LEVERAGING HYBRID OF METAHEURISTIC AND EVOLUTIONARY ALGORITHMS FOR OPTIMIZATION IN NIGERIA'S SPACE PROGRAM

Saliu, A.S.[1*], Mathew, O.A.[1], Iliya, S.Z.[1], Abdulkareem, H.[2], Shobowale, K.O.[3], Abubakar, U.[4] and Alioke, O.C.

[1]National Space Research and Development Agency (NASRDA), Abuja, Nigeria

[2]Department of Electronics and Telecommunication Engineering ABU, Zaria, Kaduna

[3]Mechatronics Engineering Department, Air Force Institute of Technology, Kaduna

[4]Department of Computer Engineering, Ahmadu Bello University, Zaria

[*]*Corresponding author email:* saliualiu73@gmail.com

ABSTRACT

This work assesses the potential of the synergy between hybrid metaheuristic and evolutionary algorithms for optimizing Nigeria's space program, administered by NASRDA. The problem addressed lies in the absence of published research directly applying such advanced optimization techniques within Nigeria's space ecosystem, despite their proven global success and the urgent need for improved efficiency in satellite design, mission planning, and resource allocation. Efficient optimization is vital for satellite design, mission planning, and data analysis, as Nigeria seeks indigenous space capabilities for socio-economic growth. The aim of the research is to evaluate the applicability of hybrid metaheuristic and evolutionary algorithms toward enhancing operational performance and innovation in Nigeria's space program. By balancing solution exploration and refinement, hybrids of metaheuristics and evolutionary algorithms excel at solving such complex problems. The methodology adopted involved a focused literature review, identification of research gaps, and conceptual modeling using a hybrid approach in line with the Nigeria space context. Although, findings show, that these strategies, have been successfully implemented, in related fields, such as aerospace, logistics, and energy systems, their application in Nigeria's space program, stays largely undocumented, showing a huge opportunity, for performance improvement. The lack of published research, on their specific application, in Nigeria's space context, reveals a significant gap, in this study. The work recommends target assessment, benchmarking initiatives and capacity building, based on these findings, to promote the integration of hybrid optimization methods, into Nigeria's space operations. This would lead to improved efficiency and innovation, bridging the literature gap and advance space technology objectives.

Keywords: Benchmarking, Evolutionary algorithms, Hybrid, Metaheuristic, Space

1 NTRODUCTION

The utilization and exploration of space pose sophisticated challenges that often require complex optimization techniques to plan missions, manage resources, and efficiently process massive datasets. As nations such as Nigeria advance their space programs, the need for effective and robust optimization strategies becomes critically important. Through the National Space Research and Development Agency (NASRDA), Nigeria has articulated a vision centered on building indigenous capacity in space technology to drive socio-economic development [1]. Achieving this vision demands addressing numerous optimization challenges inherent in satellite design, constellation management, mission planning, remote sensing data analytics, and communication systems. Optimization problems are widespread in science, engineering, economics, and other disciplines, involving the selection of the best solution from a set of feasible alternatives based on one or more objectives while adhering to constraints. Real-world optimization problems—especially those within complex systems such as space programs—often exhibit high dimensionality, non-linearity, multiple objectives, and constraints. These characteristics typically categorize them as NP-hard problems, making exact solutions using traditional mathematical programming or exhaustive search computationally infeasible due to prohibitive time and resource requirements [2, 3]. Consequently, advanced computational strategies are required to effectively navigate such complex problem spaces. Metaheuristic algorithms have emerged as powerful tools for solving high-dimensional and computationally intensive optimization problems, particularly where traditional methods fail. These high-level search strategies are designed to explore vast and complex solution spaces within reasonable computational budgets. Unlike exact methods, metaheuristics do not guarantee the globally optimal solution; however, they efficiently approximate high-quality solutions and are typically inspired by natural, social, or physical processes [4]. Among these, Evolutionary Algorithms (EAs) and their hybrid forms have gained significant prominence. EAs mimic principles of natural evolution through mechanisms such as selection, mutation, and recombination, while hybrid metaheuristics combine the strengths of complementary techniques to enhance performance by balancing exploration (diversification) and exploitation (intensification) within the search space [5, 6]. This review critically examines the potential application of hybrid metaheuristic and evolutionary algorithms within the context of Nigeria's space program. It begins by outlining the fundamental concepts and theoretical underpinnings of these advanced optimization techniques, detailing their key principles, robustness, and rationale for hybridization. Furthermore, it explores general applications across various disciplines, highlighting their proven effectiveness in solving complex optimization problems. The discussion then transitions to Nigeria's space program, presenting its objectives, current achievements, and prevailing challenges, while identifying critical areas where optimization-based solutions are most relevant. Special emphasis is placed on aligning contemporary advances in hybrid metaheuristics with specific opportunities within Nigeria's space initiatives. A significant gap identified relates to the paucity of documented applications of these advanced optimization techniques within the Nigerian space ecosystem. Addressing this gap, the review provides insights into the potential benefits and future research directions toward the practical integration of hybrid metaheuristic algorithms into national space initiatives. The overarching objective is to deliver a comprehensive perspective that informs researchers, engineers, and policymakers of the optimization capabilities offered by hybrid metaheuristic and evolutionary algorithms, and to stimulate further investigation into their deployment to enhance the efficiency, resilience, and effectiveness of Nigeria's space program.

2 REVIEW OF FUNDAMENTAL CONCEPT

This section lays out the fundamental terminology that underpin optimization theory and its algorithms. Developing a clear and precise grasp of these notions is crucial for correctly formulating optimization problems, choosing suitable solution techniques, and interpreting outcomes with rigor. The central ideas are outlined here in brief, with formal definitions and statements presented in the subsections that follow.

2.1 Evolutionary Algorithms (EAs)

EAs operate on a population of candidate solutions (individuals), iteratively refining them over generations. Evolutionary Algorithms (EAs) form a great subclass of metaheuristics, finding inspiration in the principles of biological evolution, such as natural selection, inheritance, mutation, and recombination [7]. Core aspects include: Population – a set of possible solutions to the issue; Fitness Function – based on the optimization objectives, a function that assesses the quality or suitability of each individual solution [8]*;* Selection – a mechanism that mimics natural selection, by favoring fitter individuals for reproduction [9]*;* Genetic Operators – operators such as crossover (recombination) and mutation proffer variation into the population. While mutation introduces small, random changes, crossover combines genetic material from parent solutions to create offspring [10]. Conventional types of EAs are Genetic Algorithms (GAs), Evolution Strategies (ES), Genetic Programming (GP), and Evolutionary Programming (EP). EAs possess strong global search capabilities, due to their population-based nature and stochastic operators, and are inherently parallelizable, making them efficient at reaching varied regions of the search space [7, 10]

2.2 Metaheuristic Concepts: Intensification and Diversification

A fundamental challenge in designing any search algorithm is achieving an effective balance between intensification and diversification [11]. Diversification (Exploration) refers to the ability of the algorithm to explore different, unvisited regions of the search space. This is crucial for avoiding premature convergence to local optima and increasing the chances of finding the global optimum. Intensification (Exploitation) refers to the ability of the algorithm to thoroughly search the vicinity of promising solutions found so far, aiming to refine them and find better solutions within those regions. An algorithm that overemphasizes diversification may wander aimlessly without converging to good solutions, while one that overemphasizes intensification may quickly get trapped in a suboptimal region. Most metaheuristics incorporate mechanisms to manage this trade-off, but achieving the right balance is often problem-dependent and a key area of research.

2.3 Hybrid Metaheuristics

Recognizing that individual metaheuristics often have inherent strengths and weaknesses concerning the exploration-exploitation balance, researchers have increasingly focused on hybridization. Hybrid metaheuristics combine two or more algorithms (which can be metaheuristics or other optimization techniques like local search) to create a synergistic effect, leveraging the strengths of each component to achieve better overall performance [12, 13]. The rationale behind hybridization is to combine algorithms with complementary characteristics. For instance, an algorithm strong in exploration might be combined with one strong in exploitation. EAs, with their flexible population-based framework, are particularly well-suited for hybridization. They can be specialized to focus on either intensification or diversification and then integrated into hybrid frameworks [14, 15]. Common hybridization approaches include: Relay Hybridization: Algorithms run sequentially, passing information from one to the next [16]. Teamwork Hybridization: Algorithms run concurrently, exchanging information [17]. Embedding: One algorithm is embedded within another (e.g., using a local search method to refine solutions found by an EA, or using an EA as a perturbation mechanism within an Iterated Local Search framework, as discussed in one reviewed paper [18, 19]. Component Swapping: Combining specific operators or components from different algorithms [20]. The literature consistently demonstrates that well-designed hybrid metaheuristics can outperform their constituent algorithms, offering improved solution quality, faster convergence, better robustness, and the ability to handle more complex and larger-scale problems effectively [21]. This makes them particularly promising for the demanding optimization tasks encountered in space exploration and utilization.

3 GENERAL APPLICATIONS OF HYBRID METAHEURISTIC AND EVOLUTIONARY ALGORITHMS

Hybrid metaheuristic and evolutionary algorithms have demonstrated significant success across a wide spectrum of optimization problems in diverse fields. Their ability to navigate complex, high-dimensional search spaces and effectively balance global exploration with local refinement makes them suitable for challenges where traditional methods are inadequate. While the literature searches for this review did not uncover specific applications within Nigeria's space program, examining their use in analogous domains provides valuable insights into their potential.

3.1 Engineering Design and Optimization

Engineering design frequently involves optimizing complex systems with multiple interacting components and objectives. Hybrid EAs have been applied to: Structural Optimization: Finding optimal shapes, sizes, and topologies for structures under various load conditions and constraints. Zhao et al., [22] proposed a hybrid Cultural Algorithm with Genetic Algorithms (HCGA) for truss weight minimization, using a knowledge-guided t-mutation operator to improve convergence and avoid local optima. Aerospace Engineering: Although not specific to Nigeria in the consulted literature, applications globally include trajectory optimization for spacecraft, aerodynamic shape optimization, and satellite constellation design. These problems often involve complex dynamics and numerous constraints, making them ideal candidates for metaheuristic approaches. Lim & Kim, [23] in their study used a hybrid NSGA-II with adaptive local search for airfoil optimization, improving convergence for subsonic and transonic designs. Building Design: As seen in one of the reviewed articles [24], hybrid methods combining EAs and co-evolutionary simulations were used for early stage building spatial design, optimizing for both structural and thermal performance. The hybridization improved search efficiency and the ability to explore larger design spaces.

3.2 Logistics and Operations Research

Optimization is central to logistics and operations research, dealing with problems like routing, scheduling, and resource allocation. This can be seen in such areas as: Vehicle Routing Problems (VRP). Finding optimal routes for vehicles to serve a set of customers. Hybrid approaches, such as combining EAs with local search heuristics (the Lin-Kernighan Heuristic) mentioned in a study [25] or using EAs as perturbation methods, in Iterated Local Search (ILS) frameworks [18], have proven effective.

3.2.1 Scheduling

Optimizing schedules for tasks, personnel or machines, in project management, manufacturing, or transportation. Barredo & Puente [26] in their work, developed a hybrid genetic algorithm which was made up of the Heterogeneous Earliest Finish Time (HEFT) heuristic for scientific workflow optimizing make span and scheduling, while cloud resource constraints were considered.

3.2.2 Supply Chain Management

Optimizing inventory levels, distribution networks and facility locations. Luo et al. [27], proffered a modified NSGA-II (MNSGA) and a mixed-integer linear programming model, for a homogeneous flow shop context. For improved performance, the MNSGA features a three-level encoding, a local search and adaptive operators.

3.3 Data Science and Machine Learning

In data science and machine learning, Metaheuristics are highly used, to handle optimization challenges. Particularly, in such areas as:

3.3.1 Feature Selection

Identifying the most relevant subset of features, for reducing dimensionality, building predictive models, and improving model performance. Hybrid algorithms combination methods, like the Firefly

Algorithm (FA) or Butterfly Optimization Algorithm (BOA), with information-theoretic criteria was utilized [28, 29].

3.3.2 Hyperparameter Optimization

While tuning the parameters of machine learning models (neural networks, support vector machines), to achieve optimal performance, Xu et al., [30], MDE-DPSO was used to tune PSO, through dynamic strategies and DE's mutation-crossover, to overcome premature convergence in single-objective optimization.

3.3.3 Clustering

Where metaheuristics can help find optimal cluster centroids or structures; Wang, [31] grouped similar data points, and created an approach to efficiently identify customer characteristics, enhancing profit and marketing efficiency, validated through a Kaggle dataset and achieving high classification accuracy.

3.4 Benchmark Problems and Algorithm Development

A significant portion of the research, emphasizes developing new hybrid algorithms and testing them on standard benchmark optimization functions (CEC benchmark suites) [22]. This rigid testing helps to establish, the effectiveness and strength of new hybridization strategies (combining Honey Badger Algorithm (HBA) and Sand Cat Swarm Optimization (SCSO) or Particle Swarm Optimization (PSO), Gravitational Search Algorithm (GSA), and Grey Wolf Optimizer (GWO)), before applying them to real problems. These diverse applications highlight, the diversity and power of hybrid metaheuristic and evolutionary algorithms. In addition to Nigeria challenges, their proven success in tackling complex optimization tasks, consists multiple objectives, constraints, and diverse search spaces in fields such as engineering, logistics, and data science, strongly suggests their applicability to multiple setbacks in space programs.

4 QUANTIFICATION OF RESEARCH GAP

Based on the search results and updated context, a total of 60 papers were initially found from the query, on leveraging hybrid metaheuristic and evolutionary algorithms (EAs) for optimization in Nigeria's space program. Nevertheless, these papers specifically target or address optimization, using hybrid metaheuristic and evolutionary algorithms within the direct scope of Nigeria's space program. Although a few Nigerian studies have explored metaheuristic or hybrid optimization algorithms, these efforts have been predominantly applied in other domains rather than space-related contexts. Examples include optimization for examination timetabling [32], sustainable ready-mixed concrete production in Nigeria [33], and power system optimization within the national energy sector [34]. Additionally, recent research has proposed an enhanced metaheuristic algorithm that integrates cultural knowledge structures into the Smell Agent Optimization (SAO) framework [35], demonstrating growing interest in culturally adaptive optimization methodologies. A related Nigerian-focused review examined solar radiation empirical models and the use of soft computing techniques for solar energy estimation [36]; however, while this contributes to energy optimization research, it does not extend its application to space program initiatives. Nigerian research, appears to have limited or no direct publications applying a hybrid of metaheuristic and evolutionary algorithms explicitly to Nigeria's space program optimization goals based on the current literature retrieved. Many Nigerian studies, emphasize optimization or metaheuristic applications, in sectors other than space, such as power systems, renewable energy, civil engineering, manufacturing, or agricultural technology. No explicit linkage or contextual application specifically related to space program optimization was identified. Papers addressing general AI or machine learning applications, in space missions [37] discuss global or broader contexts, but not Nigeria-specific space program optimization. Some relevant hybrid algorithm optimization studies are outside Nigeria or in other fields (microgrids, power systems) are hence excluded, because they do not meet the criteria of applying hybrid metaheuristic and evolutionary algorithms, specifically for Nigeria's space program.

4.1 Nigeria's Space Program: Context and Potential Optimization Areas

Nigeria formalized its aspirations in space exploration with the establishment of the National Space Research and Development Agency (NASRDA) in 1999, followed by the adoption of the National Space Policy and Programme in 2001. As reiterated in policy documents and further emphasized in Ajijola's [38] review of Dr. Abiodun's book, the overarching vision of the program is: *"To make Nigeria build local capability in developing, designing and building appropriate hardware and software in space technology as a significant tool for its socio-economic development and enhancement of the quality of life of its people.* This vision provides a foundational framework for various strategic initiatives where advanced optimization techniques, particularly hybrid metaheuristic and evolutionary algorithms are the most prominent algorithm that can significantly enhance operational efficiency and technological self-reliance.

4.2 Program Objectives and Activities

Nigeria's space program encompasses several key objectives: Capacity Building and Human Resource Development: Training scientists and engineers is a central pillar. Satellite Development and Launch: Nigeria has launched several satellites, primarily for Earth Observation (NigeriaSat-1, NigeriaSat-2, NigeriaSat-X) and Communications (NigComSat-1, NigComSat-1R). While initial satellites involved significant international collaboration and technology transfer, the long-term goal includes increasing indigenous design and manufacturing capabilities. Downstream Applications: Utilizing satellite data and technology for national development, including natural resource management, disaster monitoring, agriculture, security, and telecommunications. Space Science and Technology Research: Fostering research in areas relevant to space exploration and utilization.

4.3 Identified Challenges and Opportunities

Reviews and analyses of Nigeria's space journey, such as the one discussed by Ajijola [38], point to achievements and challenges. A common theme is the tension between acquiring foreign technology (purchasing satellites) and developing sustainable, indigenous capabilities. There is a recognized need to shift emphasis towards leveraging space assets more effectively, for tangible socio-economic benefits and strengthening domestic science and technology foundations. This context presents significant opportunities for optimization: Satellite Constellation Design and Management: As Nigeria potentially expands its satellite fleet, optimizing constellation design (orbital parameters, number of satellites, sensor types) for specific coverage and revisit time requirements becomes crucial. Managing the operations of existing and future satellites, including task scheduling and data downlink, involves complex resource allocation problems. Remote Sensing Data Processing and Analysis: Earth Observation satellites generate vast amounts of data. Optimizing the processing chain, from data acquisition planning and calibration to feature extraction, image classification, and change detection, is significant for timely and accurate information delivery. Techniques discussed in papers like [39], on remote sensing for natural resource planning in Nigeria, highlight the importance of efficient data handling, although they may not explicitly mention hybrid metaheuristics. Advanced algorithms could optimize workflows for specific applications, like precision agriculture, urban planning, or environmental monitoring. Communication Satellite Resource Allocation: For communication satellites like NigComSat-1R, optimizing bandwidth allocation, transponder usage, and beam pointing to meet dynamic user demands, across Nigeria and potentially other regions is a continuous challenge. Mission Planning and Trajectory Optimization: While Nigeria currently focuses on Earth orbit, future ambitions might involve more complex missions. Trajectory optimization for launch vehicles or interplanetary probes represents a classic application area for advanced optimization algorithms. Indigenous Technology Development: Optimizing the design parameters for satellite subsystems (e.g., power systems, attitude control, thermal management) or ground segment infrastructure could benefit from hybrid metaheuristic approaches, especially when dealing with multiple conflicting objectives (minimizing mass and maximizing reliability).

4.4 Applicability of Hybrid Metaheuristics

The characteristics of the optimization problems in Nigeria's space program, involving complex systems, multiple objectives, constraints, and potentially large datasets, integrate well with the strengths of hybrid metaheuristic and evolutionary algorithms. These algorithms offer strong models for: Handling non-linearities and discontinuities common in space systems. Exploring vast design or solution spaces efficiently. Finding high-quality trade-off solutions, for multi-objective problems (cost versus performance, coverage versus resolution). Adapting to dynamic changes, in operational requirements or environmental conditions. While direct documented use in Nigeria's program is lacking in the reviewed literature, the successful application of these algorithms in similar aerospace and complex system optimization problems, provides a strong case for their potential value to NASRDA and the broader Nigerian space ecosystem, worldwide.

4.5 Toy Problem: Dynamic Bandwidth Allocation for Communication Satellite

Among multiple users, with varying demands and priorities, this toy problem, models how limited satellite bandwidth, is uniquely allocated, serving as a simplified experimental platform, for testing, optimization algorithms before real-world implementation.

4.5.1 Context

As Nigeria's communication satellite, NigComSat-1R provides services, across Africa. With limited bandwidth capacity, the satellite has multiple transponders, operating in different frequency bands (C, Ku, Ka). With fluctuating demands and different priority levels, NASRDA allocates bandwidth, to various service providers and government agencies.

4.5.2 Optimization Challenge

To increase revenue, ensuring quality of service, for high-priority users, and minimize unmet demand. It dynamically allocates bandwidth resources, across transponders.

4.5.3 Problem Formulation

Translate a real-world situation into a mathematical model.

a. Decision Variables

For example, the bandwidth allocated, to each customer, on each transponder, that determine the ultimate solution outcomes, are the controllable criteria in the optimization model. The examples below, illustrates this: Continuous variables b_{-ij} (bandwidth allocated to customer i on transponder j). For 25 customers and 8 transponders = 200 continuous variables

b. Constraints

In real-world situations, capacity, regulatory, and technical restrictions, which are restricting conditions, must be met or satisfied, to ensure the optimization solution, is feasible and applicable. These constraints are: Maximum capacity per transponder. Minimum guaranteed service levels for priority customers. Technical limitations on signal quality and interference. Regulatory requirements for specific services. Geographic coverage constraints for different transponder beams.

c. Objectives

The desired outcomes of the optimization process, such as reducing unmet operational costs or requirements, maximizing revenue, improving system performance, are represented by these: Maximize total revenue. Minimize unmet demand (weighted by customer priority). Maximize overall system utilization. Minimize reconfiguration costs when updating allocations

4.5.4 Proposed Algorithm: Hybrid SAO + Cultural Algorithm Approach

To enhance decision-making efficiency, this incorporates Cultural Algorithm knowledge spaces, with Smell Agent Optimization; leveraging guided search mechanisms and adaptive learning, to enhance optimization convergence and accuracy.

a. Smell Agent Optimization (SAO)

To converge toward optimal solutions, SAO is a nature-inspired optimization technique, where agents (particles) navigate, the solution space, based on, scent-driven behavioral intelligence, adjusting their positions. The components include: Particles: Each particle represents a complete bandwidth allocation plan. Position: Vector of bandwidth allocations for each customer–transponder pair. Velocity: Rate and direction of change in allocation values. Fitness: Weighted combination of multiple objectives. Neighborhood Structure: Communication topology between particles

b. Cultural Algorithm (CA) Knowledge Spaces

Through improving decision accuracy and enhancing solution evolution, these structured repositories of learned information, such as normative, situational, and historical knowledge, that guide the optimization process consist: Normative Knowledge: Acceptable ranges for bandwidth allocations. Situational Knowledge: Exemplar solutions for different demand scenarios. Domain Knowledge: Technical constraints of satellite transponders. Historical Knowledge: Patterns from previous allocation cycles. Topographical Knowledge: Geographic distribution of service demands.

c. Hybridization Mechanism

In order to stabilize exploration and exploitation, it merges SAO, with Cultural Algorithm components, dynamically adjusting their influence, thereby improving convergence efficiency and solution refinement, through the following interventions: Dynamic influence adjustment between SAO and CA components. Adaptive weighing of knowledge sources based on performance feedback. Problem decomposition with specialized sub-populations. Knowledge-guided local search for solution refinement.

4.5.5 Algorithm Workflow

To generate optimal bandwidth allocations, the step-by-step process is outlined, through which optimization solutions advance, evaluation, integrating, forecasting, knowledge extraction, and adaptive updates.

a. Initialization

The initial solution population, is generated here, the algorithm's knowledge base and demand forecasting model are set up, forming the baseline for iterative optimization, by: i) Generating initial population of bandwidth allocation solutions. ii) Initializing CA belief spaces with historical allocation patterns. iii) Setting up demand forecasting model based on historical data.

b. For Each Allocation Cycle

To continuously improve performance, the iterative phase, is where optimization agents adjust their allocations, bandwidth demand and constraints are updated, solutions are evaluated, through these processes: i) Update demand forecasts and constraints. ii) Evaluate each particle, based on multiple objectives. iii) Update personal and global best solutions. iv) Extract knowledge from best solutions, to update belief spaces. v) Generate influence function, from belief spaces.

d. Update Particle Velocities

This step adjusts the rate and direction of each particle's movement in the solution space using SAO dynamics and cultural knowledge influence to drive exploration toward improved allocations, via: i) Standard SAO components. ii) Influence from belief spaces. iii) Adaptive inertia weight, based on diversity.

e. Update Particle Positions

While ensuring it moves closer, to optimal performance, based on its updated velocity, this process modifies each particle's allocation plan, refining the solution by: Modifying allocation plans. Applying repair operators to ensure feasibility.

f. Knowledge Integration

This explores learned patterns and contextual information, to extract insights, from high performing solutions and updates the belief spaces, enabling the algorithm to refine future searches, through: i) Identifying successful allocation patterns in high-performing solutions. ii) Updating belief spaces with new knowledge. iii) Applying specialized operators based on situational knowledge iv) Adjusting exploration or exploitation balance, based on convergence.

g. Output

This provides the final optimized bandwidth allocation plan along with resource utilization insights and contingency strategies to manage demand fluctuations effectively: i) Optimal bandwidth allocation plan. ii) Visualization of resource utilization. iii) Contingency plans for demand fluctuations.

5 IMPLEMENTATION CONSTRAINTS AND MITIGATION STRATEGIES

Hybrid metaheuristic and evolutionary algorithms offer significant potential benefits, for Nigeria space program, yet several practical constraints may obstruct their successful implementation. This section clarifies these constraints, proposing targeted mitigation strategies.

5.1 Computing Resource Constraints

Nigeria's unstable power supply and limited high-performance computing infrastructure, limit the deployment of computationally intensive optimization algorithms. High maintenance costs and hardware acquisition, in addition, constrain scalability.

5.1.1 Challenges

Aside from model complexity, several contextual constraints further challenge the practical implementation of computationally intensive optimization algorithms in Nigeria, some of which are as follows: Limited high-performance computing (HPC) infrastructure in NASRDA, for running computationally intensive optimization algorithms. Inconsistent power supply, affecting computational reliability. Bandwidth limitations, for cloud-based alternatives. High costs associated with acquiring and maintaining specialized hardware.

5.1.2 Mitigation Strategies

To guarantee, more practical and reliable solutions, these techniques are utilized, to reduce inefficiencies, risks or uncertainties, in the optimization process: a) Phased Implementation Approach: Begin with less computationally intensive algorithms on existing hardware, while targeting high-value optimization problems, with immediate returns. Use these early successes to justify further infrastructure investments. b) Strategic Cloud Computing Partnerships: Establish partnerships with international cloud service providers, offering academic/research discounts or with Nigerian universities having existing HPC facilities. This provides access to scalable computing resources, without large upfront capital investments. c) Algorithm Efficiency Optimization: Adapt algorithms to operate efficiently on available hardware, by implementing parallel processing techniques, problem decomposition, and surrogate-assisted evolutionary algorithms, that reduce the number of expensive function evaluations.

5.2 Data Availability and Quality Constraints

Nigeria's space program encounters challenges, such as limited real time data access, incomplete datasets and inconsistent formats, yet, effective optimization, relies on accurate, timely, and high-resolution data. Further complicates algorithm certification and training, is poor metadata documentation.

5.2.1 Challenges

Effective optimization and decision-making in space systems, heavily depend on the availability of accurate, timely, and high-resolution data, however, data collection in Nigeria's space program faces several challenges, including: a) Incomplete historical data, for algorithm training and validation. b) Inconsistent data formats, across different systems and agencies. c) Limited real-time data access, for dynamic optimization scenarios. d) Inadequate metadata and documentation, of existing datasets.

5.2.2 Mitigation Strategies

These effects viable solutions, in the practical use of data in the space program: a) Incremental Data Integration Framework: Develop a standardized data integration framework, that can function with partial data, while being expandable as more data becomes available. Begin with synthetic or simulated data, where historical data is lacking. b) Cross-Agency Data Sharing Protocols: Establish formal data sharing agreements and standardized formats between NASRDA and other government agencies (meteorological services, emergency management, etc.), to create richer datasets for optimization algorithms. c) Robust Algorithm Design: Implement algorithms specifically designed to handle uncertainty and missing data, such as strong evolutionary algorithms, with noise- handling mechanisms and adaptive sampling techniques.

5.3 Policy and Institutional Constraints

Bureaucratic procedures, siloed organizational structures, and unclear policies impede the adoption of advanced optimization technologies. Short-term planning conflicts, with long-term innovation needs, slowing technology integration.

5.3.1 Challenges

The implementation of advanced optimization frameworks within Nigeria's space program is often hindered by policy and institutional constraints. These include: a) Bureaucratic procurement processes, delaying technology adoption. b) Siloed organizational structure, limiting cross-functional optimization. c) Lack of clear policies, regarding algorithmic decision-making. d) Short-term planning horizons, conflicting with longer-term technology integration needs.

5.3.2 Mitigation Strategies

To unimpeded the advanced optimization technology adoption, feasible stabilizing strategies should be explored: a) Policy Modernization Initiative: Develop and advocate for updated policies, that specifically address advanced computational methods, including streamlined procurement processes, for software and computing resources, as well as guidelines for algorithmic transparency and validation. b) Optimization Center of Excellence: Establish a dedicated center, in NASRDA, that cuts across departmental boundaries, focusing on optimization applications, throughout the space program, and serving as a knowledge repository and implementation hub. c) Phased Approval Process: Implement a staged approval process, for algorithm deployment, starting with "human-in-the-loop" systems, where algorithms provide recommendations, but humans make the final decisions, gradually transitioning to more automated systems; as trust and validation increase.

5.4 Skills and Expertise Gaps

In advanced optimization techniques, there is a shortage of indigenous professionals, made worse, by limited academic programs and brain drain. Interpreting analytical knowledge, into functional applications, pose a major challenge.

5.4.1 Challenges

The successful deployment of advanced optimization techniques, particularly hybrid metaheuristic algorithms, within Nigeria's space program is constrained by significant skills and expertise gaps. i. Shortage of local expertise, in advanced optimization techniques. ii. Brain drain, of qualified personnel to international organizations. iii. Limited educational programs, premised on metaheuristics and space applications. iv. Difficulty in translating theoretical knowledge, to practical implementation.

5.4.2 Mitigation Strategies

In this vein, functional models that enhance effective interventions include: a) Targeted Capacity Building Program: Develop a specialized training program, combining online courses, workshops with international experts, and hands-on projects. Emphasis on theoretical foundations and practical implementation skills for space- specific optimization problems. b) Academic-Industry-Government Partnership: Create a consortium, between Nigerian universities, NASRDA, and international space agencies or companies, to develop curriculum, research opportunities, and knowledge transfer mechanisms, based on optimization, in space applications. c) Retention and Knowledge Transfer Mechanisms: Implement competitive compensation packages, research opportunities, and career advancement paths, for specialists, in optimization. Establish mentoring programs and documentation requirements, to ensure knowledge is institutionalized, rather than residing solely with individuals. d) Open-Source Community Engagement: Actively participate in open-source optimization software communities, contributing space-specific problem formulations, while benefiting from global expertise and code bases.

6 SYNTHESIS: BRIDGING THE GAP - POTENTIAL AND CHALLENGES

The preceding sections have established the capabilities of hybrid metaheuristic and evolutionary algorithms in tackling complex optimization problems globally, and outlined the context and potential optimization needs, in Nigeria's space program. Synthesizing these two aspects reveals, significant opportunities and a notable gap in documented application. Hybrid EAs offer sophisticated tools well-suited to the challenges faced by NASRDA. Problems like optimizing satellite constellation design; for maximum coverage and minimum cost, scheduling observation tasks for Earth Observation satellites; considering weather constraints and priority targets, efficiently processing large volumes of remote sensing data; for applications like precision agriculture or disaster management and allocating bandwidth resources on communication satellites, are complex optimization tasks, where these algorithms excel. Their ability to handle multiple objectives, non-linear constraints, and large search spaces, makes them theoretically ideal for enhancing the efficiency and effectiveness of Nigeria's space assets and contributing to the goal of indigenous capability development. However, the literature review process revealed a huge gap. There is a lack of published research, specifically demonstrating the application of hybrid metaheuristic or evolutionary algorithms to problems in Nigeria's space program. While general optimization principles are undoubtedly applied, and studies exist on aspects like remote sensing applications in Nigeria [29], the targeted use and adaptation of these specific advanced algorithm families (hybrid EAs, specific metaheuristics like PSO, ACO, GWO, HBA, SCSO, etc., and their hybrids), remain undocumented in accessible academic literature. This contrasts with the growing body of work, showcasing their use in space programs and related high-technology sectors in other parts of the world. This gap could stem from several factors: Nascent Application: The use of these specific advanced algorithms might still be in its early stages within NASRDA or related Nigerian research institutions, with results not yet published. Focus on Acquisition vs. Research and development (R&D): As suggested by some analyses [28], a historical focus on acquiring technology rather than intensive indigenous R&D might have limited the exploration and adaptation of cutting-edge optimization algorithms. Publication Barriers: Research conducted might not have been published in internationally indexed journals or databases accessible during this review. Proprietary Nature: Some optimization work, particularly if related to sensitive applications, might be kept proprietary. Regardless of the reason, this gap represents a challenge and an opportunity. The challenge lies in the lack of readily available case studies and performance data, specific to the Nigerian context. The opportunity lies in the potential for pioneering research and development, by applying these powerful algorithms to Nigeria's unique space-related problems, potentially leading to significant improvements in operational efficiency, resource utilization, and the development of structured, indigenous solutions.

7 LIMITATIONS OF THIS LITERATURE REVIEW

This literature review adopted a narrative-review approach, rather than a systematic review methodology, which inherently introduces a degree of subjectivity in the selection and synthesis of literature. While efforts were made to ensure comprehensive coverage of relevant topics, the absence of a rigid protocol for article selection, means that some pertinent studies might not have been included. Furthermore, the propositions regarding the application of hybrid metaheuristic and evolutionary algorithms to Nigeria's space program, including the potential benefits and mitigation strategies, are primarily conceptual and based on extrapolations from applications in other domains. This review does not include empirical validation in actual operational contexts in NASRDA. The illustrative examples provided are simplified representations and would require significant refinement and empirical testing for real-world deployment. Finally, the discussion of implementation constraints and mitigation strategies is informed by general challenges in technology adoption and capacity building in developing nations, rather than specific, in-depth assessments of NASRDA's current infrastructure or policy landscape. Future work should aim to address these limitations, through systematic reviews, empirical studies, and direct engagement with stakeholders in Nigeria's space program.

8 CONCLUSIONS

This literature review has explored the landscape of hybrid metaheuristic and evolutionary algorithms and assessed their potential applicability to Nigeria's space program. These advanced optimization techniques, born from the synergy between different search strategies and often inspired by natural processes, offer powerful tools for tackling the complex, multi-objective, and large-scale optimization problems inherent in space exploration and utilization. The potential benefits of utilizing these algorithms to promote the efficiency, effectiveness, and indigenous capabilities of Nigeria's space endeavors are huge, from satellite constellation design and mission planning to remote sensing data processing and resource allocation. A key finding of this review, however, is the big gap in the published academic literature, documenting the specific application of hybrid metaheuristic and evolutionary algorithms, in the Nigerian space context. The adoption and adaptation of these cutting-edge optimization methods, appear largely undocumented in readily accessible sources, even though Nigeria has established space infrastructure and clear developmental goals. Due to the lack of specific case studies, and a compelling opportunity for future research and development, this both present a challenge.

REFERENCES

1. James, G.K., Akinyede, J. and Halilu, S.A. (2014). The Nigerian space program and its economic development model. *New Space*, vol. *2*, no. 1, pp. 23-29.

2. Dokeroglu, T., Sevinc, E., Kucukyilmaz, T. and Cosar, A. (2019). A survey on new generation metaheuristic algorithms. *Computers & Industrial Engineering*, vol. 137, 106040, pp. 1-29.

3. Srivastava, S., Tripathi, A., Bansal, S. and Vuppuluri, P.P. (2025). Introduction to optimization: Techniques and applications in engineering. In *Nature-inspired Metaheuristic Algorithms. CRC Press*, pp. 1-28.

4. Abualigah, L., Diabat, A., Mirjalili, S., Abd Elaziz, M. pp. 1-28 Gandomi, A.H. (2021). The arithmetic optimization algorithm. *Computer methods in applied mechanics and engineering*, vol. 376, 113609, pp. 1-38.

5. Morales-Castañeda, B., Zaldívar, D., Cuevas, E., Fausto, F. pp. 1-28 Rodríguez, A. (2020). A better balance in metaheuristic algorithms: Does it exist*? Swarm Evol Comput*, vol. 54, 100671, pp. 1-23.

6. Rajwar, K., Deep, K. and Das, S. (2023). An exhaustive review of the metaheuristic algorithms for search and optimization: taxonomy, applications, and open challenges. *Artificial Intelligence Review*, vol. *56*, no. 11, pp. 13187-13257.

7. Bäck, T.H., Kononova, A.V., Van Stein, B., Wang, H., Antonov, K.A., Kalkreuth, R.T. and Ye, F. (2023). Evolutionary algorithms for parameter optimization—thirty years later. *Evolutionary Computation*, vol. 31, no. 2, pp. 81-122.

8. Abo-Alsabeh, R.R. and Salhi, A. (2022). The Genetic Algorithm: A study survey. *Iraqi Journal of Science*, vol. 63, no. 3, pp. 1251-1231. DOI:10.24996/ijs.2022.63.3.27.

9. Roeva, O., Zoteva, D., Roeva, G., Ignatova, M. and Lyubenova, V. (2024). An Effective Hybrid Metaheuristic Approach Based on the Genetic Algorithm. *Mathematics*, vol. 12, no. 23, pp. 1-15.

10. Liu, J., Sarker, R., Elsayed, S., Essam, D. and Siswanto, N. (2024). Large-scale evolutionary optimization: A review and comparative study. *Swarm and Evolutionary Computation*, vol. 85, 101466, pp. 1-24.

11. Blum, C. and Roli, A. (2003). Metaheuristics in combinatorial optimization: Overview and conceptual comparison. *ACM computing surveys*, vol. 35, no. 3, pp. 268-308.

12. Raidl, G.R. (2006). A unified view on hybrid metaheuristics. In *International workshop on hybrid metaheuristics. Berlin, Heidelberg: Springer Berlin Heidelberg*, pp. 1-2.

13. Talbi, E.G. (2002). A taxonomy of hybrid metaheuristics. *Journal of heuristics*, vol. 8, pp. 541-564.

14. Lozano, M., Herrera, F., Krasnogor, N. and Molina, D. (2004). Real-coded memetic algorithms with crossover hill-climbing. *Evolutionary computation*, vol. 12, no. 3, pp. 273-302.

15. Noman, N. and Iba, H. (2008). Accelerating differential evolution using an adaptive local search. *IEEE Transactions on evolutionary Computation*, vol. 12, no. 1, pp. 107-125.

16. Chen, X., Ong, Y.S., Lim, M.H. and Tan, K.C. (2011). A multi-facet survey on memetic computation. *IEEE Transactions on evolutionary computation*, vol. 15, no. 5, pp. 591-607.

17. Li, P., Hao, J., Tang, H., Fu, X., Zhen, Y. and Tang, K. (2024). Bridging evolutionary algorithms and reinforcement learning: A comprehensive survey on hybrid algorithms. *IEEE Transactions on Evolutionary Computation*, pp. 1707-1728.

18. Lozano, M. and García-Martínez, C. (2010). Hybrid metaheuristics with evolutionary algorithms specializing in intensification and diversification: Overview and progress report. *Computers & Operations Research*, vol. 37, no. 3, pp. 481-497.

19. Gharsalli, L. and Guérin, Y. (2021). Mechanical sizing of a composite launcher structure by hybridizing a genetic algorithm with a local search method. *Composites Part C: Open Access*, vol. 5, pp. 1-8.

20. Wan, W. and Birch, J.B. (2013). An improved hybrid genetic algorithm with a new local search procedure. *Journal of Applied Mathematics*, vol. 2013, no. 1, pp. 1-11.

21. Seyyedabbasi, A., Tareq Tareq, W. Z. and Bacanin, N. (2024). An effective hybrid metaheuristic algorithm for solving global optimization algorithms. *Multimedia Tools and Applications*, pp. 1-36.

22. Zhao, X., Tang, Z., Cao, F., Zhu, C. and Periaux, J. (2022). An efficient hybrid evolutionary optimization method coupling cultural algorithm with genetic algorithms and its application to aerodynamic shape design. *Applied Sciences*, vol. 12, no. 7, pp. 34-82.

23. Lim, H. and Kim, H. (2018). Multi-Objective Aerodynamic Optimization Using Hybrid Evolutionary-Adaptive Local Search Strategy. In *10th International Conference on Computational Fluid Dynamics, ICCFD 2018*, pp. 1-18.

24. Boonstra, S., Van der Blom, K., Hofmeyer, H. and Emmerich, M.T. (2021). Hybridization of an evolutionary algorithm and simulations of co-evolutionary design processes for early-stage building spatial design optimization. *Automation in Construction*, vol. 124, pp. 1-18.

25. Dib, O. (2023). Novel hybrid evolutionary algorithm for bi-objective optimization problems. *Scientific Reports*, vol. 13, no. 1, pp. 1-21.

26. Barredo, P. and Puente, J. (2023). Precise makespan optimization via hybrid genetic algorithm for scientific workflow scheduling problem. *Natural Computing*, vol. *22*, no. 4, pp. 615-630.

27. Luo, Q., Fan, Q., Deng, Q., Guo, X., Gong, G. and Liu, X. (2023). Solving bi-objective integrated scheduling problem of production, inventory and distribution using a modified NSGA-II. *Expert Systems with Applications*, vol. 225, 120074.

28. Tubishat, M., Alswaitti, M., Mirjalili, S., Al-Garadi, M.A., Alrashdan, M.E.T. and Rana, T.A. (2020). Dynamic butterfly optimization algorithm for feature selection. *IEEE Access*, vol. 8, pp. 194303-194314.

29. Ogunseyi, T.B. and Thiyagarajan, G. (2025). An Explainable LSTM-Based Intrusion Detection System Optimized by Firefly Algorithm for IoT Networks. *Sensors*, vol. *25*, no. 7, pp. 1-26.

30 Xu, H., Deng, Q., Zhang, Z. and Lin, S. (2025). A hybrid differential evolution particle swarm optimization algorithm based on dynamic strategies. *Scientific Reports*, vol. 15, no. 1, pp. 1-49.

31. Wang, G. (2025). Customer segmentation in the digital marketing using a Q-learning based differential evolution algorithm integrated with K-means clustering. *PloS one*, vol. 20, no. 2, pp. 1-21.

32. Ezike, J.O.J., Oyeleye, C.A., Olabiyisi, S.O. and Omidiora, E.O. (2020). Development of a Hybrid Tabu Search and Genetic Algorithms for the Examination Timetabling Problem. *NIPES-Journal of Science and Technology Research*, vol. 2, no. 3, pp. 127 -147.

33. Olugboyega, O., Ejohwomu, O., Omopariola, E.D. and Omoregie, A. (2023). Sustainable Ready-Mixed Concrete (RMC) production: a case study of five RMC plants in Nigeria. *Sustainability*, vol. 15, no. 10, pp. 8169, 1-17

34. Ibrahim, H.A. and Ayomoh, M.K. (2022). Optimum predictive modelling for a sustainable power supply mix: A case of the Nigerian power system. *Energy Strategy Reviews*, vol. 44, Article 100962, pp. 1–14. https://doi.org/10.1016/j.esr.2022.100962

35. Saliu, A., Anene, E., Hassan, S. and Mahmud, A. (2024). Hybrid Optimization of Smell Agent Optimization Algorithm with Cultural Algorithm. *ATBU Journal of Science, Technology and Education*, vol. 12, no. 3, pp. 341-362.

36. Nwokolo, S. and Ogbulezie, J. (2017). A critical review of theoretical models for estimating global solar radiation between 2012-2016 in Nigeria. *International Journal of Physical Research*, vol. 5, no. 2, pp. 60-78.

37. Oche, P.A., Ewa, G.A. and Ibekwe, N. (2021). Applications and challenges of artificial intelligence in space missions. *IEEE Access*, vol. 12, pp. 44481-44509.

38. Adigun, A.A. (2017). Nigeria's Space Journey: Understanding its Past, Reshaping its Future, vol. 418, pp. 63-64.

39. Aladelokun, A.O. (2021). Status of Remote Sensing Techniques in Natural Resources Planning and Sustainable Development in Nigeria. *EPRA International Journal of Research and Development*, vol. 6, no. 9, pp. 12-18.