Optimization:Background and Existing Challanges

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***Abstract*—Researchers working on problems in engineering, computer science, biology, and the physical sciences are developing advanced mathematical methods for control. Technological advances have had a major impact on the use of new analytical methods for dealing with nonlinear problems. One of the most challenging parts of control theory is tuning the parameters of nonlinear systems for an optimum solution. In the past, metaheuristic methods were tried to address this problem. They have proved to be useful when dealing with complex systems. Metaheuristic optimization techniques, unlike deterministic algorithms, excel at addressing problems with uncertain search spaces. Optimization-based control is now favored over conventional or intelligent control.**

Keywords—optimization, metaheuristic optimization, local search, global search

I. INTRODUCTION

Advanced mathematical techniques for control are being developed by researchers working on issues in engineering, computer science, biology, and the physical sciences. The application of novel analytical approaches for tackling nonlinear issues has been significantly influenced by technological advancements [1]. State may not be entirely quantifiable in most situations involving nonlinear control systems, making complicated control engineering problems difficult to address. The employment of a variety of distinct models and ideas, a lack of parameter standardization, a lack of suitable control approaches, external disruptions, and the greater level of nonlinearity of the equations that drive processes are all important challenges in the field of control technology. Another difficulty is a lack of understanding of critical variables, since the system's states might significantly affect the nature of the control design stage, allowing for excellent performance. As a result, it is clear that enhanced forecasting, control, and optimization approaches are required to ensure optimal nonlinear system performance. Understanding the system's control needs necessitates knowledge of the system; nevertheless, nonlinearities are frequently so complicated that control design for acceptable system performance is challenging [2]. New control techniques have developed over time to maintain optimal system performance that prevent interruptions, pauses, and design flaws.

Tuning the parameters of nonlinear systems for an optimal solution is one of the most difficult aspects of control theory. Metaheuristic strategies have been used to solve this challenge in the past. When dealing with complicated systems, they have proven to be beneficial. Unlike deterministic algorithms, metaheuristic optimization methods excel at solving problems with uncertain search spaces. These optimization approaches have been utilized in practically every sector of research, technology, and engineering to discover the best answer from a number of feasible solutions [3].

II. BACKGROUND AND EXISTING CHALLENGES

A. Optimization

An important paradigm which is everywhere along with wide range of utilizations is optimization. In practically all application areas such as mathematics, computer science, operation research, industrial and engineering designs, we are continually attempting to upgrade something - regardless of whether to limit the expense and vitality utilization, or to expand. The benefit, yield, execution and effectiveness. In all actuality, assets, time and money are consistently restricted; thus, optimization is unmistakably progressively significant [4].

One of the most key standards in our reality is the quest for an ideal state. It starts in the microcosm where molecules in material science attempt to frame bonds so as to limit the vitality of their electrons. At the point when particles structures strong bodies during the freezing process, they attempt to accept vitality optimal crystal structures. These procedures, of course, are not driven by any higher aim yet simply result from the laws of material science. The equivalent goes for the natural guideline of natural selection which, along with the organic development, prompts better adjustment of the species to their environment. Here, a nearby (local) optimal is a very much adjusted animal groups that rules every single other creature in its environmental factors. Homo sapiens have arrived at this level, imparting it to ants, microorganisms, flies, cockroaches, and a wide range of other creatures. For whatever length of time that mankind exists, we take a stab at flawlessness in numerous territories. We need to reach a most extreme level of joy with minimal measure of exertion. In our economy, benefit and deals must be expanded and expenses ought to be as low as could be expected under the circumstances. In this way, optimization is one of the most established sciences which even stretches out into everyday life [5].

Optimization is the study of choosing the best choice among a debilitated hover of choices [1] or it tends to be seen as unitary of the major quantifiable mechanism in system of dynamic in which judgments must be employed to enhance single or more evaluations in some affirmed set of conditions [6].

Most of the engineering and industrial design problems are based on computer simulations, which results in added complications like non-linear constraints, interdependencies amongst variables and a large solution space to optimization. Any approach which can accelerate the time of simulation and optimization process results in saving of time and money. Thus, methods of optimization can be defined as mechanism specifically designed to attain the objective of minimizing or maximizing a fitness function (or objective function) subject to given set of constraints. It must give enough good solution in enough time frame [7][8].

Each problem of optimization accompanies some decision variables, certain objective (fitness) function and few constraints. Need of employing optimization techniques is to acquire the estimations of decision variables that optimize a fitness function subject to specific constraints [4]. Decision variables are inputthing which can be controlled and thumb rule of any optimization problem is to choose minimum number of design variable. The following undertaking in the optimization is to locate the fitness or objective function in terms of the design variables and other problem parameters the constraints show functional relationships among the design variables and other design parameters satisfying certain physical phenomenon and certain resource limitations. The nature and number of constraints to be included in the formulation depend on the user. Constraints may have exact mathematical expressions or not [5].

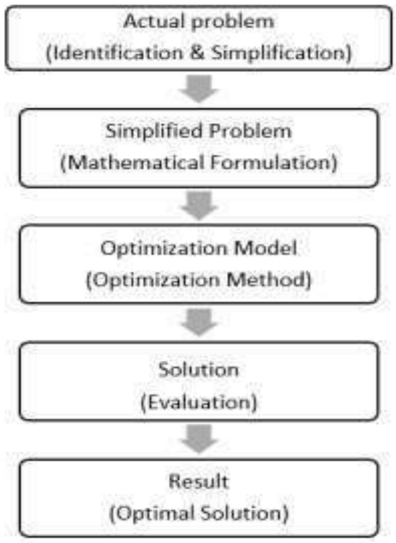

Figure 1.1 Flow chart of Optimization

This optimization vocabulary can be understood by this example:

A football coach is putting up a practice schedule for his defensive players.

- The main optimization will be to achieve maximum running yards, which will be his goal function.

- He may have his players spend time in the weight room, sprinting, or practicing ball protection during practice.A decision variable is the amount of time spent on each. However, the overall amount of time he has is limited. Also, if he totally foregoes ball protection, he may notice an increase in both rushing yards and fumbles, therefore he may set a restriction on how many fumbles he finds acceptable. These are boundaries.

- The objective function is influenced by the decision (or planned) variables, and the constraints restrict the scope of the variables[6]

An optimization algorithm is characterized by

1. the methodology through which it assigns fitness to individual
2. way of selecting an algorithm for future analysis
3. approach of applying search operations
4. the way it builds and treats its state information Literature review of optimization algorithm revel that there is no systematic classification is available. But in a broader way optimization algorithm can be classified as

   - Some problems have constraints but some problems do not have constraints.
   - Variable can be one or more than one
   - Variable can be continuous or discrete.
   - Some problems are static while some are dynamic.
   - System can be of either deterministic or stochastic.
   - Mathematical equation of optimization problem can be linear or nonlinear.
   - Design variable can be of different types[7].

5. Deterministic and stochastic optimization methods are two types of optimization algorithms. A deterministic algorithm is one that works in a physically definite way without any randomness. If we start with the same starting point, such an algorithm will arrive at the same ultimate answer. Deterministic algorithms include hill-climbing and downhill simplex. On the other hand, if the method has any

randomness, the algorithm will usually arrive at a different location each time it is run, even if the same starting point is utilized, Such Stochastic algorithms include things like genetic algorithms and PSO.

If a function's gradient is the emphasis, optimization techniques can be divided into derivativebased and gradient-free algorithms. Hill-climbing algorithms, for example, utilize derivative information and are frequently quite efficient. Derivative-free algorithms rely solely on the function's values rather than derivative information. Because some functions have discontinuities or it is costly to calculate derivatives precisely, derivative-free techniques like Nelder-Mead downhill simplex come in handy.

Optimization algorithms can be classed as trajectorybased or population-based from a separate standpoint. A trajectory-based algorithm usually works with a single agent or solution at a time, tracing out a path as the iterations progress. Hill climbing uses a piecewise zigzag pattern to connect the starting and ending points. Simulated annealing, a common metaheuristic algorithm, is another good example. Particle swarm optimization (PSO), for example, is a population-based technique that uses several agents to interact and trace multiple pathways (Kennedy and Eberhardt, 1995).

Here are two types of search algorithms: local and global search algorithms. Local search algorithms usually converge to a local optimum, not necessarily (and frequently not) the global optimum, and they are often deterministic and have no way of escaping local optima. Simple hill Where are termed as function of climbing is an example of this. Local search algorithms, on the design vector. the other hand, are ineffective for global optimization, and global search algorithms should be utilized instead. In most Here the segments of x are xi termed as decision circumstances, modern metaheuristic algorithms are suitable for global optimization, however they are not always successful or efficient.

In general form an optimization problem is defined as :

methods to the stated problem are the three key challenges in simulation-driven optimization and modelling.

$$\underset{x \in R^n}{\text{Minimize}} \quad f_i(x) \quad (i = 1,2,\ldots,M), \tag{1.1}$$

$$\text{subject to} \quad \emptyset_j(x) = 0, \quad (j = 1,2,\ldots,J), \tag{1.2}$$

$$\varphi_k(x) \le 0, \quad (k = 1,2,\ldots,K), \tag{1.3}$$

Where $f_i(x)$, $\emptyset_j(x)$ and $\varphi_k(x)$ are termed as function of the design vector.

$$x = (x_1, x_2, \ldots x_n)^T \tag{1.4}$$

variables or design variables. These design real continuous, discrete or combination of two. The function $f_i(x)$ is termed as objective (or fitness, or cost, or energy) function. In equation 1.1 if M=1 then it is termed single objective function, and if M is greater than 1 then it is termed as multi objective function. In equation 1.2 $\emptyset_j(x)$ is termed as equality constraint whereas in equation 1.3 $\varphi_k(x)$ is termed as inequality constraint. The space spanned by the values of objective function is termed as solution (or response) space and the space taken by the design variable is termed as search (or design) space [7].

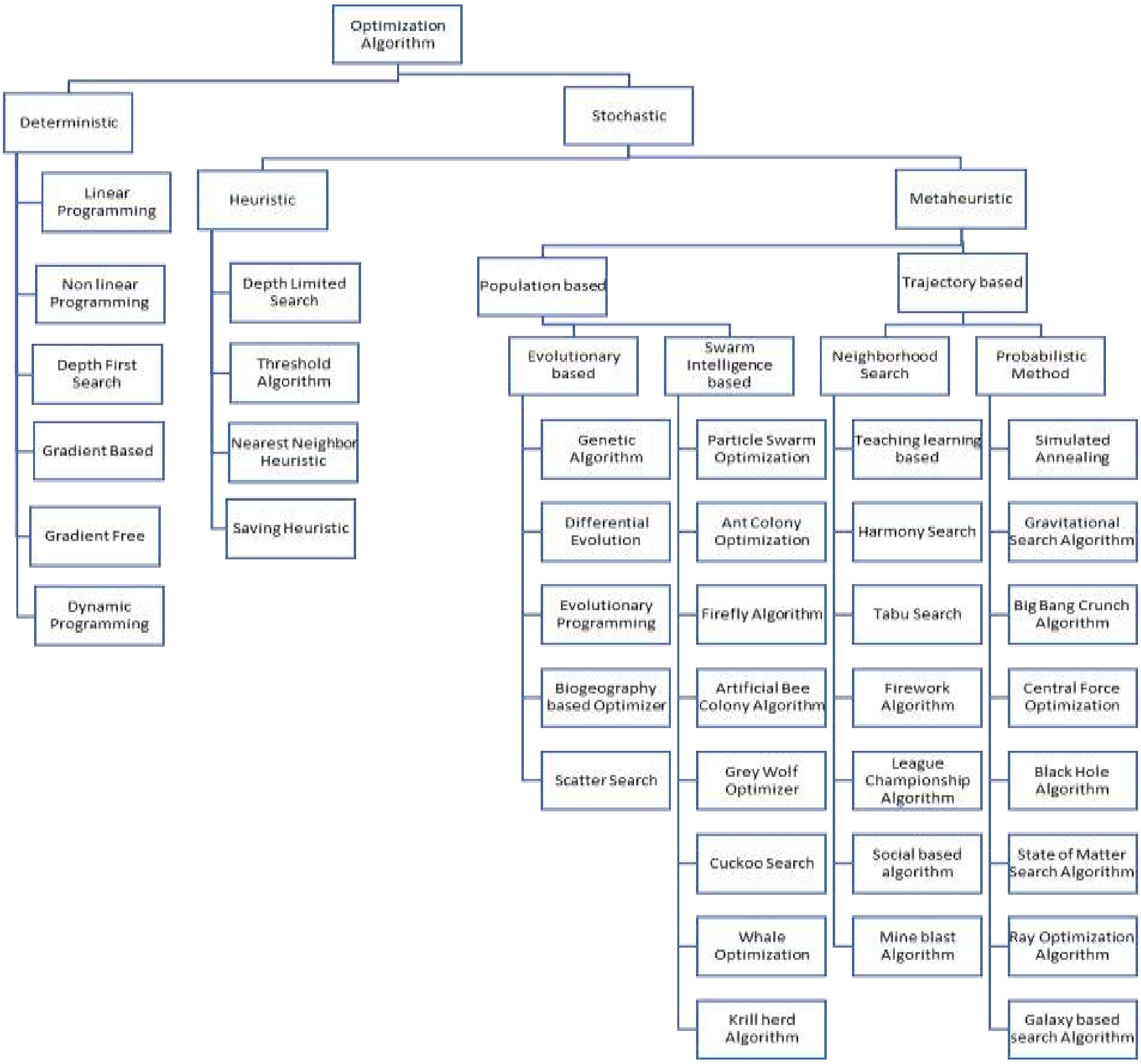

Figure 1.2 Taxonomy of optimization algorithm [8].

B. Existing Challenges in Optimization

The effectiveness of an algorithm, the effectiveness and and precision of a statistical simulator, and assigning the precision of a statistical simulator, and assigning the correct correct methods to the stated problem are the three key challenges in simulation-driven optimization and modelling. Despite their importance, there are no adequate rules or norms in place. We certainly strive to employ the most appropriate methods feasible, but the actual efficiency of an approach depends on a variety of factors, including the method's internal workings, the information required (such as fitness functions and derivatives), and implementation concerns

1) Algorithm’s Effectiveness

It's critical to have a good optimizer in order to get the best results. An optimizer is essentially an optimization technique that has been appropriately built to perform the required search. It may be connected and merged with other modelling elements. According to the No Free Lunch Theorem[9], there are several optimization methods in the literature, and no one solution is suited for all issues.

1. Algorithm’s Correctness

The selection of the appropriate optimizer or method for a particular issue is critical from an optimization standpoint. The kind of issue, the structure of the methodology, the required quality of outcomes, the modern computing resource, timeframe, availability of the method implementation, and the selection' experience will all influence the algorithm selected for an optimization job [10][11].

2) Effectiveness of statistical Solver

The most computationally intensive element of solving an optimal control problem is usually evaluating the design objective to see if a preferred approach is viable and/or optimum. Typically, we must perform these evaluations hundreds, thousands, or even millions of times. As a result, any method for decreasing computing time, whether by limiting the number of assessments or enhancing the simulator's effectiveness, saves both time and money. The major approach to decrease the amount of objective assessments is to utilise an effective algorithm, so that only a minimal number of such evaluations are required [12].

C. Metaheuristic optimization

Meta- stands for "beyond" or "higher level" in metaheuristic algorithms. They outperform simple heuristics in most cases. Local search and global exploration are used in all metaheuristic algorithms in some way. Randomization is frequently used to achieve variety of solutions. Despite the prevalence of metaheuristics, the literature lacks an agreedupon definition of heuristics and metaheuristics. The terms 'heuristics' and ‘metaheuristics' are sometimes used interchangeably by scholars. However, a recent trend has been to label any stochastic algorithms that include randomization and global exploration as metaheuristics. Randomization is an effective strategy to move away from local search and toward global search. As a result, nearly all metaheuristic methods may be used for nonlinear modelling and global optimization. Metaheuristics can be an effective technique to provide acceptable solutions to a complicated problem through trial and error in a reasonable amount of time. Because of the complexity of the problem of interest, it is difficult to search for every possible alternative or combination; instead, the goal is to identify a good practicable solution in a reasonable amount of time. There's no guarantee that the best solutions will be found, and we don't even know if an algorithm will work or why it will work if it does[13]. The goal is to create an efficient and practical algorithm that works the majority of the time and produces high-quality results. It is reasonable to predict that some of the found quality solutions will be approximately ideal, however this cannot be guaranteed [14].

1) Characteristics of Metaheuristic Algorithms

The fundamental technique to problem-solving has always been heuristic or metaheuristic – via iterations – throughout history, especially at the beginnings of human history. Heuristics were used to make many scientific breakthroughs by thinking outside the box, and frequently by coincidence. The Eureka moment of Archimedes was a heuristic victory. In reality, our daily learning experiences (at least as children) are mostly heuristic [15].According to [16] "*Metaheuristic computing is an adaptive and/or autonomous methodology for computing that applies general heuristic rules, algorithms, and processes in solving a category of computational problems.*"

Metaheuristic algorithms' high performance is often due to their ability to mimic nature's best qualities. Metaheuristic algorithms have two main characteristics: intensification and diversification. The intensification phase, also known as exploitation, searches for and identifies the best candidates or solutions based on the present best approaches. The diversification phase, also known as exploration, guarantees that the algorithm efficiently traverses the search space. A tight balance between these two components has a significant impact on an algorithm's overall efficiency. If the exploration is insufficient and the exploitation is excessive, the system may become stuck in a local optimum. Finding the global optimum would be extremely difficult, if not impossible, in this instance. On the other hand, if there is too much exploration but not enough exploitation, the system may fail to converge. The overall search performance slows down in this instance. Balancing these two components is a huge optimization challenge in and of itself [17][15].

A good technique or criterion for selecting the best solutions should be explored during the search. A typical measure is "survival of the fittest." It is predicated on continuing to update the current best solution discovered so far though. Furthermore, a certain amount of elitism should be applied. This is to ensure that the finest or fittest solutions do not become extinct and are passed down to future generations.

Each algorithm and its variants employ various methods to achieve a balance of exploration and exploitation. Certain randomization in combination with a deterministic technique might be viewed as a cost-effective means of achieving exploration or diversification. This ensures that the freshly generated solutions are distributed as widely as possible within the search space available. From the standpoint of implementation, the method used to implement the algorithm has an impact on performance. As a result, any algorithm's implementation must be validated and tested [18].

2) No free lunch theorem

There are the so-called "No free lunch theorems," which can have considerable impacts in the optimization field
(Wolpert and Macready 1997). According to this, "If algorithm A outperforms algorithm B for particular optimization functions, then B will outperform A for all other functions". In other words, if both algorithms A and B are averaged over all potential function space, they will perform equally well. That is to say, there are no algorithms that are uniformly superior. Another point of view is that for a particular optimization issue, there is no need to average over all feasible functions. The most important goal in this situation is to locate the optimal solutions, which has nothing to do with the average over all potential function space. Other researchers argue that there is no universal tool and that some algorithms outperform others for specific sorts of optimization problems based on their expertise. As a result, the main goal would be to either choose the best algorithm for a given problem or to develop bigger algorithms for the majority of problems, not necessarily all of them [19].

According to [21],Metaheuristic algorithms share the following traits:

- The algorithms are based on natural events or behaviors, and they follow specific rules (e.g., biological evolution, physics, social behavior).
- Probability distributions and random processes are used in the selection phase, which contains random elements.
- They provide a number of control parameters to modify the search method, since they are intended to be general-purpose solvers they don't depend on a priori knowledge, which is information about the process that is accessible before the optimization run begins. Nonetheless, such knowledge may be beneficial to them (e.g., to set up control parameters).

3) Existing issues with Metaheuristic Optimization

Finding the optimal answer to a problem is the optimization process. As a result, the primary challenge for metaheuristics is figuring out how to cope with this issue. Despite the fact that many metaheuristics have been suggested, only a handful metaheuristics have consistently attained the required success rate. Population-based metaheuristics, in particular, are frequently employed because they can adapt to large-scale optimization issues. Metaheuristics, as previously stated, are problem-specific algorithms. As a result, the issue is, "What is the optimal algorithm parameter specification based on the kind and size of the problem search space?" Furthermore, selecting the proper metaheuristic algorithm is a complex thing. Recent developments seek to liberalize metaheuristic methods in order to overcome these problems.

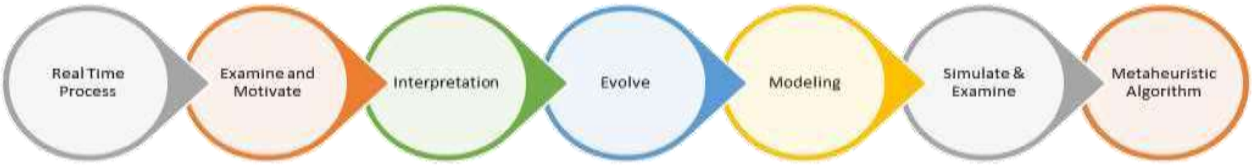

Figure 1.3 Development Procedure of Metaheuristic Algorithms [20]

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DRD-CNN: Diabetic Retinopathy detection using CNN

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Abstract- Diabetes, often known as diabetes mellitus, is a metabolic disorder in which the body generates insufficient amounts of insulin, resulting in elevated blood sugar levels. Up to 80% of persons with diabetes who have had it for 10 years or more will develop diabetic retinopathy (DR), an eye disease brought on by the disease. In this study, we use U-Net segmentation with region merging and Convolutional Neural Network (CNN) to automatically diagnose various stages of diabetic retinopathy. then group high-resolution retinal images according to the severity of the disease into 5 phases. The CNN model is trained using training datasets, and CNN will provide the likelihood that a diabetic has infected the eye. In order to effectively determine the severity of diabetic retinopathy disease, the initial goal of the model is to train it by providing the training datasets.

The EyePacs Dataset provided the testing dataset, which includes over 35,000 photos with an average of 6 million pixels per image and retinopathy scales. Images from patients representing a wide range of ages, ethnicities, and lighting conditions were included in this dataset. The Proposed technique is efficient than the existing techniques.

***Keywords:*Diabetes, retinopathy, Convolutional Neural Network (CNN), Image Classification**

1. Introduction

Diabetic Retinopathy is an eye disease which can affect the retina and can further cause permanent vision loss. Detection of diabetic retinopathy in early stage is very important to prevent blindness. Many physical tests like visual sharpness/excellent ability test, pupil (expanding/enlarging), optical clearness tomography can be used to detect diabetic retinopathy but are time consuming and affects patients also. In India itself, more than 62 million people are
suffering from diabetes.

[1] According to the International Diabetes Federation, the number of adults who are suffering from diabetes in the whole world is estimated to be 366 million in 2011 and by 2030 this would have risen to 552 million. The number of people with type 2 diabetes is increasing in every country. Most of people with diabetes live in low-and middle-income countries and don't treat diabetes seriously. India stands first with 195% (18 million in 1995 to 54 million in 2025). Previously, diabetes mellitus was considered to be