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Study on Mutual Funds Trading Strategy Using TPSO and MACD

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***Abstract*— A successful trading strategy is necessary to achieve the profit and good market forecast. In this paper, an efficient and simple trading strategy model is designed based on optimization algorithm, Turbulent Particle Swarm Optimization (TPSO) in combination with a technical indicator namely Moving Average Convergence-Divergence (MACD). To check the stability and performance of the proposed technique, different window sizes of training data are used. From the experimental finding, it turns out that proper duration of training period is very important to achieve better profit. In this presented work, a comparison has been made among different window sizes, and the best performance was obtained with training period of seven years. The performance of each fund on average has been improved more than the original about 38% and 22% for 7 and 8 years training period respectively in testing phase.**

***Keywords*— Exponential Moving Average; Moving Average Convergence – Divergence; Mutual funds; Particle Swarm Optimization; Turbulent Particle Swarm Optimization.**

I. Introduction

In the existing trading market, various investment vehicles such as deposits, stocks, real estate, foreign exchange, futures and options etc. are available. Each of these investment vehicles has its own advantages and disadvantages. For example, people choose the deposits because it is safe and has very low risk factor. But it has the disadvantage of less revenue in comparison to other investments vehicles. On the other hand, stocks have excellent potential for long-term value-added but it has higher price volatility, relatively high investment risk, and it takes time to gather information and study. Choosing a particular investment vehicle depends on its risk factor, stability and investor’s choices. There are many factors that affect the value of stocks. One example is interest rates, i.e. the amount of money you have to pay to the bank as loan money, or pay back to you to keep your money in their bank. If interest rates are high, stock prices generally go down, because if people can earn a decent amount of money by keeping their money in banks, or buying bonds, they feel like they should not take the risk in the stock market. Accounting all the risks in the investment, mutual funds are considered to be one of the safest investment vehicles that acquired all types of investment styles and all sorts of securities. It makes money with less cost by just following the flow of the market and buys number of securities and split into individual share [1]. Although, mutual funds are low risk in nature but sudden dramatic decline of stock prices across a significant cross-section of a stock market trigger the instability in the trading market. Also additional transaction fee will erode the capital in case of frequent trading. Therefore, it is necessary to implement a good trading strategy to enhance the profits, reducing the risk and to overcome big stock disaster by successful stock market forecast. Several techniques had been developed by many researchers for a successful forecast index values or stock prices as reported in the literature [2]-[5]. In this paper, we propose a trading strategy of mutual funds based on Turbulent Particle Swarm Optimization (TPSO) and trend following indicators namely Moving Average Convergence-Divergence (MACD).

The remainder of this paper is organized as follows. In section 2, we describe the introduction of particle swarm optimization (PSO) and Turbulent Particle Swarm Optimization (TPSO). The details of technical indicators which include Exponential Moving Averages (EMAs), Moving Average Convergence – Divergence (MACD) and proposed trading strategy algorithm are explained in section 3. In section 4, we discuss the details of the proposed new trading strategy method based on TPSO and MACD. The experimental details and results obtained from the new proposed investment strategy and comparison with original performance are explained in section 5. Finally, section 6 summarizes the conclusions and future work.

II. Particle Swarm Optimization

Particle swarm optimization (PSO) is a population based search algorithm based on the simulation of the social behaviour of birds, bees or a school of fishes [6]. It implements the underlying rules that enable large numbers of organisms (birds, fishes, herds) to move synchronously, often changing direction suddenly, scattering and regrouping. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). The system is initialized with a population of random solutions and searches for optima by updating generations or iterations [7]. However, unlike GA, PSO has no evolution operators such as crossover and mutation. In PSO, the potential solutions, called particles or swarms, fly through the problem space by following the current optimum particles. This behaviour mimics the cultural adaptation of a biological agent in a swarm or a particle; it evaluates its own position based on certain fitness criteria, compares with others, and imitates the best in the entire swarm. The particles attract to the position or location of the best solution (fitness) which have been achieved so far. The evaluation of the objective function historically achieved by the particle itself is called *pBest* (local best). The best value among the neighbours or all the population of the particles is called *gBest* (global best). In essence, each particle continuously focuses and refocuses the effort of its search according to both local and global best. The particle swarm optimization concept consists of, at each time step, changing the velocity and updates the location or position of each particle toward its *pBest* location. Acceleration is weighted by a random term, with separate random numbers being generated for acceleration toward *pBest* location. It also needs to update the best value, *gBest* that is tracked by particle swarm optimizer or obtained so far by any particle in the population. After finding the two best values, the particle updates its velocity and positions with the following equation (1) and (2).

$$\vec{V}_i(t+1) = w \times \vec{V}_i(t) + c_1 \times r_{i1}(t) \times \left(\vec{P}_i(t) - \vec{X}_i(t)\right) + c_2 \times r_{i2}(t) \times \left(\vec{P}_g(t) - \vec{X}_i(t)\right) \quad (1)$$

$$\vec{X}_i(t+1) = \vec{X}_i(t) + \vec{V}_i(t+1) \quad (2)$$

$$w(t) = \max w - (\max w - \min w) * t / \textit{total iteration} \quad (3)$$

where t is the current iteration number and $t+1$ is the next iteration number, $\vec{V}_i(t+1)$ represents the next velocity and $\vec{V}_i(t)$ is the current velocity of the i^{th} particle in t^{th} iteration, $\vec{P}_i(t)$ is the *pBest* of the i^{th} particle in t^{th} iteration, $\vec{P}_g(t)$ is the *gBest* of all the particles in t^{th} iteration, $\vec{X}_i(t+1)$ represents the next location or position which will be updated and $\vec{X}_i(t)$ is the current location of the i^{th} particle in t^{th} iteration. w is an inertia weight to control influence of the previous velocity, usually between 0 and 1, w can be varied in each t^{th} iteration as per equation (3), *maxw* represents the maximum limit of inertia weight and *minw* the minimum weight. $r_{i1}(t)$ and $r_{i2}(t)$ are two random numbers uniformly distributed in the range of (0,1). c_1 and c_2 are two acceleration constants; usually between 1~4. Finally, particles in the swarm will move with different velocities throughout the iterations to find the optimal location.

PSO algorithm has been used on various domains which include forecast enrolments, flow-shop scheduling, traveling salesman problem, shortest path problem, temperature prediction , job-shop scheduling etc. [8]-[14].

A. Turbulent Particle Swarm Optimization

TPSO deals to overcome the problem of premature convergence in PSO algorithm. It is due to the decrease of velocity of particles in the search space that leads to a total implosion and ultimately fitness stagnation of the swarm [15]-[18]. To drive those lazy particles, TPSO introduced the formulae which can explore a better solution. They are shown as follows [19]:

$$V_i = \begin{cases} V_{max} & \text{if } V_i > V_{max}; \\ V_{min} & \text{if } V_i < V_{min}; \\ V_{min} + 2 \times V_{max} \times \text{rand}() & \text{if } |V_i| < V_s; \\ V_i & \text{otherwise,} \end{cases} \quad (4)$$

$$V_{max} = k * X_{max}, \quad \text{where } 0.1 \le k \le 1.0 \quad (5)$$

$$V_{min} = -V_{max} \quad (6)$$

Where V_i is the calculated velocity by using equation (1), V_s is the minimum velocity threshold, a threshold parameter to limit the minimum of a particle velocity, and *rand ()* is a uniformly distributed random number in the range [0, 1]. If *Vs* is large, it will shorten the oscillation period, and facilitates a global search. On the other hand, if *Vs* is small, it facilitates a local search. *Xmax* is the maximum limit of particle location.

III. TECHNICAL INDICATORS

Technical analysis is the evaluation of securities by means of studying statistics generated by market activity, such as past prices and volume. Technical analysts do not attempt to measure a security's intrinsic value but instead use stock charts to identify patterns and trends that may suggest the nature of stock fluctuations in the future [20].

Technical indicators are the basis of technical analysis which is more objective than chart patterns. It helps to identify trends and their turning points and provides a deeper insight of balancing power between bulls and bears. The price data includes any combination of the open, high, low or close over a period of time. Technical indicators can be categorized into three groups [21]:

(i) Trend-following indicators: These are coincident or lagging indicators - they turn after trends reverse. They include moving averages, MACD (moving average convergence-divergence), MACD-Histogram, the Directional System, On-Balance Volume, Accumulation/Distribution, etc.

(ii) Oscillators Indicators: These are leading or coincident indicators and often turn ahead of prices. It helps to identify turning points. They include Stochastic, Rate of Change, Smoothed Rate of Change, Momentum, the Relative Strength Index, Elder-ray, the Force Index, Williams %R, the Commodity Channel Index, etc.

(iii) Miscellaneous indicators: These are leading or coincident indicators. It provides insights into the intensity of bullish or bearish market opinion. They include New High-New Low Index, Put-Call Ratio, Bullish Consensus, Commitments of Traders, Advance Decline Index, the Traders' Index, etc.

A. Exponential Moving Averages

An Exponential Moving Average (EMA) is one of the moving averages which is a better trend following tool than a Simple Moving Average (SMA). It responds only one time and gives greater weight to the latest data. It also responds to change faster than a SMA. At the same time, it does not jump in response to old data. Whereas, a SMA shows the average value of data in its time window. A 5-day SMA shows the average price for the past 5 days, a 20-day SMA shows the average price for the past 20 days, and so on. The value of SMA depends on two factors: values that are being averaged and the width of the MA time window. However, EMA can be described by the following relation [22]:

$$EMA = P_{tod} * K + EMA_{yest} * (1-K) \quad (7)$$

Where

N = the number of days in the EMA (chosen by the trader).

Ptod = today's price

EMA_{yest} = the EMA of yesterday

EMA calculation can be performed by the following steps:
1. Choose the EMA length, N. Let's say, to calculate for 10-day time interval.
2. Calculate the K value, that is K = 2/N+1 where N=10.
3. For calculating the first EMAyest, we need to calculate the SMA of first10 days i.e., add the closing prices for ten days and divided by 10.
4. On the 11th day, multiply the closing price of that day by K and multiply EMA_{yest} by (1-K). The evaluated result will be the corresponding 10-day EMA.
5. We keep on repeating step 4 on subsequent days to obtain their latest EMAs.

B. *Moving Average Convergence-Divergence*

Moving Average Convergence-Divergence (MACD) was constructed by Gerald Appel, an analyst and money manager in New York [22]. It consists of three EMAs which will generate two signal lines, fast MACD line and slow Signal line. Their crossovers give the trading signals i.e. "Buy" and "Sell".

The fast MACD line is made up of first two EMAs. That is after calculating the first two EMAs, we need to subtract the two and get the fast MACD line. It responds to change in prices relatively quickly. The slow Signal line is got from the third time interval EMA with using the data of fast MACD line and responds to change in prices relatively slowly.

C. *Trading Strategy*

In this paper, an efficient trading strategy is designed using three EMAs to determine good buy and sell points. Crossovers between the fast MACD and slow Signal lines identify changing market tides. Trading in the direction of a crossover means it's going with the flow of the market. The trading strategy signals are decided after the crossing point of fast MACD and slow Signal lines by the following conditions:

$$signal_k = \begin{cases} \text{buy} & \text{if Fast MACD line} > \text{Slow signal line;} \\ \text{sell} & \text{if Fast MACD line} < \text{Slow signal line;} \\ \text{hold} & \text{otherwise;} \end{cases} \quad (8)$$

Algorithm of Trading Strategy:

input three time intervals T_j, for $1 \leqslant j \leqslant 3$

calculate the EMA_{yest} T_j, for $1 \leqslant j \leqslant 2$

for k in historical price sorted by ascending date

calculate two exponential moving averages with time intervals T_1 & T_2 [for $1 \leqslant T_j \leqslant 2$]

[Using above equation (7)]

substract two EMAs and get the Fast MACD line

endfor

calculate the EMA_{yest} for time interval T_3 using the Fast MACD line data

for k in length of Fast MACD line

calculate another EMA of the Fast MACD line with time interval T_3 and gives the Slow Signal line [for T_j=3]

endfor

initialize *Capital* = 1 and *State* = holding capital

for k in historical price sorted by ascending date

if (Fast MACD Line > Slow Signal Line)

Signal$_k$=buy

if (*State* = holding capital) and (*signal*$_k$ = buy)

holding fund *FundUnit* = *Capital* / (*FundNet*$_k$ * (1+ *FundFee*)).

State = holding fund.

elseif (*State* = holding fund) and (*signal*$_k$ = buy)

State=holding fund.

else

State= holding fund.

endif

elseif (Fast MACD Line < Slow Signal Line)

Signal$_k$=sell

if (*State* = holding fund) and (*signal*$_k$ = sell)

holding capital *Capital* = *FundUnit* * *FundNet*$_k$

State = holding capital.

elseif (*State* = holding capital) and (*signal*$_k$ = sell)

State=holding capital.

else

State=holding capital.

endif

endif

endfor

if (*State* = holding fund) **then**

Capital = *FundUnit* * *FundNetLastDate*

endif

return *Capital*.

Here, we initialize the *Capital* as 1 and *State* = holding capital. The trading signals are buy, sell and hold. T_j represents the time intervals where j=1, 2, 3. EMA_{yest} is the value of EMA yesterday. *State* represents the state in holding capital or in holding fund, *FundUnit* represents holding fund unit, $FundNet_k$ represents the fund net in *k* position of date, *FundFee* represents the fund transaction fee which varies depending upon the fund. *FundNetLastDate* is the fund net of the last date.

IV. PROPOSED METHOD

A. Turbulent Particle Swarm Optimization and Moving Average Convergence and Divergence (TPSO-MACD)

In this paper, we have proposed the method which is the combination of Turbulent Particle Swarm Optimization and Moving Average Convergence – Divergence. The reason of choosing PSO algorithm are its simplicity and implemented in little code, as compared to the GA, and its performance endorsed in a wide domain of engineering design and optimization applications [3]. Another reason which makes PSO so attractive is because there are only few parameters to adjust. One version, with slight variations, works well in a wide variety of applications. In addition, TPSO algorithm can overcome the premature convergence and the problem of stagnation of the particles exploration of a new search space of PSO. It is similar to a turbulent pump and supplies some power to the swarm system to explore new search spaces (better solutions). The basic idea is to drive those lazy particles and get them to explore new search spaces. The algorithm also avoids clustering of particles and at the same time attempts to maintain diversity of population [15], [16]. Moreover, we have used trend following indicator, MACD to analysis the trading strategy because a trend is more likely to continue than reverse. This principle is one of the basic tenets of Dow Theory: A trend has a higher probability of continuation that it does of reversal [22].

B. Details of Proposed Method

The procedures of proposed method are given below:

1. Define all the constant parameters of the PSO such as *ssize* (particle size), *spar* (number of components in a particle i.e. 3 time intervals), *Vs* (minimum threshold velocity), total iterations, c_1, c_2, k, *maxw* (maximum inertia weight), *minw* (minimum inertia weight), *Xmax* (maximum limit of particle location), *Xmin* (minimum limit of particle location), *Vmax* (maximum velocity), and *Vmin* (minimum velocity).
2. There are three time intervals to calculate the Exponential Moving Averages (EMAs).
3. But the lengths of time intervals for calculating the EMAs are an unknown variable. It is difficult to decide which time interval will give the best trading points.
4. By using the optimization algorithm namely PSO helps to decide the length of the time intervals.
5. The time intervals represent the location of a particle i.e., each particle contains three time intervals.
6. After obtaining the time intervals of all the particles from PSO, it is used by the trading strategy algorithm.
7. Calculate the EMA_{yest} for first two time intervals of all the particles.
8. Calculate the first EMA using the historical price and 1st time interval of each particle.
9. Calculate the second EMA using the historical price and 2nd time interval of each particle.
10. Subtract the second EMA from first EMA and gets the fast MACD line for all the particles.
11. Calculate the third EMA using the fast MACD line and 3rd time interval of each particle.
12. It gives the slow Signal line.
13. We decide the trading signal points: “Buy”, “Sell”, or “Hold” using the fast MACD line and slow Signal line data.
14. We calculate the returned capital as per trading strategy algorithm for all the particles.
15. Now the returned capital will represent as the fitness values of all the particles in Particle Swarm Optimization.
16. Assign the fitness values to *pBest* and its location to *pBestLocation*.
17. Select the maximum of fitness value and assign to *gBest*. Its particular location is assigned to *gBestLocation*.
18. Calculate the particle velocity according to the equation (1).
19. Update all the particles location according to the equation (2).
20. Repeat the steps from 6 to 19 until the total iteration is satisfied.
21. After the criterion is met, finally we have got the maximum fitness value as *gBest*, and its corresponding location as *gBestLocation* which will be the best time intervals for testing data.
22. The obtained *gBest* will be the return capital in training whereas in testing phase we will get the capital using the *gBestLocation* as length of time intervals.

V. DISCUSSION OF EXPERIMENT AND COMPARISON

A. Experiment Details

In this paper, we have focused on mutual trust companies of Taiwan which have taken from “Taiwan Large-Cap Equity” and “Taiwan Small/Mid-Cap Equity”. The reason is they are the most popular invested funds. The data are collected from the website www.cnyes.com. In this experiment, we set the initial capital as \$1. The length of three time intervals used in this trading strategy model is chosen within the range of 10 to 150. The minimum threshold velocity V_s is taken as 1 and k is equal to 0.5. The total 50 particles are taken in the calculation with 150 iterations. c_1 and c_2 values are taken as 2 and 2.7 respectively. The maximum inertia weight is taken as 1.4 and minimum is 0.4. Experiments are conducted at different window sizes i.e. 1-year, 2-years, 3-years, 4-years, 5-years, 6-years, 7-years, 8-years for training data and one year data has been used for testing of the mentioned window sizes.

A performance measure parameter so called return on investment (ROI) is used to evaluate the efficiency of an investment or to compare the efficiency of a fund. This parameter can be calculated from the following equation [19]:

$$ROI = \frac{GainFromInvestment\ -\ CostOfInvestment}{CostOfInvestment} \qquad (9)$$

The *CostOfInvestment* is the beginning money which will be used for the investment. The *GainFromInvestment* is the return money from the investment. For example, we have \$100 at the beginning of the investment. The final return of the investment is \$200. Then the ROI is 100 (or 100%). The time intervals for calculating the return of investment with different window sizes for training and testing are given in the table I & II.

TABLE I
DIFFERENT WINDOW SIZES FOR TRAINING PHASE

Training							
One Year	**Two Years**	**Three Years**	**Four Years**	**Five Years**	**Six Years**	**Seven Years**	**Eight Years**
20000703-20010702	20000703-20020702	20000703-20030702	20000703-20040702	20000703-20050704	20000703-20060703	20000703-20070702	20000703-20080702
20010703-20020702	20010703-20030702	20010703-20040702	20010703-20050704	20010703-20060703	20010703-20070702	20010703-20080702	
20020703-20030702	20020703-20040702	20020703-20050704	20020703-20060703	20020703-20070702	20020703-20080702		
20030703-20040702	20030703-20050704	20030703-20060703	20030703-20070702	20030703-20080702			
20040705-20050704	20040705-20060703	20040705-20070702	20040705-20080702				
20050705-20060703	20050705-20070702	20050705-20080702					
20060704-20070702	20060704-20080702						
20070703-20080702							

TABLE II
DIFFERENT WINDOW SIZES FOR TESTING PHASE

Testing							
One Year	**Two Years**	**Three Years**	**Four Years**	**Five Years**	**Six Years**	**Seven Years**	**Eight Years**
20010703-20020702	20020703-20030702	20030703-20040702	20040705-20050704	20050705-20060703	20060704-20070702	20070703-20080702	20080703-20090702
20020703-20030702	20030703-20040702	20040705-20050704	20050705-20060703	20060704-20070702	20070703-20080702	20080703-20090702	
20030703-20040702	20040705-20050704	20050705-20060703	20060704-20070702	20070703-20080702	20080703-20090702		
20040705-20050704	20050705-20060703	20060704-20070702	20070703-20080702	20080703-20090702			
20050705-20060703	20060704-20070702	20070703-20080702	20080703-20090702				
20060704-20070702	20070703-20080702	20080703-20090702					
20070703-20080702	20080703-20090702						
20080703-20090702							

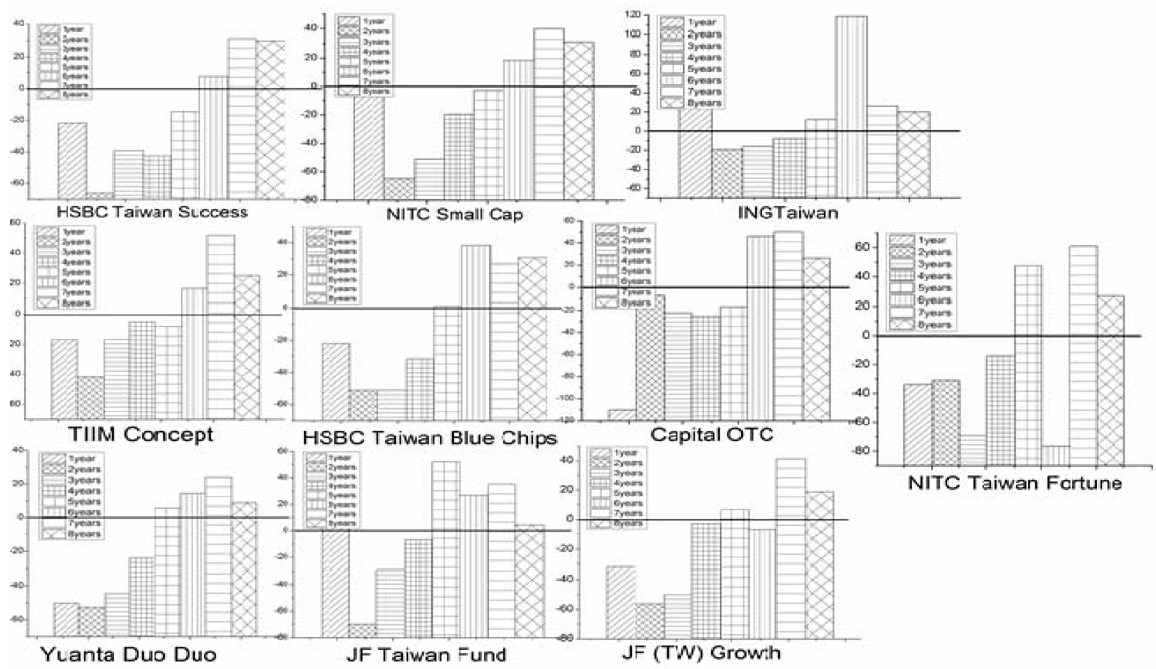

Fig. 1 Bar chart of different window sizes for testing

The generalized formulae for calculating the return of investment (ROI) of different window sizes for training and testing of the original performance of the mutual funds and the proposed method TPSO-MACD trading strategy model are shown as below:

$$ROI_{oTraining/oTesting} = \frac{Net_{i,j} - Net_{m,n}}{Net_{m,n}} \tag{10}$$

$$ROI_{TPSO-MACDtraining/TPSO-MACDtesting} = \frac{Capital_{i,j} - Capital_{m,n}}{Capital_{m,n}} \tag{11}$$

Where i = Last date of the taken data period
j = End year of the month of the taken data period
m = Beginning date of the taken data period
n = Beginning year of the month of the taken data period

For example, the formula for calculating the return of investment (ROI) of a given window size (say 8 years) for training and testing of the original performance of the mutual funds and the proposed method TPSO-MACD trading strategy model are shown as below:

$$ROI_{oTraining} = \frac{Net_{2\ July\ 2008} - Net_{3\ July\ 2000}}{Net_{3\ July\ 2000}} \tag{12}$$

$$ROI_{oTesting} = \frac{Net_{2\ July\ 2009} - Net_{3\ July\ 2008}}{Net_{3\ July\ 2008}} \tag{13}$$

$$ROI_{TPSO-MACDtraining} = \frac{Capital_{2\ July\ 2008} - Capital_{3\ July\ 2000}}{Capital_{3\ July\ 2000}} \tag{14}$$

$$ROI_{TPSO-MACDtesting} = \frac{Capital_{2\ July\ 2009} - Capital_{3\ July\ 2008}}{Capital_{3\ July\ 2008}} \tag{15}$$

Where *Net 3 July 2000* represents the fund net in 3 July 2000, *Net 2 July 2008* represents the fund net in 2 July 2008, *Net 3 July 2008* represents the fund net in 3 July 2008, *Net 2 July 2009* represents the fund net in 2 July 2009. *Capital 3 July 2000* represents the beginning capital in training phase by TPSO-MACD in 3 July 2000 (i.e., 1), *Capital 2 July 2008* represents the return capital in training phase by using TPSO-MACD in 2 July 2008, *Capital 3 July 2008* represents the beginning capital in testing phase by using TPSO-MACD in July 3, 2008 (i.e., 1), *Capital 2 July 2009* represents the return capital in testing phase by using TPSO-MACD in July 2, 2009.

B. *Experimental Data*

For testing our proposed method, ten mutual funds data are considered for the experiment based on the available data. The fund names and number of total experimental data are shown in the Table III. However, similar investigation will be carried out in future on recent dataset.

C. *Comparison*

Different window sizes (i.e., different time periods) of training data are used to check the performance of our proposed technique. From the experimental finding, it turns out that proper duration of training period is very important to achieve better profit. From window sizes analysis, seven years training period gives the best performance in comparison with other window sizes for the taken mutual funds.

For example, in 1-year window size there are eight values of original ROI as well as experimental ROI. We have summed up the values and subtracting sum of original ROI from experimental sum value. Similarly, we have followed for other window sizes and draw the bar chart. Figure 1 shows the bar chart between return on investment with respect to different window sizes for testing phase. The comparison of original performance and proposed algorithm of mutual funds have shown for seven and eight years training period in Table IV and V respectively. As these training period have shown the better stability and performance among the window sizes. From the tables IV & V, the performance of proposed algorithm shows better profit than original. Figure 2 shows the trading strategy of testing phase by following the variation of net value of the fund with respect to the time period (in months).

TABLE III
TABLE OF FUND NAMES AND NUMBER OF TOTAL DATA

SL. No.	Fund Names	Number of total experimental Data
1	HSBC Taiwan Success	2438
2	NITC Small Cap	2515
3	ING Taiwan Aggressive Growth Selec	2515
4	TIIM Concept	2511
5	HSBC Taiwan Blue Chips	2527
6	Capital OTC	2521
7	Yuanta Duo Duo Equity Fund	2522
8	JF (TW) Taiwan Fund	2514
9	JF (TW) Growth	2512
10	NITC Taiwan Fortune	2515

TABLE IV Comparison of original performance and TPSO-MACD trading strategy model for 7years

Fund Name	ROIotraining (%)	ROIotesting (%)	ROITPSO-MACDtraining (%)	ROITPSO-MACDtesting (%)
HSBC Taiwan Success	58.92256	-16.96842	138.11	-13.47
	115.04907	-5.32663	152.25	22.46
	173.97163	**-22.29505**	**290.36**	**8.99**
NITC Small Cap	38.32676	-31.8322	110.68	-11.23
	40.0507	-18.43034	104.76	0.67
	78.37746	**-50.26254**	**215.44**	**-10.56**
ING Taiwan Aggressive Growth Selec	-47.95118	-16.88742	33.95	-18.04
	-2.90135	1.5625	84.63	29.16
	-50.85253	**-15.32492**	**118.58**	**11.12**
TIIM Concept	94.48995	-30.89245	164.9	-5.11
	87.9668	19.32002	195.48	45.35
	182.45675	**-11.57243**	**360.38**	**40.24**
HSBC Taiwan Blue Chips	20.47809	-9.27022	83.53	-14.82
	80.39216	-2.6087	106.07	29.82
	100.87025	**-11.87892**	**189.6**	**15**
Capital OTC	140.35733	-32.49354	203.03	-6.32
	106.65788	4.52726	218.98	28.47
	247.01521	**-27.96628**	**422.01**	**22.15**
Yuanta Duo Duo Equity Fund	50.57034	-36.08678	166.87	-17.26
	69.6567	5.79987	168.28	11.03
	120.22704	**-30.28691**	**335.15**	**-6.23**
JF （TW） Taiwan Fund	-6.18153	-35.43046	36.54	-14.53
	-16.39871	4.67172	23.56	19.12
	-22.58024	**-30.75874**	**60.1**	**4.59**
JF （TW） Growth	0.31082	-21.46451	51.92	-2.18
	15.87629	4.34326	39.36	26.54
	16.18711	**-17.12125**	**91.28**	**24.36**
NITC Taiwan Fortune	-4.0481	-35.14831	40.38	-11.9
	2.7027	-20.89188	64.57	16.84
	-1.3454	**-56.04019**	**104.95**	**4.94**

TABLE V Comparison of original performance and TPSO-MACD trading strategy model for 8years

Fund Name	ROIotraining (%)	ROIotesting (%)	ROITPSO-MACDtraining (%)	ROITPSO-MACDtesting (%)
HSBC Taiwan Success	32.795	-5.327	119.278	24.62
NITC Small Cap	-3.198	-18.430	95.83	12.668
ING Taiwan Aggressive Growth Selec	-56.234	1.563	48.156	21.612
TIIM Concept	34.922	19.32	188.728	44.378
HSBC Taiwan Blue Chips	9.960	-2.609	63.522	28.024
Capital OTC	64.74	4.527	196.902	30.854
Yuanta Duo Duo Equity Fund	- 2.915	5.8	148.662	14.666
JF （TW） Taiwan Fund	-38.967	4.672	18.598	8.922
JF （TW） Growth	-20.599	4.343	51.878	23.356
NITC Taiwan Fortune	-36.032	-20.892	33.28	5.79

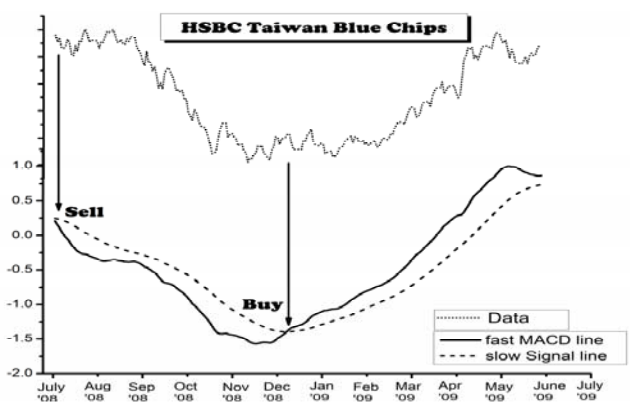

Fig. 2 Trading strategy signals and original data of HSBC Taiwan Blue Chips

VI. CONCLUSIONS

A trading strategy model is developed by using Turbulent Particle Swarm Optimization and Moving Average Convergence – Divergence for improving trading profit. We used TPSO algorithm to adjust the time intervals of Exponential Moving Averages of MACD to fit the fund characteristics. Using MACD, it is able to respond relatively quickly and slowly to the changes in prices. Different window sizes of training data are used to check the stability and performance of our proposed technique. A comparison made between the performance of the original funds and proposed TPSO-MACD method for different window sizes shows that seven years training period gives the best performance. The experimental result gives a profit of 38% and 22% for 7 and 8 years respectively using our proposed method in comparison to original performance in testing phase. This finding indicates that proper duration of training period is very important to achieve better profit. In future, we plan to employ our proposed TPSO-MACD trading strategy model for analysis Stock Markets, and other trading schemes.

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