

Power Aware Spectrum sensing and Sleep Scheduling Technique for Cognitive Radio Networks

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Abstract: In a cognitive radio networks (CRN), the secondary users (SUs) opportunistically access the channels where the primary users (PUs) are not present. In existing spectrum sensing techniques, the sensing interval is mostly static and the final spectrum sensing decision becomes inaccurate due to incorrect sleep schedules of SUs. To resolve these issues, this paper proposes a power aware spectrum sensing and sleep scheduling (PASS) technique for CRN. In this technique, the spectrum sensing intervals (SIs) of SUs are adaptively determined based on the required transmission power and battery capacity of SUs. The correctness of cooperative spectrum sensing decisions is validated at the fusion center, based on which the sleeping schedules of the SUs are determined. The proposed technique is implemented in NS2 and simulation outcomes show that PASS attains higher probability of successful detection and throughput with reduced energy consumption.

Keywords: Cognitive; SU; CRSN; IoT; Spectrum

1. Introduction

By utilizing spectrum resources more efficiently, the notion of cognitive radio (CR) has evolved to alleviate the shortage of restricted radio spectrum resources. By using an idle licensed channel in its immediate vicinity, the CR can help alleviate the dilemma of limited unlicensed spectrum resources and underused licensed frequency resources. Cognitive radio sensor networks (CRSNs) have lately emerged as a hot issue in IoT paradigms as a specific use of CR technology.

Secondary users (SUs) can gain access when the PUs aren't using the channels they've been allotted. This is the basic goal of cognitive radio. Cognitive radio systems need that SUs understand the behaviours of PUs in order to avoid interference with the PUs on the same spectrum band. As SUs have limited sensing capabilities, cooperative spectrum sensing is used to aggregate SUs' sensing information in order to improve PU occupancy detection accuracy. As a precaution, the spectrum sensing method should be able of quickly and accurately detecting white holes [3].

The energy and spectrum management solutions for the future generation of wireless networks have become the most important issues, and hence have received growing attention. To avoid interfering with other radios, SUs must frequently check for the presence of PUs. For

cognitive radio networks, this higher energy consumption is required. The amount of energy necessary for cooperative spectrum sensing (CSS), in which numerous SUs communicate their sole decisions to generate a more accurate global decision of the existence of PUs, grows as the number of SUs expands. Currently, researchers are concentrating on energy efficient CSS as and analyzing the detection performance and false alarm rate. The PU-SU collaboration, the computing cost of the detection method, and the exact measurement of the noise variance all play a role in the selection of a spectrum sensing technology [9].

1.1 Problem Statement and Objectives

In power aware spectrum sensing techniques, the sensing interval is mostly static and does not based on the battery capacity and the received throughput. The final spectrum sensing decision becomes inaccurate due to incorrect sleep schedules of SUs.

Based on the problem statement, the objectives of the proposed work are stated as follows: Design a power aware spectrum sensing technique which adaptively determines the sensing interval based on the battery capacity and the received throughput, thereby ensuring accurate spectrum sensing decisions.

In this paper, we propose to design power aware spectrum sensing and sleep scheduling (PASS) technique for CRN.

The main contributions of this technique are listed below:

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- (i) In the spectrum sensing algorithm, the sensing intervals of SUs are adaptively determined based on the required transmission power and battery capacity of SUs
- (ii) A new algorithm is proposed for validating the correctness of cooperative spectrum sensing decisions at the fusion center, based on which the sleeping schedule of SUs are determined.
- (iii) The energy consumption of idle users are reduced by adaptively setting sensing interval based on battery capacity and energy consumption of SUs with bad sensing decisions are reduced by adjusting the sleeping interval.

2. Related Works

First, the energy efficiency of ZilongJin et al [1] was examined. This analysis reveals the best SSN ratio for increasing network lifespan by enhancing the detection probability of co-operative detection (CDP). When it comes to spectrum sensing performance, simulation findings demonstrate that a certain SSN ratio may effectively improve the network's lifetime.

Cooperative spectrum sensing has been proposed by Yuan Gao et al [5] that includes a pre-detection and sleeping policy. Pre-detection is used at the beginning of primary user detection, when all sensing nodes are included in order to increase detection performance of the primary user. The sleeping policy is implemented to each sensing node at the completion of the pre-detection process and the beginning of the local detection transmission, in order to reduce sensing energy

consumption. As long as global detection and false alarm probability, as well as interference to the primary user can be tolerated, they were able to define the issue of reducing maximum average energy consumption per sensor node in Rayleigh fading channels.

An energy harvesting (EH)-based CRN has been suggested by Zan Li et al. [6]. A partially observable Markov decision (POMDP) process framework and a Markov decision process (MDP) framework are utilised to optimise the long-term average weighted aggregate of the SU's throughput and the interference due to PUs.

As an example, Cao and colleagues [7] studied the topic of energy-efficient spectrum sensing for remote estimate of a generic linear dynamic system, and develop an optimization problem that reduces sensor energy consumption while ensuring required estimation performance. [7] Mixed integer nonlinear programming was used to represent the issue and an optimization technique was developed that takes into account the time of sensing, which channels are to be scanned, and how long each channel is to be scanned.

In EEISS, a spectrum sensing technique which deals with energy efficiency and inference avoidance is proposed by E N Ganesh and M Ramchandran [8]. Depending on the energy levels of SUs, the spectrum sensing time is dynamically approximated, and the transmission power is set in accordance with the amount of PU interference and the SU battery levels. Based on these constraints, a game theory model is developed to maximise throughput.

S.No	Author	Name of the Approach	Metrics	Drawbacks
1	ZilongJin et al [1]	Cluster formation algorithm based Spectrum sensing nodes (SSN) selection	Improves the network life time and detection probability	The spectrum sensing interval is static and not modified.
2	Yuan Gao et al [5]	Combined pre-detection and sleeping policy	Reduces the energy consumption of spectrum sensing	The sleeping period and the SI are not adjusted using battery energy and interference.
3	Zan Li et al [6]	POMDP and MDP framework.	Increased Throughput	Energy consumption is not minimized
4	Xianghui Cao et al [7]	Simulated annealing based optimization algorithm	Energy expenditure	The sensing interval is not based on battery power.
5	M Ramchandran	EEISS	probability of	The sensing

$$W_j = S_j + (W_j - \Delta I), \text{ if } B_{cap} \leq B_{cap}^{\min} \quad (3)$$

If and Bcap is high, then the SI is little bit increased by the step value ΔI . Or else, if Bcap is less, then it should be decreased by the same step value.

3.3 Co-operative Spectrum Sensing

The spectrum sensing phase is divided into two sub-phases: pre-detection and the continuous detection.

3.3.1 Pre-detection

In pre-detection, the N SRs identify the presence of a PU using energy detection method to improve the detection accuracy.

The energy spent over a spectrum band is estimated and compared to a threshold value when the energy detection

method is used for spectrum sensing. The existence of PU is presumed if the remaining battery energy is larger than the threshold; otherwise, the spectrum is regarded to be free.

There are two hypotheses that may be used to describe spectrum sensing as a binary hypothesis problem [13]:

$$H_0: y[n] = w[n], \text{ (PU is absent)}$$

$$H_1: y[n] = s[n] + w[n], \text{ (PU is present)} \quad (4)$$

Where $n=1, 2, \dots, N$.

Samples of the received signal, AWGN noise, and PU signal samples are all represented by $y[n]$ and $w[n]$. N, the observation interval, is denoted by n.

Figure 2 shows the block diagram of the energy detection method.

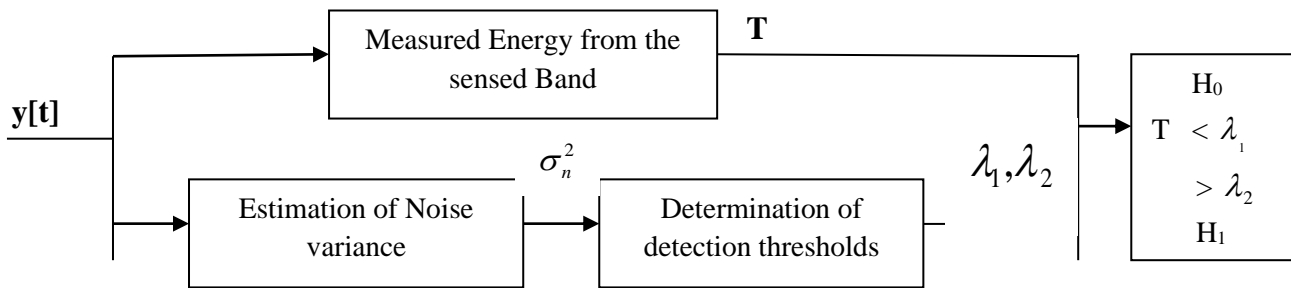


Fig 2 Energy Detection Method

As seen from Figure 2, the detection process consists of measuring the remaining battery energy over the sensed band and comparing the measured energy level with a detection threshold.

An evaluation of this comparison results in one of the hypotheses of Eq.(4) being picked as true, and the SU selects whether or not to access the band.

The decision policy for energy detection is given by [15]

$$T = \sum_{n=1}^N (Y[n])^2 \quad (7)$$

Local decision rule at SR_i is indicated as E_i by reference to the pre-detection phase received energy.

Decision	Condition
=====	=====
H_0	If $E_i \leq \lambda_1$
H_1	If $E_i \geq \lambda_2$
No decision	If $\lambda_1 < E_i < \lambda_2$

The detection threshold is obtained from as follows:

$$\lambda_D = \sigma_w^2 (Q^{-1}(P_{FA})\sqrt{2N} + N) \quad (9)$$

Where $Q(\cdot)$ denotes the Gaussian Q-Function

3.3.2 Continuous Detection

In this phase, an adaptive sleeping schedule is applied at SR_i to reduce the energy consumption of SRs with bad decisions. (ie) The SRs which satisfies the condition

$\lambda_1 < E_i < \lambda_2$ are made to sleep for the period P_s . During the sleep period, the sleeping SRs deactivates its sensing module.

3.4 Adaptive Adjustment of Sleep Duty Cycle

Then the sleep period of the receiver radio is determined based on Bcap as

$$\text{Time}_{\text{sleep}} = \text{Int}_{\text{sl}} + \rho (B_{\text{cap}}^{\text{max}} - B_{\text{cap}}) \quad (10)$$

Where Int_{sl} is the number of sleep intervals and ρ is a weighting constant. The SU transmits the wake-up signal to the SR only if it has sufficient battery capacity.

3.5 Cooperative Spectrum Sensing Decision Algorithm

In this algorithm, the correctness of CSS decisions will be validated at the fusion center based on which the sleeping schedule of SUs are determined.

The steps involved in this algorithm are as follows:

1. SI of SUs is adaptively determined based on the required transmission power and battery capacity of Sus (explained in section 3.2)
2. Local decision is performed based on the sensing interval.
3. Decision is sent to the fusion centre.
4. FC validates the sensing decisions and the nodes with poor spectrum sensing decisions are put into sleep mode with a sleeping period of time ST.
5. The value of ST is determined based on the battery energies of sleeping SUs and the correctness of other SU's decisions. i.e.

5.1 When the battery capacity is greater, then the transmit power of SU will be high and sleep mode will be off.

5.2 When the battery capacity of SU is less, then the transmit power will be less to increase the energy efficiency of the system and the node is put to sleep mode with more ST.

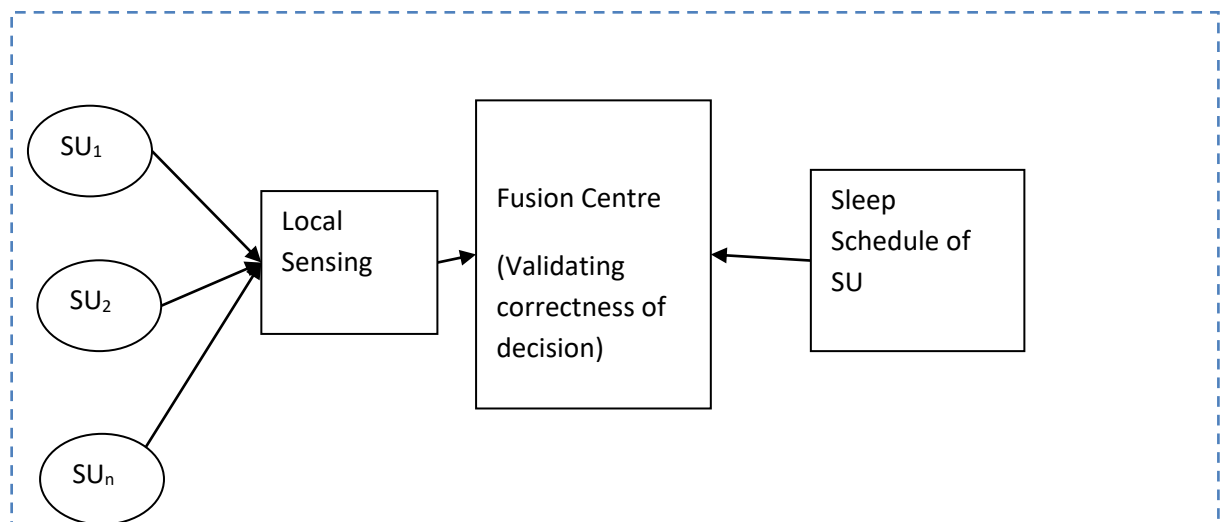


Fig 3 Decision making at fusion center

4. Experimental Results

In this section, the performance of proposed Power Aware Spectrum sensing and Data transmission (PASS) is implemented in CRAHN patch of NS2. The PASS is

compared with the Combined Predetection and Energy efficient spectrum sensing CPEESS [5] scheme. Table-1 shows the simulation parameters used in the experiments.

Parameter	Value
Number of CR users	25 to 100
Topology Size	1000m X 1000m
Distance between ST and SR	300m
Path loss exponent (η)	4
Type of Propagation	Two Ray Ground
Channel model	Rayleigh
Type of Modulation	BPSK

Initial Energy	15 μ J
Transmit power	66 mW
Receive power	39 mW
Channels	10
Detection Probability (P_d)	0.3 and 0.6
Missdetection probability (P_f)	0.01
Default SI	0.1

Table -1 Simulation settings

A. Effect of Increased CR users

In order to analyze the effect of increased CR users, the number of CR users is varied from 25 to 100 and the

performance is evaluated based on the metrics transmission latency, probability of successful detection, throughput and residual energy.

Nodes	PASS (sec)	CPEESS (sec)
25	2.12	3.03
50	2.32	3.77
75	2.84	4.41
100	3.08	4.42

Table 2: Results of Latency for CR users

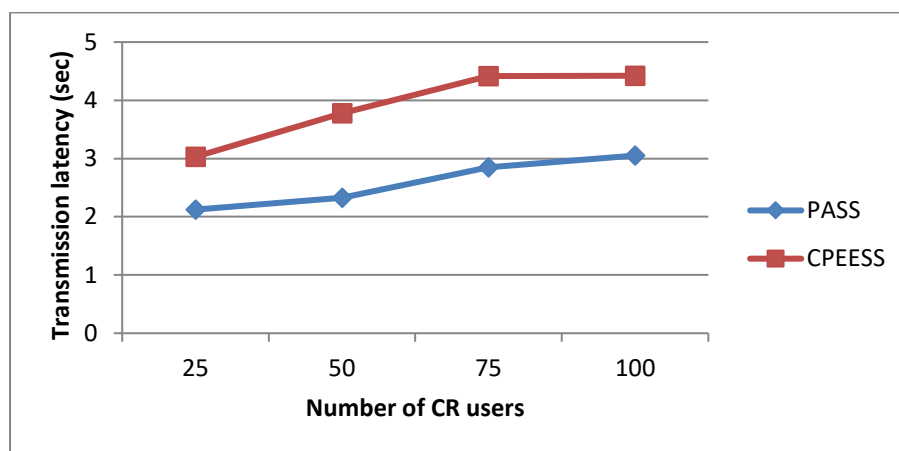


Fig 4 Transmission Latency for CR users

Table 2 and Figure 4 show the results of transmission latency for the two schemes in presence of increased CR users. It can be seen that the latency of PASS is 34% less when compared to CPEESS.

Nodes	PASS	CPEESS
25	0.9463	0.8717
50	0.8817	0.8339
75	0.8530	0.8101
100	0.7623	0.7063

Table 3: Result of successful detection for CR users

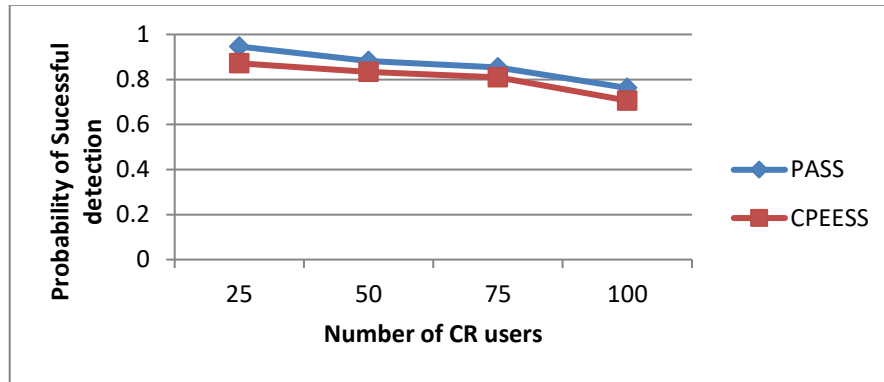


Fig 5 Probability of successful detection (PSD) for CR users

Table 3 and Figure 5 show the results of PSD for the two schemes in presence of increased CR users. It can be seen that PASS has 6% higher detection probability when compared to CPEESS.

Nodes	PASS (Mb/s)	CPEESS (Mb/s)
25	39.99	33.84
50	37.12	25.77
75	31.68	23.59
100	27.78	21.80

Table 4 Results of Throughput for CR users

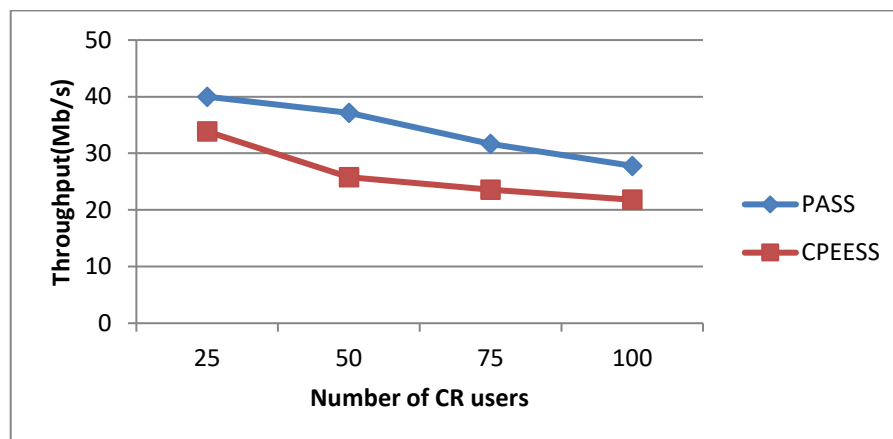


Fig 6 Throughput for varying CR users

Table 4 and Figure 6 show the results of measured throughput for the two schemes in presence of increased CR users. It can be seen that PASS has 23% higher throughput when compared to CPEESS.

Nodes	PASS (Joules)	CPEESS (Joules)
25	10.01	10.98
50	11.33	15.33
75	11.55	12.32
100	11.55	13.06

Table 5 Results of Energy Consumption for CR users

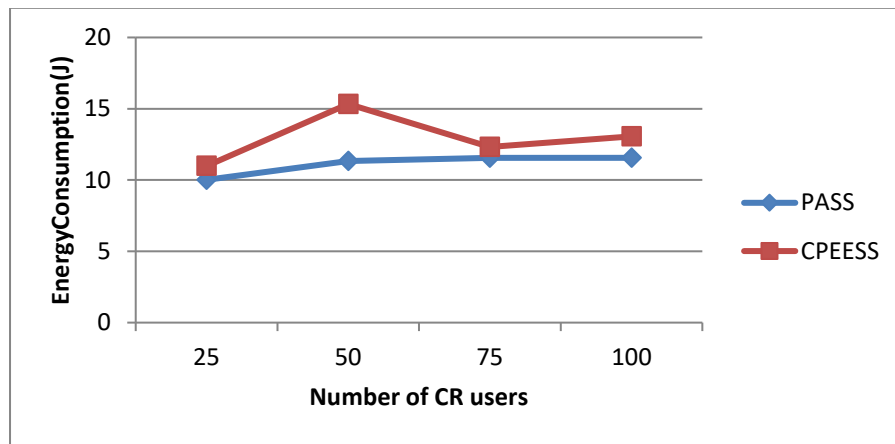


Fig 7 Energy Consumption for CR users

Table 5 and Figure 7 show the results of energy consumption for the two schemes in presence of increased CR users. It can be seen that PASS has 13% lesser energy consumption when compared to CPEESS.

5. Conclusion

This paper proposed an optimized spectrum sensing technique for CRN. In this technique, the SI of SUs is adaptively determined based on the required transmission power and battery capacity of Sus. The correctness of cooperative spectrum sensing decisions is validated at the fusion center based on which the sleeping schedule of SUs are determined. The major benefit of this scheme is that the energy consumption is reduced by adaptively setting spectrum sensing interval and sleeping interval in terms of battery capacity. The proposed technique is implemented in the NS2 and the performance is compared with CPEESS scheme. Simulation outcomes show that PASS attains higher PSD and throughput with reduced energy consumption.

References

- [1] Zilong Jin, Yu Qiao, Alex Liu, and Lejun Zhang, "EESS: An Energy-Efficient Spectrum Sensing Method by Optimizing Spectrum Sensing Node in Cognitive Radio Sensor Networks", Hindawi, Wireless Communications and Mobile Computing, Volume 2018, Article ID 9469106, 11 pages, 2018.
- [2] Ji Wang, Ing-Ray Chen, Jeffrey J.P. Tsai, Ding-Chau Wang, "Trust-based Mechanism Design for Cooperative Spectrum Sensing in Cognitive Radio Networks", Computer Communications, 2017.
- [3] Zhiguo Sun, Zhenyu Xu, Zengmao Chen, Xiaoyan Ning and Lili Guo, "Reputation-Based Spectrum Sensing Strategy Selection in Cognitive Radio Ad Hoc Networks", Sensors, 2018.
- [4] Adele Khalunezhad, Neda Moghim, Behrouz ShahgholiGhahfarokhi, "Trust-based multi-hop cooperative spectrum sensing in cognitive radio networks", Elsevier, Journal of Information Security and Applications 42 (2018) 29–35, 2018.
- [5] Yuan Gao, Zhixiang Deng, Dongmin Choi, Chang Choi, "Combined pre-detection and sleeping for energy-efficient spectrum sensing in cognitive radio networks", J. Parallel Distrib. Comput., 2017.
- [6] Zan Li, Boyang Liu, Jiangbo Si and Fuhui Zhou, "Optimal Spectrum Sensing Interval in Energy-Harvesting Cognitive Radio Networks", IEEE, 2017.
- [7] Xianghui Cao, Xiangwei Zhou, Lu Liu and Yu Cheng, "Energy-Efficient Spectrum Sensing for Cognitive Radio Enabled Remote State Estimation over Wireless Channels", IEEE, 2014.
- [8] M Ramchandran and E N Ganesh, "Energy Efficient and Interference-aware Spectrum Sensing Technique for Improving the Throughput in Cognitive Radio Networks", IOP Conference Series: Materials Science and Engineering 993 (2020) 012092
- [9] Abbass Nasser, Hussein Al Haj Hassan, Jad Abou Chaaya, Ali Mansour and Koffi-Clément Yao, "Spectrum Sensing for Cognitive Radio: Recent Advances and Future Challenge", Sensors, March 2021
- [10] Fabrício B. S. de Carvalho, Waslon T. A. Lopes, Marcelo S. Alencar, "Performance of Cognitive Spectrum Sensing Based on Energy Detector in Fading Channels", International Conference on Communication, Management and Information Technology (ICCMIT), Procedia Computer Science, Elsevier, 2015
- [11] Yasmin Hassan, Mohamed El-Tarhuni, and Khaled Assaleh, "Learning-Based Spectrum Sensing for Cognitive Radio Systems", Journal of Computer Networks and Communications, Hindawi, 2012
- [12] M Ramchandran and E N Ganesh, "MBSO Algorithm For Handling Energy-Throughput Trade-Off In Cognitive Radio Networks", The Computer Journal, Oxford, May 2021

- [13] Daniela Mercedes Martínez Plataa, Ángel Gabriel Andrade Reátiga,” Evaluation of energy detection for spectrum sensing based on the dynamic selection of detection-threshold”, International Meeting of Electrical Engineering Research (ENIINVIE), Elsevier, 2012
- [14] Ranga, K. K. ., Nagpal, C. K. ., & Vedpal, V. (2023). Trip Planner: A Big Data Analytics Based Recommendation System for Tourism Planning. *International Journal on Recent and Innovation Trends in Computing and Communication*, 11(3s), 159–174.
<https://doi.org/10.17762/ijritcc.v11i3s.6176>
- [15] Kamau, J., Goldberg, R., Oliveira, A., Seo-joon, C., & Nakamura, E. Improving Recommendation Systems with Collaborative Filtering Algorithms. *Kuwait Journal of Machine Learning*, 1(3). Retrieved from <http://kuwaitjournals.com/index.php/kjml/article/view/134>
- [16] Juneja, V., Singh, S., Jain, V., Pandey, K. K., Dhabliya, D., Gupta, A., & Pandey, D. (2023). Optimization-Based Data Science for an IoT Service Applicable in Smart Cities. In *Handbook of Research on Data-Driven Mathematical Modeling in Smart Cities* (pp. 300–321). IGI Global.