Research Article

Heuristic Load-Balancing Optimization Model For Cognitive Radio Networks Using Iot

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Article History: Received: 11 January 2021; Revised: 12 February 2021; Accepted: 27 March 2021; Published online: 16 April 2021

Abstract: The Internet of Things (IoT), via different communication models, connects network resources through the Internet. A main IoT technology is the cognitive radio network, which can resolve spectrum problems in IoT applications effectively. A novel approach is proposed in our paper for IoT sensor networks to achieve the channel status in typical Cognitive-IoT model produces more spectrum holes which it leads a Quality-of-Service issue due to the channel allocation and spectrum allocation errors. To minimize the error rate, we proposed a Heuristic Load-balancing optimization model (HLBO) for OFDM-based Cognitive radio network model. Proposed model categorizes channel scheduling process by considering resource allocation and load. The proposed HLBO employs a load optimization algorithm to enhance channel status, based on different traffic states the load optimization model predict the spectrum allocation rate based on the channel and sub-channel status.

Keywords**:** Internet of Things, Cognitive Radio Networks, Load optimization, Heuristic technique, NS-3.23**.**

1. Introduction

The efficiency of CR techniques can be improved by enabling the temporary use of the allowed spectrum of unused priority users [1-3], which would lead to lower priority secondary users. Secondary users also choose to exit an existing channel if the data on this type of channel are transmitted by first users [4-6], and then the main user has an important preventive priority for transmitting the data to secondary users. The selection of spectrum is an important CR network method that allows the secondary user to choose the right channel for transmitting data on candidate channels [7]. Therefore, a reliable spectrum decision methodology must consider the traffic statistics for initial users and also secondaries to allocate traffic load of secondary users to these applicant networks. Different disruptions from original users, sensing bugs like failed identification, and false alarm for initial users and the different channel capabilities affect entire device life of secondary users' connection. Owing to interruptions from initial users, the transmission time of a secondary link was likely to require several spectrum handoffs [8]. This will increase the entire device time for several spectrum handoffs. Simultaneously a false alarm occurs when a primary consumer is wrongly identified by the detector [9-10]. This makes the whole device time for secondary user connections very longer as secondary users are not able to transfer data even on a single channel. If the identification of a prime user fails, the primary user and secondary user collision with data, transmission and extension of the whole time of secondary user connections. Capability and transmission speeds of different channels may in future vary, leading to different service times for secondary users [11]. Therefore, the possessions of diverse handoffs, sensing errors, with heterogeneous channel capability should be incorporated into spectrum decision methods for CR Networks. The objective channel for disrupted SUs is tested for load balance by a new optimistic probabilistic sequence technique [12]. To evaluate this proposed approach for evaluating latency and load balance efficiency, the preliminary M/M/1 tail setting network priority model is needed. And the balance is proposed as a new indicator of quantitative performance. The proposed approach reveals the benefits of the proposed probabilistic sequence design by equalisation and capability growth as compared with other alternative spectrum handoff approaches. Moreover, with low network loads, the longer data delivery time is increased.

Our main goal in this paper is to achieve and calculate load balance accurately. The achievement of balance would improve network capacity and reliability by preventing early overload of heavily charged channels. To this purpose an analysis on sequence probabilistic technology is proposed in the cognitive radio network based on the preventive resumen priority (PCR) M/M/1 queue network architecture, to test the carry-based spectral handoff load balance and latency performance. No limitations on the particular SU channel are applied, unlike [13] and [14]. After any interruption, it can remain or change your channel and the impacts of sensing errors are studied by both PU and SUs (missing identification and false alarm).

This paper summarises our contributions as follows:

- Implement a new technology for the selection of the probabilistic target channel. This method enables SUs to pick the target channel more effectively after each interruption. The proposed method is intended to exceed delay and balance factors under some statements and certain sensing error tolerance.
- To implement a load balancing function model for the selection of the aim channel for the load balancing.

- Implement a new quantitative metric, known as variance in the channel's occupying probabilities, to calculate load balance.

2. Related Work

Examines the alternative energy efficiency for cooperative spectrum sensing, Ejaz et al. [15] develops an optimization problem that initially depends on spectrum sensing performance for the traffic between energy and energy usage. The two main format goals for low-performance systems, although sometimes contradictory, are performance and total power. These have not been extensively studied in the same times in cognitive radio networks for developing spectrum sensing algorithms. The goal was to reduce energy consumption and reporting in spectrum sensing collaborative selects to a vital agency and transfer of information if reliability restrictions are met and secondary users are provided with a certain throughput.

Xing et al [16] are providing continuous time models for dynamic spectrum with the Markov spectrum tag, which are now usable on an open spectrum wireless network. The success of air time justice is revealed with the random admission to the protocol. Also proposed in the homo egualis (HE), company version is a channel access protocol distributed version using the simplest close-by statistics. These channels are used by agile radios of the spectrum. Protocols allowed. Protocols allowed. Zhu et al. [17] have suggested the cognitive radio spectrum handoff channel reservation system, allowing the chosen chain analysis of markov for cognitive radio to join certified bands. This approach was alike to the channel reservation that is utilized to solve forced termination and blocking of QoS in a circuit-shifted community. This makes considerably better efficiency if a correct range of channels is allocated. By considering centralised spectrum allocations in the network of resourced wireless sensors, in order to resolve a multi-objective problem with a shift in game theory, Byun et al., [18] suggested a new strategy. The scheme would also be feasible if a non-cooperative set of rules is to be disbursed for spectrum bands. Some studies have only shown that cognitive radio has been implemented in WSNs. Jiang et al [19] suggest a way to collectively recall and get right of entry to trouble under two eventualities: a synchronous state of affairs wherein primary community be slotted by a non-slotted asynchronous state of affairs. If complicated SU behaviour, the joint spectrum sensing and access problems are characterised as a sport of evolution and the evolutionary approach is solid (ESS). In addition, this analysis built an expensive set of rules for SUs to converge into ESS, where every SU sees and accesses Channel Number One through possibilities that are simply recognised by its workers outside applications and finally achieves the preferred ESS.

In order to efficiently address problems related to the optimisation of common access by SUs and PUs, Dudin et al., [20] suggested a deep queue architecture applicable to access optimization. Different forms of PUs have multiple service time and pre-emptive preferences over SUs in this study. When PUs takes the whole server, the SUs will pass a server. In addition, Markovian marked arrival technique describes the arrival stream. The transition in service time is phase-like. Effect of SU tests was considered as a major issue. The implementation of Instructed systems for SUs by Balapuwaduge et al., [21] can be initially based on time gap tolerance of disrupted elastic services. SUs can gather full power from the use of CA (dynamic channel assembly) methods with multi-channel cognitive radio networks, while the channel assignment schemes generate high blockage and pressured ends while primary users develop stronger. In a multiple channel network, queues are delegated to special times and elastic users one after the other and channel control services are spread through those queues to a stronger precedent for real-time services. The work on the proposed CA Strategy is to be investigated with queues in the future by constant time markov chain designs.

In a cognitive radio network respectively, jianget et al. [22] implement different techniques for the asynchronous sensing of spectrum and for asynchronous spectrum access in which the SU can be permitted to dynamically distinguish initial channels from PU syncing. It also explains key techniques, related solutions and powerful applications of the asynchronous spectrum sensing and the access methods, particularly in non-cooperative and cooperative scenarios two essentially asynchronous spectrum sensing techniques. Wang et al., [23] have introduced an empirical concept to define queue dynamics in cognitive multi-channel radio networks (CRNS). The architecture includes essential techniques and modifications for the lesser layers, incorporating spectral sensing failure, intermediate access control protocols, adaptive modulation hyperlink, encoding and auto-repeat requests, as well as a short length of buffer. The dynamic of the queue was modelled to explore the impacts on quality of service of the SUs. Average time, packet loss and high performance are compensated by the performance indicators.

2.1 Internet of Things (IoT) Systems

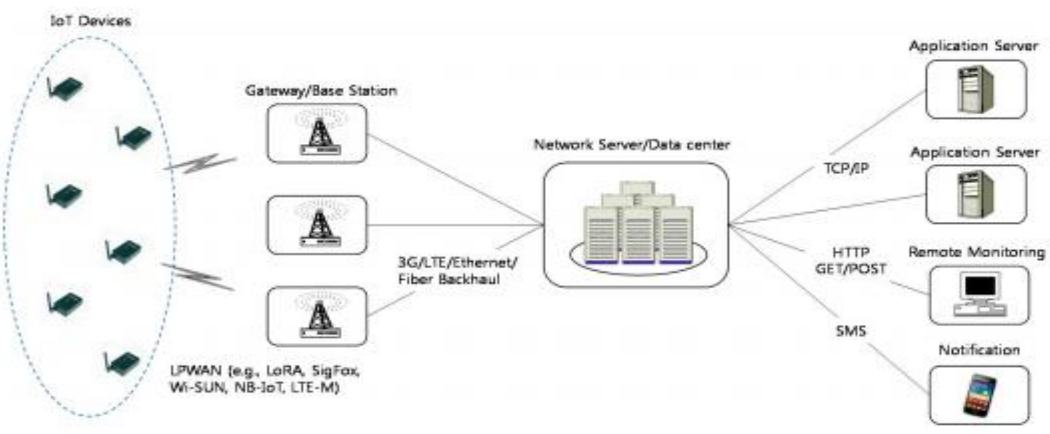

Figure 1. Low power network end-to-end Internet of Things (LPWAN)

IoT devices can also share other facts, including event readings, with the network server. These documents provide the control of spectrum allocation statistics and spectrum transmission-awareness of the channel depending on the relevant topology. CR-LPWANS, where IoT sensors are randomly positioned geographically based on the sensing target, is a regular activity loop. It really depends on the high binding time for which routes can be available between CR-LPWANS coverage strength and sensor nodes and network servers.

The IoT Framework has a mobile network architecture as shown in Figure 1. The internet of things (IoT). We understand that CR-LAWNs consist of uniformly disbursed IoT (or basis) and IoT (or sensor) devices over network. These IoT devices can be presumed to adjust the arbitrary process of transmission to maintain statistical transmission. We depend also on at least one way from the IoT tool to the statistical transmission gateway. In the end, the gateway node collects all the data from all IoT equipment. The collected data is then submitted to the information server. In CR-LPWANS, every IoT tool depends on the reading of the quarter to show its movements. In order to extend sensor records across the network Local readings on any IoT sensor node between sensor nodes and critical network servers shall be exchanged.

3. Research Methodology

In this section, proposed system is analyzed for load balancing by providing formulas Delay and probability of k interruptions for arrival rate.

3.1. Arrival rate of type-I SU

Theorem 1: Arrival rate of type-i SU (SU is nothing but which has phased i interruptions) of default channel η at channel k (ω(k) i,η) be expressed as below.

$$\omega_{i,\eta}^{(k)} = \begin{cases} \lambda_s^{(\eta)}, & i = 0 \\ \lambda_s^{(\eta)} p_0^{(\eta)} r_k^{(\eta)} \pi_{j=1}^{i=1} \sum_{l=1}^{M} r_l^{(\eta)} p_j^{(l)}, & i \geq 1 \end{cases} \quad (1)$$

Where the empty product is known to be unified and p(k) I was probability for interruption of type-I SU in channel k, as assessed below

$$p_i^{(k)} = \frac{\lambda_p^{(k)}}{\lambda_p^{(k)} + \mu_s^{(k)}} \quad (2)$$

The arrival rate (ω(k) I, η) to channel k be calculated by utilizing integration of trates from all channels ω(j) $i - 1, \eta, j = 1, 2, .., M$ involving only section of users that have been disturbed (with probability p (j) $i - 1$).

Then we only hit users through the likelihood r (η)k k on our channel of interest. Consequently, the recurrence formula can be seen

$$\omega_{i,\eta}^{(k)} = r_k^{(\eta)} \sum_{j=1}^{M} \omega_{i-1,\eta}^{(j)} p_{i-1}^{(j)}, i \geq 2 \quad (3)$$

In the case of a default channel ̈Type 0 SU, the arrival rate can be inferred as follows.

$$\omega_{0,\eta}^{(k)} = \lambda_s^{(\eta)} \quad (4)$$

In this case λ(η) is determined by applying the initial channel selection with Pη as follows from total SU load coming into network (λ stot)

$$\lambda_s^{(\eta)} = \lambda_{s_{tot}} P_\eta \quad (5)$$

For a regular channel Type-1 SU η,

If his default channel ± channel with probability p (β) 0 is disrupted, then he will select the channel k with a chance r (η) k.

Therefore, his rate of arrival is to channel k.

$$\omega_{l,\eta}^{(k)} = \lambda_s^{(\eta)} p_0^{(\eta)} r_k^{(\eta)} \quad (6)$$

By resolving the recurrence relationship in equation (3) by induction with initial condition: (1), Where p(k)i be possibility of PU interruption before transmission is completed.
Depending on M/M/1 queueing procedure for every channel, time before the PU interruption was highly distributed by μ(k)p parameter.
And transmission for channel k is separated by the μ(k)s parameter until the transmission is completed.
So, it can be evaluated as in the likelihood of a PU disruption (2).
The equation proof (1) is therefore done (2).
Corollary 1: The type-i SU arrival rate of channel k can be described in the manner set below from all default channels (ω(k) i).

$$\omega_{i,\eta}^{(k)} = \sum_{\eta=1}^{M} \omega_{i,\eta}^{(k)} \quad (7)$$

The time limit due to n breaks is assessed as below

$$\sum_{i=1}^{n} E[D_i] = r_{\eta}^{(\eta)} \frac{1}{\mu_p^{(\eta)} - \lambda_p^{(\eta)}} + \sum_{k \neq \eta} [r_k^{(\eta)} (E[W_s^{(k)}] + t_s) \quad (8)$$

Where E[W(k)s] was time to wait for the SU to channel k, should the operating channel be changed.
It was shown as follows

$$+(n-1) \sum_{k=1}^{M} r_k^{(\eta)} [r_k^{(\eta)} \frac{1}{\mu_p^{(\eta)} - \lambda_p^{(\eta)}} + \sum_{l \neq k} [r_l^{(\eta)} (E[W_s^{(l)}] +)]) \quad (9)$$

Where E[W(k)s] was time from when the SU reaches channel k, until it can start the transmission of channel k data.
The model M/M/1 (PRP) queue can be shown as below (10).

$$E[W_s^{(k)}] = \frac{\frac{2\lambda_p^{(k)}}{(\mu_p^{(k)})^2} + \frac{2\sum_{i=()}^{n max} \omega_i^{(k)}}{(\lambda_p^{(k)} + \mu_s^{(\eta)})^2} + \frac{2(\lambda_p^{(k)})^2}{\left(\mu_p^{(k)}\right)^2 (\mu_p^{(k)} - \lambda_p^{(k)})}}{2[\left(1 - \frac{\lambda_p^{(k)}}{\mu_p^{(k)}}\right) - \frac{\sum_{i=(0)}^{n max} \omega_i^{(k)}}{\lambda_p^{(k)} + \mu_s^{(\eta)}}]} \quad (10)$$

Proof: The SU decides either to live on the current channel k and wait until busy traffic time of PUs by the probabilities r (η) k or moves at tail of tail of some other l channel than k after each interruption through the probability r (η) l.

The M/M/1 model of PU network gives [17] for staying the working period.

$$E[D_{stay}] = \frac{1}{\mu_p^{(k)} - \lambda_p^{(k)}} \quad (11)$$

However, the pause may be formulated in terms of alteration

$$E[D_{change}] = E[W_s^{(k)}] + t_s \quad (12)$$

Where E[W(k)s] was time of expectation from when an SU arrives in channel k before the data transfer in channel k can be initiated. In accordance with the (PRP) M/M/1 model,
The following can be assessed [6]:

$$E[W_s^{(k)}] = \frac{\frac{2\lambda_p^{(k)}}{(\mu_p^{(k)})^2} + \sum_{i=()}^{n max} \omega_i^{(k)} E\left[\left(\phi_i^{(k)}\right)^2\right] + \frac{2(\lambda_p^{(k)})^2}{\left(\mu_p^{(k)}\right)^2 (\mu_p^{(k)} - \lambda_p^{(k)})}}{2(1 - \frac{\lambda_p^{(k)}}{\mu_p^{(k)}} - \sum_{i=()}^{n max} \omega_i^{(k)} E[\phi_i^{(k)}])} \quad (13)$$

If φ(k) I the reliable type-i SU service period at channel k, which means that this SU spends the current time on this channel before it is cut off by the PU For an assumed M/M/1 queue system,
Time for an interruption is a minimum of two exponential distributions, which are called as the time (with rate λ(k) p) and time it takes before transmission is done (with rate μ(η) s).
Consequently, I can express first and second moments of φ(k) I as
There is also a possibility to express first and second moment of φ(k) I as

$$E[\phi_i^{(k)}] = \frac{1}{\lambda_p^{(k)} - \mu_p^{(k)}} \quad (14)$$

$$E\left[\left(\phi_i^{(k)}\right)^2\right] = \frac{2}{(\lambda_p^{(k)} - \mu_p^{(k)})^2} \quad (15)$$

The formula is replaced in (14) and (15) by (13) (10). The current channel should be the default channel μ when the first interruption occurs. The delay can therefore be measured as follows:

$$\mathrm{E}[D_1] = r_{\eta}^{(\eta)} \mathrm{E}[D_{stay}] + \sum_{k \neq \eta} r_k^{(\eta)} \mathrm{E}[D_{change}], i = 1 \quad (16)$$

The current channel can however be any M channel in the network, at any other interruption. $E[D_i]$ is also worded accordingly.

$$\mathrm{E}[D_1] = \sum_{k=1}^{M} (r_k^{(\eta)} [r_k^{(\eta)} \mathrm{E}[D_{stay}] + \sum_{i \neq k} r_l^{(\eta)} \mathrm{E}[D_{change}] \quad (17)$$

Delay due to n breaks can be indicated in (16) and (17) as substituted by (11) and (12) (9)

$$\Pr(\mathrm{N=n}) = (\textstyle\sum_{i=1}^{M} r_i^{(\eta)}(1-P_n^{(i)})) \times (P_0^{(\eta)} \pi_{j=1}^{i=1} \sum_{i=1}^{M} (r_i^{(\eta)} P_j^{(i)}) \qquad (18)$$

Here p(k)i be type-i SU interruption like in channel k (2).

Proof: The likelihood of a n intrusion (including an n+1 sequence), is a product of probability that the last channel (p (no int) is not interrupted and probability of interruption on the first channel is interruption. The last network channel with the possibility r (η) i. can be from the M channel this channel has a chance of no interference (1 − p(i)n).

Henceforth, the equation is as follows

$$\mathrm{P(no\ int)} = \textstyle\sum_{i=1}^{M} r_i^{(\eta)}(1-P_n^{(i)}) \qquad (19)$$

The default channel η is the first channel for any SU. The probability of interruption is p (η) 0 on this channel. The SU can be on any channel I according to the likelihood r (μ) I for interference of the other n − 1. In this case, M i = 1 r (η) i p (i)j is likely to be interrupted. Therefore,

$$\mathrm{P(int)} = P_0^{(\eta)} \pi_{j=1}^{i=1} [\textstyle\sum_{i=1}^{M} (r_i^{(\eta)} P_j^{(i)} \qquad (20)$$

For each SU, regardless of the default channel β the following relationship is considered "LB(k)"

And depends only on target channel k's traffic parameters:

$$\mathrm{LB(k)} = \mathrm{C\ x}\ (\frac{1}{\lambda_p^{(k)}+\lambda_s^{(k)}})^r \qquad (21)$$

3.2 Optimization Issue Formulation

In our work, in order to avoid interference, we apply the statistical method for CSI in CRBS and PU, which increases cognitive IOT network spectral efficiency and ensures probabilistic disability conditions

Let cm, k denote the SU allocation denoter for the m^{th} CR secondary users on the k^{th} SU. For example, if cm, k = 1, k^{th} SU was allocated to m^{th} CR secondary users. And also imagine every SU can only be allocated to one CR secondary users and that is the constraint condition (22).

$$\textstyle\sum_{m=1}^{M} C_{m,k} \leq 1, C_{m,k} \geq 0, \forall_m, k \qquad (22)$$

Let pm, k indicates the transmission power for the m^{th} CR secondary users on the k^{th} SU, P_{max} indicates the high transmission power for cognitive IOT network and Pk max indicate high transmission power for the k^{th} SU. We here add the limiting condition to guarantee viability of the power allocation (23)

$$\sum_{m=1}^{M} \textstyle\sum_{k=1}^{k} C_{m,k}P_{m,k}, k \leq P_{max}, 0 \leq P_{m,k} \leq CP^{k}{}_{m,k}, \forall_m, k \qquad (23)$$

Let bm, k indicates the transmission cost for the m^{th} CR secondary users on the k^{th} SU.

Ik is the interference power on the k^{th} SU and

η be background noise power.

Then, bm, k could be written as

$$b_{m,k} = \frac{W}{K}\log_2(1+\frac{P_{m,k}h_{m,k}}{\Gamma(l_k+\eta)}) \qquad (24)$$

Where hm, k denotes the immediate CSI among CRBS and the m^{th} CR secondary users on the k^{th} SU.

I be the capability gap related to Bit Error Rate (BER) and the BER target

$$\Gamma = -\frac{\ln(5BER_m^{target})}{1.5} \qquad (25)$$

Where BER target m be target BER for the m^{th} CR secondary users.

Let In max indicate the threshold of interference for the nth PU and

$\in_n$ Denote upper bound needed on odds of crossing nth PU interference threshold. This because $\boldsymbol{g_k^n}$ is uncertainty, the state of PU intervention is cast as an unintentionally restricted condition. Therefore, we add a limit.

$$Pr\{\textstyle\sum_{m=1}^{M}\sum_{k=1}^{K} C_{m,k}P_{m,k}g_k^n < l_{max}^n\} \geq 1-\varepsilon_{n,}\forall_n \qquad (26)$$

Where Pr{·} shows the possibility.

Let $\{\varphi m\}\frac{M}{m=1}$ indicates predefined values which are used to ensure the proportional fairness rate desire for CR secondary users. In the resource allocation issue of cognitive IOT system, the proportional fair is normally defined by the ratio of the m^{th} secondary users's strength to the m+1th secondary users's strength. In addition, in this work we follow as a proportional equal description the ratio of the secondary user capacity m + 1th secondary user capacity. Proportional fair rate demand could therefore be guaranteed.

$$\frac{\sum_{k=1}^{K} c_{m,k}b_{m,k}}{\sum_{k=1}^{K} c_{m+1,k}b_{m+1,k}} = \frac{\emptyset_m}{\emptyset_{m+1}}, \forall_m \qquad (27)$$

With the above considerations, we formulate the chance-restricted optimization problem as follows.

$$max_{C_{m,k}P_{m,k}} \textstyle\sum_{m=1}^{M}\sum_{k=1}^{K} c_{m,k}b_{m,k}$$

$$\mathrm{S.t.C1.}\textstyle\sum_{m=1}^{M} C_{m,k} \leq 1\ , and\ C_{m,k} \geq 0, \forall_m, k$$

$$\mathrm{C2.}\textstyle\sum_{m=1}^{M}\sum_{k=1}^{K} C_{m,k} \leq 1,\ and\ 0 \leq P_{m,k} \leq P_{max}^{k}, \forall_m, k$$

$$\mathrm{C3.}\ Pr\{\textstyle\sum_{m=1}^{M}\sum_{k=1}^{K} C_{m,k}P_{m,k}g_k^n < l_{max}^n\} \geq 1-\varepsilon_{n,}\forall_n$$

$$\text{C4.}\ \frac{\sum_{k=1}^{K} c_{m,k} b_{m,k}}{\sum_{k=1}^{K} c_{m+1,k} b_{m+1,k}} = \frac{\emptyset_m}{\emptyset_{m+1}}, \forall_m \qquad \text{(28a-28d)}$$

The limiting conditions shall apply where objective function (12) maximises the cognitive IOT network's spectral efficiency and (28a)–(28d).

4. Real Time Heuristic Algorithms

Initialization

1. Initialize all sub channels and power allocation. (ρ k, n, l $= 0$, pk, n, l $= 0$ for all k, n, l)

Sub channel allocation for fairness

2. Sort a set of sub channel gains (hk, n, l for all k, n, l) in descending order.
3. Assign sub channels to each secondary user (ρk, $n1 = 1$) according to the sorted subchannel order.
4. If a secondary user receives α sub channels, stop allocating sub channels to that secondary users

Sub channel allocation for capacity maximization

5. Assign the remaining sub-channels to secondary users with the best channel gain.
6. Count the number of sub-chains each IOT transceiver serves (Ml for all l)
7. Find the l_1 IOT transceiver which serves the most sub channels and l_2 serves the smallest number of sub channels.
8. Among the sub channels allocated to l_1 (ρk, n, $l_1 = 1$), select the subchannel that has the smallest difference between h k, n, l_1 and h k, n, l_2 h.
9. If |Ml1 − Ml2| is larger than €, or the minimum difference of channel gain evaluated in line 8 is larger than δ, go to the power-distribution step
10. The load balance step will be repeated in the load-balancing step to adjust the serving stations selected in line 8 from l_1 and l (2).
11. The total transmission power of each IOT transceiver is distributed equally to the subchannel assigned to that station.

4.1 Load Balancing Optimization

Load balancing provides the assignment of appropriate machine resources to different tasks. This is a process which has a particular effect on the overall system performance. Normal resource algorithms usually take as an input a list of tasks or approaches which could be completed in a specific period with the assistance of a device planner. A flow chart is used to help you resolve company dependencies. The scheduler from past, useful resource allocation is primarily based on the sub-service priority version and the allocation of sub-companies' responsibilities to each of the channels, such that the overall performance of the machine is exhausted. That is a well-known trouble, with huge amount of research contributions closer to green utilization of the weight balancing on to be had sources in such systems the use of diverse precise and heuristic processes

Inputs: $\mathrm{N} = \{1, 2, \ldots\ldots\ldots, \mathrm{N}\}, \mathrm{M} = \{1, 2, \ldots., \mathrm{M}\}, \mathrm{P} = \{P_1, P_2, \ldots. P_M\}$

$$R_{G*N} = [R_{gn}]$$

Outputs: $Y_{M*N} = [Y_{pn}]$

Step 1. Initialization:

$$Y_{pn} = 0, \text{for p} = 1, \ldots.\text{M and n} = 1, \ldots, \text{N}$$

Step 2.While P ≠ {}:

Find $\tilde{p} \in$ M an $\tilde{n} \in$ N with $R\tilde{p}\tilde{n} \geq Rpn \forall g, n$

If $\sum_{n=1}^{N} y_{mn} \geq P_m$

P → P / $\{P_{\tilde{p}}\}$

M → M / $\{\tilde{p}\}$

Else

set $y_{p\ \tilde{n}} = 1$

N ← $N\{\tilde{n}\}$

Step 3. While N ≠ {}:

Find p^*, n^* such that $R_{p^*n^*} \geq R_{pn} \forall\, p, n$

S`et $x_{p^*n^*} = 1$, $N \leftarrow N/\{n^*\}$

Algorithm 2: Optimal Load Balancing

Step 1

Step 1: Initialize Subcarriers N and Group of total available SUs K_N served by Based Station B

Step2: Generate Distinctive group of multicast sets G, Assign a members group to the BS k_m, m $= 1\ldots.$ M

Step 3: Determine the SUs y_{mn}, data rate variables r_{zn}, R_{zn} and number of SUs assigned to each multicast group $N_m \to 0$

Step 4: Extract the total throughput assigned to the group m∗ and their corresponding sub carrier n∗.

Step 4: To discover the group with the highest R_{mn} on a specific SU.

Step 5: Subcarrier n∗ is assigned to group m∗ and it is excluded from the set of available SUs N.

Step6: Iterative this process until all multicast groups are included in the system set G have got their SU allotments $\mathrm{Pg}, \mathrm{m} = 1, \ldots, \mathrm{G}$.
Step 7: Stop the process if there is no more available SUs, despite the fact that few multicast groups may have a smaller number of SUs than $\mathrm{Pg}, \mathrm{m} = 1, \ldots, \mathrm{G}$.
Step8: **Assign** the remaining SUs N is to the group K which have good amount of capacity.

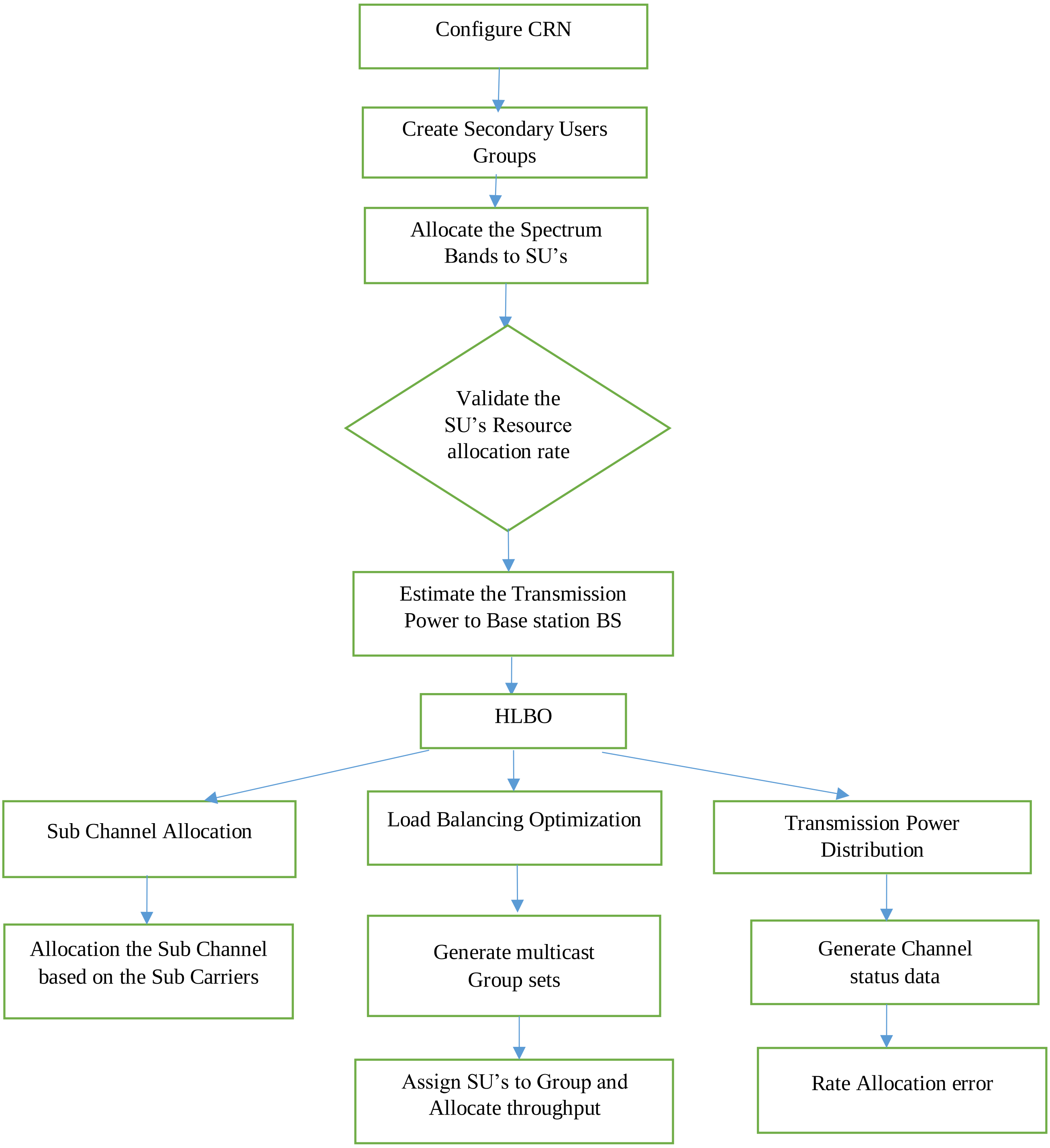

Figure 2: Flow chart for cognitive radio network.

5. Results and Discussion

In this section, we analyse performance of proposed Heuristic Load-balancing Optimization model (HLBO) to determine the rate allocation. In cognitive radio networks, we simulated primary and secondary consumers, Base station and Channels, for different simulation times and bandwidth rates. We configure the CRN-IOT in ns3 simulator by configuring Heuristic Load-balancing Optimization model (HLBO) to determine the performance of proposed HLBP on following performance parameters packet delivery ration (PDR), Average throughput, Average delay, overhead network and energy usage. We equate HLBO to Optimal STM(OSTM) efficiency. The framework proposed is simulated with the Table 1 simulation parameters of the network simulator-3 (NS-3). We take a different arrival of data into account in this case, we varied data arrival rate from 500Mb to 800Mb for the configured network with 100 sec simulation time.

Table 1. Simulation time

No. of Nodes	50
Area Size	1000 X 1000 m
Mac	WiMAX
Routing protocol	HLBO
Simulation Time	100 sec
Receiving Power	0.395
Sending power	0.660
Idle Power	0.035
Initial Energy	10.0 J to 50 J
Data rate	500-800 Mbps

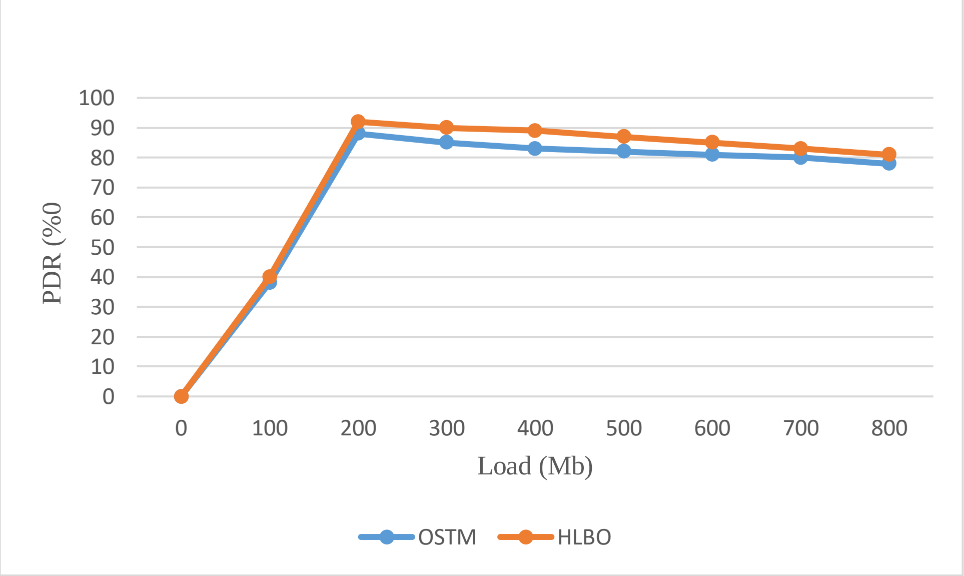

Figure 3: Traffic Load Vs Packet Delivery Ratio

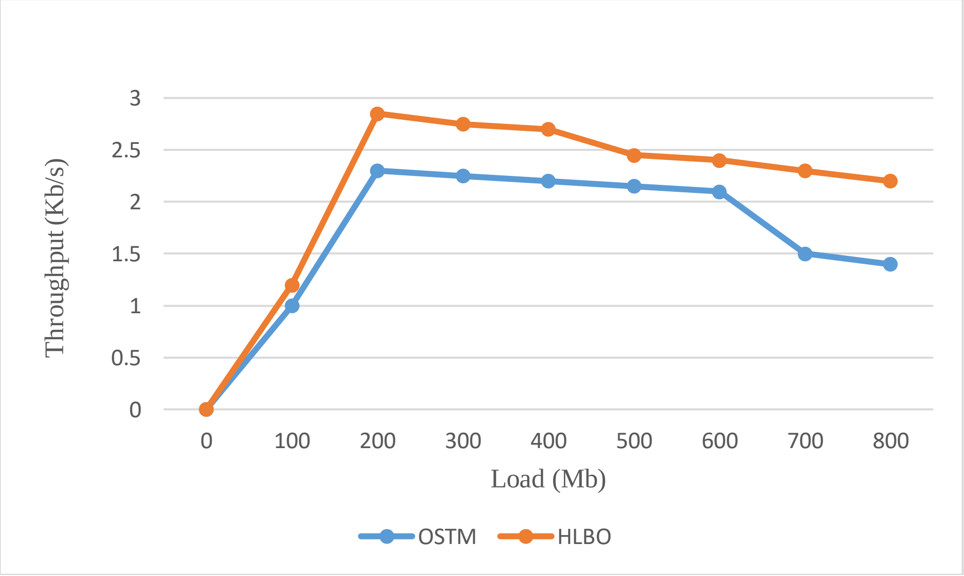

Figure 4: Traffic Load Vs Throughput

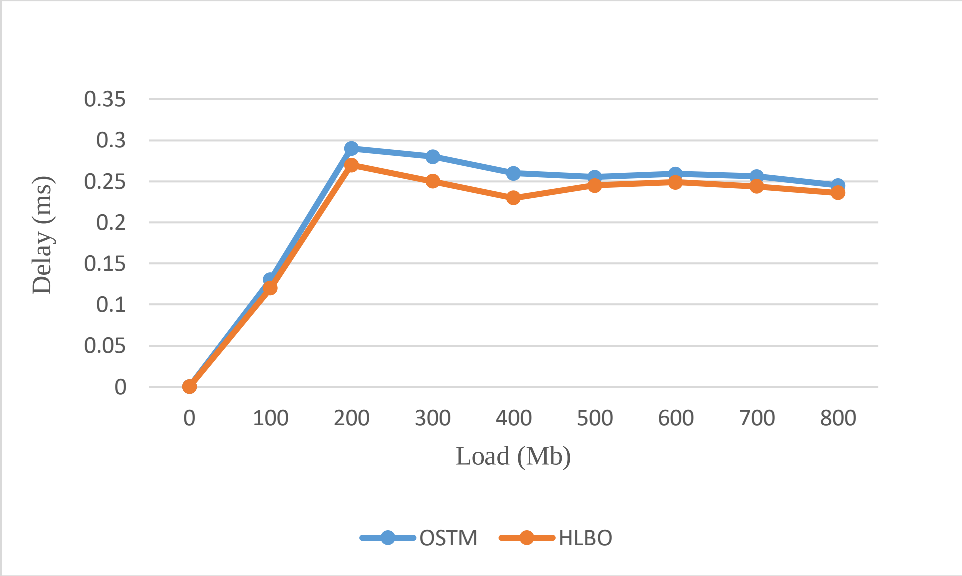

Figure 5: Traffic Load Vs End-to-End Delay

The HLBO and OSTM techniques packet transmission ratios for various traffic load scenarios are shown in Figure 3. We may infer that our proposed HLBO approach has a packet delivery relationship 8.1 percent higher than OSTM.

Figure 4 demonstrates the average overhead for various traffic load scenarios for HLBO and OSTM techniques. On the basis of the simulation results, the average HLBO throughput rate increased in comparison to the OSTM process. The end-to-end delay of HLBO and OSTM techniques for various traffic load scenarios is shown in Figure 5. The delays were increased when traffic in both schemes increased, with a higher delay for traffic load in comparison with HLBO OSTM.

6. Conclusion and Future Enhancement

In this paper we propose heuristic model for IOT-based Cognitive Radio network optimization of load balancing. Proposed HLBO organizes the load balancing scheme to minimize the SNR error rate and allocates the optimized channels to the secondary users based the channel state. To identity channel availability and allocation rate status the proposed HLBO scheme estimates the optimal channel spectrums to organize efficient bandwidth rate based on amount of secondary users assigned to a channel to minimize resource allocation errors and maximize data handling performance. The Load balancing optimization method is utilized for bandwidth minimization for increasing QoS and spectrum balancing reduction by organizing group of secondary users in to multicast groups. Based on the simulation results the throughput is improved up to 14.17%, for different traffic load. We enhance this document to create the distributed framework for managing the interference and resource allotment in IoT sensor networks for the optimal location and operating channel.

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