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Addressing Resource Allocation Challenges in Wireless Networks with Cultural Smell Agent Optimization Algorithms: A Literature Survey

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Abstract

The increasing difficulty and evolution of new wireless networks, specifically with the arrival of 5G technologies, require enhanced resource allocation strategies, that can adapt well to changing conditions. Established optimization methods often lack the capacity to address the scalability, flexibility, and real-time needs of such environments. This paper particularly reviews present optimization algorithms, highlighting evolutionary and swarm intelligence techniques, with specific stress on Cultural Algorithms (CAs) and Smell Agent Optimization (SAO). To take advantage of their varied strengths, it assesses the idea of merging the CA and SAO approaches into one algorithm. Although the Smell Agent Optimization emphasizes evaluating nearby options, premised on swarm behavior; using stored knowledge, Cultural Algorithms provide general guidance. Through examining previous research gaps, limitations, and the challenges faced, in wireless resource allocation, this paper advocates a new culturally motivated smell agent algorithm, aimed at improving adaptability, efficiency, and performance, in wireless networks. The proposed approach will offer strong solutions for evolving large-scale wireless environments, as well as promising to address scalability issues and improve convergence rates This work presents a foundational basis for future research in integrating nature-inspired metaheuristics to optimize resource management in next-generation wireless systems.

Keywords: *Wireless networks, resource allocation, cultural algorithms, optimization algorithms, smell agent.*

1.0 Introduction

In the modern integrated world, Wireless Sensor Networks (WSNs), have appeared as a pivotal technology, allowing the gathering and transmission of data, across shared environments, for practices; ranging from environmental monitoring, to industrial automation and smart cities [1]. With restricted computational abilities, energy resources, and communication bandwidth, these networks consist of numerous sensor nodes. The effective operation of WSNs, highly depends on the optimal allocation of these sparse resources, to increase network performance, longevity, and reliability [2]. Various important aspects encompass resource allocation in WSNs, including power allocation, channel assignment, computation offloading, and task scheduling. Due to the inherent constraints of WSNs, the optimization of these resources presents significant challenges, in form of limited energy supply, dynamic network topology, and heterogeneous node capabilities [3]. The need to satisfy several, often conflicting, goals, such as maximizing throughput, minimizing energy consumption, ensuring security, and reducing latency [4], further amplifies the difficulty.

Conventional optimization techniques, such as linear programming [5], dynamic programming [6], and convex optimization [7], have been relied on by previous approaches to resource allocation in WSN. Nevertheless, in WSN, these methods are often challenged by the non-convex, mixed-integer, and NP-hard nature of resource allocation problems. The difficulty of finding an exact optimum due to its computational demands, along with the non-guaranteed results of current global optimization strategies, drives the imperative to invent superior, high-performing optimization techniques.

Recently, in the research community, nature-inspired metaheuristic algorithms have gained credible attention, as effective tools, for solving difficult optimization problems [8]. While these algorithms are motivated by natural phenomena, with a focus on evolutionary and swarm intelligence methods, the review explores current optimization techniques, for resource allocation. By studying recent algorithms and their utilization, this work evaluates the possibility of hybridizing Cultural Algorithms (CA) and Smell Agent Optimization (SAO).

2.0 Optimization Algorithms Fundamental

Optimization algorithms are mathematical methods used to find the best possible solution to a problem under given constraints. They are essential in fields like engineering, economics, machine learning, and operations research.

2.1 Cultural Algorithms

Evolutionary algorithms that utilize a belief space to streamline optimization, are called cultural Algorithms (CAs). This belief space collects and stores knowledge from the population, leading to improved search efficiency. Increasingly evident is the utility of CAs in networking environments. For example, authors in [9] showed CAs' flexibility in adapting to changing conditions by employing meta-heuristic methods, potentially including CAs for dynamic task allocation in Internet of Thing (Io)T networks. In the same vein [10], used evolutionary algorithms to optimize resource allocation in wireless networks. These works have shown the potential of CAs for optimizing network performance.

2.2 Smell Agent Concepts

Based on swarm intelligence principles which birthed the Smell Agent Optimization (SAO) algorithm [11], agents utilize "smell" for sniffing, trailing, and random movements, in SAO. When analyzed on standard benchmarks and when applied to hybrid renewable energy systems, the algorithm exhibited great efficiency. In relation to the study [12] investigated ACO for routing protocols in wireless sensor networks. They suggested that pheromone-based mechanisms, analogous to smell-based trails, could enhance local search capabilities.

2.2.1 SAO Model

The model uses three modes to search for the best possible positions which are explained below

(a) Sniffing Mode:

As smell molecules are prone to diffusing in the agent's location, this process is initiated with arbitrarily prompted inceptive smell molecule's locality. Using equation (1) with N amount of Smell molecules and D quantity of decision variables, the smell molecules can be initialized. Equation (2), in the search space is used to generate the highest position of the agent, which gets activated by the position vector in equation (1) given by [13,11].

$$m_i^{(t)} = \begin{pmatrix} m_i(1,1) & \dots & m_i(1,D) \\ \vdots & \vdots & \vdots \\ m_i(N,1) & \cdots & m_i(N,D) \end{pmatrix} \quad (1)$$

$$m_i^{(t)} = (ub_i - lb_i)r_0 + lb_i \quad (2)$$

The upper and lower bound, defined for decision variables, are represented by ub and lb, while r_0 represents an arbitrary digit generated in the range of [0,1].

Assigned to each smell molecule, is the initial velocity, by which they diffuse from the smell source, given by equation (3)

$$vel_i^{(t)} = \begin{pmatrix} vel(1,1) & \dots & vel(1,D) \\ \vdots & \ddots & \vdots \\ vel(N,1) & \cdots & vel(N,D) \end{pmatrix} \quad (3)$$

Eq. 4 is used to update the current position of the smell molecules since it diffuses in a Brownian form [14]

$$m_i^{(t+1)} = m_i^{(t)} + (\Delta t) vel_i^{(t+1)} \quad (4)$$

Δt is assumed to be unity in SAO, which reveals the agent constantly taking a successive step one after the other during the process of optimization and the new position is given by equation (5) given by [11].

$$m_i^{(t+1)} = m_i^{(t)} + vel_i^{(t+1)} \quad (5)$$

Equation (6) is used to compute the new velocity of the smell molecule due to that fact; the smell molecule, until it gets to the agent's position, diffuses in an irregular manner.

$$vel_i^{(t+1)} = vel_i^{(t)} + vel \tag{6}$$

where Eq. 7 gives the updated component of the velocity vel [11].

$$vel = (\sqrt{\frac{3K_0 T_a}{M}}) \times r_1 \tag{7}$$

where
K_0: Boltzmann constant
T_a: Temperature
M: mass of smell constant
As a smell molecule is Brownian, same as gas molecules, then its updated velocity in (7) is got from the idea behind hydro static pressure of gases. Respectively, the values of T and M have been experimentally determined to be 0.825 and 0.175.

(b) Trailing Mode:

It (mode) conditioned the agent's searching behaviours towards finding the origin of a smell. The agent uses the equation below to move towards the discovered new position, if it finds it better than the previous position, while searching for origin of a smell.

$$m_i^{(t+1)} = m_i^{(t)} + r_2 \times olf \times (m_{agent}^{(t)} - m_i^{(t)}) - r_3 \times olf \times (m_{worst}^{(t)} - m_i^{(t)}) \tag{8}$$

where r_2 *and* r_3 are randomly selected numbers in range [0,1], r_3 is used to penalize olf on $m_{worst}^{(t)}$ while r_2 is used to penalize the influence of olf on $m_{agent}^{(t)}$.
The present smell position and the worst smell fitness are obtained from the sniffing mode, in order, to facilitate effective trailing of the smell's path by the agent. This assists the algorithm in improving the balance between exploitation and exploration as seen in equation (8). The value of the olfaction lobes should be considered properly during selection, since choosing a small olf value shows weak olfaction, which favours restricted searching, although, choosing a big olf value indicate stronger olfaction which is better for global search [11].

(c) Random Mode:

The agent's ability to follow a scent gets difficult over a long distance, because the smell molecules become too spread out (their concentration is compromised).The resulting change and weak intensity of the scent makes the agent lose the trail, causing it to feel trapped in a local solution (local minima) rather than finding the true source. Consequently, if the agent loses the trail or can't find the source agent, it automatically switches into a random search mode indicated by equation (9) given by [11].

$$m_i^{(t+1)} = m_i^{(t)} + r_4 \times L_s \tag{9}$$

Where r_4 is a random number, selected to stochastically sanction the value of the step length L_s, and L_s is a constant, indicating the step length. Figure 2.5 proffers the conceptual framework of SAO, where the agent is shown as the cat; while the smell source is represented by a circle.

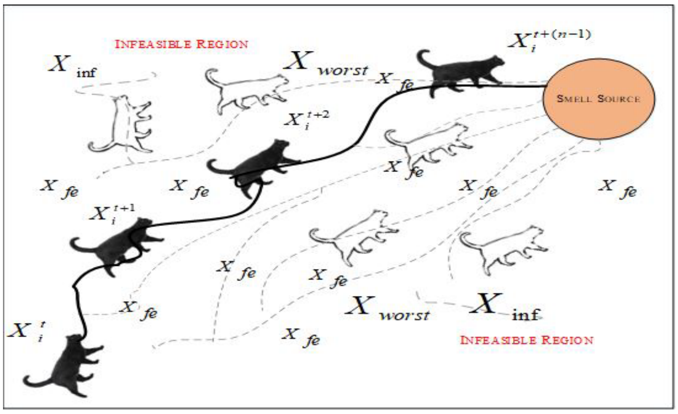

Figure 1: Conceptual framework of SAO [11]

2.3 CA Model

In solving a great number of varied issues in search and optimization, Evolutionary Computation (EC) methods have been successfully implemented, as a result of the objectivity of their operational functions, that can yet have optimum effect in positions of small or no domain knowledge. Therefore, evolution is a learning and an optimization process [15,16,]. In culture, what is being learned, including the way to learn, is embedded into culture itself. As the highest in a complex adaptive knowledge-based system, culture can be seen as the most general infrastructure. CA was developed initially by Reynolds [17] in 1994, to model the evolution of the cultural component of an EC system over time as it gathers experience. As a means for building consensus and amplifying a group or individual behaviour, is the cultural evolution process. This means that, “conceptual beacons” that identify ideal and unideal behaviour for individuals in a population (society) are accumulated during cultural evolution [16]. The Cultural Algorithm framework provides a mechanism supporting the dual inheritance system, featuring, the individual phenotypic evolution at the micro evolutionary and the human culture at the macro evolutionary level [18]. Cultural Algorithm’s structure Key Components are:
(i) Methods to acquire knowledge, acceptance function
(ii) The belief space awareness types,
(iii) The degree of self-adaptation, and
(iv) Procedure to explore knowledge in guiding the people through the influence function.
Thus, the goal would be to optimize cultural systems themselves, to solve any type of optimization problem.

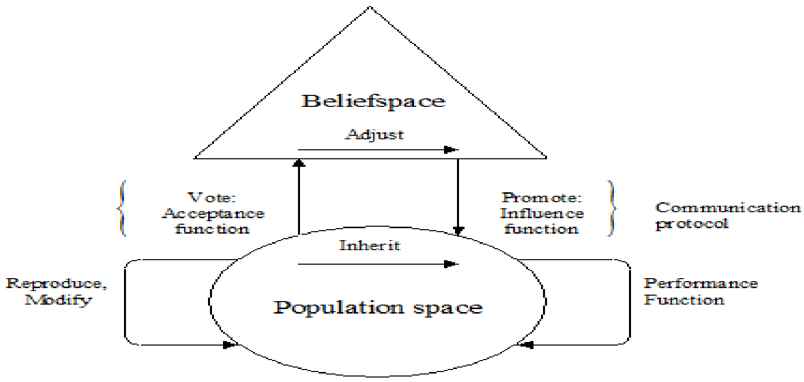

Figure 2: Cultural algorithm framework [18]

Figure 2 showing the social population and a belief space, incorporated in the algorithm. Individuals that are experienced are selected from the population space, by the acceptance function. This is utilized for creating embedded solutions, in the belief space. The belief space stores and manipulates knowledge acquired from the individuals, combined with experience in the population space [16]. This embedded knowledge in the belief space can exploit the evolution of the population component, through the influence function. With the dual components relating via a communications protocol, invariably, the Cultural Algorithm can be seen as a two-inheritance system evoluting at the population level and the belief space level. This sets rules that group *acceptable* individuals, capable of updating the belief space [16]. It is evident that the development and growth of a society is determined by the creative mind of committed minorities.

2.3.1 Knowledge Representation in Belief Space

Guiding the evolutionary search, is the belief space, comprising normative, domain, situational, temporal, and spatial knowledge [18, 19]. In guiding search towards optimal resource allocation in wireless networks, this work highlights the central role of situational knowledge (elite solution retention). In addition, normative knowledge (dynamic adjustment of decision variable ranges like bandwidth and power) enhances convergence efficiency and reduces computational cost, critical for adapting to evolving wireless environments. Situational and normative knowledge offer the best of pragmatic and computationally effective perspective for real-time wireless network optimization, though, other belief space components exist.

The belief space formal syntax, B_s, is a pair structure, used in here, $< K, D_n >$, where K is a set of best individuals or exemplars, comprising the situational knowledge. D_n, the normative component, is a set of interval information for the individual n parameters. Each of these n intervals in the belief space is represented as a triple$< xc_j, L, U >$. xc_j denotes the closed *interval* for variable j, that is a continuous set of real numbers x represented as a few pair:

$$xc_j = [l_j, u_j] = \{x | l_j \leq x \leq u_j\} \tag{10}$$

(a) Normative Knowledge

Normative knowledge is a set of variable ranges; norms or standards for behaviours of individuals and guidelines, in which adjustments of individuals can be made [18]. This type of knowledge relates to the obtainable or viable solution space of the optimization problems. It provides standards and guidelines for individual behaviour by which individual adjustments can be contained [19]. The component of Normative knowledge, is given, in the belief space N_p as:

$$N_p = \langle xc, U, L, \ D_n \ \rangle, \tag{11}$$

Where the closed interval for variable j, is denoted by xc_j; which is a progressive set of real numbers x, represented in (10), while U, L, and D, are n -dimensional vectors. L_j and U_j are the values of the fitness function associated with the bound l_j and u_j, respectively. On the other hand, the lower and upper bounds for the j^{th} variable, are l_j and u_j. Generally, l_j and $u_j$are initialized with the lower and upper bounds of individuals, while the L_j and U_j are initialized with positive infinity.

Often, if they are not there already, normative knowledge, leads individuals to "dive into the good range" [16]. Based on normative knowledge, in the belief space, the parameter values for individuals selected by the acceptance function, are used to calculate the current acceptable interval for each parameter. This perspective enables conservativeness; achieved by narrowing the interval and progressiveness, while widening the interval [19]. The formulated interval update rule is given as follows:

For the left boundary and its score for parameter j [19]:

$$l_j^{t+1} = \begin{cases} x_{i,j}^t & if x_{i,j}^t \leq l_j^t or f(x_i^t) < L_j^t \\ l_j^t & otherwise \end{cases} \tag{12}$$

$$L_j^{t+1} = \begin{cases} f(x_i) & if \ x_{i,j}^t \leq l_j^t \ or \ f(x_i^t) < L_j^t \\ L_j^t & otherwise \end{cases} \tag{13}$$

where i^{th} individual affects the lower bound for parameter j. l_j^t Represents lower limit for parameter j at generation t and L_j^t denotes the performance score (fitness) for it. For the right boundary and its score for parameter j:

$$u_j^{t+1} = \begin{cases} x_{k,j} & if \ x_{k,j} \geq u_j^t \ or \ f(x_k) < U_j^t \\ u_j^t & otherwise \end{cases} \tag{14}$$

$$U_j^{t+1} = \begin{cases} f(x_k) & if \ x_{k,j} \geq u_j^t \ or \ f(x_k) < U_j^t \\ U_j^t & otherwise \end{cases} \tag{15}$$

Where, k^{th} individual affects the upper bound for parameter j. u_j^t, at generation j, represents upper limit for variable at generation t and U_j^t, as well as denotes the performance score for it.

(b) Situational Knowledge

Situational knowledge provides useful, set of exemplary cases, for the translation or interpretation of specific individual experience. Knowledge such as these, guides individuals to "move towards the exemplars [20];[16];[17]. This situational knowledge exemplar set integrates only the best solution discovered thus far, that is (17), at iteration t.

$$x_s = \langle x_s^t \mid x_s^t = \left\{ x_1^t, x_2^t, \ldots x_n^t \right\} \rangle \tag{16}$$

The initial solution can be set to the best found in the first iteration. This solution will then be iteratively improved using the following update rule [10]:

$$x_{sj}^{t+1} = \begin{cases} x_{sbest,j}^{t+1} & if \quad f(x_{sbest,j}^{t+1}) < f(x_s^t) \\ x_{sj}^t & otherwise \end{cases}, \tag{17}$$

Where x_{sbest}^{t+1} represent the best agent at generation t+1.

(c) Acceptance Function

Individuals capable of impacting the forming of a new or current belief space, is selected by an acceptance function. Though, a few distinctive classes for acceptance function can be employed. Deterministic in nature, are t*he first class* of functions and they strictly use data about the absolute relative hierarchy (above average individuals) or ranking (top 10%, top 20%, top 30%, top 40%, and top 50%-median of individuals in the population, respectively) for the purpose of selecting the individuals that will be used in updating the belief space [19];[11]. *The second class* of functions are also deterministic but use temporal information for the many generations previously explored. This function is expressed below:

$$accept_{20\%'}(M^t) = m \cdot \beta + \lfloor m \cdot \beta / c \rfloor \tag{18}$$

Where the current number of generations is *c,* the size of the population is *m*. Since 0.2 is used for *β*, this is like top 20%.

3.0 Combining Cultural Algorithms with Smell Agent Concepts

Integrating cultural algorithms with smell agent mechanisms could yield a hybrid approach with unique advantages. While smell agents enhance local exploration, potentially improving convergence and adaptability, the belief space of CAs could provide high-level guidance. Although no direct implementations exist, authors in [21] merged cultural algorithms with genetic algorithms, for multi-objective optimization, demonstrating enhanced performance. This suggests that resource allocation challenges in wireless networks can be effectively addressed by cultural smell agent approach.

3.1 Cultural Smell Agent Optimization (CASAO)

Smell Agent Optimization (SAO) and Cultural Algorithms (CAs) boast distinct strengths when applied to complex optimization problems. SAO excels at exploration, efficiently navigating the search space. However, it can struggle with exploitation, potentially getting stuck in suboptimal solutions due to premature convergence. Conversely, CAs offer a structured approach for knowledge sharing and exploiting existing information. This strength can become a weakness, as CAs might prioritize known solutions and struggle to explore new areas of search space, potentially leading them to miss the global optimum. By combining SAO's exploration prowess with CA's knowledge-sharing mechanisms, the resulting hybrid algorithm to be known as Cultural Smell Agent Optimization (CASAO) has the potential to achieve a superior balance between exploration and exploitation. This could lead to significantly improved performance in solving complex optimization problems across various domains.

4.0 Optimization Algorithms for Resource Allocation in Wireless Networks Based Reviews

In [22], the authors introduced a genetic algorithm design, to make channel allocation in 5G networks fairer and increase throughput. In [23], the authors used Particle Swarm Optimization (PSO) for power control which resulted in energy efficiency advantages. Authors in [24] highlighted that metaheuristics could easily tackle complicated, non-linear problems, but struggle in many-node networks as solutions often converge slowly. This result calls for algorithms that combine being efficient with the ability to scale. Table 1 summarizes key studies about making optimal use of wireless networks' resources. Several techniques and problems dealing with the interplay between different network devices have been explored by scientists, focusing on critical goals like managing power use and ensuring quality of service to customers in variable networks.

Table 1: Summary of review

Authors (Year)	Nature of Research	Proposed Solution	Challenges
[25]	Resource Allocation, Using Evolutionary Approach for 5G Mobile Communication Based NOMA	A new method for allocating resources for 5G with the AOA was developed, by paying attention to channel conditions, user movement and how different services are used, so that throughput, spectral and energy efficiency improve.	AOA faces limitations in handling the stochastic nature of wireless environments, scalability issues, constraint integration, premature convergence, and lacks specialized operators for practical deployment.
[26]	A Resource Allocation Algorithm, for Cognitive Radio Networks, Based on Hybrid Spider Wasp Optimization	Introduced Spider Wasp Optimization (SWO) and its hybrid version (HSWO with GA) to solve a non-convex optimization problem for maximizing channel capacity in cognitive radio networks under interference, power, and fairness constraints.	The SWO-GA hybrid lacks structured knowledge accumulation, limiting its search guidance and adaptability in dynamic wireless environments, with risks of premature convergence despite GA-induced diversity
[27]	Multi-objective Optimization for Dynamic Resource Allocation in Heterogeneous Unmanned Aerial Vehicle-Base Station	Proposed a heterogeneous UAV-based station architecture within a C-RAN framework. Introduced two meta-heuristic algorithms: GARAH (energy and delay minimization) and SARAH (balancing efficiency, latency, and handovers) for multi-objective optimization.	Multi-objective optimization introduces high computational cost, slower convergence, limited knowledge sharing, and difficulty handling complex wireless constraints.
[28]	Hybrid Models in Wireless Sensor Networks, for Forecasting Allocative Localization Error	RBF models optimized via Coot, Smell Agent & Northern Goshawk (RBCO, RBSO, RFNG, RSNC)	No mechanism for incorporating prior search knowledge
[29]	An Advanced Energy Efficient Resource Allocation for Software-Defined WSN Using Hybrid Optimization Algorithm	Hybrid Election-based Ladybird Beetle Optimization (HELBO)	Lacks knowledge accumulation mechanism
[30]	A multi-agent-based dynamic charging strategy, for UAV-assisted wireless rechargeable sensor networks	The combined optimization problem was created, as a partially observable Markov decision process (POMDP) and solved, using the g-MAPPO algorithm	Limited parallelization and knowledge sharing
[31]	Energy-Aware Resource Allocation for Energy	Iterative algorithm with inner approximation	Limited exploration of diverse strategies

Authors (Year)	Nature of Research	Proposed Solution	Challenges
	Harvesting Powered Wireless Sensor Nodes		
[32]	A Hierarchical Traffic Offloading Mechanism in a Multi-Hop Multi-Connection Wireless Sensor Network, for End-to-End Reliability	Hierarchical Traffic Offloading Mechanism (HTOM) with Stackelberg game and Lyapunov DPP	Computational complexity; modeling challenges
[33]	An Online Strong Resource Distribution Algorithm for Mobile Edge Computing	Dynamic Fault Tolerance Task Packing (DFTTP) algorithm	Lacked broad global exploration and adaptive learning
[34]	Co-Design of a Wireless Networked Control System, for Reliability and Resource-Efficiency	RL-based approach for network and control optimization	Learned policies lack interpretability
[35]	Energy Efficiency Maximization, in Wireless Sensor Networks Deploying Discrete Power Splitters, for Intercluster Transmission	Variable-dimension expansion for cooperative SWIPT	Not robust for fixed-dimensional problems
[36]	Resource allocation and Energy-efficient deployment, for O-RAN-enabled UAV-assisted communication	Double-loop algorithm with Dinkel Bach and BCD	Slow convergence and local optima issues
[37]	Energy Efficient Resource Distribution, for Wireless Powered Short Packet Communication Networks	Golden section, bisection, and successive convex approximation methods	Unsuitable for multi-dimensional complexity; lacks global search
[38]	Trajectory Design and Resource Allocation for Edge Computing Integration and Multi-UAV-Assisted Sensing, Communication	Multi-agent proximal policy optimization algorithm to handle the decision-making problem, with attention mechanism	Requires extensive data and resources; slow adaptation
[39]	Resource Allocation Strategy with MI Communication and Hybrid Acoustic, in AUV-Assisted Edge Computing UWSN	Alternating iterative algorithm for optimization	Local optima, slow convergence, poor constraint handling
[40]	Optimal AI model splitting and resource	DRL-based method for model splitting and allocation	Low efficiency, instability, lack of interpretability

Authors (Year)	Nature of Research	Proposed Solution	Challenges
	allocation in multi-user wireless sensing systems, for device-edge co-inference		
[41]	On-Demand Collaborative Sensing with Digital Twins-Driven Resource Distribution	Resource allocation using digital twins	Relies on accurate data; vulnerable to noise
[42]	Resource optimization for UAV-assisted SWIPT systems and Joint trajectory: A comparative study of nonlinear and linear energy harvesting models	Iterative BCD algorithm for trajectory and power	Slow convergence and prone to local optima
[43]	UAV Trajectory Design and Joint Resource Allocation, in Air-Ground Integrated IoRT Sensors Network with Clustered NOMA, for Data Collection	TD3-based algorithm for resources and trajectory	Low sample efficiency; exploration-exploitation balance
[44]	Improving Energy Efficiency in WSN through Routing for Resource and Adaptive Memetic-Based Clustering	Hybrid Memetic Evolutionary Algorithm (HMEA), with optimization and memetic clustering	Relies on genetic information; complex implementation
[45]	AI-Based Decision Support System, Optimizing Wireless Sensor Networks, for Consumer Electronics in E-Commerce	AI techniques for efficiency and performance	Limited exploration and adaptation capabilities
[46]	Delay-aware Online Resource Allocation, over Wireless Networks, for Buffer-aided Synchronous Federated Learning	Buffer-aided FL with adaptive data release	Relies on all clients completing updates
[47]	Data-Centric Resource Allocation, with Lossy Links Based on Compressive Sensing, for Machine-Type Communications	Greedy algorithm for compressive sensing	Specialized, not general-purpose

Authors (Year)	Nature of Research	Proposed Solution	Challenges
[48]	Joint Resource Optimization with Integrated Sensing, Computation and Communication, for Federated Edge Learning	Joint SC2 optimization with BCD and Lyapunov	Multiple limitations in function selection and accuracy
[49]	Utilizing Machine Learning Approach, in Wireless Sensor, to Forecast Average Location Determination Errors	RFR with SAO and GJOA	No performance-enhancing mechanisms explored
[50]	Algorithm for Cultural Bat Optimization: An Improved Variant of Bat Algorithm	CABAT with cultural evolution	Its effectiveness for wireless resource allocation was not tested
[51]	A Novel Applications and Orca Cultural Algorithm	OCA combining OA and CA	Lacks research on wireless resource allocation
[52]	Resource allocation strategy on actor-critic, for online wireless sensor networks based	Actor-Critic RL for optimal allocation	Struggles with high-dimensional, dynamic networks
[53]	Nature-inspired Algorithms: A comprehensive survey for Wireless Sensor Networks	Nature-Inspired Optimization Algorithms Concerning the Optimal Coverage in WSNs	Excludes learning mechanism structure

5.0 Challenges and Research Gaps

Examining recent approaches to resource allocation in wireless networks reveal significant problems preventing them from working efficiently. The lack of exploration and adaptability in most approaches results in less than desirable solutions and a lack of adaptiveness when conditions or objectives shift [39]. Some methods struggle to make lucid and explainable decisions [32]. As shown in [50] and [33], many are inappropriate for high- or low-dimensional challenges. Though, some algorithms tend to converge slowly and often get stuck in the local optima [50]. Some of the methods, in addition, require extensive training data and computing power which make them impractical for real-time, evolving environments [36]. Some often do not respond well to discrete data, tough problem limits or relying on their past searches [51]. Some novel algorithms face challenges when operating in high-dimensional, changing environments. Some require series of samplings to learn and struggle in exploitation and exploration strategies [50,41]. Some algorithms are either inherently limited or lack proven efficiency for wireless resource provisioning, revealing that another adaptive solution is necessary [49,50].

6.0 Conclusions

The proposed Cultural Smell Agent Optimization Algorithm would be designed to fix known issues in wireless resource allocation by intelligently hybridizing Cultural Algorithms and Smell Agent Optimization. It would use the three modes of SAO search mechanism to explore the entire solution space and find new solutions. Simultaneously, the Cultural Algorithm component, which maintains a belief space to store and update successful strategies, would allow the agents to adapt to new learnings and use known best practices. This dual approach, which involves agents gathering and sharing knowledge to prevent repeating tasks, would make the algorithm highly efficient and adaptive in complex, dynamic wireless environments. By relying on past experience instead of analyzing heavy new data, it would conserve resources and promises to deliver stronger, more reliable resource allocation than current methods.

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