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# A HYBRID FORECASTING MODEL FOR PREDICTION OF STOCK VALUE OF TATA STEEL USING SUPPORT VECTOR REGRESSION AND PARTICLE SWARM OPTIMIZATION

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## ABSTRACT:

Financial time series forecasting has always draws a lot of attention from investors and researchers. The inclination of stock market is extremely complex and is inclined by various factors. Hence to find the most significant factors to the stock market is really important. But the high noise and difficulty residing in the financial data makes this job very challenging. Many researchers have used support vector regression (SVR) and comparatively overcome this challenge. As the dormant high noises in the data impair the performance, reducing the noise would be competent while constructing the forecasting model. To achieve this task, integration of SVR with particle swarm optimization (PSO) is proposed in this research work. This paper analyzes a series of technological indicators used in usual studies of the stock market and executes support vector regression and particle swarm optimization algorithm.

The performance of the proposed approach is evaluated with 18 years' daily transactional data of Tata Steel stocks price from Bombay Stock Exchange (BSE). Empirical results show that the proposed model enhances the performance of the previous prediction model.

This approach is compared with existing models with real data set and gives more accurate results which give more accuracy with MAPE 0.7 % (approximately).

**Keywords:** Stock market, Financial time series forecasting; Support vector regression; particle swarm optimization.

## INTRODUCTION

Stock market analysis has always been an essential part of the financial sector of any country. Most of investors are presently depending upon Intelligent Trading Systems for prediction of stock market price based on various conditions. Precision of these forecast systems is necessary for better investment decisions with minimum risk factors. Prediction of stock price has been beneficial for both the individual and institutional investors. Predicting stock market price is a moderately challenging task. Technological analysis is an admired approach to study the stock market analysis.

Researchers use various machine learning and artificial intelligent approaches to forecast future trends or price. Artificial neural network (ANN), support vector machine (SVM), and logistic regression (LR) have been used by many for this kind of forecasting tasks. Among all these SVM is considered to one of the best performing technique provided appropriate initialization of its regularization parameters is made.

We used the support vector regression and particle swarm optimization technique for forecasting the stock price of TATA STEEL. Support vector regression requires its hyper parameters (i.e., cost and gamma) to be optimized to perform better and hence particle swarm optimization (PSO) is used to optimize the same. Technical indicators used in this analysis are calculated from the historical trading data. Lagged data in the time series domain have always been influencing the forecasting accuracy. The availability of lagged data for our proposed model PSO-SVR leads to better performance than standard SVR.

The rest of this paper is organized as follows. Literature review is highlighted in Section-2 and a brief description of SVR and PSO are given in Section 3. Then in Section-

4, the methodology and the process involved in the hybrid model under study, i.e., PSO-SVR, is explained. In Section-5, experimental analysis are presented and finally, the paper is concluded in Section-6.

## 1. LITERATURE REVIEW

The authors Vapnik et al, 1999 [1] represented that support vector machine is a learning system paying attention to statistical learning theory. Support vector machine has been utilized by Kim KJ, 2003 [2] and Hu, Su, Hao & Tang 2009 [3] for forecasting financial time series. Kim KJ analyzed the effect of the value of the upper bound C and the kernel parameter $\delta^2$ in Support Vector Machine and concluded that the prediction performances of Support Vector Machines are sensitive to the value of these parameters.Tony Van Gestel, Johan A. K. Suykens, Dirk-Emma Baestaens et al , 2001[4] proposed the model combining Bayesian evidence framework with least squares support vector machines for nonlinear regression and validated on the forecast of the weekly US short term T-bill rate and the daily closing prices of the DAX30 stock index. Wei Huang, Yoshiteru Nakamori, & Shou-Yang Wang, 2005 [5] summarized the stock trading decision support systems and proposed Supprt vector machine is a superior tool for financial stock market prediction. Yuling Lin, Haixiang Guo & Jinglu Hu in 2013, [6] propose a Support Vector Machine based stock market prediction model. They implemented the piecewise linear principle, and the characteristic weights are integrated to put up the optimal separating hyperplane, which assesses for stock indicator and control over fitting on stock market expectation. They tried this methodology on Taiwan stock market datasets and establish that this method performs result in compare to the conventional stock market prediction system. Lucas Lai & James Liu, 2014 [7] implemented the Support Vector Machine and Least Square Support Vector Machine models for prediction of stock market. They have considered three ate systems- General Autoregressive Conditional Heteroskedasticity (GARCH), Support Vector Regression (SVR) and Least Square Support Vector Machine (LSSVM) with the wavelet kernel for configuration of three narrative algorithms namely Wavelet-based GARCH (WL_GARCH), Wavelet-based SVR (WL_SVR) and Wavelet-based Least Square Support Vector Machine (WL_LSSVM) to resolve the non-parametric and non-linear financial time series issue. Shom Prasad Das & Sudarsan Padhy,2012 [8] incorporated the Back Propagation Technique (BP) and Support Vector Machine Technique (SVM) to forecast future prices exchange in the Indian stock market.They have shown that Support Vector Machines gives the better overview than that conventional methods. Yongsheng Ding, Xinping Song & Yueming Zen 2008, [9] constructed Support Vector Machine based on basic data forecast to the stock crises and the financial position of the companies in the Chinese market. They have applied 10-fold cross-validation and grid-search technique to obtain the optimal hyper parameters C and $\gamma$ for different kernel functions. They have compared the prediction performance of the Support Vector Machines with four dissimilar kernels and cocluded the 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 (Logit). The results of empirical analysis show that the RBF kernel SVM superior than other kernel SVM and BPNN, MDA, and Logit models. Shen, Shunrong, Haomiao Jiang & Tongda Zhang 2012 [10] proposed a forecast algorithm which makes use of the sequential among global stock markets and different financial substance to predict the next day stock value using Support Vector Machines. They have used the same algorithm with individual regression algorithm to forecast the actual growth in the markets. At last they build a basic trading model and distinguish its performance with the existing algorithm. Puspanjali Mohapatra, Soumya Das, Tapas Kumar Patra & Munnangi Anirudh, 2013 [11] proposed a comparative study of particle swarm optimization (PSO) based hybrid swarmnet and simple functional link artificial neural network(FLANN) model. Both the models are initially trained with least mean square (LMS) algorithm, then with particle swarm optimization (PSO) algorithm. The models are predicted the stock price of two different datasets NIFTY and NASDAQ on different time horizons (one day, one week, and one month) ahead. The performance is evaluated on the basis of Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). It was verified that PSO based hybrid swarmnet performed better in comparison to PSO based FLANN model, simple hybrid model trained with LMS and simple FLANN model trained with LMS. Mohammed Siddique, Debdulal Panda, Sumanjit Das at el., 2017, [12] proposed a hybrid model to forecast stock price using Artificial Neural Network (ANN) model optimized by particle swarm optimization (PSO), which consisting of an effective algorithm for predicting next day high price of Yahoo stock value and Microsoft stock value. M. Karazmodeh, S. Nasiri, and S. Majid Hashemi, 2013, [13], proposed an improved hybrid Improved via Genetic Algorithm based on Support Vector Machines (IPSOSVM) system to predict the future stock prices. Rohit Choudhry, and Kumkum Garg, 2008, [14], proposed a hybrid GA-SVM system for predicting the future stock prices. Cheng-Lung Huang, Jian-Fan Dun, 2008 [15], proposed a new hybrid PSO–SVM system to solve continuous valued and discrete valued PSO version. They have shown that experimental results optimize the model parameters and search the discriminating feature subset simultaneously.

## 2. METHODOLOGY USED

### 1. Support Vector Machine for Regression

Support Vector Machines is one of the best binary classifiers. SVM create a decision boundary such that the majority of the points in one category falls on one side of the boundary while most points of other category fall on the other side of the boundary. Consider an n-dimensional feature vector X = ($x_1$, $x_2$, ... ... $x_n$). We can define a hyperplane

$$\alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \dots \dots + \alpha_n x_n = \alpha_0 + \sum_{i=1}^{n} \alpha_i x_i = 0$$

Then elements in one category will be such that the sum is greater than 0, while elements in the other category will have the sum be less than 0. We construct a label, $\alpha_0 + \sum_{i=1}^{n} \alpha_i x_i = Y$, where Y ϵ {-1, 1} is the label classifier.We can rewrite the hyperplane equation using inner products $Y = \alpha_0 + \sum_{i=1}^{n} \beta_i Y_i X(i) * X$,Where $*$ represents the inner product operator and inner product is weighted by its label.

The margin of the optimal hyperplane is obtained by maximizing the distance from the plane to any point. The maximum margin hyperplane (MMH) splits the data very well. The essential aspect is that only the points neighboring to the boundary of the hyperplane are participated in selection; all other points are irrelevant. These points are known as the support vectors, and the hyperplane is known as a Support Vector Classifier (SVC) as it places each support vector in one class or in the other class. The inner products in SVC are weighted by their labels and it maximize the distance from hyperplane to the support vector.

The basic concept of SVM is to maximize the margin hyperplane in the feature space. The principle of normal Support Vector Machine for Regression (SVR) model, a supervised machine learning technique developed by Vapnik et al.[1], is described below.

Given a sample data-set S = ($x_1$; $y_1$); ($x_2$; $y_2$); :::($x_k$; $y_k$) representing k input-output pairs, where each $x_i \in X$ is a subset of $R^n$, denoting the n dimensional input sample space and matching target values $y_i \in Y$ is a subset of R for (i = 1; 2; :::; k). The objective of this regression problem is to find a function f : $R^n \rightarrow R$, to approximate the value of y for hidden and unlabeled x, which is not present in the training sample data-set. Through a nonlinear mapping function ϕ, the input data is mapped from $R^n$ to a higher dimensional space $R^m$, where m > n, and hence the estimating function f is defined as

$$f(x) = w^T \phi(x) + b \text{ ------------------------------------------(1)}$$

where $w \in R^m$ is the regression coefficient vector, $b \in R$, is the bias or threshold value.The objective of the support vector regression is to find a function f that has the most ϵ-deviation from the target $y_i$.We want to determine w and b such that the value of f(x) can be determined by minimizing the risk.

$$R_{reg}(w) = \frac{1}{2} \|w\|^2 + K \sum_{i=1}^{l} L\epsilon(y_i, f(x_i)) \text{-----------------(2)}$$

where, where K determines the trade-off between the flatness of the f(x) and the amount up to which deviations greater than ϵ are tolerated. Also K is the penalty factor which is a user defined constant that determines the transaction between the training error and the penalizing term $\|w\|^2$ and $L\epsilon(y_i, f(x_i))$ is the ϵ-intensive loss function, defined as

$$L\epsilon\left(y_i, f(x_i)\right) = \begin{cases} |y_i - f(x_i)| - \epsilon, & |y_i - f(x_i)| \geq \epsilon \\ 0, & |y_i - f(x_i)| < \epsilon \end{cases} \text{ ----(3)}$$

The minimization of risk functional equation (2) can be reformulated by introducing non-negative slack variables $\gamma_i$ and $\xi_i$ as

$R_{reg}$ $(w, \gamma_i, \xi_i)$ = Minimize $\frac{1}{2}\|w\|^2 + K\sum_{i=1}^{l}(\gamma_i + \xi_i)$--(4)

subject to constraints

$$\begin{cases} y_i - W^T x_i - b \le \in + \gamma_i \\ W^T x_i + b - y_i \le \in + \xi_i \\ \gamma_i, \xi_i \ge 0 \end{cases} \text{-----------------------(5)}$$

where $\frac{1}{2}\|w\|^2$ is the regularization term preventing over learning $(\gamma_i + \xi_i)$ is the pragmatic risk and K > 0 is the regularization constant, which controls the trade-off between the empirical risk and regularization term.

By introducing Lagrange multipliers $\alpha_i$, $\beta_i$, $\mu_i$ and $\eta_i$ the quadratic optimization problem (4) and (5) can be formulated as

$$L = \frac{1}{2}\|w\|^2 + K\sum_{i=1}^{l}(\gamma_i + \xi_i) - \sum_{i=1}^{l}\alpha_i(\in + \gamma_i - y_i + W^T x_i + b) - \sum_{i=1}^{l}\beta_i(\in + \xi_i + y_i - W^T x_i - b) - \sum_{i=1}^{l}(\mu_i\gamma_i + \eta_i\xi_i) \text{-----------------------------------------(6)}$$

The dual of the corresponding optimization problem (4) and (5) is represented as

$$\text{Maximize } -\frac{1}{2}\|w\|^2 + K\sum_{i,j=1}^{l}(\alpha_i - \beta_i)(\alpha_j - \beta_j)(x_i)^T x_j - \in\sum_{i=1}^{l}(\alpha_i + \beta_i) + \sum_{i=1}^{l}(\alpha_i - \beta_i)$$

Subject to constraints

$$\begin{cases} \sum_{i=1}^{l}(\alpha_i - \beta_i) = 0 \\ \alpha_i, \beta_i \in [0, K] \end{cases}$$

By changing the equation $w = \sum_{i=1}^{l}(\alpha_i - \beta_i)x_i$ , the function f(x) can be written as

$$f(x) = \sum_{i=1}^{l}[(\alpha_i - \beta_i)x_i]^T \phi(x) + b \text{---------------------(7)}$$

consequently by applying Lagrange theory and Karush-Kuhn-Tucker condition, the general support vector regression function can be expressed as

$$f(x) = \sum_{i=1}^{l}(\alpha_i - \beta_i)K(x_i, x_j) + b \text{--------------------------(8)}$$

where $K(x_i, x_j)$ known as Kernel function.

The value of kernel function is equal to the inner product of $x_i$ and $x_j$ in the feature space $\phi(x_i)$

and $\phi(x_j)$ such that

$$K(x_i, x_j) = \phi(x_i).\phi(x_i) \text{--------------------------------(9)}$$

## 2. Particle Swarm Optimization (PSO)

Particle swarm optimization (PSO) is one of the leading meta-heuristic optimization methods which is motivated by birds and fishes co-ordinated, collective social behavior. It was originally introduced by Kennedy and Eberhart in the year 1995. In PSO, each particle flies through the multidimensional search space and adjusts its position in every step until it reaches an optimum solution. In particle swarm optimization each particle has some fixed distance from the food source and the fitness value of each particle gives the output. Each particle i maintains a trace of the position of its previous best performance in a vector called $p_{best}$. The $n_{best}$, is another 'best' value that is tracked by the particle swarm optimizer. This is the best value achieved faraway by any particle in that neighborhood of the particles. When a particle takes the total population as its topological neighbors, the best value is known as the global best and is called $g_{best}$. Every particles can share information about the search space representing a possible solution to the optimization problem, each particle moves in the direction of its best solution and the global best position discovered by any particles in the swarm. Each particle calculates its own velocity and updates its position in each iteration. Calculate the $P_{best}$ value for each particle. The velocity and the location of the particles in each iteration are updated. From that particle best ($p_{best}$) the global best ($g_{best}$) value is determined.

### Working Process of PSO

Step: 1 Initialize the swarm particle in the search space randomly.

Step: 2 Calculate the fitness value by using objective function and consider it as $p_{best}$.

Step: 3 update the velocity and the location for each Particle.

Velocity of each particle is updated by using the equation

$V_t = (w^* \, v_{t-1}) + (c_1{}^*r_1{}^* \, (gb_{t-1} - p_{t-1})) + (c_2{}^* \, r_2{}^*(pb_{t-1}{}^k - p_{t-1}{}^k))$

Location of each particle is updated by using the equation $P_t = P_{t-1} + V_t$

Step: 4 update the $P_{best}$ and $g_{best}$.

Step: 5 stop if max iteration is reached otherwise repeat from step 2.

## 3. PROPOSED MODEL

The proposed model is built using particle swarm optimization (PSO) and support vector regression (SVR). In this model SVR is at the core of the prediction mechanism and PSO optimizes the free parameters of SVM. In SVR, proper selection of kernel type, regularization parameter, and the ϵ-insensitive loss are the most critical to determine. In this proposed model, we have used radial basis function (RBF) kernel due to the nonlinearity nature of dataset under study, and mathematically, RBF kernel is defined as $K(u, v) = e^{-\gamma ||u-v||^2}$, where $\gamma = \frac{1}{2\sigma^2}$ .The free parameters of SVR that are optimized by PSO are cost and gamma. The detailed flowchart of optimizing the hyper parameters of SVR is shown in figure-1

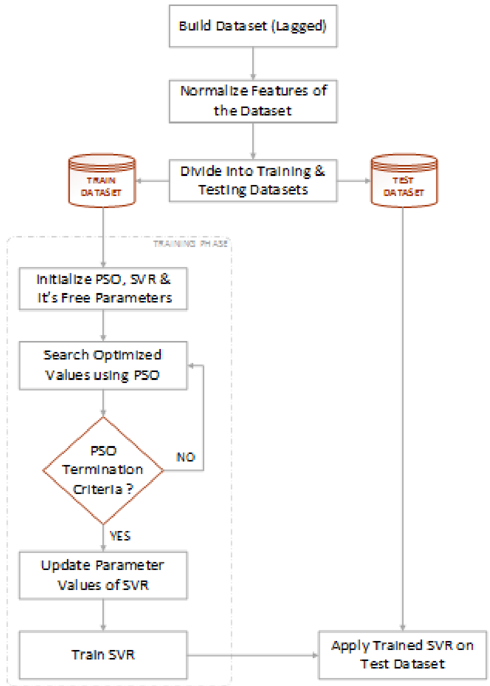


Figure-1: Flowchart of PSO-SVR mechanism

Here the dataset comprises of features based on time-series. The model is built upon the concept of lagged (past period) values of the last 5 days. Normally for each day the 7 attributes mentioned in Table-1 are captured and used as key attributes for this time-series forecasting mechanism.

Table-1: Variables and its description

| Sl. | Variable | Description |
|---|---|---|
| 1 | Open Price | The price at which the stock first trades upon opening of an exchange on a trading day. |
| 2 | Highest Price | The highest price of a share on a trading day. |
| 3 | Lowest Price | The lowest price of a share on a trading day. |
| 4 | Close price | The price at which the stock last trades upon closing of an exchange on a trading day. |
| 5 | No. of Shares | Total quantity of shares traded on a trading day. |
| 6 | No. of Trades | Total number of trades happened on a trading day. |
| 7 | Turnover | Total value of stock traded on a trading day. |

In order to avoid numerical difficulties during computation and to prevent dominance of features with greater numerical ranges over smaller numerical ranges, normalization has been implemented during pre-processing stage. Here, normalization of data has been achieved by linearly scaling to [0, 1] using the following equation

$$\mathrm{NV_i} = \frac{\mathrm{A_i} - \mathrm{A_{min}}}{\mathrm{A_{max}} - \mathrm{A_{min}}}, \text{for } \mathrm{i} = 1, 2, 3, \dots \dots \mathrm{l}$$

where, $\mathrm{A_i}$ is the actual value of the i-th feature, l is the total number of data points available, $\mathrm{A_{max}}$ and $\mathrm{A_{min}}$ are the maximum and minimum values respectively, and $\mathrm{NV_i}$ is the corresponding normalized value.

After diving the dataset into training and testing datasets, the model building process starts using the training dataset by initializing the parameters of PSO and SVR. The optimized values of the hyper parameters of SVR are searched using PSO and the processing of searching continues till the termination criteria are reached. Finally, SVR is built using the optimized values attained in the search process and applied on the testing dataset.

## 4. EXPERIMENTAL RESULTS AND DISCUSSIONS

### 4.1 Evaluation Criteria

To evaluate the performance of the proposed regression model, we have used three standard statistical metrics. They are mean absolute error (MAE), root mean squared error (RMSE), and mean absolute percentage error (MAPE) and their details have been described in Table 2. As MAE, RMSE, and MAPE indicate variants of the differences between the actual and predicted values, it is important to note that smaller the error value, better the performance.

| Sl | Metric | Definition | Description |
|---|---|---|---|
| 1 | Mean Absolute Error (MAE) | $\frac{1}{l}\sum_{i=1}^{l}\lvert y_i - d_i\rvert$ | Sum of absolute differences between the actual value and the forecast divided by the number of observations |
| 2 | Root Mean Squared Error (RMSE) | $\sqrt{\frac{1}{l}\sum_{i=1}^{l}(y_i - d_i)^2}$ | Square root of sum of the squared errors divided by the number of observations |
| 3 | Mean Absolute Percentage Error (MAPE) | $\frac{1}{l}\left(\sum_{i=1}^{l}\left\lvert\frac{y_i - d_i}{d_i}\right\rvert\right)100$ | Average percentage of absolute of errors divided by actual observation values |
| where,<br>l is the total number of instances or records under evaluation,<br>$d_i$ is the desired output value, i.e., actual or true value of interest, and<br>$y_i$ is the estimated value obtained using a prediction algorithm. | | | |

### 4.2 Comparison of Results

In this study, the performance of our proposed hybrid model i.e., PSO-SVR is compared with standard SVR model. Here, PSO-SVR model is designed with Support Vector Machine for Regression (SVR) at its core and Particle Swarm Particle Swarm Optimization (PSO)for optimizing the hyper parameters of SVR.

In this study, the dataset are categorized into training and testing datasets and applied to the models for training and testing phases of the models respectively for predicting the next day opening price. Out of 4143 numbers of data of Tata Steel (from 24-July-2001 to 19-March-2018) three-fourth of the data are used for building the training dataset and rest one-fourth for the testing dataset. Errors evaluated with MAE, RMSE, and MAPE in training phase are 2.7602, 5.7413, and 0.6899 % (approx) respectively and the errors in testing phase are 2.9291, 6.4949, 0.7085 % (approx.) respectively. The Table-2 shows the error measures found for both the models, i.e., Standard SVR and PSO-SVR. This empirical study shows that PSO-SVR outperformed Standard SVR in all the three evaluation criteria.

Table-2: Comparison of Performance of Standard SVR and PSO-SVR Models on Training and Testing Datasets

| | | **Models** | |
|---|---|---|---|
| | | **Standard SVR** | **PSO-SVR** |
| **Training** | **MAE** | 4.145735418 | 2.760213993 |
| | **RMSE** | 7.857402569 | 5.741340821 |
| | **MAPE** | 1.75813745 % | 0.68994578 % |
| **Testing** | **MAE** | 12.54774696 | 2.929112587 |
| | **RMSE** | 22.50747649 | 6.494903279 |
| | **MAPE** | 3.21849913 % | 0.708516926 % |

The Figures-2 to 5 shows the comparison of the actual stock vale and prediction of stock values using PSO-SVR. It also includes the absolute error.

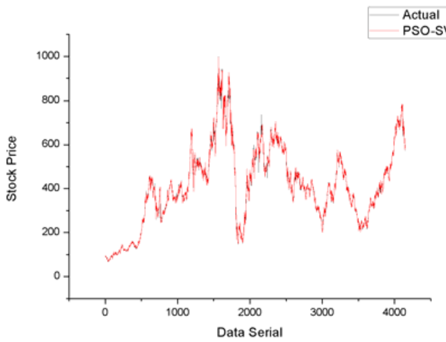


Figure-2: Actual Verses Prediction of PSO-SVR on complete dataset

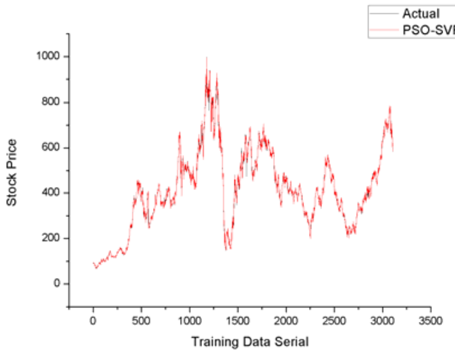


Figure-3: Actual Verses Prediction of PSO-SVR on training dataset.

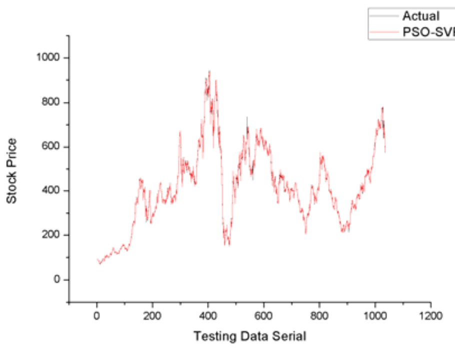


Figure-4: Actual Verses Prediction of PSO-SVR on testing dataset.

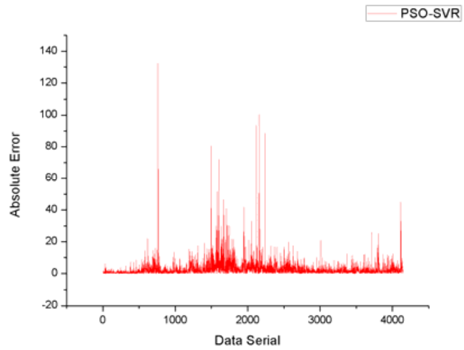


Figure-5: Absolute error of PSO-SVR.

## 5. CONCLUSION

Our proposed model for addressing the problem of next day stock price prediction presents results that are quite acceptable not only from the research point of view but also from practical use as well. The results demonstrated by PSO-SVR has attained 0.7 % (approx.) mean absolute percentage error (MAPE) on the testing dataset. The proposed model also outperforms Standard SVR in all the three evaluation measures, i.e., MAE, RMSE, and MAPE. These results were possible to be achieved due to the use of Particle Swarm Optimization (PSO) to optimize the free parameters (cost and gamma) of Support Vector Machine for Regression on the lagged time-series dataset. The dataset was build using 35 attributes which is composed of 7 attributes for the last 5 days of the prediction day.This model can also be extended by varying the number of lagged attributes present in the dataset. From the application point of view, we are quite hopeful that our proposed model (PSO-SVR) will be of great help to forecast not only the stock price but also every aspect in the financial domain.

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