DETERMINATION OF EQUIVALENT CIRCUIT PARAMETERS OF A SINGLE PHASE TRANSFORMER FROM NAME-PLATE DATA USING PSO

Thesis submitted in partial fulfillment of the requirements for the

degree of

MASTER OF ELECTRICAL ENGINEERING

By

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Acknowledgement

Words are often less to revels one's deep regards. With an understanding that work like this can never be the outcome of a single person. I take this opportunity to express my profound sense of gratitude and respect to all those who helped me through the duration of this work.

I express my gratitude and sincere thanks to my supervisor Prof. Suparna Kar Chowdhury, Professor, Electrical Engineering Department, Jadavpur University for her constant motivation and support during the course of my report. I truly appreciate and value her esteemed guidance and encouragement from the beginning. I am indebted to her for having helped me shape the problem and providing insights towards the solution**.**

I would like to thank Dr.Swapan Kumar Goswami, Head of the Department, Electrical Engineering, Jadavpur University, for providing me with the necessary facilities for carrying out this thesis.

I am also very much thankful to Mr. Diptarshi Bhowmick and Mr. Arunava Chatterjee, research scholar, Jadavpur University, for their sincere co-operation and association for fulfilment of this thesis. I am also thankful to Rajkumar Roy for his helping hand.

I am also thankful to my batch mates who devoted their valuable time for the successful completion of dissertation. I extend my gratitude to the other researchers and scholars for their valuable advice. It would be rather little to say anything about the above-mentioned persons further.

Signature

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LIST OF ABBREVIATIONS

Harmony Search –HS

Least Error Square Algorithm –LESA

Recursive Least Square - RLS

Bacterial Foraging Algorithm -BFA

Genetic Algorithm -GA

Particle Swarm Optimization - PSO

Firefly Algorithm -FA

Harmony memory size - HMS

Harmony memory considering rate - HMCR

Pitch adjusting rate - PAR

Harmony memory - HM

Bat Algorithm - BA

Cuckoo Search - CS

Maximum Likelihood Estimation – MLE

CHAPTER – 1

INTRODUCTION

1.1 BACKGROUND:

Transformers are one of the vital components of any power system. An accurate estimation of system behavior including load flow studies, protection, and safe control of the system demands, accurate estimation of equivalent circuit parameters of all system components. Due to transformer failure, extensive utility service interruption occurs that lead to replacement of large power transformer. A better understanding of the state of health of the transformer can help the utility companies manage resources more effectively and anticipate issues well before an emergency strike. For this, we need to estimate the parameter of the transformer as accurately as possible without interrupting the service.

Parameter estimation plays a critical role in accurately describing system behavior through mathematical models such as statistical probability distribution functions, parametric dynamic models etc. Accurate parameter values are required for secure operation of power system. All the major security and economy related applications need accurate values of the network parameters. Parameter errors may arise from inaccurate manufacturer's data, changes in the circuit not reported to the data base operators or operating conditions differing from the ideal assumption made for theoretical calculations, inaccurate length and other dimension measurement etc.

Usually, either transformer condition assessment can be done by direct measurement approaches or model based approaches. Both approaches are based on the fact that during a fault condition, the transformer will have slightly different physical or chemical characteristics compared with normal operating condition. In the measurement -based approaches, representative parameters are directly measured by specialty sensors and data acquisition devices, such as Dissolved Gas analyzers [8], [11] Degree of Polymerization testing and Partial Discharge monitoring etc.

The model-based methods, however, adopt the transformer ideal equivalent circuit model with all of the parameters and measurement referred to one side of the transformer.
To develop robust method for parameter identification it is required to quantify the information content about machine parameters on measured data. This is prominent when we are bound to the terminal measurements such as transformer primary and secondary voltages, currents.

Generally, transformer parameters estimation method can be divided into different categories [17] depending on what data is available, and what data is used for:

- ***Parameter calculation from transformer physical construction***. This method requires detailed knowledge and circuitry of the machine construction of every part such as geometrical configuration and material used their effect on the transformer parameter. It is the most sophisticated procedure, since it is closely related to the physical reality and considers all possible effects on parameters of the transformer and it is the costliest since it is based on field calculation method such as finite element method.
- ***Parameter estimation based on steady state transformer models***. This method is based on iterative solution on transformer under steady state network equations. This is the most common method for parameter estimation since this is comparatively easy and the required data is easily available.
- ***Frequency domain parameter estimation*** [35], [26]. Currently available transformer models with single-valued parameters getting from test do not imply the transformer considering the presence of harmonics. Accurate modeling of transformer should be such that we can consider the change of signal frequency and loading condition as they occur.
- ***Time-domain parameter estimation***. The time domain transformer measurements [4] are performed and model parameters are adjusted to match the measurements. The data acquisition system is required for this method. Since all parameters cannot be observed from the measurable quantity, the transformer model should be simplified. This method is costly.
- ***Real-time parameter estimation***. Real time system means the developed model will respond to input immediately. This technique is used by simplified transformer model [42], [15] that are fast enough to continuously update the transformer parameters.

A power transformer is most costly and essential equipment of an electrical system. So for getting high performance and continuous service it is desired to perform various maintenance activities. For this maintenance, we need to know the proper electrical equivalent circuit parameters of the transformer. In general, for determining the parameters of transformer it is required to perform the open and short circuit tests. The method is only suitable for off-line measurements. For these two tests, we require separate arrangement of transformer that means need to hamper the circuit condition from the normal operation.

Therefore, interruption occurs with respect to continuity of service, which is highly undesirable. For open circuit test rated voltage is applied to the low voltage side at rated frequency with high voltage side left open. The open circuit voltage, current and power is measured in the low voltage side and by applying no load equivalent circuit; the core parameters (R_C, X_m) are calculated. In the short circuit test, a reduced voltage (6 to 8 percent of rated voltage) is applied to the high voltage side at rated frequency to obtain rated current in the high voltage side while low voltage side is short-circuited. The value of the short circuit voltage, current and active power are measured by using the approximate short circuit equivalent circuit, the windings parameters (R_{eq}, Xeq) referred to the low voltage side is computed. To obtain the parameters of each winding separately a certain assumption is made by considering equal primary and secondary resistance and inductance. Using the approximate equivalent circuit on these two tests may produce erroneous parameters value, which yields to inaccurate results in the calculation of the voltage regulation, efficiency and many other such calculations. The obtained parameters do not express exactly the transformer performance on loading condition. Besides these, the test does not account for nonlinearity of the core or presence of harmonic in the waveforms. To overcome the above mention problem and without hampering the circuit condition of the transformer the estimation of transformer parameters is required from normal operating condition, which is expected.

1.2 LITERATURE REVIEW:

References [42], [15], [32], [10] give a method to estimate transformer fundamental parameters including turns ratio, series winding resistance, series leakage inductance, shunt magnetizing inductance, and shunt core loss resistance. The proposed enhanced technique does not require transformer outage and/or specialty sensors. Rather, it utilizes the two terminal synchronized voltage and current measurements, which can be readily retrieved from the transformer Intelligent Electronic Device (IED). The proposed method is able to estimate single-phase transformer parameters in less than a cycle.

References [40], [9], [21], [29], [37] suggest a simple and effective evolutionary computation based method to estimate the equivalent circuit parameters of a single phase transformer from its name plate data without the need to conduct any experimental measurements. Two techniques, namely particular swarm optimization and genetic algorithm are employed to track the nameplate data by minimizing certain objective functions.

Satrajit Chakrabarty et al. [39] has proposed a novel method for measurements of transformer leakage inductances by Markov Linear Unbiased Estimator (MLUE) based on the electromagnetic circuit equation. Leakage inductance of each winding of transformer is used as priori parameter for monitoring transformer state windings. It enables protection to act rapidly and reliably and implement different ideas from different protection.

References [19], [22], [1], [41], [17], [43] provide a comprehensive discussion on Least Square Method for estimation of transformer winding parameters. Through the elimination of the ratio of flux change with respect to time from the equation, the discrete flux balance equation is obtained from discrete process. Using the derivative of voltage and current as the input and output variables, the leakage inductance and resistance of both winding as the identification parameters, an identification model for transformer is built. A modified orthogonal method is adopted here, which can improve the classical gram-schmidt orthogonal method in the calculation.

Online dynamic parameter estimation method of transformer equivalent circuit is proposed in the references [16], [20], [25], [33]. The dynamic parameters of transformer, including its resistances and inductances are estimated by the recursive least square routine on the measured terminal voltages and currents. The harmonic content of the measured input parameters is included in the proposed method. The estimation is done in the normal loading condition. Therefore, estimation of parameters is obtained in real time condition taking the saturation effect into account. Forgetting factors are proposed and used to accelerate the convergence of estimation in this method to improve the accuracy of the parameters.

Reference [4] propose a method for online estimation of transformer model parameters. This approach is based on linear least error square (LES) algorithm and uses the digitized samples of the input current and voltage as well as for the output of the transformer windings. The proposed method estimates the parameter in two steps; while in first step the algorithm is identifying the winding parameters and in the second step identifying the core parameters.

References [35]- [26] implement a methodology which consists of traditional open and short circuit test of the transformer to determine the equivalent circuit parameters and frequency response of the system. They used the approximate polynomial function, which is characterized as a Linear Least Square problem, which may satisfactorily represent the behavior of the parameters of the developed model.

References [6], [38], [7], [5], [3] identify the transformer model parameters by the maximum likelihood estimation method which utilizes the time-domain responses of the transfer function, and initial value of the transformer model parameter. They developed a transformer model at high frequency. Time constants of the transformer transfer function are estimated from the frequency response measurements. Then time response of transfer function in conjunction with maximum likelihood is used to estimate the transformer model parameters.

1.3 OBJECTIVE OF WORK:

The dissertation partial fulfills the following objectives:

i. To explore parameters estimation techniques of a distribution transformer.
ii. To study the application of particle swarm optimization for estimation of transformer parameters.
iii. To estimate the transformer parameters by using single objective function.
iv. To compare the result obtained from classical technique and intelligent technique, PSO.

1.4 ORGANIZAION DISSERTATION:

Chapter 1 consists of an introduction of transformer parameter estimation. It also includes brief literature review and background. It focuses on the objective of the thesis.

Chapter 2 elaborates the literature review of the techniques of transformer using classical and intelligent algorithms.

Chapter 3 elaborately discusses the theory and numerical example of Particle Swarm Optimization technique.

Chapter 4 presents the result of parameters estimation of transformer obtains from particle swarm optimization and comparison their result with conventional method. Furthermore, overall conclusion and future prospective of the thesis are also highlighted.

CHAPTER – 2

DIFFERENT PARAMETERS ESTIMATION METHODS OF TRANSFORMER

2.1 INTRODUCTION:

The system study has parameter estimation as one of the important problem to solve. The conventional method of using short-circuit test data of parameter determination provides an approximate equivalent circuit. This method needs minimum of two tests, firstly short circuit test and second one is direct current resistance test. The both tests are conducted at supply conditions different from normal operation. Due to the importance of transformers to power systems, investments in studies are justified in order to develop mathematical models to better understand equipment characteristics. In the estimation of equivalent circuit parameter, a good accuracy is required as they directly influence the performance computation such as voltage regulation and efficiency. Hence, a powerful tool is needed to estimate the transformer equivalent circuit parameter. Due to the importance of transformer in power system, different estimation methods of transformer are discussed in this section.

2.2 EQUIVALENT CIRCUIT:

When the impedance is referred to the primary side, the equivalent circuit of the real transformer [26] becomes the one shown in Fig. 2.1.

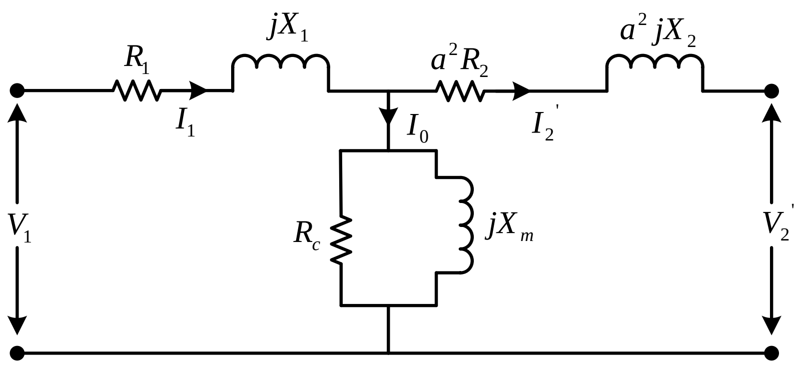

Figure 2.1 Equivalent circuit of a real transformer

Where,

R_1 - primary winding resistance

R_2 - secondary winding resistance

R_c - core lose resistance

X_m- magnetizing reactance

X_1 - primary winding reactance

X_2- secondary winding reactance

I_1- Primary current

I_2' - Secondary current

I_0 - no-load current

V_1 - primary terminal voltage

V_2' - Secondary terminal voltage

a - transforming ratio

2.3 PARAMETER ESTIMATION METHODS:

Parameter estimation is the process of using sample data to estimate the parameters of a selected system. Parameters can be estimated by different ways. Brief explanation of methods is as below:

2.3.1 Equivalent circuit method:

Traditional method open circuit and short circuit test are conducted to determine the steady state parameters of a transformer. In the open-circuit test a voltage equals to the rated primary voltage at rated frequency is applied to the primary windings with the secondary windings remain open. The current and active power at the low voltage windings is measured in open circuit voltage, and the core parameters (R_c, X_m) are calculated from the approximate no load equivalent circuit. Whereas in the short-circuit test, a reduced voltage at rated frequency is applied to the high voltage windings to get the rated current in the primary windings, while the secondary windings are short-circuited. The short circuit current, voltage and active power values are measured and the windings parameters (R_{eq},X_{eq}) referred to the primary side are computed by using the approximate short circuit equivalent circuit.

The advantage of using equivalent circuit method [16] is simplicity of the process and power consumption is less as compared to full load loss. Though the method is simple, result obtained is erroneous. As we do not consider normal operation during the experiment. Therefore, the result deviates from the true value.

2.3.2 Least Error Square Algorithm (LESA):

The digitized sample of input voltage and current as well as output current and voltage of transformer are used in least error square method. The method of least square [43] is about estimating parameter by minimizing the squared deviation from expected value to observed value. If we assume response variable **Y** and input variables **X.** Mathematical expression of the least square method is:

$$Y = f(x) + \text{noise}$$

here f is called a regression function. This function (*f*) is determined from the n sample input data and their responses $(x_1, y_1). . . (x_n, y_n)$.

The unknown values of the parameters β_0, β_1 ... are estimated by finding numerical values for the parameters, which minimize the sum of the squared value offsets from the expected value. The least squares estimator, denoted by$\hat{\beta}$. The least sum of squares criterion that needs to be minimized in order to obtain the parameter estimates can be written as:

$$Q = \sum_{i=1}^{n} \left[y_i - f(x_i, \hat{\beta})\right]^2$$

Unknown parameters can be estimated by using this method from the following equation

$$\hat{\beta} = (X'X)^{-1}.XY$$

Advantage of Least Error Square method is that it can be implemented to:

- Identify the online parameters of the transformer from normal operating condition.
- Identify the internal fault by measuring the variation of parameters from actual value [16].

2.3.3 Recursive Least Square Estimation (RLS):

By using Recursive Least Square algorithm, online dynamic parameters of transformer can be estimated at the actual operating condition. RLS estimation is an iterative algorithm that can be updated based on the new coming measurement [42]. The RLS is an adaptive method which recursively finds the coefficients that minimize a weighted linear least square cost function relating to the input signals. Compared to most of its competitors, the RLS exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity. This algorithm should be executed when the system is in steady state operation. RLS algorithm is capable of online estimation and allows gradual variation of system parameters. Figure 2.2 shows the procedure as a simple block diagram from which estimated parameters is updated every time step.

If k is assumed to be the time step number, the RLS algorithm performs the following stages in k^{th} step [20]

1. Initial conditions: The initial value of the estimated parameter vector $\hat{\theta}$ is set equal to zero. The initial covariance matrix P is assumed to be diagonal matrix with large positive numbers.
2. Compute estimate $\hat{y}$

   $\hat{y}(k) = \hat{\theta}^T(k-1)x(k)$
3. Compute the estimation error of *y(k)*

   $\varepsilon(k) = y(k) - \hat{\theta}^T(k-1)x(k)$
4. Compute the estimate covariance matrix at instant k

   $$P(k) = P(k-1) - \frac{P(k-1)x(k)x(k)^T P(k-1)}{1+x(k)^T P(k-1)x(k)}$$
5. Compute estimation vector at instant k

   $\hat{\theta}(k) = \hat{\theta}(k-1) + P(k)x(k)\varepsilon(k)$

Continues the updating process until a weighted quadratic cost function is minimized. The advantages of RLS method are:

- It is capable of online estimation and allows gradual variation of system parameters.
- This algorithm can be readily implemented in machine drive systems.

There is also a major drawback of this algorithm that it cannot be used in the worst operational situations when the system is in transient state or continuous to oscillate largely.

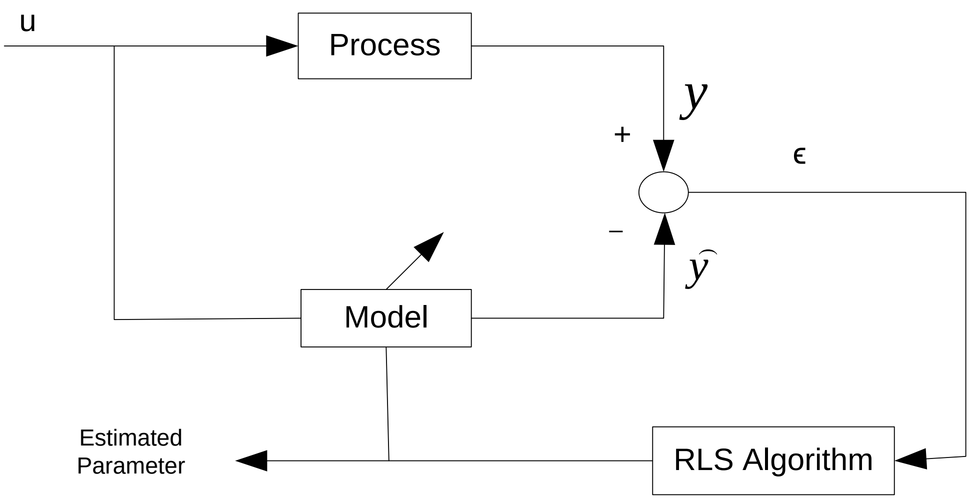

Figure. 2.2 RLS identification method

2.3.4 Harmony Search Algorithm (HS):

The HS was initially proposed by Geem [12]. The application of optimization techniques in engineering can be found in many analysis problems arising in engineering model development. Many optimization problems in various fields have been solved using diverse optimization algorithm. Traditional optimization techniques such as linear programing, non-linear programing and dynamic programing have had major roles in solving these problems. However, their drawbacks generate demand for other types of algorithm, such as heuristic optimization approaches. However, there are still possibilities of deserving new heuristic algorithm based on natural or artificial phenomena. A new heuristic algorithm imitating the improvisation of music players have been developed and named Harmony Search. This method is an emerging meta-heuristic optimization algorithm, which has been employed to cope with numerous challenging tasks during the past decade.

HS algorithm should follow any of the three rules below:

- Choosing any value from the HS memory.
- Choosing an adjacent value from the HS memory.
- Choosing a random value from the possible value range.

The above three rules of the HS algorithm are effectively directed by two essential parameters: Harmony Memory Considering Rate (HMCR) and Pitch Adjusting Rate (PAR).

Figure 2.3 shows flowchart of basic HS method, in which there are four principal steps are involved.

- **Step 1**. Initialize the HS memory. The initial Harmony Memory (HM) is filled with randomly generated solution vector to the optimization problem. For n dimensional problem, an HM with the size of Harmony Memory Size (HMS) can be represented as follows:

$$HM=\begin{bmatrix} x_1^1, x_2^1, & \cdots, & x_n^1 \\ \vdots & \ddots & \vdots \\ x_1^{HMS}, x_2^{HMS}, & \cdots, & x_n^{HMS} \end{bmatrix}$$

  Where $[x_1^i, x_2^i, \ldots \ldots., x_n^i]$ (i=1, 2… HMS) is a solution candidate. HMS is typically set to be between 50 and 100.

- **Step 2.** Improvise a new solution $[x_1', x_2' \ldots x_n']$ from the HM. Each component of this solution, x_j', is obtained based on the HMCR. The HMCR is defined as the probability of selecting a component from the present HM members, and 1-HMCR is, therefore probability of generation is randomly. If x_j' comes from the HM, it is chosen from the jth dimension of a random HM member, and it can be further mutated according to the PAR. The PAR determines the probability of a candidate from the HM to be mutated.
- **Step 3.** From the viewpoint objective function value, if the new harmony vector $[x_1', x_2', \ldots., x_n']$ is better than worst harmony in HM, then old harmony is replaced by new one.
- **Step 4.** Repeat step 2 to step 3 until a preset termination criterion, e.g., the maximum number of iterations, is met.

  Apparently, the HMCR and PAR are two basic parameters in the HS algorithm, which control the component of solutions and even affect the convergence of speed. The HMCR is used to set the probability of utilizing the historic information stored in the HM. For example, 0,8 indicates that each candidate of new solution will be chosen from the HM with the probability of 80% and 20% from the entire range.

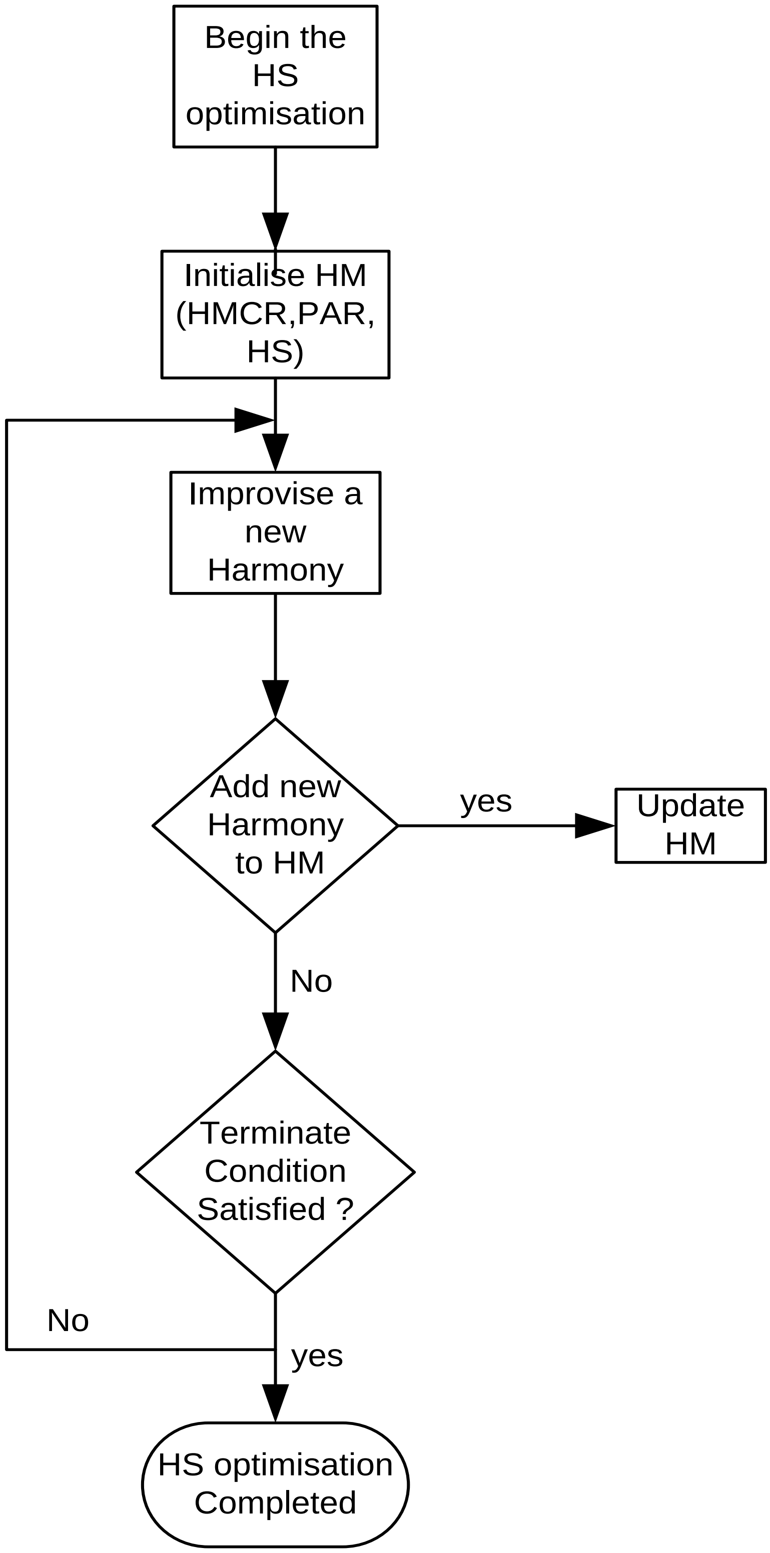

Figure. 2.3 Harmony Search Flow Chart

This method claims the following merits:

- HS does not require different gradients; thus, it can consider continuous as well as discontinuous function.
- HS can handle discrete variables as well as continuous variables.
- HS does not need initial value setting for the variables.
- HS is free from divergence.
- HS may escape local optima.

In addition to the transformer parameter estimation, HS has also been widely used in a large variety of fields, including transportation, manufacturing, robotics, control, and medical science.

2.3.5 Maximum Likelihood Estimation (MLE):

The principle of maximum likelihood estimation (MLE) originally developed by R.A. Fisher in the 1920s, states that desired probability distribution is the one that makes the observed data "most likely" which means that one must seek the value of the parameter vector that maximize the likelihood function. The resulting parameter vector, which is sought by searching the multi-dimensional parameter space, is called the MLE estimate.

Under very broad condition, maximum-likelihood estimators have the following general properties:

- Maximum likelihood estimators are consistent.
- They are asymptotically unbiased, although they may be biased in finite samples.
- If there is a sufficient statistic for a parameter, then the MLE of the parameters is a function of sufficient statistic.
- They are asymptotically normally distributed.
- They are asymptotically efficient.

In electrical machine parameter identification, maximum-likelihood (ML) estimation has been proven to be an excellent stochastic identification method for improving precision and convergence efficiency [5], [7]. Transient response of a transformer can be described by a set of discrete linear difference equations [6] given below:

$$x(k+1) = Ax(k) + BU(k) + w(k)$$

$$y(k+1) = Cx(k+1) + v(k+1)$$

Where,

x = state vector

***U* =** input vector

***Y* =** output vector

w and ***v* =** noise vectors

A, B, and ***C*** = system matrices

A, B, and ***C*** are the function of the parameter vector θ which are to be estimated. To apply the maximum likelihood estimation (MLE), the first step is to specify the maximum likelihood function [3]. Here likelihood function is denoted by L (θ), where θ are the transformer parameters to be estimated. L (θ) is defined as:

$$L(\theta) = \prod_{1}^{N}\left[\frac{1}{\sqrt{(2\pi)^m \det\left(R(k)\right)}}\exp\left(-\frac{1}{2}e(k)^T R(k)^{-1} e(k)\right)\right]$$

where e (k), R (k), N and m denote the estimation error, the covariance of estimation error, number of data points and dimension of the output vector y respectively. The covariance of estimation error [38] is defined as:

$$R(k) = COV(e(k), e(k)^T)$$

$$e(k) = y(k) - \hat{y}(k)$$

As shown in figure 2.4 the estimation error is defined as difference between the input/output measurement of the system (transformer) and estimated output when the system is subjected to the same input. Maximizing L (θ) is equivalent to minimizing negative logarithm of L (θ) which is defined as:

$$V(\theta) = -\log L(\theta)$$

$$V(\theta) = \frac{1}{2}\sum_{k=1}^{N}[e(k)R(k)^{-1}e(k)] + \frac{1}{2}\sum_{k=1}^{N}\log\det\left(R(k)\right) + \frac{1}{2}mN\log(2\pi)$$

Assuming that the log-likelihood function is differentiable, and then it must satisfy the following partial differential equation known as the likelihood equation:

$$\frac{\partial \ln L(\theta)}{\partial \theta} = 0$$

This is because the definition of maximum or minimum of a continuous differentiable function implies its first derivative will be zero at some points.

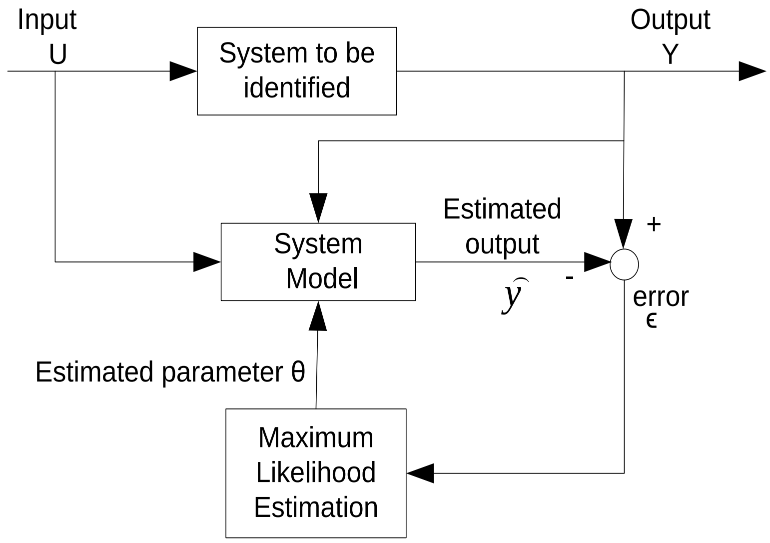

Figure. 2.4. Maximum Likelihood Estimation flow chart

Merits of this method are following:

- The ML identification method has applied to the parameters estimation of many engineering problems.
- Maximum likelihood provides a consistent approach to parameter estimation problems of noise-corrupted data. This means that maximum likelihood estimates can be developed for a large variety of estimation situations and the estimate will converge to the true parameter value if the number of iteration goes to infinity. This is not the case for least square estimation.
- They have approximate normal distributions and approximate sample variance that can be used to generate confidence bounds and hypothesis tests for the parameter.

The demerits of this method are:

- The main disadvantage of MLE algorithm is the complexity and extensive computational requirements.
- The likelihood equation needs to be specifically worked out for a given distribution and estimation problem.
- Maximum likelihood estimates can be heavily biased for small samples. The optimality properties may not apply for small samples.
- Maximum likelihood can be sensitive to the choice of starting values.

2.3.6 Genetic Algorithm (GA):

J.H. Holland first introduced genetic algorithms in the mid-60. Today, genetic algorithms constitute one of the most popular heuristics for global optimization. Just like others evolutionary algorithm, they exploit population of candidate solutions. The unique characteristic of their essential variants is the binary representation of solutions, which require a translation function between binary representation and actual variable of the system. For example, in real-valued optimization problems, all real candidate solutions must be translated from and to binary vectors. The biological notation is retained in genetic algorithms; thus, the binary representation of a solution is called its chromosome or genotype, while the actual form is called its phenotype. A typical genetic algorithm requires two things, one is a genetic representation of the solution domain and other is a fitness function or objective function to evaluate the solution domain. Evolution in genetic algorithm [38] is achieved by three fundamental genetic properties: selection, crossover and mutation. Population size depends on the nature of the nature of problem, but typically contains several hundred or thousands possible solutions. Among the generated population, those with the lowest function value, a number of parents are selected from the current population. Three steps of the GA are discussed below:

- **Selection:** During each successive generation, a proportion of the existing population is selected to breed a new generation. The criteria for selecting individuals from population for parents can be either stochastic or deterministic. It always depends on its function value. Thus, deterministic selection approaches directly find the best solution, which has lowest function value, whereas stochastic selection assign higher probability to the best solution. The fitness function is defined over the genetic representation and measures the quality of represented solution. The fitness function is always problem dependent.
- **Crossover or Recombination:** Crossover is the process of recombining the information carried by two individuals i.e. parents to produce new offspring. This is similar to the biological reproduction where DNA sequence of parents are mixed to produce offspring DNA sequence that contains genetic information from parents. There different representation for crossover scheme. Among them binary representation is most closely related to the natural phenomenon.

  Let $p = \{p_1, p_2 \dots \dots ., p_n\}$ and $q = \{q_1, q_2, \dots . ., q_n\}$ be two n dimensional binary parent vectors selected randomly from the parent pool generated by the selection procedure. Then a crossover point $k \in \{1,2, \dots . ., (n-1)\}$ is defined, and each parent is divided into two parts that are recombined to produce two offspring, $O_1 = \{p_1, p_2, \dots, p_k, q_{k+1}, \dots\dots, q_n\}$ and $O_2 = \{q_1, q_2, \dots . q_k, p_{k+1}, \dots . , p_n\}$. If we denote two symbols "$\otimes$" and "$\oplus$" to represents two parent p and q respectively (thus "$\otimes$" and "$\oplus$" can be either 0 or 1). Then crossover can be represented schematically as follows:

parent p: $\otimes\otimes\otimes\otimes\otimes\otimes \mid \otimes\otimes\otimes\otimes$ parent q: $\oplus\oplus\oplus\oplus\oplus\oplus \mid \oplus\oplus\oplus\oplus$

Offspring O_1: $\otimes\otimes\otimes\otimes\otimes\otimes \mid \oplus\oplus\oplus\oplus$ Offspring O_2: $\oplus\oplus\oplus\oplus\oplus\oplus \mid \otimes\otimes\otimes\otimes$

Figure. 2.5. one-point crossover

This procedure is also called one-point crossover, as it uses a single crossover point. Similarly, we have 2-point crossover, which is shown below:

parent p: $\otimes\otimes\otimes \mid \otimes\otimes\otimes \mid \otimes\otimes\otimes\otimes$ parent q: $\oplus\oplus\oplus \mid \oplus\oplus\oplus \mid \oplus\oplus\oplus\oplus$

Offspring O_1: $\otimes\otimes\otimes \mid \oplus\oplus\oplus \mid \otimes\otimes\otimes\otimes$Offspring O_2: $\oplus\oplus\oplus \mid \otimes\otimes\otimes \mid \oplus\oplus\oplus\oplus$

Figure. 2.6 Two-point crossover

In general, we can have an arbitrary number of crossover point, producing multipoint crossover schemes.

- **Mutation:** Mutation is the biological process by which it enables to change one or more biological properties radically, in order to fit an environmental change or continue their evolution by producing offspring with higher chances of survival. In nature, mutation constitutes an abrupt change in the genotype of an organism, and it can be inherited either by parents to children or acquired by an organism itself. In real valued representation, mutation can be defined as the replacement of a vector component with a random number distributed over its corresponding range.

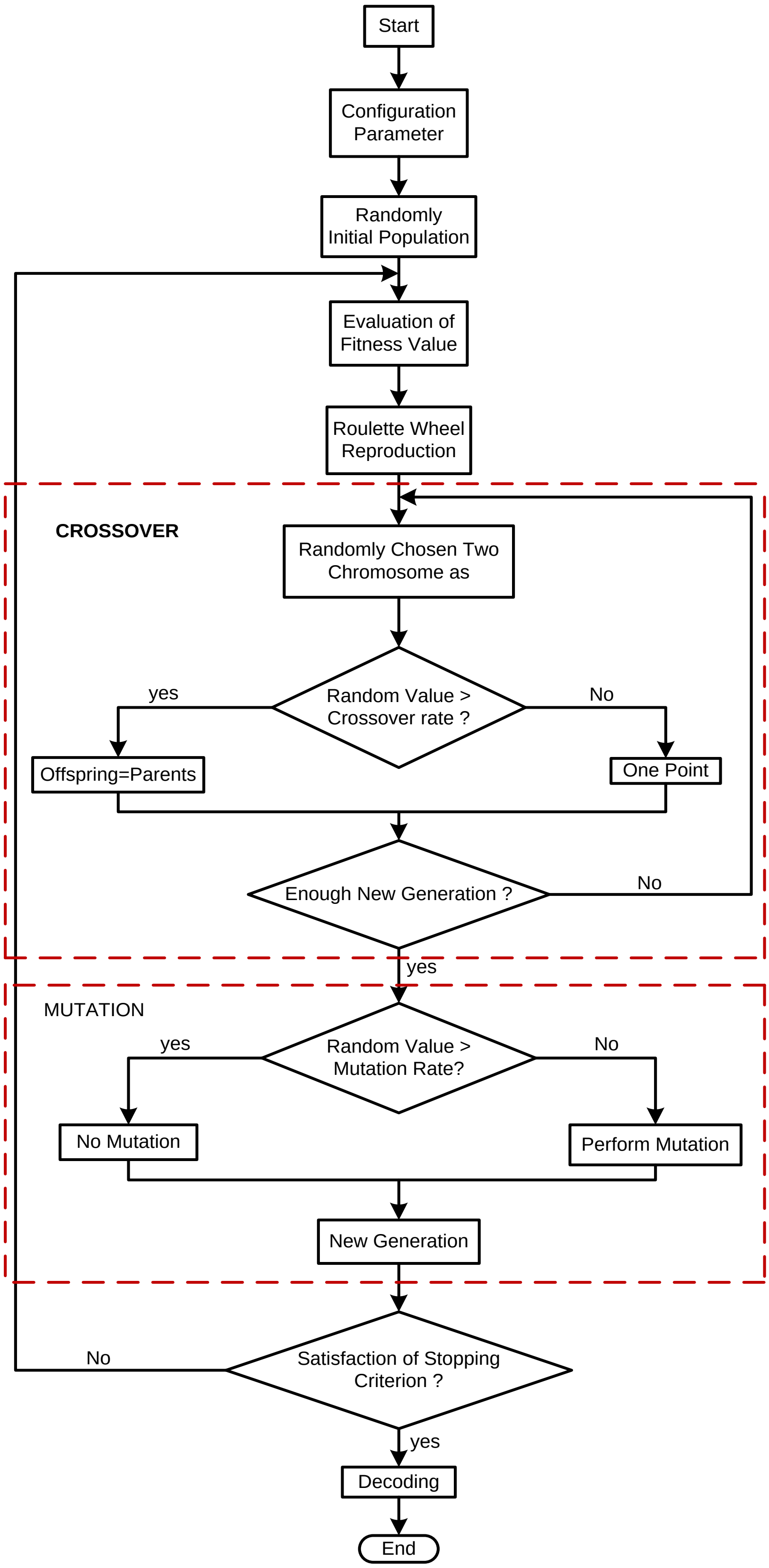

Figure. 2.7. Flow chart of Genetic Algorithm

The main drawbacks of GA are:

- No guarantee of finding global maxima.
- This method takes sufficient time for convergence.
- It has incomprehensible solution. There are a lot of complexity in the system

2.4 CONCLUSION:

In this chapter, we have carried out the literature review of the parameter estimation techniques pertaining to single-phase transformer. These techniques are broadly classified as classical and intelligent algorithm based methods. This chapter also briefly discusses the pros and cons of these techniques employed for parameter estimation of a transformer. In the next chapter, Particle Swarm Optimization (PSO) is discussed in detail.

CHAPTER – 3

PARTICLE SWARM OPTIMIZATION METHOD

3.1 INTRODUCTION:

Optimization is the act of obtaining the best result under given circumstances. In design, construction, and parameters estimation of any engineering system, engineers have to take many technological and managerial decisions at several stages. The ultimate goal of all such decisions is either to minimize the effort required or to maximize the desired benefit. Since the effort required or the benefit desired in any practical situation can be expressed as a function of certain decision variables, optimization can be defined as the process of finding the conditions that give the maximum or minimum value of a function. The parameters estimation problem inherently transformed to optimization problem of a required model for a given set of test data so that model fit the data as closely as possible. A general formulation of nonlinear constrained is given by

Minimize $F(x)$ for $x = (x_1, x_2 \ldots x_N)$

Subject to $g_j(x) \geq 0\ for\ j = 1,2, \ldots, J$ and $h_k(x) = 0\ for\ \ k = 1,2, \ldots., K.$

Where, x are variables (a set of designed parameters)

$F(x\ )$ is objective function to be minimized

$g_j(x\ )$ is inequality constraints

$h_k(x)$ is equality constraints

The determination of parameters might be carried out by minimizing the quadratic error between the approximate value and exact value i.e. we have to minimize the value of objective function. Objective function can be defined as:

$$F(x) = \sum_{i=1}^{N} [y_i - f(x, \theta_i)]^2$$

where y_i is test data at the test condition θ_i

$f(x, \theta_i)$ is predicted value at the test condition θ_i

The conventional design procedures aim at finding an acceptable or adequate design that merely satisfies the functional and other requirements of the problem. In general, there will be more than one acceptable design, and the purpose of optimization is to choose the best one of the many acceptable designs available. Thus, a criterion has to be chosen for comparing the different alternative acceptable designs and for selecting the best one. The criterion, with respect to which the design is optimized, when expressed as a function of the design variables, is known as the *criterion, merit, or objective function*. The choice of objective function is governed by the nature of problem.

3.2 SOURCE OF INSPIRATION:

The PSO algorithm was originally proposed by Kennedy and Eberhart in 1995. Several optimization techniques have been developed during last two decades based on the analogy of swarm behavior of natural creatures. Particle swarm optimization, abbreviated as PSO, is based on the behaviour of a colony or swarm of insects, such as ants, termites, bees, and wasps; a flock of birds; or a school of fish [9]. The PSO utilizes a cooperative swarm of particles, where each particle symbolizes a candidate solution to a specific optimization problem. The particle swarm optimization algorithm imitators the behaviour of these social organisms. The word particle denotes, for example, a bee in a colony or a bird in a flock. Each individual or particle in a swarm behaves in a distributed way using its own intelligence and the collective or group intelligence of the swarm. As such, if one particle discovers a good path to food, the rest of the swarm will also be able to follow the good path instantly even if their location is far away in the swarm. Optimization methods based on swarm intelligence are called behaviourally inspired algorithms as opposed to the genetic algorithms, which are called evolution-based procedures. Other evolutionary computation techniques, such as Ant Colony (ACO) and Genetic Algorithm (GA), also follow the natural behavior. ACO mimics the concept and the behavior of ant colony metaphor in swapping information through pheromone. It was observed that real ants, which are almost blind and have very simple individual capabilities, are capable of finding the direct path between their home colony and food source.

In the context of multivariable optimization, the swarm is assumed to be of specified or fixed size with each particle located initially at random locations in the multidimensional design space. Each particle is assumed to have two characteristics: a position and a velocity. Each particle wanders around in the design space and remembers the best position (in terms of the food source or objective function value) it has discovered. The particles communicate information or good positions to each other and adjust their individual positions and velocities based on the information received on the good positions.

As an example, consider the behaviour of birds in a flock. Although each bird has a limited intelligence by itself, it follows the following simple rules:

1. It tries not to come too close to other birds.

2. It steers toward the average direction of other birds.

3. It tries to fit the "average position" between other birds with no wide gaps in the flock.

Thus, the behaviour of the flock or swarm is based on a combination of three simple factors:

1. Cohesion—sticks together.

2. Separation—does not come too close.

3. Alignment—follows the general heading of the flock.

The PSO is developed based on the following model:

1. When one bird locates a target or food (or maximum of the objective function), it instantaneously transmits the information to all other birds.

2. All other birds descend to the target or food (or maximum of the objective Function), but not directly.

3. There is a component of each bird's own independent thinking as well as its Past *memory.* Thus, the model simulates a random search in the design space for the maximum value of the objective function. As such, gradually over many iterations, the birds go to the goal (or maximum of the objective function).

3.3 BASIC CONCEPT:

PSO is based on two fundamental disciplines: social science and computer science. In addition, PSO uses the swarm intelligence concept, which is the property of a system, whereby the collective behaviors of unsophisticated agents that are interacting locally with their environment create coherent global functional patterns. It is robust stochastic optimization method based upon the behavior of swarms observed in nature. The method captures the concept of social intelligence and cooperation. Therefore, the cornerstones of PSO can be described as follows.

- **Social concepts:** It is known that “human intelligence results from social interaction.” Humans too are characterized by agnate behaviours, especially at the level of social organization and belief formulation. However, these interactions can become very complex, especially in the belief space, where, in contrast to the physical space, the same point (a belief or an idea) can be occupied concurrently by large groups of people without collisions. The aforementioned aggregating behaviours characterized by the simplicity of animal and physical system or the abstractness of human social behaviours, intrigued researcher and motivated their further investigation through extensive experimentation and simulation.
- **Swarm intelligence principles:** swarm intelligence is a branch of artificial intelligence that studies the collective behaviour and emergent properties of complex, self-organized, decentralized system with social structure. Intense research in systems where collective phenomena are met prepared the ground for the development of swarm intelligence. Swarm intelligence can be broadly classified by considering five fundamental principles.
    1) **Proximity principle:**
       The population should be able to carry out simple space and time computation.
    2) **Quality principle:**
       The population should have ability to respond to environmental quality factor.
    3) **Diverse response principle:**
       The population should have ability to produce a plurality of difference responses.
    4) **Stability principle:**
       The population has to retain ability for robust behaviour under mild environmental changes.
    5) **Adaptability principle:**
       The population should be able to change behaviour when it is dictated by environmental factor.

3.4 VARIANT OF PSO:

Particle swarm optimization consists of swarm of particles, where particle symbolize a potential solution. Exploration is the ability of a search algorithm to explore different region of the search space in order to locate a good optimum. Exploitation, on the other hand, is the ability to concentrate the search around a promising area in order to refine a candidate solution [23].

Placing the PSO method in a mathematical framework, let A⊂Rn be the search space and, f: A →Y⊆R, be the objective function. In order to keep explanation as simple as possible, we also assume that A is the feasible space of the problem at hand i.e., there are no further explicit constraints posed on the candidates solution. Also, note that no additional assumptions are required regarding the form of objective function and search space. As mentioned earlier PSO is a population-based algorithm i.e. it exploits a population of potential solution to probe the search space concurrently. The population is called the swarm and its individuals are called particles. The swarm is defined as a set:

$$S = \{x_1, x_2, \dots \dots, x_N\}$$

of N particles (candidates solution) defined as:

$$x_i = (x_{i1}, x_{i2}, \dots \dots, x_{in})^T \in A \qquad i = 1,2, \dots \dots, N$$

Indices are arbitrarily assigned to particles, while N is the user-defined parameter of the algorithm. The objective function$f(x)$, is assumed to be available for all points in A. Thus, each particle has unique objective function value.

The particles are assumed to move within the search space iteratively. This is possible by adjusting their position using a proper position shift, called velocity and denoted as:

$$v_i = (v_{i1}, v_{i2}, \dots \dots, v_{in})^T, \quad i = 1,2, \dots \dots, N$$

Velocity is also adapted iteratively to render particles capable of potentially visiting any region of A. If t denotes the iteration counter, then the current position of i-th particle and its velocity will be henceforth denoted as $x_i(t)$ and $v_i(t)$ respectively.

Velocity is updated based on information obtained in previous steps of the algorithm. This is implemented in terms of a memory, where each particle can store the best position it has ever visited during its search. For this purpose, besides the swarm, S, which contains the current positions of the particles, PSO maintains also a memory set:

$$P = \{P_1, P_2, \dots \dots, P_N\}$$

This contains the best position:

$$p = (p_{i1}, p_{i2}, \dots., p_{iN})^T \in A \quad i = 1,2, \dots., N$$

ever visited by each particle.

PSO is based on simulation models of social behaviour; thus, an information exchange mechanism shall exist to allow particles to mutually communicate their experience. The algorithm approximates the global minimizer with the best position ever visited by all particles. Therefore, it is a sensible choice to share this crucial information. Let g be the index of the best position with lowest function value in p at a given iteration.

The position of the particle is changed by adding a velocity, $v_i(t)$ to the current position:

$$x_i(t+1) = x_i(t) + v_i(t+1)$$

And,

$$v(t) = v_i(t-1) + c_1 r_1\big(localbest(t) - x_i(t-1)\big) + c_2 r_2\big(globalbest(t) - x_i(t-1)\big)$$

with $x_i(0) \sim U(x_{min}, x_{max})$,

where t denotes the iteration counter, r_1 and r_2 are random variables uniformly distributed within (0,1) and $c_{1,}c_2$ are weighting factors, also called the cognitive and social parameter respectively.

At each iteration, after the update and evaluation of particles, best positions (memory) are also updated. Thus, the new best position of x_i at iteration $(t+1)$ is defined as follows:

$$P_i(t+1) = \begin{cases} x_i(t+1) & \text{if } \mathrm{f}\big(x_i(\mathrm{t}+1)\big) \le \mathrm{f}\big(P_i(\mathrm{t})\big) \\ P_i(t) & \text{otherwise} \end{cases}$$

The new determination of index g for the updated best position complete one iteration in PSO.

3.5 FURTHER REFINEMENT OF PSO:

Early PSO variants execute satisfactorily for simple optimization problem. However, their crucial deficiencies were revealed as soon as they are applied in case of harder optimization problem with large search space A. The variation is influenced by a number of control parameters, namely the dimension of the problem, the number of particles i.e.

population size, acceleration coefficients (c_1, c_2), inertia weight (w), neighbourhood size, number of iteration and the random value (r_1, r_2) which scale the contribution of the cognitive and social component. In the following paragraph, refinement of the variations has been developed and discussed to address deficiencies of original PSO model.

- **Swarm explosion and velocity clamping:** The first substantial issue verified by several researcher was the swarm *explosion* effect. It refers to the uncontrolled increase of magnitude of velocity of swarm resulting in swarm divergence. It is stochastic variables, and therefore subject to creating uncontrolled trajectory, making the particle follow wider cycles in the search space. If the velocity v of a particle exceeds the maximum allowable speed limit, it will set a maximum value of velocity $v_{max}$and it is given for the velocity v_i [39].

$$if\ \ v_{id} > v_{max} \quad then\ \ v_{id} = v_{max}$$
$$else\ if\ \ v_{id} < -v_{max}\ \ then\ v_{id} = -v_{max}$$

High value of v_{max} will cause global exploration, whereas lower value of v_{max} result in local exploration v_{max} controls the movement of the particle and aspect of exploration and exploitation. Velocity clamping does not influence the position of the particles. This only decreases the size of step velocity. Research work done by Fan and Shi [40] have shown that an appropriate dynamically changing velocity can improve the performance of PSO algorithm. The following equations are used to initialize the maximum, minimum velocity and from these the dynamically changing velocity is defining as:

$$v_{max} = (x_{max} - x_{min})/N;$$

where N is the number of intervals in the kth dimension selected by the user and x_{max} and x_{min} are the maximum and minimum position of the particle. The problem is that if all the velocity is equal to v_{max} the particle will continue to search within hypercube and will probably remain in the optima but will not converge in the local area.

- **Selection of acceleration constant:** Acceleration constant c_1 (cognitive) and c_2(social) control the movement of each particle towards its individual and global best position respectively. In the first version of PSO, a single weight $c_1 = c_2$ was used instead of two distinct weight. However, the latter offer better control of the algorithm, leading superior to previous version. The effect of considering a random value for acceleration constant assistances to create an uneven cycling for the trajectory of particle when it is searching about the optimum value. In case of good starting, point it usually taken as$c_1 = c_2 = 2$. It is important to note that c_1 and c_2 should not be necessarily equal since the weight for individual and group experience can vary according to the field of application.

- **Selection of constriction factor:** Experiential study performed on PSO indicate that even when acceleration constant and maximum velocity are defined correctly, still particle may diverge i.e. go to infinity, a phenomenon known as "*explosion"* of the swarm. Two methods, "*constriction factor*" and "*inertia constant*" are required to prevent from this type of divergence. Velocity update equation that using constriction coefficient changes to:

$$v_i(t) = \mathcal{X}\{v_i(t-1) + c_1 r_1(localbest - x_i(t-1)) \\ + c_2 r_2(globalbest - x_i(t-1))\}$$

here $\mathcal{X}$ is called "*constriction coefficient*" and it can be defined by the following mathematical expression:

$$\mathcal{X} = \frac{2k}{\left|2 - \emptyset - \sqrt{\emptyset(\emptyset - 4)}\right|}$$

with $\emptyset = \emptyset_1 + \emptyset_2$

$\emptyset_1 = c_1 r_1$

$\emptyset_2 = c_2 r_2$

Equation above is used under the constraints that $\emptyset \geq 4$ and $k \in [0,1]$. The constriction approach was developed as a natural, dynamic way to confirm convergence to stable point, without the requirement for velocity clamping. Condition $\emptyset \geq 4$ and $k \in [0,1]$ of the swarm is guaranteed to convergence.

Usually the constriction coefficient increases the convergence of the particle over time by damping the oscillation once the particle is concentrated on the best point in an optimal region. The main drawback of this method is that the particles may follow wider cycle and may diverge when the individual best performance is far away from the neighbourhood's best performance (two different region)

- **Inertia weight:** Although the use of maximum velocity limit improved the performance of early PSO variants, it is not satisfactory to render the algorithm efficient in complex optimization problem. Despite the mitigation of swarm explosion, the swarm was not able to focus its particles around the most promising solution. To overcome this type of problem a new variant was introduced, it is called "*inertia weight*". It is a technique to control an exploration and exploitation abilities of the swarm, and as mechanism to eliminate the need of velocity clamping. The inertia weight w controls the momentum of the particle by weighing the influence of previous velocity- actually controlling how much memory of the previous flight direction will influence the new velocity. By considering the effect of inertia weight the velocity equation is modified to the following equation:

$$\boldsymbol{v_i}(t) = wv_i(t-1) + c_1r_1\big(localbest - x_i(t-1)\big) + c_2r_2(globalbest - x_i(t-1))$$

here w is the *inertia weight.* The rest of the parameters remaining same as the early equation. Inertia weight showing how much the amount of memory from the previous flight direction will affect the new velocity. The inertia weight can be considering either fixed or dynamically changing with the number of iteration. Essentially, this parameter controls the exploration of the search space. Therefore, the inertia weight should be selected in such a way that the effect of $v_i(t)$ fades during the execution of algorithm. Thus, a decreasing value of inertia weight with time is preferable choice. A very common choice is the initialisation of w to a value slightly greater than 1.0 (e.g., 1.2) allow the particle to move freely in order to find global optimum neighbourhood fast. Once the optimal region is found, the value of inertia weight can be decreased in order to narrow the search. Finally, it reaches to zero to eliminate the oscillatory behaviour in the latter stage.

In general, a linearly decreasing scheme for w can be mathematically described as follows:

$$w(t) = w_{up} - (w_{up} - w_{low})\frac{t}{T_{max}}$$

where t stands for iteration counter, w_{low} and w_{up} are the desirable lower and upper value of inertia weight and T_{max} is the maximum number of iteration. The above equation shows a linearly decreasing time dependent inertia weight with starting value, w_{up} at iteration $t = 0$ and final value, w_{low}, at the last iteration $t = T_{max}$.

Fig. 3.1 illustrates diversity for swarm without and with inertia constant. From this figure, it is seen that obviously, the use of inertia weight has a remarkable effect on swarm diversity, which almost disappears after 300 iterations, in contrast to the case of simple velocity clamping, which almost retains the same diversity throughout the search.

However, the main disadvantage of this method is that once the inertia weight decreased, the swarm loss its ability to search new area because it is not able to recover its exploration mode.

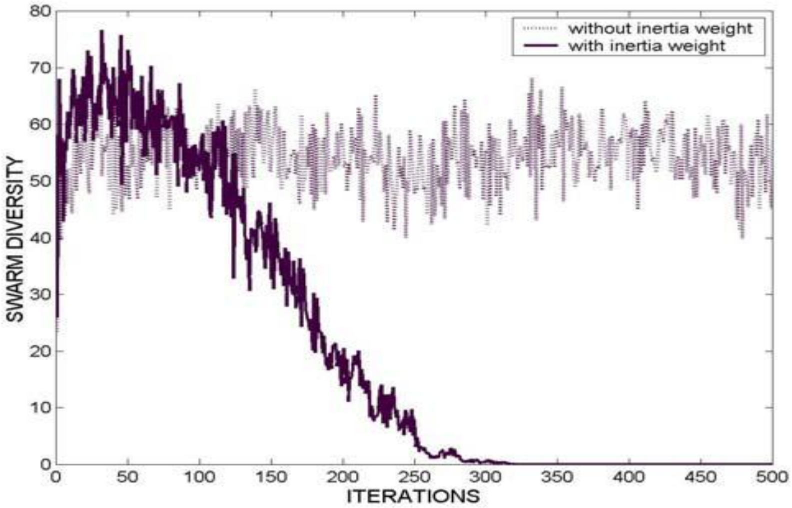

Figure. 3.1. Swarm diversity during search with (solid line) and without (dotted line) inertia weight

3.6 INITIALIZATION TECHNIQUE OF PSO:

Initialization is perhaps the less studied part of PSO and other evolutionary algorithms. This may be due to the general demand for developing algorithms that are not very subtle in the initial conditions. However, it can be experimentally shown that, in various problems, initialization can have a substantial impact on performance.

Uniform random initialization is most popular scheme in evolutionary computation due to the requirement for equally treating each part of a search space with undisclosed characteristics. However, alternative initialization methodologies that use different probability distributions or employ direct search methods to provide first step of algorithm have proved very useful.

In the following section, we discuss the most common probabilistic initialization technique and opposition based initialization technique.

- **Random probabilistic initialization:** In the context of PSO, the quantities that need to be initialized prior to application are the particles as well as their velocities and best positions. The best position consists of best solution already recognized by each particle, while current particle position symbolizes candidate new solution. Since no information on the promising regions of the search, space is expected to be available earlier to initialization; the initial particles and the corresponding best positions are considered to coincide. In addition, in constrained optimization, we are interested in identifying feasible solutions, i.e., solutions that do not violate problem constraints. For this purpose, the initialization of swarm and best positions within the feasible search space, $A \subset R^n$, is desirable.

  The most popular technique in evolutionary computation is "*random uniform initialization*". According to this convention, each particle of the initial swarm and consequently initial best position is drawn by sampling a uniform distribution over the search space A. The applicability of this approach depends on the form of the search space. If *A* is given as an *n*-dimensional bounded box:

$$A = [a_1, b_1] \times [a_2, b_2] \times \ldots \times [a_{n,} b_n]$$

  Then any of the available pseudo random number generator can be directly used to produce uniformly distributed number within it. In practice, it is very common; each component of particle is generated as a uniformly distributed pseudo-random value within the interval [0, 1] and then scaled the magnitude according to direction of search in space A. In addition to this, we scale the pseudo-random number value of the velocity component, in order to clamp it within limit $[-v_{max}, v_{max}]$ as described previously. When a large number of subsequent experiments are conducted, re-initialization of pseudo random generator with different seed may be occasionally essential in order to obtain unbiased experimental result.

- **Opposition based initialization:** To improve the performance of PSO, opposition based initialization method of population has been proposed in this paragraph. The idea of opposition-based learning is proposed by Tizoshi [18], which has been incorporated in several machine-learning algorithm [44]. The social phenomenon of good and bad says that if one person is good, then his /her opponent is bad. It rarely occurs that two persons are completely good and completely bad at the same time. This is purely natural thing. The description of concept which is proposed in this section is described as under:

A swarm particle P_i in PSO can be defined as:

Particle:

$P_i \in [a, b]$ where $i = 1,2,3, \dots, D$ and $a, b \in R$

Opposite particle:

Every particle P_i has a unique opposite particle P_{opi} in initially defined hyperspace, which can be defined as:

$P_{opi} = a + b - P_i$ where $i = 1,2,3, \dots, D$ and $a, b \in R$

D represent the number of dimension and R represent real numbers.

Let us take an example. For a single dimensional particle, $P_i = 12 \in [10, 20]$; then opposition based population can be calculated as $P_{opi} = (10 + 20) - 12 = 18$

In this method first, the initial basic population of swarm is initialised randomly. Then the basic swarm is used to create opposite swarm. Fitness of each individual particle (swarm) is calculated then fitter one from both are selected for optimal solution using standard PSO algorithm.

The rationale behind this approach is the basic idea of opposition-based learning: if we begin with a random guess, which is very far away from the existing solution, let say in worst case it is in the opposite location, then we should look in the opposite direction.

3.7 COMPUTATIONAL IMPLEMENTATION OF PSO:

Consider an unconstrained optimization problem:

Maximize objective function $f(x)$ with $X_{low} \leq X \leq X_{up}$

where X_{low} and X_{up} denote the lower and upper boundary of variable X respectively. The PSO procedure can be implemented through the following steps:

1. Assume the size of total number of swarm (number of particles) is N. To bring down the total number of function evaluation needed to find a solution, we must assume the smaller size of swarm. But with very little number of swarm it may lead to take longer time to find a solution, or in some case it may not be able to find a solution at all. In general, a size of 20 or 30 particles are assumed for the swarm as a compromise.

2. Create the initial population in the range X_{low} and X_{up} randomly as X_1, X_2, . . ., X_N. Hereafter, for convenience position of particle j and its velocity in iteration i are denoted as X_j^i and V_j^i respectively. Thus the particles generated initially as $X_1^{(0)}, X_2^{(0)}, \dots., X_N^{(0)}$. The vectors $X_j^{(0)} (j = 1,2, \dots, N)$ are called particles or vector of coordinates of particles. Evaluate the objective function corresponds to the particles as $f\left[X_1^{(0)}\right], f\left[X_2^{(0)}\right], \dots, f\left[X_N^{(0)}\right]$.

3. Find the velocity of particles. All particles will be moving to the optimal point with a velocity. Initially, all particle velocities are assumed to be zero. Set the iteration number as $i = 1$.

4. In the i-th iteration find the following two important parameters used by a typical particle j:

a. The historical best value of $X_j^{(i)}$ (coordination of j-th particle in the current iteration$i$), $P_{best,j}$ with the highest value of objective function, $G_{best,j}$ with the highest value of the objective function $f\left[X_j^{(i)}\right]$, encountered by particle j in all the previous iteration.

The historical best value of $X_j^{(i)}$(coordinate of all particle up to that iteration), G_{best}, with the highest value of objective function $f[X_j^{(i)}]$ encountered in all the previous iterations by any of the N particles.

b. Find the velocity of j-th particle in the i-th iteration as follows:

$$V_j^{(i)} = V_j^{(i-1)} + c_1 r_1 \left[P_{best,j} - X_j^{(i-1)}\right] + c_2 r_2 \left[G_{best} - X_j^{(i-1)}\right],$$

$$j = 1,2, \dots, N$$

where, c_1, c_2 are the cognitive (individual) and social (group) learning rate respectively and $r_{1,} r_2$ are uniformly random number within [0, 1].

c. Update the position or coordinate of j-th particle in the i-th iteration as:

$$X_j^{(i)} = X_j^{(i-1)} + V_j^{(i)} \ ; , \quad j = 1,2, \dots, N$$

where, a time step of unity is assumed in the velocity term in the above equation. Evaluate the objective function corresponding to the particle as $f\left[X_1^{(i)}\right], f\left[X_2^{(i)}\right], \dots, f\left[X_N^{(i)}\right]$.

d. Check the convergence rate of current solution. If the positions of all the particles converge to the same set of value, the method is implicit to have converged. If the convergence criterion is not satisfied, then step 4 is repeated by updating the iteration number as$i = i + 1$, and by calculating the new value of $P_{best,j}$ andG_{best}. The iteration process is reiterated until the termination condition is satisfied.

3.8 NUMERICAL EXAMPLE:

Find the maximum of the following function

$$f(x) = -x^2 + 2x + 11$$

in the range $-2 \le x \le 2$ using PSO method. Use four particles ($N = 4$) with the initial position$x_1 = -1.5$, $x_2 = 0.0$, $x_3 = 0.5$, $x_4 = 1.25$. Show the detailed computation for iterations 1 and 2.

Solution:

1. Choose the number of particle, $N = 4$.
2. The initial population chosen randomly as given in the data can be represented as $x_1^{(0)} = -1.5$, $x_2^{(0)} = 0.0$, $x_3^{(0)} = 0.5$ and$x_4^{(0)} = 1.25$.

Evaluate the objective function at each point of the initial population$x_j^{(0)}$, $j = 1,2,3,4$ as $f_1 = f\left[x_1^{(0)}\right] = f(-1.5) = 5.75$, $f_2 = f\left[x_2^{(0)}\right] = f(0.0) = 11$, $f_3 = f\left[x_3^{(0)}\right] = f(0.5) = 11.75$, and $f_4 = f\left[x_4^{(0)}\right] = f(1.25) = 11.9375$.

3. Set the initial velocity to each particle is zero:

$$v_1^{(0)} = v_2^{(0)} = v_3^{(0)} = v_4^{(0)} = 0$$

   Set the iteration number as $i = 1$ and go to step 4

4. Find the following three steps:
   a) Find $P_{best,1} = -1.5$, $P_{best,2} = 0.0$, $P_{best,3} = 0.5$, and $P_{best,4} = 1.25$ and $G_{best} = 1.25$
   b) Find the velocity of each article (by assuming $c_1 = c_2 = 1$ and using the random number within the range (0,1) as $r_1 = 0.3294$ and $r_2 = 0.9542$):

   $$v_j^{(i)} = v_j^{(i-1)} + c_1 r_1\left[P_{best,j} - x_j^{(i-1)}\right] + c_2 r_2\left[G_{best} - x_j^{(i-1)}\right], \quad j = 1,2,3,4$$

   $$v_1^{(1)} = 0 + 0.3294(-1.5 + 1.5) + 0.9542(1.25 + 1.5) = 2.6241$$

   $$v_2^{(1)} = 0 + 0.3294(0.0 - 0.0) + 0.9542(1.25 - 0.0) = 1.1927$$

   $$v_3^{(1)} = 0 + 0.3294(0.5 - 0.5) + 0.9542(1.25 - 0.5) = 0.7156$$

   $$v_4^{(1)} = 0 + 0.3294(1.25 - 1.25) + 0.9542(1.25 - 1.25) = 0.0$$

   c) Find the new value of $x_j^{(1)}$, $j = 1,2,3,4$ as $x_j^{(i)} = x_j^{(i-1)} + v_j^{(i)}$

   $$x_1^{(1)} = -1.5 + 2.6241 = 1.1241$$

   $$x_2^{(1)} = 0.0 + 1.1927 = 1.1927$$

   $$x_3^{(1)} = 0.5 + 0.7156 = 1.2156$$

   $$x_4^{(1)} = 1.25 + 0.0 = 1.25$$

5. Evaluate the objective function at the current position of the four particles $x_j^{(1)}$:

   $f\left[x_1^{(1)}\right] = f(1.1241) = 11.9846$, $f\left[x_2^{(1)}\right] = f(1.1927) = 11.9629$,

   $f\left[x_3^{(1)}\right] = f(1.2156) = 11.9535$, $f\left[x_4^{(1)}\right] = f(1.25) = 11.9375$

   Check the convergence of current solution. Since it is seen that current value of $x_j^{(1)}$ do not converge, we have to increment the number of iteration as $i = 2$ and go to next step:

6. Find the following three step:
    a) Find $P_{best,1} = 1.1241$, $P_{best,2} = 1.1927$, $P_{best,3} = 1.2156$, $P_{best,4} = 1.25$ and $G_{best} = 1.1241$
    b) Calculate the new velocity of each particle (by assuming $c_1 = c_2 = 1$ and using random number within (0,1) as $r_1 = 0.1482$ and $r_2 = 0.4867$):
    So that

$$v_1^{(2)} = 2.6241 + 0.1482(1.1241 - 1.1241) + 0.4867(1.1241 - 1.1241) = 2.6241$$

$$v_2^{(2)} = 1.1927 + 0.1482(1.1927 - 1.1927) + 0.4867(1.1241 - 1.1927) = 1.1593$$

$$v_3^{(2)} = 0.7156 + 0.1482(1.2156 - 1.2156) + 0.4867(1.1241 - 1.2156) = 0.6711$$

$$v_4^{(2)} = 0.0 + 0.1482(1.25 - 1.25) + 0.4867(1.1241 - 1.25) = -0.0613$$

    c) Find the new value of $x_j^{(2)},\ j = 1,2,3,4$ as $x_j^{(i)} = x_j^{(i-1)} + v_j^{(i)}$

$$x_1^{(2)} = 1.1241 + 2.6241 = 3.7482$$

$$x_2^{(2)} = 1.1927 + 1.1593 = 2.3520$$

$$x_3^{(2)} = 1.2156 + 0.6711 = 1.8867$$

$$x_4^{(2)} = 1.25 - 0.0613 = 1.1887$$

7. Find the objective function at these current position as:

$$f\left[x_1^{(2)}\right] = f(3.7482) = 4.4480,\ f\left[x_2^{(2)}\right] = f(2.3520) = 10.1721,$$

$$f\left[x_3^{(2)}\right] = f(1.8867) = 11.2138,\ f\left[x_4^{(2)}\right] = f(1.1887) = 11.9644$$

Check the convergence of this step. Since the value of $x_j^{(2)}$ do not converge, we have to increment the iteration number as $i = 3$ and repeat just like step 4 until convergence is achieved.

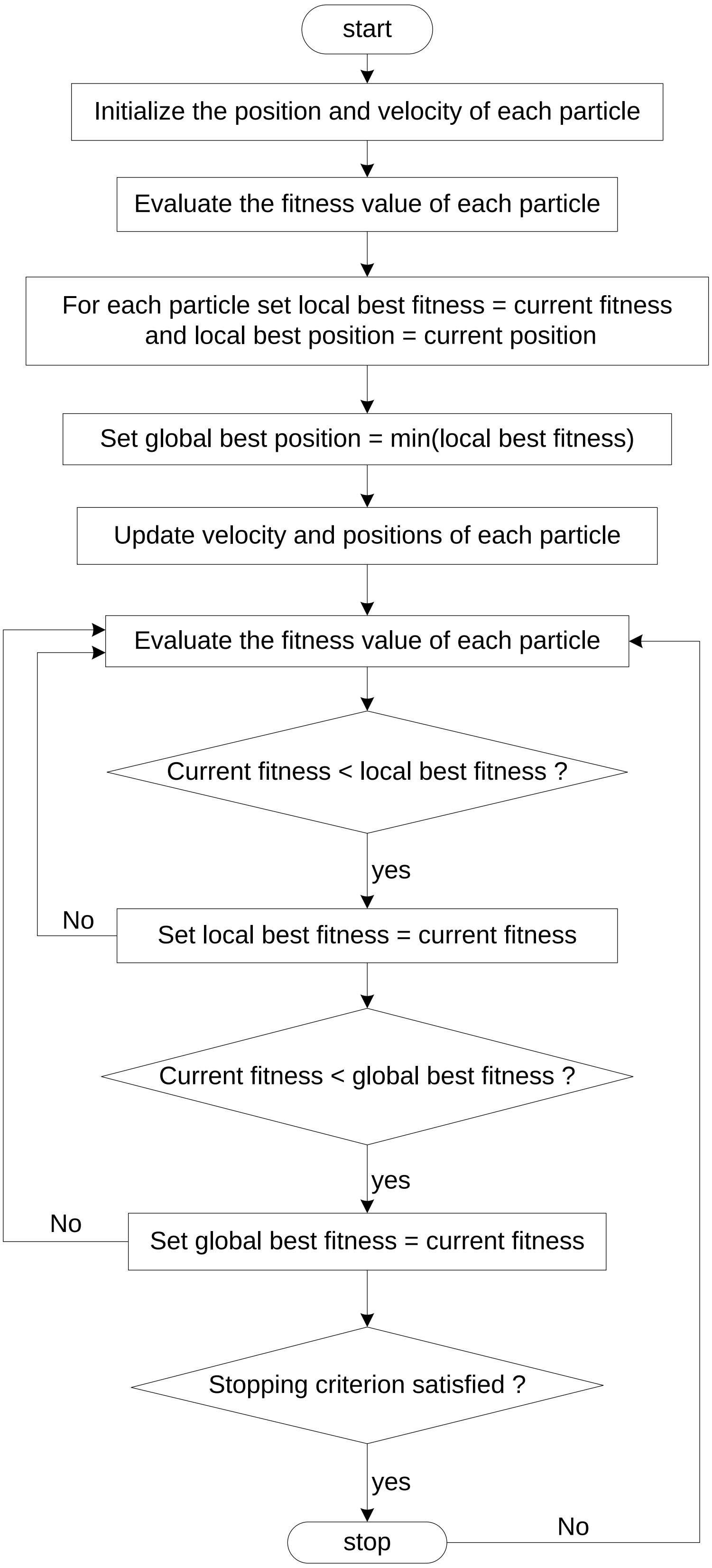

Figure. 3.2. Particle Swarm Optimization flowchart

3.9 PENALTY FUNCTION TECHNIQUE FOR CONSTRAINED OPTIMIZATION:

Constrained optimization problems are encountered in several applications. The constrained optimization problem can be represented as the following nonlinear programing problem:

$$\min_{x} f(x), \qquad x \in S \subset \mathbb{R}^n$$

Subject to the linear or nonlinear constraints

$$g_i(x) \leq 0, \qquad i = 1, \dots, m.$$

The formulation of the constraints in the above equation is not restrictive, since an inequality constraint of the form $g_i(x) \geq 0$ can also be represented as $-g_i(x) \leq 0$, and an equality constraint, $g_i(x) = 0$, can be represented by two inequality constraints $g_i(x) \leq 0$ and $-g_i(x) \leq 0$.

One of the most popular approaches for tackling for constrained problem is the use of penalty function. The constrained problem is transformed to an unconstrained one, by penalizing the constraints and building a single objective function, which in turn is minimized using an unconstrained optimization algorithm [2]. This is most probably the motivation behind the popularity of the penalty function approach.

The search space in constrained optimization problem consists of two kind of points: feasible and unfeasible. Feasible points satisfy all the constraints, whereas unfeasible points violate at least one of them. The penalty function technique solves the constrained optimization problem through a sequence of unconstrained optimization problems. If the penalty values are high, the minimization algorithms usually get trapped in the local minima. On the other hand, if the penalty values are low, they can hardly identify realistic optimal solutions.

Penalty functions are distinguished into two main categories: stationary and non-stationary. Stationary penalty functions use fixed penalty values throughout the minimization, whereas in contrast, in non-stationary penalty functions, the penalty values are dynamically modified.

In general, a penalty function is defined as:

$$f_P(x) = f(x) + P(x), \qquad x \in A \subset \mathbb{R}^n$$

where $f(x)$ is the original objective function, and $P(x)$ is a penalty term. Obviously $P(x)$ should be elected such that:

$$P(x) = 0\,, \quad \text{If } x \text{ is a feasible point.}$$

$$= a > 0\,, \quad \text{Otherwise}$$

in order to penalize only infeasible solution. Also $P(x)$ can be either fixed to a prescribed value for all infeasible solution or proportional to the number of violated constraints and degree of solution.

Recently the following penalty function is used exhibiting very promising result as:

$$f_P(x) = f(x) + h(t)H(x), \qquad x \in A \subset \mathbb{R}^n$$

where $f(x)$ is the original objective function, $h(t)$ is the penalty value, dynamically changing with the number of iteration t and $H(x)$ is a penalty factor defined as:

$$H(x) = \sum_{i=1}^{k} \theta(q_i(x)) q_i(x)^{\gamma(q_i(x))}$$

where $q_i(x) = \max\big(0, g_i(x)\big), i = 1,2, \dots, k;\ \theta(q_i(x))$ is a multistage assignment function and $\gamma(q_i(x))$ is the power of penalty function.

The above mentioned penalty function takes all constraints into consideration, based on their corresponding degree of violation, whereas user can manipulate each one freely, based on its level of significance.

3.10 MERITS AND DEMERITS OF PSO:

This method claims the following merits:

- PSO is based on the intelligence.
- It can be applied into both scientific research and engineering use.
- The PSO have no overlapping and mutation calculations.
- The search can be carried out by the speed of particle.
- During the development of several generations, only the most optimistic particle can transmit information onto the other particles, and the speed of the researching is very fast.
- After that, the calculation in PSO is very simple.
- Compared with other developing calculation, it occupies the biggest optimization ability and it can be completed easily.
- The last one is PSO adopts the real number code, and it is decided directly by the solution and the number of dimension is equal to the constant of solution.

Demerits of this method are as follows:

- This method easily suffers from the partial optimism, which causes less exact at the regulation of its speed and the direction.
- Then the method cannot work out the problem of scattering and optimization and the method cannot work out the problems of non-coordinate system.

3.11 CONCLUSION:

In this chapter we have discussed about basic concept, different controlling factor and initialization technique of PSO. After that, this method is represented in a flow chart. A numerical example of PSO is also provided for our ease of understand about mathematical implementation of the method.

In the next chapter, the results are presented and discussed. The electrical parameters are calculated from open and short circuit test and are compared with the results obtained from PSO.

CHAPTER – 4

EXPERIMENTAL SETUP, RESULTS & CONCLUSION

4.1 INTRODUCTION:

In this chapter, the equivalent circuit parameters of a transformer have been estimated using Particle Swarm Optimization. The parameters were determined in the laboratory from short circuit and open circuit test data. The estimated parameters have been compared with measured value.

4.2 METHODOLOGY:

The formulation of estimation problem attempts to solve the constrained optimization problem. It is done by implementing Particle Swarm Optimization (PSO). In this work, our goal is to formulate the objective function and to minimize the same. The values of parameters viz. resistance and reactance referred to primary side (R_{eq},X_{eq}), core loss resistance (R_c) and magnetizing reactance (X_m) are estimated by using Particle Swarm Optimization algorithm and compare with that obtained from the experiment.

4.3 PARTICLE SWARM ALGORITHM FOR TRANSFORMER PARAMETER ESTIMATION:

Step 1. Define the number of parameters to be evaluated for a Transformer.

Step 2. Set the parameter of PSO initially viz. cognitive acceleration constant, social acceleration constant and constriction coefficient.

Step 3. Define objective function.

Step 4. Choose the value of user-defined parameter and the range for the given objective function parameters.

Step 5. In this step, a random estimation of the transformer electric circuit parameters ($R_1, X_1, R_2', X_2', R_c, X_m$) is initialized.

Step 6. Objective function is evaluated for all particles in the initial population. Parameters of the objective function are calculated based on the equivalent circuit parameter estimated in the previous step from the equivalent circuit applying Kirchhoff's circuit law at the rated loading condition.

Step 7. The position and velocity are updated to obtain a new set of transformer parameters.

Step 8. Unless the termination condition (either number of iteration or minimization of fitness value) is satisfied, the updating process is repeated. Otherwise the optimization process ends and best parameter value ($R_1, X_1, R_2', X_2', R_c, X_m$) is preserved.

4.4 RESULTS AND DISCUSSION:

The developed method in the thesis gives rise to a simple and effective evolutionary computation-based technique to estimate the equivalent circuit parameters of a single-phase transformer from its nameplate data without the need to conduct any experimental measurements. MATLAB m-file is developed to determine the parameter of the transformer. The parameters are estimated using PSO method.

In the reference [40], the authors have proposed the idea of transformer parameter estimation by applying PSO. The author used the following objective function.

$$J = \min\{(I_1 - I_{1est})^2 + (I_2 - I_{2est})^2 + (V_2 - V_{2est})^2 \qquad \ldots\ldots\ldots\ldots\ldots\ldots (4.1)$$

where I_1, I_{1est} and I_2, I_{2est} are nominal nameplate and estimated currents of primary and secondary windings, respectively. V_2, and V_{2est} are the nameplate-rated and estimated voltages of the secondary winding.

The authors have used the above objective function. By considering the objective function (4.1), the result for 15 kVA transformer is given in the reference [40] as follows:

Table 4.1: Estimated parameters of 15 kVA transformer taking objective function (4.1)

Parameter	Actual Value (Ω)	Computed using PSO (Ω)	% Error
R_1	2.45	2.25	-8.16
X_1	3.14	4.082	30
R_2'	2.0	2.2	10
X_2'	2.2294	1.8526	-16.9
R_c	105000	99517	-5.22
X_m	9106	9009	-1.07

Table 4.2: 15 kVA transformer data at full load taking objective function (4.1)

Transformer data	Actual Value	Computed using PSO	% error
I_1 (A)	6.2	6.2004	0.0056
I_2' (A)	6.2	6.2008	0.0128
V_2' (V)	2383.8	2384.7	0.0385
Efficiency	98.5	98.52	0.0202

4.4.1 FURTHER IMPROVEMENT OF THE PROPOSED RESULT:

For different boundary value of the parameters, a set of parameter values come in spite of same nameplate data, though magnitude of current, voltage and efficiency remain near rated value. There is various reason for this. These are discussed below.

Current density and voltage per turn may differ in spite of same flux density. Because, though turns ratio is same but actual number of turn may be different.

Again though flux density and current density are same but due to different voltage per turn and winding configuration different possible parameters value may be obtained.

4.4.1.1 FOR TWO DIFFERENT BOUNDARY VALUE OF PARAMETERS, THE OBTAINED RESULTS ARE GIVEN BELOW:

Case 1

Table 4.3: Boundary values of transformer parameters

Parameter	R_1	X_1	R'_2	X'_2	R_c	X_m
Lower Boundary	0.01	0.01	0.01	0.01	100000	1000
Upper Boundary	100	100	100	100	200000	10000

Using the above mentioned boundary values, following results are obtained.

Table 4.4: Estimated parameters of 15 kVA transformer taking objective function (4.1)

Parameter	Actual Value (Ω)	Computed using PSO (Ω)	% Error
R_1	2.45	1.94	-20.82
X_1	3.14	2.45	-21.97
R'_2	2.0	2.25	12.5
X'_2	2.2294	1.62	-27.33
R_c	105000	117424.25	11.83
X_m	9106	7568.97	-16.88

Table 4.5: 15 kVA transformer data at full load taking objective function (4.1)

Transformer data	Actual Value	Computed using PSO	% error
I_1 (A)	6.2	6.24	0.64
I_2' (A)	6.2	6.21	0.161
V_2' (V)	2383.8	2378	-0.24
Efficiency	98.5	95.8	-2.74

Case 2

Table 4.6: Boundary values of transformer parameters

Parameter	R_1	X_1	R_2'	X_2'	R_c	X_m
Lower Boundary	0.001	0.001	0.001	0.001	10000	100
Upper Boundary	1000	1000	1000	1000	200000	10000

Using the above mentioned boundary values, following results are obtained.

Table 4.7: Estimated parameters of 15 kVA transformer taking objective function (4.1)

Parameter	Actual Value(Ω)	Computed using PSO (Ω)	% Error
R_1	2.45	4.57	46.38
X_1	3.14	3.40	8.28
R_2'	2.0	3.749	87.45
X_2'	2.2294	15.80	608.71
R_c	105000	76957.76	-26.70
X_m	9106	8527.18	-6.35

Table 4.8: 15 kVA transformer data at full load taking objective function (4.1)

Transformer data	Actual Value	Computed using PSO	% error
I_1 (A)	6.2	6.18	-0.323
I_2' (A)	6.2	6.13	-1.129
V_2' (V)	2383.8	2345	-1.627
Efficiency	98.5	97.14	-1.381

From the above table it is seen that for different boundary value, parameters values are changing but current, voltage and efficiency remain almost same as the rated values.

To overcome the above-mentioned problem, we need to consider some more constraints to the objective function (4.1) to improve the parameter values. The results obtained with the modified objective function are tabulated below. Convergence characteristic of each case is also shown with two graphs. For each case, first graph represents the convergence characteristic of all run, and second graph represent the convergence characteristics of best run, which gives minimum value of objective function among all runs.

4.4.1.2 BY MODIFYING THE OBJECTIVE FUNCTION, THE OBTAINED RESULTS ARE GIVEN BELOW:

Case 1

Considering maximum no load current in the objective function:

The modified objective function is as follows:

$$J = min\left\{\left({(I_1 - I_{1est})}/{I_1}\right)^2 + \left({(I_2 - I_{2est})}/{I_2}\right)^2 + \left({(V_2 - V_{2est})}/{V_2}\right)^2 + \right.$$
$$\left. + \left({(I_{0rat} - I_{0est})}/{I_{0rat}}\right)^2\right\} \qquad \text{………………..} \quad (4.2)$$

Table 4.9: Estimated parameters of 15 kVA transformer taking objective function (4.2)

Parameter	Actual Value (Ω)	Computed using PSO (Ω)	% Error
R_1	2.45	2.466	0.653
X_1	3.14	3.38	7.64
R_2'	2.0	1.1	-45
X_2'	2.2294	2.5667	15.13
R_c	105000	105056.814	0.0541
X_m	9106	9103.697	-0.025

Usually we know that no load current of a transformer is 4 to 5 percent of full load current. So we have considered here 5 % of no load current. Therefore, parallel branch parameter is improved much better than table (4.1).

Table 4.10: 15 kVA transformer data at full load taking objective function (4.2)

Transformer data	Actual Value	Computed using PSO	% error
I_1 (A)	6.2	6.45	4.03
I_2' (A)	6.2	6.22	3.54
V_2' (V)	2383.8	2376.1	-0.32
Efficiency	98.5	95.56	-2.98

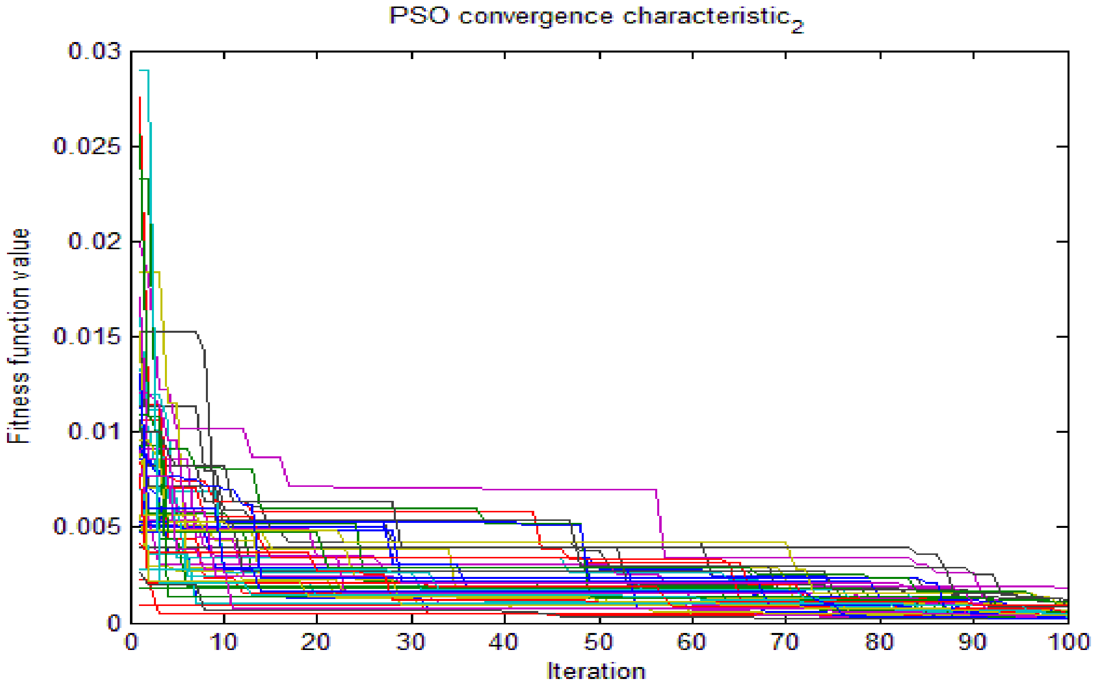

Figure 4.1: Convergence characteristics of all run (case 1)

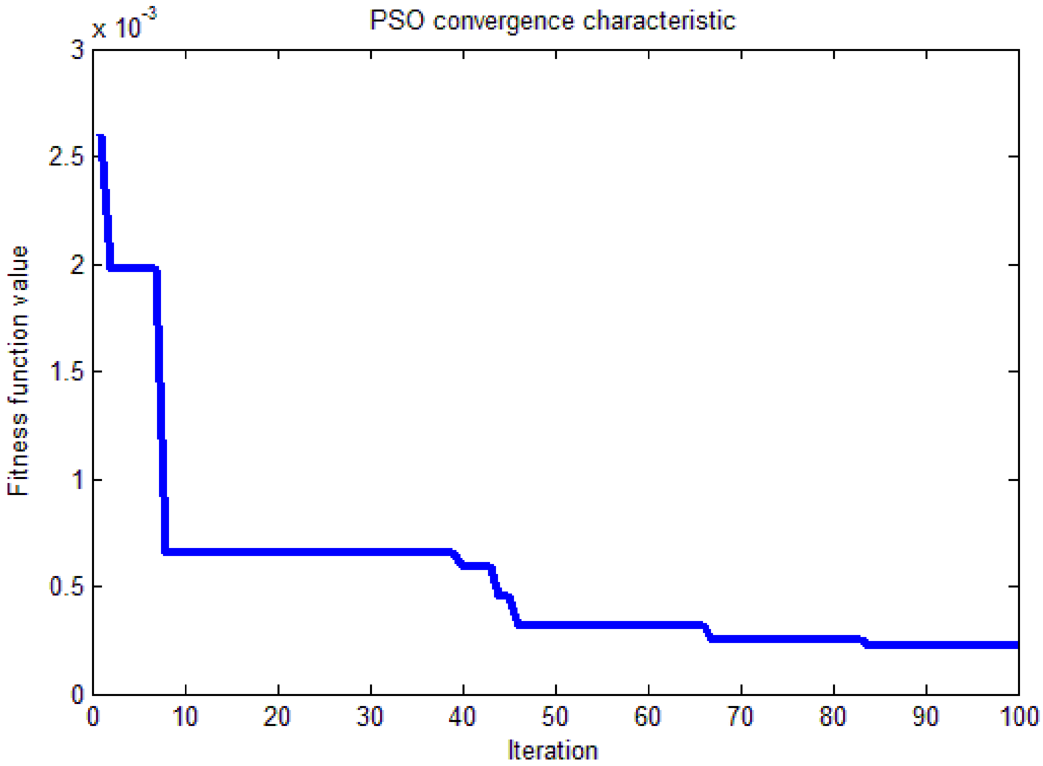

Figure 4.2: Convergence characteristics of best run (case 1)

Case 2

Considering percentage impedance and no load current in the objective function:

The modified objective function is as follows:

$$J = min\left\{\left(\frac{(I_1 - I_{1est})}{I_1}\right)^2 + \left(\frac{(I_2 - I_{2est})}{I_2}\right)^2 + \left(\frac{(V_2 - V_{2est})}{V_2}\right)^2 + \left(\frac{(pu(Z) - pu(Z)_{est})}{pu(Z)}\right)^2 + \left(\frac{(I_{0rat} - I_{0est})}{I_{0rat}}\right)^2\right\} \quad \text{.................. (4.3)}$$

Table 4.11: Estimated parameters of 15 kVA transformer taking objective function (4.3)

Parameter	Actual Value (Ω)	Computed using PSO (Ω)	% Error
R_1	2.45	2.66	8.57
X_1	3.14	3.22	2.54
R_2'	2.0	1.779	-11.05
X_2'	2.2294	2.15	-3.56
R_c	105000	104933.263	-0.063
X_m	9106	9138.72	0.359

Depending on power transformer and distribution transformer percentage impedance is different. Usually percent impedance of power transformer is high for protection purpose to limit fault current and for distribution transformer it is low to minimize the voltage regulation. Here our study is on distribution transformer. So we have considered low value of percentage impedance. This scheme can also be applied for power transformer with proper percentage impedance. After considering percentage impedance and no load current simultaneously, series and parallel branch parameters, both are further improved. It is clearly understandable from the above table.

Table 4.12: 15 kVA transformer data at full load taking objective function (4.3)

Transformer data	Actual Value	Computed using PSO	% error
I_1 (A)	6.2	6.24	0.64
I_2' (A)	6.2	6.21	0.16
V_2' (V)	2383.8	2371.3	-0.52
Efficiency	98.5	98.47	-0.03

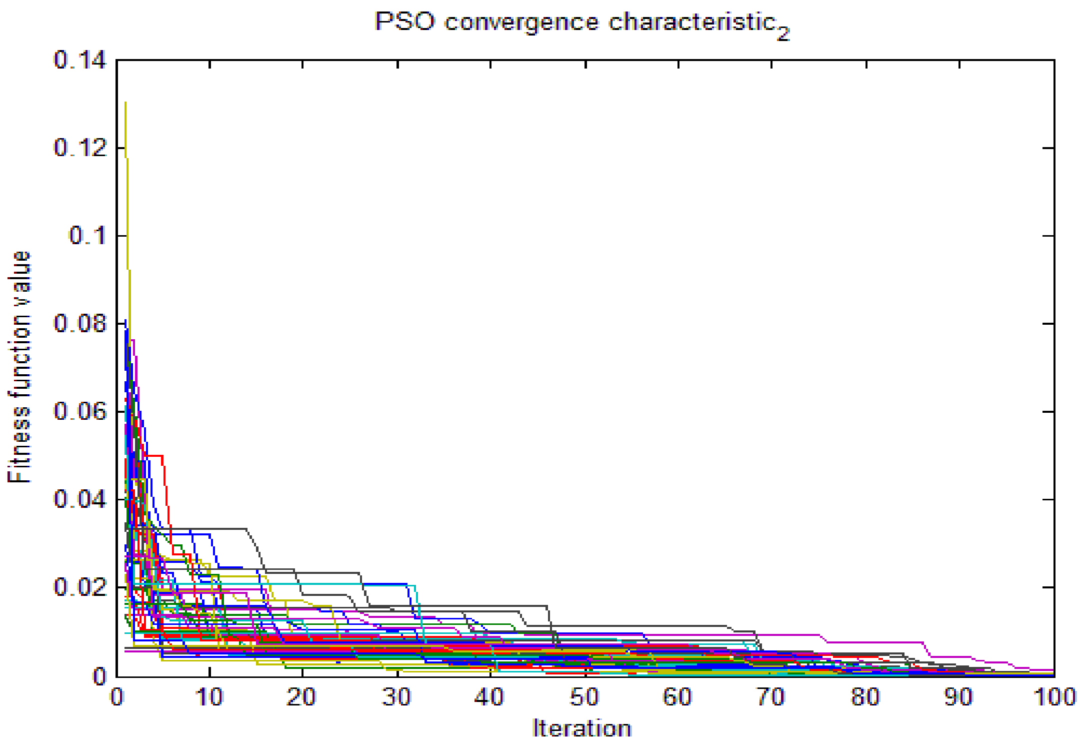

Figure 4.3: Convergence characteristics of all run (Case 2)

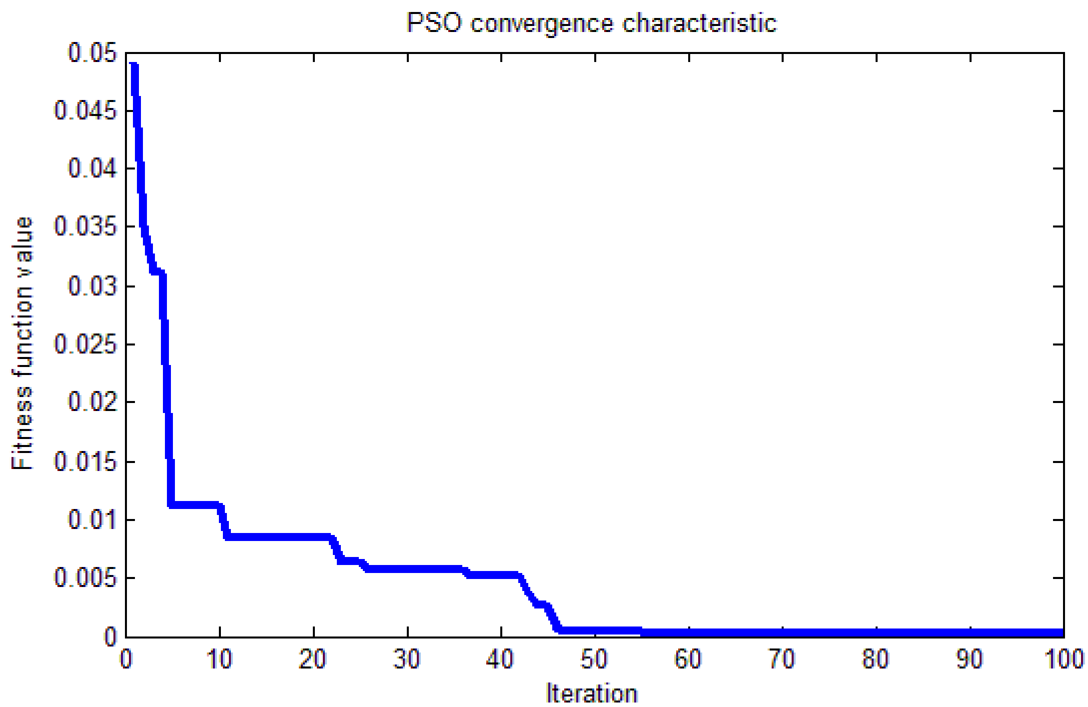

Figure 4.4: Convergence characteristics of best run (Case 2)

Table 4.13: Comparison Table of % Error of Parameter of 15 kVA transformer

Parameter	Estimated % Error Before improvement	Estimated % Error After improvement
R_1	-8.16	8.57
X_1	30	2.54
R_2'	10	-11.05
X_2'	-16.9	-3.56
R_c	-5.22	-0.063
X_m	-1.07	0.359

4.4.2 EXPERIMENTAL RESULT:

In this thesis work, the PSO algorithm for transformer parameter estimation is done on 3 kVA transformer. Details of this transformer are given below. The actual value of the parameters is computed from the conventional open circuit test and short circuit test. Finally, the obtained result from PSO are compared with actual value. Here we have done the experiment considering objective function (4.3)

4.4.2.1 EXPERIMENTAL SETUP:

The rating of the transformer on which experiment was carried out is given in the following table.

Table 4.14: Specification of Transformer used for the experiment

Type	Distribution
Rating	3 kVA
Primary voltage	110 V
Secondary voltage	220 V
Frequency	50 Hz

4.4.2.2 EXPERIMENTAL DETERMINATION:

The problem includes the computation of Open and Short circuit tests and then calculates the equivalent circuit parameters referred to primary side (here low voltage side) of the transformer.

The O.C and S.C test data are listed are listed below for a single-phase 3 kVA. transformer.

Open circuit test from LV side	110 V	2.7 A	63 W
Short circuit test from HV side	7.9 V	13.7 A	86.2 W

4.4.2.3 Computation from O.C test data:

Let us represent the test data in the approximate equivalent circuit (Figure 4.5) of the transformer as following.

As HV side is open circuited, there will be no current in the branch $r_{e1} + jx_{e1}$. So entire power of 63W is nearly degenerated in R_{cl}. The no load current I_{01} = 2.7A is distributed into: magnetizing component I_{m1} and core loss component I_{cl} as showed in the phasor diagram figure 4.5.

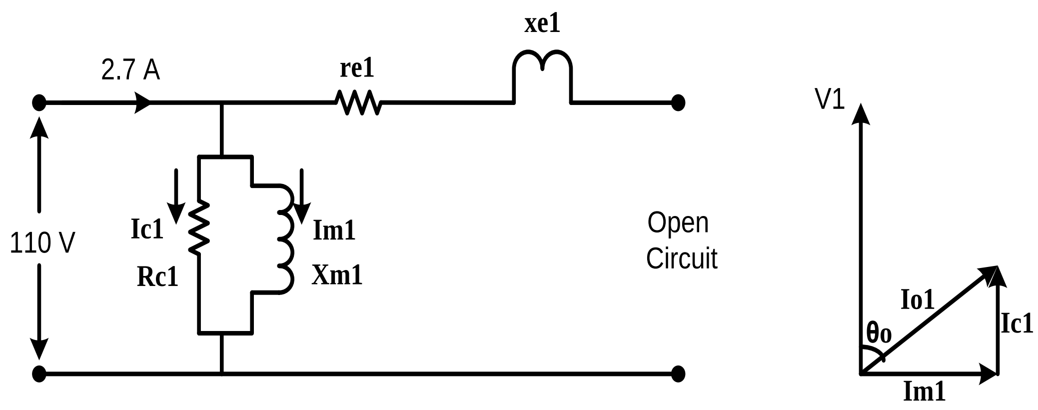

Figure 4.5: O.C equivalent circuit and phasor diagram

No load (or O.C) power factor $\cos\theta_0 = \frac{63}{110\times2.7}$

$$= 0.2121$$

$$\theta_0 = \cos^{-1} 0.2121$$

$$= 77.76^{o}$$

Hence $\sin\theta_0 = 0.9773$

After identifying the value of $\cos\theta_0$ and $\sin\theta_0$ and stating to the no load phasor diagram, I_{m1} and I_{c1} can be analyzed as follows.

Magnetizing Current (I_{m1}) = $I_{01}\sin\theta_0$

$$= 2.7 \times 0.9773$$

$$= 2.64 \text{ A}$$

Core loss Current (I_{c1}) = $I_{01} \cos \theta_0$

$$= 2.7 \times 0.2121$$

$$= 0.5727 \text{ A}$$

Thus the parallel branch parameter $X_{m1}$and R_{c1} can be calculated as:

Magnetizing reactance (X_{m1}) = $\frac{V_1}{I_{m1}}$

$$= \frac{110}{2.64}$$

$$= 41.67\ \Omega$$

Resistance representing core loss (R_{c1}) = $\frac{V_1^2}{P}$

$$= \frac{110^2}{63}$$

$$= 192.06\ \Omega$$

It is observed that from open circuit test parallel branch impedance can obtained. Reactance, resistance in the parallel branch are representing magnetizing, and core loss component respectively.

4.4.2.4 Computation from S.C test data:

As the test has been done from the HV side with LV side shorted, we draw the equivalent circuit mentioned to the HV side as in figure.4.6. Parameters are denoted by using suffix 'sc'. Important point to note here is the absence of the parallel branch. Because of the voltage applied during S.C test is quite low causing a low flux level. Hence, magnetizing and core loss component of currents will be very less compared to the rated current flowing through $r_{sc} + jx_{sc}$. In this case, power drawn from the supply is nearly degenerated in winding resistances i.e. r_{sc}

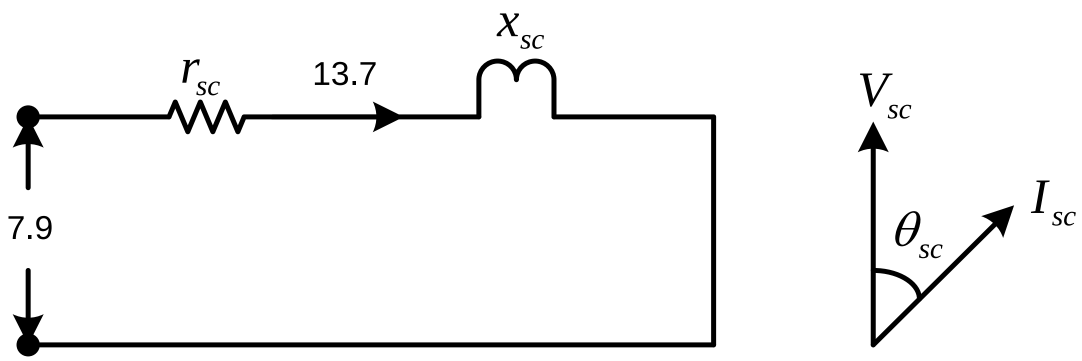

Figure.4.6: SC equivalent circuit and phasor diagram

Calculation of series impedance is rather easy and as below:

Power drawn, $P_{sc} = I_{sc}^2 r_{sc}$

$$r_{sc} = \frac{P_{sc}}{I_{sc}^2}$$

$$= \frac{86.2}{13.7^2}$$

$$= 0.4593\ \Omega$$

Now short circuit impedance, $(Z_{sc}) = \frac{V_{sc}}{I_{sc}}$

$$= \frac{7.9}{13.7}$$

$$= 0.5766\ \Omega$$

Reactance, $(x_{sc}) = \sqrt{Z_{sc}^2 - r_{sc}^2}$

$$= \sqrt{0.5766^2 - 0.4593^2}$$

$$= 0.3486\ \Omega$$

4.4.2.5 Equivalent circuit referred to LV side:

The parallel branch parameters R_{cl} = 192.06 Ω and X_{m1} = 41.69 Ω are calculated w.r.t LV side. So, no more transformations are needed. However, series parameters r_{e2} and x_{e2} are calculated from the above test data. Hence, we need to calculate r_{sc} and x_{sc} so as to rightly show the equivalent circuit referred to primary side.

$$\text{Turns ratio } a = \frac{110}{220} = 0.5$$

$$\text{But we know } R_{eq} = a^2 r_{sc}$$

$$\text{and } X_{eq} = a^2 x_{sc}$$

$$\text{Thus} R_{eq} = 0.5^2 \times 0.4593 = 0.1148\ \Omega$$

$$\text{and } X_{eq} = 0.5^2 \times 0.3486 = 0.0872\ \Omega$$

So the equivalent circuit referred to LV side are shown with all the parameter values in figure 4.7

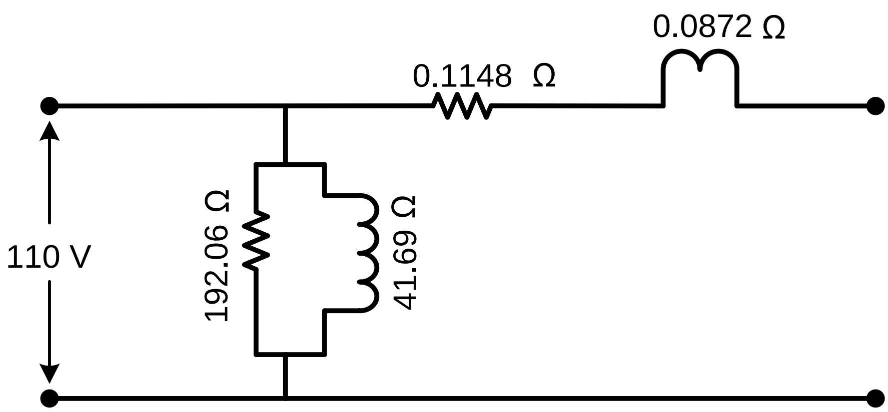

Figure 4.7: Equivalent circuit referred to LV side.

4.4.2.6 RESULTS OBTAINED FROM PSO FOR 3 kVA TRANSFORMER:

The estimated parameters value and convergence characteristics of 3 kVA transformer using objective function (4.3) are as below:

Table 4.14: Estimated parameters of 3 KVA transformer

Parameter	Actual Values (Ω)	Computed using PSO (Ω)	% Error
R_{eq}	0.1148	0.1293	12.63
X_{eq}	0.0872	0.1027	17.8
R_c	192.06	181.56	-5.47
X_m	41.69	41.33	-0.864

Here actual value is obtained from short circuit and open circuit test. As there is no provision to separate the short circuit resistance and reactance as primary and secondary, so we have compared the total series resistance and reactance getting from PSO with actual one.

Table 4.15 3 KVA transformer data at full load

Transformer data	Experimental Value	Computed using PSO	% error
I_1 (A)	27.5	27.38	-0.4363
I_2' (A)	26.7	26.61	-0.3370
V_2' (V)	106.9	106.43	-0.4396
Efficiency	95.13	94.65	-0.5046

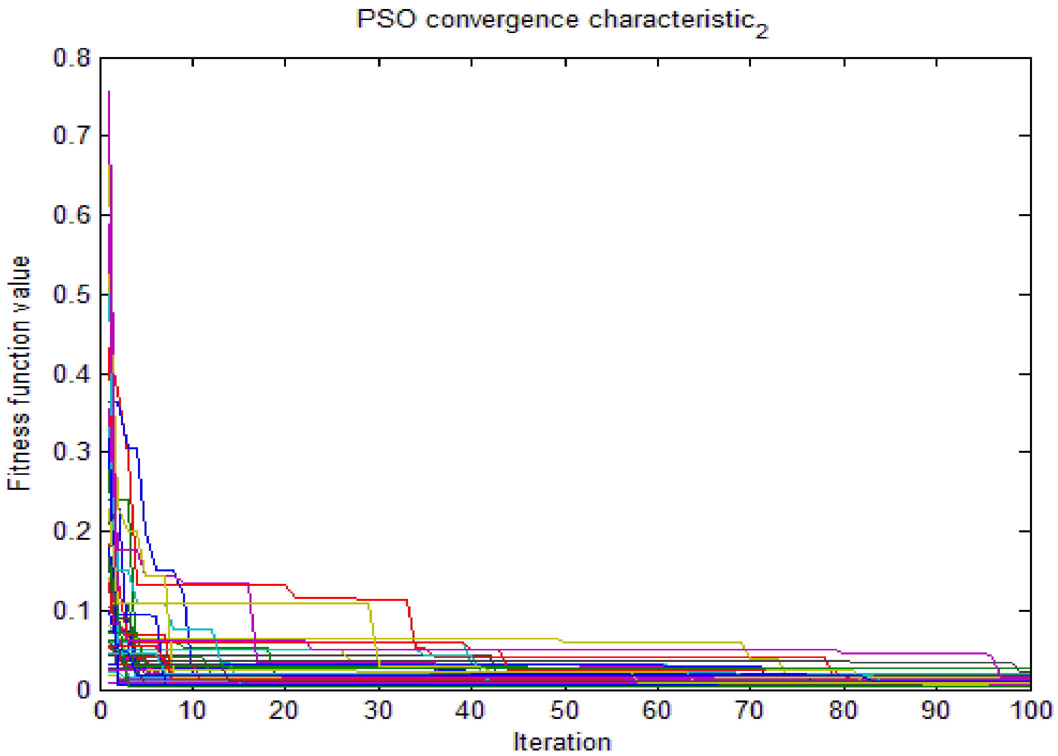

Figure 4.8: Convergence characteristics of all run for 3 kVA transformer

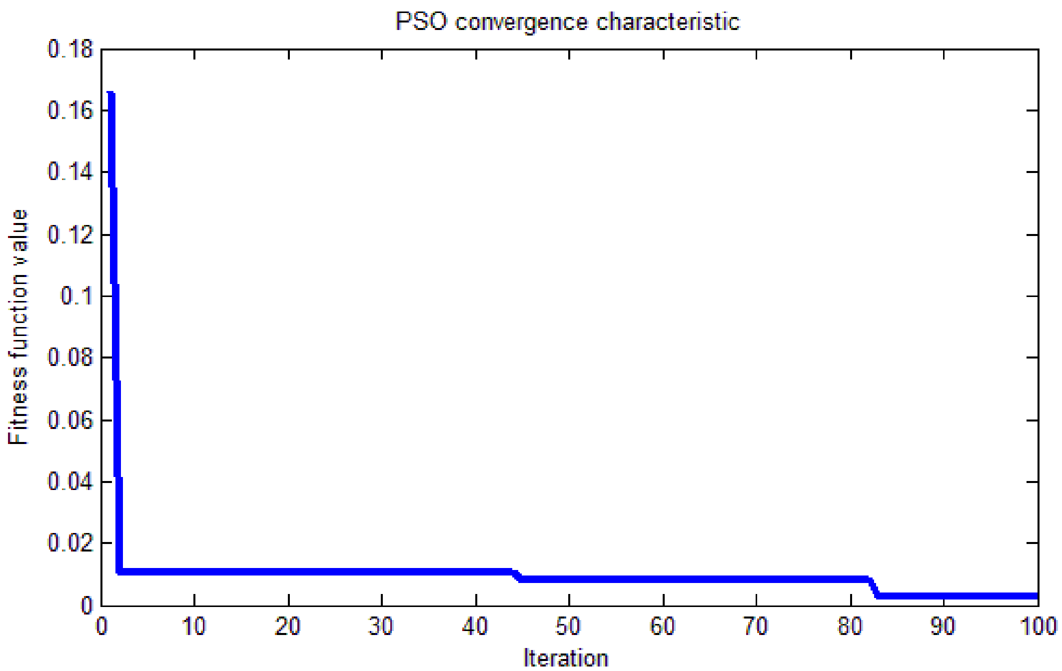

Figure 4.9: Convergence characteristics of best run for 3 kVA transformer

4.5 CONCLUSION:

This thesis work proposes a simple, rapid and effective technique to estimate the equivalent electric circuit parameters of a single phase transformer based on the utilization of transformer nameplate data without conducting any experimental tests. The identification process is carried out using evolutionary technique, PSO method. This method is very simple. Compared to other optimization method it occupies the biggest optimization ability. The simulation result shows a reasonable degree of accuracy. So this optimization method is very much attractive compared to other optimization technique.

The result is improved by incorporating different factor step by step. Here the experiment is conducted nearly at full load condition.

4.6 FUTURE SCOPE:

Accuracy of the result can be further improved by considering some more constraints to the objective function. Future work will try to understand where the algorithm suffers in order to understand any limitation. Here the experiment is done on a single-phase transformer. This algorithm could be extended to estimate the distributed parameters of three-phase transformer, which will facilitate power transformer condition monitoring and other power system studies involving power transformer. Modified or improved approach (like modification of variants of particle swarm optimization) of PSO can be implemented for parameter estimation purpose. Hybridization algorithm like GA, BFA etc. can also be used to improve the performance. Except PSO, newly developed nature inspired other algorithm like Firefly Algorithm (FA), Bat Algorithm (BA) and Cuckoo Search (CS) can be further applied to validate the results.

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