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Throughput maximization with channel access fairness model using game theory approach

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ABSTRACT

The adoption of cognitive radio (CR) technology into wireless sensor networks (WSNs) effectively addresses the spectrum scarcity problem of traditional unlicensed spectrum. Allocating and managing limited network channel to secondary user (SUs) considering dynamic behavior pattern of primary users (PUs) is a critical issue of CR-WSN. Recently, various channel access methodologies using statistical, reinforcement learning (RL), game theory (GT), and deep learning (DL) model have been presented for CR-WSN. However, the existing channel access methodologies has following two limitations: i) fails to assure balance between maximizing throughput of SUs with minimal interference to PUs considering multi-channel CR-WSNs environment; and ii) maximizing throughput with minimal collision assuring access fairness among SUs considering energy constraint CR-WSNs. In addressing the research issues, this paper present throughput maximization channel access fairness using game theory (TMCAF-GT) model. The TMCAF employ both shared and non-shared channel access mechanism employing GT model for assuring throughput maximization with minimal interference and access fairness. Experiment outcome shows the TMCAF-GT provides superior throughput with minimal collision.

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1. INTRODUCTION

The wireless sensor networks (WSNs) encompasses large number of inexpensive sensor device deployed in hazardous location for monitoring area and communicates through wireless means [1]. The inexpensive deployment nature of WSNs has led to growth of internet of things (IoTs) environment [2] for providing different applications such as environmental monitoring, disaster relief, military, and forest fire management. In general, these applications demand higher throughput with less delay. Alongside, prerequisite better spectrum availability with lesser energy consumption. As more and more applications demand wireless communication (i.e., spectrum resource), the existing wireless network such as 2.4 GHz and fifth generation network require effective channel access mechanism [3]. Cognitive radio networks (CRNs) have been used in addressing spectrum scarcity problem of large-scale WSNs (LS-WSNs) [4]. In CRNs, there exist two users such as primary users (PUs) and secondary users (SUs) where SUs accesses the primary channel in the absence of primary users without inducing interference to PUs. Recently, extensive work has been done incorporating CRNs technologies into large-scale WSNs [5]. Alongside, the existing method aimed at addressing energy and spectrum scarcity issues of CR-WSNs. The architecture of CR-WSNs is shown in Figure 1.

The spectral utilization performance can be enhanced through channel sharing [6], [7], opportunistic channel access (OCA) [8], and sensing based channel sharing [9]. The sensing-based channel sharing mechanism, the SUs accesses the channel according spectrum detection outcomes; thus, aid in providing flexibility with improved spectrum utilization. However, it has certain challenges such as interference of SUs affecting PUs because of imperfect channel sensing measurement. Alongside, under multi-user channel access mechanism, each SUs will have different channel state information affecting the overall performance of SUs.

Recently, number of works have been designed for maximizing throughput (i.e., spectrum usage) of SUs with minimal interference (i.e., less collision) to primary network [10]–[15] under small to large density wireless sensor networks. The existing methods predominantly focused on allocating optimal channel access in CR-WSNs for maximizing the objective function with certain quality of service (QoS) constraint [10] using known channel availability statistics [11], [12]. Further, these existing models are designed considering random mobility of secondary users where channel usage pattern are obtained through reinforcement learning [13]. However, when sensor nodes mobility is dynamic in nature all these methods provide poor performance [14]. Further, it is important to study the channel access model under imperfect channel sensing considering dynamic mobile nature of LS-WSNs [15]. How to bring a balance between maximizing throughput with minimal collision and assures access fairness is the key to design efficient spectrum access model. Alongside, the energy constraint of WSNs must also should be taken into considering in designing enhance channel access mechanism.

In addressing the research challenges, this paper present throughput maximization with channel access fairness (TMCAF) model. The TMCAF employs both shared and non-shared channel access mechanism in maximizing throughput with minimal collision; thereby assuring energy efficiency. In order to provide fair resource allocation game theory model provides an effective mechanism [16], [17]. Game theory-based channel access mechanism are used to maximize objective function of CR-WSNs [18]–[20] are also studied. The adoption of distributed channel access mechanism leveraging both shared and non-shared channel access environment in TMCAF aided in improving access fairness with higher energy and performance efficiency of CR-WSNs. The significance of research work is: i) the throughput maximization channel access fairness using game theory (TMCAF-GT) employs both shared and non-shared channel access mechanism; there by leveraging the benefits of both mechanisms, ii) a game theory model is presented for both shared and non-shared channel access mechanism for assuring optimal throughput to SUs with access fairness assurance, iii) the channel usage patter is established to reduce interference to PUs under multi-channel CR-WSNs environment, and iv) the TMCAF-GT improves throughput with minimal collision in comparison with existing channel access mechanisms.

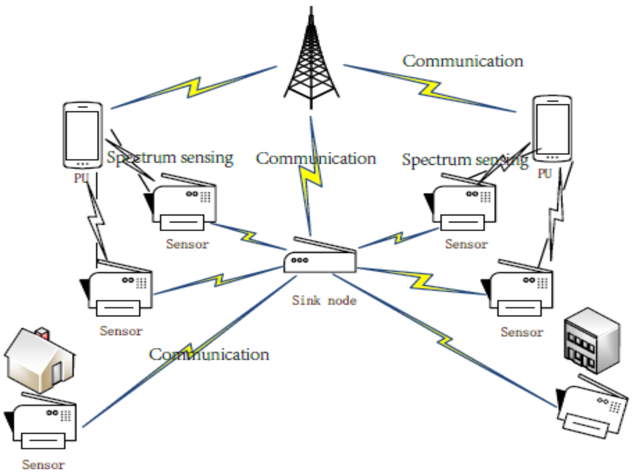

Figure 1. Architecture of CR-WSN

2. LITERATURE SURVEY

This section study various recently modelled channel access and selection scheme using cognitive radio in modern senor network for provisioning modern applications. They presented model by combining CR and simultaneous wireless information and power transfer (SWIPT) into IoTs environment [21]. The model is focused in addressing limited spectrum availability and energy efficiency issues of device connected through IoTs environment. Here the IoTs devices is considered as the SUs and for enhancing the overall throughput of network, the IoT devices can perform spectrum switching in adaptive manner. They showed that in standard cognitive radio network, the SUs looks out for idle channels by sensing the whole spectrum available, which induces delay, consumes huge amount of energy, and takes more time to process data-intensive applications

[22]. The model utilizes multi-objective parameter and probability-based approach for establishing ideal channel prior to perform transmission. The model is efficient in addressing packet collision in ideal channel considering different arrival rate of primary and secondary users and under different channel optimization configurations. Here they presented a channel access scheme by establishing PUs presence and average energy efficiency if network optimization in CR-WSN [23]. The optimization constraint is modeled through mathematical model. Alongside the performance is measured through ratio of average throughput with respect to average energy efficiency achieved. Further, the work aimed at reducing energy consumption of channel access by SUs, as they are battery powered. In particular, the model is designed to maximize the total throughput while energy consumption is kept at minimal through improved sensing. The improved sensing is achieved through maximizing the sensing time of SUs with power constraint and with minimal bandwidth usage.

They focused on addressing power and uplink channel resource allocation problems to SUs in IoTs environments [24]. The optimization problem is addressed using non-accurate spectrum sensing and non-accurate channel state information (CSI) under shared channel large-scale cognitive radio IoTs environments. They employed hybrid model using both overlay and underly CR network for assuring ideal through with reliability for secondary users [25]. In modern large-scale CR-WSNs, the SUs will assist (i.e., as relay nodes) PUs for communicating packets using underlay mode; in return the PUs allows the SUs to access its spectrum for communicating its data using overlay mode. Considering such communication, they modeled multiple fair channel allocation policy and comparative analysis in terms of energy efficacy and spectrum efficiency is studied. Aimed at reducing power consumption of SUs considering multiuser ad hoc network [26]. The model is focused on optimizing both power-splitting coefficient and transmit power of secondary users in distributed manner. They constructed a IoTs environment composed of both power beacons and sensor nodes with CR capability. The nodes are powered using power beacons [27]. The objective is to maximize the rate at which (i.e., minimize) device behaves as source. The optimization problem of channel allocation of power beacons and nodes, link activation, routing packet over intermediate nodes, and beamforming of power beacons is jointly considered. Further, using CR a distributed max-min rate and game theory (GT) model is designed for adjusting the transmit power in iterative manner. Here they presented a channel selection model using Q-learning technique [28]. The model focus in studying the randomness behavior of primary users in WSNs and energy harvest mechanism.

An effective channel allocation design is modeled that address interference issues considering multiuser CR environment [29]. The Stackelberg game is used for maximizing profit of PUs and maximize the communication by secondary users. They modelled a machine learning model using CSI for establishing the position of SUs; however, collecting information frequently induces significant control channel overhead [30]. The limitation of optimal channel access mechanisms using machine learning-based [13], [14] approach is addressed using game theory approach [18]. Nonetheless, using existing GT-methods [19], [20] fails to provide access fairness assurance [31] with performance and energy prerequisite of CR-enabled LS-WSNs [30]. In addressing research limitation in next section, a novel optimal channel access mechanism is designed assuring access fairness and throughput maximization using game-theory approach.

3. THROUGHPUT MAXIMIZATION WITH CHANNEL ACCESS FAIRNESS USING GAME THEORY MODEL FOR LARGE-SCALE COGNITIVE RADIO WIRELESS SENSORR NETWORK

This section presents a novel channel access mechanism namely TMCAF-GT. The TMCAF-GT first provides channel state estimation to obtain mobility pattern and channel usage structure of PUs. Then, using this information a shared and non-shared channel access mechanism assuring throughput maximization and access fairness together using game theory model. Lastly, the novel TMCAF-GT algorithm is presented.

3.1. Channel state estimation

In CR-WSNs, whenever a sensor node looks for channel for performing certain communication, it performs sensing for establishing channel availability. Poor channel allocation method might induce interference to the primary users; thus, efficient CSI measurement plays very important part in designing of efficient channel allocation design mitigating interference. The model presented in [32] is used for measuring average channel accessible ω_j of channel j at any instance is estimated as (1).

$$\omega_j = \left(1 - \varphi_j\right) + \varphi_j \alpha_{i,j} = 1 - \varphi_j \alpha_{b,j.} \tag{1}$$

Where φ_j defines the average region occupied by current sensor nodes on respective channel j as described:

$$\varphi_j = {}^{4S_j^2}\big/_{M_{q,j}^2}. \tag{2}$$

$\alpha_{i,j}$ represent the probability that PUs will be active in channel j under steady-state and $\alpha_{b,j}$ represent probability that PUs will not be using channel j under steady-state. The parameter $T_{V,j}$ defines the state when sensor node goes out of range of PUs coverage area and therefore, $U_{V,j}$ follows an exponential distribution with $\beta_{V,j}$, where,

$$\beta_{V,j} = \beta_{\mathbb{b},j} + \frac{w}{g(M_{Q,j}-S_j)}\alpha_{\mathbb{b},j}. \tag{3}$$

based on ideal assumption that:

$$\alpha_{B,j}\beta_{B,j} = \alpha_{V,j}\beta_{V,j}, \tag{4}$$

where,

$$\alpha_{B,j} = \omega_j, \tag{5}$$

and,

$$\alpha_{V,j} = 1 - \omega_j \tag{6}$$

we can obtain $T_{B,j} \rightarrow T_{V,j}$ transition rate $\beta_{B,j}$ as shown in (7).

$$\beta_{B,j} = \frac{\omega_j}{1-\omega_j}\beta_{V,j} == \frac{\varphi_j\alpha_{\mathbb{b},j}}{1-\varphi_j\alpha_{\mathbb{b},j}}\left(\beta_{\mathbb{b},j} + \frac{w.\alpha_{\mathbb{b},j}}{g(M_{Q,j}-S_j)}\right). \tag{7}$$

Thus, $U_{B,j} \sim e(\beta_{B,j})$. The operative channel accessibility (OCA) δ of channel j as the mean session period in which channel j is accessible for a sensor node to communicate can be expressed as (8).

$$\delta_j = \gamma_j . U''_{B,j} = \frac{\gamma_j}{\beta_{B,j}} \tag{8}$$

Where $\gamma_j \in (0,1)$ is the interference parameter that defines the optimal level of interference to the primary users. It must be noted that, higher the γ will result in more interference to PUs and at the same time, will result in more spectrum opportunity. Here every SUs has knowledge of temporal channel usage pattern and spatial distribution of PUs in CR-WSNs [32]. In this way the ideal channel accessibility i.e., $\beta_j, j \in \mathcal{M}$, considering dynamic mobility pattern. In this work the SUs uses game theory model to sense and access the channel where every SUs tries to maximize its utility without violating access fairness among other contending SUs. The TMCAF-GT employs both shared and non-shared channel access mechanism assuring the existence of Nash equilibrium (NE).

3.2. Shared channel access mechanism

In shared channel access mechanism, the available channel is assigned to sensor nodes considering random backoff time u_j. Here channel is assigned to sensor nodes only if channel is available and can utilize till time slots ends where other SUs will be idle mode. On the other side, if channel is not available a random backoff window u_j is initialized. In shared channel access mechanism, the channel is given to SUs as (9).

$$s(o) = {}^{1}\!/_{o} \tag{9}$$

In addition, every respective SUs utility is expressed as (10).

$$V^{j}_{u\{rnd\}} = \frac{\mu_j}{o_j}. \tag{10}$$

Where $g_{rnd}(o) = 1$. The pure NE of shared channel access mechanism is obtained considering game γ. Let consider a game for shared channel access mechanism under certain congestion vector $o = (o_1, o_2, o_3, \ldots, o_D)$ provides NE-set (o) with bounds described in following equation should be assured.

$$\begin{cases} o_j = \left\lceil \frac{\mu_j O - \sum_{a\neq j, a\in D}\mu_a}{\sum_{a\in D}\mu_a} \right\rceil + X_0 \;\; j = 1,2,3,\ldots,D \\ \sum_{j=1}^{D} o_j = O \end{cases} \tag{11}$$

Where $X_0 \in \{0,1,\dots,\lceil \mu_j|O| + \mu_j(|\mathcal{D}|-1)/\sum_{a\in D}\mu_a\rceil - \lceil \mu_j|O| - \sum_{a\neq j,a\in D}\mu_a/\sum_{a\in D}\mu_a\rceil - 1\}$.

3.3. Non-shared channel access mechanism

In non-shared channel access mechanism, each SUs sense the channel with probabilities $\mathcal{P}$ and the overall throughput experience by different SUs is measured as (12).

$$pl(\mathcal{P}) = \mathcal{P}(1-\mathcal{P})^{o-1} \tag{12}$$

The throughput can be maximized by considering $pl'(\mathcal{P}) = 0$; then, $\mathcal{P} = \frac{1}{o}$ using non-shared channel access mechanism is obtained as (13).

$$g_*(o) = \frac{1}{o}\left(1-\frac{1}{o}\right)^{o-1} \tag{13}$$

In non-shared channel access mechanism, $g_*(o) = (1-1/o)^{o-1}$, with $g_*'(o) < 0$ and $g_*''(o) > 0$. In addition, if o turn out to be inestimable, then overall throughput attainable using non-shared channel access mechanism is obtained as (14).

$$\lim_{o\to\infty} gS_*(o) = \frac{1}{\mathcal{G}} \tag{14}$$

The utility of SUs u that selects channel j using shared channel access mechanism is established as shown in (15).

$$V_{k\{*\}}^{j} = \mu_j \frac{1}{o_j}\left(1-\frac{1}{o_j}\right)^{o_j-1} \tag{15}$$

On contrary to shared channel access mechanism, it is challenging in establishing pure NE using non-shared channel access mechanism. Let consider a game with O number of SUs and D number of channels; every SUs will access the channel in ascending order one by one. Every sensor node prior to accesses the channel tries to select optimal strategy ($\mathcal{O}$). In this way, every senor node is assured of achieving pure Nash equilibrium by selecting optimal solution in different iteration. However, in assuring access fairness with throughput maximization in next section a novel channel access mechanism leveraging benefit of both shared and nonshared resource access mechanism is modeled.

3.4. Throughput maximization with channel access fairness using game theory model

The working of throughput maximization channel access fairness using game theory by combing both shared and non-shared channel access mechanism is given in Algorithm 1. In Algorithm 1, each sensor nodes select a random backoff time and wait for it to get completed to commence the communication that maximize it O. Once sensor nodes obtain the channel it broadcast it O to other sensor nodes. In this work for assuring fair channel access mechanism a random backoff is considered and at the same can assure good performance using TMCAF-GT which is proven through simulation study in next section.

Algorithm 1. Throughput maximization with channel access fairness using game theory model
```
Step 1. Start
Step 2. Perform sensing for acquiring accessible channel 𝒟
Step 3. Inform and sort in decreasing order the accessible channel [μ1,μ2,…,μD] using (7)
and (8) considering time ut.
Step 4. Each sensor nodes initialize a random backoff time uj from (0,uj↑).
Step 5. While current time ≤ (ut + uj↑) do
Step 6.     if the backoff time of sensor nodes j is completed then
Step 7.         if shared channel access mechanism, then
Step 8.           Choose the 𝒪 with a unrestricted channel
Step 9.         End if
Step 10.        if non-shared channel access mechanism, then
Step 11.           Choose the channel with higher 𝒪.
Step 12.        End if
12.        Broadcast the chosen channel identifier
13.    End if
14. End while
15. Each sensor node tires to select a channel access mechanism that benefits their
objective function 𝒪.
16. return
```

4. RESULT AND DISCUSSION

This section presents the outcome achieved using proposed TMCAF-GT model and existing channel access mechanism [28], [30]. The throughput and collision are performance metrics considered for validating channel access models in CR-WSNs. The simulation parameter used for studying model is described in Table 1. The simulator used for modelling TMCAF-GT and ECA is implemented using C# programing language. Experiment is conducted on Intel I-5 class processor and 8 GB RAM.

Table 1. Network parameter considered for simulation

Network parameter	Value
Network size	$100\,m * 100\,m$
Number of sensor nodes	$25, 50, 100, 200$
Initial energy of sensor node	1.0 joules
Modulation scheme	16 −QAM
Coding rate	$3/4$
Bandwidth	18 Mbps
Number of frequency channels	5
Time slots	$12\,\mu s$
Message information size	27 bytes
MAC used	TMCAF
Mobility of sensor nodes	$2, 4, 6, 8$ cycle per frame

4.1. Throughput

This section studies the throughput performance of TMCAF-GT and ECA considering different scenarios such as under varied density, varied speed, and varied slots size. Higher value indicates better performance. The throughput achieved under varied density size is graphically given in Figure 2. The devices size is varied from 25, 50, 100 and 200 with mobility speed set to 5 cycle per frame and simulation is conducted. The TMCAF-GT produces better result for all the cases; an average improvement of 23.34% is achieved using TMCAF-GT in comparison with ECA. In another case study, the mobility speed of sensor device is varied and throughput produced is graphically displayed in Figure 3. The mobility speed is varied from 2, 4, 6, 8 cycle per frame with device size set to 100 and simulation is conducted. The TMCAF-GT produces better result for all the cases; an average improvement of 32.904% is achieved using TMCAF-GT in comparison with ECA. In another case study, the slot size is varied and throughput produced is graphically displayed in Figure 4. The slot size is varied from 5, 10, 15, 20 with mobility speed and sensor device set to 5 cycle per frame and 100, respectively and simulation is conducted. The TMCAF-GT produces better result for all the cases; an average improvement of 26.74% is achieved using TMCAF-GT in comparison with ECA. The result achieved from Figures 2-4, shows the TMCAF-GT achieves very good result considering varied density (i.e., small-large), mobility speed (low-high), and channel availability (limited-full).

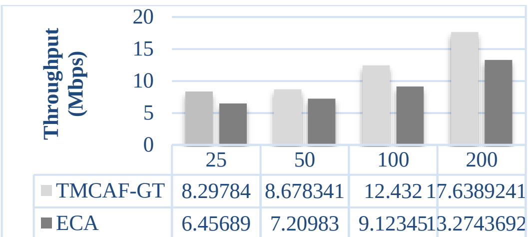

Figure 2. Throughput vs density

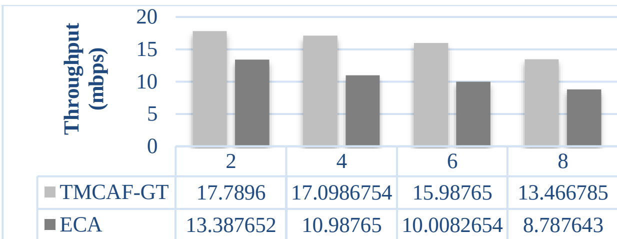

Figure 3. Throughput vs speed

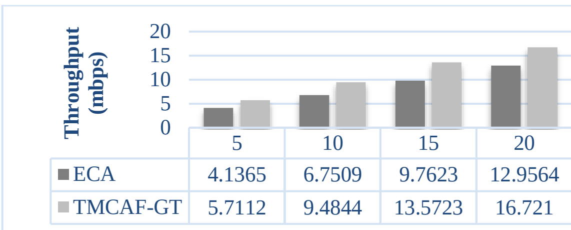

Figure 4. Throughput vs slots

This section studies the collision performance of TMCAF-GT and ECA considering different scenarios such as under varied density, varied speed, and varied slots size. Lower value indicates better performance. The collision achieved under varied density size is graphically given in Figure 5. The devices size is varied from 25, 50, 100, and 200 with mobility speed set to 5 cycle per frame and simulation is conducted. The TMCAF-GT produces better result for all the cases; an average collision reduction of 23.34% is achieved using TMCAF-GT in comparison with ECA. In another case study, the mobility speed of sensor device is varied and collision produced is graphically displayed in Figure 6. The mobility speed is varied from 2, 4, 6, 8 cycle per frame with sensor node size set to 100 and simulation is conducted. The TMCAF-GT produces better result for all the cases; an average collision reduction of 32.904% is achieved using TMCAF-GT in comparison with ECA. In another case study, the slot size is varied and collision produced is graphically displayed in Figure 7. The slot size is varied from 5, 10, 15, 20 with mobility speed and sensor device set to 5 cycle per frame and 100, respectively and simulation is conducted. The TMCAF-GT produces better result for all the cases; an average collision improvement of 26.74% is achieved using TMCAF-GT in comparison with ECA. The result achieved from Figures 5-7, shows the TMCAF-GT achieves very good result considering varied density (i.e., small-large), mobility speed (low-high), and channel availability (limited-full).

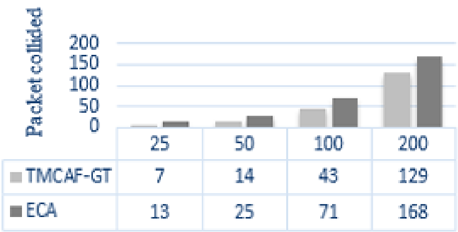

Figure 5. Collision vs density

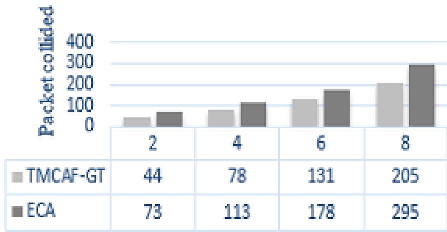

Figure 6. Collision vs speed

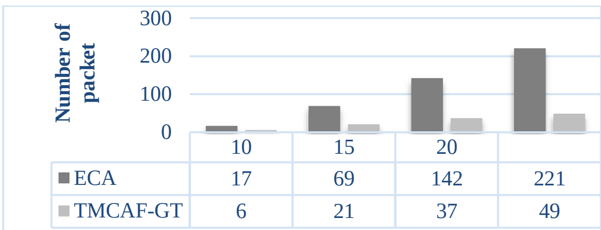

Figure 7. Collision vs slots

5. CONCLUSION

This paper studies the challenges involved in designing efficient channel access mechanism in CR-WSNs. Especially as WSNs is getting more crowded and spectrum becomes more scares and energy constraint of WSNs makes designing channel access mechanism very difficult. This paper considers aforementioned challenges and designed a new channel access mechanism namely TMCAF-GT using channel access pattern, and game theory model. Alongside, the TMCAF-GT leverages the benefit of both shared and non-shared channel access mechanism. Experiment is conducted to study scalability by varying density and to study availability slots size are varied and to study robustness the speed is varied. The TMCAF-GT produces very good throughput performance with minimal collision. The reduction of collision in network assures less interference and same time energy efficiency in improved by reducing additional sensing for retransmitting packet. However, the TMCAF-GT employ a random backoff time; as a result, some resource will be wasted. In addressing such issues, in future a dynamic backoff time optimization model can be incorporated into TMCAF-GT and study the model considering different network parameter.

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