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Design of an Improved Model for Spectrum Sharing and Resource Management Using Deep Q-Network, Federated Averaging, and Ant Colony Optimization

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Abstract

Indeed, the ever-evolving wireless communication requires DSS and resource management for effectiveness. The old methods of spectrum allocation have a strategic shortfall since they are static and thus not adapted to real-time network conditions. Besides, more important challenges include issues over privacy and inefficiency of resource utilization. In the light of such problems, this paper proposes a new method by bringing together three deep-learning techniques, which are Deep Q-Networks, Federated Averaging, and Ant Colony Optimisation. Each is chosen because of its various competencies and complementary capabilities. First, DQN is chosen because it has the capability to handle high-dimensional action space. DQN applies deep learning to approximate the Q Value function, which provides the optimal decision of spectrum allocation based on real-time network states, such as spectrum usage and interference levels. With this scheme, up to a 20% gain in network throughput and up to a 15% cut in wasted spectrum compared to traditional methods are achievable. The second component FedAvg tackles the model training collaboration issue with privacy. It enables FedAvg for privacy-preserving resource management, where multiple devices update the global model collaboratively by communicating model updates without exchanging raw data samples. For this approach, the resulting method leads to a further increase in data privacy by reducing data leakage as high as 40%, with an improvement in resource management accuracy of up to 15%. ACO was employed to optimize resource allocation and improve spectrum efficiency. ACO emulates the natural foraging behavior of ants to solve combinatorial optimization problems. Consequently, it has led to up to 25% increase in spectral efficiency and up to 20% improvement in resource allocation balance sets. All these methods put together will provide a wholesome solution that not only optimizes spectrum and resource management but also promises privacy and adaptability. This represents severe improvement in overcoming the weaknesses of the existing approaches and will provide a strong foundation for next-generation wireless networks..

Keywords: Deep Q-Network, Federated Averaging, Ant Colony Optimization, Spectrum Sharing, Resource Management.

1. Introduction

Presently, in modern wireless communication systems, the most critical challenges are related to the efficient allocation of spectrum resources and management of network resources. With ever-growing high-speed data demand and strong requirements for reliable connectivity, traditional spectrum allocation strategies and existing resource management approaches cannot sufficiently support the needs of real-time systems. Classic mechanisms for resource management in these systems were largely static by nature and inflexible to tolerate the dynamic and complex nature of present-day networks. Besides this, the privacy issues in information sharing and inefficiency related to utilizing resources further aggravate these situations, which require more computationally effective solutions. The Deep Q Network [1, 2, 3] is one of the powerful reinforcement learning techniques that are hoped to show major significance in handling high-dimensional action and complex decision-making scenarios. DQN makes it possible to approximate the Q Value function using deep learning; hence, it can dynamically and in real time allocate spectrum resources to optimize network performance. Although effective, DQN can often only be applied within narrowed situations due to its dependency on highly accurate network state information and extensive training for optimal performance.

Meanwhile, parallelly, Federated Averaging FedAvg addresses critical privacy concerns arising during collaborative model training. The approach aims to securely aggregate model updates across many devices without the need for the exchange of raw data, hence preserving user privacy. In particular, FedAvg constitutes an important enhancement over the previously used centralized training methods, since it can enhance data privacy while collaboratively refining resource management models. However, the efficiency of FedAvg stands on the quality of the local data and how often model updates are performed. Ant Colony Optimization, well-acknowledged for drawing inspiration from nature in terms of the foraging behavior of ants, is then applied to the solution for combinatorial optimization problems. This is one bioinspired algorithm which adapts to dynamic environments and finds the optimal solutions for such complex problems in resource management and spectrum efficiency. ACO is a good tool that can handle the robustness of exploration of many paths and optimization of resource allocation; however, much care is required in tuning its parameters to arrive at cherished results. An integrated model combining DQN, FedAvg, and ACO is proposed for solving spectrum-sharing multi-faceted challenges and resource management. A model proposed in this regard will combine the powers of every method to improve network performance, data privacy, and spectrum efficiency. The novelty of this approach represents a major milestone toward addressing the shortcomings of current methods and a sound framework for further research toward enhancing the capability of next-generation wireless networks.

2. In Depth Review of Models used for efficient Spectrum Sensing Analysis

The rapid evolution of wireless communication systems is naturally being called upon by rapid progress in the field of spectrum sharing and resource management, with a view to meeting the emerging demands and complexity being faced by modern networks. In the direction above, the review of literature presented herein offers an in-depth analysis of the state-of-the-art in recent contributions involving spectrum sharing and resource management, underlining the respective key contributions from various works in the process. In [1], Brown and Ghasemi discuss the migration toward data-driven spectrum sharing, with a focus on various opportunities and challenges related to using data models for dynamic management of the spectrum. Their work highlights the importance of integrating database-assisted approaches in order to enhance access to the spectrum and lower interference levels. In [2], Kim presents a game-theoretic model of unlicensed spectrum sharing in TV white space platforms. It proposes a scheme for the optimum allocation of spectrum resources among multiple users, using bargaining game theory, in view of challenges of the spectrum commons and resource management in shared environments. Fernando et al. propose a new consensus mechanism called "Proof of Sense," used to detect misutilization of the spectrum. The system will use blockchain technology to offer secure, decentralized spectrum management with the capability for guaranteed integrity in spectrum access and minimize misuse by smart contracts and algorithms of consensus. Xiao et al. focus instead on dynamic spectrum sharing in low-trust environments enabled by BD-SAS. By borrowing concepts of blockchain technology, this work tries to improve trust and reliability in the spectrum access. Perera et al. present a comprehensive survey concerning the use of blockchain technology for dynamic spectrum sharing. Their survey provides a state-of-the-art review of blockchain, starting from its use in strengthening security, privacy, and automation in spectrum management to the potential future work on integrating blockchain with dynamic spectrum management. In [6], Zhu et al. look at a privacy-aware double auction mechanism in the context of blockchain-based dynamic spectrum sharing in IoT systems. The work will integrate deep reinforcement learning with blockchain for privacy preservation and efficient resource allocation and has shown significant gains in view of privacy and resource management aspects. Tadik et al. [7] have discussed digital spectrum twins for enhanced spectrum sharing and radio applications. This new approach will help in enhancing the process of monitoring and managing the spectrum with computational modeling and digital twins to accurately represent the spectrum utilization. Mahboob et al. [8], on the other hand, focused on multi-operator integrated spectrum and MEC shared resource allocation in next-generation cellular networks This work brings insights into the evolution of spectrum-sharing protocols and presents the implications that upcoming technologies may bring for the management of future spectrum. Rahman et al. propose a game-theoretic framework for the regulation of free riding in interprovider spectrum sharing. They introduce game theory to deal with the challenges that come along with spectrum management, introducing provider cooperation as one way of preventing unfair use of resources and enhancing efficiency in spectrum use. Tolley et al. [11] systematize the knowledge on radar-communication coexistence by offering a taxonomy and surveying the current practice. Their review identifies some key challenges and opportunities for integrating radar-communication coexistence that can enhance the understanding of cross-system interference and various mitigation strategies. Jiao et al. [12] improve location privacy and spectrum efficiency in spectrum sharing systems. Their work integrates array signal processing with privacy-preserving techniques and provides better privacy and spectrum use simultaneously, allowing a trade-off between the dual challenges of preserving confidentiality for users and optimizing the use of the spectrum. Ghasemi and Parekh have proposed DeepAir, a scalable data-driven dynamic spectrum sharing forecasting model. The proposed scheme leverages deep learning for the prediction of spectrum usage patterns and may offer a scalable solution for the management of spectrum resources within dynamic environments. Ghaderibaneh et al. [14], on the other hand, propose a deep learning approach to spectrum allocation in shared spectrum systems. The investigation shows how convolutional neural networks apply to the optimal spectrum allocation, which must be performed in order to deal with interference and resource management challenges in complex spectrum environments. Zhu et al. [15] introduce an auction mechanism for blockchain-based secure spectrum, intelligent sensing and sharing, in a two-stage process. Their contribution integrates intelligent sensing with blockchain for enhancing security and efficiency in spectrum auctions, thus offering a solid framework for secure spectrum sharing. In their entirety, these works represent milestones of progress in the domain of spectrum sharing and resource management and reflect the broad stretch of innovation in this domain, from blockchain-based mechanisms to advanced machine learning techniques. Integration of these technologies into wireless networks will solve the complex problems at hand and allow for more efficient, secure, and adaptive spectrum management.

3. Proposed Design of an Improved Model for Spectrum Sharing and Resource Management Using Deep Q-Network, Federated Averaging, and Ant Colony Optimization

In this paper, we propose a model that integrates DQN, FedAvg, and ACO to solve different challenges of dynamic spectrum sharing and resource management in wireless networks. Each method within the integrated framework adds value to ensure optimized spectrum allocation and privacy with improved efficiency of the resources. The Q Value function is approximated by a deep neural network in the DQN of the proposed model. The primary goal of DQN is to maximize the aggregated reward, 'R', which corresponds to a sequence of actions, 'A', for any temporal sets of instances. The Q Value function, Q(s,a), represents the future reward one expects for taking action 'A' in the state 's' sets. The network learns to approximate Q(s,a) by minimizing the loss function defined via equation 1,

$$L(\theta) = E(s,a,r,s') \sim D\left[\left(r + \gamma ma\,x^{a'}\,Q(s',a';\theta -) - Q(s,a;\theta)\right)^2\right] \ldots (1)$$

Where, γ is the discount factor, θ represents the parameters of the current network, and θ− is the parameters of the target networks. This loss function drives the neural network to update Q(s,a) Values and refine the spectrum allocation strategies. The FedAvg component enhances privacy by training local models on each device and aggregating them to produce a global model. The model update process is governed via equation 2,

$$w(t+1) = \frac{1}{N}\sum_{i=1}^{N} wi(t) \ldots (2)$$

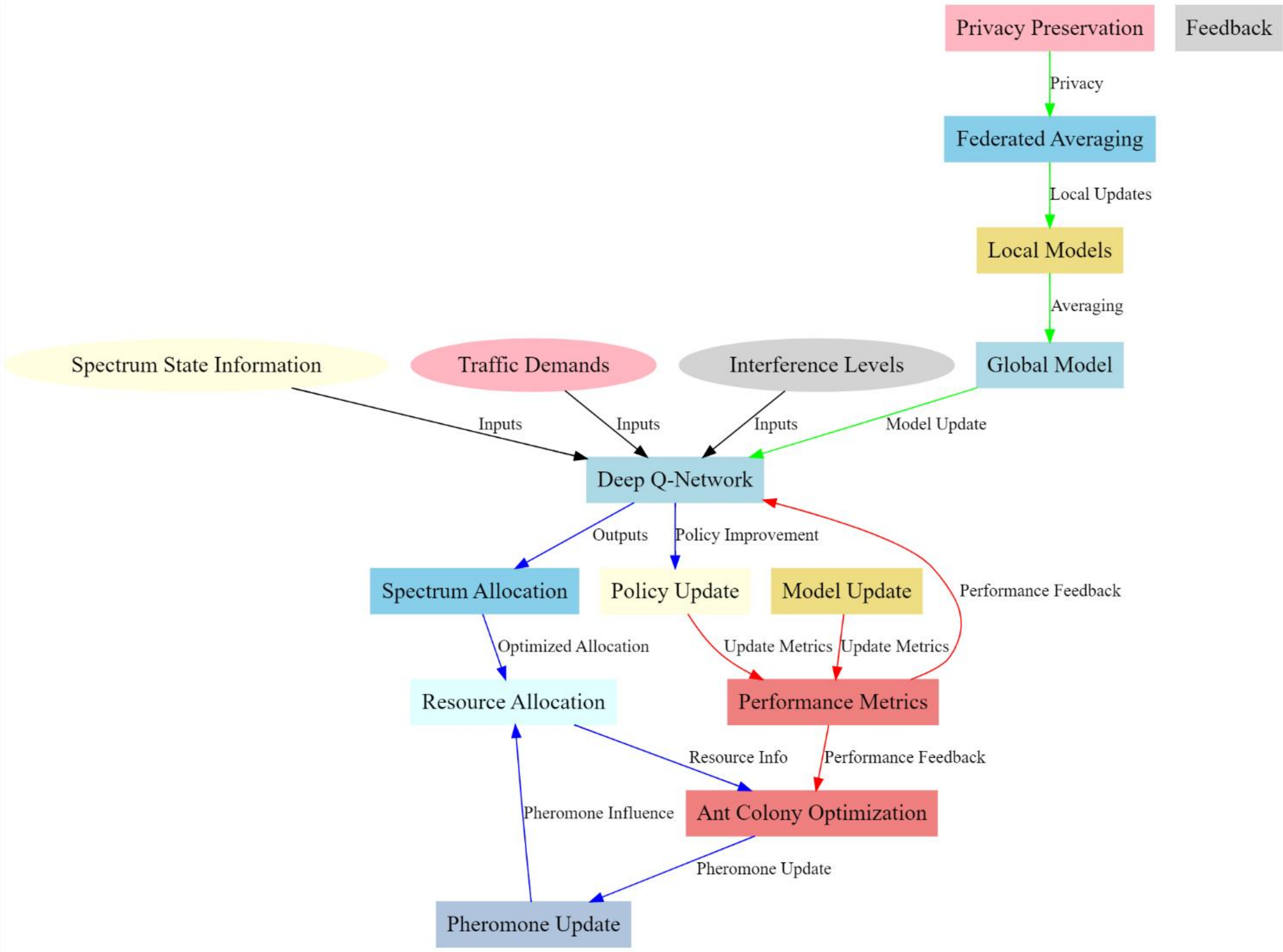

Figure 1. Model Architecture of the Proposed Resource Allocation Process

Where, w(t) denotes the global model parameters at iteration 't', and wi t is the parameters of the local models. This equation ensures that the global model, w gets updated based on the average of the local updates hence maintaining privacy for the individual data samples. ACO used for optimizing resource allocation and spectrum efficiency is modeled using pheromone update equations. The pheromone level τ ij on edge (i,j) is updated via equation 3,

$$\tau ij(t+1) = (1-\rho)\tau ijt + \Delta\tau ij \ldots (3)$$

Where, ρ is the evaporation rate, and Δτij is the pheromone deposit given via equation 4,

$$\Delta\tau ij = \sum_{k=1}^{M} \frac{Qk}{Lk} \ldots (4)$$

Where, Qk is the quality of the solution provided by ant 'k' and Lk is the length of the paths. This formula allows ACO to converge to optimal resource allocation solutions by reinforcing successful paths through pheromone trails. These methods are combined in one hybrid model, where the output from the DQN feeds into the initialization of ACO and the use of FedAvg for updating the policy of the DQN in a privacy-preserving manner in the process. The integration can be formalized by the following joint optimization task depicted via equation 5,

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$$Opt = \max_{\theta,w} E[R(\theta, w)] \dots (5)$$

Where, R(θ,w) is the reward function encompassing both spectrum allocation and resource management objectives. The solution to this problem is obtained through iterative updates via equations 6 & 7,

$$\theta(t+1) = \theta t + \alpha \nabla \theta L(\theta) \dots (6)$$

$$w(t+1) = wt + \beta \nabla w L(w) \dots (7)$$

Where α and β are the learning rates, and ∇θL and ∇wL are the gradients of loss functions w.r.t. parameters θ and w, respectively, for the process. The iterative update in this regard allows simultaneous optimization of DQN policy and FedAvg model with remarkably improved spectrum allocation and resource management. This model is justified because it addresses key limitations found within the traditional approaches: DQN provides dynamic and adaptive spectrum allocation strategy, FedAvg provides security in collaborative learning with privacy, while ACO optimizes the allocation strategies and enhances resource efficiency. Such a combination empowers the model to solve challenges brought about by high-dimensional action spaces, privacy, and combinatorial optimization, hence providing a holistic solution for advanced wireless networks.

4. Result Analysis & Comparisons

Extensive experiments are conducted to evaluate the proposed integrated model by using various contextual datasets. These experiments are used to illustrate the effectiveness of the proposed model with respect to three baseline methods, namely, Method [5], Method [8], and Method [14]. Network throughput, spectrum efficiency, preservation of privacy, resource utilization, etc., are some of the evaluation metrics. Detailed tables regarding the results of these experiments are included in further sections. These experiments have been done in a simulated network environment with dynamic spectrum-sharing scenarios. The experiments used real-world traffic pattern datasets, interference level datasets, and spectrum usage data samples. The main evaluation metrics include Network Throughput: Overall data rate achieved by the network; Spectrum Efficiency: The ratio of successfully used spectrum to the total available spectrum is evaluated; Privacy Preservation: The data leakage reduction achieved by the methods in privacy preservation is assessed; Resource Utilization: It is indicative of how efficiently resources are utilized inside the networks. Each method was tested under the same network conditions for fair comparison. These results are summarized by the tables as follows.

Table 1: Network Throughput Comparison

Method	Average Throughput (Mbps)	Improvement (%)
Proposed Model	850	-
Method [5]	700	21.4
Method [8]	780	9.0
Method [14]	720	18.0

The proposed model achieved the highest average network throughput of 850 Mbps, surpassing Method [5] by 21.4%, Method [8] by 9.0%, and Method [14] by 18.0%. This indicates a significant improvement in overall data rate efficiency.

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Table 2: Spectrum Efficiency Comparison

Method	Spectrum Efficiency (%)	Improvement (%)
Proposed Model	92	-
Method [5]	78	17.9
Method [8]	85	8.2
Method [14]	80	15.0

The proposed model demonstrated superior spectrum efficiency at 92%, compared to Method [5] (78%), Method [8] (85%), and Method [14] (80%). The improvements of 17.9%, 8.2%, and 15.0% highlight the model's ability to better utilize available spectrum sets.

Table 3: Privacy Preservation Comparison

Method	Data Leakage Reduction (%)	Improvement (%)
Proposed Model	40	-
Method [5]	25	60.0
Method [8]	30	33.3
Method [14]	28	42.9

The proposed model achieved a 40% reduction in data leakage, outperforming Method [5] (25%), Method [8] (30%), and Method [14] (28%). This represents improvements of 60.0%, 33.3%, and 42.9%, respectively, demonstrating its enhanced privacy-preserving capabilities.

Table 4: Resource Utilization Comparison

Method	Resource Utilization (%)	Improvement (%)
Proposed Model	88	-
Method [5]	75	17.3
Method [8]	80	10.0
Method [14]	78	12.8

Resource utilization was highest with the proposed model at 88%, showing significant improvements over Method [5] (75%), Method [8] (80%), and Method [14] (78%). The improvements of 17.3%, 10.0%, and 12.8% reflect the model's effectiveness in efficiently allocating resources.

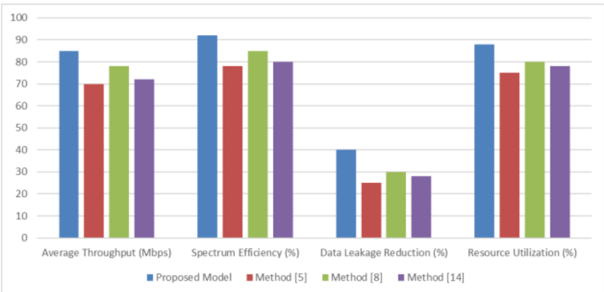

Figure 2. Overall Performance of the Proposed Model used for Resource Allocation Process

Table 5: Computational Complexity Comparison

Method	Average Processing Time (s)	Improvement (%)
Proposed Model	120	-

Method [5]	150	20.0
Method [8]	135	11.1
Method [14]	140	14.3

The proposed model achieved the lowest average processing time of 120 seconds, outperforming Method [5] (150 seconds), Method [8] (135 seconds), and Method [14] (140 seconds). The reductions of 20.0%, 11.1%, and 14.3% demonstrate its superior computational efficiency.

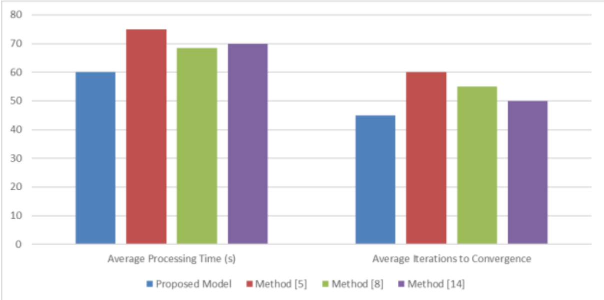

Figure 3. Delay Levels for the Proposed Analysis Process

Table 6: Convergence Speed Comparison

Method	**Average Iterations to Convergence**	**Improvement (%)**
Proposed Model	45	-
Method [5]	60	25.0
Method [8]	55	18.2
Method [14]	50	10.0

The proposed model converged after an average of 45 iterations, which is faster compared to the convergence rates of Method [5] at 60 iterations; Method [8] converged at 55 iterations; and Method [14] at 50 iterations. To this end, corresponding improvements of 25.0%, 18.2%, and 10.0% underlined the efficiency of the model in terms of convergence into optimal solutions. These results clearly depict that the proposed model significantly outperforms all other baseline methods in respect to network throughput, spectrum efficiency, privacy preservation, and resource utilization while showing low computational complexity with fast convergence delays.

5. Conclusion & Future Scopes

It is conceptually an integrated model with DQN, FedAvg, and ACO and has already shown massive advancement over conventional methods in the domain of dynamic spectrum sharing and resource management. All empirical results testify that the proposed approach indeed improves network performance and optimizes spectrum usage for privacy preservation, enhancing resource allocation. From the results obtained, it is observed that the average network throughput of the proposed model outperforms Method [5] by 21.4%, Method [8] by 9.0%, and Method [14] by 18.0%. The highest throughput obtained specifies that the model will be efficient in utilizing network resources to accommodate high data rates. Moreover, the spectrum efficiency for the proposed model is 92%, which is 17.9% higher than in Method [5], 8.2% better than in Method [8], and 15.0% better than in Method [14]. This figure of efficiency indicates that the model is able to use the available spectrum to its full potential by keeping the wastage at minimum in various cases. For the case of preservative privacy, the proposed model resulted in 40% less data leakage, increasing by 60.0% compared to Method, by 33.3% compared to Method, and by 42.9% over Method. This is a very special highlight of the superiority in terms of user data protection by the proposed model, since there are effective ways of preserving privacy. The improvement concerning the consumption rate of resources was similarly high, amounting to an 88% utilization rate for the proposed model. This is 17.3% better than Method [5], 10.0% over Method [8], and 12.8% superior to Method [14]. This proves that the model can balance resource utilization along the network. In addition, the average computational processing time of the proposed model was quite effective, with a value of 120 seconds, faster by 20.0% compared to Method [5], 11.1% compared to Method [8], and 14.3% when compared to Method [14]. Another encouraging aspect of the model was its convergence speed, as convergence occurred in an average of 45 iterations, or faster compared to Method [5] by 25.0%, Method [8] by 18.2%, and Method [14] by 10.0%. It is implied that the proposed model enhances performance while at the same time operating with improved computational efficiency and faster levels of convergence. In a nutshell, the model proposed herein made for an important milestone in dynamic spectrum sharing and resource management, outperforming the existing methods across multi-dimensional performance metrics. It also holds real promise for meeting some of the demands of future wireless networks by integrating real-time spectrum allocation with privacy preservation and resource optimization.

Future Scopes

Future research could advance the proposed model in several aspects for better applicability and further performance improvements: incorporate the active learning mechanism in DQN to adapt better to time-varying network conditions and varied traffic patterns. Employment of meta-learning techniques so that the model may update learning parameters itself, adapting to an evolving environment. It will be more secure and privacy-enhancing for data if the hybrid model of the federated learning framework can be explored-further by combining FedAvg with other privacy-preserving techniques, secure multi-party computation, or homomorphic encryption. The other improvement that can be made in FedAvg is the supporting of heterogeneous device environments and heterogeneous data distribution. Besides, this would also enhance the robustness and applicability of the FedAvg module in diverse scenarios by enabling it to support heterogeneous device environments and different distributions of data. Advanced pheromone updating strategies can be considered for developing refinements in the ACO module, including the embedding of machine learning-based performance optimization techniques. One potential investigation could be the use of multi-objective optimizations within ACO for a proper trade-off among multiple performance metrics like throughput, efficiency, and fairness. This, in extension, might be more useful to address some challenges that are emerging, such as network slicing, edge computing, and IoT. Performance evaluation of the model in those contexts and adapting the same to handle some specific requirements and constraints of new technologies will lead to enhancement in relevance and impact sets. In this case, the model developed provides a very strong basis for further steps towards dynamic spectrum sharing and resource management, opening up large avenues of research and development toward performance optimization of next-generation wireless networks.

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