Exploring Optimization Algorithms: A Review of Methods and Applications

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Abstract

This article review focuses on feature selection as the main parameter that plays a major role in tuning machine learning models. Several algorithms of optimization such as MFO (Moth-Flame Optimization), the GA-GSA algorithm's hybrid type, SOA (Seagull Optimization Algorithm), WOA (Whale Optimization Algorithm), GOA (Grasshopper Optimization Algorithm), HGSO (Henry Gas Solubility Optimization), and SafeOpt are widely used in engineering design, power systems scheduling, The paper stresses the importance of optimization in improving efficiency, lessening mistakes and increasing understandability of machine learning models. The literature addresses the widest directions in the usage of optimization for the following fields of science such as structural engineering, additive manufacturing, and landslide susceptibility mapping. A comprehensive summary table is generated, which shows an overview of each study, algorithm, focus, and methodology and has a stoke of key findings. The conclusions reveal the adaptiveness, competitiveness and compossibility of the optimization algorithms applied to a wide range of domains. The summary shows how optimization has the potential to change decision-making processes and activities by being a decisive factor that determines the future of branches of various industries. The main objective of this work is to direct researchers and practitioners by providing them with some innovative ideas and approaches and offering insights on the existing cutting-edge approaches while laying the groundwork for future innovations in optimization.

Keywords: Optimization Algorithms; Metaheuristic Optimization Methods; Deep Learning; Optimization Applications; Machine learning models.

1. Introduction

These days, model optimization is a big job [1-3], and it is important to stress how important feature selection is for getting the best speed and clarity [4]. This literature study is the first step toward a more in-depth look at a lot of different optimization methods. The goal is to find answers to hard problems that come up in lots of different areas. A lot of different metaheuristic optimization methods are at the start of this journey through analysis. The Moth-Flame Optimization (MFO), the Seagull Optimization Algorithm (SOA), the Whale Optimization Algorithm (WOA), and many more are some of these. This paper takes a close look at the Grasshopper Optimization Algorithm (GOA), the Henry Gas Solubility Optimization (HGSO), and the brand-new SafeOpt algorithm.

What optimization means in machine learning and why it is important: It is becoming the most important thing to do in the field of optimizing machine learning models. One important thing that makes a big difference in how well these models work and how easy they are to understand is the choice of features [5-7]. As the need for machine learning solutions that work quickly and are easy to understand grows, it becomes more important to focus on optimization methods. What can optimization algorithms do? This literature review gets right to the point by looking at several optimization algorithms that are created to handle problems that are unique to various areas.

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Many things are talked about in this paper, like the Moth-Flame Optimization (MFO) [8-11] method and how well it works in engineering design, power systems, financial load scheduling, medical imaging, non-linear optimization, and bio-inspired computing. Optimization is very useful and adjustable so that it can be used in lots of different ways in real life. Lots of attention on new algorithms: That is when the GA-GSA [12] hybrid method comes up. It is a new way to do optimization that works well for tricky non-linear optimization problems with lots of limitations. Putting the Genetic Algorithm (GA) [13-15] and the Gravitational Search Algorithm (GSA) [16-17] together is a fresh and new way to find the best answers. Answers Based on Biology: When it comes to bio-inspired answers, the Seagull Optimization Algorithm (SOA) is the star, SOA is a powerful tool for computers, just like the way birds move and plan their moves [18-21]. Forty-four basic test routines and real-world business problems were used to show how useful and flexible it is. They show how it can be used to solve tough issues when there are few choices. Looking into ways to make whales better: This is where the Whale Optimization Algorithm (WOA) comes in as a method based on the tricky bubble-net search methods. By being used in many areas, such as image processing, robot path planning, grouping, and classification, WOA shows that it is a strong algorithm that can handle a lot of different situations [22-24]. Great Ways to Find Your Way: There is a detailed look at different metaheuristic optimization methods, which shows their pros and cons. The Grasshopper Optimization Algorithm (GOA) is one of these great things. It shows how flexible and simple it is to use to solve hard optimization problems in areas like industrial design, picture processing, and power system control [25-26]. New and innovative SafeOpt algorithm: It is the most important step forward in a study that the SafeOpt algorithm was made. It can take much work to fine-tune the settings for machine learning algorithms. SafeOpt not only ensures the best performance but also puts system safety first. Due to its unique method based on regularity rules and Gaussian process priors, it sets the bar for how safe algorithms can be [27].
Can be used in many places: In the real world, these algorithms are used in many areas, not just theory. They are used in engineering design, power systems, financial load scheduling, medical imaging, non-linear optimization, and bio-inspired computers, to name a few. These optimization tools are very important for fixing hard problems because they can be used in many areas. This long opening sets the stage for a full study of optimization algorithms, with a focus on how important they are for changing machine learning and how problems are solved in a lot of different areas. As we go along, we study and break down each algorithm to find out what makes it unique and how it fits into the ever-changing field of optimization in machine learning.

2. Literature Review

The optimization of machine learning models can now be achieved by feature selection, which is instrumental in the models' performance and interpretability. A number of optimization algorithms under examination are being presented in this literature review. Every one of them has been designed to handle a particular issue in and around a specific zone. The Moth–Flame Optimization (MFO) algorithm museum is an addition to our review and facilitates the in-depth study of key traits. In addition to it, we have new ways of solving it, like the new joint GSA–GA approach and the bio-inspired Seagull Optimization Algorithm (SOA). The AGA also covers the whale optimization algorithm (WOA), the imperialist competitive algorithm and their workability in structural engineering. It also mentions the Grasshopper Optimization Algorithm and how well it is efficient in so many other domains as well. The research discusses the HGSO algorithm, the cellular structures of additive manufacturing, and why it is significant to select the right adjustment parameters for machine learning algorithms. We make sure we simplify every technique, what it is great at, and how it compares to the other methods.

Table 1: Summary of related works.

Ref.	Focus	Methodology	Key Findings
[28]	MFO	Comprehensive review	This paper talks in great depth about the Moth–Flame Optimization (MFO) method and how it can be used in medical imaging, engineering design, power systems, and economic load scheduling. It looks at the MFO studies, use cases, theory reviews, and similarities with other algorithms that have been written. This study looks at where MFO is now, what its limits are, and where more research could be done. In the fields of health, engineering, teamwork, data mining, and efficiency, it can teach people what they need to know.

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[29]	GA-GSA hybrid algorithm	Non-linear optimization with multiple constraints	This paper talks about a brand-new GA-GSA mixed method that can be used for complicated nonlinear optimization. GSSA and GA are genetic algorithms that are used to find the best answers and make the first results better. We use benchmark questions to check how well the suggested method works and to show that it makes more money than other ways. There are statistical tests that make sure the conclusions that are drawn from the data are right.
[30]	SOA	Bio-inspired computing algorithm	This paper talks about a Seagull Optimization Algorithm (SOA), a computer tool that works like a seagull and is based on biology. SOA was put through 44 normal test functions and nine metaheuristics. It was then used to solve seven real-life business problems. This shows how adaptable and helpful it is for solving big problems when you don't have many choices. Experiments have shown that SOA can be used with other refining methods.
[31]	WOA	Whale Optimization Algorithm	The paper talks about Optimization Algorithm (WOA). This is a method that was designed to look like bubble-net hunts. Along with image processing, robot path planning, grouping, and classification, it looks at how WOA can be used in a lot of different areas. The literature study talks about WOA's hybridizations, versions, and uses in engineering. It focuses on how it can be used to solve optimization problems and how well it does that.
[32]	Metaheuristic optimization algorithms	Active control of structures	This paper look at the good and bad points of different metaheuristic optimization methods to find the best way to control structures, going beyond what the linear quadratic regulator (LQR) can do. The Wavelet-based LQR method, which is made up of six optimization methods, can find the best feedback answers more quickly and without having to solve Riccati equations. The findings help improve active control methods in the area of building engineering.
[33]	GOA	Goal Programming Optimization Algorithm	The paper talks about the Grasshopper Optimization Algorithm (GOA) and how it can be used in various fields, like industrial design, picture processing, machine learning, and power system control. The study looks at how flexible and simple GOA is to use when trying to solve tough optimization problems. This gives a full picture of what it can be used for and how well it works.
[34]	HGSO	Henry Gas Solubility Optimization	The paper talks about the HGSO algorithm, which is built on Henry's law and finds the best way to dissolve gases. People talk about how the program makes money, but they don't go into as much detail about the search area. HGSO is competitive and good at handling hard optimization problems, as shown by validation tests that use standard functions and real-life optimization issues.
[35]	HGSO	Henry Gas Solubility Optimization	The paper talks about the Henry Gas Solubility Optimization (HGSO) method once more, but this time it looks at how well it does against seven other well-known algorithms and how it makes money. It works well for handling hard optimization problems, as shown by the test results.

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[36]	SafeOpt	SafeOpt algorithm	The paper talks about the SafeOpt algorithm better by looking into how to pick the best adjusting settings for machine learning algorithms. Because it always goes above a certain amount, the program makes sure that the system is safe. Regularity principles, the Gaussian process prior, and context factors analysis are used to make sure that what you know can be safely used in new scenarios. The program does a good job of safely setting system parameters, as shown by both theoretical study and tests on a quadrotor vehicle.
[37]	PSO-ANN	Landslide susceptibility mapping	The paper talks about making a mixed model for mapping the risk of landslides that uses PSO-ANN to fix issues with standard ANN models. LSM maps from the Layleh Valley in Iran are used in large amounts for the study to check how correct they are. You can see that the PSO-ANN method is more stable and works better than standard ANN models. Two ways to measure how well something works are the coefficient of determination (R2) and the root-mean-squared error (RMSE). It is also possible to rank things using a color intensity ratio (CER) and a total order structure.

Review:

In [28] the moth–flame optimization (MFO) method comprehensively, its main parts are also explained. MFO has developed as a strong metaheuristic algorithm that has been applied successfully to solve various optimization problems in domains like engineering design, economic load schedule, medical imaging, and power and energy systems, just to name a few. The literature on MFO has been the subject of many research papers written by people who discuss the number of papers and use cases of the literature. There is also the theoretical analysis and comparison with other algorithms. They also discuss the various kinds/hybrids of MFO. The outcomes have something to do with the present status of the MFO, what is wrong with it and what studies might be conducted to have an in-depth understanding. These subjects, such as health, engineering, teamwork, data mining, and optimization, are important for the people working in the subjects to use as they show the pros and cons of MFO.

In [29] outlines an innovative GA-GSA hybrid algorithm, which can be used to solve non-linear optimization with multiple constraints. The GSA is the type of search technology used to enhance the initial results. Then, mutation, crossing, and selection are implemented by the genetic agents to make each answer perfect. Several benchmark problems with various objectives, constraints, and decision variables are set, which allows the assessment of the effectiveness of the method. By evaluating the method suggested and comparing the results to several other methods, it becomes evident that it is much more profitable. Also, statistics tests are employed in order to be sure that the conclusions drawn are correct.

The Seagull optimization algorithm (SOA) is the focus of [30]. This bio-inspired computing algorithm was designed to tackle tough computing jobs. Seagulls are imitated in the way they move around and attack in natural settings, and similar behavior is adopted in the program. Our actions are converted into mathematical models that assist us in searching for more and utilizing the chance as much as possible in the search space. The SOA algorithm is set to a match against nine other well-established metaheuristics in a set of 44 standard test functions to find out which one of them yields the best result. The issue examined is how hard it is to do math and how the problems add up together. These strategies are employed to solve seven real-life business problems, including the ones with limited. This displays its convenience. The tests proved the fact that the algorithm copes well with big-scale, hard problems that have constraints. It is comparable to other optimization methods due to this.

Back in 2016, when the Whale Optimization Algorithm (WOA) was released. The crux of this approach lies in productivity. What is WOA short for? The preying method of "bubble-net hunting" is presented in [31]. The WOA will optimize, thereby solving problems in various applications. The fine-tuning process makes use of multiple alterations to give the most accurate and efficient responses. As modeling complexity increases and engineers make quick decisions, metaheuristics are being adopted in research. Since the last time WOA was established, there have been changes and hybrid strategies. It was designed to address the use of the algorithm by engineers in tasks such as classification, robot path planning, clustering, image processing, and so on. Applications of WOA algorithms for optimization problems in engineering cover the largest share of the literature. That is, the WOA, in many forms, will be illustrated and unveiled.

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The optimal and best active control of structures shall be seen in [32]. The way in which different metaheuristic optimization algorithms compare with each other provides insight. The LQR issues, as well as a point from which it does not affect outside stimulation, are taken into account. The research is squarely based on Wavelet-based LQR to come up with the optimal feedback solutions. It does this by combining six smart optimization methods: the imperialist competitive algorithm, BAT, BEE, DE, FF, HS, and the principal algorithm imperialist competition. In the proposed approaches, there is no absolute necessity to solve Riccati equations to account for the effects of excitation on the control. We can see that the Improvement-Based Competitor Algorithm is better at getting better answers through competition with other buildings that shocks have damaged. It is able to accomplish this task by ensuring that the structure reactions have been drastically reduced and that control energy is used less than in other LQR methods. With the application of effective optimization approaches, the results assist in improving the activeness of control methods in structural engineering.

The well-known method of search by the meta-heuristic tool known as the Grasshopper Optimization Algorithm (GOA) is used broadly [33], for instance, in engineering design, imaging processing, machine learning, etc. Additionally, it has an application in controlling power systems. This study we are about to peruse is a heavy study on the Grasshopper Optimization Algorithm and how it can be used in real-world projects. With two objectives or more or in the binary or chaotic environment, it means that all the ways it can be used have been represented. It is a versatile instrument that is being used in numerous ways, from assessing the level of functioning to being used as an instrument. End of the journey, they all reach conclusions shaped by them. Through this survey, we can now properly evaluate and understand how to implement the GOA algorithm in order to solve hard optimization problems efficiently.

The Henry Gas Solubility Optimization is described in [34]. it comes from Henry's law, the gas law, which only tells you how much gas is dissolved in the substance and its features are altered. The income generation plan of HGSOO is more oriented to revenue than a detailed study of the search area. In this manner, an issue or answer that is close to perfection or ideal will not be getting near where it is placed within the category. The approach was tried on 47 standard functions as well to rule out any overfitting issue in addition to the CEC'17 test set and three real-life optimization problems. It is competent and surpasses seven popular algorithms in the HGSO results, abbreviations for their names include PSO, GSA, CS, GWO, and EHO. It also solves hard optimization problems as the proof data tests.

The advantages of these networks of plates, struts, or small unit cells include a high strength-to-weight ratio, efficient energy absorption, and a minimum amount of material required. In contrast to traditional methods, Additive Manufacturing (AM) technology enables the fabrication of complex geometries, for example, cellular structures, step by step, adding the material from digital data files. Although different research lines widely employ cellular structures, most existing reviews tend to focus on specialized parts of lattices, leaving other regions untouched.[35] focuses on providing a thorough account of the various lattice morphologies, designs, and the AM of cellular structures. Besides, it also highlights the difficulties and possibilities of the application of additively manufactured structures as well as their unique properties. The review points out the need for more research in cellular structure design, optimization, characteristics, as well as applications and AM. In contrast, there are high limitations and gaps in the current literature. The goal of this is to give an insight into AM cellular structures for researchers and industrial practitioners.

Choosing the optimum values for tuning parameters of machine learning algorithms is an issue that frustrates many people. The importance of these parameters cannot be underestimated in terms of how well the algorithms will perform. Automation is done through the utilization of Bayesian optimization and other data-efficient optimization algorithms. Nevertheless, while the algorithms are employed on real-world robotic platforms, they can perform a fatal operation on, for example, dangerous parameters, which can ultimately result in system downfall. We improve upon the SafeOpt approach, and then we offer a more generic algorithm that guarantees the safety of the system. It is done by [36] that performance will always exceed a certain level. Unlike other methods, each safety requirement could be predefined, and it is not necessary to be related to the goal. By putting safety first, this algorithm surveys the landscape of available alternatives. Here, the method relies on since it has regularity assumptions and a Gaussian process prior. This does context factors analysis to ensure that what you know is fully transferable into new situations. Theoretical study and experimental validation on a quadrotor vehicle demonstrate that this algorithm is effective in obtaining analysis rapid and automatic optimization of system parameters tuning.

This study design focuses on finding out how landslides can occur using a mixed model that uses PSO-ANN as the integrator. The main reason for the [37] is that the PSO optimization feature will be used to correct the problems that regular ANN models have, such as that they will take too long to learn and get stuck in local minima. In this study, huge data sets gathered in the Layleh Valley, Kermanshah, Iran, were applied. You can get 168,970 training

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datasets and 42,243 testing datasets out of it. Some processes, like the network design, weights, and PSO algorithm factors, are changed to improve the accuracy of LSM maps. Some of the driven data has been slope aspect, elevation, soil type, distance to road and more. The chances that a catastrophe will occur can be inferred from the intake of the information in the output area. The assessment instruments in this case include the coefficient of determination (R2) and root-mean-squared error (RMSE), which are used to compare the accuracy of both ANN and PSO-ANN models... Color intensity ratio (CER) and a total order structure are employed in the work to rank the samples. As it can be understood from the comparison of R2 values of training and validation datasets between PSO-ANN and main ANN models, the PSO-ANN approach is more stable than the main ANN model.

For a while, this in-depth research helps you understand the latest optimization algorithms for different areas. The literature has been rich and diverse, we have had success with metaheuristics such as MFO, GSA-GA, SOA and WOA. These are the ones applied: lots of optimization strategies, biological algorithms, and hybrid models in the recent study. It indicates the dynamics of the field. The cellular structures used in additive manufacturing are being studied, which have shown to make the design, optimization, and use of parts much less problematic. The role of a good selection of machine-learning program tuning parameters is stressed uniformly, too. This collection of various studies provides the possibility of getting glimpses of the latest techniques and paving the way for future projects in feature selection and optimization. Thus, it assists scholars as well as business practitioners.

3. Understanding Optimization

Optimization, a concept that is important in many areas, is needed for the attainment of perfect solutions. The optimization technique involves a set of goals that enable you to pick the most suitable solution from the set of acceptable alternatives, and it aims to enhance various processes so that they become as efficient and effective - particularly within mathematical and computing models. Reducing errors around machine learning and optimization is critical for training models to deliver results. Algorithms' error rates are significantly reduced, and performance is boosted by very careful adjustments to real-time data collection. Interpretability and efficiency of the model get improved with the identification of essential attributes through the feature selection, which is an optimization process. A variety of algorithms based on nature, including Moth–Flame Optimization (MFO), Whale Optimization Algorithm (WOA) and Seagull Optimization Algorithm (SOA), have been developed, which offer a cutting-edge solution to complex problems.

Optimization, a most versatile and fundamental principle, is the heart of many successful problem-solving approaches. The main idea of the optimization process is a systematic and strategical approach, which will provide for its maximum effectiveness or functionality. This is the mathematical and computational method that finds the optimum solution from among available alternatives with the given parameters or constraints. Improving efficiency, cutting costs, or attaining optimal performance, depending upon the context, is the primary objective. This idea of optimization spreads around the disciplines of engineering, operations research, economics, machine learning, and logistics. Civil engineers optimize designs for resource-efficient and economical structures, business managers rely on optimization for better decision models, economists use optimization to formulate economic models, machine learning needs optimization algorithms for training, and logistics turn optimized route planning into reality, among other things. Optimization invades every domain of science as well as good old sectors of business and management, allowing one to make a set of crucial decisions, allocate resources effectively and improve efficiency, progressing science, engineering, business and beyond.

3.1 Optimization Applications

The optimization algorithms used in many different fields lead to a whole reshaping of how things are done and how decisions are made. The optimization ability of the Imperialist Competitive Algorithm in design, optimization, and control of energy demonstrates the importance of optimization in structural engineering for the building of superior-performing buildings. Optimization methods play a significant role in additive manufacturing since they guide the design and production of complex cellular structures with high strength-to-weight ratios and, thus, progressing materials science and manufacturing technology. Machine learning and data mining domains use optimization for feature selection and parameter tuning to boost predictive performance and interpretability. Particle swarm optimization, together with artificial neural networks (PSO-ANN) [38-39] and other optimization methods, improve the accuracy of earth sciences in landslide susceptibility mapping (LSM) [40]. Therefore, risk assessment and reduction are simplified. The case study of SafeOpt further highlights the significance of optimization in robots for obtaining the most appropriate tuning parameters and operating safely. The diversity of these instances demonstrates the flexibility of optimization techniques, highlighting their capability to tackle

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complicated problems and optimize processes in many areas. Due to the continuous progress in technology, the field of optimization will become a more and more important factor that will determine the future of industries.

Figure 1 shows that optimization methods are used at different times in the life of an AI system to make it work better. Control techniques, research techniques, operation techniques, and artificial intelligence techniques are some types of optimization methods. It is possible to improve AI systems in other ways as well, such as by making predictions more correct and reacting more quickly. What kind of AI system is it, and how well does it need to work? Decide the best way to optimize it.

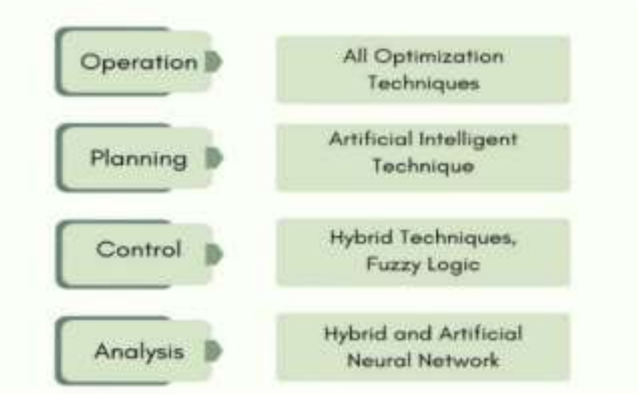

Figure 1: Optimization Methods.

3.2 Optimization for Moth-Flame (MFO)

MFO (Moth-Flame Optimization) has a principle that mimics moths around the fire. It can discover a way to advance something with this principle. Quite a number of individuals tend to regard MFO as a metaheuristic technique that is very efficient with a lot of optimization tasks. Things that fly do: This concept originates from the manner intrinsic to moths: light is their guiding principle. When more attractive lamps come along, the moths will approach them without a helm. It looks like moths and light with the biggest slope is thought as an efficient determinant. Things that matter: The improvement of things in many fields of power systems, medical images, engineering design, and economic load scheduling have shown a proof that the methods of the MFO are effective. The MFO algorithm takes it inspiration from the natural world to come up with the best solution, and it does that by solving the equation this way. Engineering Design: By being smart in using resources and conforming to the design's requirements, MFO has managed to somehow make engineering designs better. Load Scheduling: MFO assists utilities in doing this in a cost-effective manner which in turn leads to lower energy distribution prices. notably, the part showing that MFO manages to improve the appearance of bruises denotes the fact that it can treat a range of issues.

Figure [2] reveals the way in which a bug (a butterfly) moves across a grid and the process of burning a grid. The bug and the fire begin exactly at the same point on the screen. Then, it relocates to the fire without any plan, however, the fire doesn't move. The frame features different time marks that show the route of the bug (wiggly lines) and the route of the fire (straight lines). The graph needs to be made clear that it is a bug or where the mosquito originated from. It also doesn't explain why the bug randomly goes around or why it will cease 1 second after that.

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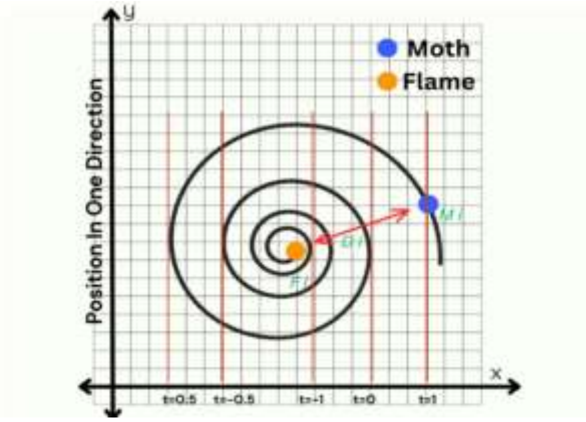

Figure 2: The Way In Which a Butterfly Moves Across a Grid.

It means to look at least two different ways to do the same thing. One possible review of a book would talk about MFO and other optimization methods, listing the pros and cons of each. It is possible to think that an MFO works better when used with different processes. Some things: The report talks about where MFO is, and now the study shows where it could be better or where more work needs to be done. Students can look for problems that were listed, ways to use them, and new things that can be mixed in a different order when they move on; It's important to stress what we've learned so far about MFO and how efficiency fits into your plan. Moth-Flame Optimization can be used in many technical and science areas and help people learn by doing. Moth-Flame Optimization is a useful metaheuristic technique that can be applied to numerous scenarios. There is still more research being done on MFO, which should help show how well it works and find better ways to use it to solve tough situations.

4. Conclusion

The applications of optimization algorithms extend across diverse fields, reshaping how decisions are made and tasks are accomplished. The Imperialist Competitive Algorithm's prowess in energy design and control underscores optimization's significance in achieving superior-performing structures. Additive manufacturing benefits from optimization methods, directing the design and production of complex cellular structures, advancing materials science and manufacturing technology. In machine learning and data mining, optimization plays a pivotal role in feature selection and parameter tuning, enhancing predictive performance and interpretability. The integration of optimization algorithms like PSO-ANN (Particle Swarm Optimization with artificial neural networks) improves accuracy in earth sciences, specifically in LSM (landslide susceptibility mapping), simplifying risk assessment and reduction. The diverse instances presented in this review illustrate the versatility of optimization techniques in tackling complex problems and optimizing processes across various domains. As technology continues to advance, optimization becomes an increasingly critical factor determining the future of industries. Feature selection emerges as a key player in optimizing machine learning models, contributing significantly to their performance and interpretability. The array of optimization algorithms discussed in this literature review, from Moth-Flame Optimization to Particle Swarm Optimization with artificial neural networks, offers a nuanced understanding of their strengths, applications, and comparative evaluations. This synthesis of research findings aims to guide researchers and practitioners, providing insights into cutting-edge approaches and laying the groundwork for future innovations in the realm of optimization.

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