IMPROVED REACTIVE POWER DISPATCH USING SLIME MOULD ALGORITHM.

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CERTIFICATE OF APPROVAL

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List of Acronyms

OPF- Optimal Power Flow

ORPD- Optimal Reactive Power Dispatch

SMA- Slime Mould Algorithm

MA- Metaheuristic Algorithm

ED- Economic Dispatch

UC- Unit Contribution

MCS- Monte Carlo Simulation

IA- Interval Arithmetic

GA- Genetic Algorithm

PSO- Particle Swarm Optimization

DEPSO- Diversity Enhanced Particle Swarm Optimization.

ABSTRACT

Optimal Reactive Power Dispatch (ORPD) problem is a genuine concern for any power system. It is important to determine the ideal reactive power dispatch for different kinds of load conditions. ORPD is responsible for reducing the active power loss in a system by adjusting the reactive power control variables and consequently influences the economics and net efficiency of the power System. The optimization of reactive power also ensures the voltage stability and thus maintains the security and reliability of the system. Slime Mould Algorithm (SMA) is a novel Metaheuristic Algorithm (MA) which replicates the behaviour of slime mould for searching and collecting food with the help of the excellent exploratory capabilities of slime mould. This paper brings forth the feasibility of the application of SMA to the realm of optimal reactive power flow. In this thesis, IEEE 30-bus test method is used to show the feasibility of this method. The findings were analyzed and compared to other approaches that are used for solving ORPD problems. SMA is a more efficient and robust system even compared to the most recent swarm intelligence based metaheuristic algorithms and presents a possibility for unparalleled efficiency.

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CHAPTER 1

INTRODUCTION

1.1Motivation

The modernization of the power sector has given rise to new innovations in power grid activity and planning. The electrical power grid is such a complex network, consisting primarily of a generation, transmission and distribution network for the delivery of electricity on a range of load requirements [1].Existing operational requirements of the power grid need more careful attention in order to provide adequate supply, in an economic and productive fashion, for an improvement in the pace of demand growth. The need for reactive power management has been established by the utility planners and the operators to retain sufficient voltage at critical points and to monitor unwanted reactive power flows [2]. The preparation and maintenance of the modern power grid is projected to have a substantial effect due to the presence of intermittent renewable energy. Analytical methods used in the conventional grid, such as power flow analysis, Optimal Power Flow (OPF), Economic Dispatch (ED) and Unit Contribution (UC), will require suitable changes to accommodate uncertainty from renewable sources [3]. While local control systems have been developed to govern the generation of these renewable sources, they have not been able to meet the dispatch orders of the system operators and to balance the supply and demand of electricity.

A wide range of stochastic techniques, such as Monte Carlo Simulation (MCS) and Interval Arithmetic (IA), have been used in the literature to model and analyze the uncertainties resulting from these energy sources [3]. Some of these techniques are essentially costly to use. The amount of precision needed for power system implementations could be missing. The aim of the power flow analysis is to plan ahead and account for various hypothesized circumstances. The Newton-Raphson (NR) method is a solution process which can have problems of integration for large systems by using a flat-start or reaching the full capability of the system [4].

Often, traditional power flow solution approaches require iterative action where PV-PQ bus swapping as the reactive power on the generator bus breaks the constraints [5].

So, there is a need of a more reliable, scalable and stable power flow approach for undertaking analytic control system studies taking into account. In order to achieve this, a variety of optimization frameworks are suggested in this area that help to achieve the power flow solution steps as optimization constraints. So, in this paper a new optimization algorithm is proposed which helps to improve the power flow problems.

1.2 History of Optimal Power Flow

Optimal power flow or OPF has had a long history of its own. It was first explored by Carpentier in 1962 and it took a while to become a successful algorithm that might be used on a regular basis. Present interest in the OPF focuses on its capability to solve the optimal solution that takes ensures the security of the particular device. The ultimate purpose of solving the OPF for a minimal generation cost and require that the optimization estimate still balances the whole power flow-at the same time. The objective function can take different forms other than reducing generation costs. It is normal for OPF to be expressed as a minimization of electrical losses in the transmission lines, or to be expressed as a minimum generation change and other controls from the optimum operating point.

1.3 Literature Review

The efficient generation and transmission of electrical energy is one of the most effective ways of reducing the waste of natural resources as well as the global carbon footprint while reducing the cost of electricity making is available to more people. Optimal Power flow (OPF) is the field which primarily focuses on reducing the thermal fuel cost of electrical energy by the optimization of the various operating variables. The optimum condition is attained by adjusting the available controls to minimize the desired objective function while also subjecting it to the system limitations and security constraints. One of the important goals of OPF is to determine the optimum planning of the power system and the determination of the best operating levels. Another important objective is to ensure the system security as well as maintaining voltage stability and power quality. OPF does all these optimizations while taking into account the operating ranges of the various equipment involved. In the extended branches of OPF various other factors are brought into consideration such as the system security. The environmental dispatch of the power is also of concern for OPF. The OPF problems are nonlinear and non-convex and thus can be quite a challenging problem for regular computational algorithms to solve. ORPD is a sub problem of optimal power flow. ORPD is primarily focused on the minimization of real power by regulating the reactive power in the system. In the initial days of power loss minimization, various conventional methods such as linear and non-linear programming, quadratic programming and Newton Raphson methods were primarily used [6-11]. These methods were pretty rudimentary in nature as they were very resource intensive for the computing device to implement especially as the system grew more and more complex. These techniques required many assumptions and the outcome would often depend on the accuracy of said assumptions. Furthermore, these methods have to do a considerable amount of rounding off for the discrete variables in order to converge to a suitable solution.

This rounding off results in approximations which lead to reduced accuracy and performance as well as high computational demand. It has been shown in various studies that the application of heuristic techniques [12] in such optimization of ORPD results in far better performance compared to traditional methods. These heuristic techniques provide a more realistic chance of reaching the optimum. These methods reduce the tendencies of classical methods of to settle to local optima to a large extent. Genetic Algorithm and Particle Swarm Optimization algorithms are some practical examples [13-17] among many others [18-21]. By choosing the appropriate initial values we can reach near the global optimum in many cases. The addition of various penalty functions helps to combat the rounding off issue further. As such, many new techniques have been created which incorporate metaheuristics methods in the ORPD. Swarm Intelligence techniques such as Honey Bee mating Optimization (HBO) [22] and its variants, Particle Swarm Optimization (PSO) and its various enhancements [23-26], Artificial Bee Colony (ABC) [1] and its variants, Gray Wolf Optimizer (GWO) [27], Ant Lion Optimizer (ALO) [28], Dragon Fly Optimization (DFO) [29] have been used. Physics based methods such as Harmony Search Algorithm (HSA) and Gravitational Search Algorithm (GSA) [30-31] have also been successfully been implemented for ORPD purposes along with their enhancements [32]. Evolutionary algorithms such as Genetic Algorithm (GA) and its variants, Differential Evolution (DE) [33] and JAYA algorithm [34] have also been employed in multiple problems regarding power system optimization including ORPD. Over the years, several improvements or upgraded variants of these metaheuristic algorithms have been invented and published bearing some sort of improvement. Despite of these advancements the improvements have been rather incremental and the issue of getting stuck in the local optima still remains. This work aims to present a novel metaheuristic technique in the field of ORPD with the objective of achieving unprecedented efficiency and accuracy.

1.4 Thesis Objective

The main objective of this thesis is to solve the ORPD problem of a sample test system (IEEE 30-bus test system) by adopting SMA. To be more specific, the objectives include:

- To develop a code for solving and providing the result of ORPD for the aforementioned test system. This loop is flexible and can be used for trying to solve the problem with various algorithms.
- To develop the code in such a way that the individual optimized values of each of the variables is provided in the final result.
- To apply and adapt the theorized SMA in the previously mentioned code and check the performance of this algorithm for this particular problem.
- To apply and adapt previously used and recognized algorithms (PSO and DEPSO) and compare their performances with the performance of SMA.

1.5 Thesis Organization

- In Chapter 1, the introduction to the thesis is provided which describes the inspiration behind the analysis. It lays out a systematic analysis of the literature, which concentrates on the power flow analysis problem and the deterministic and stochastic OPF problem. It also states the basis on which the previous efforts have been progressively carried out throughout the past few decades leading to the current effort.
- In Chapter 2, the background review of our topic is pointed out and the methodologies used in the analysis discussed in this study. The key topics relevant to this study are also discussed in this chapter before describing the solution. This chapter also describes the multiple constraints and boundary conditions.

- In Chapter 3, the problem formulation of our thesis is highlighted. In this section the problem formulation has been discussed in detail and the mathematical model of each formulation is shown.
- In Chapter 4, the methodology of solving the optimal reactive power dispatch problem is described. The main focus of our thesis was the SMA method. However, the PSO and DEPSO methods have been implemented in this work and thus discussed in detail. The flowcharts, mathematical models, constraints, limitations etc. have been elaborated in this section.
- In Chapter 5, the simulation criteria and conditions are described. The test system used for simulation is explained in detail and the parameters and various arbitrary values are noted. The control variable limits chosen are tabulated. The details of the computing device used for simulation and results compilation are also mentioned. The results obtained after simulation are tabulated and compiled in this section.
- In Chapter 6, the whole thesis is summarized and concluded. The future prospects of this area of study is also stated for further research.

CHAPTER 2

THEORY OF OPTIMAL POWER FLOW

This chapter points out the background to the methods and methodologies used in the analysis discussed in this study. The key topic relevant to this is also discussed in this chapter before describing the solution.

2.1 Optimal Power Flow

- ### Power Flow

Power flow is a steady state study, the purpose of which is to determine

- Voltages.
- Currents.
- Active power.
- Reactive power.

In a network under a certain load condition. In the power flow problems the generator injections, generator voltages and loads are given and after performing the load flow analysis all the bus voltages, voltage angles and branch currents are obtained.

- ### Economic Dispatch

Economic dispatch deals with the minimization of the operating fuel cost. Economic dispatch is the short-term calculation of the optimum performance of a variety of electricity generation plants to meet the grid load at the minimum possible cost.

Power flow doesn't deal with the associated costs and Economic dispatch doesn't bother about the line limits. Optimizing the generator when applying the transmission line limits combines economic dispatch with power flow which is known as optimal power flow.

2.2 Power Flow Constraints.

In the power flow calculations and optimization, there are certain constraints which can't be violated or exceeded in order to meet the demands and the certain limitations of the different components of the system. These constraints can be divided into two parts; inequality constraints and equality constraints.

2.2.1 Inequality Constraints

While producing generation there must be some limitations. The generation voltage must be within the limits, insulating material must be properly selected, the transformer tapping shouldn't violate the limit. The Inequality Constraints are given below:

- **Reactive power generation limits**

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{2.1}$$

- **Voltage magnitude limits**

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N_B \tag{2.2}$$

- **Transformer tap-setting constraint**

$$T_k^{min} \leq T_k \leq T_k^{max} \tag{2.3}$$

- **Power flow limit constraint of each transmission line**

$$S_{lm} \leq S_{lm}^{max} \tag{2.4}$$

Q, V, T *and* S represent reactive powers, voltage, transformer tap and thermal limit of transmission line respectively. Subscripts B, g correspond to bus, generator and indices *i*, *k* and *m* represent the number of the generator, bus and line.

2.2.2 Equality Constraints

- Responsive power flow balance calculations for all buses except for the slack bus.

$$P_{gi} - P_{di} - v_i \sum_{j \in N_i} v_j \left(g_{ij} cos\theta_{ij} + B_{ij} sin\theta_{ij} \right) = 0 \tag{2.5}$$

- Reactive power flow balance calculations for all PQ buses (load buses)

$$Q_{gi} - Q_{di} - v_i \sum_{j \in N_i} v_j \left(g_{ij} sin\theta_{ij} + B_{ij} cos\theta_{ij} \right) = 0 \tag{2.6}$$

P, Q, G *and* B respectively denote real and reactive powers, conductance and susceptance. Subscripts *g*, *d* correspond to generator, demand and indices *i*,*j* represent the number of the generator, load.

2.3 Optimal Reactive Power Dispatch

Optimal Power Flow (OPF) is an area that focuses on reducing the expense of electrical energy transfer by optimizing the different variables. The two sub problems within OPF are the Optimal Reactive Power Dispatch (ORPD) and Optimal Real Power Dispatch (ORPD). ORPD is a sub problem of OPF. Due to the nature of the generators and the majority of loads, complex power is obtained from the power system. The active power is utilized while the reactive power remains in the system. ORPD is primarily focused on the minimization of real power by regulating the reactive power in the system. This is achieved by optimizing the control variables such as the transformer tap ratios, outputs of the generator buses and outputs of the reactive power compensators, usually in the form of capacitors. Another significant role of ORPD is the maximization of voltage stability and the power quality. In order to ensure the stability of the system ORPD employs various techniques to keep the voltages of the load buses within the predetermined tolerances of the specific power system. This is crucial to prevent the numerous electrical equipment and devices from getting damaged. The basic function of the various optimization methods is to determine the values of the control variables for which the power losses are minimum, while keeping the parameters within the limits of the system while satisfying the various equality and inequality constraints. ORPD is a nonlinear, non-convex, multivariable constrained optimization problem.

So, the optimality of the reactive power dispatch can be achieved when transmission losses are minimized and bus voltage deviations are within the limits.

2.4 Objective Function

2.4.1 Objective function

The formulation of limits on equality and inequalities in the model of control the framework and its operating limitations are properly addressed in the preceding subsections. However, these statistical limits do not explain one particular state of the network. An overwhelming number of states in the power structure can only be computed when these restrictions are taken into consideration. Thus, the option of an objective to simulate special, potentially extreme or ideal states of the power system inevitably follows. There are primarily two goals that today's electricity utilities are seeking to accomplish. In addition to taking into account organizational constraints:

- Reduction of the total cost of the generated power.
- Reduction of active transmission losses.

The objective function is the summation of the total active power loss or reactive power loss in the transmission lines and the penalty function. The required Static square penalty function is used to overcome inequality constraints which are shown in equation (2.9). Static penalty function neutralizes the infeasible solutions and penalizes those which violate the feasibility. Then the modified objective function (function of fitness) would be given in equation (2.7)

$$F_p = \sum_{k \in N_E} P_{kloss} + Penalty\ Function \tag{2.7}$$

Where,

$$Penalty\ Function = k_1 * \sum_{i=1}^{N_G} f\left(Q_{gi}\right) + k_2 * \sum_{i=1}^{N_G} f(V_i) + k_3 * \sum_{i=1}^{N_G} f(S_{lm}) \qquad (2.8)$$

k_1, k_2, k_3 are constants which are selected by trial and error process.

$$f(x) = \begin{Bmatrix} 0 \\ (x - x^{max})^2\ if\ x > x^{max} \\ (x^{min} - x)^2\ if\ x < x^{min} \end{Bmatrix} \qquad (2.9)$$

2.4.2 Penalty Function

The objective of the penalty functions is to turn constrained problems into unregulated problems by adding an external penalty for violation of constraint. Penalty function is needed when there is a possibility of violating the constraints. There are certain reasons for this violations.

- Line flow violations.
- Reactive power violations.
- Bus voltage violations.

Despite of these improvements, there are areas that can benefit from further improvement such as the quicker convergence to the optima and faster identification of the global optima from the multiple local optima.

CHAPTER 3
PROBLEM FORMULATION

This chapter highlights the formulations of the problems and discusses the equations that are relevant to it.

3.1 Problem formulation

The goals of the work are to minimize the actual power transmission losses in the system and the bus voltage deviations must be within the limits. Control variables under consideration include PV bus voltages (Vg), transformer tap ratios (Tk) and reactive power outputs (Qc). The current study can be mathematically represented as three formulations.

3.1.1 Formulation -1 (Minimization of active power losses.)

Since the reduction of active utilities, this is the common goal of utilities, power losses are both cost-effective (economic reasons) and cost-effective.

$$min \sum_{k \in N_B} P_{kloss} = \sum_{k \in N_B} g_k(v_i^2 + v_j^2 - 2v_i v_j cos\theta\_ij\ ) \tag{3.1}$$

$$F_1 = min \sum_{k \in N_B} P_{kloss} + Penalty\ Function \tag{3.2}$$

Where,

$$k = (i, j); i \in N_B(Total\ no\ of\ buses), j \in N_i(No\ of\ buses\ adjucent\ to\ bus\ i)$$

$$\sum_{k \in N_B} P_{kloss} = Total\ Real\ power\ Losses\ in\ the\ Transmission\ line.$$

$g_k = conductance\ of\ branch\ k(pu)$.

$v_i, v_j = voltage\ magnitude(pu)\ of bus\ i\ and\ j\ respectively.$

$\theta_{ij}\ = bus\ voltage\ angle\ difference\ between\ bus\ i\ and\ j(rad)$

3.1.2 Formulation 2

Minimization of bus voltage deviation

Here, the reference bus voltage is 1 per unit. From this formulation 2, it is calculated how much of the respective bus voltages are deviated from the reference value.

$$F_2 = \sum_{lb=1}^{N_{lb}} |V_{lb} - V_r| \qquad (3.3)$$

Where,
V_r=reference voltage.
V_{lb}=bus voltage magnitudes.

3.1.3 Formulation 3

The minimization of bus voltage deviations is crucial to the effectiveness of the overall system. For this problem we have two different objectives in the same solution where the Real Power is minimized while simultaneously bus voltages are within the limits. This is done by weighted sum method where the weights are varied from zero to one. The following equation is utilized:

$$F_1 = min \sum_{k \in N_B} P_{kloss} + Penalty\ Function \qquad (3.4)$$

$$F_2 = \sum_{lb=1}^{N_{lb}} |V_{lb} - V_r| \qquad (3.5)$$

$$min \sum F = \min(P_1 + P_2) \tag{3.6}$$

$$P_1 = w_1 * F_1 \; and \; P_2 = (1 - w_1) * F_2 \tag{3.7}$$

Here, F is the objective function of the multi objective problem.

$F1$ is the objective function of the Total Power Loss.

$F2$ is the objective function of the Total bus voltage deviations.

$P1$ is the objective function of the Total Power Loss multiplied by the weight.

$P2$ is the objective function of the Total bus voltage deviations multiplied by the weight.

w_1 is the weight.The range of w_1 is between 0 and 1

CHAPTER 4
SOLUSION METHODOLOGY

This chapter deals with the solution methodologies of our problem. There are numerous ways of solving this ORPD problem. Some of the methods are conventional methods and some of the methods are intelligent methods. By using conventional methods we can get the accurate results for the power system. But one of the drawbacks is that the processing time is high. On the other hand, using intelligent methods, we can use higher computing power and various algorithms that are processed by some uniform distribution of numbers. Here we've been comparing three processes. In this section we are going to discuss all the methodologies in detail.

4.1 Introduction of Particle Swarm Optimization

4.1.1 Origins

Particle Swarm Optimization is a stochastic algorithm that is motivated by the existence of social activity and complex movements of coordination between insects, birds and fish. In 1986, Craig Reynolds defined this mechanism in three basic behaviors:

- **Separation**: Separation of the local flock mates. Figure 4.1[40] shows the movement of the flock mates. In this step the local flock mates are randomly separated which is denoted by blue triangles.

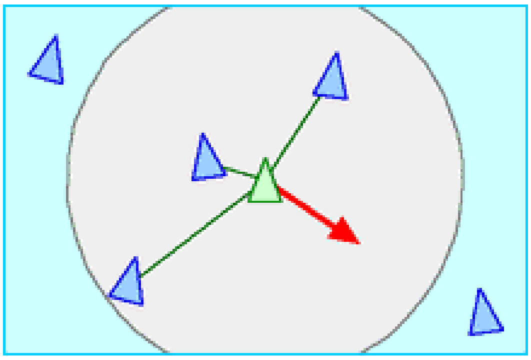

Figure 4.1: Separation of the flock mates

- **Alignment**: Shift onto the average location of the local flock mates. **Figure 4.2** [40] Shows the average location of the flock mates. In this step the average position of the flockmates are determined.

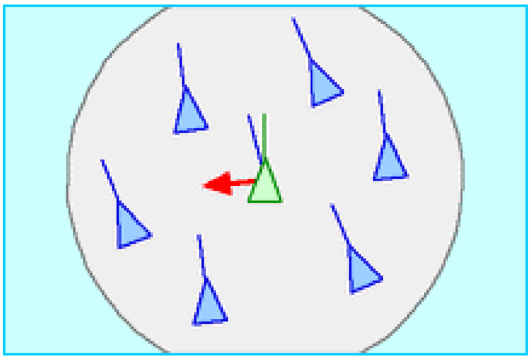

Figure 4.2: Alignment of the flock mates.

- **Cohesion**: Finally Shift towards the average position of the local flock mates. **Figure 4.3** [40] shows all the flock mates are moving towards the average position. The Global best is denoted by green triangle which is moving towards the average position.

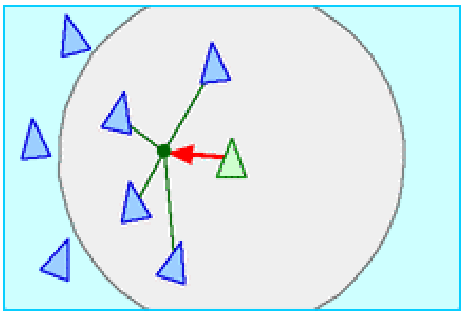

Figure 4.3: Cohesion of flock mates.

4.1.2 Concepts

Particle Swarm optimization is one of the most simple and effective algorithms. PSO emulates the process of finding food expressed by fish schools or bird swarms, thus developing its specific name. They used a set of agents (particles) that represent a swarm running about in a solution space searching for the best solution. The dimensions of the global optimum are based on the number of variables of the problem. Each particle in the searching space changes its flight characteristics by its own flying experience and also the flying behavior of other particles. Each particle varies its moving speed continuously in accordance with the flying experience of itself and its colleagues.

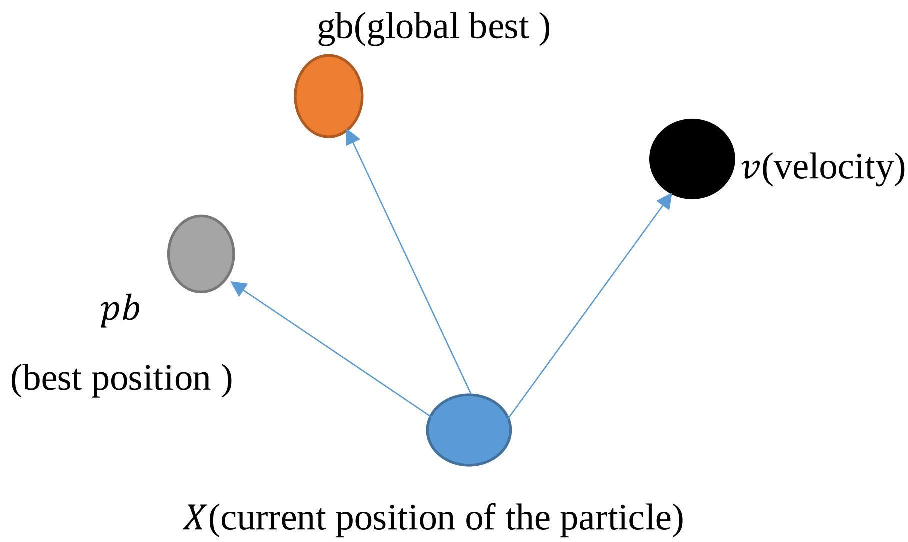

Figure 4.4: Particles' movement in PSO.

Figure 4.4 shows that X is the current position of a single particle,pb is the best possible solution obtained initially,gb is the global solution obtained so far. So the particle has got three solution of movements. Each particle modifies its position according to the following:

- The current velocity(v).
- The distance between the pb and the current location.

- The comparison between its present position X and the optimal position (gb) and measure the distance.

4.1.3 Parameters

The location of each particle can be updated based on its own best position, the global best position between the particles and its previous velocity vector according to the following equations:

$$v_i^{k+1} = w * v_i^k + c_1 * r_1 * \left(p_b - x_i^k\right) + c_2 * r_2 * (g_b - x_i^k) \qquad (4.1)$$

$$x_i^{k+1} = x_i^k + \gamma * v_i^{k+1} \qquad (4.2)$$

where,

v_i^{k+1} : *The velocity of* i^{th} *particle at* $(k+1)^{th}$ *iteration*

w : *Inertia weight.*

v_i^k : *The velocity of* i^{th} *particle at* k^{th} *iteration.*

c_1, c_2: *acceleration constants.*

r_1, r_2: *Randomly generated.*

p_b: *The best location of the particle obtained based on it's own observation*

g_b: *Global best position of the particle*

x_i^{k+1} : *The position of* i^{th} *particle at* $(k+1)^{th}$ *iteration*

x_i^k : $The\ position\ of\ i^{th}\ particle\ at\ k^{th}\ iteration.$

γ: $Constriction\ factor.$

Suitable range of inertia weight gives improved alignment between global and local experiments.

$$w = w_{\max} - \frac{w_{\max} - w_{\min}}{iter_{\max}} \times iter \tag{4.3}$$

Where,

w_{max} $is\ the\ value\ of\ inertia\ weight\ at\ the\ beginning\ of\ iteration.$

$w_{min}$$is\ the\ value\ of\ inertia\ weight\ at\ the\ end\ of\ iterations.$

$iter\ is\ the\ current\ iteration\ number.$

$iter_{max}$ $is\ the\ maximum\ number\ of\ iterations.$

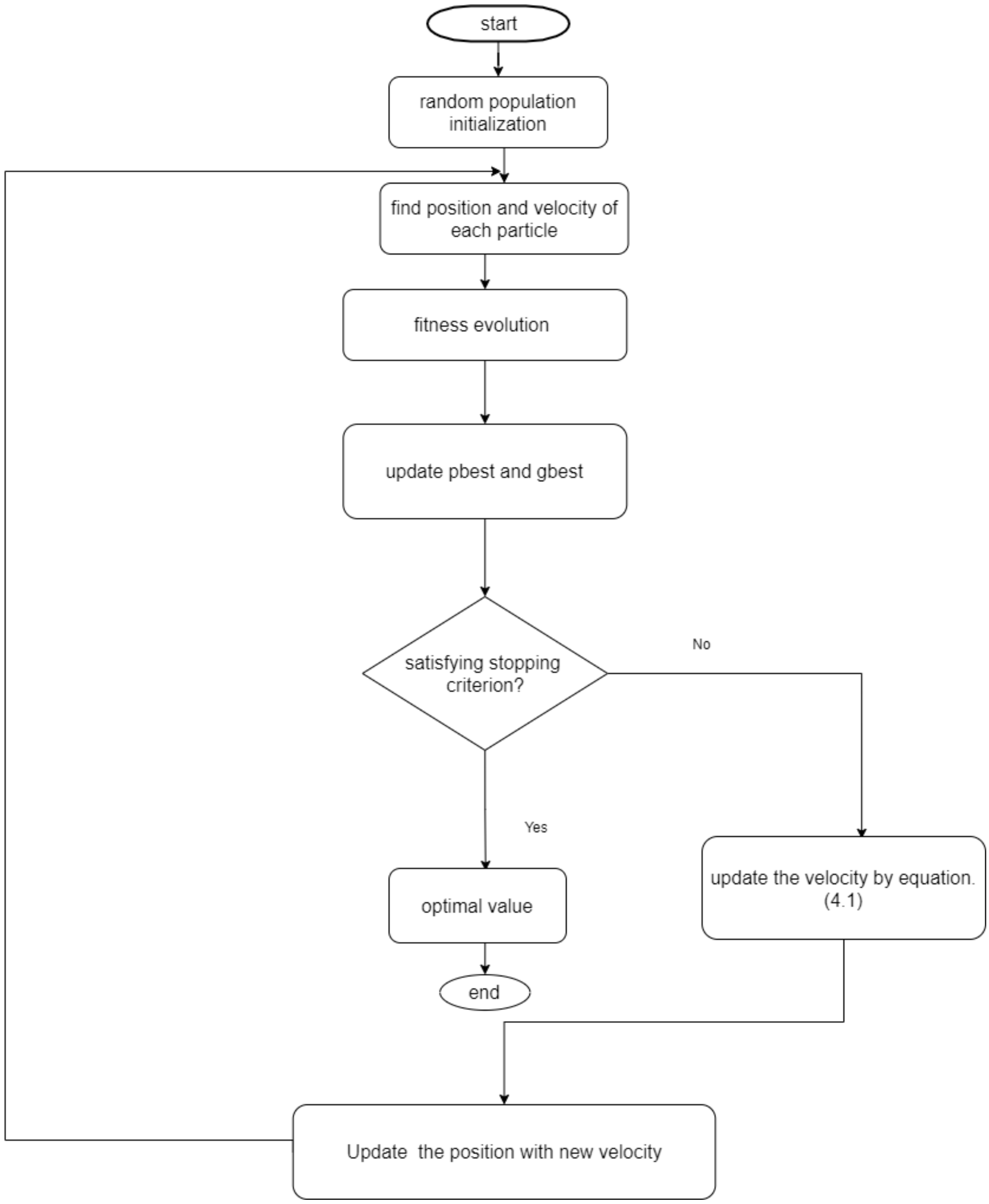

Figure 4.5: Flow chart of PSO

Here, the starting parameters are initialized and the particles are generated. After the random generation, the position and velocity of the particles are calculated. Then the local and global optima are determined. The velocities of the particles are updated according to equation (4.1) until the limit of iterations and then the optimal value is determined.

4.1.4 Advantages and Disadvantages

Advantages:

- Easy to implement.
- No need to go for the derivation process.
- Effective Global Search Algorithm.
- Impercipient to scaling of design variables.

Disadvantages:

- A tendency towards rapid and premature convergence at mid-optimal points.
- Sometimes its local search ability is poor.

4.2 Diversity Enhanced Particle Swarm Optimization

4.2.1 Origins

In a particular solution space, particles throughout the swarm move in an unpredictable manner. So that's why There is still the probability of spatial aggregation and, thus, of early convergence due to the congestion of the particles. Diversity-enhanced PSO (DEPSO) provides a very powerful technique for the treatment of crowding of the particles. DEPSO is an effective approach of solving these types of problems without adding additional penalty function. In this paper reactive power dispatch problem reactive power can be controlled using some controlled variables such as shunt capacitor which is supposed to be a discrete, transformer taps which is supposed to be integer in nature. So we want to solve our problem by updating the velocity of each particle in a different method. We can simply update the velocities in three stages:

- Positive Conflict phase.
- Attraction phase.
- Repulsion phase.

The control variables are given below:

$$CV = (CVc, CVd, CVi) \tag{4.4}$$

Where,

$CVc = vectors\ of\ continuous$.

$CVd = vectors\ of\ discrete.$

$CVi = vectors\ of\ integer.$

By using this method it assures that there is no chance of particles of getting stuck in the local minima. The velocity of each particle has updated differently. The distance between the particles is estimated by diversity.

4.2.2 Concepts

- If the diversity factor is greater than the higher diversity factor then the particles are attracted to each other. In Figure 4.6 [25] the movements of the particles are represented by blue dots. The diversity of the two blue dots are greater than the average diversity factor so the particles are attracted to each other.

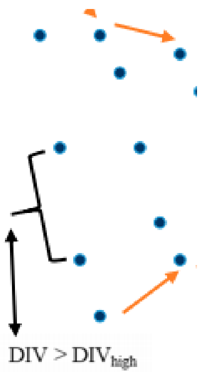

Figure 4.6: Particle movement in DEPSO ($DIV > DIV_{high}$)

- If the diversity factor is less than the lower diversity factor then the particles are repulsive to each other. In Figure 4.7 [25] it shows that the blue dots are close to each other so the diversity of these points are less than the average diversity. That's why the particles repulse each other.

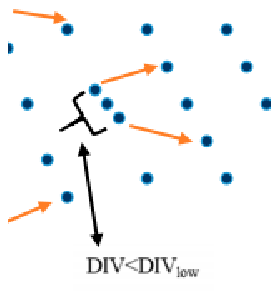

Figure 4.7: Particle movement in DEPSO ($DIV < DIV_{low}$)

- If the diversity factor is between the range of higher diversity and lower diversity then the particle moves through the positive conflict phase. In figure 4.8 [25] shows that the blue dots are aligned in the same manner. So that's the particles are moving towards the positive direction.

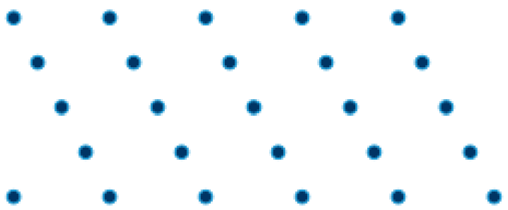

Figure 4.8: Particle movement in DEPSO
($Div\ value\ is\ between\ DIV_{high}\ and\ DIV_{low}$)

The Corresponding Equations are given below:

$$v_i^{k+1}\begin{cases}\chi\left[v_i^k + c_1\zeta_i^k\left(pb_i^k - x_i^k\right) + c_2\xi_i^k\left(gb_i^k - x_i^k\right)\right] \\ \quad Attractive\ phase \\ \chi\left[v_i^k - c_1\zeta_i^k\left(pb_i^k - x_i^k\right) - c_2\xi_i^k\left(gb_i^k - x_i^k\right)\right] \\ \quad repulsion\ phase \\ \chi\left[v_i^k + c_1\zeta_i^k\left(pb_i^k - x_i^k\right) - c_2\xi_i^k\left(gb_i^k - x_i^k\right)\right] \\ \quad positive\ conflict\ phase\end{cases} \tag{4.5}$$

The diversity factor needs to be calculated,

$$DIV(k) = \frac{1}{m_p}\sum_{i=1}^{m_p}\sqrt{\sum_{j=1}^{n_p}\left(x_{i,j} - x_{jcap}^k\right)^2} \tag{4.6}$$

$$x_{jcap}^k = \frac{\sum_{i=1}^{m_p} x_{i,j}^k}{m_p} \tag{4.7}$$

Where,

m_P = Number of particles.

n_v= Number of variables.

C_1= Cognitive scaling factor.

C_2= Social scaling factor.

The range of diversity factor can be selected based on the problem definition.

For this method, the values are selected by trial and error method.

4.2.3 Flowchart

In this portion we would like to draw the flowchart of PSO and DEPSO together.

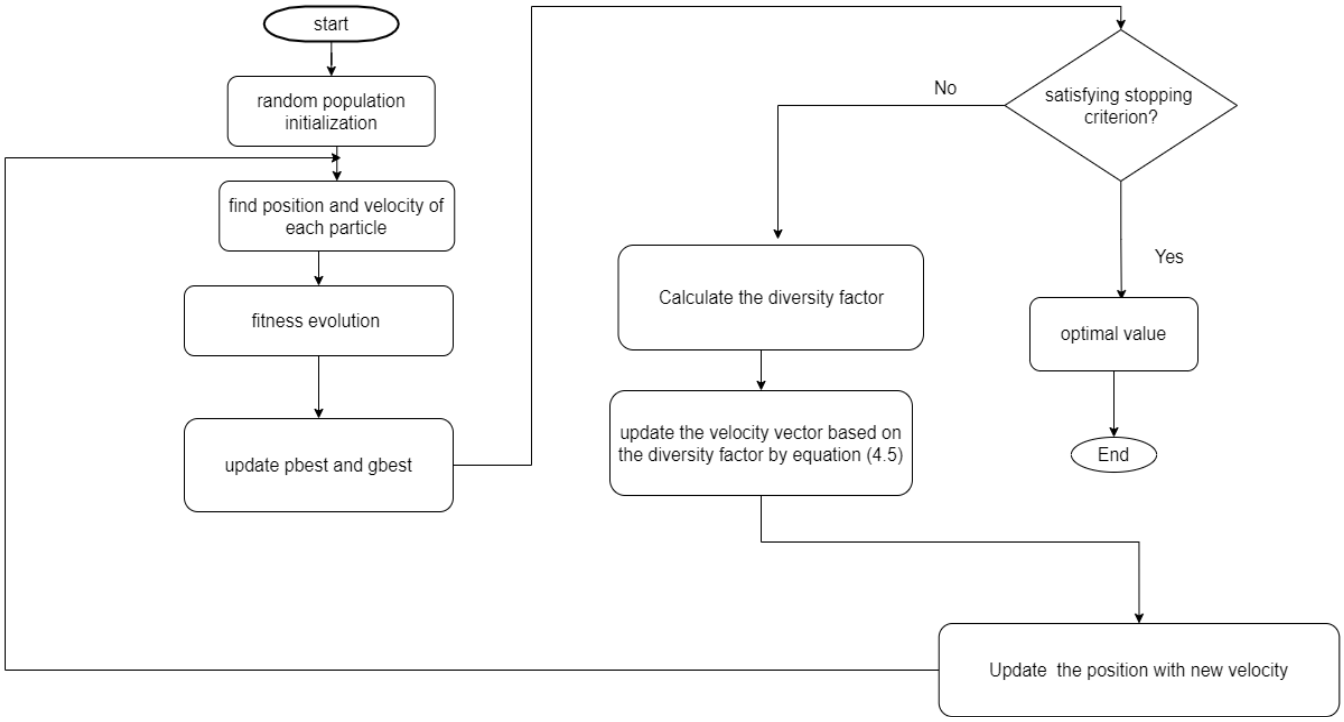

Figure 4.9: Flow chart of DEPSO

Here, the starting parameters are initialized and the particles are generated. After the random generation, the position and velocity of the particles are calculated. Then the local and global optima are determined. The velocities of the particles are updated in three phases according to equation (4.5) until the limit of iterations and then the optimal value is determined. The diversity factor can be updated using equation (4.6).

4.3 Slime Mould Algorithm

4.3.1 Origins

The Slime Mould Algorithm is a new metaheuristic algorithm which takes inspiration from the nature based living species. This method is based on the foraging phase of the life of a slime mould. It is a stochastic optimizer which randomizes the initial search space and thus it helps with the random nature of the problem at hand. This nature of the algorithm is expected to be useful in non-linear and non-convex problems.

4.3.2 Concepts

The Slime Mould Algorithm is mainly based on the Oscillation Mode of a slime mould. During the foraging phase, a slime mould has the habit for approaching towards the food. It does this by forming vein like structures from the center of its position. When the slime mould requires food, it gradually extends itself outwards in search of food. This process is done by the natural Oscillation mode of a slime mould. The slime mould has the capability to act as a bio-oscillator which is the driving force behind the expansion and formation of the vein like structures [35-37]. This characteristic gives slime mould excellent observation and efficient food gathering ability. When the slime mould eventually gets into contact with a required food, it starts absorbing the food and bringing it towards the center or the initial position of the mould. These nutrients are transported via the vein like structures formed as mentioned earlier. The slime mould also has the capability of determining which food particle is suitable for it and thus it decides which it should focus on. If a large and nutritious food is available, then the vein tends to be larger and when the food is smaller in comparison or less nutritious, the veins formed will be smaller and the amount of food transferred from it will be less. This nature helps it to focus on the main particles and focus less on the less important parts. If the situation is such that there is abundance of nutritious food particles, in that case the veins formed towards the smaller food particles starts to dissolve. Gradually those smaller veins disappear and only the more important veins remain. This process is shown in **Figure 4.10** [39].

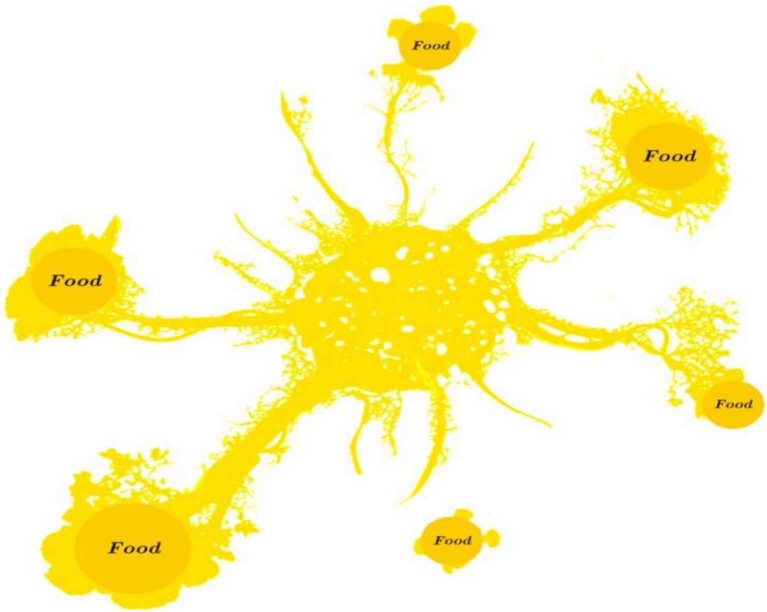

Figure 4.10: Slime mould search phase.

While returning to the center, the slime mould does not just randomly select a path; rather it chooses the path which it deems is the easiest and the path of least resistance. In various lab results it has been shown that the most efficient path it chooses it shockingly similar to the optimal path chosen by humans or other solution methods.

These characteristics are actually very efficient and have the potential to become a very important source of inspiration from which we can develop an effective algorithm for determining an optimal solution. From the above discussion we can see that the slime mould initially starts to spread randomly and then forms connections with the food particles. Then it gradually starts to determine the importance of the different food particles. Finally, the largest vein signifies the optimal solution as it is the most nutritious. It has to be mentioned that the slime mould also has the characteristic of forming the most efficient path towards the center. This attribute ensures the most efficient path towards the optima. This effect is shown in **Figure 4.11** [39].

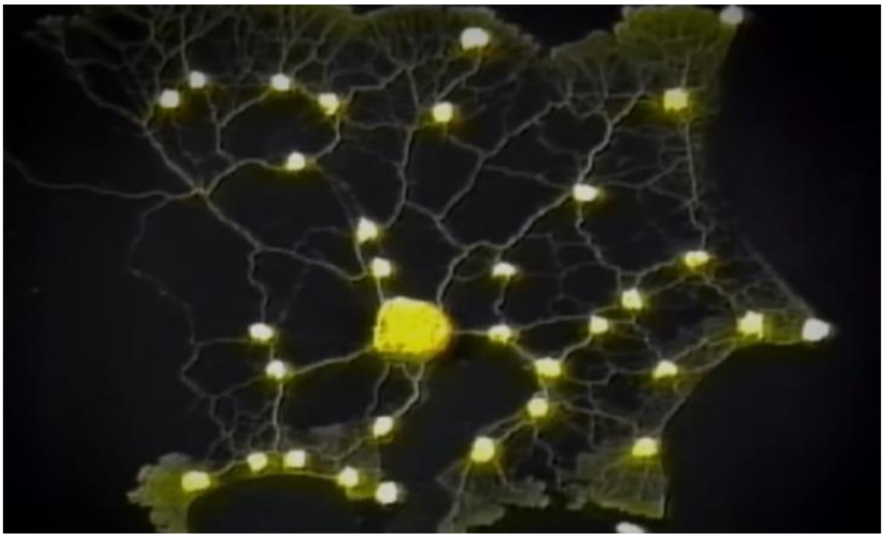

Figure 4.11: Foraging of slime mould

The SMA utilizes these characteristics of the slime mould and aims to develop a computational algorithm with the goal of optimization and finding the global efficiently. The aforementioned bio-oscillator is emulated by this algorithm by the use of adaptive weights which simulate the positive and negative feedbacks of the slime mould.

The algorithm begins with the initiation of the setting parameters and the generation of the particles. Here, the particles represent the slime mould. After setting the initial position of the slime mould, the location of each of the particles of the slime mould is updated through a series of equations by utilizing adaptive weights. The ideal location is obtained as a result of the back and forth movement which occurs due to the combination of the weight and the inequality constraints. The weight of the equation is also updated which is a factor of the sorted version of best fitness i.e. the best location set for the particles from the previous iteration. After the desired number of iterations, the final best fitness obtained is the optimal solution.

4.3.3 Solution steps

The steps followed to develop the algorithm is described below:

- **Initializing**:

The number of iterations, as well the number of the particles is specified. The dimension is set to the number of control variables. Here, the algorithm will simulate the number of the control variables as the limbs of the slime mould in order to optimize the solution. The increase in the number of particles increases the accuracy but also requires higher processing power.

- **Generating the particles**:

The particles are generated randomly. Then we identify whether the randomized particles fall within our search space and bring back the ones that fall outside our scope. The best and the worst combinations are recorded as best fitness and worst fitness respectively initially. This is the basis on which the program runs the first iteration of calculations.

- **Determining the weights**:

Then the weights are determined through the following equations derived from (1).

$$W\left(Smellindex(i)\right) = \begin{cases} 1 + r.\log\left(\frac{bf - S(i)}{bf - wf} + 1\right), i \leq \frac{N}{2} \\ 1 - r.\log\left(\frac{bf - S(i)}{bf - wf} + 1\right), others \end{cases} \qquad (4.8)$$

Where,

N=No of Swarm.

i=current Swarm.

bf= best fitness.

wf= worst fitness.

S=Smell order.

r=random value at [0,1]

$SmellIndex$ denotes the sorted fitness values.

The weights are updated in accordance with the dimensions i.e. the number of control variables. The weight is factor of the $SmellIndex$ and it depends on the best fitness obtained from the previous iterative process.

- **Updating the fitness and positions**:

The best fitness is recorded after each iteration and saved as the destination fitness. The data is obtained from the sorted fitness value from $SmellIndex$. This value is critical for the solution as the final solution of the process will be obtained from the best fitness of the $SmellIndex$.

- **Updating the location of Slime Mould or the search agents/particles**:

This step simulates to what extent the slime mould approaches the food i.e. the minimum solution. The higher the probability of finding the optima, the faster the particles approach towards that solution; which essentially emulates the contraction of the venous tissue structure of the slime mould.

The search process for finding the solution is initiated when the randomized value exceeds the z parameter. This begins the search procedure for finding the optimal solution. After that the local optima are determined. When the solution starts to approach the p parameter it gets close to the global optima and hence the final result.

The formula for updating the location of the slime mould is as follows:

$$X_1 = rand.(UB - LB) + LB, rand < z \qquad (4.9)$$

$$X_2 = X_b(t) + vb.(W.X_A(\text{t})\text{-}X_B(t)), r < p \qquad (4.10)$$

$$X_3 = v_c.X(t), r \geq p \qquad (4.11)$$

Where $UB\ and\ LB$ denote the lower and upper boundaries of search range

$rand$ and r denote the random value in [0,1]. t denotes the current iteration, X_b shows the individual location with the maximum odor concentration presently investigated. v_B is a parameter with an interval of $[-a, a]$

W is the weight of slime mould. X, X_1, X_2, X_3 are the location vectors of slime mould, X_A and X_B are two individuals that we randomly selected from the current population.

$$a = \text{arctan h}\left(-\left(\frac{t}{\text{max}_{\text{t}}}\right) + 1\right) \qquad (4.12)$$

The parameter a is responsible for setting the limit of the v_B.

$$v_B = [-a, a] \qquad (4.13)$$

v_C oscillates from -1 to 1 and eventually gets zero.The parameter p can be updated by following equation:

$$P = \tanh|S(i) - DF)| \qquad (4.14)$$

$where, S(i)\ is\ the\ fitness\ of\ X\ and\ DF\ is\ best\ fitness\ attained\ of\ all\ iterations$

.

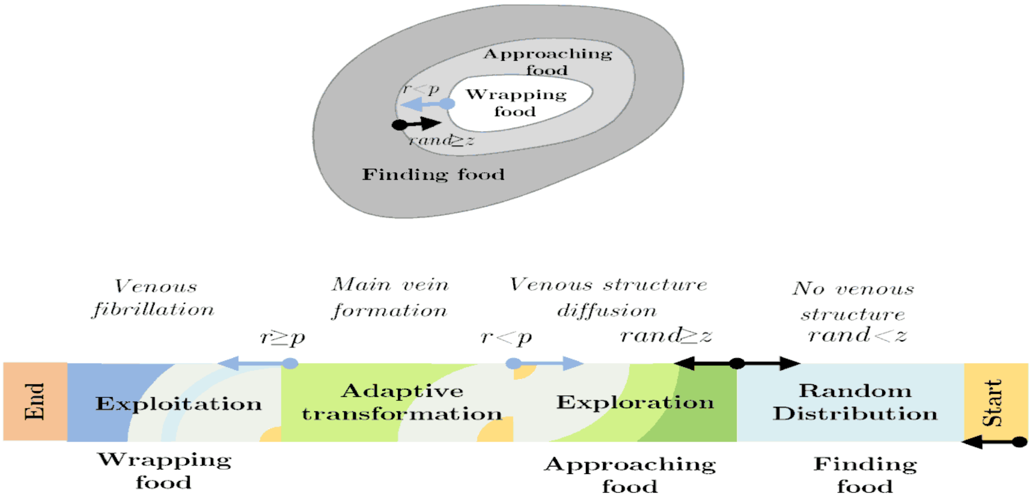

Figure 4.12: The steps of SMA.

Here, the X_1 indicates the position which does not proceed to grapple the food. X_1 is chosen when the solution is deemed unsuitable due to the value of $rand$ compared to the value of z parameter. In this case, the particles avoid approaching or exploring that portion of the search space altogether. When this condition is obtained the algorithm goes back to searching for the feasible solutions. These conditions are explained in **Figure 4.12** [39].

X_2 represents the position which the slime mould attains when the solution gives a promising value and is potentially a solution. These are considered as local optima. Each of these positions has a probability to be the final solution. X_3 is the position which the solution converges to when the value nears the global optima. This is the best possible solution among all the probable solutions. Our final solution will be obtained from this section of the search space.

The solution steps and the whole algorithm is explained in the flowchart [**Figure 4.13**].

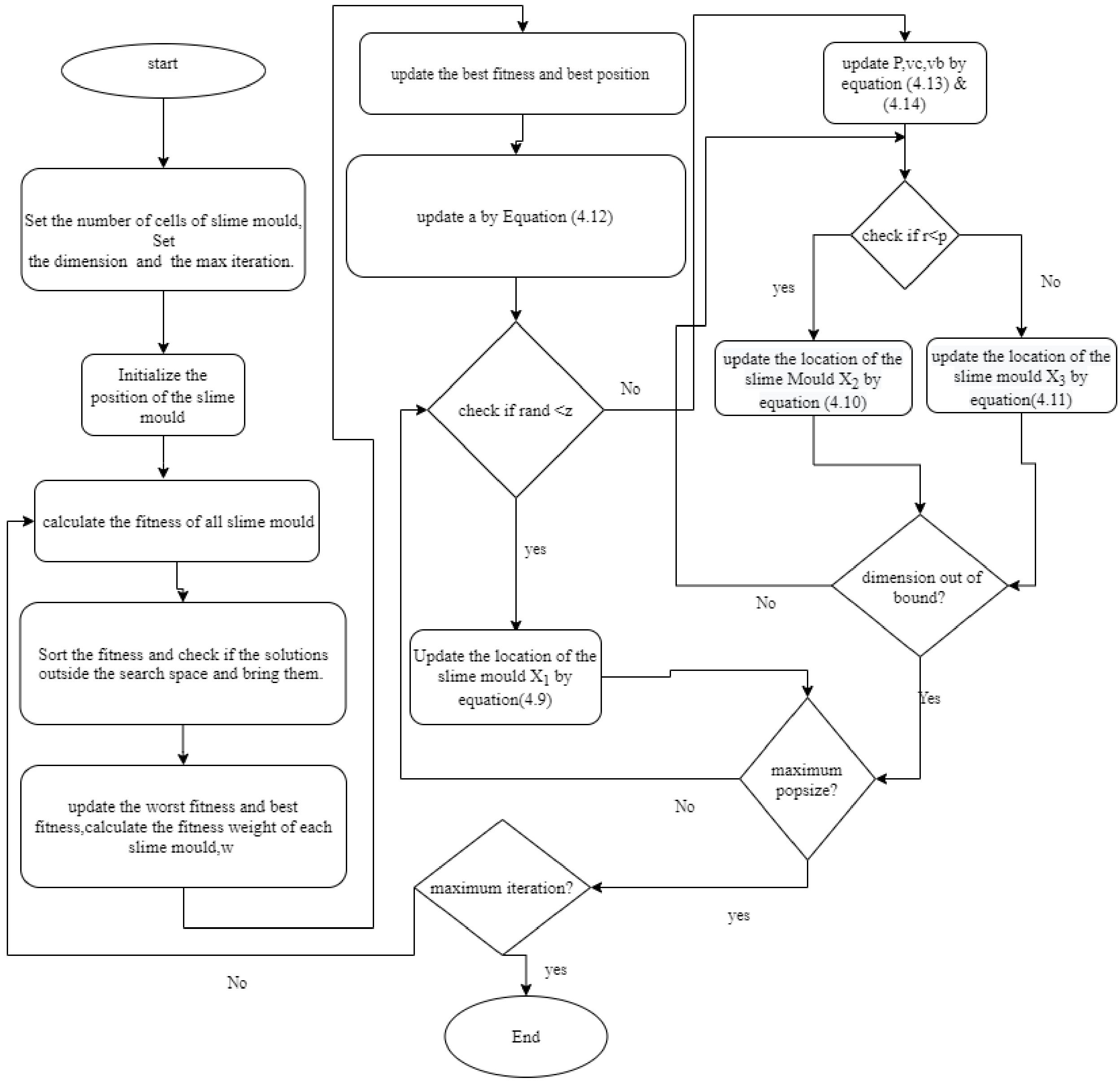

Figure 4.13: Flowchart of slime mould.

4.3.4 Advantages of this Algorithm.

For the case of using SMA to solve the problem of ORPD, it has to be mentioned that there are several reasons why a versatile algorithm like this can be useful for solving this sort of problem.

- The SMA is a metaheuristic algorithm and is thus much better for solving non-linear problems compared to traditional classical methods. This is because the initial generation is randomized and thus has a better chance of reaching the optimum location. This is desirable as the traditional methods have the disadvantageous nature of sometimes giving the local optima as the result.
- As it is a metaheuristic method, SMA is not as focused as the traditional methods for determining the exact value of the solution. Instead, it tries to get very close to the ideal solution. These features might seem like a disadvantage, but in reality we use these methods in our computational devices and metaheuristic methods are less resource intensive. As a result, they provide a better overall result for the same amount of processing power.
- The traditional methods often required several assumptions such as the initial values and the upper and lower bounds of the search limits etc. In most cases, the accuracy of the result is heavily dependent on the

assumptions. If the assumptions are off by a few percent, the result can vary by a lot.

- The heuristic and metaheuristic methods bring a new approach to computational optimization. These methods take inspiration from nature and builds algorithms that can optimize a problem. They randomize the particle generation process which helps to reach the global optima by differentiating between the local optima on multiple stages of the solution finding process.
- The introduction of penalty function ensures the efficient and automated way of keeping the solution within the boundary limits in each and every iteration.
- SMA uses a different approach from the other prominent metaheuristic algorithms. As this method uses variable adaptive weights, the search range of the location of the particles is constantly updated at the end of each iteration. This adaptive nature makes this method highly versatile and flexible which in turn improves its efficiency and overall speed. However, the effectiveness of the method is subject to the boundary parameters. If chosen correctly, this method should provide best or close to the best result of any metaheuristic method.

CHAPTER 5

SIMULATIONS AND RESULTS

5.1 Implementation in test systems

The ORPD solution has done by MATLAB separately using PSO, DEPSO and SMA. In figure 5.1 [36] the standard IEEE 30-bus test systems has been shown. The efficacy of SMA over PSO and DEPSO algorithms has been tested by evaluating it on standard IEEE 30-bus test systems. The whole data set of IEEE bus 30 has been found in [38]

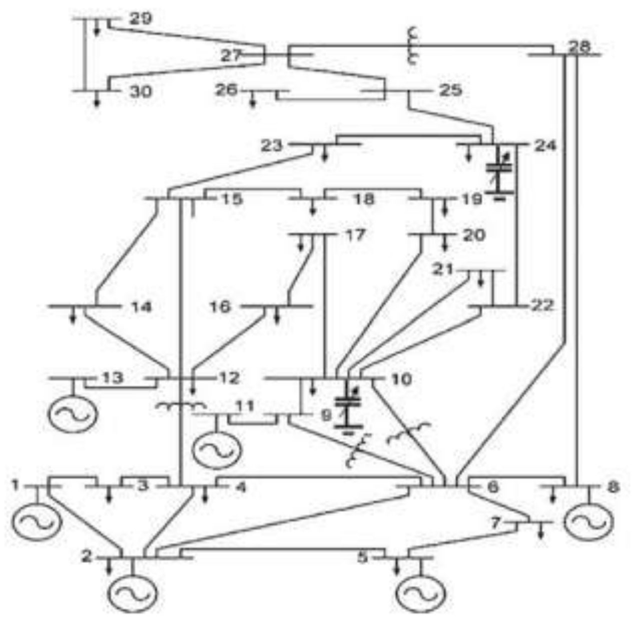

Figure 5.1 :IEEE Bus -30

5.2 System Description

- The simulations are carried out in MATLAB 2017a in a laptop running Windows 10 Pro, equipped with an Intel core i5 7200U CPU (3.1GHz) and 8GB of RAM.

- The search space consists of 13 control variables which are six generators, four transformers and three shunt capacitors. The generators are installed at buses 1, 2, 5, 8, 11, 13. The Transformers are installed in between buses 6 and 9, buses 6 and 10, buses 4 and 12, buses 27 and 28. The shunt capacitors are installed at buses are 3, 10 and 24. The shunt capacitors used here are considered as the reactive power source. All the limits used in this study have been considered per unit. The upper and lower boundary limits of the generators and load bus voltages, transformer taps and reactive compensation devices are stated in **Table 5.1.**

Table 5.1: Control Variable Limits

Transformer Tap Limits.(pu)		Generator bus voltage settings. (pu)		Load Bus Voltage Settings. (pu)		Reactive power Source limit.(pu)	
T_k^{max} 1.10	T_k^{min} .95	V_g^{max} 1.10	V_g^{min} .95	V_{lb}^{max} 1.05	V_{lb}^{min} .95	Q_c^{max} .15	Q_c^{min} .1

This standard test has been chosen so that it can be easily analyzed and compared with the other previous research efforts. The detailed parameters are stated in **Table 5.2**.

Table 5.2: System Description

Description	30- Bus
No of Bus	30
No of lines	41
No of generators.	6

No of Transformers.	4
No of Reactive power sources.	3
Control Variables.	13
Base Case Real power loss.	17.557
Base Case Reactive power loss	67.69

In this thesis, the control variables in the above mentioned Table 1 are to be optimized. By optimizing the values of these control variables the minimum real power loss is obtained while maintaining voltage deviation within the predetermined range.

To demonstrate the applicability of SMA, the test results have been compared with two other established methods, namely PSO and DEPSO methods. The variables and parameters of those methods were taken by careful considerations from previous researches and in some cases by extensive trial and error processes.

5.2.2 Setting Parameters

All the parameters which are used in all of three algorithms have some constant values. These values are fixed for that particular algorithm and these values are found by trial-and-error method since we have to consider the most economical and most efficient condition throughout our whole simulation. But for SMA there is a special constant named z which is only used for this algorithm. All the parameters and their corresponding values are given in the **Table-5.3**.

Table 5.3: Setting parameters

No		PSO	DEPSO	SMA
1	Population size	50	50	50
2	Constant Associated with penalty Function(k_1,k_2,k_3)	10000	10000	10000
3	Acceleration constant (C1, C2)	2.1 and 2.0	2.1 and 2.0	-
4	Constriction factor	0.729	0.729	-
5	Max. and Min. inertia weights	1 and 0.2	1 and 0.2	-
6	Max. and Min. velocity of particles	0.003 and -0.003	0.003 and -0.003	-
7	Convergence criterion	100 iterations	100 iterations	100 iterations
8	Upper diversity factor	-	-.96	
9	Lower diversity factor	-	-1.01	
10	Value of z			.003

Here, the population size indicates the number of particles in case of PSO and DEPSO while in case of SMA, the population size indicates the number of slime moulds that perform the optimization. The number of iterations and the population sizes have been chosen and deemed to be sufficient for the demonstration of the working nature of the methods. The acceleration coefficients and the constriction factors were chosen taking reference from the previous research efforts and maintained for the purpose of uniformity. The diversity factors of DEPSO were taken through trial-and-error process. The value of the z parameter was also chosen through trial and error.

5.3 SIMULATION & RESULTS

The results obtained after running the simulations are tabulated in **Table 5.4**. In this table the formulation 1 and formulation 3. The 13 control variables are optimized by the three algorithms and for those values the final minimized value of the real power loss is obtained.

Table 5.1: Parameters obtained after optimization

Variable name		Formulation 1			Formulation 3	
Algorithm	PSO	DEPSO	Slime Mould	PSO	DEPSO	Slime Mould
V1	.9925	.9946	1.061854	.9641	1.0196	1.06191
V2	.9989	1.0095	1.045886	1.0173	1.0024	1.04669
V5	1.0646	.9305	1.013313	1.0110	1.0297	1.01322
V8	1.0017	1.0349	1.01976	.9757	1.0016	1.01924
V11	1.0448	1.0211	1.059526	1.0429	0.9882	1.05951
V13	1.0252	1.0359	1.060227	.9906	0.9821	1.06016
T1	1.0170	.9531	1.014885	.9799	1.01	0.979351
T2	1.0461	.9598	0.95	.9511	1.03	0.980462

T3	1.0363	1.0173	0.982607	.9531	0.99	0.983304
T4	1.0299	1.0073	0.96075	.9693	1.03	0.957279
Q3	14.7135	14	14.46819	14.5731	11	14.5297
Q10	13.9956	15	14.87733	14.1405	9	14.3193
Q24	12.03	14	12.99436	14.4219	15	12.7342
Real power loss (MW)	17.4601	17.4356	17.31501	17.5562	17.535	17.3262
Reactive power loss (MVAR)	67.565	67.5474	65.9022	67.6869	67.6052	65.8833

5.3.1 Convergence Curve

In the comparison of these three algorithms, for the total power loss against total convergence criterion one hundred iterations have been taken. It can be easily observed that initially the total loss is very high but after 100 iterations the loss becomes minimized and for Slime Mould algorithm loss is minimum comparing with other algorithms which is shown in **Figure-5.2**.

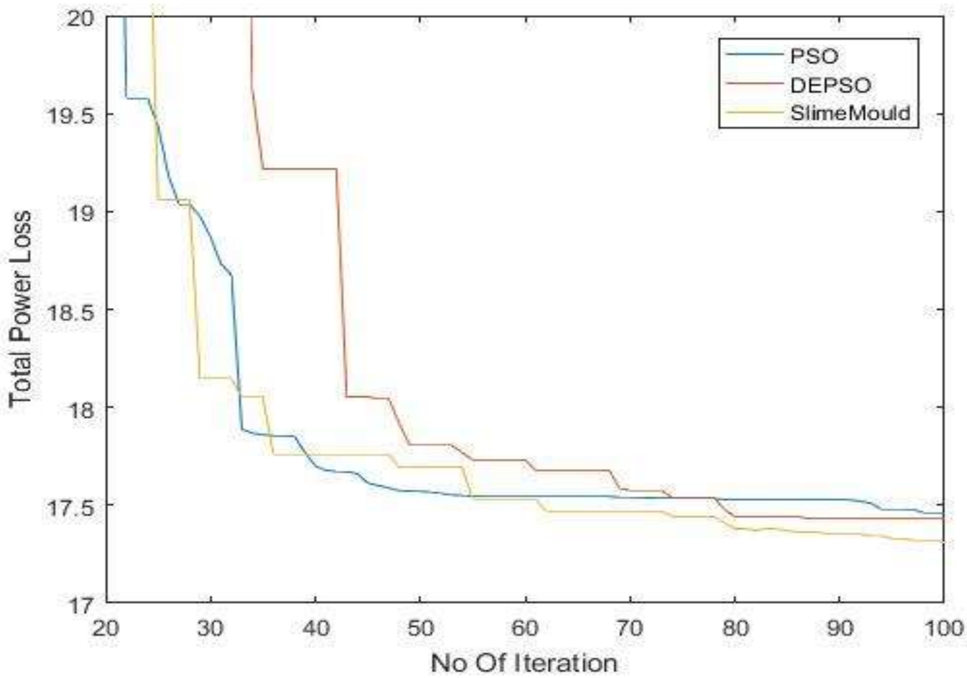

Figure 5.2: Convergence Curve

5.3.1 Average Performance

The average performance is extremely crucial for determining the actual performance of an algorithm. As these metaheuristic methods are stochastic and randomized methods, the average performance justifies the overall efficiency of the algorithm. After running the simulations 20 times, it can be observed that besides the excellent peak performance, the use of SMA also provides very consistent and reliable performance in comparison to PSO and DEPSO. The average values are a clear indication of that fact. The deviation from the best result to the worst result is remarkably low in case of SMA. Inspection of the data tables paints a clear picture of the advantages of this method over the others which is shown in **Table-5.5**.

Table 5.2: Comparison of results after 20 simulation runs

Compared items	PSO	DEPSO	SMA
Worst fitness	18.5026	18.01	17.42068
Best fitness	17.4601	17.43564	17.326
Average fitness	17.981	17.723	17.36587

5.3.2 Power Loss Reduction

The base case power loss obtained without optimization is 17.557 MW [25]. All of the methods managed to improve on that value to some extent on all three formulations. But the improvement was the highest in case of SMA. The following table shows the relative improvement from the base case power loss for the respective methods.

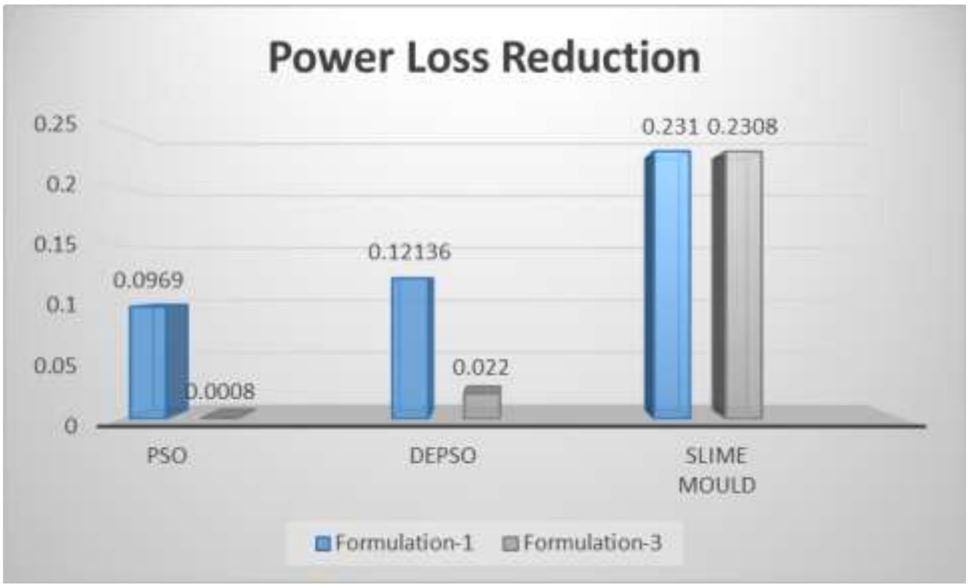

Figure 5.3 : Power loss reduction

The voltage deviation, a key requirement of ORPD problems and power system analysis in general, is maintained within acceptable ranges during the use of SMA. Of course, it should be mentioned that this characteristic was also preserved in the other two discussed methods. It can be observed that the voltages are not much deviated from our nominal value which is 1pu. Also, all the voltages are in the range of limits which is conserved for the voltage deviation. All the voltage deviations are shown in the **Figure-5.4**.

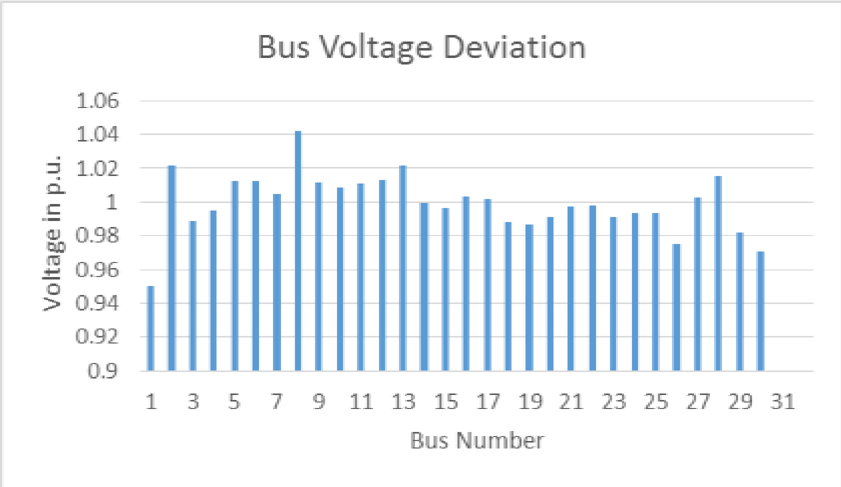

Figure 5.4: Bus Voltage Deviation.

CHAPTER 6
SUMMARY OF THE THESIS AND FUTURE SCOPE

6.1 Summary and Conclusion

The objective of this study was to showcase the viability of this novel optimization algorithm in the field of power system optimization and reactive power dispatch. This method demonstrates the advantage of SMA in comparison to other previously known stochastic algorithms. As demonstrated, this algorithm exhibits outstanding performance and convergence characteristics. The improvements were 1.32% in case of real power loss minimization and 1.31% in case of minimization of real power losses and total bus voltage deviations with respect to the base case losses. The voltage profile was stable with the program providing results that show deviations within the widely accepted tolerance levels. This is an improvement from almost all the processes which have been used to solve similar problems in the past. In future, this method may be considered for the reactive power dispatch in practical distributed generating systems for unprecedented efficiency and robustness. The whole work of the thesis can be summarized as follows:

- The optimization algorithms used for solving ORPD problems have been improving throughout the years through the efforts of many researchers. This thesis hopes to add to that effort by providing a new way of solving such problems with better efficiency than any other method before it. The improvisation of SMA into the ORPD problem was the primary focus of this thesis.

- The whole solution finding process is based on several constraints. These equality and inequality constraints are responsible for keeping the solution within the limits of our system. Careful consideration of these constraints and prudent selection of the parameters of the constraints are essential for successful implementation any algorithm. The application of penalty function provides further enhanced performance by implementing additional conditions for the solution.
- The main goal of this study is to minimize the real power loss of a power system. Voltage stability is also ensured by limiting the voltage deviations within acceptable limits. The superiority of SMA is demonstrated by comparing with other renowned methods.
- The usefulness of an optimization algorithm is acceptable and can be used in the real world if it is reliable and consistent. Thus, the efficiency that is obtained from one demonstration must be replicated when the stochastic process is run again and again despite of its random nature.

6.2 Future Scope:

- **Enhanced versions:**

  Through the years we have seen the application of numerous metaheuristic algorithms for solving the problem of ORPD. A significant portion of research has gone into upgrading and enhancing those methods for gaining greater performance. It can be expected that such endeavours focused on this method can also provide even better performance.

- **Reduction of the number of operator controlled parameters:**

  By analyzing the SMA we can see that quite a few of the parameters had to be chosen and set by the operator. This opens the door for errors and inefficiencies as the net performance of the program is dependent on the expert choice of those parameters. This makes the whole process reliant on the expertise of the operator which is not ideal. The whole process should be such that the efficiency is retained regardless of the skill of the people involved. This self-sufficiency can be incorporated by automation of the process of determining the values of these parameters. In this study, these parameters (such as the z parameter and the initial values of the v_B and v_C) were chosen either by trial and error process or by randomization. By systematic automation of the determination process of these parameters we can reduce the possibility of inconsistent results.

- **Introduction of advanced distribution functions:**

The even and uniform distribution of the generated particles is essential for proper search of the entire search space. This is why the random distribution was adopted in this study. But this has some drawbacks. If we can generate more particles nearer to the final solution region instead of evenly distributing it, we may get the result with even fewer numbers of iterations. To do this, proper knowledge and understanding of the higher probability locations is needed for finding the ideal solutions. By using this knowledge the whole process can be made more efficient by reducing the length of the iterative process.

This might be achieved by incorporating machine learning and artificial intelligence within the system in order to predict the probable solution region. The machine learning algorithm can be trained by using it in practical problems the generation of the particles can be weighted heavily in the high probability regions and lightly in the low probability regions. This will increase the chance of finding the global optima faster, increasing the speed of the algorithm.

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