Parametric Optimization of Hall Effect Using Flower Pollination Algorithm and Cuckoo Search Optimization Techniques

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Abstract. Developing a precise model for Hall effect using experimental statistics is crucial for managing, simulating, and optimizing Hall coefficient of Hall effect devices. In this work, two powerful optimization techniques such as Flower Pollination Algorithm(FPA) and Cuckoo Search Optimization(CSO) are utilized to estimate Hall co-efficient of Hall effect study. Additionally, accurately anticipate the Hall effect's I-V characteristics validating the suggested approach. Three criteria were selected in order to conduct a comparison analysis between these two algorithms, specifically: RMSE, convergence speed, and computation time.Based on the results, it was determined that FPA performed unparalleled with regard to less computing time, convergence speed, and least RMSE.

Keywords: Hall Coefficient, FPA, CSO ,Optimization, RMSE.

1 Introduction

An essential idea in both physics and engineering, the Hall voltage explains how charge carriers behave in the presence of magnetic fields and has real-world applications in many different domains.The Hall Effect [1,2] is the term used to describe the tendency of charge carriers to be impacted by the effect of a magnetic field whenever a current carrier is put in one. When a magnetic field is present and a current pass through a conductor, the moving charge carriers—electrons or holes are affected by the magnetic force. The potential difference generated across the conductor due to this charge separation is what refer to as the Hall voltage. This Hall voltage is in

direct proportion to the electric current, and in straight coherence to the employed magnetic field [3,4].The Hall coefficient (R_H) is a fundamental parameter that characterizes the Hall effect in a material. Hall coefficient (R_H) is depend on Hall voltage (V_H), current (I), magnetic field strength (B) and thickness of the conductor(t).Here, model parameter for Hall effect is Hall coefficient (R_H). Engineers must accurately determine the Hall Effect parameters from experimental data in order to develop an very precise mathematical framework that describes the unplanned current-voltage (I-V) interconnection of the hall effect. This is a crucial work for system construction, quality checking, and performance estimation.

Heuristics, which are general guidelines or tactics that direct the search process toward more effective answers, are the foundation of metaheuristics.Metaheuristics [5] is a bunch of ideas that can be utilized to define heuristic methods that can be practiced to a wide arrangement of distinct issues. Metaheuristics can be extensively grouped into two classifications: Single-arrangement rested and Populace rested strategies. The commonly used Single-arrangement rested metaheuristics is Simulated Annealing(SA),Tabu Search etc. and famous Populace rested metaheuristics is Genetic Algorithm (GA) [6], Particle Swarm Optimization (PSO) [7],Flower Pollination Algorithm (FPA) [8] etc.. Numerous researchers have been applied different metaheuristics such as Cuckoo search Optimization (CSO), Firefly Algorithm (FA), FPA, Evolutionary Algorithm, and Grey Wolf Optimization (GWO) to the parameter perception troubles of various semiconductor devices. In the visible spectrum, [9] a multi-crystal quarter wave phase retarder was created and used FPA to maximize the thickness of four birefringent plates. A novel cuckoo search technique based on a cloud model is employed and estimating the step size factor using an exponential function was reported [10].But, parametric estimation of Hall coefficient (R_H) for Hall effect has not been done previously.

In this attempt, Flower Pollination Algorithm (FPA) and Cuckoo search Optimization (CSO) algorithms are applied for parametric optimization of Hall coefficient (R_H) for Hall effect.The residual of the document is ready herewith. The mathematical explanation of the FPA and CSO starting and parameter estimate problem is provided in Section II. The consideration push on to investigational statistics, methodology, and replication results. The conclusion is provided in the next part with the assistance of references.

2   Mathematical Description

The Hall Voltage (V_H) can be mathematically expressed as

$$V_H = \frac{B.I}{R_H t} \tag{1}$$

and current (I) can be rewritten as

$$I = \frac{V_H.R_H t}{B} \tag{2}$$

Where R_H is the Hall coefficient,B is magnetic field strength(0.5 Tesla) , I is current flowing through the conductor and t is thickness of the conductor(0.01 meters). So, in current-voltage (I-V) relationship of the hall effect ,Hall coefficient(R_H) is to be estimated.

3   Flower Pollination Algorithm (FPA)

The Flower Pollination Algorithm (FPA)[11,12]is a nature-enlivened enhancement calculation devised by Xin-She Yang in 2012. It depends on fertilization interaction of blossoming plants, which is fundamental for their multiplication. FPA mimics the behavior of natural pollination, specifically how flowers attract pollinators like insects, birds, and wind to transfer pollen, leading to the creation of new plants (solutions).Biotic cross-fertilization can be expected as a strategy for world fertilization, and dust wearing pollinators follow Lévy trips eventually of transportation (Rule 1). For neighborhood fertilization, abiotic fertilization and self-fertilization are utilized (Rule 2).Pollinators might also broaden flower credibility, that's coherence to parallel of vegetation i.e. fertilization opportunity (Rule 3). The switching of nearby to worldwide pollination may be managed through a switch possibility p ϵ [0, 1], barely biased in the direction of local pollination (Rule 4).The following two equations, in turn, are used to conduct global and local pollination, or search:

$$X_i^{t+1} = X_i^t + L(\lambda)(X_i - g^*) \tag{3}$$

$X_i^t$is the pollen $i$or solution vector X_i at iteration t, g^* is the latest supreme solution among all solution in latest iteration and $L(\lambda)$is a step size

$$X_i^{t+1} = X_i^t + \varepsilon(X_j^t - X_k^t) \tag{4}$$

Here X_j^t and $X_k^t$are dust from various blossoms of parallel plant species.The rationale behind using FPA as an optimization technique is its superior convergence and accuracy compared to other well-known metaheuristic methods[13].

4   Cuckoo Search Optimization (CSO)

Cuckoo Search Optimization (CSO) is a nature-enlivened metaheuristic calculation created by Xin-She Yang and Suash Deb in 2009. It is roused by progeny dependents of some cuckoo species, especially their system of dropping eggs in the homes of other host birds. The algorithm also incorporates the Lévy flight conduct of birds and natural product flies, which is utilized to upgrade the hunt interaction. CS is fully relied on levy's flight to generate new answers. Cuckoo Search algorithm has three glorified amenities [14]:

1) Each cuckoo drops each egg in turn, and dumps it in a haphazardly picked home

2) The best homes with excellent of eggs (arrangements) will abide to the backing ages

3) The amount of open host homes is immutable, and the egg dropped by a cuckoo is found by the host bird with a likelihood $P_a \in [0, 1]$.

When propagating latest solutions $X_i^{(t+1)}$ for say, a cuckoo i, a Lévy flight is performed

$$X_i^{(t+1)} = X_i^t + \alpha \oplus Lévy(\lambda) \tag{5}$$

Where α is step size. $\oplus$ refers entry-wise multiplications. The Lévy flight [15,16] is an arbitrary walk with inconsistent step length from an Lévy distribution

$$Lévy \sim u = t^{-\lambda} \quad (1 < \lambda \leq 3) \tag{6}$$

5   Objective Function

Every optimization technique gauges a solution's quality using an objective function or fitness value. The objective of the gauge work is to limit the mistake between the mimicked and estimated current by deciding the most ideal qualities for the obscure boundaries. The root mean square of the mistake (RMSE) is characterized as Eq. (6) can be utilized as goal capability:

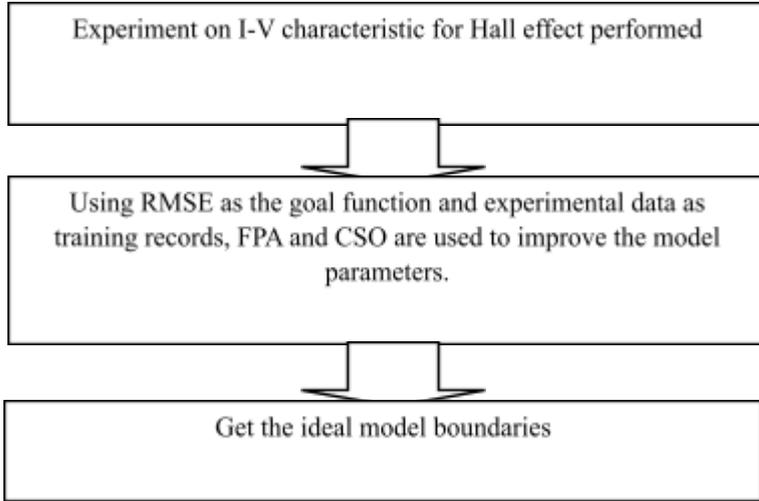$$RMSE(X) = \sqrt{\frac{1}{n}[f(V_H, I, X)]^2} \tag{7}$$

Where n is set of hall voltage and current and $X = \{R_H\}$ for finding out current-voltage (I-V) relationship of the hall effect.

6   Materials and Methods

The two primary phases in the metaheuristic-based optimization of Hall effect model parameters are as follows : (1) Experimentation in laboratory where set of Hall Voltage (V_H) and current(I) are observed and (2) Implementation of FPA and CSO to optimize the model parameters of current(I) for hall effect.The circuit arrangement for determining voltage and current relationship of hall effect is shown in figure 1.Here Hall voltage is measured for both the directions of the current and magnetic field. Then Hall voltage is considered as a function of current keeping the magnetic field constant and as a function of magnetic field keeping a suitable value of current as constant. The magnetic field is measured by the Gauss Meter. Hall voltage (V_H) is increasing gradually in laboratory and corresponding current is increasing rapidly that is being observed.The details of these steps are explained in Figure 2.

Fig. 1. Experimental set up for Hall Effect

Fig. 2. Stepwise methodology for the present research

The Flower Pollination Algorithm (FPA) and Cuckoo Search Optimization (CSO) algorithms have been utilized to optimize the hall effect settings in the next section of this artwork. In our current issue, aspect of quest for the metaheuristic is 3 as the info factors of enhancement process are R_H.The fitness function is computed and trained using experimental data. As the fitness function, RMSE is employed. For FPA and CSO,number of population and total number of iterations are set as 50 and 1000 respectively.The lower and upper limit i.e. search range for hall coefficient(R_H) is chosen as [4×10^{-5}, 20×10^{-5}]. Following the last stage of generation, an excellent optimization technique will produce a good solution, or an exceptional aggregation of input parameters with a minimum RMSE. The computed I-V characteristics and the observed I-V characteristics of the Hall Effect should be almost identical in the most practical circumstances.

7   Result & Discussion

This section presented the results and discussed them in order to get some important comments on the paintings' conclusions. Initially,8 readings of hall voltage(V_H) and current(I) have been taken experimentally for hall effect.The experimental I-V characteristic of hall voltage(V_H) and current(I) for hall effect is depicts in figure 3 which is exponential. Next, FPA and CSO have been carried out to this investigational dataset to find out supreme values of hall coefficient (R_H).RMSE and computational time for both FPA and CSO algorithms are tabulated in table 1 for hall effect analysis. It can be
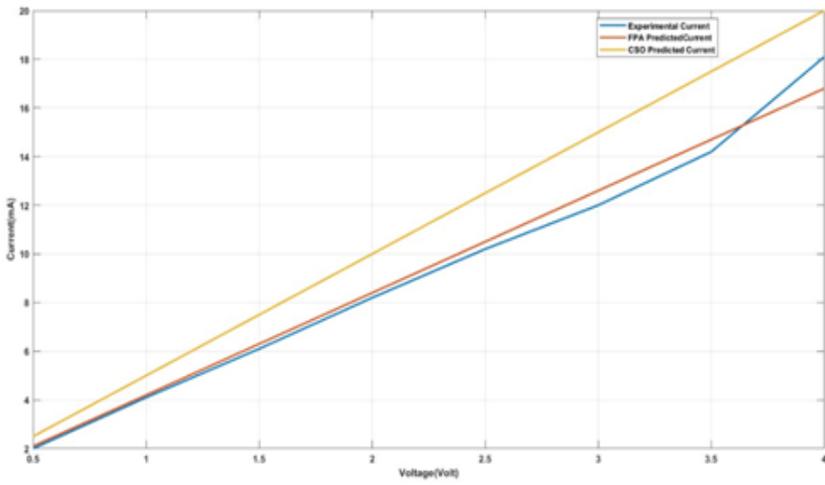
clearly said from the table 1 that FPA provides better results with regard to less RMSE and small elapsed time.

Table 1. Comparative study based RMSE & Computational Time for I-V characteristics
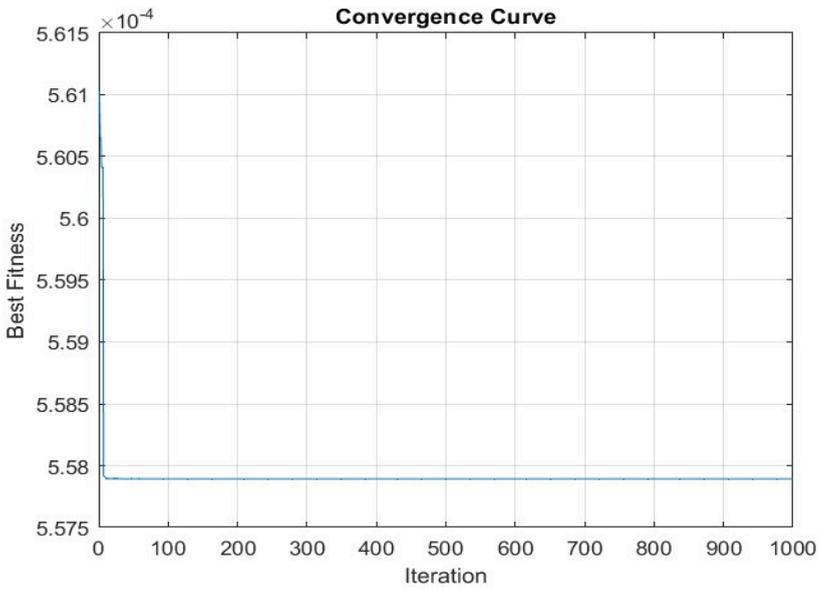
Name of the Algorithm	Computational Time	RMSE
FPA	38.5395 sec	5.58E-04
CSO	85.2925 sec	0.0021

The computation time of an optimization method is the amount of time it takes to get the objective function's minimal fitness value. From the above table, it can be concluded that FPA takes less amount of computational time to provide the least fitness value. Figure 3 displays experimental I-V characteristic of hall voltage (V_H) and current (I) with FPA and CSO predicted output. It may be observed from the graph that there is small amount of variation among experimental and predicted output. From the qualities diagram, it is apparent that FPA produces the fittest current than different calculations.
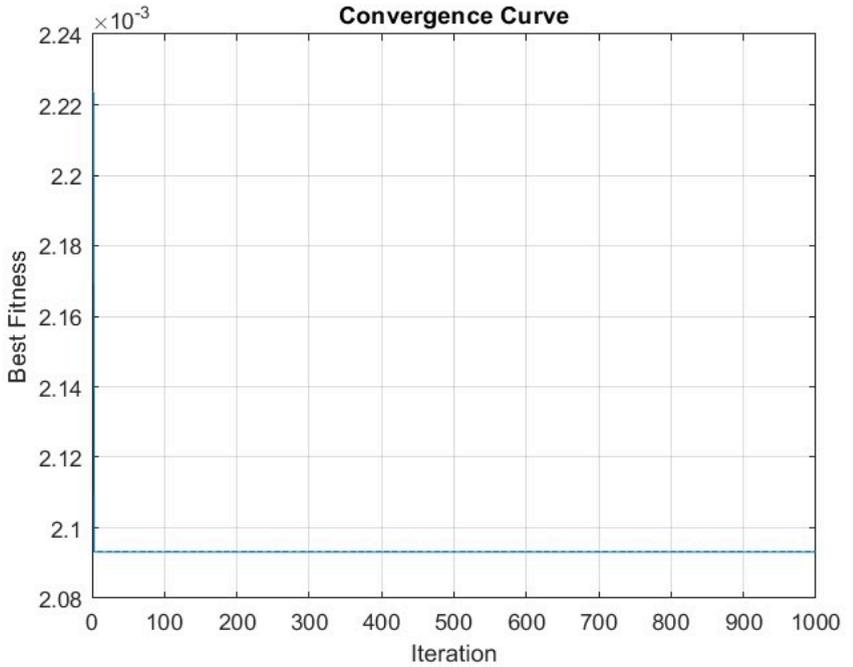
Another criterion for determining the optimal method for any function's optimization is convergence speed. The optimal algorithm for the optimization of a particular issue is indicated by a stable state or a drop in convergence speed with an increase in iterations. Figure 4 and figure 5 suggest convergence graph for FPA and CSO respectively. FPA shows better result than CSO in case of convergence speed.In the estimation of the Hall coefficient, the goal is often to minimize the error. FPA can quickly and precisely converge to the best answer by striking a balance between locally exploiting potential regions and globally searching the search space compared to CSO.Table 2 shows the optimal parameters values of hall coefficient(R_H) for FPA and CSO.

Fig. 3. Comparative I-V characteristics among experimental,

FPA and CSO predicted output

Fig. 4. Convergence graph of FPA for I-V characteristics of hall effect

Fig. 5. Convergence graph of CSO for I-V characteristics of hall effect

Table 2. Optimal value of hall coefficient(R_H) for hall effect

Algorithm	I-V Characteristics , Hall coefficient(R_H)
FPA	8.40×10^{-5}
CSO	10×10^{-5}

8   Conclusion

A productive and precise method to regulate the largest parameters of the Hall coefficient (R_H)) of the Hall Effect is presented in this paper. Two distinct metaheuristic optimization techniques FPA and CSO have been utilized for the optimization where RMSE error between investigational and predicted value of hall current was used as fitness function.Three crucial

criteria should be selected for the optimal version identification: convergence speed, computing time, and the training dataset's RMSE. The calculated I-V feature in both cases is almost exactly the same as the experimental I-V feature of the Hall effect, validating the suggested strategy; nevertheless, my method of RMSE, calculation time, and convergence pace FPA repercussions is more than CSO.For a better and more precise parameter optimization of the hall effect in the future, other sophisticated and hybrid optimization approaches may be employed.

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