Spectrum Knowledge and Real-Time Observing Enabled Smart Spectrum Management

JIANZHAO ZHANG, YONG CHEN, YONGXIANG LIU, AND HAO WU
The Sixty-third Research Institute, National University of Defense Technology, Nanjing 210007, China

Corresponding authors: Jianzhao Zhang (jianzhao63s@nudt.edu.cn) and Yong Chen (chy63s@126.com)

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ABSTRACT Spectrum is the indispensable resource for 5G wireless systems and beyond. The dynamic spectrum management (DSM) framework with spectrum sharing among different kinds of users is essential to satisfy the sustainable rapid increase of the bandwidth requirement. Based on the analysis of the DSM as well as the latent applications of the machine learning and artificial intelligence (AI) in the spectrum access, this paper will address the problem of incorporating intelligence into the spectrum management. Firstly, the spectrum opportunity (SOP) related information is layered into the spectrum data, the spectrum information and the spectrum knowledge based on the processing and abstractive level. The spectrum knowledge is formally defined as the extendible and scalable information to reason and predict the SOP usability as well as the outcome of the SOP occupancy. Then the smart spectrum model (SSM) is proposed with the spectrum knowledge as the key enabler and the coupled SOP exploration and exploitation as the core feature. Under the SSM framework, the spectrum knowledge and real-time observing (SKRO) enabled SOP exploration scheme is designed, which can make use of both the historical information and the real-time sensing information for smart SOP exploration. Extensive simulations are provided which demonstrate that the SKRO enabled SSM can achieve much better SOP utilization while satisfying the required legacy assurance. Specifically, in the low signal to noise environment, at least 16.55% gains on the SOP utilization ratio can be obtained compared with the DSM.

INDEX TERMS Smart spectrum management, dynamic spectrum management, spectrum opportunity exploration, spectrum knowledge.

I. INTRODUCTION

For its indispensability in various domains for economic, social, cultural, and scientific purpose, the electromagnetic spectrum has been regarded as a catalyst for economic development [1]. The numbers and bandwidth requirement from 5G wireless systems and beyond will confront with an explosive growth. According to the estimation of Cisco, the wireless cellular data traffic will increase by seven-fold between 2017 and 2022, with monthly mobile data traffic increased from 11.5 exabytes in 2017 to 77.5 exabytes in 2022 [2]. To account for that sharply rising requirement, the spectrum utilization and management scheme should keep pace with the evolvement. In the past decades, impressive improvements on the spectrum efficiency have been achieved. The dynamic or even real-time access of vacant spectrum is becoming possible with the cognitive and reconfiguration capability of cognitive radio (CR) technology. Meanwhile, the “exclusive use” based static spectrum management mode is transforming to the “spectrum sharing” based dynamic spectrum management (DSM) scheme [3].

DSM aims to enable more intensive and flexible spectrum utilization through authorizing spectrum sharing among multiple classes of users rather than one kind of exclusive users [4]. Massive research results have demonstrated the validity and preference of DSM, i.e., a study from Europe shown that the required spectrum for 5G could be reduced from 76GHz with exclusive occupancy to 19GHz under dynamic sharing framework [5]. Consequently, shared use of spectrum has been regarded as the fundamental approach to mitigate the artificial spectrum scarcity problem [6]. The paradigm shift to spectrum sharing requires the co-evaluation
of wireless networks and regulatory mechanisms. The sharing of spectrum was deemed to be essential to meet the spectrum demand in the report of President’s Council of Advisors on Science and Technology (PCAST) of the United States [7], which was actualized by the Federal Communications Commission (FCC) with a three-tiered Federal sharing scheme for 3550-3700 MHz band, termed Spectrum Access System (SAS) [8]. In Europe, a sharing framework termed licensed shared access (LSA) was proposed for the exploitation of TV white space (TVWS). Experiments of LSA systems in Finland, France and Italy had demonstrated its feasibility and superiority [9]. Considering the constraint of the propagation characteristics of the mm-Wave band and the potential of TVWS, the database-driven spectrum sharing scheme and deployment scenarios for 5G were presented in [10]. It is safe to envision that more and more spectrum bands will be opened for secondary access to alleviate the spectrum scarcity problem as well as to promote the social worth of the spectrum resource.

A. SOP EXPLORATION

Under the envisioned DSM systems, the secondary users (SUs) explore the usable spectrum opportunity (SOP) and execute communication on it with the precondition of no insufferable interference to the primary users (PUs) [11], [12]. Termed as SOP exploration, the mission of the former procedure is to ascertain which part of the spectrum can be utilized in the dimensionality of frequency, time, space, code, etc. As the spectrum sharing will never be allowed by regulatory authorities without authentic protection of legacy users, the SOP exploration with legacy assurance is regarded as the most important practical issue for the application of DSM [13]. Existing SOP exploration approaches include the spectrum sensing, resorting to spectrum database, and the spectrum prediction. Spectrum sensing is the most straightforward approach which ascertains the SOP usability through analyzing the received signals on the interested band. Yet the sensing and analysis are time and energy consuming, and the performance is constraint by the electromagnetic environment. The more reliable approach is resorting to geo-location spectrum databases, which provide the distribution and activity of PUs. Much research has demonstrated the preference of this method in improving the spectrum utilization [14], [15]. Many proposed DSM frameworks, including SAS, LSA, and IEEE 1900.5 have taken spectrum database as the basic SOP information source [4], [16]. On the other hand, the collection and update of the SOP information in the spectrum database may be frequent to guarantee the validity of the information, cost of which is inconvenient especially in the dynamic spectrum environment [17], [18]. The third approach is the spectrum prediction, which determines the intending SOP usability through the analysis of the correlations in the spectrum occupancy statistics. Much efforts have been devoted to the design of the spectrum prediction algorithms, benefits of which to the spectrum sensing, the planned spectrum mobility, as well as the spectrum access have been shown in many literature [19]–[21]. Besides that, more intelligent models such as reinforce learning and deep reinforce learning have also been used in the online optimization of SOP exploration [22]–[24]. Furthermore, a comprehensive comparison on the performance of thirteen detection approaches of PUs in 3.5GHz band base on a large amount of measurement data had shown that the deep learning based method performed best [25].

B. DSM AND THE TRANSITIONS TO SSM

The development of DSM schemes has been closely coupling with the evolvement of the SOP exploration approaches. The spectrum sensing based DSM frameworks such as the DARPA XG networks were the earliest concerned candidates. Then the concerns gradually transitioned to the spectrum databases enabled DSM proposals, which had been authorized for spectrum sharing in 3.5GHz band, 5GHz band, and TV white space (TVWS). Recently, with notable progress in the spectrum data mining and the artificial intelligence (AI), many advanced spectrum management models were proposed. A prediction-based spectrum management scheme was proposed in [26], which adopted the spectrum prediction and users’ mobility prediction to improve multiple system performance metrics. In [27], a smart spectrum management model for vehicle-to-everything communication was proposed, which combined spectrum measurement, modeling, and database to assist vehicles with spectrum information. A hunger marketing based spectrum management strategy for satellite communication systems was proposed in [28] to stimulating the desire of users for better plan of the bandwidth requirement and better spectrum management. An AI-based hierarchical cognitive cellular network framework was proposed in [29] which integrates AI and CR technology into a sophisticated multi-agent system for more efficient spectrum sharing. In [30], an auto-learning framework adopting machine learning to the network optimization was proposed, following which the automatic model construction, experience replay and solution recommendation could be executed for the spectrum utilization as well as other optimizations. The edge computing and blockchain were suggested in [31] and [32] respectively to provide more sufficient and reliable assistance to users. In [33], we have probed into the possibility and initiative model of the SSM.

It can be seen that more intelligence has been incorporated into the DSM. However, the diversity of the SOP exploration ability of the network has not been considered and the interconnection of SOP exploration and exploitation was not fully optimized in existing literature. Furthermore, although the remarkable profit is expectant for the intelligence provided by AI, the spectrum big data and the reinforcement learning, the requirement on the information and the computing resource of the intelligent processing may not be satisfied. The existing proposals suffer from the parameter sensitive problem of the machine learning, for which the trained neural network or the Q-table may need frequent rebuild for the variation of the spectrum environment [34]. It will be preferable
and more practical to investigate the smarter framework to accommodate diverse spectrum environment with efficient SOP utilization.

C. CONTRIBUTIONS OF THE PAPER

To solve the problems of inefficient SOP exploration and the absence of systematical smart spectrum management scheme, the SSM model and the joint SOP exploration scheme will be proposed in this study. Firstly, the SOP related information for spectrum sharing is layered into the spectrum data (SD), the spectrum information (SI), and the spectrum knowledge (SK), based on the processing and abstractive level. Being more general than existing intelligence in the SOP exploration approaches, the SK can not only be the spectrum prediction models, trained neural network, but also be the relations of SOP usability and utilization efficiency in multiple domains, which are flexible, extensible and customizable. Then the SSM model with the SK as the key enabler is defined, following which the coupled SOP exploration and exploitation can be achieved. Thirdly, the joint SK and real-time observing (SKRO) SOP exploration scheme is proposed which combines the historical spectrum information and the spectrum sensing for efficient SOP exploration. Extensive simulation results demonstrate that the proposed scheme can effectively promote SOP utilization especially in the low signal to noise (SNR) environment.

Main contributions of the paper can be summarized as follows.

- A three-layer SOP information model is proposed which differentiates based on the processing and abstractive level of the spectrum related information. Specifically, a generalized definition of the SK is proposed, following which the SK is extendible, scalable, and with the preference of modeling the multi-domain relations.
- A novel SSM model, with the SK as the key enabler and the coupled SOP exploration and exploitation as the core feature, is proposed and its difference with the current static allocation scheme and the DSM framework is analyzed. Following the SSM, the intelligence can not only be incorporated into the SOP exploration, but also be used for the entire procedure of the SOP utilization.
- A SKRO based SOP exploration scheme is proposed, which can concurrently make use of the advantages of the SK and the real-time spectrum sensing. Thus the smart SOP exploration in various spectrum environment can be achieved.
- Extensive simulations are executed to evaluate the performance of the DSM and the proposed SSM, which demonstrate for the first time the preferences of adopting the SSM in the spectrum sharing.

The rest of the paper is organized as follows. In section II, we propose the layered SOP information framework. The SSM model is proposed in Section III, followed by the SKRO enabled SOP exploration scheme in Section IV. Simulation results are provided in Section V and a brief conclusion in Section VI.

II. HETEROGENEOUS SOP INFORMATION PROCESSING AND THE LAYERED FRAMEWORK

A. SOP RELATED INFORMATION IN SPECTRUM SHARING

As no insufferable interference is allowed to PUs, the SOP in the spectrum sharing framework is defined as the portion of the spectrum which is accessible for SUs in the divisions of time, space, frequency band, etc. Correspondingly, the policy and service provisions, propagation models, geographical information, the distribution of legacy users are all influential to the SOP. The accurate SOP usability can be deduced based on the real-time collection and processing of the related information, which is unfortunately unaffordable and unpractical for both time and bandwidth constraints in DSM. Thus, it is reasonable to estimate the SOP usability based on the analysis of the acquired SOP related information.

B. LAYERED SOP INFORMATION MODEL

The form of the SOP related information can be raw sensing data, structured data, trained spectrum prediction model, etc. On the breadth division, more kinds and amount of the information brings more comprehensive awareness of the SOP usability environment, while on the depth division, higher processing and abstractive level of the information leads to more profound cognition of the SOP usability. Considering both breadth and depth of the information, we propose a three-layer SOP information model, as depicted in Fig.1. For the breadth division, it stands to reason that more and more range of the spectrum related information can be collected through appropriate sensor networks and the SUs themselves. With the given amount of data, the processing level of the information is the decisive factor for the efficiency of SOP exploration.

1) LAYER 1: SD

The SD is in the form of number, figure, character, etc., with the feature of large volume and full information about the spectrum environment. For the DSM in a given area, the
spectrum data can be the detected power or other indicators on the interested frequency at arbitrary time. As a result of the continuous feature in the temporal, spacial, and spectral divisions, the structure of the SD can be very complicated and hard to be utilized without further processing.

2) LAYER 2: SI
The SI is defined as the structured SD under the spectrum usage related context, for which the value is quantified, modeled and arranged. This kind of information may be the historical PU spectrum occupancy information, the propagation feature of the given domain, the spectrum management and usage notes, etc. Compared to the SD, the usability of SI is better for its structure and context information, while on the other hand the contained information decreases during the discrete and quantitative processing.

3) LAYER 3: SK
The SK in the model is defined as the information which can be used to recognize, reason, and predict the SOP usability as well as the outcome of the utilization. Based on enough SI, the SK is obtained through the data mining and knowledge construction. The form of the SK can be the spectrum prediction model, the spectrum management paradigms [24], spectrum access strategy [35], etc. Compared with the SI, the SK can be more directly used for the SOP exploration and exploitation. Being more generalized than the temporal relation in the spectrum prediction models, the relation contained in the SK can be temporal, spacial, spectral divisions and even inter-domains. Thus the decision can be made based on the multi-domain reasoning. Another feature of the SK is the scalable characteristic, which can be extended or pruned for the specific usage.

C. COMPARISONS OF THE THREE LAYERS
From Layer 1 to Layer 3, the processing and abstractive level, as well as the supporting to spectrum utilization, increase gradually. The differences are illustrated in the example of the spatio-temporal SOP related information in Fig.2, in which the horizontal coordinate denotes the time index, the vertical coordinate represents the frequency index, and the grids stand for the time or frequency domains, which are not necessarily uniform and determined following the spectrum usage requirement.

The element in the SD can be the detected power \( p_{x,y} \) at the arbitrary point \((x, y)\). As it is impossible and unnecessary in almost all the scenarios to obtain and process all the data points in the domain, the interested area is partitioned, the value in each grid is represented by a quantity, and the SI set is structured as \( \{p_{m,n}|m, n = 1,2,3,4,5\} \). Thus the detected power on the interested frequency and time can be stored, processed, and used, although there is unavoidable loss of information in this simplification. Then the SK can be constructed on the basis of the SI to make further use of the obtained information. In the example, the knowledge \( sk_1 \) is formalized as \( \langle p_{3,3}, p_{4,4}, p_{5,5}, r_1 \rangle \), in which

\[ p_{m,m} (m = 3,4,5) \text{ stands for the power at the time slot } t_m \text{ on frequency band } b_m, \text{ and } r_1 \text{ represents the reliability of the spectrum knowledge. The knowledge } sk_1 \text{ means that the power at the time slot } t_5 \text{ on frequency band } b_5 \text{ will be } p_{5,5} \text{ with reliability } r_1, \text{ given the fact that the detected powers are } p_{3,3} \text{ and } p_{4,4} \text{ in the corresponding points. Similarly, the SK } sk_2 \text{ indicates that the power on band } b_2 \text{ at the time slot } t_4 \text{ will be } p_{4,2} \text{ with reliability } r_2 \text{ if the detected powers on } b_1 \text{ and } b_2 \text{ at time slot } t_1 \text{ are } p_{2,1} \text{ and } p_{3,2}, \text{ respectively. As a scalable insistence, the SK } sk_2 \text{ may be extended to } \langle p_{2,1}, p_{3,2}, p_{3,3}, p_{4,2}, r_3 \rangle \text{ or pruned to } \langle p_{2,1}, p_{4,2}, r_4 \rangle \text{ if the corresponding relationships exist.}

D. ACCESSIBILITY AND OVERHEAD
The layered SOP model provides a new insight to the spectrum information processing and incremental assistance to the spectrum usage.

For SU’s, the SD can be directly sampled, the SI can be constructed locally or inquired from the spectrum database as needed, and the SK can be filtered beforehand, latter two of which can be jointly used with real-time observing if needed as proposed in Section IV. The SI and SK can be easily accessed in the environment with efficient infrastructure assistance, while the offline and instructive feature of the SK will support the SU’s a lot in the infrastructure-less environment.

The collecting, processing and usage of the spectrum related information can be based on the geo-location spectrum databases for SAS, LSA, and the spectrum sharing systems for TVWS, in which the granularity of the SI can be determined by both the operation mode of the PUs and the requirement of the secondary small-cells or micro-cells. Furthermore, the spectrum data mining and knowledge construction of the SK may be developed based on latest models such as AI and deep learning, based on the heterogeneous information in the spectrum databases. Thus the additive overhead will be in the model construction process. On the other hand, the SOP exploration and exploitation overhead will be reduced with the assistance from the SK for its features of recognizing, reasoning and predicting. In short, much of the overhead on the processing of the spectrum related information is moved from their usage process to the SK construction process. Correspondingly, the information stored in the spectrum databases can be fully utilized and
abstracted to accommodate to the online usage of the users with less overhead.

III. THE PROPOSED SSM MODEL

A. DEFINITION OF SSM

Definition 1 Smart Spectrum Management: The SK enabled resource management model which constructs SK and optimizes resource management through intelligent learning and decision based on both the historical spectrum related information and the real-time observing of the spectrum environment.

The main differences of the SSM with DSM and the current static allocation (SA) management model lie both in SOP related information assistance and SOP utilization ability, as illustrated in Fig. 3.

Under the currently dominate SA scheme, the spectrum is licensed based on middle/long time requirement prediction, and the licensed users use the given frequency in the static and exclusive mode. Following the transforming DSM scheme, the SOP is determined through real-time/sub real-time sensing or resorting to the spectrum database, and the SUs access the discovered SOP opportunistically or coordinately with each other. Following the intending SSM, the SOP is discovered based on the historical SK as well as the real-time observation of the spectrum environment. Following that, the SUs intelligently access the explored SOP through learning from the historical experience and flexibly adapting to the current requirement and SOP usability conditions.

Compared with the two predecessors, the most distinctive feature of the SSM it the joint SK and real-time observing enabled decision. For a given area, the working framework of SSM is illustrated in Fig. 4. Firstly, the SI of multiple PUs networks, the spectrum environment, and other domains is collected and stored, based on which the inter and multi-domain relations of the SI are mined and the SK are constructed. When there are secondary networks working in the same area, the SI and SK are filtered and pushed them. The spectrum decision of the SUs can be made based on the SK and the their own real-time observing. For the more instructive and multi-domain feature of the SK, the efficiency of the spectrum management can be well improved. Furthermore, the deficiency of the existing SOP exploration methods can also be overcome.

B. COUPLED SOP EXPLORATION AND EXPLOITATION

One of the characteristics of the SSM is the coupling of SOP exploration and exploitation, being different from the unattached or joint design in DSM [36], [37]. As depicted in Fig.5, the two procedures of SSM are coupled through metrics of the SOP utilization, with the assistance of the SK database. The relation in the SOP exploration and exploitation will be mined and the corresponding SK will be constructed if the multi-domain dependence is discovered, in which the metrics related to the two procedures of the spectrum sharing such as the protection threshold of PUs and the SOP length are adopted. For example, a SU may discover the best spectrum sensing interval given the SK about the working mode of PUs, in which the SOP exploration and exploitation are coupled by the SOP length. This kind SK can be mined from the SI about the PUs and the experience of SUs.

IV. SKRO BASED SOP EXPLORATION

The most distinctive features of the SSM is the SOP exploring based on both the historical spectrum information and the real-time observing of the spectrum environment. In this section, we propose the SKRO based SOP exploration scheme.

A. THE FRAMEWORK OF SKRO

The framework of the SKRO based SOP exploration scheme is illustrated in Fig.6. The exploring is triggered by the requirement with some performance metrics. For example, a new SU may be informed that it can access a channel if the inference ratio to the licensed users is not bigger than...
a specific threshold. In this study, we choose the detection probability of PU signals as the concerned metric while other metrics such as false alarm probability can also be adopted.

Given the detection probability threshold $P_d$, the set of the SK is firstly inspected and the decision of SOP occupancy or back off can be made if there are some SK satisfying the threshold. Otherwise, the spectrum sensing is adopted to further ascertain the usability of the SOP.

### B. MATCHING RATIO OF THE SK

It is impossible to construct a SK database that covers all possible conditions of the SOP exploration in SSM. Thus it is essential to evaluate the applicability of the SK to the requirement of the SOP exploration. So we defined a parameter $\varphi (\varphi \in [0, 1])$ to represent the matching ratio of the SK to the SOP exploration scenarios. Let $\varphi = 1$ represent that all the SOP exploration in SKRO can be executed according to the SK, and the spectrum sensing has to be used if $\varphi = 0$.

Taking the spectrum prediction model as an example of the SK, which is constructed based on the temporal relations of the usability of SOPS. The universal usability prediction (UUP) model proposed in [18], is taken as a representative instance for the estimation of the parameter $\varphi$. Following UUP, the usable probability of the SOP in the $k_b(k = 1, 23, ...)$ slot after the construction of the model is given by

$$a_k = \begin{cases} 0.5 + 0.5e^{-\tau \cdot k} c_k = 1 \\ 0.5 - 0.5e^{-\tau \cdot k} c_k = 0 \end{cases}$$

where $c_k = 1$ denotes the usable state of the SOP, $c_k = 0$ means that the SOP is unusable, and $\tau$ is a distortion parameter. In (1), the uncertainty of the prediction varies in an inverse proportion with its difference to 0.5, which denotes complete uncertainty. With the given reliability threshold $P_d$, the predicted SOP usability probability should satisfy $a_k \leq 1 - P_d$ for all the slots with $c_k = 0$. Then the maximal predicted length should be

$$k^* = \left\lfloor -\frac{1}{\tau} \ln(2P_d - 1) \right\rfloor$$

in which $\left\lfloor \cdot \right\rfloor$ is the floor round function. Correspondingly, with the UUP as the SK database, the parameter $\varphi$ can be given as

$$\varphi = \begin{cases} 1, & k \leq k^* \\ 0, & \text{otherwise} \end{cases}$$

### C. ENERGY DETECTION WITH OPTIMAL SENSING TIME

The energy detection with optimal sensing time (EDOS) will be adopted if the spectrum sensing is required. Here the term optimal denotes the best choice of the sensing time to maximize the utilization ratio of the SOP with given detection probability threshold.

Under the additive white Gaussian noise (AWGN) environment with signal to noise ratio $\gamma$, the detection probability $P_d$ and the false alarm probability $P_f$ can be given by [38]

$$P_d = Q\left(\frac{\lambda - (\gamma + 1)\sigma_n^2}{\sigma_n^2(\gamma + 1)\sqrt{f_s\rho}}\right)$$

and

$$P_f = Q\left(\frac{\lambda - \sigma_n^2}{\sigma_n^2\sqrt{2f_s\rho}}\right)$$

in which $\lambda$ is the detection threshold, $\sigma_n^2$ is the variance of the AWGN, $f_s$ denotes the sampling rate, $\rho$ is stands for the sampling duration, and the Q-function $Q(\cdot)$ is given by

$$Q(x) = \frac{1}{\sqrt{2\pi}} \int_{x}^{\infty} e^{-t^2/2}dt$$

Combine (4) and (5), we can get

$$P_f = Q(\sqrt{f_s\rho/2} + (\gamma + 1)Q^{-1}(P_d))$$

Then the utilization ratio of the SOP, i.e., the percentage of the discovered SOP in all usable SOP, can be computed by

$$\mu_{ss} = (1 - Q(\gamma \sqrt{f_s\rho/2} + (\gamma + 1)Q^{-1}(P_d)))(1 - \rho)$$

It can be seen from (8) that in a specific noise environment with given protection threshold for PUs and sampling rate of SUs, $\mu_{ss}$ is determined by the sampling duration. To evaluate the influence of the variation of $\rho$ on $\mu_{ss}$, we compute the partial derivative of $\mu_{ss}$ with given $\gamma$, $P_d$ and $f_s$ by

$$\mu_{ss}' = \sqrt{\gamma f_s/\rho} \left(1 - \rho\right) e^{-\gamma \sqrt{f_s/\rho} + \gamma + 1)Q^{-1}(P_d)} \left(1 - Q(\gamma \sqrt{f_s\rho/2} + (\gamma + 1)Q^{-1}(P_d))\right)$$

It can be figured out that both the former and latter part of $\mu_{ss}'$ will decrease with the increasing of $\rho$. So the $\mu_{ss}'$ monotonically decreases for the variable $\rho$, indicating its concave property. Then the maximal $\mu_{ss}$ and the corresponding optimal sampling duration $\rho^*$ can be easily computed through newton method or tripartite method [39]. The Fig.7 and Fig.8 present the variation of $\rho^*$ and $\mu_{ss}$ for different $\gamma$ and $P_d$ respectively. It can be seen from the results that the optimal sensing times vary with the parameter $\gamma$, and there is a unitary $\rho^*$ for a given protection threshold $P_d$, validating the existence and uniqueness of the optimal sampling duration in EDOS.
V. PERFORMANCE EVALUATION

A. SIMULATION SETUP

Since there is no similar smart solutions of spectrum management, the performance of the SKRO enabled SSM on SOP utilization will be compared with that of the EDOS enabled DSM, which are denoted by SKRO-SSM and EDOS-DSM respectively in the following simulations. The concerned performance metrics include the protection of legacy users quantified by the interference ratio of secondary users to PUs $i_{PU}$, and the utilization ratio of the SOP quantified by $μ_{ss}$. The target is maximizing $μ_{ss}$ on the precondition of satisfying the threshold $i_{PU}$, which is $i_{PU} = 0.1$ if no further specification.

For EDOS-DSM, the influential parameters are the sampling rate $f_s$ and the SNR $γ$. The most important parameters for SKRO-SSM are the matching ratio $ϕ$ which represents the ratio of holding applicable SK, and the reliability of the applicable SK, which will be randomly generated in $[P_d, 1]$ if no other notification. The randomly generated PSK signals with bandwidth of $2 \times 10^3$Hz are taken as the primary signals. In each simulation, the SOP exploitation performance of the two frameworks will be evaluated in the sequence of $1 \times 10^4$ slots. All the presented simulation results are the average of 500 randomly generated sequences.

B. RESULTS AND ANALYSIS

Firstly, the performance of EDOS-DSM in different SNR environment are evaluated. The results of $μ_{ss}$ and $i_{PU}$ for $f_s$ of $5 \times 10^3$, $7 \times 10^3$, and $1.2 \times 10^4$ are presented in Fig. 9 and Fig. 10 respectively. It can be seen that the legacy protection requirement can always be satisfied and better performances can be achieved in bigger SNR environment. The simulation results are closely coincided with the theory analysis, validating the correctness of the analysis. Furthermore, although the SOP exploitation can be improved with bigger $f_s$, the $μ_{ss}$ can be rather low, i.e., below 50%, in the low SNR environment.

Then the SKRO-SSM with different matching ratio $ϕ$ is simulated under different legacy users protection threshold $P_d$ and $γ$. It can be observed from the results in Fig. 11 and Fig. 12 that both $μ_{ss}$ and $i_{PU}$ are improved with the increasing of $γ$, while the variable trends are contrary for the variation of $ϕ$. The interference ratios to legacy users are always lower than the thresholds and more protection induces lower utilization ratios of SOP. In the low SNR environment, the SKRO-SSM with bigger SK matching ratio obtain more utilization of SOP, while the relative relationship crosses contrarily after a specific value of $γ$. The reason is that the SK dominates the SOP exploration in the SKRO in the low SNR environment.
environment while the spectrum sensing is preferable in the high SNR environment. The crossing point for SKRO-SSM with $P_d = 0.9$ is $\gamma = -4$, remarkably bigger than that of SKRO-SSM with $P_d = 0.7$.

Finally, we compare the SKRO-SSM with the EDOS-DSM in the low SNR environment with the variation of $f_s$ and $\phi$ respectively. Firstly, the $\mu_{ss}$ and $i_{PU}$ are compared with fixed $\gamma = -10$dB, $\varphi = 0.8$, and variable $f_s$ from $4 \times 10^3$ to $8 \times 10^3$. From the results in Fig. 13, it can be observed that the SKRO-SSM performs much better than the EDOS-DSM on $\mu_{ss}$, while obtaining similar values of $i_{PU}$. The average increases are 32.76% and 16.55% for the thresholds $P_d = 0.9$ and $P_d = 0.8$ respectively. Then the schemes are compared for the environment of $\gamma = -12$dB and $\gamma = -9$dB with the variation of $\varphi$. It can be seen from the results in Fig. 14 that the SKRO-SSM always perform obviously better that EDOS-DSM for $\varphi \in [0.5, 0.95]$, with average increase of 76.62% and 21.04%. The preference of the SKRO-SSM probably results from its flexibility and the intelligence in the SK.

VI. CONCLUSION

In this paper, the problem of incorporating intelligence into the spectrum management was addressed. Under the proposed layered SOP information framework, the SK was formally defined. Furthermore, the SSM was defined with the SK as the key enabler. Extensive simulation results were provided and the preference of SSM were demonstrated.

Although the SSM model and the SK have been defined and validated through extensive simulation, the problem of the SK constructing needs further research. The efficient mining model of the SD and the multi-dimensional SK construction will be the focus of our future work.

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YONGXIANG LIU received the M.S. degree in communications and information systems from the Nanjing Institute of Communications Engineering, Nanjing, China, in 1999. He is currently a Professor with The Sixty-third Research Institute, National University of Defense Technology, Nanjing. His research interests include wireless communications, spectrum management, and communication anti-jamming.

HAO WU received the Ph.D. degree in communications and information systems from PLA Army Engineering University, Nanjing, China. He is currently an Associate Professor with the National University of Defense Technology. His current research interests include spectrum sensing and spectrum management.