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A Hybrid Forecasting Model for Prediction of Stock Index of Tata Motors using Principal Component Analysis, Support Vector Regression and Particle Swarm Optimization

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Abstract: ***This paper presents an extremely precise prediction method which improved the decision of the investors on daily direction of the stock market. Among the studies that focus on daily stock market forecasting, the hybrid machine learning techniques are more appreciated than the conventional data mining procedures. With an intent to produce such a model with more accurate predictions, this paper analyzes a series of technological indicators used in usual studies of the stock market and uses principal component analysis (PCA), along with support vector regression (SVR) and particle swarm optimization (PSO) algorithm. Feature extraction is such a procedure that can remove the unnecessary and unrelated factors, and reduce the dimension of the input variables from the original dataset. The feasibility and efficiency of the proposed PCA-SVR-PSO hybrid model was applied to forecast the daily closing prices of stock index of TATA Motors. The performance of the proposed approach is evaluated with 4304 (from 1st January 2001 to 6th April 2018) trading days historical stock price data of Tata motors collected from Bombay Stock Exchange (BSE). The total data sets were splits into two parts, 80% of the data (3444) has been used in the training phase and rest 20% of the data (860) for the testing phase. We compared our results with ANN-PSO and SVR-PSO hybrid models. The experimental results reflect that the proposed hybrid model incorporating PCA is more practicable and better performs than SVR-PSO.***

Keywords: ***Stock market; Feature extraction; Principal component analysis; Support vector regression; Particle swarm optimization.***

I. INTRODUCTION

Forecasting of financial market is an inspiring and demanding field for both the investors and financial institutions. The share market is an interrelated to the economy of a country. The stock index is depends upon the state stability of the market. It is very complicated for an investor to judge the best time for transaction of share as many constraints affect the stock market. The major aspect of the stock market is uncertainty due to the various factors such as political events, economic conditions and the demand of the trader's. This uncertain feature makes very difficult for prediction. The best approach to forecast the stock price by reducing the level of uncertainty by applying feature extraction method. Even though a lot of methodology has developed in the field of financial prediction, still a competent model, which improves the prediction accuracy, can attract and put a positive impact to the investors. In forecasting of stock price feature extraction technique plays a vital role. PCA examine the large number features of the data sets, and extract the most significant features. Forecasting of stock market is a moderately demanding job. Technological investigation is an admired moves towards analyze the features of stock market. Machine learning and artificial intelligent algorithm were used by many authors for forecasting in various fields. In this proposed hybrid model PCA extracts the relevant features and improves the prediction accuracy. While SVR plays the key role in prediction mechanism, PSO optimized the regularization parameters of SVR. The projected hybrid model PCA-SVR-PSO leads to improved accuracy as compared to the previous SVR-PSO model. This proposed regression model consisting of PCA, SVR and PSO. The proposed model PCA-SVR-PSO outperforms the previous SVR-PSO model.

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II. LITERATURE REVIEW

The authors Vapnik et al, (1999) represented that support vector machine is a learning system paying attention to statistical learning theory. SVM was utilized by Kim K. J. (2003) and Hu, Y. et al. (2009) for forecasting financial time series output. Kim K. J. analyzed the impact of the upper bound C and the kernel parameter δ in Support Vector Machine and concluded that the forecasting performances of SVM are very responsive to the value of the parameters. Gestel, T. V. et al. (2001) proposed a model combining Bayesian evidence framework with least squares SVM for nonlinear regression and found correct when applied for the forecast of the weekly US short term T-bill rate and the daily closing prices of the DAX30 stock value. Huang, W. (2005) summarized the stock trading decision support systems and proposed support vector machine is a superior tool for financial stock market prediction. Fei, S. et al. (2009) planned a PSO-SVM hybrid model to forecast the feasibility of dissolved gases contented in power transformer oil and the investigational outcomes specified that the PSO–SVM model obtained better prediction accuracy in comparison to grey model. Lin, Y. et al.

(2013) proposed a Support Vector Machine used stock market forecasting model. They implemented piecewise linear principle, where characteristic weights are integrated to put up the optimal separating hyper plane, which assesses expectation for stock market and found performs good result in compare to the conventional stock market prediction system. Lai, L. and Liu, J. (2014) implemented the SVM and least square SVM models for prediction of stock market. They have considered three systems GARCH, SVR and Least Square SVM using wavelet kernel for configuration of three narrative algorithms .They are WL_GARCH, WL_SVR and WL_LSSVM and used to solve the non-parametric and non-linear financial time series problems. Das, S. P. and Padhy, S. (2012) incorporated the Back Propagation Method (BP) and SVM Method for forecasting exchange price in the Indian stock market. They have shown that support vector machines give the better overview than that conventional method.

Ding, Y. et al. (2008) constructed Support Vector Machine to forecast share market crises and the economical condition of the companies in the China. They have applied 10-fold cross-validation and grid-search technique for getting optimal hyper parameters C and γ used in different kernel functions. They have matched the forecasting output of the SVM with four dissimilar kernels and concluded, Radial Basis Function kernel (RBF) is the best performance among four. They also statistically compared the prediction accuracy with Back Propagation Neural Network (BPNN), Multiple Discriminate Analysis (MDA) and logistic regression. It can be concluded that the RBF kernel SVM superior than other kernel SVM and BPNN, MDA, and Logit models. Mohapatra, P. Et al. (2013) proposed a relative study of PSO based hybrid swarm net and simple FLANN. This two models are trained with least mean square algorithm and particle swarm optimization respectively. The models have predicted the price of two separate databases NIFTY and NASDAQ during dissimilar time intervals (day, weekly, and monthly) basis. The outcome is measured according to RMSE and MAPE. It was concluded that PSO based hybrid swarm net is good as relative to PSO based FLAN. Karazmodeh, M. (2013) planned an improved hybrid GA based SVM system to forecast the future share market prices. Huang, C. L. and Tsai, C.Y. (2009) proposed a new hybrid PSO–SVM system to solve continuous valued and discrete valued PSO version. The outcomes obtained by using support vector machine for GDP prediction of different countries from the research study of Li and Xiao (2004), Shan and Xiaodong (2008), and Udomsin et.al. (2014) found, this type of advance have very good ability to forecast data analysis. Due to global optimization and better generalization ability of SVM, the use of SVM for short term prediction is comparatively accurate as stated by Li and Xiao (2004). Shan and Xiaodong (2008) have used grid search based SVM for the purpose of prediction of GDP of Fujian province and got very good results. The model used grid search method to find optimal value of the parameters (C, γ, a, ϵ) of SVM and gives average correctness as high as 98.12%. Khashei, & Bijari, (2011) has applied a hybrid ARIMA-ANNs models to forecast time series real data set. Kim, K.J. and Lee, W. B. (2004) proposed a genetic algorithm based feature transformation model with artificial NN to forecast the stock market index. Vieira et al. (2013) analyzed that using modified binary PSO algorithm the parameters of SVM can be optimized correctly. Lu, C. J. et al. (2009) presented a two-stage ICA–SVR prediction model and applied to the financial time series data of Nikkei 225 and TAIEX index. Tharwat, A. et al. (2017) proposed a Bat Algorithm based SVM model (BA-SVM), which search the parameters of SVM to minimize the error. Sudhir et al. (2014) had implemented a similar hybrid model designated as SVM-PSO model for forecasting monthly stream-flow. The study performed a performance comparison of SVM-PSO with ANN and ARMA models. It was observed that based on appropriate initialization of the important parameters of PSO, i.e., acceleration constants, population size, inertia weight, and minimum error gradient, the SVM-PSO model outperformed its competing models. In the domain of finance, Das and Padhy (2015) projected SVM-TLBO hybrid model by combining SVM and TLBO for studying long past years value of shares and then forecasting the price of future stock.

III. METHODOLOGY USED

3.1 Principal Component Analysis

Principal component analysis is a dimension reduction technique, which removes the principle inconsistency of the data sets. The computational principle of PCA is to formulate a mapping from the higher dimensional data components onto a lower dimensional space. PCA is a multivariate feature extraction technique, which performs a projection of a collection of observations of probably associated variables on the linear space into a set of uncorrelated variables, which is called as principal components (PC). The objective of PC is to maximize the variance of the data and to minimize information loss when projected. More the variance of data is present along a principal component, higher that principal component is ranked. PCA reduced the higher dimensional data space to a lower dimensional. PCA is popular for computational analysis using eigen decomposition.

PCA attempts to extract the maximum variance of principal component, which are constructed by taking linear combinations of all variables. Eigen value concept used to measures the variance of the variables. The less eigen value of variables associated with principal component has less priority and may be overlooked as compared to the variable has greater eigen values.

Let us consider 'n' number of data and each consists of 'n' number of features variables. Our aim to reduce the feature variable such that each data can be represent with only k features, $k < n$. We take $x_1, x_2, \ldots, x_n$ represents 'n' row vectors, each row vectors has 'n' numbers of columns. Consign row vectors into a matrix $\vec{X} = (x_1, x_2, \ldots \ldots \ldots \ldots x_n)^T$ of dimensions $n \times n$. Principal component can be expressed from the system of equation of n equation and n variables given by $y_j = \sum_{i=1}^{n} \vec{a_i}^T \vec{X}$, j=1,2,3,……, n, where x_i, $i = 1, 2, 3, \ldots \ldots$, nare the original variables, j=1, 2, 3,……, n are the principal components & $\vec{a_i}$ are the coefficient vectors. $\vec{a_i}$ be calculated by maximizing $\mathrm{Var}(y_j)$ with constraints $\vec{a_i}^T\vec{a_i} = 1$ and $\mathrm{Cov}(y_j, y_k) = \vec{a_i}^T(\sigma_{ij})_{n\times n}$ $\vec{a_i} = 0$, for $k = 1,2,3,..(j-1)$, and $(\sigma_{ij})_{n\times n}$ is the covariance matrix of $\vec{X} = (x_1, x_2, \dots, x_n)^T$, which is symmetric definite matrix. So $\vec{X}$ has n number of distinct characteristic roots $\lambda_1, \lambda_2, \dots, \lambda_n$ and n number of characteristic vectors. Let $\lambda_1 \geq \lambda_2 \geq \dots \dots \dots \geq \lambda_n \geq 0$ and the orthogonal eigen vectors $\vec{e_1}, \vec{e_2} \dots\dots\dots \vec{e_n}$. The k^{th} principal component of $x_1, x_2, \dots \dots \dots \dots x_n$ is given by $y_k = a_{k1}x_1 + a_{k2}x_2 + \dots\dots + a_{kn}x_n$, for $k = 1, 2, \dots, n$. with $\mathrm{Var}(y_k) = \vec{e_k}^T(\sigma_{ij})_{n\times n}\,\vec{e_k} = \lambda_k$ and $\mathrm{Cov}(y_i, y_j) = 0, i \neq j$.

3.2 Support Vector Machine for Regression

SVR is a procedure based mathematical optimization problem optimizing real function by supplying values from within an allowed set and then computing the function. In other words, it tries to get a hyper plane in the original input space so as to cluster the given training set properly. It also maximizes the distance from the closest instances on both sides of the hyperplane (Scholkopf & Smola 2002, Kecman 2001). In regression calculation, the data points that realize the maximal margin are called "Support vectors". The SVR is an extension of SVM, which is a ML technique used to learn structure from data. It was introduced by Vapnik in seventies (Vapnik 1996). The aim is to learn the mapping: $\chi \mapsto Y$ where $x\epsilon\,\chi$ is some object and $y\epsilon Y$ is a class label. Moreover, the SVM is a classification problem which categories data based on some classification. For example, a two class classification can be represented as $x\epsilon\mathbb{R}^n$ and $y\epsilon\,\{\pm 1\}$.

3.3 Particle Swarm Optimization

PSO was first intended for social behavior (representation of the flocking and schooling of birds and fish. The basic concept on which the model was developed based on food searching of birds scattered randomly (without any knowledge of the field a priori) or go together before they could locate the place where good quality food can be found. During this process of searching, there is always few birds that can locate the good quality food very well, that is, these birds are perceptible of the place where the good quality food can be found, having the better food resource information. Due to information update or sharing among them they reach the place where good quality food can be found. This behavior is delineated with a population of particles (or individuals) called as swarm, which evolves in each iteration by moving towards the optimal solution in the search space. Each particle is associated with two attributes, i.e., current position and velocity, and each of them have the knowledge of local best position (lbesti) that each has found and global best position (gbest) that has been found by all the particles. In each iterative step, the particles move from the current position by applying their associated velocity. The direction and magnitude of the velocity is determined by the velocity in the previous iteration, simulating momentum, and relative location to lbesti and gbest. The moving process that dynamically adapts the velocity and position of the particles in the evolution of each generation is described as follows.

$$v_i^{k+1} = w \times v_i^k + c_1 \times rand \times (lbest_i^k - x_i^k) + c_2 \times rand \times (gbest^k - x_i^k) \text{ and } x_i^{k+1} = \alpha v_i^k + x_i^k$$

where v_i^{k+1} and v_i^k denote the velocity of the i^{th} particle in $(k+1)^{th}$ and k^{th} iteration, respectively. w is the initial weight coefficient; c_1 and c_2 are the positive constants of social learning factors, x_i^{k+1} and x_i^k denotes the position of the i^{th} particle in $(k+1)^{th}$ and k^{th} iteration, respectively; α is the controlling weight factor of the velocity.

IV. PROBLEM FORMULATION

In this paper, we proposed a hybrid regression model by applying of principal component analysis to previously worked SVR-PSO model. This hybrid model, referred as PCA-SVR-PSO, is considered to forecast the share value of Tata motors. Performance of this novel model was evaluated by predicting the stock price of Tata motors. We considered the 4304 (from 1st January 2001 to 6th April 2018) trading days historical stock price data of Tata motors collected from Bombay Stock Exchange (BSE). The total data sets were splits into two parts, 80% of the data (3444) has been used in the training phase and rest 20% of the data (860) for the testing phase.

The dataset under study comprises of 7 features (shown in Table-I) that are daily recordings of time-series data, along with lagged (past period) values of the last 5 days.

Table- I: Features of Stock market taken for the model

Sl.	Features	Description
1	Open Price	Opening price of stock exchange on a trading day.
2	Highest Price	Highest price on a trading day.
3	Lowest Price	Lowest price on a trading day.
4	Close price	Closing price of stock exchange on a trading day.
5	Number of Shares	Total quantity of shares traded on a trading day.
6	Number of Trades	Total number of trades happened on a trading day.
7	Turnover	Total value of stock traded on a trading day.

V. PROPOSED PCA-SVR-PSO HYBRID MODEL

5.1 Pre-processing

As the quantity of data values is very huge, so we first normalized the data. Normalization of data has been adopted to avoid numerical difficulties during computation and overcome the dominance of features with greater numerical ranges over smaller numerical ranges. Normalization of data removes the gross influences of the data. It minimizes the redundancy and maximizes the integrity as a result the performance of algorithm is improved. In the process of normalization the range of original data set is transferred to a new scale and it reduced the range, which proceeds to carry the data more rapidly. In this proposed hybrid models the data set is normalized using the equation

$NV_k = \frac{A_k - A_{min}}{A_{max} - A_{min}}$, $for\ k = 1,\ 2,\ 3,\ \dots\dots, l$, Where, A_k represents the original value of the k^{th} features

5.2 Design and Implementation

The proposed model consists of three components, PCA, SVR and PSO. In this process PCA plays a key role to extract the most significant attribute from the dataset, SVR is used to address the forecasting mechanism and PSO optimizes the parameter C. The regularization parameters C control the influence of each support vectors. In this proposed model as the data sets are nonlinearity in nature so we have used RBF as kernel function and mathematically, RBF kernel is defined as $K(u,v) = e^{-\gamma||u-v||^2}$, where $\gamma = \frac{1}{2\sigma^2}$ The hyper parameters of SVR that requires to be optimized by PSO are sigma and gamma. The flowchart given in "Fig. 1", describes the important of the prediction mechanism of the hybrid model. PCA is the first component that receives the dataset. The PCA is utilized considering the regression aspect of the problem. Once the task of feature extraction is over, the obtained extracted features are forwarded to the SVR, which is optimized by PSO.

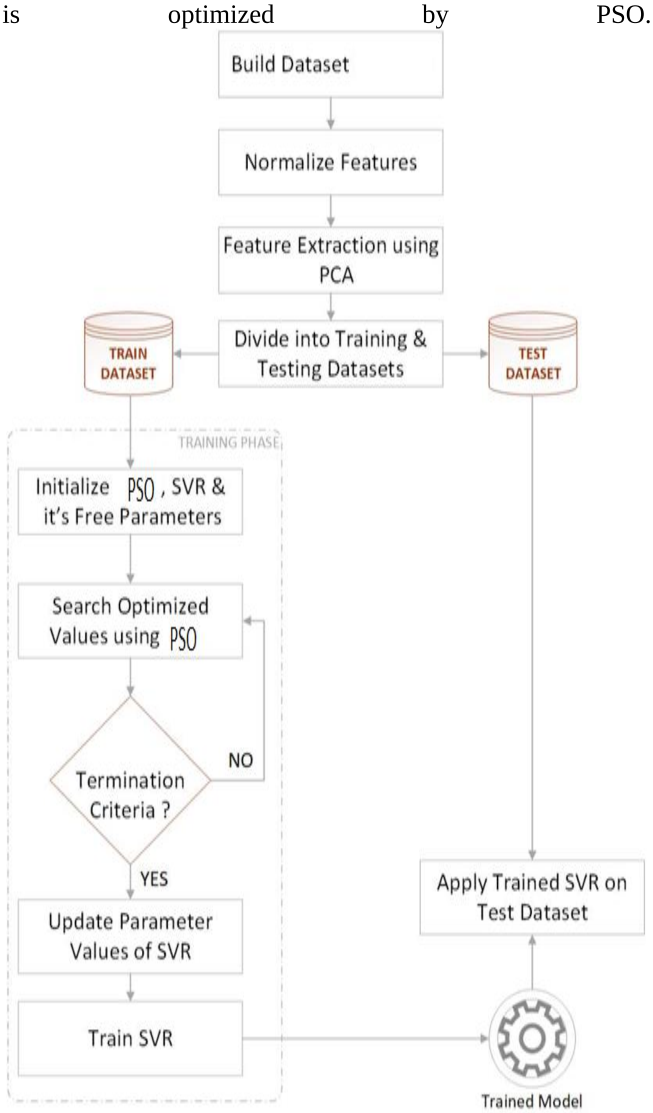

Fig. 1. Flowchart of PCA-SVR-PSO model

After splitting the data sets for training and testing phase with a predefined proportion of 80% and 20%, we extracted the relevant data by using PCA then we initialized the parameters of PSO and SVR and this filtered data were applied for building the training model. The optimized values of the C and γ are obtained through PSO and the termination criteria. Finally to evaluate the efficiency of the proposed PCA-SVR-PSO hybrid model, the same is applied to the testing dataset. The restrictive range of C 'regularization parameter' has taken between 0.032 and 40000 and the range of 'γ' is taken between 0.00003 and 20. The value of ϵ insensitive loss is fixed to 0.002. Our novel hybrid machine learning models PCA-SVR-PSO designed and tested to predict share price of Tata motor.

Table- II: Algorithmic parameters used in SVR

SVR Parameters	Parameter value
SVM Type	Epsilon SVR
Kernel Type	Radial Basis Function
C	0.032 to 40000
γ	0.00003 to 20
ϵ	0.002

VI. RESULTS AND DISCUSSION

6.1 Evaluation Criteria

For the performance measure of the presented hybrid model, we have used three standard statistical metrics. They MAE, RMSE and MAPE and their details have been described in Table- III Our main intention is to minimize the forecasting error to obtained better accuracy in the proposed hybrid model.

Table- III: Performance measure principle in the hybrid model

Sl	Metric	Definition
1	MAE	$\frac{1}{l}\sum_{i=1}^{l}\lvert y_i - d_i\rvert$
2	RMSE	$\sqrt{\frac{1}{l}\sum_{i=1}^{l}(y_i - d_i)^2}$
3	MAPE	$\frac{1}{l}\left(\sum_{i=1}^{l}\left\lvert\frac{y_i - d_i}{d_i}\right\rvert\right)100$
Here, l is the total records for evaluation, d_i is original value, and y_i is the estimated value obtained by prediction mechanism.		

6.2 Comparison of Results

In this paper, the performance of our novel model i.e., PCA-SVR-PSO is compared with our previously worked SVR-PSO model using the different dataset. In the proposed model we have incorporated PCA to reduce the dimension of features SVR which parameters were optimized through PSO algorithm. After splitting the total datasets for training and testing phase, the training datasets go through the feature extraction mechanism. PCA reduced the dataset having 40 attributes to a dataset comprising of only 13 features. The training and testing datasets are applied to the above hybrid model for training and testing phases to forecast next day opening price. Out of 4304 numbers of data of Tata motors (from 01-January-2001 to 06-April-2018) ¾ of data are used for building the training dataset and rest ¼ for the testing dataset. Errors evaluated with MAE, RMSE, and MAPE in training phase are 2.6665, 4.2202, and 0.6143 % (approx) respectively and the errors in testing phase are 2.7608, 4.3131 and 0.6349 % % (approx.) respectively. The Table-IV shows the error measures found for both the models, i.e., previously obtained results of PSO-SVR and results obtained using PCA-SVR-PSO method. This empirical study shows that PCA-SVR-PSO performed better than SVR-PSO in all the three evaluation criteria.

Table- II: Evaluation of Performance of SVR-PSO with PCA-SVR-PSO Models on Training and Testing Datasets

		Models	
		SVR-PSO	**PCA-SVR-PSO**
Training	**MAE**	2.760213993	2.666533
	RMSE	5.741340821	4.220245
	MAPE	0.68994578 %	0.614357357 %
Testing	**MAE**	2.929112587	2.760897934
	RMSE	6.494903279	4.31315835
	MAPE	0.708516926 %	0.634979 %

The “Fig. 2” to “Fig. 5” shows the comparison of the actual stock value and prediction of stock values using PCA-SVR-PSO. It also includes the absolute error.

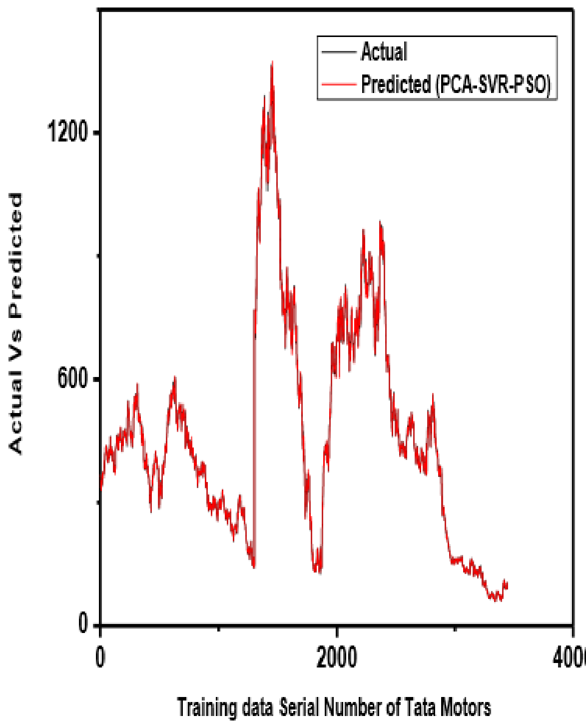

Fig. 2. Actual Verses Prediction of PCA-SVR-PSO on Complete dataset

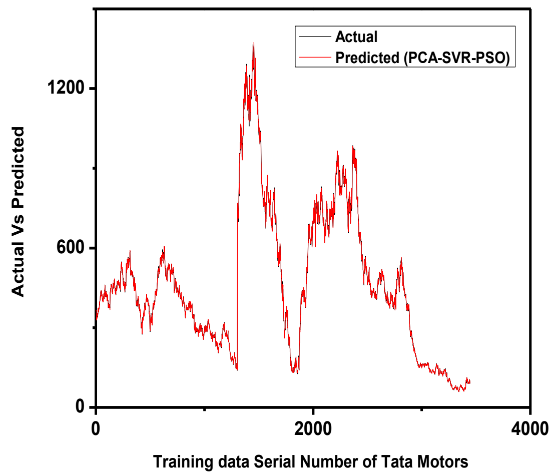

Fig. 3. Actual Verses Prediction of PCA-SVR-PSO on Training dataset.

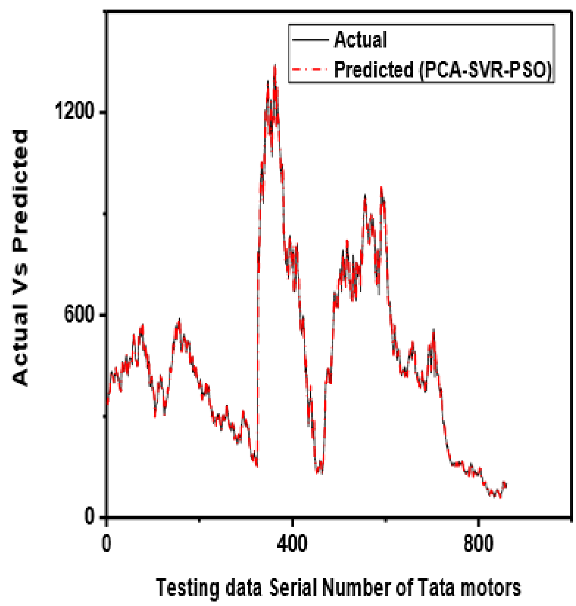

Fig. 4. Actual Verses Prediction of PCA-SVR-PSO on Testing dataset.

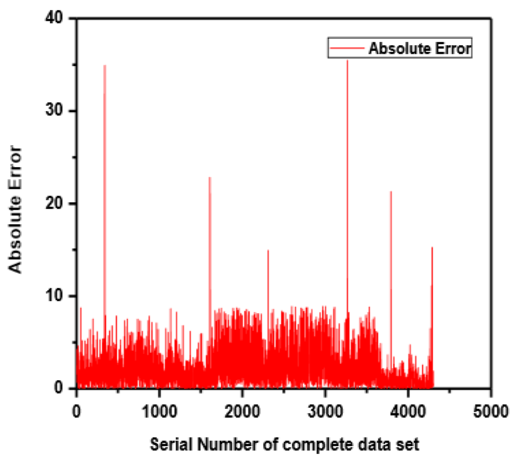

Fig. 5. Absolute error of PCA-SVR-PSO

VII. CONCLUSION

Our PCA-SVR-PSO hybrid model which is comprising of three leading techniques, is applied to the forecasting problem of next day stock price and the results specify that the model is acceptable not only for research but also from application view point. The dataset was composed of 35 attributes which includes eight critical features (mentioned in Table-1) for the last five days of the day to forecast. PCA removed the least influential features producing a dataset with 11 features. The testing results obtained from the empirical study demonstrated 0.65 % (approx.) MAPE. The PCA-SVR-PSO model also outperformed SVR-PSO in above three mentioned evaluation measures. Such remarkable performance is achieved due to the application of PCA on the lagged time-series dataset and use of PSO which has optimized the hyper parameters of SVR. Based on the outcome of this piece of research work, we propose to use our proposed PCA-SVR-PSO hybrid model for the future applications of regression based forecasting tasks.

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