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*Article*

# Applying Case-based Reasoning to Tactical Cognitive Sensor Networks for Dynamic Frequency Allocation

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**Abstract:** This paper proposes a cognitive radio engine platform for making exploitation of available frequency channels usable for a tactical wireless sensor network in presence of incumbent communication devices known as the primary user (PU) required to be protected from undesired harmful interference. In the field of tactical communication networks, it is desperate to find available frequencies for opportunistic and dynamic access to channels in which PU is in active. This paper introduces a cognitive engine plaform for determining available channels on the basis of case-based reasoning technique deployable as core functionality on cognitive radio engine to enable dynamic spectrum access (DSA) with high fidelity. Towards this, this paper introduces a plausible learning engine to characterize channel usage pattern to extract best channel candiates for the tactical cognitive radio node (TCRN). Performance of the proposed cognitive engine is verified by conducting simulation tests which confirm the reliability in functional aspect of the proposed cognitive engine covering the learning engine as well as the case-based reasoning engine with showing how well TCRN can avoid the collision against the PU operation considered as the etiquette secondary user (SU) should have.

**Keywords:** tactical cognitive radio sensor network; case-based reasoning; cognitive radio engine; channel occupancy probability; military tactical communications

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## 1. Introduction

Demand for frequencies is continuously and rapidly increasing in military wireless communications due to the evolution and diversification of tactical weapon systems, and it is gradually becoming more difficult to acquire additional frequencies for military wireless communications due to the expansion of commercial-side frequency demand due to the appearance of 5G and IoT (Internet of Things)[1][2][3]. The importance of excavating additional frequency resources for the purpose of military applications such as tactical sensor networks has been handled with major issue to fulfill demand for interoperability and compliance with various tactical weapon systems and wireless surveillance equipment which is one of use cases of wideband sensor network to obey the C4I (Command, Control, Communication, and Computer Intelligence) perspective[4]. In many articles, it has been emphasized that, the supply of spectrum resources for reliable military weapon system operations is very urgent with considering that, military frequency has a term of 10 years[5]. Due to the evolutional tendency of military operations which is moving toward network-centric warfare, innovative, advanced, intelligent frequency management scheme providing operating frequency resources at the right time and right place is desperate goal to be fulfilled subject to satisfying stable management and quality of service (QoS). In this context, this paper proposes a cognitive radio engine platform embedding the learning engine and the case-based reasoning engine which is capable of effective frequency allocation without producing harmful interference which is prime concern for secure coexistence for TCRNs in presence of PU in military tactical wireless communications environment.

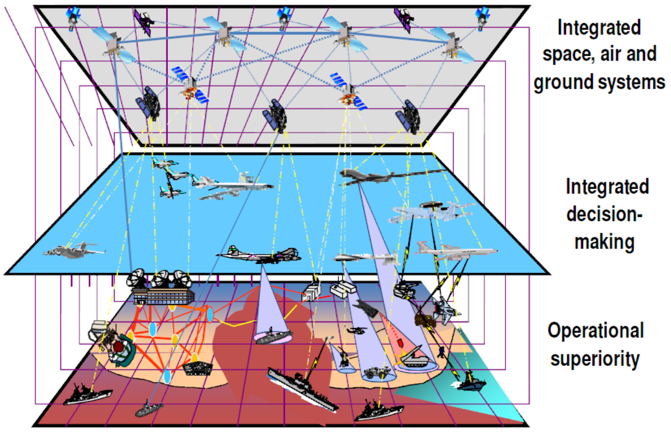


**Figure 1.** Change in usage pattern due to increased frequency demand[6].

This paper introduces a PU traffic modeling which can be interpretated as the activity of a PU channel occupancy, and proposes a case-based reasoning method deployable to tactical sensor networks. In addition, to characterize the PU traffic status, the paper proposes the learning engine enrolling to acknowledge available candidate channels. Chapter 2 in this paper discusses the current state on development of cognitive radio engine platforms and Chapter 3 proposes the structure of the cognitive radio engine platform together with its functionality, as well as the PU traffic modeling, the quantification of occupancy probability, and case-based reasoning technique with its applications. Chapter 4 releases the simulation results for verifying superior performance of the proposed case-based reasoning technique coupled with learning engine proposed in this paper. Chapter 5 releases the concluding remarks.

## 2. Current Cognitive Radio Research and Development in Military Usage

Currently, the United States uses Link-16 tactical communications networks which are equipped with DSSS (Direct Sequence Spread Spectrum) and FH (Frequency Hopping) for jamming the enemy and defending against attacks[7][8]. Link-16 is based on a non-IP type fixed hardware platform, due to the limited spectrum resource, it is necessary to define the number of users and the frequency hopping pattern beforehand. Because of Link-16's style of predefined fixed wireless resource allocation, it is difficult to use in a modern weapon system's wireless network, which has an increased need for high-capacity data transmission.

The DARPA(Defense Advanced Research Projects Agency) in United States, has developed its neXt Generation (XG) program to realize a cognitive engine whose major role is the acquisition of the surrounding radio environment through spectrum sensing equipped with a cognitive radio engine consisting of a policy engine (composed of the learning and reasoning engines) that helps new entrant in tactical wireless network acquiring appropriate frequencies while not interfering with pre-existing[7]. The cognitive radio engine platform is based on the policy engine developed by DARPA XG, and it is broadly composed of "policy language," "on-node policy components," and "off-node policy components"[9]. One of the "on-node policy components" is the "Policy Database," which stores the policy reasoning data and policy priorities generated by the "Policy Conformance Reasoner," including the policy data for using cognitive radio nodes[10]. The learning engine introduced in XG program stores policy strategies on the existing PU's occupied channels, and the reasoning engine arranges the priority of the occupied channel for data transmission by the learning engine. Policy strategy expressed in data format is renewed by comparing the PU occupied channel data acquired at the current point in time with the reference occupied channel history that was previously stored, and then the renewed data is sent to the learning engine. The proposed learning engine can be seen as the "Policy Database" entity DARPA's policy engine, and the reasoning engine can be considered to play a role of the "Policy Conformance Reasoner."

The IEEE P1900.5 standard presents the functional definition and requirement relevant to a cognitive radio engine and policy language deployable to policy-based wireless systems[11][12][13]. Table 1 shows the main components and functions composing the cognitive radio engine proposed by the IEEE P1900.5 standard. Figure 2 shows the data transfer flow with related interface between the cognitive radio engine components described in Table 1.

**Table 1.** IEEE P1900.5 cognitive radio engine components[14].

| Components | Main Functions |
|---|---|
| PMP (Policy Management Point) | Provide and manage policy information related to radio regulations and provide new policy data. This corresponds to frequency managers, system administrators, and operators |
| SSRC (System Strategy Reasoning Capability) | Opportunistically check for access opportunities using REM (Radio Environment Map) data and request information on whether or not transmission to PCR is possible |
| PCR (Policy Conformance Reasoner) | Compare SSRC requests and existing policies transmitted from the PMP, perform the reasoning process, verify the suitability of changed policies, approve or reject SSRC requests |
| PE (Policy Enforcer) | Execute communications service based on verified policy information transmitted from the PCR or SSRC |

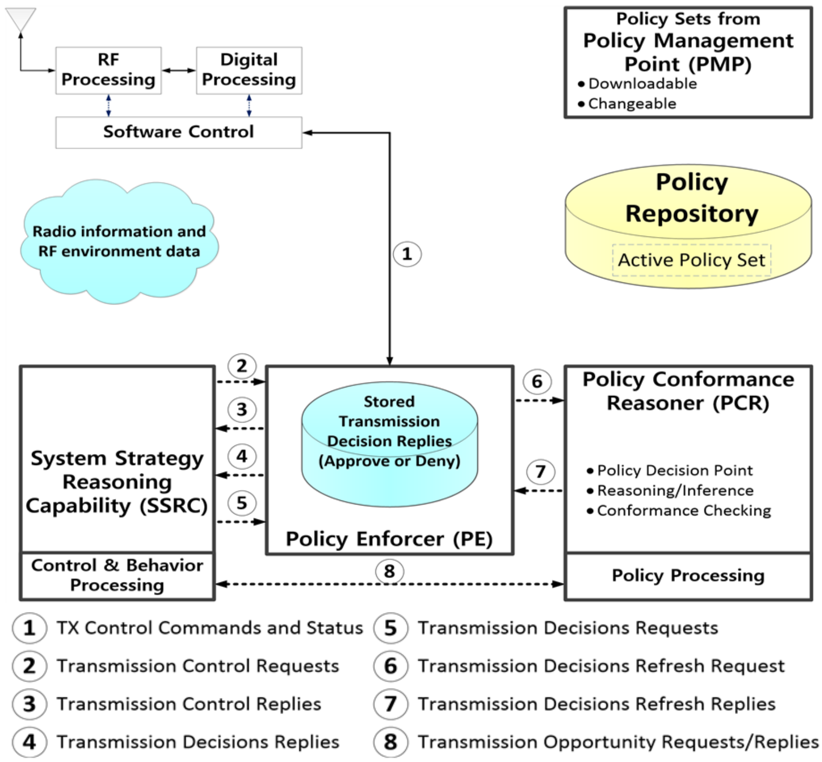


**Figure 2.** IEEE P1900.5-based cognitive radio engine processing diagram[12].

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## 3. Cognitive Radio Engine Platform Usage Scenario

### 3.1. Structure and Roles of the Proposed Cognitive Radio Engine

The proposed cognitive radio engine platform requires a step to calculate the probability of PU channel occupancy that can allow to estimate PU channel usage patterns via carrying out cognition engine equipped with spectrum sensing functionality. In this paper, the PU channel occupancy pattern observed by the spectrum sensing is assumed to be perfect, and obtained via actual spectrum sensing was considered complete, and the the PU state duration time is presumed to be random following an exponential distribution and the occupancy patterns corresponding to every channel are independent. Fig. 3 depicts the whole structure of the proposed cognitive radio engine platform.

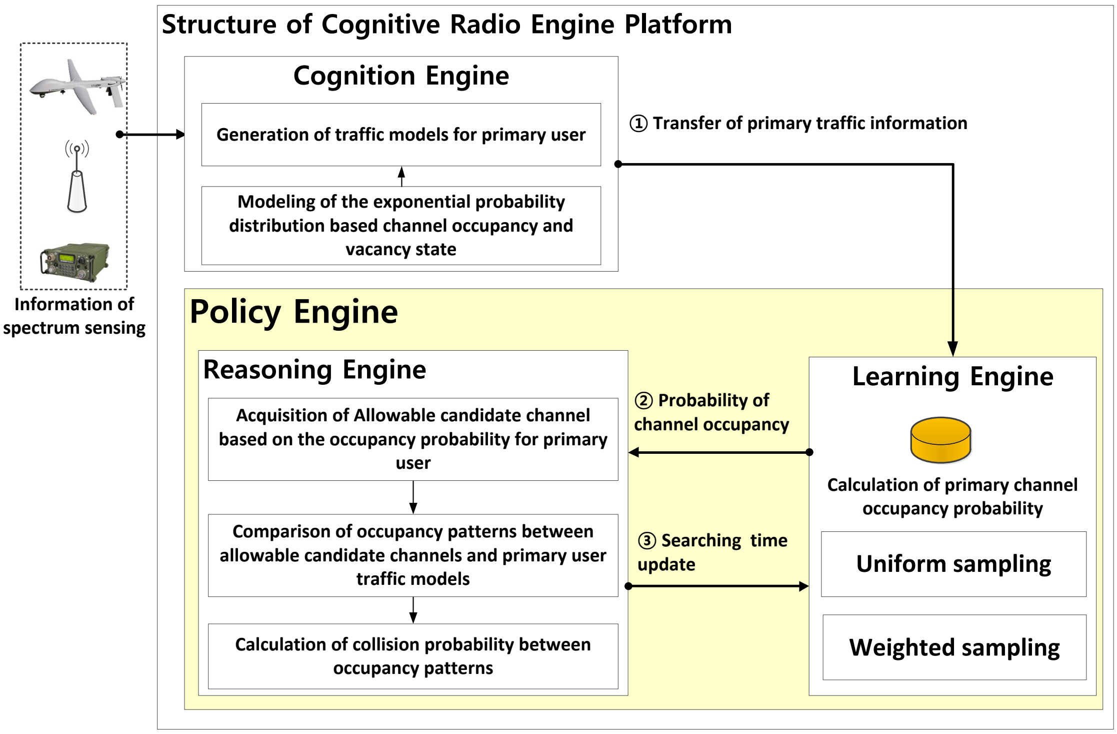


**Figure 3.** Proposed cognitive radio engine structure

In Fig. 3, one of major roles assigned to learning engine is the quantification of the PU occupancy probability from observations in temporal domain for every channel to be inspected, which information is delivered from the cognition engine. The process of quantifying a PU occupancy probability associated with a certain channel is carried out by sampling the PU's channel usage patterns during a fixed time slot and calculating the channel occupancy. Towards this, this study considers uniform sampling and weighted sampling techniques whose details are explained in later. Furthermore, one of major roles of reasoning engine is the exploitation of a group of the available candidate channel in behalf of the TCRN for dynamic access to the spectrum in which PU is possibly in active. As the side information to consolidate the set of available channels, PU traffic pattern constructed by PU occupancy probability is transferred from the learning engine.

A process to choose the available candidate channels is conducted by making arrangement of channels in ascending order with referring to a series of PU occupancy probability per channel and the top ranked channel is the first priority candidate to be used. Next, all the ranks calculated by every sampling techniques considered in this paper for all the inspected channels are used to make the ranking in order in composite fashion. Ultimately, a group of available channel candidates for the

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cognitive radio node is selected subject to guaranteeing a minimum collision probability as possible as it can. The methods of assigning rank considered in this study are classified into rank-sum based on the sum of the ranks of the occupancy probability values of each channel, and prob-sum, which selects a group of available channel candidates based on the sum of the occupancy probabilities of each channel. To verify the performance of the the reasoning engine the number of collisions with the existing PU whose traffic pattern is a priori prescribed is counted provided that the TCRN uses the channel assigned by reasoning engine. In addition, the number of samples and reasoning period are considered as important steering parameters to achieve the optimal available channel candidates.

### *3.2. Modeling Primary User Traffic in a Cognition Engine*

The way of generating PU traffic model is handled in this subsection using an appropriate statistical distribution PU channel occupancy pattern regarding as the result of spectrum sensing. First of all, it was assumed that the PU channel usage patterns corresponding to every channel are independent and that the PU channel occupancy data acquired is perfect. Figure 4 is a conceptual diagram representing the process of switching of PU state between ON and OFF states.

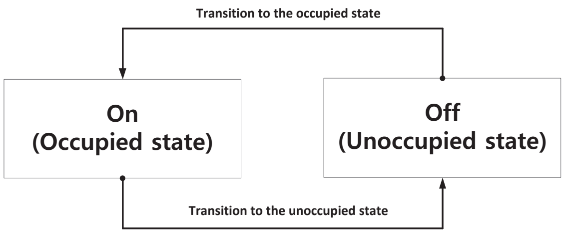


**Figure 4.** Conceptual diagram of changes in PU channel occupancy states

Figure 4 reflects the PU channel state transitions, and (1) indicates the formulation of the the probability of a PU being in OFF state along the total observed channels[15] given by.

$$P^n_{off} = \frac{\lambda^n_\alpha}{\lambda^n_\alpha + \lambda^n_\beta}. \tag{1}$$

In addition, (2) and (3) define the exponential probability distribution functions, in which the mean value $\lambda^n_\alpha$ of the random variable which is the duration time interval of PU OFF state, whereas the mean value $\lambda^n_\beta$ is the duration time interval of PU ON state:

$$f_{\alpha,n}(x) = \begin{cases} \lambda^n_\alpha e^{-\lambda^n_\alpha x} & x \geq 0 \\ 0 & x < 0 \end{cases}, \tag{2}$$

$$f_{\beta,n}(x) = \begin{cases} \lambda^n_\beta e^{-\lambda^n_\beta x} & x \geq 0 \\ 0 & x < 0 \end{cases}. \tag{3}$$

Here it can say that the PU's channel usage can be dynamically adjusted by modifying the $\lambda^n_\alpha$ and $\lambda^n_\beta$ values. Precisely, (3) is used to calculate the mean value of $P^n_{off}$ versus $N$, the total number of channels to be observed. Figure 5 shows the the distribution in a form of histogram about $P^n_{off}$ designated as the probability of the PU OFF provided that the total number of channels $N$ is $1,000$. Here, to generate the distinctive PU traffic pattern according to the channel, this paper presumed that the $\lambda^n_\alpha$ and $\lambda^n_\beta$ values are also random variable following two different exponential distributions.

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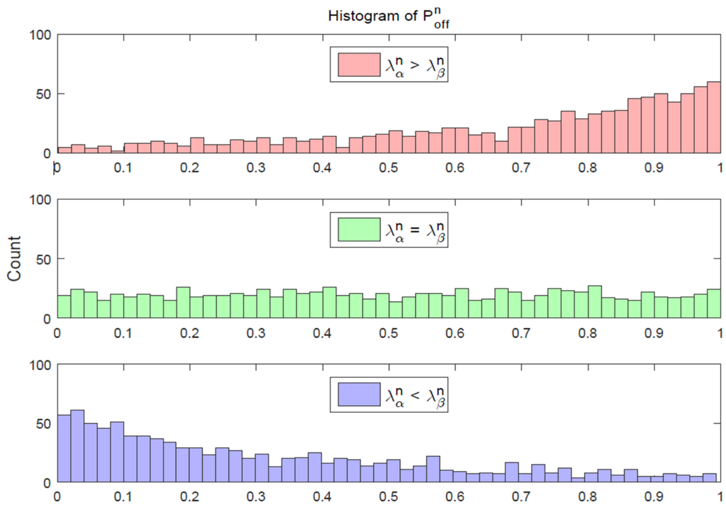
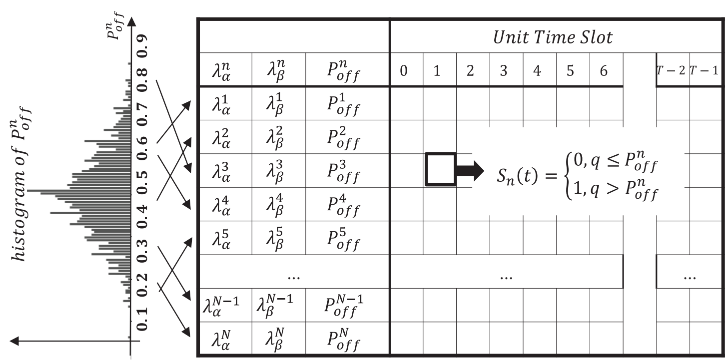



**Figure 5.** Off-state probability histogram of primary user.

As can be seen in the preliminary simulation results in Fig. 5, when $\lambda^n_\alpha > \lambda^n_\beta$, there are many channels in OFF state, so it can explain that the frequency of PU channel occupancy is low. Thus, there would be high opportunity of usage for the cognitive radio node. Whereas if $\lambda^n_\alpha < \lambda^n_\beta$, the updated histogram reflecting channel occupancy probabilities is somewhat skewed to the left, it means that the PU traffic is somewhat heavy so that the opportunity of usage becomes low. After generating value $P^n_{off}$ for the above PU channel OFF state in terms of $\lambda^n_\alpha$ and $\lambda^n_\beta$, the next step is to define the instant of time when the PU activity state is changed. Equation (4) determine whether or the PU state is changed for a particular unit of time designated by slot $t$ at channel index $n$. Once the random variable $q$ is chosen in the range of $0 < q < 1$, the PU state can be specified as the following:

$$S_n(t) = \begin{cases} 0 & q \leq P^n_{off} \\ 1 & q > P^n_{off} \end{cases}. \tag{4}$$

Fig. 6 shows a conceptual diagram for generation PU traffic, in which the PU channel's occupied or unoccupied state at each time slot is designated to 0 or 1, as defined in Eq. (4).




| Ch. | $\lambda^n_\alpha$ | $\lambda^n_\beta$ | $P^n_{off}$ | Unit Time Slot | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 |
| Ch.1 | 1 | 1 | **0.5** | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 |
| Ch.2 | 1 | 4 | **0.2** | 1 | 1 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 |
| Ch.3 | 4 | 1 | **0.8** | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 1 |

**Figure 6.** State transitions for occupied and unoccupied states of each channel modeled as 0 and 1.

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For example, the below in Fig. 6 shows modeling a state transition associated with three channels. Among them, for the case of Ch.1, $\lambda_{\alpha}^{n}$ and $\lambda_{\beta}^{n}$ are the same such that the “OFF (0)” state and the “ON (1)” state appear at the same ratio, and their mean values are 1. Similarly, the other kinds of PU traffic models can be generated by assigning PU ON and OFF state patterns through the statistical modeling described above.

### *3.3. Occupancy Probability Calculation in the Learning Engine*

Along the execution of learning engine, the PU occupancy probability with respect to each observed channel can be calculated by counting time slots where PU is in ON state over the whole observation time $T$, which can be also expressed in the exact theoretical formula as shown in (5)[15]:

$$P_{on}^{n} = \frac{\lambda_{\beta}^{n}}{\lambda_{\alpha}^{n} + \lambda_{\beta}^{n}}. \tag{5}$$

In the way of calculating PU occupancy probability making use of empirical observations instead of Eq. (5), it is necessary to employ the sampling method to acquire the PU’s channel usage patterns guaranteeing the accuracy. Towards this, this paper considers the uniform sampling and the weighted sampling method. At first, the uniform sampling divides the overall time interval $T$ into individual unit time slots having uniform size, and estimates the PU channel occupancy probability from the samples reflecting PU traffic. Furthermore, the uniform sampling PU channel occupancy probability calculation methods can be divided into systematic count-based sampling (CB) and random count-based sampling (RB) according to how the method sets the size of the sampling interval, which is defined as the individual unit time slot[16][17]. Figure 7 depicts the process for showing the uniform sampling, in which the mean value of the “OFF” and “ON” intervals is 1.

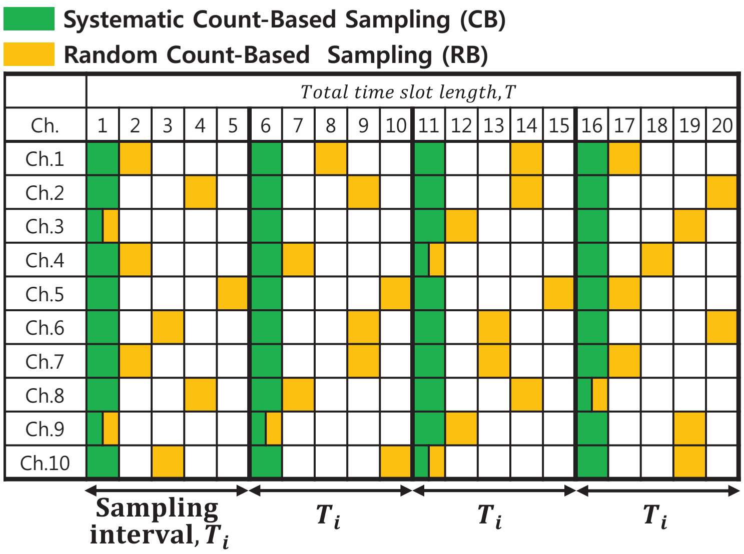


**Figure 7.** Uniform sampling technique concept and process for CB and RB methods.

As in Fig. 7, the CB method is taking samples at the consistently fixed time slot over every sampling interval. On the other hand, the RB method specifies the time slot to be sampled at random over each sampling interval. Consequently, the PU occupancy probability can be calculated by observing samples containing the state of PU traffic. Equation (6) indicates the occupancy probability of $n$th channel using observed samples obtained by CB sampling method. And (6) can be shared for RB sampling method

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$$P^n_{CB} = \frac{1}{M}\sum_{m=1}^{M} S_n\left(m\right). \tag{6}$$

In (6), $M$ indicates the overall number of samples, and $S_n(t)$ represents the status of PU activity indicator so that 0 reads ON state and 1 reads OFF state at the mth time slot from channel $n$. In this paper, besides the conventional sampling methods,their weighted versions are proposed. More precisely, With applying these approaches, the PU occupancy probability can be estimated with considering temporal correlation. Therefore, recently obtained samples are weighted larger, whereas the past samples are weighted relatively smaller weights. Here the weight can be interpreted by the well-known forgetting factor, and corresponding weighting process namely tapering samples observed with applying CB and RB. Equation (7) corresponds to the estimated PU occupancy probability via the WCB sampling method [17].

$$P^n_{WCB} = \sum_{m=1}^{M} w_m S_n(m), \tag{7}$$

$$w_m = \frac{1}{K}e^m, K = \sum_{m=1}^{M} e^m. \tag{8}$$

With the help of (8) the greatest weight is multiplied to the most recent sample indexed by M, and the least value is multiplied to the oldest sample. Furthermore, $K$ in (8) is the normalization factor which is equivalent to the sum of the exponential values. Similiar to (7) and (8), WRB based PU occupancy probability calculations can be carried out upon the randomly chosen samples. Table 2 summarizes the features of uniform sampling and weighted sampling.

**Table 2.** Main features of uniform sampling and weighted sampling methods.

| **Sampling Methods** | **Main Features** |
|---|---|
| Uniform Sampling | • (CB) Divides the time slots to be sampled at fixed time slot in the sampling interval<br>• (RB)Divides the time slots to be sampled at random time slot in the sampling interval slots of random size and position |
| Weighted Sampling | • (WCB) Assigns exponentially decaying weights from the present to the past unit time slots sampled by CB.<br>• (WRB) Assigns exponentially decaying weights the present to the past unit time slots sampled by RB |

### *3.4. Available Channel Extraction Method via conducting the Reasoning Engine*

#### 3.4.1. Reasoning from PU Traffic Reference Model

This paper considers the case-based reasoning approach in order to extract a group of available channels for the cognitive radio node operating in tactical sensor network. Towards this, first of all, inspecting the histogram representing the channel usage pattern of PUs is conducted by the learning engine. At second step, the resulting histogram is matched with reference traffic models precedently stored in learning engine so as to distinguish and aware which traffic model is highly relevant. At third step, as a final step in case-based reasoning process, the appropriate number of channels turn out to be extracted. To give some insight how to match PU traffic pattern, Table 3 releases the example showing features characterizing the shape of the histogram in terms of the mean, variance, skewness, and kurtosis. There are nine reference traffic models which can be distinguishable by analyzing those intrinsic signatures determining the shape of histogram.

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**Table 3.** Example of the reference PU traffic models

| PU Traffic Model | 1 | 2 | 3 | ... | 9 |
|---|---|---|---|---|---|
| Mean ($\mu$) | 0.1 | 0.2 | 0.3 | ... | 0.9 |
| Variance ($\mu_2$) | 0.025 | 0.052 | 0.069 | ... | 0.025 |
| Skewness ($\gamma_1$) | 2.888 | 1.569 | 0.850 | ... | -2.776 |
| Kurtosis($\gamma_2$) | 9.540 | 1.792 | 0.308 | ... | 9.505 |

In Table 3, the first traffic model at the leftmost has a lowest mean value, and the mean value gradually increases toward the 9th traffic model. Thus, the first traffic model reflects the situation of the low PU activity for every channel, whereas the 9th traffic model corresponds to the high PU activity. In this work, PU traffic models stored up to the previous reasoning period is regarded as reference PU traffic models. The reasoning engine performs the determination which traffic model among the reference PU traffic models is matched the newly acquired histogram constructed by the recently observed samples relevant to PU traffic. Here, to assess the degree of similarity, the mean and the second, third, and fourth central moments can be utilized to match the traffic models[18][19]. The mean value of $P_{on}^n$ is denoted as the central moment associated with the histogram representing the distribution showing the frequency of the PU occupancy probability value. The $k$th central moment is defined by (9)

$$\begin{aligned} \mu &= P_{on}^{Avg} = \frac{1}{N}\sum_{n=1}^{N} P_{on}^n, \\ \mu_k &= \frac{1}{N}\sum_{n=1}^{N}\left(P_{on}^n - P_{on}^{Avg}\right)^k. \end{aligned} \tag{9}$$

Furthermore, the relationships introduced in Eq. (10) describe how to generate the second moment through the fourth moment, i.e.

$$\begin{aligned} \mu_2 &= m_2 - \mu^2, \\ \mu_3 &= m_3 - 3\mu_2 + 2\mu^3, \\ \mu_4 &= m_4 - 4\mu m_3 - 6\mu^2 m_2 - 3\mu^4 \; . \end{aligned} \tag{10}$$

Here, the second central moment becomes the variance of $P_{on}^n$, and the third and fourth central moments are used to achieve the skewness and the kurtosis. With the help of (10), the skewness $\gamma_1$ and the kurtosis $\gamma_2$ are calculated by (11):

$$\gamma_1 = \frac{\mu_3}{\mu_2^{3/2}}, \quad \gamma_2 = \frac{\mu_4}{\mu_2^3} - 3. \tag{11}$$

The mean, variance, skewness, and kurtosis corresponding to the ith traffic model, which is one of I models composing the overall PU reference traffic model structured at previous reasoning period, is calculated based on recently acquired samples. To assess the similarity, (12) evaluates the individual errors in the mean, variance, skewness, and kurtosis between the overall reference PU traffic model and the recently constructed PU traffic model as the following:

$$\begin{aligned} \varepsilon_\mu(i) &= \frac{|\mu^{ref}(i) - \mu^{mea}|}{\mu^{ref}(i)}, \qquad \varepsilon_{\mu_2}(i) = \frac{|\mu_2^{ref}(i) - \mu_2^{mea}|}{\mu_2^{ref}(i)}, \\ \varepsilon_{\gamma_1}(i) &= \frac{|\mu_{\gamma_1}^{ref}(i) - \mu_{\gamma_1}^{mea}|}{\mu_{\gamma_1}^{ref}(i)}, \qquad \varepsilon_{\gamma_2}(i) = \frac{|\mu_{\gamma_2}^{ref}(i) - \mu_{\gamma_2}^{mea}|}{\mu_{\gamma_2}^{ref}(i)}. \end{aligned} \tag{12}$$

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If some index of traffic model turn out to be one of reference PU traffic models gives the composite error as explained in (13), it can conclude that the corresponding two traffic models are coincident so that the verification of model associated with newly incoming PU traffic is completed by conducting

$$\min_{i \in I} \left( \varepsilon_{\mu}(i) + \varepsilon_{\mu_2}(i) + \varepsilon_{\gamma_1}(i) + \varepsilon_{\gamma_2}(i) \right) . \tag{13}$$

By applying the exhaustive search to search out the correct index of a reference PU traffic model, subsequently, it is possible to acquire the information about the optimal reasoning period and the optimal number of samples in the sense of minimizing the collision probability, which are supplementary stored in reasoning database.

#### 3.4.2. Calculating Available Channel Candidates from Reasoning Results

To exploit the group of available channels to be allocated to cognitive radio nodes, a process at first is to arrange the PU occupancy probabilities in ascending order and decide the ranking of entire channels. This paper examines the performance related to the PU collision probability with applying individual sampling methods such as uniform sampling methods (CB and RB), weighted sampling methods (WCB and WRB) together with rank-sum and prob-sum reasoning methods. Here, collision probability means the probability of an event that the cognitive radio node incorrectly uses the channel which is already occupied by PU.

Towards this, the $j$th channel is ranked at as $R_{CB}(j)$, $R_{RB}(j)$, $R_{WCB}(j)$, and $R_{WRB}(j)$ resulted from performing the cognition engine followed by the learning engine, and $R$ is an integer subject to obeying $1 \leq R \leq N$. For example, if the rank of channel $j$ calculated by executing the CB sampling method is as shown in (14)[15]:

$$R_{CB}(j) = rank\left(P_{CB}^{j}\right) . \tag{14}$$

Here, the $rank()$ function is used to decide the ranking of every channel assessing the occupancy probability which are calculated and sorted in learning engine. The range of the rank is shown in (15), which is the same as the overall number of channels as the following:

$$Range\left\{R_{CB}(1), \ldots, R_{CB}(N)\right\} = N . \tag{15}$$

Furthermore, (16) releases the proposed rank-sum reasoning approach, which aggregate ranks derived from executing each sampling method. As a result, upon this method, the channel having the minimum rank sum is regarded as a candidate channel. This paper denotes this approach as the rank-sum reasoning method whose relevant formulation is

$$R_{Rank-sum}(j) = R_{CB}(j) + R_{RB}(j) + R_{WCB}(j) + R_{WRB}(j) . \tag{16}$$

Besides this, (17) defines the prob-sum reasoning method that specify the candidate channel via sorting the sum of the occupancy probabilities of each sampling method in ascending order given by

$$R_{Prob-sum}(j) = P_{CB}(j) + P_{RB}(j) + P_{WCB}(j) + P_{WRB}(j) . \tag{17}$$

Similar to the rank-sum reasoning method, the channel having the minimum probability sum is designated as a candidate channel. In below, Table 4 shows the PU occupancy probability represented in percent, which is quantified with adopting individual sampling method, and rank-sum and prob-sum methods gives rise to the composite ranking referring to CB, RB, WCB and WRB.

As shown in Table 4, the reasoning method proposed in this paper for determining candidate channels and prob-sum do not select the channel with the lowest PU occupancy probability for specific sampling approach but select a reliable candidate channel which is the most competitive channel regarding either the composite ranking or the aggregated occupancy probability. Moreover, another

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**Table 4.** Calculated occupancy probability and channel ranking Table.

| | CB | | RB | | WCB | | WRB | | Rank-sum | | Prob-sum | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Rank** | Ch. | Prob. | Ch. | Prob. | Ch. | Prob. | Ch. | Prob. | Ch. | Sum | Ch. | Sum |
| 1 | Ch.2 | 0.58 % | Ch.1 | 5.43 % | Ch.2 | 5.54 % | Ch.2 | 3.26 % | Ch.2 | 6 | Ch.2 | 28.23 % |
| 2 | Ch.1 | 10.61 % | Ch.3 | 16.48 % | Ch.3 | 5.98 % | Ch.1 | 8.31 % | Ch.3 | 9 | Ch.1 | 45.64 % |
| 3 | Ch.3 | 11.84 % | Ch.2 | 18.85 % | Ch.4 | 11.27 % | Ch.3 | 15.08 % | Ch.1 | 11 | Ch.3 | 48.15 % |
| 4 | Ch.4 | 12.95 % | Ch.4 | 20.36 % | Ch.6 | 15.33 % | Ch.6 | 20.58 % | Ch.4 | 16 | Ch.4 | 66.44 % |
| 5 | Ch.5 | 19.06 % | Ch.5 | 22.12 % | Ch.1 | 20.06 % | Ch.4 | 21.86 % | Ch.6 | 20 | Ch.5 | 88.51 % |
| 6 | Ch.6 | 31.95 % | Ch.6 | 24.72 % | Ch.5 | 25.14 % | Ch.5 | 22.19 % | Ch.5 | 22 | Ch.6 | 92.58 % |

critical point is how many channels are turn out to be reliable, in order to clarify this, the guideline can be recommended from the PU reference traffic model containing relevant information corresponding to the traffic matched subject to minimizing collision probability.

## 4. Simulation

### *4.1. Simulation Scenario*

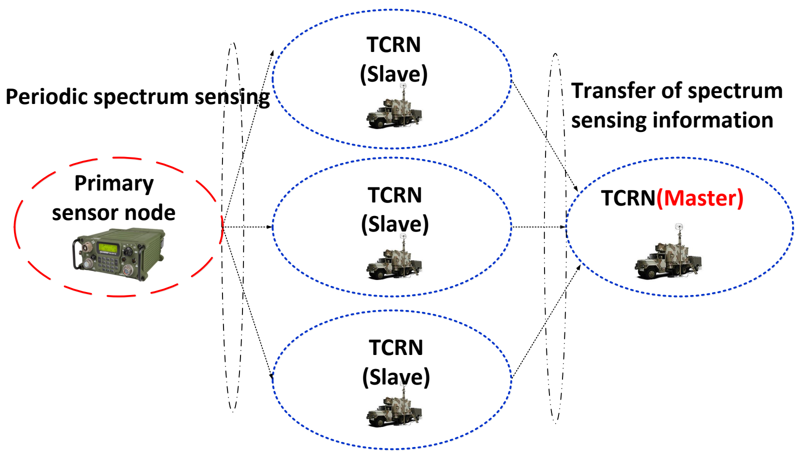


**Figure 8.** Simulation scenario environment.

Fig. 8 shows a simulation scenario for evaluating performance of the proposed cognitive engine platform. In Fig. 8, there is one PU radio needed to be protected from the interference arising by neighbored cognitive radio nodes. In addition, in simulation environment, four cognitive radio nodes are deployed in which one plays the role of master, and the other operates the role of slave. The slave-type TCRNs perform spectrum sensing process to observe PU activity periodically equivalent to channel occupancy state. Furthermore, every slave-type node deliver the acquired sensing information holding channel occupancy state to the master TCRNs. Then, the master TCRNs is making decision which channels are appropriate so that the cognitive radios equipped with the cognitive engine use those channel in secure without interfering the PU.

In simulation, the PU channel occupancy characteristic acquired by the master TCRN with the help of spectrum sensing technology is artificially generated so as to produce a PU traffic model following a specific statistical distribution. Fig. 9 shows a diagram of the simulation process.

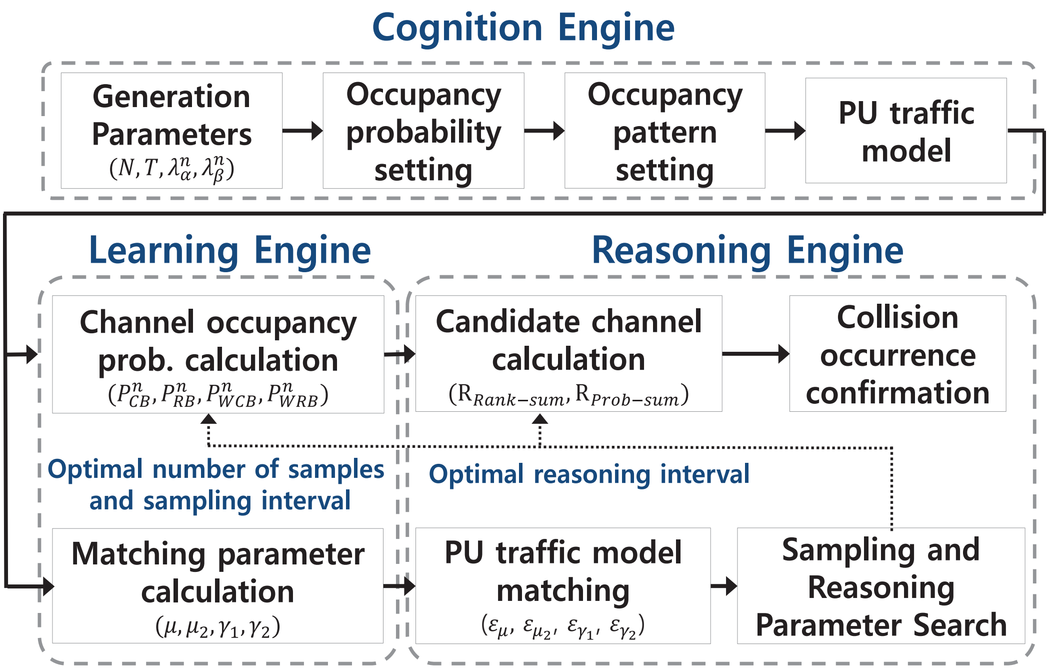


**Figure 9.** Simulation analysis flow chart.

As shown in Fig. 9, the PU traffic model can be characterized in the simulation based on the probability distribution in the form of an exponential distribution. In other words, the temporal duration in 'ON' and 'OFF' state statistically follow the exponential distribution. The learning engine uses the PU traffic model generated in the previous reasoning period to quantify PU channel occupancy probabilities corresponding to overall channels based on CB, RB, WCB, and WRB. Finally, the reasoning engine assisted by rank-sum and prob-sum methods gives rise to candidate channels available candidate channels for the usage of cognitive radio node. After performing a series of assignments, the probability with a priori prescribed PU traffic for simulation is calculated in order to verify how good the proposed cognitive engine works.

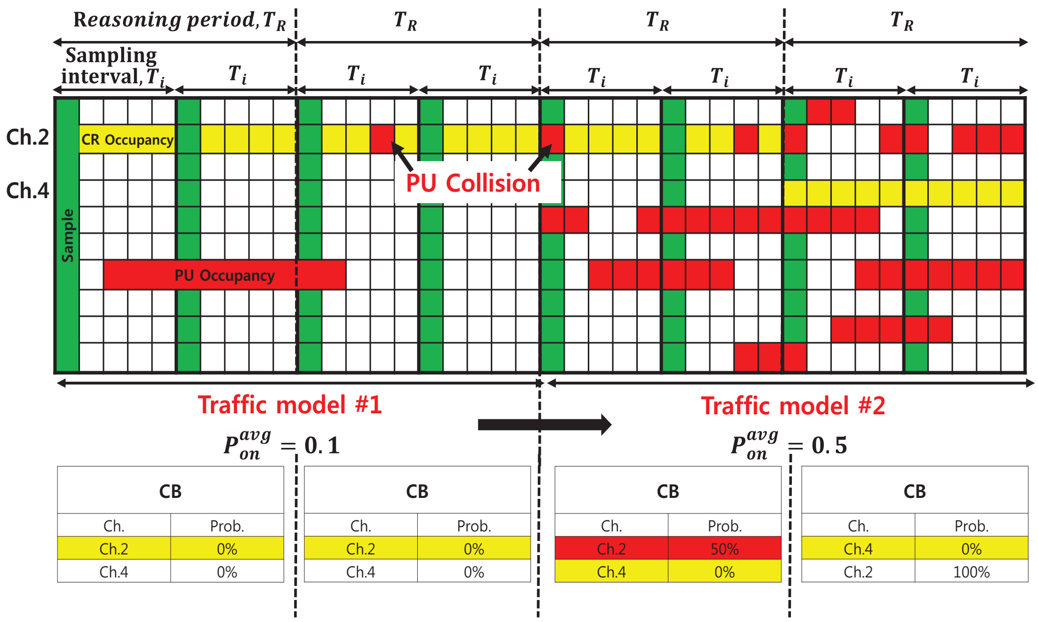


**Figure 10.** Definition of collision and example of periodic operation of CR engine.

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To help the comprehension, Fig. 10 depicts an example of the consecutive operation of the CR engine, as a result, the candidate channels can be exploited at every reasoning period. The learning engine calculates the occupancy probabilities for each sampling method and replaces those with the previous ones if needed at the end of each reasoning period. The reasoning engine exploits the available candidate channels for a certain TCRN. This process repeats periodically, and the suitable reasoning period and the number of samples can be achieved as by-products by matching the recently acquired traffic pattern with the past traffic model resulting the most similar distribution of PU occupancy probability.

### *4.2. Simulation Results*

Figure 11 shows a series of the histogram relevant to the PU traffic model created in the learning engine representing the distribution of PU occupancy probability. In Fig. 11, when the value of $P_{on}^{Avg}$ is 0.1, 0.2, 0.3, or 0.4, the channel PU occupancy state probability value $P_{on}^{n}$ is generally found in positions that have small values. When the $P_{on}^{Avg}$ value is 0.5, a histogram is distributed with left-right symmetry. Further, when the $P_{on}^{Avg}$ value is 0.6, 0.7, 0.8, or 0.9, the PU occupancy probability $P_{on}^{n}$ is seems to be biased at the position of large values.

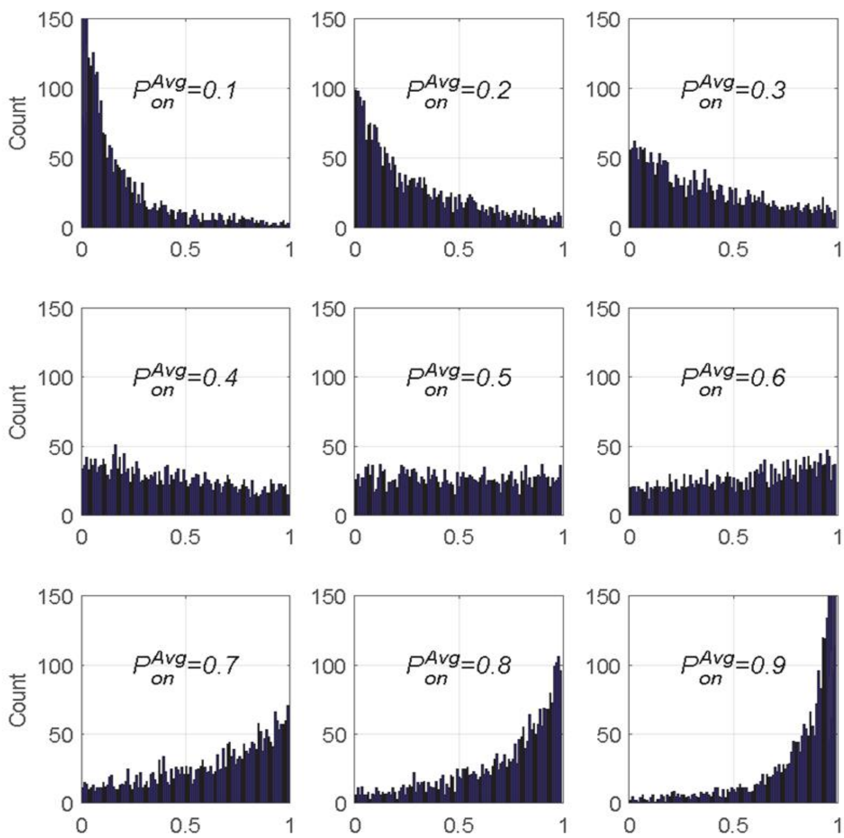


**Figure 11.** Results of PU traffic model generation based on exponential probability distribution (M=2,700).

Table 5 shows the parameter type and setting values used for verifying performance of the case-based reasoning proposed in this paper deployed in cognitive radio engine platform also Fig. 11 shows the PU reference traffic models, in which the average of channel occupancy probability $P_{on}^{Avg}$ was enforced to be incremented from 0.1 to 0.9 so that nine PU traffic models were consecutively generated for every time slot interval which is set to be 300 slots. The overall time slot interval $T$ was set as 2,700 slots, and the total number of channels $N$ was set as 500. In Fig. 11, the OFF state is shown in blue regarding channels that the cognitive radio nodes can used. The ON state that is shown in red

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**Table 5.** Simulation test parameter types and setting values.

| Parameter Type | Setting Value |
|---|---|
| Overall number of channels, $N$ | 1,000 |
| Overall time slot interval, $T$ | 2,700 slots |
| PU traffic model's unoccupied channel probability mean value, $P_{on}^{Avg}$ | 0.1,0.2,...,0.9 |
| Number of PU traffic models, $I$ | 9 |
| Time slot interval for each traffic model | 300 slots |

implies the situation that the cognitive radio nodes can hardly find the channel to be used. Overall, as the value $P_{on}^{Avg}$ about the averaged probability of PU channel occupancy increases, clearly it can say that the frequency of the PU occupancy is increased.

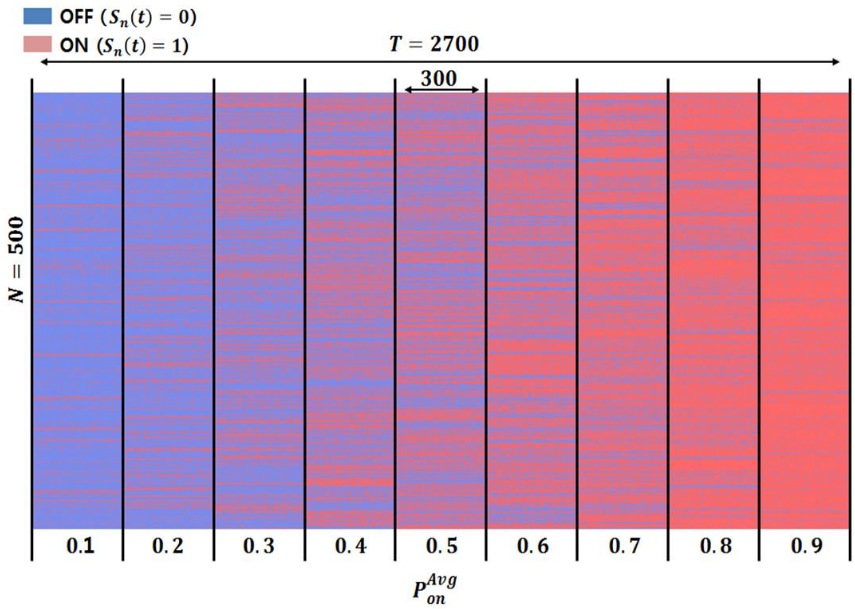


**Figure 12.** Result of Traffic Model Generation according to Average Value of Channel Occupancy Probability of PU.

#### 4.2.1. Collision Probability Behavior According to Sampling and Reasoning Methods

Figure 13 shows the results of a collision probability depicted for comparison's sake, which is tightly engaged with the PU traffic model generated in Fig. 12. Along the simulation test, the CB, RB, WCB, and WRB sampling methods in the learning engine and the rank-sum and prob-sum reasoning methods are set to have 20 samples, a reasoning period of 20 slots, and a sampling interval of 5 slots. In the simulation test results in Fig. 13, when the PU traffic model's channel occupancy probability value $P_{on}^{Avg}$ is low, there are many channels available due to a low channel occupancy probability such that the collision probability becomes low for every sampling method and reasoning method. Conversely, as $P_{on}^{Avg}$ gradually increases, the PU traffic becomes heavy, naturally, the probability of a collision increases due to the frequent change of the PU's occupancy pattern.

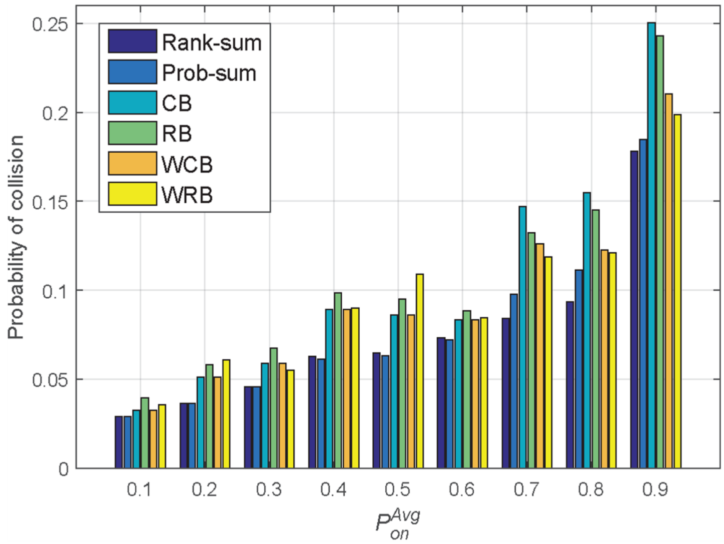


**Figure 13.** Comparison of collision probability for each sampling method according to changes in traffic (Reasoning period = 20 slots, Number of samples = 20 slots, Sample interval = 5 slots).

For the case of the uniform sampling method, it seems a relatively low collision probability in PU traffic models with an $P_{on}^{Avg}$ value of 0.1, 0.2, or 0.3. This means whenever PU occupancy pattern is sparsely, the uniform sampling method gives rise to high fidelity on candidate channels. For the another case of the weighted sampling method, the collision probability is sustained at the low level compared with the uniform sample case even though $P_{on}^{Avg}$ value is 0.7, 0.8, or 0.9. This means that a weighted sampling method is superior to the uniform sampling in the sense of minimizing collision probability when there is a continuous PU occupancy pattern.

#### 4.2.2. Collision Probability Behavior According to Reasoning Period for Fixed Number of Samples

The simulation results in Fig. 14 show the collision probability when the number of samples, and the sampling interval are fixed at 20 samples and 5 slots, respectively, and the reasoning period is enforced to be changed from 5 to 40 slots.

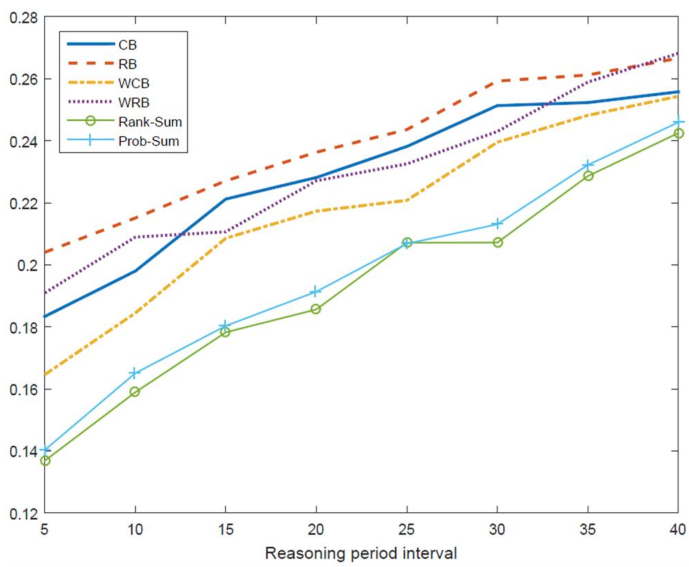


**Figure 14.** Comparison of collision probability according to reasoning period (Number of samples = 20 slots, Sample interval = 5 slots).

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In Fig. 14, it can be seen that the PU collision probability increases as the reasoning period became longer for the fixed number of samples taken at the same sampling interval. This means that a highly reliable policy can be established if the reasoning period becomes shorter as possible as it can. If the required collision probability level is set to be 25%, it means that the reasoning period must be 25 slots or less

#### 4.2.3. Collision Probability Behavior According to Number of Samples for Fixed Reasoning Period

The simulation test results in Fig. 15 show the coliision probability when the reasoning period and the sampling interval are fixed to 20 slots and 5 slots, respectively, and the number of samples is changed from 5 to 45.

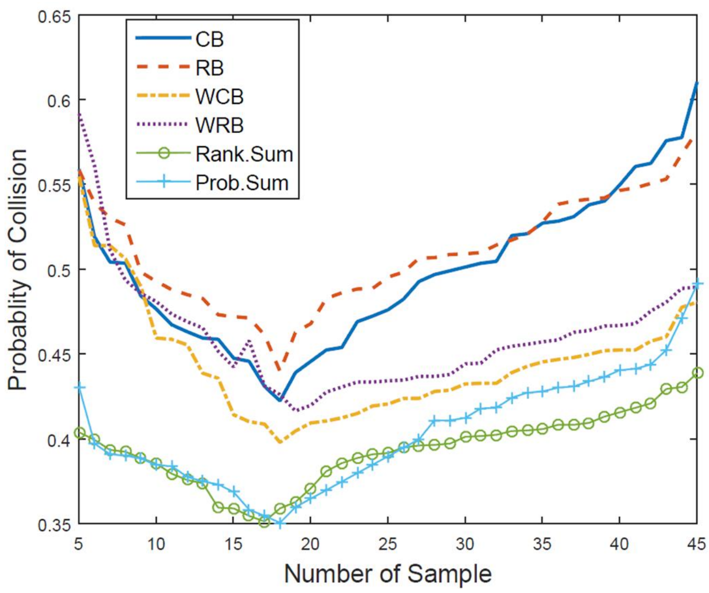


**Figure 15.** Comparison of collision probability according to number of samples (Reasoning period = 20, Sample interval = 5).

The simulation results in Fig. 15 reveal that, when the number of samples needed for calculating occupancy probability was changed while the reasoning period remained the same, the lowest collision probability can be achieved if the number of samples was in the range of 16 to 18. In uniform sampling methods such as CB and RB, the collision probability rapidly increases as the number of samples is getting larger. Conversely, in WCB and WRB, when the number of samples increased, it did not have a noticeable effect on the performance in candidate channel reasoning. Furthermore, if the number of samples is insufficiently small or unnecessarily large, the collision probability becomes high so that the reasoning capability becomes declined and the reliability becomes deteriorated. Specially, for the long period of sampling interval, it is unable to respond quickly against rapid changes in the PU occupation state.

## 5. Conclusions

This paper has proposed a novel cognitive engine platform structure comprising of cognition engine, learning engine, and reasoning engine, which is suitable for future tactical cognitive sensor networks enabling dynamic spectrum access in present of incumbent device namely as PU. Towards this, a PU traffic model is generated with obeying probability distributions assisted with using spectrum sensing technology under a certain PU environments. Through this, PU occupancy probability performed in the learning engineis confirmed with performing comparative works employing either the currently available or the proposed. Sampling methods to achieve more realistic accurate PU

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occupancy patterns. This paper also introduced a case-based reasoning engine that can exploit candidate channels for cognitive radio with taking into account the PU's various channel usage patterns. In the simulation result, CB, RB, WCB, and WRB sampling methods together with rank-sum and prob-sum reasoning methods were used for quantifying the PU occupancy probability as well as achieving highly reliable candidate channels. Moreover, the collision probability and the behaviors were analyzed as performance indicators to verify the superiority of the proposed cognitive engine platform.

**Author Contributions:** The individual contributions of authors are as follows. Jae Hoon Park developed and simulated the CR engine. Jeung Won Choi and Soo Bin Um directed the research. Joo Pyoung Choi contributed to the refinement of the algorithm and the interpretation of the simulation results. The paper was drafted by Jae Hoon Park and subsequently revised and approved by Won Cheol Lee.

**Conflicts of Interest:** The authors declare no conflict of interest.

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