A New Hybrid Model with Passive Congregation for Stock Market Indices Prediction

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Abstract—In this paper, we propose a new hybrid learning model for stock market indices prediction by adding a passive congregation term to the standard hybrid model comprising Particle Swarm Optimization (PSO) with Genetic Algorithm (GA) operators in training Neural Networks (NN). This new passive congregation term is based on the cooperation between different particles in determining new positions rather than depending on the particles selfish thinking without considering other particles positions, thus it enables PSO to perform both the local and global search instead of only doing the local search. Experiment study carried out on the most famous European stock market indices shows significantly the influence of the passive congregation term in improving the prediction accuracy compared to standard hybrid model.

Keywords—Global Search, Hybrid Model, Passive Congregation, Stock Market Prediction

I. INTRODUCTION

STOCK market indices movement is affected by many complex events such as political and social situations, interest rate, business cycles, and monetary policies, thus it is a non-stationary and time invariant process fluctuating rapidly in a short period of time. It is so difficult to build an accurate prediction model for stock market indices. For example, Recurrent Neural Networks (RNN) trained by back propagation learning algorithm [1] and FeedForward Neural Networks (FNN) trained by optimum feature transformation [2] were used in stock market indices prediction. Also, Genetic Algorithm (GA) operators was used in learning (FNN) giving better results than back propagation learning algorithm in stock market indices prediction [3]. As training an ensemble of neural networks for the same task can produce more accurate results than using individual neural network [4]. Particle Swarm Optimization (PSO) was used in training Selective Neural Network (PSOSEN) in stock market indices prediction giving more accurate promising results than other training algorithm [5]. However, as PSO is a population-based search algorithm starting with an initial population of randomly generated solutions called particles; it could easily stuck in a local optimum because it converges towards the global best found so far which is not guaranteed to be even a local optimum [6]. To overcome local optimum problem, GAs' operators like selection, crossover, and mutation were introduced into the PSO while training neural networks to make the global search by exploring new regions through the whole search space [7]. Based on this recognition, a new hybrid model based on (PSO) incorporated with (GA) operated were applied in training Flexible Neural Tree (FNT) to increase the prediction accuracy of stock market indices [8].

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However, in this hybrid model, only the GA operators are responsible in doing the global search while the PSO algorithm itself is still restricted in doing the local search around its best position and the global best position without any capability in doing the global search which lead to poor model performance in terms of accuracy, convergence speed and robustness [9]. To overcome this problem and improve the model performance, each particle in the swarm should not to be restricted in local search and should be capable of performing the global search [10].

Thus, we introduce our new proposed hybrid model inspired by the passive congregation biological mechanisms of school of fishes and flock of birds by inserting the position difference between other two particles into the particle position update equation. This term enables each particle to compare between its performance using both its selfish thinking and the cooperation with other particles to adjust its position in new better regions in the search space. This new hybrid model will train the Sigmoid Diagonal Recurrent Neural Networks (SDRNN) which we have proved in our previous works that it is the more suited to the real practical problems than other networks architectures [11], [12]. We analyze the most three famous European stock market indices which are CAC40, DAX, and FTSE100 and compare the performance between our proposed hybrid model and the standard one.

Simulations results show significantly that the passive congregation term positively enhance the prediction accuracy and keep the fast convergence speed and robustness while the standard hybrid model could not achieve the desired enhancement. This paper is organized as follows: section II reviews main concepts of the hybrid model and section III introduces our passive congregation model. Experimental study is presented in section IV.

II. HYBRID MODEL

The hybrid model consists of two parts, first the Particle Swarm Optimization (PSO) and the second one is the Genetic Algorithm (GA) operators

A. Particle Swarm Optimization (PSO)

PSO is a population based stochastic optimization technique developed by Kennedy and Eberhart and each particle in the swarm represents a possible potential solution of the optimization problem in D-dimensional space [13]. At the kth generation the ith particle in the swarm is represented by its current position $X_i(k) = \left(x_{i1}(k), x_{i2}(k), .., x_{iD}(k)\right)$, its current velocity $V_i(k) = \left(v_{i1}(k), v_{i2}(k), ..., v_{iD}(k)\right)$, and its current fitness function $F_i(k)$. The particle position and velocity are updated in the next generation by the following equations

$$V_i(k + 1) = w * V_i(k) + C_1 * \varphi_1 * \left(X_g - X_i(k) \right)$$

$$+ C_2 * \varphi_2 * \left(X_{ibest} - X_i(k) \right) \qquad (1)$$

$$X_i(k + 1) = X_i(k) + V_i(k + 1) \qquad (2)$$

Also the ith particle autographical memory remembering its best previous position $X_{ibest}(k) = \left(x_{ibest1}(k), x_{ibest2}(k), .., x_{ibestD}(k) \right)$ associated with the particle current best fitness function F_{best} and the global best position obtained so far $X_g = \left(x_{g1}, x_{g2}, .., x_{gD} \right)$ corresponding to the global best fitness function F_g of all particles in the swarm. From (1), the first term represents the inertia of the particle pervious velocity and w is inertia weight; the second term is the social term representing the cooperation among all particles where C_1 is the social constant and the third term is the cognition term which represents the private thinking and the selfish behavior of the particle itself where C_2 is cognitive constants and both φ_1 and φ_1 are random variables in the range [0, 1].

B. Genetic Algorithm (GA) operators

The second part of the hybrid model is applying the GA operators which are selection, crossover, and mutation and they are used after the fitness evaluation of all the swarm particles in each generation to increase the diversity and to give particles the ability to fly to new regions in the search space. Selection is the process of selecting highly performance particles as parents in the creation of a new generation, the crossover operator produces two new children particles by recombining the information of the two selected parents, and the mutation operator is used to mutate the new generated particles [14]. Thus, the worst (S*Ψ) particles performance are discarded and removed from the population where Ψ is the breeding ratio determining the discarded proportion of the swarm and its value is arbitrary selected in the range [0.0, 1.0] [7]. Then, parents particles are selected randomly from the remaining (S*(1-Ψ)) particles, to undergo crossover operator producing new child particles using the Velocity Propelled Averaged Crossover (VPAC) [7] to accelerate the new particles away from their parents' direction according to the following equations.

$$X_1^C(k + 1) = \frac{X_1(k) + X_2(k)}{2} - \beta_1 * V_1(k) \qquad (3a)$$

$$X_2^C(k + 1) = \frac{X_1(k) + X_2(k)}{2} - \beta_1 * V_2(k) \qquad (3b)$$

Where $X_1^C(k + 1)$ and $X_2^C(k + 1)$ are the positions of the two generated child particles, $X_1(k)$ and $X_2(k)$ are the positions of the parents particles, $V_1(k)$ and $V_2(k)$ are their associated velocities and β_1 and β_2 are two uniformly distributed random variables in the range [0, 1]. For the mutation process, all variables in the new created child particles are equally probable to be mutated [14], [15].

III. HYBRID PASSIVE CONGREGATION MODEL

Biologists found out that in a spatially well-defined group such as school of fishes or flock of birds, each individual can monitor both the environment and its immediate surrounding such as the position and the speed of neighbors, so they proposed two types of biological mechanisms to realize these requirements which are active aggregation and passive congregation [16].

Active aggregation is the transfer of necessary and active information among different individuals in the entire group such as the place with the most food and displays their social behaviors, this mechanism can be represented by the social term in (1) because it transfers the best position found so far to all particles in the swarm. Passive congregation is an attraction from one individual to others but does not display social behaviors. Individuals may have law fidelity to other group members if they have little or no genetic relation between them, also each individual has multitude of potential information from other group members helping in reducing the possibility of miss detection and incorrect interpretations. Thus, the passive congregation helps individuals to make global search in the whole search space and find new regions with better solutions [16].

Thus, the cognitive term in (1) is not enough to represent the passive congregation mechanism because it displays only particle's best previous position without thinking of other particles positions. To fully represent this mechanism, a passive congregation term is included and described as the position difference between two other randomly selected particles in the swarm. Thus in each generation, the ith particle passive congregation term $P_i(k + 1)$ is written as follows:-

$$P_i(k + 1) = C_3 * \varphi_3 * \left(X_l(k) - X_m(k) \right) \qquad (4)$$

Where $X_l(k)$ and $X_m(k)$ are the positions of particles l and m respectively and $i \neq l \neq m$, C_3 is the passive congregation constant and φ_3 is random variable in the range [0, 1]. The new i^{th} particle velocity with passive congregation $V_i^P(k + 1)$ is constructed by inserting this passive congregation term instead of the cognitive term in (1) and is written as follows:-

$$V_i^P(k + 1) = w * V_i(k) + C_1 * \varphi_1 * \left(X_g - X_i(k) \right)$$

$$+ P_i(k + 1) \qquad (5)$$

From the above equation, the new velocity is based on other cooperative thinking between different particles while the standard velocity in (1) is based on the selfish thinking of the particle without any cooperation with other particles. Consequently, the ith new particle position with passive congregation $X_i^P(k + 1)$ is calculated as follows:-

$$X_i^P(k + 1) = X_i(k) + V_i^P(k + 1) \qquad (6)$$

The fitness function $F_i^P(k + 1)$ associated with this passive congregation term is compared with the standard one $F_i^S(k + 1)$ associated with the cognitive term, if $F_i^P(k + 1)$ is better than $F_i^S(k + 1)$, so the passive congregation term improves the fitness function and the selected particles help in making

correct interpretation through the global search in the whole search space enabling the original particle to find new position with better performance. On the other hand, if the passive congregation term doesn't improve the fitness function, so there is no genetic or little genetic relation between this particle and the other selected particles. Thus all particles in the swarm can perform the global search by comparing the standard fitness functions associated with the original cognitive term and the passive congregation fitness function associated with the passive congregation term. The proposed algorithm can be summarized in the following steps

Step1 (Initialization): randomly create an initial swarm of particles and setup the required inertia, social, cognitive, and perturbation constants. At each generation, for each particle in the swarm do the following

Step2 (Cognitive term utilization): update the velocity $V_i(k + 1)$ and position $X_i(k + 1)$ using the cognitive term as in (1) and (2) and compute its associated fitness function $F_i(k + 1)$.

Step3 (Passive congregation term construction): randomly select two other particles to construct the passive congregation term $P_i(k + 1)$ using equation (4).

Step4 (Passive congregation term utilization): compute both the velocity $V_i^P(k + 1)$ and position $X_i^P(k + 1)$ using the passive congregation term as in (5) and (6) and compute its associated fitness function $F_i^P(k + 1)$

Step5 (Fitness Check): Select the particle fitness functions $F_i(k + 1)$ as the minimum of the standard fitness function $F_i^S(k + 1)$ and the passive congregation fitness function $F_i^P(k + 1)$, then modify accordingly both the particle best position and the global best position

Step6 (Selection): after modifying all particles positions, velocity, and fitness in the current generation, select the particles with the worst performance part according to the breeding ratio Ψ to be replaced with other particles selected randomly as parents particles from the remaining part of the swarm

Step7 (Crossover): construct the new child particles $X^C(k)$ to replace the worst particles as in (3-a), and (3-b).

Step8 (Mutation): select randomly with equal probability one variable in the search space from the new children particles to be mutated. Return to step 2 to start a new generation.

IV. EXPERIMENTAL STUDY

In our experiments, the used stock market indices data were obtained from the Yahoo Finance website [17].These indices are CAC40 representing a capitalization-weighted measure of the 40 most significant values among the 100 highest market caps on the Paris stock exchange, DAX representing the 30 major German companies trading on the Frankfurt stock exchange, and FTSE100 is a share index of the 100 most highly capitalised UK companies listed on the London Stock exchange and they are shown in Fig.1,2 and 3 respectively.
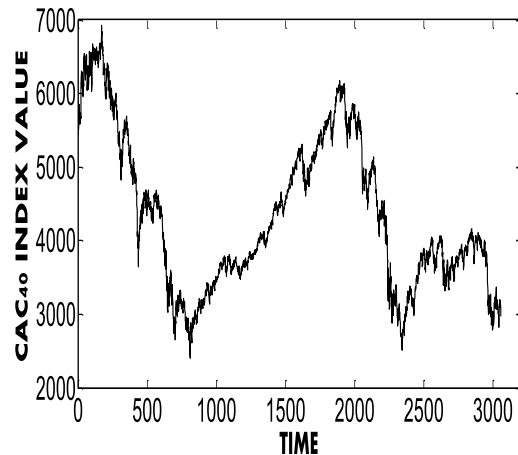

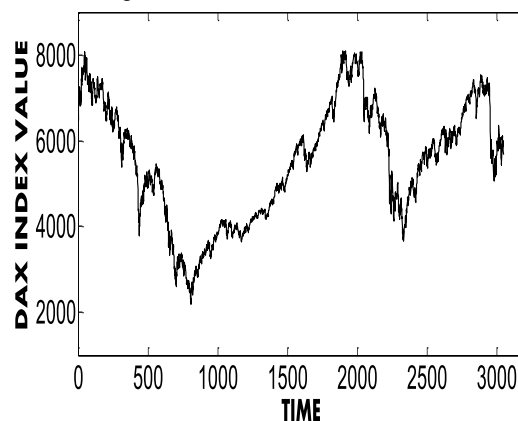Fig. 1 CAC40 index value movement
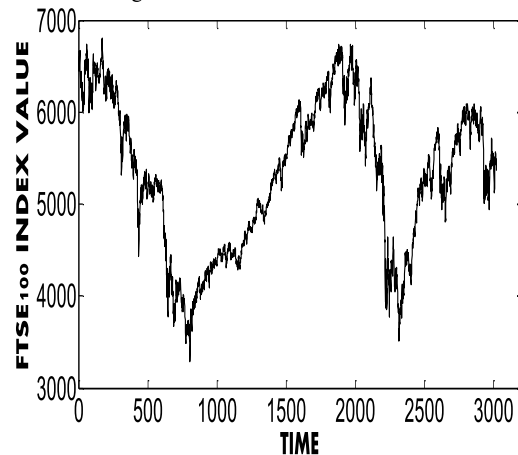

Fig. 2 DAX index value movement

Fig. 3 FTSE100 index value movement

Form these above figures; it is obvious that there is a high fluctuation in the movement of the stock market indices in both the uptrend and downtrend movement directions which increase the possibility of trapping in a local minimum leading to poor performance accuracy. Thus the need for accurate prediction model increases to handle these fluctuation movements.

The neural network architecture used as the stock market indices predictor is the Sigmoid Diagonal Recurrent Neural Network (SDRNN) because it was proved in our previous work that this architecture is better than other different architectures for reducing the error and increasing the accuracy in many applications [11],[12]. Preliminary researches suggested that input comprises daily open, maximum, and closing values while the output is the next day closing value [5], [8], so the size of the SDRNN is 4, 4, 1(i.e.; 4 input neurons, 4 hidden layer neurons and 1output neuron) and the input vector contains previous day open, maximum, and closing values beside the delayed predictor output value, while the output of the neural network predictor is the today predicted closing value. Both the standard hybrid model and our hybrid with passive congregation model are used to train the predictor weights set and the accuracy of these two models are compared to show the influence of our proposed model. In our experiment, we choose a swarm size of 40 particles, number of generations is set to 80, breeding ratio 0.1 and all constants and inertia are set to one

The assessment of the prediction performance and accuracy of reducing this fitness function as much as possible is done in terms of the Maximum Absolute Difference (MAX) and the Mean Absolute Percentage Error (MAPE) [5], [8] and they are defined as follows:

$$MAX = \max_{n}\left(\left|Y_a(n) - Y_p(n)\right|\right) \quad (7)$$

$$MAPE = \frac{1}{N}\sum_{n=1}^{N}\left(\frac{\left|Y_a(n) - Y_p(n)\right|}{Y_a(n)} * 100\right) (8)$$

Where N is the size of the data set, and $n = 1,2,...,N$ and $Y_a(n)$ is the actual stock market closing price and $Y_p(n)$ is the predictor output at the nth sample. Also, the fitness function is defined as the sum square error between the actual output and the predicted output divided by the data size [5], [8] and can be defined as follows:

$$F = \frac{1}{N}\sum_{n=1}^{N}\left(Y_a(n) - Y_p(n)\right)^2 \quad (9)$$

The data was divided into two parts which are training data and testing data [5], [8], the training data were chosen starting form 3/1/2000 to 1/1/2006 while the testing data was chosen from3/1/2006 to 14/12/2011 and the best fitness obtained through all generations using both standard model and our proposed passive congregation model with for CAC40, DAX and FTSE100 are shown in Figure 4, 5, and 6 respectively.
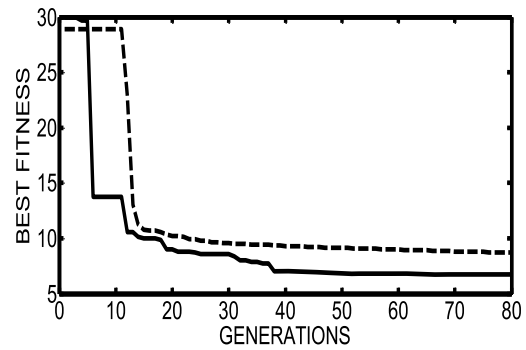

Fig. 4 CAC40 best fitness where the dotted line represents the best fitness obtained using the standard model and the solid line represents the best fitness obtained using the passive congregation model
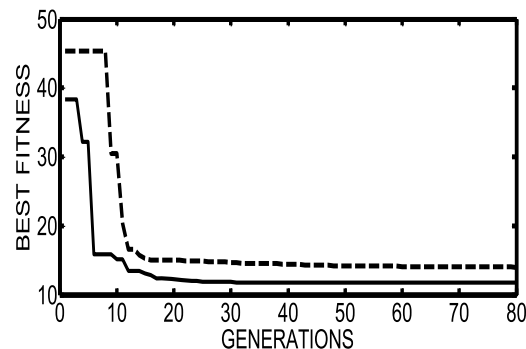

Fig. 5 DAX best fitness where the dotted line represents the best fitness obtained using the standard model and the solid line represents the best fitness obtained using the passive congregation model
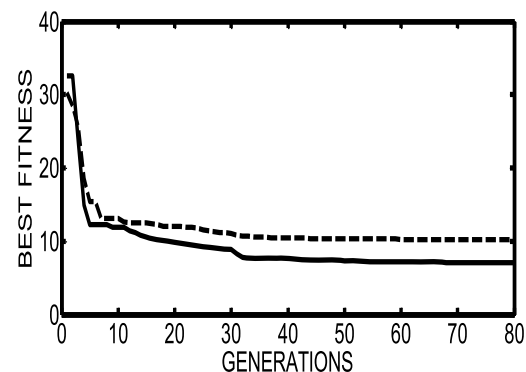

Fig. 6 FTSE100 best fitness where the dotted line represents the best fitness obtained using the standard model and the solid line represents the best fitness obtained using the passive congregation model

The plots in Figs. 4,5, and 6 show that our proposed model reduces successfully the required fitness function within a small number of generations while the standard one failed throughout the whole generation. Also, although the best fitness function of both CAC40 and FTSE100 indices using our proposed hybrid model were worse than the performance using the standard one during the first few generations, they became better during the following generations due to the existence of the passive congregation term which enables all particles in the swarm to perform the global search to find new regions with better solutions in the whole search space

The MAX performance measurements using both standard model and the passive congregation model in both the training and testing for these stock market indices are shown in Tables I and II respectively.

TABLE I
MAX PERFORMANCE MEASUREMENT IN TRAINING USING STANDARD MODEL AND PASSIVE CONGREGATION MODEL

MAX Training		
	Standard	Passive Congregation
CAC40	55	84
DAX	68	97
FTSE100	107	168

TABLE II
MAX PERFORMANCE MEASUREMENT IN TESTING USING STANDARD MODEL AND PASSIVE CONGREGATION MODEL

MAX Testing		
	Standard	Passive Congregation
CAC40	57	87
DAX	71	99
FTSE100	109	174

The MAPE performance measurements using both standard model and the passive congregation model in both the training and testing for these stock market indices are shown in Tables III and IV respectively.

TABLE III
MAPE PERFORMANCE MEASUREMENT IN TRAINING USING STANDARD MODEL AND PASSIVE CONGREGATION MODEL

MAPE Training		
	Standard	Passive Congregation
CAC40	0.12%	0.74%
DAX	0.11%	0.72%
FTSE100	0.28%	0.91%

TABLE IV
MAPE PERFORMANCE MEASUREMENT IN TESTING USING STANDARD MODEL AND PASSIVE CONGREGATION MODEL

MAPE Testing		
	Standard	Passive Congregation
CAC40	0.13%	0.77%
DAX	0.13%	0.75%
FTSE100	0.29%	0.94%

The performance measurements shown in Tables I, II, III and IV indicate obviously that our proposed model is superior to the standard one and yields better perdition accuracy in all the three stock market indices for both the training and testing phase and the obvious poor performance of the standard hybrid model is due to the particles positions are dependent on their own thinking without knowing any information about others warm particles. This disadvantages is avoided in our passive congregation model because each particle position is dependent on other particles positions which is useful for avoiding miss detection and increasing the correct interpretation.

For the future work, our proposed hybrid model can be used in other stock market application such as prediction of the stock market indicators and classification of the markets trends. Also, it could be used to obtain more accurate financial models in representing complex financial problems.

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