Comparison of Optimization Using Hybrid Genetic Algorithm-Backpropagation and Hybrid Particle Swarm Optimization-Backpropagation for Tide Level Forecasting

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Abstract. Evolutionary computation or evolutionary algorithm has been used in many areas. For the last ten years, evolutionary computation became a powerful method to solve problems in the real world. Forecasting is a well-known method to determine the direction of the future for better results. Hybridization between the Genetic Algorithm and Particle Swarm Optimization to Backpropagation Neural Network are applied to forecast tide level data. The experiments based on a comparison of these two algorithms prove that Particle Swarm Optimization with Backpropagation Neural Network is exceeding Genetic Algorithm in measuring tide level forecasting.

1. Introduction

Evolutionary computation (EC) has been a widely popular research field since the Genetic Algorithm invented by Joseph Holland in 1975 [1]. The term EC is also used to refer to an Evolutionary Algorithm (EA)[2]. During the last years, EA is used in a wide variety of research and applications. The application of EAs to real-world problems have steadily and significantly expanded such as image processing, portfolio selection, vehicle routing, time series prediction, communications optimization, data mining, economic modeling, software engineering, and training Artificial Neural Networks (ANN), coevolution and encryption [3-5]. One of the most applied studies cases in EC is optimization. EA has been involved in many optimization problems because it’s robustness that can be used to solve almost any optimization problem [3,6].

There are many different EA have been developed, including hybrid EC. Most popular EC are Genetic Algorithms, Evolution Strategies, Grammatical Evolution, Evolutionary Programming, Genetic Programming, Learning Classifier Systems, Differential Evolution, and Particle Swarm Optimization [5,7]. Hybridization of evolutionary computation is prominent due to their effectiveness in handling various real-world problems with complexity, examining bottleneck, noisy environment, multi-objectivity, imprecision, and uncertainty [8,9]. For some study cases or issues, one variant EA can be used to find the desired solution, but there are several types of problems where simple EA is unsuccessful to meet an optimal solution. The example hybridization of EA with other algorithms are as follows: neural network, fuzzy logic, ant colony optimization (ACO), bacterial foraging optimization, heuristics algorithm, multi-objective hybrid genetic algorithm (Mo-HGA) and hybrid sampling strategy-based multiobjective evolutionary algorithm (HSS-MoEA) [9,10].

In this research, we focus on comparing the performance of hybrid of EC with neural networks to solve forecasting problems. Forecasts are essential for decision-making in many areas of expertise: businesses, medical, and environment[11,12]. The purpose of this experiment is to improve the
performance and quality of the solutions gained by EA. EC variant used in this experiments is Genetic Algorithm and Particle Swarm Optimization combination with Backpropagation Neural Networks (BPNN). Hybridization between Genetic Algorithm and Backpropagation neural network is called Genetic Algorithm-Backpropagation (GA-BP) and Particle Swarm Optimization-Backpropagation (PSO-BP) for a combination between Particle Swarm Optimization and Backpropagation neural network.

2. Related Works

Genetic Algorithm and Ant Colony are tested and compared to know which algorithm has the best performance to optimizing course scheduling[13]. Performance measured is based on computational time and memory used. The experimental results showed that the genetic algorithm has a better performance than the ant colony optimization algorithm.

Rohini and M. Natarajan compared Genetic Algorithm (GA) with Particle Swarm Optimization (PSO), Ant Colony Optimization, and Tabu Search for university course scheduling system. The result of the research showed GA is worked better than Ant Colony, PSO, and Tabu Search because they have more insignificant penalty[14].

Three EC algorithms, namely GA, Differential Evolution (DE) and PSO, are compared gain optimization toward benchmark function. The comparison using the same parameters setting which are the number of generation, population size, number of dimensions, GA crossover probability, GA mutation probability, DE crossover probability DE differential weight, PSO inertia weight, PSO acceleration constant, PSO Random number, PSO Maximum velocity, PSO Maximum position and Number of testing. The experiments showed that GA worked better compared to DE and PSO in best minimum fitness and faster than DE and PSO. DE is faster than PSO, but based on the minimum and average fitness, PSO has better performance than DE[15].

GA and Grammatical Evolution (GE) are used to design the automated Genetic Programming (GP) classification algorithms. The automated GP classification results are compared to GA, GE, and manual design. The measurements of classification results are based on predictive accuracy and design times. The results showed that on average, across all datasets, the predictive accuracy of GP classifiers by GE is higher than GA and manual design. GP classification algorithms using the GA and GE were found to have fewer design times than manual design [16].

Optimization using hybrid GA and PSO ensemble with neural network and fuzzy integration type-1 and type-2 are proposed by Pulido and Melin. Study case for this research is prediction using the Taiwan Stock Exchange (TEX) time series data. The implemented method is compared to the traditional method in TEX[17].

PSO and GA are compared to decide the moisture diffusion coefficients of Pressboard Transformer Insulation. The PSO method proved to reduce the time spent in the determination of the moisture diffusion coefficient because of the robustness of PSO. PSO also simplified the methodology so that no need to apply any statistical analysis to ascertain the parameters of the moisture diffusion coefficient. [18].

3. Methodology

Data set used for forecasting in this research is time series data of tide level. A total number of data sets being used in this research is 1000, split into 700 for training, and the rest is to testing. Using the hybrid EC, the forecast process using GA-BP and PSO-BP shows in Figure 1. The first step to forecast is normalized the data set to ensure the data are scaling into comparable and acceptable data[19]. The architecture of BPNN is then initialized several neurons in the input layer. The architecture of PSO is set or initialize with standard PSO parameters, namely number of the swarm, c1, c2 inertia min, and inertia max. The architecture of GA initializes with parameters, namely the number of generation, population size, GA crossover probability, and GA mutation probability. BPNN architecture in this research is using five nodes in the input layer, three nodes in the hidden layer, one hidden layer, and one node in the output layer. One output layer is representing the prediction results. Configuration BPNN for GA-BP and PSO-BP displayed in Figure 2.
Figure 1. Flowchart of Forecast Using GA-BP and PSO-BP

Figure 2. BPNN Architecture for Tide Level Forecast

4. Results and Discussion
GA-BP and PSO-BP are testing using different parameter setting to gain precise accuracy. The parameter setting used in GA-BP are maximum iteration = 200, error target = 0.05 and chromosome number = 5, and variations of crossover probability, mutation probability shows in Table 1.
Table 1. Crossover Probability and Mutation Probability Setting for GA-BP

| No | Crossover Probability | Mutation Probability | Mean Squared Error (MSE) |
|----|-----------------------|-----------------------|--------------------------|
| 1  | 0.1                   | 0.1                   | 0.036759635              |
| 2  | 0.2                   | 0.1                   | 0.037658204              |
| 3  | 0.3                   | 0.1                   | 0.036658933              |
| 4  | 0.4                   | 0.1                   | 0.03671506               |
| 5  | 0.5                   | 0.1                   | 0.036328457              |
| 6  | 0.6                   | 0.1                   | 0.035598314              |
| 118| 0.5                   | 0.9                   | 0.037043519              |
| 119| 0.6                   | 0.9                   | 0.03741581               |
| 120| 0.7                   | 0.9                   | 0.036418678              |
| 121| 0.8                   | 0.9                   | 0.036696323              |
| 122| 0.9                   | 0.9                   | 0.03707204               |

Experiments show that crossover probability = 0.7 and mutation probability = 0.1 is the best because produces the smallest MSE. A variant of parameter setting used in testing PSO-BP are c1 = 1, c2 = 1, inertia min = 0.4, inertia max = 0.9 and the varying number of iteration, learning rate, and the number of the swarm can be seen in Table 2.

Table 2. Iteration, Learning Rate and Swarm Setting for PSO-BP

| No | Iteration | Learning Rate | Swarm | MSE       |
|----|-----------|---------------|-------|-----------|
| 1  | 10        | 0.1           | 10    | 0.043618  |
| 2  | 10        | 0.2           | 20    | 0.048769  |
| 3  | 10        | 0.3           | 30    | 0.009557  |
| 4  | 10        | 0.4           | 40    | 0.008882  |
| 5  | 10        | 0.5           | 50    | 0.010515  |
| 6  | 10        | 0.6           | 60    | 0.004941  |
| 31 | 30        | 0.1           | 10    | 0.009262  |
| 32 | 30        | 0.2           | 20    | 0.008243  |
| 33 | 30        | 0.3           | 30    | 0.006634  |
| 34 | 30        | 0.4           | 40    | 0.007604  |
| 35 | 30        | 0.5           | 50    | 0.006153  |
| 36 | 30        | 0.6           | 60    | 0.005955758|

The results of testing using different setting parameters from PSO-BP indicate the finest number of iteration = 20, learning rate = 0.9 and number of swarm = 90 with MSE = 0.003646227. Using the optimum parameters from GA-BP and PSO-BP tide level data are applied to achieve forecast data. Figure 3 illustrated the comparison of GA-BP, PSO-BP, and actual data.
Forecast result between GA-BP, PSO-BP and Actual Data (target) are slightly not too different, but based on Mean Absolute Percentage Error (MAPE) shows in Table 3, PSO-BP is a better algorithm than GA-PSO to forecast tide level because it has the smallest error.

| Evolutionary Algorithm | MAPE   |
|------------------------|--------|
| GA-BP                  | 10.57% |
| PSO-BP                 | 7.78%  |

5. Conclusions
The performance of GA-BP and PSO-BP trained Neural Network is compared in terms of testing tide level data for forecasting. Different parameters of GA-BP and PSO-BP are setting to get optimum value. Results of prediction using GA- GA-BP and PSO-BP are compared with actual data or target. The accuracy of prediction is measured by MAPE. Results show that PSO-BP is given better prediction results than GA-BP with an error of 7.78 % while GA-BP is 10.57 %.

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