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Maximizing Efficiency through Transformer Parameter Estimation Using the Corona Herd Immunity Algorithm: An Experimental Approach

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Abstract: - This paper enhances transformer efficiency by accurately estimating equivalent circuit parameters using two nature-inspired optimization algorithms: Corona Herd Immunity Optimization (CHIO) and the Human Felicity Algorithm (HFA). Accurate parameter estimation is essential for improving transformer performance and enabling condition-based monitoring. CHIO draws inspiration from the concept of herd immunity, particularly as applied during the COVID-19 pandemic, while HFA is modeled on the human drive for happiness and well-being. The proposed methods are tested on three transformer types: a 1 kVA, 240/100V power transformer; a 15 kVA, 2400/240V distribution transformer; and a 66 kVA, 415/415V isolation transformer. Experimental validation is conducted at Neo Teletronix Pvt. Ltd., where power and isolation transformers are analyzed. Optimizing these parameters improves operational reliability, reduces energy losses, and extends transformer lifespan—key benefits for grid integration and industrial power systems. The optimized parameters also enhance predictive maintenance and fault detection, minimizing downtime. Results obtained using CHIO are benchmarked against experimental data and compared with established algorithms like Particle Swarm Optimization (PSO) and the Gravitational Search Algorithm (GSA), showing that CHIO consistently delivers superior performance in transformer efficiency optimization.

Keywords: Transformer, Parameters estimation, Efficiency, Corona herd immunity algorithm, Human Felicity Algorithm

Table 1. Denotation of parameters

V_p	Primary Supply Voltage (V)	**PSO**	Particle Swarm Optimization
V'_S	Secondary Load Voltage (V) referred to primary	JOA	Jaya Optimization Algorithm
R_P	Primary Resistance (Ω)	GA	Genetic Algorithm
X_P	Primary Reactance (Ω)	AHO	Artificial Hummingbird Optimizer
R_C	Core loss component of resistance (Ω)	ICA	Imperialist Competitive Algorithm
X_m	Magnetizing Reactance (Ω)	GSA	Gravitational Search Algorithm
R'_S	Secondary Resistance (Ω) referred to primary	SL-GSA	Stochastic Leader Gravitational Search Algorithm
X'_S	Secondary Reactance (Ω) referred to primary	AMBPSO	Adaptive Mutated Boolean PSO
I_P	Primary Current (amp)	HBMO	Honey Bees Mating Optimization
I'_S	Secondary Current (amp) referred to primary	TS	Tabu Search
Ie	Exciting Current (amp)	LMS	Least Mean Squares
Z_P	Primary Impedance (Ω)	BFA	Bacterial Foraging Algorithm
Z'_S	Secondary Impedance (Ω) referred to primary	I	Iteration

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Z_m	Shunt Branch Impedance (Ω)	HIP	Herd Immunity Population
P_{out}	Output power of the transformer	BRr	Basic Reproduction Rate
P_{in}	Output power of the transformer	MaxAge	Max Age
η	Efficiency	Xini	Matrix after initialization
Pc	Core loss	Xini_norm	Normalization of initial matrix
Pcu	Copper loss	D	Distance between two normalized parameters
N	Number of solutions	SD	Social Distancing
P	Number of variables		

I. INTRODUCTION

Power and distribution transformer is the most vulnerable equipment in power system network. When a failure or any abnormal condition occurs in service, the effect can be dangerous. It's not only due to extensive outages, but it can face multiple consequences i.e. costly immediate repairs and severe injury. The failure of the transformer just breaks the reliability of the system. The transfer function of each transformer is different and it can be measured with the help of frequency response analysis or equivalent circuit parameters. Also parameter estimation of the transformer is one of the imperative approaches to maintain the reliability of the system and also helps for condition monitoring to detect the internal winding deformation. The estimation of transformer equivalent parameters also helps to recognize the performance and behavior of the system and also study the load flow, control and protection system on grid connected operation. The parameter estimation process is also affected by saturation of the core material, order of the harmonics presence and transient condition of the transformer. The performance characteristics of transformer in both steady-state and transient state can be estimated with the help of equivalent circuit parameters. During fault, transformer will be disconnected from the network so optimal parameters have been obtained using experimental setup. So that calculating algorithm needs precise data those are available rarely. To overcome this situation, optimization algorithm has been proposed to estimate parameters of equivalent circuit.

Mohamed et. al [1] proposed a novel optimization algorithm i.e. Coyote optimization algorithm (COA) based on social behavior of coyote to estimate the parameters of single and three phase transformer in steady state condition. It has the capability to provide accuracy of results and it's superiority proves by comparing results with PSO and JOA. In [2,10,19], behavior of swarms based algorithm (PSO) and genetic algorithm (GA) have been implemented to estimate the equivalent electrical circuit parameters of single-phase transformer based on nameplate data. M. Calasan et.al [3] presented Chaotic Optimization Approach to determine optimal value of parameters of step down single phase transformer based on nameplate data and load data obtained from experiments using different objective functions. In report [4], an artificial tool i.e. artificial hummingbird optimizer (AHO) has been used to identify the unknown parameters of two different rated step down transformers and compare the results with other existing optimizing method. Illias et. al [5] proposed Imperialist Competitive Algorithm (ICA) and Gravitational Search Algorithm (GSA) to calculate approximately the transformer parameters for three different step down transformers. The optimized results are compared with nameplate data to illustrate the minimum average error to prove the closeness of the parameters. In [6], Particle swarm optimization (PSO) technique and H-G diagram based resistance estimation techniques has been proposed to find out optimal parameters of single phase transformer and three phase induction motor and then compared with the nameplate data. It has been observed that the effect of loading is very less on single phase transformer. In [7], Bacterial Foraging Algorithm has been proposed to calculate equivalent circuit parameters on 2kVA single phase step down core type transformer. J. Lou et.al. [8], calculate the parameters of single phase transformer by an analytical method (S-parameters method). This method is highly suitable for high frequency system (1GHz). Mainly vector network analyzer has been used to calculate the parameters by S-parameter method. Camilo et. al [9] proposed Black-Hole Optimization technique to estimate the equivalent parameter of three different rated distributed transformer by measuring only voltage and current. It has been concluded that BHO proved its effectiveness to calculate the voltage, current even power also but not so much effective with respect to other optimization technique in terms of equivalent parameters. Darzi et. al [11] proposed stochastic leader GSA (SL-GSA) inspired by random value to converge global optimization problem. The applicability of

SL-GSA was implemented for six benchmark functions, and the results are compared with some of its variants. In [12], an approach had been proposed to determine equivalent circuit parameters of single phase induction motor using no-load and blocked rotor test. Core loss was not included. Zaharis et. al[13] proposed new PSO variant called Adaptive Mutated Boolean PSO (AMBPSO) to estimate weights of excitation implemented on array elements. Interference correlation matrix has not been considered but Gaussian noise is also considered. In this [14], Honey Bees Mating Optimization (HBMO) combined with the Tabu Search (TS) had been proposed for application of antenna arrays. The proposed methods had been implemented taking into consideration of uniform antenna array and results obtained confirms it's effectiveness by comparing with Least Mean Squares (LMS) and Genetic Algorithm (GA). In [15], a new variant of gravitational search algorithm is introduced for application of optimum design of retaining walls. This method had been implemented for minimization of weight, cost and emissions of absorbing structure. The errors between estimated and manufactured value of equivalent circuit parameters has been minimized using Evolutionary Algorithm [16, 17]. Results obtained from experiment shows that the proposed algorithm performs continuously and runs significantly faster. Chandan et. al [18] proposed prowess of Machine Learning to estimate optimum values for given objective function. Neural Network and optimization algorithm has been used to obtain optimal values Evolutionary Algorithm based approach has been used to get better execution time and then it is compared with other existing methods. Arjona et. al [20] proposed hybrid genetic algorithm to estimate parameters of synchronous generator using the dc-step voltage is presented. The difference in the reciprocal impact of the field and d-axis damper windings is considered. A sudden three-phase short-circuit test is conducted at the generator terminals to validate the estimated parameters. The measured data is then juxtaposed with the simulation results of the machine model, utilizing the parameters derived from the dc-step voltage, to verify their accuracy. Recent research has focused on various optimization strategies to determine the equivalent circuit parameters of transformers, thereby enhancing their performance and efficiency. Sharma and Patel [21] introduced a hybrid algorithm combining genetic algorithms and simulated annealing for transformer loss minimization, providing a novel approach to efficiency improvement in electrical systems. Gupta and Khan [22] utilized evolutionary algorithms to optimize transformer parameters, aiming at reducing electrical losses while improving performance. Singh and Wang [23] explored the application of metaheuristic algorithms in transformer design, providing insights into their effectiveness in improving transformer efficiency. Hernandez and Wang [24] demonstrated the use of particle swarm optimization in transformer modeling to minimize core and copper losses, thereby improving the precision of the transformer equivalent circuit. Zhang and Liu [25] proposed the novel application of the Corona Herd Immunity Algorithm for parameter optimization in power systems, suggesting its potential for transformer loss minimization. Jain and Mehta [26] focused on genetic algorithms for loss minimization in transformers, highlighting the importance of advanced algorithms in improving the design process. Patel and Shukla [27] emphasized the role of swarm intelligence algorithms in optimizing transformer parameters, reducing losses, and enhancing the overall system performance. Banerjee and Gao [28] explored herd immunity algorithms in power systems optimization, including their application to transformers, to achieve minimal energy loss. Kumar and Reddy [29] applied hybrid metaheuristic optimization techniques to transformer design, specifically focusing on loss minimization and overall system efficiency. Finally, Mehta and Bhatia [30] reviewed various modern optimization techniques, including genetic and herd immunity algorithms, for reducing losses in transformers, underscoring the potential of these approaches for more efficient electrical designs.

Section 2 describes representation of equivalent circuit which formulates objective function. Section 3 presents overview of proposed algorithms i.e. CHIO and HFA, Section 4 illustrates the simulation results and experimental set-up along with discussion and lastly conclusion is presented in Section 5.

II. PROBLEM FORMULATION BY REPRESENTING OF EQUIVALENT CIRCUIT

The performance of any electrical system or machine can be effectively analyzed with the help of equivalent circuit of that system. The performance characteristics of transformer (single phase or three phase) have been directly influenced by equivalent circuit parameters. Open circuit test and short circuit test are the conventional methods to estimate the transformer parameters. The estimation of equivalent circuit parameters of transformer depends on physical features and operating condition. Some modern tools have to be incorporate accurately and efficiently to estimate the parameters depending on actual application. A number of optimized techniques have been exploiting to maximize the efficiency of the transformer by minimizing the different losses in the transformer based on the experimental equivalent circuit parameters.

Fig 1 shows the equivalent circuit parameters considering primary and secondary side of the single phase transformer or three phase transformer (per phase) referred to primary side.

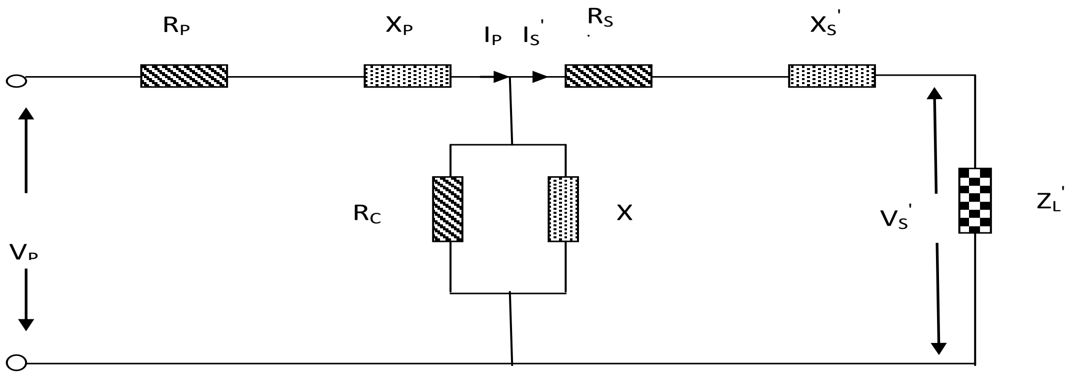


Fig. 1 Steady state per phase equivalent circuit of Transformer

ZP=Primary Impedance (Ω)= RP + j XP

Z'S=Secondary Impedance (Ω) referred to primary = R'S + j X'S

Zm=Shunt Branch Impedance (Ω)= RC ‖ j Xm

The KVL equations of steady state equivalent circuit are

$$I_P(Z_p+Z_m)-I_S'\,Z_m=V_p$$

(1)

$$Z_S'I_S'+\;V_S'+\;Z_m(I_S'-I_p)=0 \qquad (2)$$

Equation (1) & (2) can be represented in matrix form, which is reflected on equation (3)

$$\begin{bmatrix}(Z_p+Z_m) & (-Z_m)\\ Z_m & -(Z_m+Z_S')\end{bmatrix}\begin{bmatrix}I_p\\ I_S'\end{bmatrix}=\begin{bmatrix}V_p\\ V_S'\end{bmatrix}$$

(3)

$$[Z][I]=[V]$$

(4)

$$[I]=[Z]^{-1}[V]$$

(5)

The main objective of this work is to maximize the efficiency by minimizing the variable losses and calculate the optimized value of equivalent circuit parameters at that maximum efficiency condition.

Core loss (Pc) and Copper loss (Pcu) are the main electrical losses of transformer. The value of core loss does not depend on the load of application but the copper loss completely depends on load or load current (I_S') itself. So, other objective of this present work is to minimize the load current to get maximum efficiency.

Total Loss (PL) = Pc + Pcu

(6)

$$P_L = P_c + (I_S')^2(R_S')$$

(7)

Output power of the transformer (P_{out}) = $V_S' \, I_S'$

(8)

Input power (P_{in}) of the transformer in terms of output power and losses is

$P_{in} = P_{out} + P_L = P_{out} + P_c + P_{cu} = P_{out} + P_c + (I_S')^2 (R_S')$

(9)

Efficiency of the transformer is

$$\eta = \frac{\text{Pout}}{\text{Pin}} = \frac{V_S' \, I_S'}{V_S' \, I_S' + \text{Pc} + (I_S')^2 (R_S')}$$

(10)

Two evolutionary algorithms namely Corona Herd Immunity Optimization (CHIO) and Human Felicity Safety (HFS) algorithm have been proposed to get optimum set of equivalent circuit parameters in single phase and three phase transformer for maximization of efficiency and minimization of losses. So the objective function has been considered as eq. no. (12)

$$F_{obj} = Max(efficiency) + Min(Loss)$$

(11)

$$F_{obj} = \max\left\{\frac{V_s' I_s'}{V_s' I_s' + P_C + I_s'^2 R_s'}\right\} + \min\left\{I_s'^2 R_s'\right\} \tag{12}$$

III. OPTIMIZATION ALGORITHMS

Several optimization techniques have been implemented during the last few decades as mentioned in literature survey to obtain equivalent circuit parameters of transformer. In this paper, two recently developed optimization algorithm based on current scenario namely Corona Herd Immunity Optimization (CHIO) and Human Felicity Algorithm (HFA) had been implemented to solve the proposed problem.

Al-Betar et al. [31] recently introduced the Corona Herd Immunity Optimization (CHIO) algorithm, a novel metaheuristic approach inspired by nature. The inspiration behind this concept stems from utilizing herd immunity as a strategy to combat the Corona virus outbreak. The fundamental idea involves infecting and recovering the majority of the population to achieve herd immunity. Subsequently, the immune individuals act as a protective barrier, essentially a firewall, shielding the remaining susceptible individuals from infection. This inspirational concept is translated into an optimization technique and rigorously tested across various standard test functions and engineering problems.

Mohammad Verij kazemi and Elham Fazeli Veysari [32] introduced a novel optimization algorithm to solve engineering issues namely human felicity algorithm (HFA). The core concept behind the Human Flourishing Agenda (HFA) draws inspiration from humanity's relentless pursuit of happiness and well-being. With the time, change of felicity is possible with change of thought, the objective function is human felicity in society and the search space optimization is the human thought in society, the objective function within this framework is to maximize human felicity within society, while the search space optimization focuses on the collective human thought and its impact on societal well-being.

3.1 Overview of CHIO Algorithm

Step 1: Initialization:

Every problem should initially be approached as an optimization challenge that warrants optimization methodologies. Additionally, it's crucial to differentiate between two pivotal elements: the representation of the solution and the objective function. Algorithmic parameters encompass the maximum number of iterations (I), the population size for herd immunity (HIP), and C0, denoting the initial infected cases. Within CHIO, there exist two control parameters: the basic reproduction rate (BRr), governing the virus transmission rate between individuals, and max age (MaxAge), determining an infected individual's status based on their infection age. After population, matrix will be formed with 'N' number of individuals (row) and 'P' parameters (column). The flow chart of CHIO algorithm is shown in Fig 2.

$$X_{ini} = X_{\min} + rand * \left(X_{\max} - X_{\min}\right)$$

(13)

The norm of initial matrix is as follows having size [N X P]

$$X_{ini\_norm} = \frac{X_{ini}(N,P) - \min(X_{ini})}{\max(X_{ini}) - \min(X_{ini})}$$

(14)

Step 2: Population of herd immunity creation

CHIO individuals maintain a memory matrix of dimension called the herd immunity population (HIP). In terms of equality and inequality limits, these people are set up normally.

Step 3: Containment Zones

The factors about containment zones are based on disease propagating nature of COVID 19. The containment factors are rooted in the way COVID-19 spreads. They primarily encompass (a) social distancing, (b) mask usage, and (c) calculating antibody rates in individuals following their initial infection. Once patient-zero (PZ) infects a portion of the population, we assess these containment factors for each individual. The mathematical modeling for each containment factor is elaborated upon below.

Social Distancing (SD) : Similar to how COVID-19 requires isolating infected individuals to reduce infection rates, our study adopts a similar approach post-initial infection. We assess the Social Distancing (SD) factor for each individual. To do this, we create an SD matrix that quantifies the distance between various parameters within a population. In its simplest form, the distance (D) between two normalized parameters, m and n, can be computed as shown in equation (15).

$$D = m - n \; ; \; m \neq n$$

(15)

It seems that you are discussing the calculation of the SD (Standard Deviation) factor based on a normalized matrix denoted as X_{ini_norm}. Following this, an SD matrix is constructed, denoted as (16), which uses the information from X_{ini_norm} and considers the distances among parameters with dimensions equal to N × j × P. This SD matrix is composed of p sub-matrices, each with dimensions equal to N × j.

$$SD = \left\{X_{ini\_norm}(N,P) - X_{ini\_norm}(j,P)\right\}; \quad j = 1:N \;\;, N \neq j$$

(16)

It appears that you are discussing the impact of the SD (Social Distancing) factor on the infection rate (IR) in the context of the spread of a contagious disease. In this context, the SD factor is inversely related to the infection rate, implying that a higher value of the SD factor corresponds to a lower infection rate. The threshold distance (TD) is defined as the distance below which the infection can spread due to a violation of the SD factor. In this scenario, the practical value of the threshold distance (TD) is normalized within a range of 0 to 1, where 0 represents the minimum value of the threshold distance, and 1 represents the maximum value corresponding to 6 feet, as recommended by the World Health Organization (WHO) guidelines.

Step 4: Evolution of herd immunity

New solution will be updated based on 'infected case', 'susceptible case' and 'Immune case' principle. New solution will be updated according to percentage of basic reproduction rate using eq. (17).

$$X_{ini}^{new} = \begin{cases} X_{ini} & ; random\_number \geq Basic\ reproduction\ rate \\ X_{ini} + r \times \left(X_{ini}^{j} - X_{ini}^{c} \right) & ; random\_number \leq \frac{1}{3} \times Basic\ reproduction\ rate\ //\ Affected case \\ X_{ini} + r \times \left(X_{ini}^{j} - X_{ini}^{m} \right) & ; random\_number \leq \frac{2}{3} \times Basic\ reproduction\ rate\ //\ susceptible case \\ X_{ini} + r \times \left(X_{ini}^{j} - X_{ini}^{v} \right) & ; random\_number \leq Basic\ reproduction\ rate\ //\ immuned case \end{cases} \quad (17)$$

improve. If the immunity rate does not improve within this specified number of iterations, the case is considered as having died.

Step 6: Stopping Criteria

When stopping criteria is reached, the optimum solution is obtained.

3.2 Overview of Human Felicity Algorithm (HFA)

The pursuit of happiness and well-being has long been a central focus in various fields, including psychology, philosophy, and economics. In recent years, there has been increasing interest in applying technological advancements, such as artificial intelligence and algorithms, to study and enhance human well-being.

"Human felicity algorithm" could be an algorithm designed to identify patterns or factors that contribute to human happiness and well-being, perhaps by analyzing various data points, including social interactions, behavior, and environmental factors. Such an algorithm might aim to provide insights or recommendations for individuals or communities to improve their overall well-being and life satisfaction.

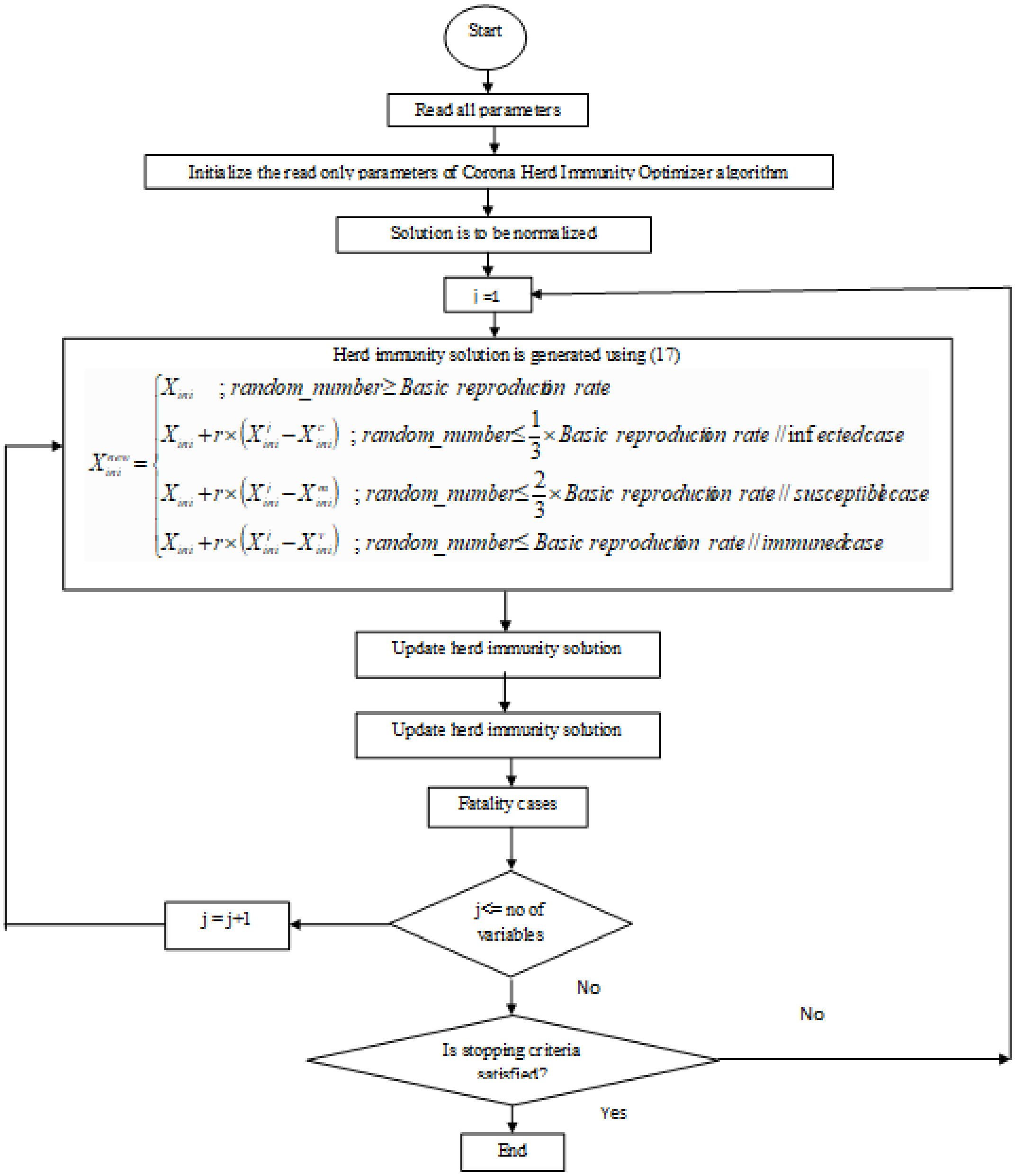
Npop represents the population size within society, and if the level of well-being (felicity) relies on the P parameter, initially, individuals are randomly situated within a P-dimensional mindset. There are three societal occurrences: 1) exploration within one's vicinity, 2) identification of elites followed by intellectual alignment with them, and 3) abrupt alterations in personal perspectives. These events are denoted by j, k, and i, respectively. The expression felicity (n, j, k, i) signifies the well-being of the nth individual in society during their jth local exploration, kth alignment, and ith perspective shift.

3.2.1 Local search

Every person holds a perspective toward each societal parameter. To enhance their well-being, individuals modify one or more dimensions of these parameters. These modifications occur randomly and are guided by the principles outlined in Equation (18).

$$felicity(n, j+1, k, i) = felicity(n, j, k, i) + s(n) \quad (18)$$

s(n) is the nth individual’s step length. When the size, s(n), is too extensive, an individual swiftly transitions from point 1 to point 2 during the initial phase of the local search. Consequently, the vicinity around position 1 remains inadequately explored, rendering this step unsuitable. Conversely, a small selection of s(n) restricts each person's search to a minute area. Ideally, the aim is to explore the region demarcated by a red circle. A substantial radius overlooks precision in exploration, while a small radius fails to cover the appropriate zone. If adjusting attitudes based on personal experiences leads to increased tranquility, members of society are inclined to follow suit. However, the number of movements in this direction must be finite. The maximum limit of movements in a single direction is denoted by $N_{unidirection}$.



$$X_{ini}^{new} = \begin{cases} X_{ini} & ; random\_number \geq Basic\ reproduction\ rate \\ X_{ini} + r \times (X_{ini}^{j} - X_{ini}^{c}) & ; random\_number \leq \frac{1}{3} \times Basic\ reproduction\ rate\ //\ infected case \\ X_{ini} + r \times (X_{ini}^{j} - X_{ini}^{m}) & ; random\_number \leq \frac{2}{3} \times Basic\ reproduction\ rate\ //\ susceptible case \\ X_{ini} + r \times (X_{ini}^{j} - X_{ini}^{v}) & ; random\_number \leq Basic\ reproduction\ rate\ //\ immuned case \end{cases}$$

Fig 2. Flowchart of CHIO Algorithm

4. RESULTS WITH DISCUSSION

4.1 Experimental Set Up

The proposed algorithm has been implemented on to determine equivalent circuit parameters for single and polyphase induction motors by minimization of global errors depicted in equation (1). The experimental tests i.e. no load and blocked rotor tests are performed at Electrical Machine Laboratory located at Netaji Subhash Engineering College, West Bengal, India. The photograph of experimental set up along with measuring instruments is shown in Fig. 4(a) and Fig. 4(b). The Table 2 depicts the specification of single and polyphase induction motor for tests. The open and short circuit test results are shown in Table 3. These records are helped to determine equivalent circuit parameters by using the proposed CHIO and HFA algorithms. Another two induction motors specification have taken from [8] and the details are depicted on Table 4.

3.2.2 Altering societal perceptions to align with the worldview shaped by influential figures

As previously noted, influential individuals experiencing greater felicity impact the collective mindset.

Nonetheless, a thriving society benefits from the presence of multiple elites. Moreover, certain individuals within the community may remain unaffected by the influence of these societal elites. The upper limit for the frequency of altering population perspectives under elite influence is denoted by $N_{alteration}$.

3.2.3 Thought revolution

Various factors such as mortality, conflict, loss of loved ones, and unique life circumstances can trigger profound intellectual and spiritual transformations in certain individuals within society, potentially leading to positive changes for the community. Additionally, external factors can prompt significant shifts in people's attitudes. In all these instances, a new collective mindset emerges, superseding previous attitudes. Within the framework of HFA, the society replaces the attitude of N_{rev} with a new one, safeguarding the elites to prevent societal deterioration. HFA allows all individuals except the elites to undergo a shift in their thinking. The count of individuals experiencing intellectual transformation at any given stage is denoted by N_{rev}. The maximum frequency of a revolution influenced by public opinions is represented by $N_{revolution}$.

IV. RESULT AND DISCUSSION

To examine the robustness of the proposed technique, three case studies on single-phase transformers of different ratings are analyzed. The estimated transformer parameters using CHIO and HFA are compared with the actual pre-known parameters of the three transformers. After implementation of these algorithms, optimized value of parameters has obtained where minimum loss and maximum efficiency will be achieved. Three single phase transformer in different ratings have been used for proving efficacy of proposed algorithms. The facility of 'Neo Teletronics Private Limited' has been used to estimate manufacture data from experimental set up. The lab view has been depicted in Fig 3.

The ratings of three transformers are as follows.

Transformer 1: Nameplate Data: 66-kVA, 415/415 V, 50 Hz

Transformer 2: Nameplate Data: 1 kVA 240/100V, 50 Hz

Transformer 3: Nameplate Data: 15 kVA, 2400/240 V, 50 Hz

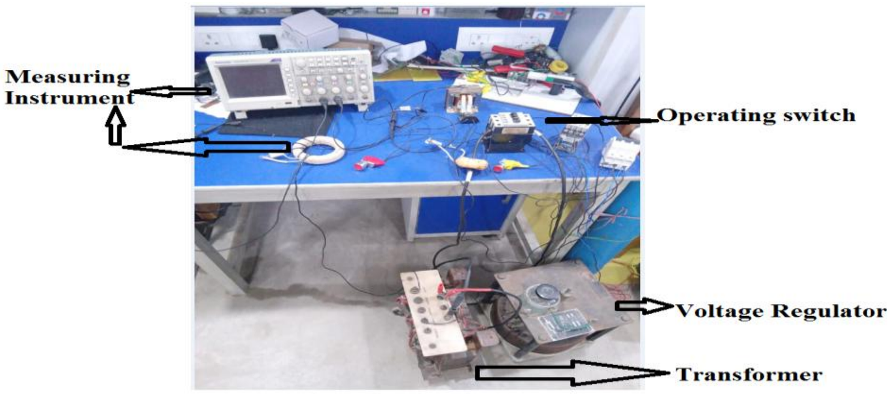


Fig. 3 Experimental Set up

It seems that while both techniques can estimate transformer-winding parameters, there's a noted issue with estimating small parameters such as resistance and leakage inductance due to their inherently low values. Even with accurate measurement techniques, small parameter values can lead to significant errors in estimation. It has been observed that parameters obtained from CHIO provide less error than HFA technique.

The Table 3, presumably includes calculations derived from the results obtained in Table 1. It appears that despite the challenges in estimating small parameters, both CHIO and HFA techniques have provided accurate operating parameters of the transformer, such as currents, and efficiency, loss and power factor. Again it can be concluded from Table 3, parameters obtained from CHIO gives maximum efficiency and minimum loss compared to other algorithm.

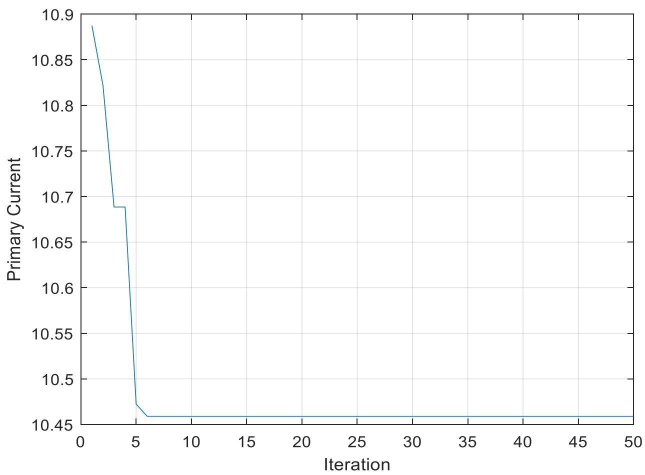
Fig 4, 5 and 6 depicts convergence characteristics of primary current, loss and efficiency with respect to iteration respectively using CHIO algorithm. Fig 7, 8 and 9 is following the same convergence characteristics respectively assisted by HFA technique. Fig 10 shows comparison between two proposed algorithms for maximization of efficiency.

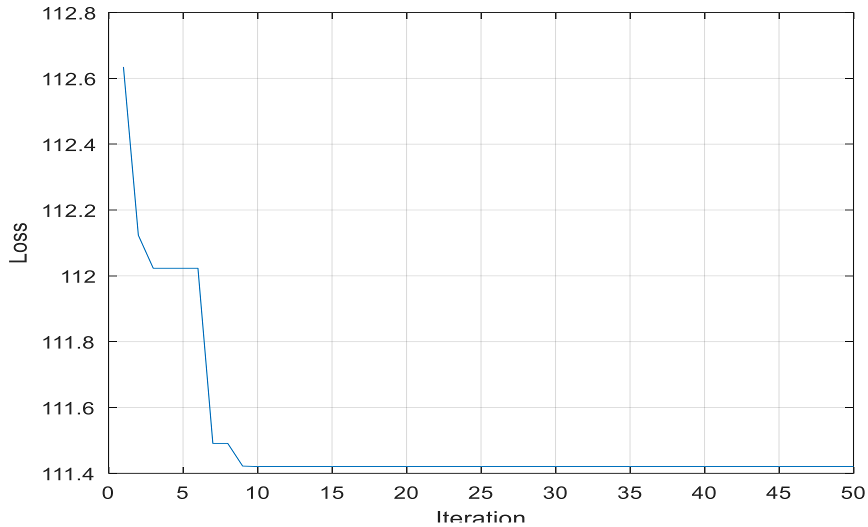
Table 2. Optimized value of parameters for 66-kVA, 415/415 V, 50 Hz transformer [Transformer 1]

Parameter	**Manufactured value (Ohm)**	**Optimized value (Ohm) (CHIO)**	**Error (%)**	**Optimized value (Ohm) (HFA)**	**Error (%)**
R_1	0.01893	0.0152	19.7	0.0157	17.06
R_2	0.0274	0.0252	8.03	0.0298	-8.76
X_1	0.1151	0.1525	-32.49	0.1512	-31.36
X_2	0.1151	0.1825	-58.56	0.1795	-55.95
R_c	1759.966	1735.25	1.4	1935.12	-9.95
X_m	101.19	91.8815	9.9	95.3095	5.81

Table 3. Comparative result of Primary Current, Loss and efficiency between CHIO and HFA technique for 66-kVA, 415/415 V, 50 Hz transformer [Transformer 1]

Algorithm	**Primary current(Amp)**	**Power factor**	**Loss (Watt)**	**Efficiency (%)**
Analytical Value	14.8097	0.1733	103.3612	90.2019
CHIO	10.1751	0.3609	99.7214	96.4585
HFA	10.4589	0.35	111.42	96.3425




112.8
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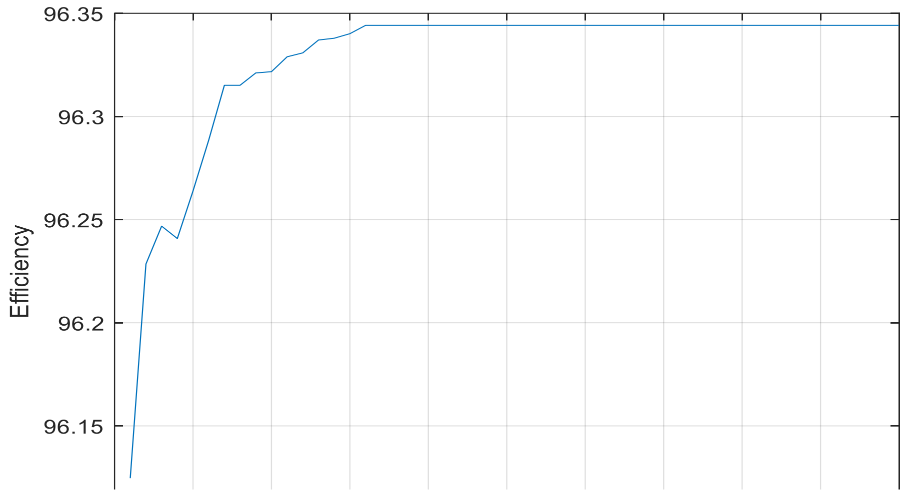
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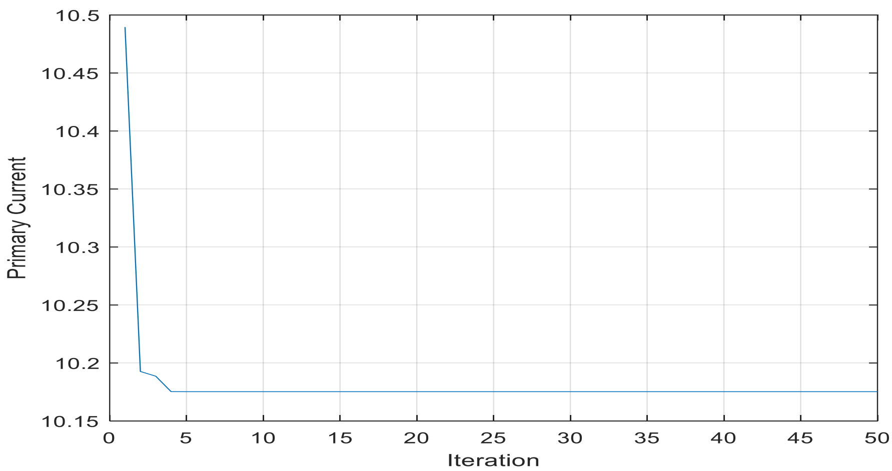
Efficiency


10.5
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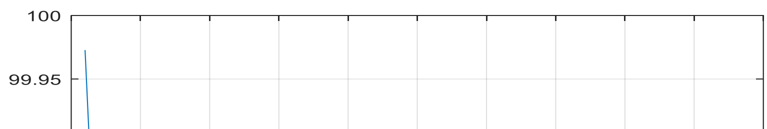
Iteration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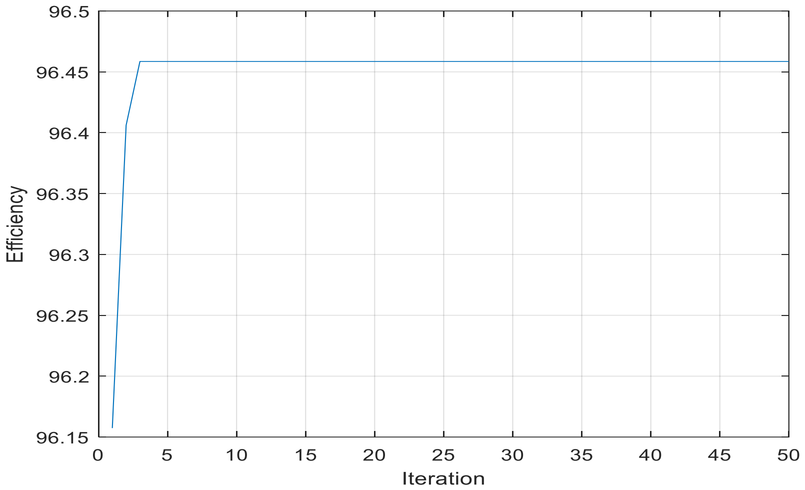
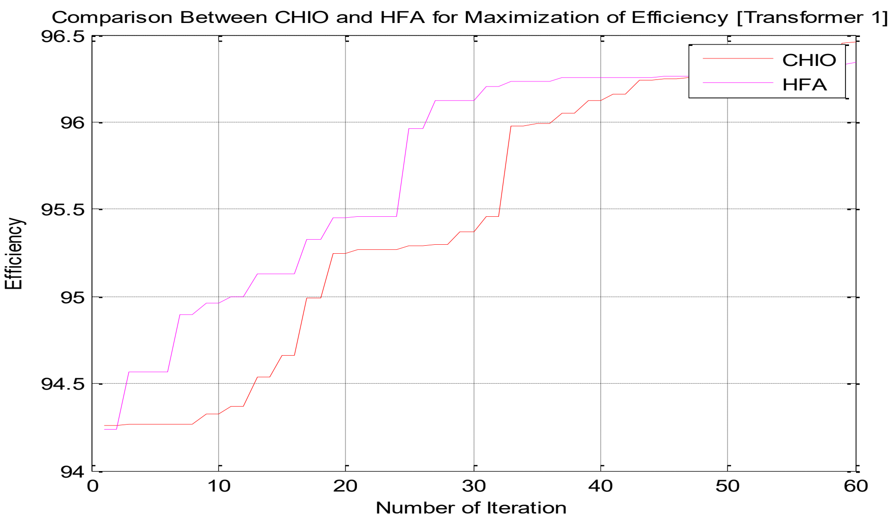


Fig 9. Convergence Characteristic of Efficiency Vs. Iteration using HFA Technique [Transformer 1]



4.2

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Fig 10. Comparison between CHO and HFA Techniques for maximization of Efficiency [Transformer 1] and optimized value from proposed algorithms and errors have been shown also. It has been observed that parameters obtained from CHIO provide less error than HFA technique.

After getting optimized parameter value, loss and efficiency has been calculated that is shown in Table 5. Again it can be concluded from Table 5, parameters obtained from CHIO gives maximum efficiency and minimum loss compared to other algorithm.

Fig 11, 12 and 13 depicts convergence characteristics of primary current, loss and efficiency with respect to iteration respectively using CHIO algorithm. Fig 14, 15 and 16 are following the same convergence characteristics respectively assisted by HFA technique. Fig 17 shows comparison between two proposed algorithms for maximization of efficiency.

Table 4. Optimized Value of Parameters for 1 kVA , 240/100V,50 Hz Transformer [Transformer 2]

Parameter	**Manufactured value(Ohm)**	**Optimized value (Ohm) (CHIO)**	**Error(%)**	**Optimized value (Ohm) (HFA)**	**Error(%)**
R_1	0.364	0.3941	-8.27	0.3940	-8.24
$R_2^{'}$	0.00262	0.0035	-33.59	0.0033	-25.95
X_1	0.2375	0.2519	-6.06	0.2521	-6.21
$X_2^{'}$	0.0412	0.0418	-1.46	0.0421	-2.18
R_c	2000	1975.25	1.24	1955.19	2.24
X_m	201	212.2156	-5.58	208.2156	-3.59

Table 5. Comparative result of Primary Current, Loss and efficiency between CHIO and HFA technique for 1 kVA , 240/100V,50 Hz Transformer [Transformer 2]

Algorithm	Primary current(Amp)	Power factor	Cu Loss (Watt)	Efficiency (%)
Analytical Value	5.3457	0.8295	38.5537	94.6450
Method 1	4.1296	0.8033	33.6320	96.2658

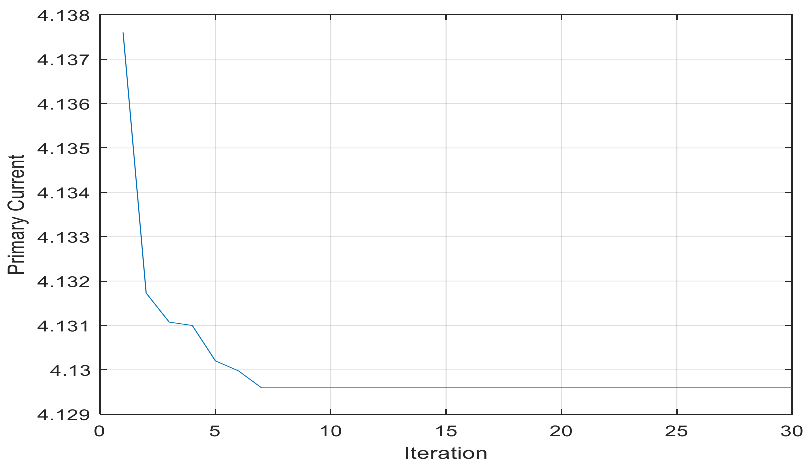


Fig 11. Convergence Characteristic of Primary Current Vs. Iteration using CHIO Algorithm [Transformer 2]

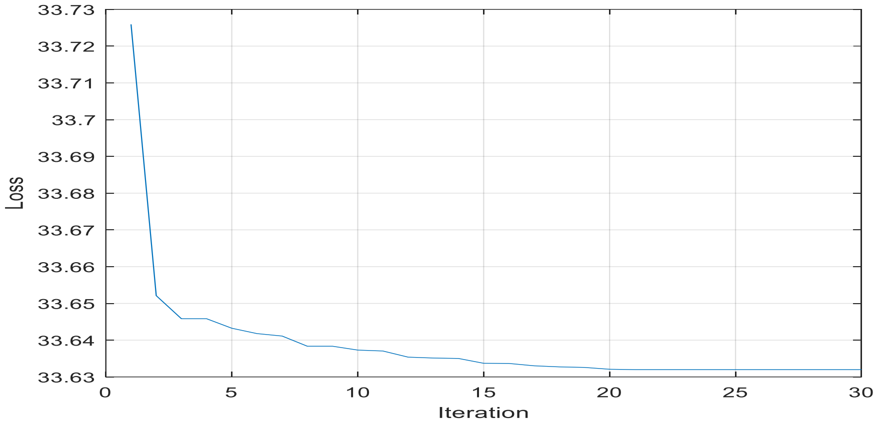


Fig 12. Convergence Characteristic of Loss Vs. Iteration using CHIO Algorithm [Transformer 2]

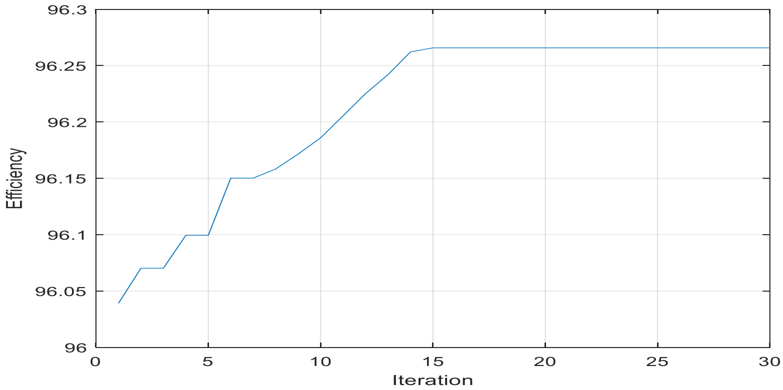


Fig 13. Convergence Characteristic of Efficiency Vs. Iteration using CHIO Algorithm [Transformer 2]

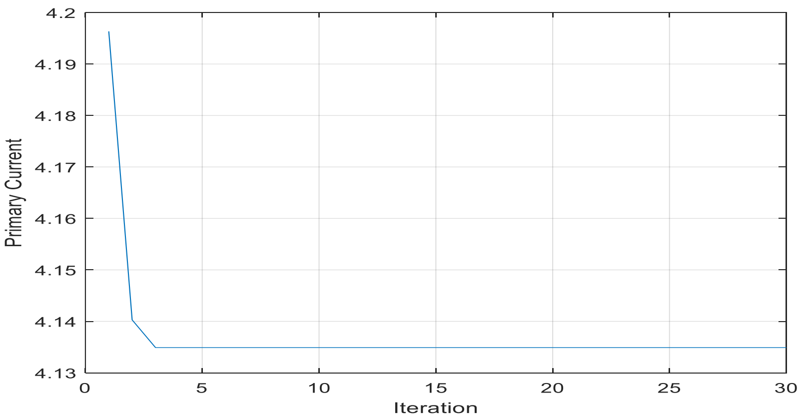


Fig 14. Convergence Characteristic of Primary Current Vs. Iteration using HFA Algorithm [Transformer 2]

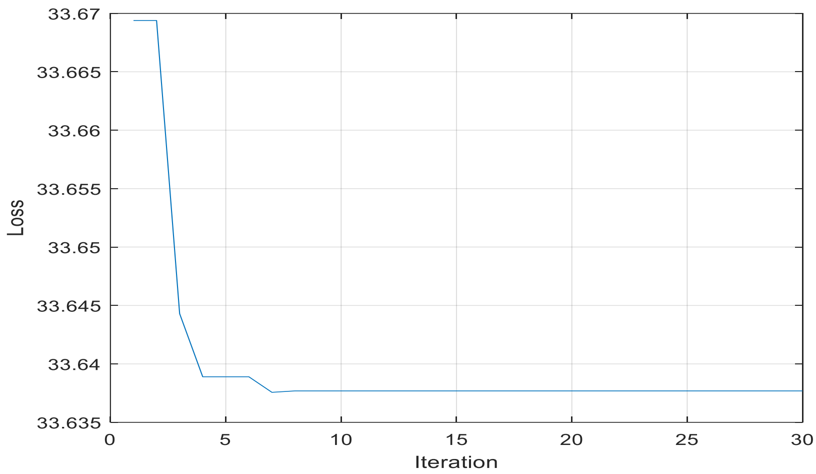


Fig 15. Convergence Characteristic of Loss Vs. Iteration using HFA Algorithm [Transformer 2]

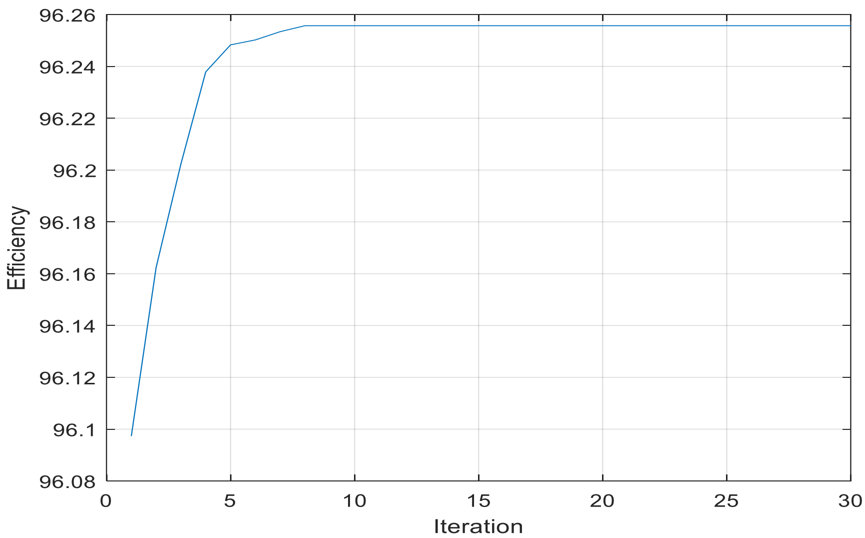


Fig 16. Convergence Characteristic of Efficiency Vs. Iteration using CHIO Algorithm [Transformer 2]]

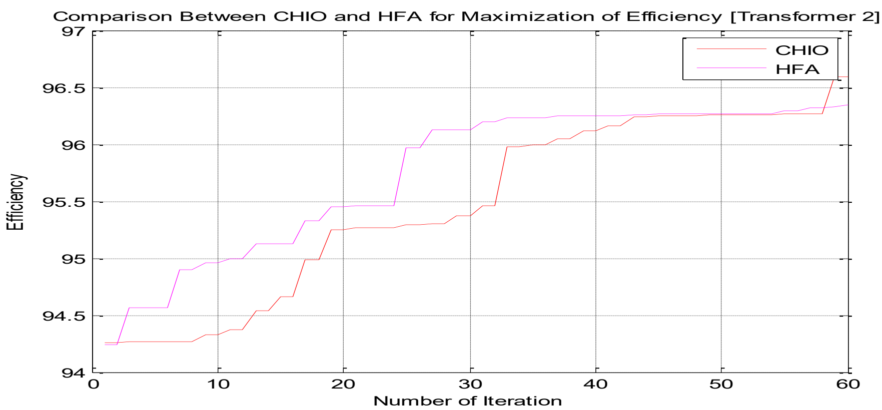


Fig 17. Comparison between CHO and HFA Techniques for maximization of Efficiency [Transformer 2]

4.3 Case Study 3

Proposed algorithms have been implemented on another single phase transformer rated as 15 kVA, 50 Hz, 2400/240 V for calculation of equivalent circuit parameters to achieve maximum efficiency. Manufacturer data of Transformer 3 is taken form literature survey [2]. The optimized values of parameters have been compared with already established algorithms such as PSO [2] and GSA [5]. Table 6 also shows the percentage error followed by CHIO, HFA, PSO and GSA.

Moreover, it can be observed from Table 6, average errors of above mentioned transformer is obtained using CHIO as depicted in Table 6. Table 7 shows comparative result of efficiency between mentioned four optimization algorithms.

Fig. 18 and 19 shows convergence characteristic of efficiency with respect to iteration using CHIO and HFA respectively. It can be observed that CHIO converges slightly faster than HFA. Therefore, obtained results in this work, it can be concluded that CHIO can provide superior performance than HFA, PSO [2] and GSA [5] in three different rated single-phase transformers' equivalent circuit parameters. Fig 20 shows comparison between two proposed algorithms for maximization of efficiency.

Table 6. Optimized Value of Parameters for 15kVA, 2400/240V, 50 Hz Transformer for Maximization of Efficiency [Transformer 3]

Parameter	Manufactured value (Ohm)	Optimized value(CHIO) (Ohm)	Optimized value(GSA) (Ohm)	PSO [2]	GSA [5]
R_1	2.45	1.9712	2.0214	2.25	2
R_2'	2	1.4792	1.512	2.2	1.81
X_1	3.14	3.9567	2.9508	4.082	3.11
X_2'	2.2294	1.8592	1.9512	1.8526	2.26
R_c	105000	127894	130250	99517	104281
X_m	9106	10017	8195	9009	9094.87

Table 7. Comparative result of efficiency by CHIO and HFA with PSO and GSA for 15kVA, 2400/240V, 50 Hz Transformer [Transformer 3]

	Actual	**CHIO**	**HFA**	**PSO [2]**	**GSA [5]**
Efficiency (%)	98.5	98.5230	98.4917	98.52	98.48

Table 8. Improvement of Efficiency of CHIO over HFA for Transformer Parameter Estimation

	Transformer 1	Transformer 2	Transformer 3
CHIO	96.4585%	96.2658	98.5230 %
HFA	96.3425%	96.2557	98.4917%

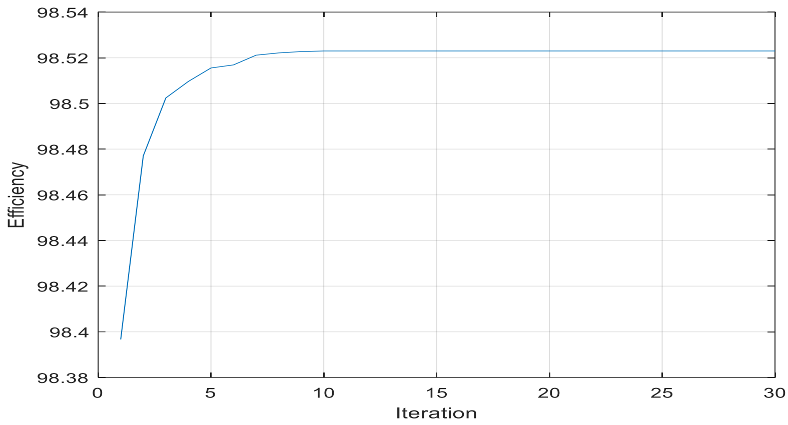
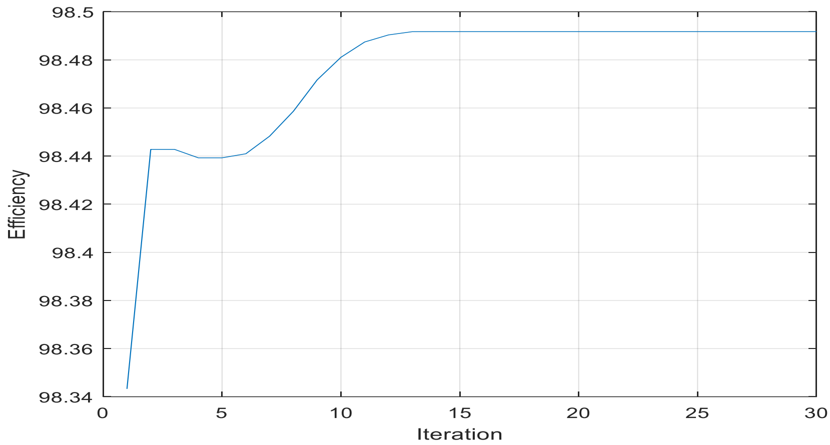
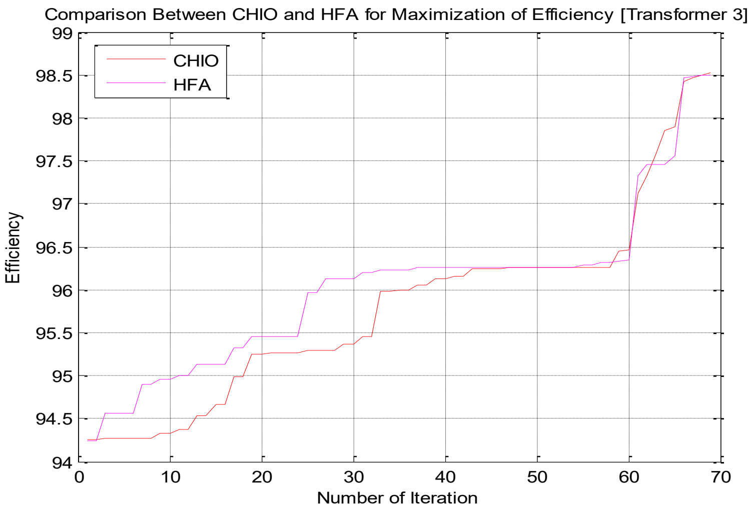


Fig 18. Convergence Characteristic of Efficiency Vs. Iteration using CHIO Algorithm [Transformer 3]





PSO and GSA.

5. CONCLUSION

The study successfully introduced the application of Corona Herd Immunity Optimization (CHIO) and Human Felicity Algorithm (HFA) to estimate parameters from nameplate data for single-phase transformers across three different ratings. Comparative analysis between CHIO, GSA, PSO, and HFA revealed that CHIO produced lower average errors and maximum efficiency in estimated transformer parameters compared to actual data. CHIO exhibited faster convergence than HFA and demonstrated superior error reduction over PSO and GSA in comparison to CHIO. Consequently, employing CHIO yielded the most accurate results in estimating transformer equivalent circuit parameters. Future endeavors may explore applying these algorithms to optimize more than 6 parameters. Additionally, considering the broader frequency range beyond the reported 50 Hz used in the comparison could enhance the results, given the limitations of past studies confined to this frequency.

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Compliance with Ethical Standards

The authors declare that they have no conflicts of interest to disclose. This research did not involve any studies with human participants or animals performed by any of the authors. Informed consent is not applicable.

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