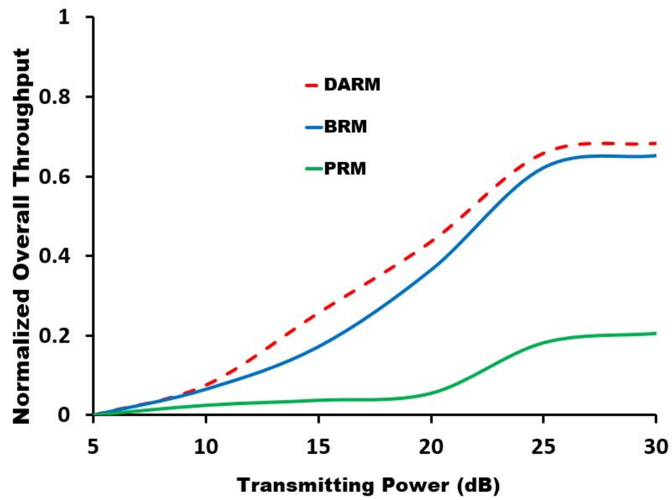


Fig. 4: Transmitting power

Scenario 1 - Transmission Power .
Under different transmission power schemes, the proposed algorithm prediction performance was examined and validates, such that the model was first subjected to the two defined re-configuration conditions (i.e. the PRM and BRM. However, under a dynamic value variation condition known as the Dynamic Adjustable input parameter Reconfigurable Mode (DARM), Figure 4 is able to presents improvement to the models prediction capability, such that as the CRs node dynamically increases the power transmission values a better overall throughput was achieved. Hence, the possibility of achieving greater resource for the WCS under the DARM become enhanced, which later translate into better QoS enhancements.

Scenario 2 - Data-rate .
The model was further subjected to another input parameter variation, specifically, the continuous demand for higher data-rate in todays WCSs that is heavily developed on higher data based communication services. Under this investigative condition, the effect of data-rate input parameter and its impact on our implemented algorithm for the CR intelligence adaptation was evaluated and in this analysis, all the selected input parameter values were fixed while the data-rate values were dynamically varied. Under this data-rate variation condition, the developed models prediction generalization capabilities were equally used to predict the amount of overall throughput available as the parameter values dynamically varied.

Figure 5 shows the obtained results demonstrating the performance improvement of the developed model, such that as the data rate increases, the predicted outputs were also increases. This implies that if the rate at which information or frames are being transferred within the WCS can be

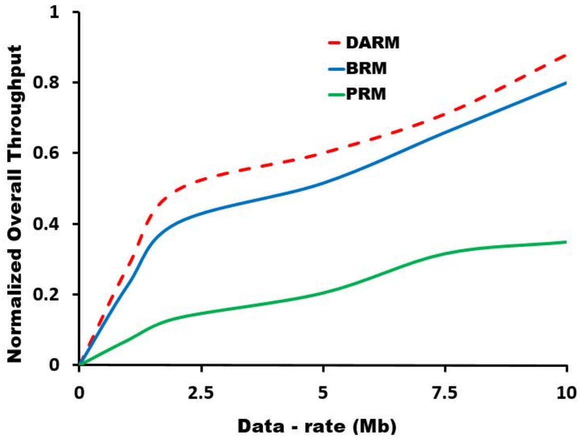


Fig. 5: Data-rate

increased continuously - says from 1Mbps to 5Mbps; then the number of frames that will get dropped as error will automatically become reduced and in terms of the amount of predicted overall throughput the resources available within the WCS is similarly get increases. By this in large quantities is the number of transmitted frames that will be delivered successfully to the receiving nodes. From the two scenarios in Figure 4 and Figure 5, it can been seen that data-rate can be considered as a key radio feature compared to the transmission power. The prediction performance obtained by the model was better under data-rate dynamic adjustment than when nodes transmission power were dynamically increased. This was also evaluated under three different communication domains, namely the rural, residential and urban centre.

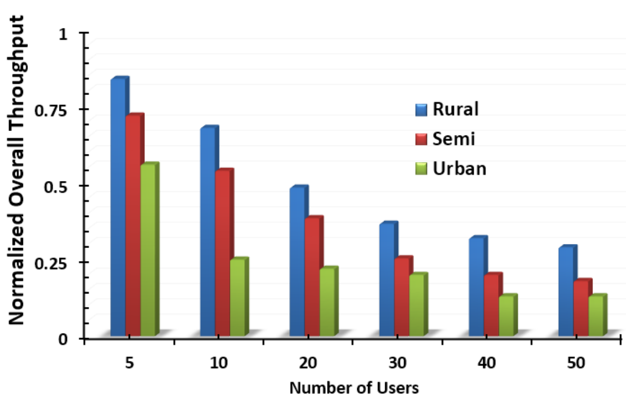


Fig. 6: Users-Density VS Domain

Scenario 3 - User-Density .
The proposed model was also evaluated under three WCS environmental states using the simulation of rural, residential and urban communication areas. To analysis the models prediction capability under these scenarios, the model was dynamically adjusted with a different number of nodes. The results were summarized in Figure 6 and can be seen that the prediction engine as proposed was able to predict higher overall throughput for the rural communication domain above the remaining two domains. Implying that, as the CR user moved between the three defined domains, starting from the urban region the average of about 47.52% of resources are predicted to be available because the region spectrum state is known to be heavily congested. However, as the users travelled out of this domain into the semi-urban or residential domain the predicted overall throughput as the available resources at such state was 51.48%, this was found to be a little higher in the predicted value because the domain is known to be less noisy than the urban centre. Finally, as the users moved into the rural area, a more enhanced prediction performance was recorded as the region was able to produce a prediction output of about 57.25% overall throughput. As the numbers of CR nodes increases their impacts on the model can be seen in Figure 6, while the simulation details used for the three WCSs environmental domains are listed in Table IV.

TABLE IV: FLS-LE Intelligence Prediction

WCS - State	**Urban**	**Rural**	**Semi-Urban**
Users	100	45	55
CR - Speed	15mph	25mph	25mph
Data Rate	6mbps	5mbps	5.5mbps
Transmit Power	3P	P	1.5P

B. *Prediction Efficiency*

Prediction efficiency and its improvement on the WCSs was another performance investigation carried out on our developed algorithm. This was performed by comparing the overall prediction efficiency (η) using Equation 5, to compare the algorithm predicted output differences in percentage between the three defined re-configuration modes, i.e. the PRM, the BRM and the algorithm Dynamic Adjustable Re-configuration Mode (DARM). As presented and listed in Table IV, the algorithm prediction was more efficient at the DARM, where the input parameter values were dynamically assigned until the best predicted output is obtained. With about 11.40% DARM prediction efficiency better than the PRM and 5.34% improved over the BRM.

$$\eta = \frac{F^{"} - X^{"}}{F^{"}} * 100\% \qquad (5)$$

Where: $F^{"}$ is the DARM prediction output and $X^{"}$ is for any of the two modes prediction output.

VI. Conclusion

We proposed a FL based prediction algorithm as a part of CR intelligence engine for an effective management for today's WCS's complex spectrum states. The performance of the proposed scheme has been evaluated by means of simulation and the predicted results obtained for different communication conditions are compared and analysed. In order to adapts dynamically to different WCS environmental conditions and at the same time produces better resources in terms of the amount of overall throughput at such condition, the developed FL-based prediction algorithm selects optimal TX-Ps. Which are based on the value variations of number of nodes, data-rate and nodes transmission power, taking into consideration the level of floor noise available in each communication conditions. The results have shown that the developed FL based prediction algorithm performs better under the DARM than the other two modes which are PRM and BRM, justifies that with good input-mapping generalization from the model, suitable resources in terms of overall throughput will be made available for WCSs users and in overall enhances its performances. Knowledge about how the developed model prediction performance analysis can be extend to cover a more or highly complex WCS environmental conditions, such as faster mobility and a good QoS for online video streaming WCSs, when considering a delay sensitive radio feature as the CR input parameter forms the future works of this paper.

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