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CYBER SECURITY IN POWER SYSTEMS USING METAHEURISTIC AND MACHINE LEARNING ALGORITHMS

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Abstract:

Metaheuristic optimization algorithms are tools based on mathematical concepts that are used to solve complicated optimization issues. These algorithms are intended to locate or develop a sufficiently good solution to an optimization issue, particularly when information is sparse or inaccurate or computer capability is restricted. Power systems play a crucial role in promoting environmental sustainability by reducing greenhouse gas emissions and supporting renewable energy sources. Using metaheuristics to optimize the performance of modern power systems is an attractive topic. This research paper investigates the applicability of several metaheuristic optimization algorithms to power system challenges. Firstly, this paper reviews the fundamental concepts of metaheuristic optimization algorithms. Then, six problems regarding the power systems are presented and discussed. These problems are optimizing the power flow in transmission and distribution networks, optimizing the reactive power dispatching, optimizing the combined economic and emission dispatching, optimal Volt/Var controlling in the distribution power systems, and optimizing the size and placement of DGs. A list of several used metaheuristic optimization algorithms is presented and discussed. The relevant results approved the ability of the metaheuristic optimization algorithm to solve the power system problems effectively. This, in particular, explains their wide deployment in this field.

Keywords: metaheuristic; optimization; power systems; transmission networks; power dispatching; emission dispatching; distribution power network; distributed generations (DGs)

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1 INTRODUCTION

Optimization is a mathematical and computer science discipline that explores strategies and approaches for finding the perfect solution to the considered optimization issue. Solving such problems involves minimizing or maximizing one or multiple objective functions using the dependent optimization variables, which can be integers or real values [1]. Engineering, economics, logistics, medicine, and other disciplines can use optimization algorithms for decision-making. Traditional (or exact) optimization methods, including linear programming (LP) [2], nonlinear programming (NLP) [3], and dynamic programming (DP) [4], have been established to address multiple optimization issues. These algorithms have several advantages, such as being time efficient and ensuring convergence to local optima. Nevertheless, these optimization methods suffer from significant problems, such as escaping from local solutions, divergence probability, complex handling constraints, or computational challenges in computing first or second-order derivatives [5]. Metaheuristic algorithms can solve optimization problems with a lower possibility of falling into the previously mentioned problems [6]. In contrast to traditional algorithms, metaheuristic algorithms are often based on empirically inspired theoretical foundations. They can be inspired by natural phenomena or the behavior of living beings. They are flexible algorithms that can be adjusted, combined, or modified to fit the intended problem, such as combining three algorithms to resolve the power system stability [7]. These algorithms stochastically explore high-dimensional search spaces, offering robustness and global search capacity benefits. However, their stochastic behavior cannot guarantee a successful optimal solution selection [8]. These algorithms have been used for multiple fields, such as medicine [9], industry [10], and chemical applications [11,12].

The proposed paper has many common points with the other articles that talk about metaheuristic optimization algorithms and their applications in electrical engineering. As mentioned

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previously, enhancing the power system performance is crucial. For this reason, we have focused in this paper on deploying metaheuristic optimization algorithms to optimize power system performance. So, this study provides a comprehensive review of several electrical engineering problems. Then, this study provides an overview of the most common metaheuristic algorithms for resolving these optimization issues in the power systems field. We have cited and discussed some papers that present the employment of metaheuristic optimization algorithms to solve these problems. This paper is organized as illustrated in Figure 1. The paper starts with an introduction that presents the paper's context, its objectives, and the research gap. Then, the metaheuristic optimization algorithms are explained in Section 2, including a global presentation of these algorithms, their fundamental properties, and classification. The main problems of the power systems are presented and discussed in Section 3. A set of papers that use metaheuristic optimization algorithms for solving these problems are also presented. Then, this paper ends with a conclusion that summarizes the whole paper.

2 LITERATURE SURVEY

Initial research focused on machine learning algorithms[10,11]for credit card fraud detection, but did not address the issue of imbalanced classification. Several undersampling, oversampling, and hybrid sampling methods have been developed to address this issue, however they are insufficient to boost accuracy. So some work will be done utilizinga meta-heuristic approach to optimizefeature selection and increase classification accuracy. This section describes some of the existing work towarddetecting CCfraud.Chun-Yang Peng et al [12] have created a hybrid sampling approach that combines the DBSCANN, BNF, and OBN methods. It first finds borderline noise samples using BNF, then utilizes OBN to discover outlier samples and DBSCANN to cluster the samples. They employ SVM for binary classification of 16 different datasets and evaluate classifier performance using Gmean and AUC scores. V. Cerqueira et al [13] have used a layered learning strategy for dealing with imbalances in a 100-dataset benchmark. It builds a layer using an agglomerative clustering approach and divides it into three groups: pure majority, pure minority, and mixed. Based on their findings, LL+SMOTE outperforms other sampling approaches such as CURE and Balanced RF, Random Under-sampling and Oversampling. To create samples, Wei Wei et al [14] have devised a weighted complexity process (WCP) based on sampling approach. They filter the generated majority samples based on their weighted complexity and choose the best majority samples for balanced data set construction. They use CART and KNN for classification, and their performance is measured by AUC, accuracy, and F1-measure.For prediction, Akira Tanimoto et al [15] have used cost-sensitive learning and stratified sampling. They tweak the baseline logistic regression and SVCby utilizingnear miss positive instances to balance the dataset. They compare the GPU Kernal performance data set with 12 distinct datasets from the UCI repository. According to their findings, the proposed technique obtained greater than 90% balanced accuracy.Jun Wang et al [16] have proposed LDL with Class shared and Class specific Knowledge for multi-class autism spectrum disorder (NYU dataset) classification. They employ SMOTE to deal with class imbalances and the Augmented Lagrange method to find the best solution. To test the performance of the classifier, they employ the assessment parameters ChebyShev,Cosine,Clark,Canberra,Inter section,Kullbeck-Leibler, and MAP.Piyush Bhardwaj et al [17] created a machine learning system based on SMOTE for prediction. They forecast the performance of the classifier in terms of precision, recall, F1-score, and ROC curve. They utilise seven classifiers for classification: XGB, RFC, GNB, Adaboost, SGD, SVC, DTC, and KNN. Adaboost, according to their survey,provides good accuracy when compared to other models.Venkata Krishnaveni Chennuru et al. [18] employed a SA-based under-sampling strategy to balance the dataset and obtain sensitivity measures ranging from 0.68 to 0.86. Bharat Kumar Padhi et al. [19] created a RockHyrax Swarm optimization technique for optimal relevant feature selection from imbalanced high dimensional Europian

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credit card fradulant data set in 2013. They use NBC,DTC,SVM, and KNN for classification.

3 METAHEURISTIC OPTIMIZATION

The optimization process may be presented as the process of determining the best method to use existing resources while not breaking any restrictions that may exist. This strategy consists of multiple steps: mathematically defining a system model that reproduces its behavior, determining its variables and constraints, establishing the objective function, and, finally, seeking the states that produce the most desirable results by maximizing or minimizing the objective function. The optimization search strategy can be performed using any of its appropriate categories, such as quantum-based techniques, meta-heuristic-based approaches, and multi-objective-based techniques [22]. However, the main purpose of solving complicated optimization issues is to find a solution, regardless of how good it is. When at least a solution is found, numerous methods can be used to enhance it. This is the fundamental principle behind developing metaheuristic optimization algorithms.

Meta means upper level or beyond, while heuristic means to know, find, or direct an investigation, which is where the word heuristics originates. On the other hand, heuristics represents a collection of rules applied while addressing a problem based on experience [23]. Metaheuristics are approximate methods that combine basic heuristic principles to produce a more efficient exploration and exploitation of research space [24], where the search space is the space that includes all the possible solutions that are bounded by the physical system limitations. The dimensions of the search space depend on the number of optimization variables that represent the set of the required parameter. Voß et al. [25] define a metaheuristic as a repeated process that leads and modifies tasks while employing subordinate heuristics to facilitate obtaining optimal or near-optimal outcomes. The MA can function with single or many solutions using a minimization or maximizing approach at each iteration. Metaheuristic algorithms have been created to deal with the increasing complexities of the problem, particularly with the inclusion of uncertainties into the system, which may surpass the constraints of traditional algorithms.

Pre-processing:

The initial stage in cleaning and organizingdata is pre-processing. Credit card fraud data is sourced from University of California Irvine machine learning repository. The null and missing values are initially substituted with -1, and the features are normalizedusing a conventional scalar technique.

4 EXPERIMENTAL RESULTS AND DISCUSSION

The experiment for credit card fraud detectionis carried out on Windows 10 with Intel CORE i3 processor. The google Collaboratory,necessary packages and sklearn for classification.The imbalanced-learn package has been used for sampling and sklearn Niapy package has been used for meta heuristic algorithm grey wolf optimization. The result discussion is divided into four subsections. The first subsection describes the data set and evaluation metric used for experimental analysis. The second subsection choose the best classifierRFC based on evaluation. The third subsection shows the performance of RFC after sampling. The sampling process is carried out by oversampling method SMOTE, SMOTETomek, ADASYN and combined sampling approach SMOTEENN. The fourth subsection discuss about the proposed HGWRF and non-optimization techniques.4.1 Data set and Evaluation metrics:The data set is collected from UCI repositories and CCdataset contain 28382 samples with 21 features having majority classes 23122 and minority classes 5260.The outline description of credit card fraud data setis shown in Table1. From this 21 features, the statistical summary

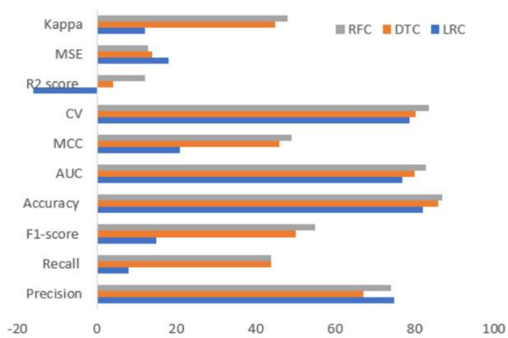

Figure 1. Performance analysis of RFC,DTC and LRC for CC dataset

5 CONCLUSION:

This paper provided an extensive study relating the use of metaheuristic optimization techniques to solve power system problems in order to guarantee sustainable environments. As power system topologies and sizes expand, so do the associated concerns. These issues can include optimizing power flow in transmission and distribution systems, optimizing reactive power dispatching, optimally combining economic and emission dispatching, optimizing Volt/Var regulating in the distribution power network, and optimizing DG scale and location and unit commitment. The significant goal of this study is to examine the application of numerous metaheuristic optimization methods to power system challenges. These difficulties and their restrictions can be described mathematically as optimization problems that can be addressed using optimization techniques. Metaheuristic optimization algorithms represent methods for addressing complicated optimization problems that are mathematically grounded. These algorithms are intended to locate or provide sufficiently feasible solutions to a given problem. In the beginning, this research examined the fundamental concepts of metaheuristic optimization algorithms as well as their classifications. The seven problems concerning electricity systems were then presented and explored. For each task, a list of various metaheuristic optimization strategies was provided. According to the results, employing the metaheuristic optimization algorithm to tackle the performance of current power systems is an appealing issue for academic researchers and industry patterns because of their exceptional ability to successfully manage these challenges. Based on the achieved results, the particle swarm optimization (PSO) and the genetic algorithm (GA) are the most used metaheuristic optimization algorithms due to several reasons, such as the date of their first utilization, and their simplicity to understand and to implement. However, due to the recent progress in these algorithms, newer algorithms can replace them. For example, the salp swarm algorithm (SSA) can be implemented more easily with higher performance and limited camping time. In terms of accuracy, the bald eagle search algorithm (BES) can generate excellent results but requires more computing time. So, the choice of

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an appropriate algorithm depends on the nature of the problem and the accuracy of the desired results.

With raised interest in AI in the last months, they may replace the current solving algorithms (including the metaheuristic algorithms). However, the metaheuristic algorithms are increasingly enhanced, so merging them with existing algorithms can provide enhanced performance for each problem.

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