SVR PARAMETERS OPTIMIZATION USING PSO AND WAPSO IN STOCK PRICE PREDICTIONS

Muhamad Ihsanul Qamil[1], Irwan Budiman[2], Muhammad Itqan Mazdadi[3], Dodon Turianto Nugrahadi[4], Mohammad Reza Faisal[5]
[12345]Ilmu Komputer FMIPA ULM
A. Yani St. KM 36 Banjarbaru, South Kalimantan
Email: j1f115037@mhs.ulm.ac.id[1], irwan.budiman@ulm.ac.id[2], mazdadi@ulm.ac.id[3], dodonturianto@ulm.ac.id[4], reza.faisal@ulm.ac.id[5]

Abstract

This study discusses the optimization of Support Vector Regression (SVR) parameters to predict stock prices using Particle Swarm Optimization (PSO) algorithm and Weight Attribute Particle Swarm Optimization (WAPSO) algorithm to improve SVR accuracy and to determine the effect of the inertia weight attribute in the optimization. WAPSO is a Particle Swarm Optimization algorithm with the addition of an inertia weight attribute. The implementation of the SVR, SVR-PSO and SVR-WAPSO algorithms is carried out on three LQ45 stock data, namely TLKM, BBRI and ADRO. The results of the accuracy of the implementation of the SVR algorithm are 79.02493% (TLKM), 67.83047% (BBRI), 88.94952% (ADRO), the SVR-PSO algorithm is 98.64916% (TLKM), 98.32181% (BBRI), 97.90267% (ADRO) and the SVR-WAPSO algorithm is 98.64921% (TLKM), 98.32496% (BBRI), 97.89889% (ADRO). Based on statistical tests in 3 data, it is concluded that the weight attribute has an effect in increasing the mean fitness value so that WAPSO has a better mean fitness value. The difference in the increase in the mean fitness value at WAPSO and PSO on TLKM data is 0.1230, BBRI data is 0.2202, and ADRO 0.0597.

Keywords: *SVR, PSO, WAPSO, Stock Price Prediction*

1. INTRODUCTION

Investment in the form of stock on the capital market in Indonesia has increased marked by reaching the highest number of stock trades in February 2017 since the Indonesian stock market was established according to the records of the Indonesia Stock Exchange (IDX) and an increase in the Indonesian Stock Price Index (IHSG) by 15%. This makes stocks one of the most promising investment objects. Based on IDX operational data and data from the Kustodian Sentra Efek Indonesia (KSEI) the number of new Indonesian capital market investors increased 23.47% throughout 2016 [5]. One of the most popular and influential stock indices on the Indonesia Stock Exchange is the LQ45 index because it is the driving force for the IHSG. The LQ45 index also contains blue chip stocks, which refers to large companies that have stable income [1].

Support Vector Regression (SVR) is a regression version of the Support Vector Machine (SVM) introduced by Vapnik, Steven Golowich and Alex Smola in 1997. The underlying rationale of SVR is to map data sets to a non-linear high-dimensional feature space and solve the regression problem in this dimensional feature space. Support Vector Regression (SVR) is one method which is used for predictions or forecasting because it can recognize patterns from time series data and can provide good predictions results if parameters can be determined properly.

So an optimization method is needed to determine the SVR parameters so that the SVR can be adjusted optimally applied in stock price predictions [5].

PSO was introduced by Kennedy and Eberhart in 1995. The way the PSO works is similar a flock of birds or fish in finding the source of food to which each individual is named the particles and the population are called swarms (colonies). PSO initialized with a set of particles as candidate solutions at random positions. Every particle given the starting position and starting velocity. When a particle finds the direction food source, other particles will follow towards the source food [4].

The PSO model continues to be developed to get better optimization. The PSO model developed in this study is PSO with the addition of inertia weight attribute so called WAPSO. WAPSO is used to reduce speed during the iteration, which allows the population to converge the target points more accurately and efficiently than the original algorithm [2].

Therefore, this study conducted to find out whether the optimization of SVR parameters using WAPSO is still better than the optimization of SVR parameters using PSO in the case of stock price predictions. In addition, it is also to determine the effect of the weight attribute on the fitness value in the optimization of the SVR parameters. Stock price data used is stock data from LQ45 index.

2. RESEARCH METHODOLOGY

The flow of this research can be seen in Figure 1 below:

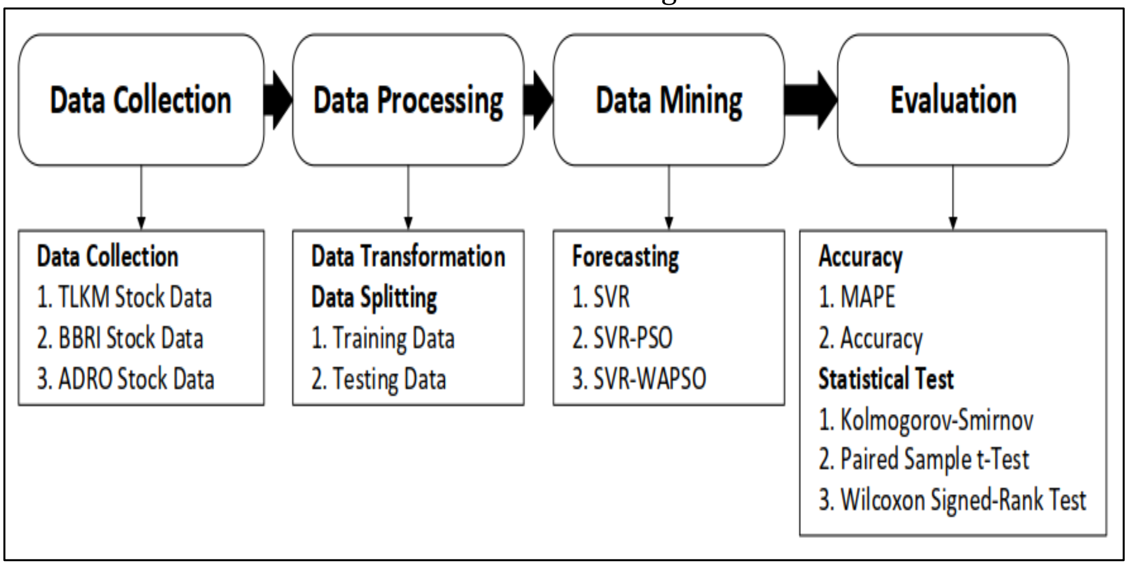

Figure 1. Research flow of stock price predictions

2.1 Data Collection

Data collection is a process to obtain stock price data that will be used in predictions. In this study will use stock closing price data for stock price predictions.

2.2 Data Processing

Data processing is divided into two stages, the first is data transformation and the second is data splitting. Data transformation is to transform the data form into many features or time series data with a certain window size. Data splitting is a process to splitting the data into training data and testing data based on predetermined ratio.

2.3 Data Mining

Data mining phase implements forecasting using 3 algorithms namely SVR, SVR-PSO and SVR-WAPSO. The first algoritm is SVR which is Support Vector Regression algorithm without parameter optimization. The second algorithm is SVR-PSO which is Support Vector Regression algoritm with parameter optimization using Particle Swarm Optimization algorithm. The third algorithm is SVR-WAPSO which is Support Vector Regression algoritm with parameter optimization using Weight Attribute Particle Swarm Optimization algorithm.

2.3.1 SVR Implementation

Time series data can be predicted using Support Vector Regression (SVR) algorithm. Sequential learning in SVR can be used to solve non-linear problems [5]. Before calculate with SVR algorithm, normalize the data first using this equation (1):

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)} \quad (1)$$

x' : result of normalization
x : current data value
Min(x) : smallest data value
Max(x) : the largest data value

Then implement SVR algorithm steps as follows:

a. Initialize SVR parameters such as complexity (C), lamda (λ), epsilon (ε), sigma (σ) and gamma (γ). Intialization of initial values α_i^* and α_i each is 0 and maximum iteration.
b. Calculate the distance between data for training data and testing data, with the following formula:
   Distance = $|data_i - data_j|^2$ (2)
c. Calculating the Hessian Matrix with the following equation:
   $R_{ij} = K(x_i, x_j) + \lambda^2$ for i, j = 0, …, n (3)
d. The process of sequential learning. For each data, i = 0, ..., n, do with the following steps:
   1. Calculating Error value
      $E_i = y_i - \Sigma_{i=1}^{n}(\alpha_i^* - \alpha_i)R_{ij}$ (4)
   2. Calculate the value of $\delta\alpha_i^*$ and $\delta\alpha_i$
      $\delta\alpha_i^* = min\{max[\gamma(E_i - \varepsilon), -\alpha_i^*], C - \alpha_i^*\}$ (5)
      $\delta\alpha_i = min\{max[\gamma(-E_i - \varepsilon), -\alpha_i], C - \alpha_i\}$ (6)
   3. Calculate the value of α_i^* and α_i
      $\alpha_i^* = \alpha_i^* + \delta\alpha_i^*$ (7)
      $\alpha_i = \alpha_i + \delta\alpha_i$ (8)
   4. Convergence has occurred, when it reaches maximum iteration or max $|\delta\alpha_i^*| < \varepsilon$ and max $|\delta\alpha_i| < \varepsilon$ then the process stops. If you do not meet these requirements then repeat the sequential learning process in step four.
e. Forming the forecasting function. The forecasting function is used to predict the target value in the test data, with the following equation:
   $f(x) = \Sigma_{i=0}^{n}(\alpha_i^* - \alpha_i)\, K(x_i, x_j) + \lambda^2$ (9)

f. After forming the forecasting function, it will get the output is still normalized. Then do the process of denormalization for its output back to its original value.
g. Calculate the error value using Mean Absolute Persentage Error (MAPE).

$$MAPE = \frac{100}{n} \Sigma_{i=1}^{n} \left| \frac{A_i - R_i}{A_i} \right| \quad (10)$$

h. Done.

In this study used Radial Basis Function (RBF) kernel because compared to other kernels, this kernel provides the best performance to predict the load. Here is equation of RBF kernel [2]:

$$K(x_i, x_j) = \exp\left(-\frac{\|x - x_i\|^2}{2\sigma^2}\right) \quad (11)$$

Description:

$data_i$: data before
$data_j$: data after
R_{ij} : matrix hessian
$K(x_i, x_j)$: kernel used
λ : scalar variabel
n : number of data
E_i : error of *i* data
y_i : actual value of *i* data
α_i^* : non-negative vector of lagrange coefisien
α_i : lagrange multipliers
A_i : the actual result
R_i : the forecasting result
x : value of data feature used for forecasting
x_i : value of training and testing data
σ : value of radial base

The Flowchart of stock price predictions using SVR algorithm is shown in figure 2.

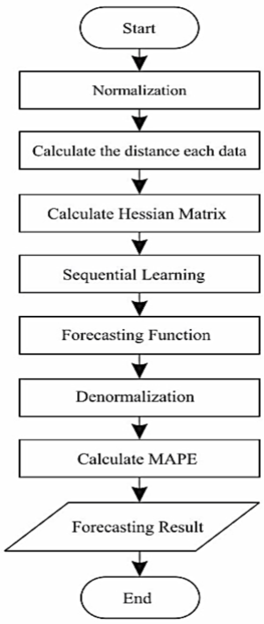

Figure 2. Flowchart of SVR algorithm

2.3.2 SVR-PSO Implementation

Forecasting using SVR-PSO will use SVR as prediction/forecasting algorithm and PSO as optimization algorithm. Original PSO not use inertia weight attribute. The steps for the SVR-PSO algorithm are as follows [3]:

a. First step is initialization initial such as SVR parameter range (complexity (C), lamda (λ), epsilon (ε), sigma (σ) and gamma (γ)), maximum PSO iteration, PSO particle population number, and kernel.

b. Particle initialization, the initial velocity of each particle is 0 and the initial position of each particle is random using following equation:

$$x = xmin + rand[0,1] * (xmax - xmin) \quad (12)$$

x : position particle or value of SVR parameter
$xmin$: minimum value of SVR parameter range
$xmax$: maximum value of SVR parameter range

c. Use SVR algorithm to evaluation the early particle (first evaluation), SVR algorithm steps as figure 2 and calculate fitness value with the following equation:

$$fitness = \frac{1}{1+MAPE} \quad (13)$$

d. Update c_1 and c_2

$$c_1 = \left(c_{1f} - c_{1i}\right) * \frac{iter}{itermax} + c_{1i} \quad (14)$$

$$c_2 = \left(c_{2f} - c_{2i}\right) * \frac{iter}{itermax} + c_{2i} \quad (15)$$

e. Update velocity

$$v'_{id} = v_{id} + c_1 * r_1 * (p_{id} - x_{id}) + c_2 * r_2 * (p_{gd} - x_{id}) \quad (16)$$

Velocity clamping with rule:
If $v'_{id} > v_{max}$ then $v'_{id} = v_{max}$
If $v'_{id} < v_{min}$ then $v'_{id} = v_{min}$

f. Update position

$$x'_{id} = x_{id} + v'_{id} \quad (17)$$

Normalizes the position (position clamping) with rule:
If $x'_{id} > x_{max}$ then $x'_{id} = x_{max}$
If $x'_{id} < x_{min}$ then $x'_{id} = x_{min}$

g. Second particle evaluation using SVR and calculate fitness value.
h. Update Pbest.
i. Update Gbest.
j. Repeat from step 4 to step 9 until iteration reaches the maximum value.
k. Optimal SVR parameters obtained.
l. Forecasting using Optimal SVR parameters.
m. Done.

Information:
Maximum and minimum velocity can calculate with equation:

$$v_{max} = k\,(x_{max} - x_{min})\ k \in [0,1] \quad (18)$$

$$v_{min} = -v_{max} \quad (19)$$

Description:
c_1 and c_2 : Acceleration coeficient
$iter$: now iteration
$itermax$: maximum iteration
r_1 and r_2 : random number selected from [0-1]
$Pbest/p_{id}$: best previous position (local)
$Gbest/p_{gd}$: best particle position in D dimension (global)
x'_{id} : newest particle position (after update)
x_{id} : previous particle position (before update)
v'_{id} : newest particle velocity (after update)
v_{id} : previous particle velocity (before update)
The Flowchart of forecasting using SVR-PSO algorithm is shown in figure 3.

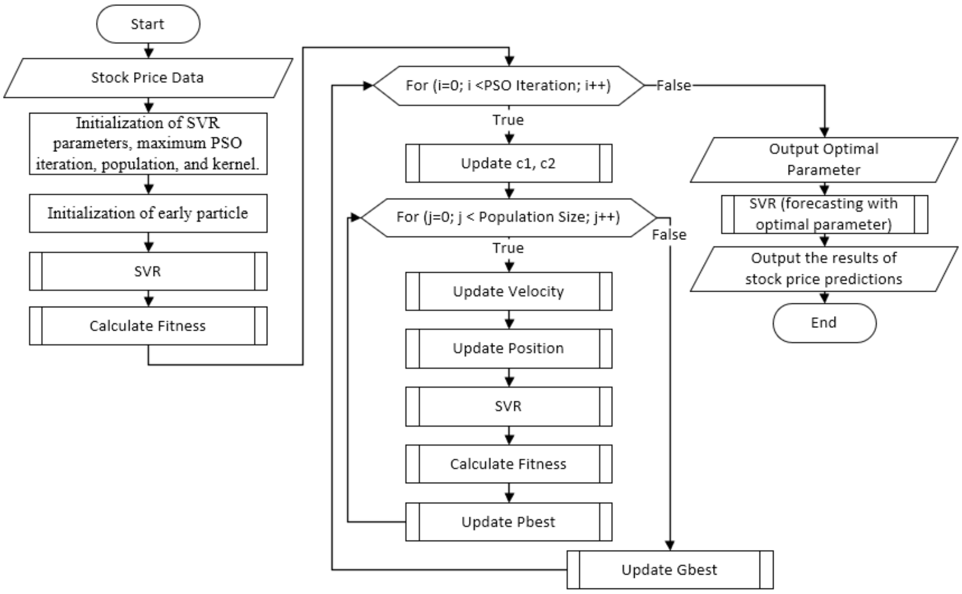

Figure 3. Flowchart of SVR-PSO algorithm

2.3.3 SVR-WAPSO Implementation

Forecasting using SVR-WAPSO will use SVR as prediction/forecasting algorithm and WAPSO as optimization algorithm that optimize SVR parameter. The steps for the SVR-WAPSO algorithm are almost the same as those for the SVR-PSO, except that there is an additional weight attribute. The steps SVR-WAPSO are as follows [2][3]:

a. First step is initialization initial such as SVR parameter range (complexity (C), lamda (λ), epsilon (ε), sigma (σ) and gamma (γ)), maximum WAPSO iteration, WAPSO particle population number, and kernel.
b. Particle initialization, the initial velocity of each particle is 0 and the initial position of each particle is random using equation (12).
c. Use SVR algorithm to evaluation the early particle (first evaluation), SVR algorithm steps as figure 2 and calculate fitness value with equation (13).
d. Update w

$$w = w_{max} - iter * \frac{w_{max} - w_{min}}{itermax} \quad (20)$$

e. Update c_1 and c_2 with equation (14) and equation (15).

f. Update velocity

$$v'_{id} = w * v_{id} + c_1 * r_1 * (p_{id} - x_{id}) + c_2 * r_2 * (p_{gd} - x_{id}) \quad (21)$$

Velocity clamping with rule:

If $v'_{id} > v_{max}$ then $v'_{id} = v_{max}$

If $v'_{id} < v_{min}$ then $v'_{id} = v_{min}$

(v_{max} and v_{min} can calculate with equation (18) and (19))

g. Update position with equation (17). Normalizes the position (position clamping) with rule:

If $x'_{id} > x_{max}$ then $x'_{id} = x_{max}$

If $x'_{id} < x_{min}$ then $x'_{id} = x_{min}$

h. Second particle evaluation using SVR and calculate fitness value.

i. Update Pbest.

j. Update Gbest.

k. Repeat from step 4 to step 9 until iteration reaches the maximum value.

l. Optimal SVR parameters obtained.

m. Forecasting using Optimal SVR parameters.

n. Done.

Description:

w : inertia weight attribute

The Flowchart of forecasting using SVR-WAPSO algorithm is shown in figure 4.

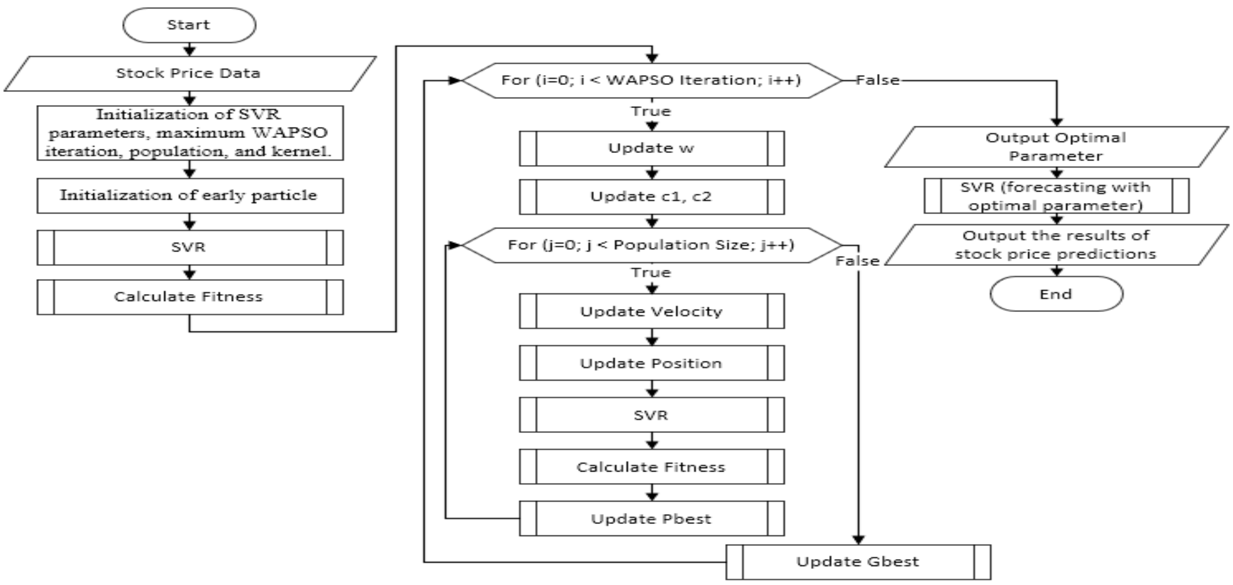

Figure 4. Flowchart of SVR-WAPSO algorithm

2.4 Evaluation

The evaluation phase is divided into two stages, namely the accuracy stage and the statistical test stage. The accuracy stage will evaluate forecasting result in form MAPE and calculate the accuracy. Forecasting results are stated to have high accuracy if the MAPE value is less than 10% and is declared inaccurate if the MAPE value is more than 50%. Accuracy can be obtained from 100% minus MAPE [2]. The statistical test stage will compare the mean fitness value of the SVR-PSO with the SVR-WAPSO to determine the effect of inertia weight attribute on the fitness value. Kolmogorov-Smirnov is a normality test that used to determine the distribution of the mean fitness value data. If data distribution is normal then use Paired Sample t-Test method for statistic test, but if data distribution is not normal then use Wilcoxon Signed-Rank Test method for statistic test [3].

3. RESULTS AND DISCUSSION

3.1 Results

Data obtained from yahoo finance and there are three stock price data that will be used in predictions. The three stock price data are PT Telekomunikasi Indonesia Perseroan (Telkom) (TLKM) stock data from the IT sector, Bank BRI (BBRI) stock data from the banking sector and Adaro Energy Tbk (ADRO) stock data from the energy sector. Stock data range is taken from December 2017 to August 2019. The three stock price data are obtained from yahoo finance. TLKM, BBRI and ADRO stock data will predicted using SVR, SVR-PSO and SVR-WAPSO algorithms.

Table 1 Amount of data collected

No	Stock Data	Range Data	Total Data
1.	TLKM	27 December 2017 - 30 August 2019	438
2.	BBRI	27 December 2017 - 30 August 2019	438
3.	ADRO	27 December 2017 - 30 August 2019	438
		Total	1314

Data transformation performed in data processing, where data from close price column used to make 3 feature or 3 windows size time series data become column Day-3, column Day-2, column Days-1 and column Actual. Total data will be 435 row. Then split the data into training data and testing data with rasio 90% : 10%. Total training data is 391 data and testing data is 44 data.

Table 2 TLKM training data

Index	Date	Day-3	Day-2	Day-1	Actual
0	1/1/2018	4300	4390	4440	4440
1	1/2/2018	4390	4440	4440	4410
2	1/3/2018	4440	4440	4410	4230
...	...	...	...	...	...
390	7/1/2019	3980	4090	4140	4220

Table 3 TLKM testing data

Index	Date	Day-3	Day-2	Day-1	Actual
391	7/2/2019	4090	4140	4220	4250
392	7/3/2019	4140	4220	4250	4240
393	7/4/2019	4220	4250	4240	4250
...	...	...	...	...	...
434	8/30/2019	4380	4370	4380	4450

3.1.1 Calculation of SVR Algorithm

Normalize the data first with equation (1) and the result will be as bellow:

Table 4 TLKM training data after normalization

Index	Date	Day-3	Day-2	Day-1	Actual
0	1/1/2018	0.858333	0.933333	0.975	0.975
1	1/2/2018	0.933333	0.975	0.975	0.95
2	1/3/2018	0.975	0.975	0.95	0.8
...	...	...	...	...	...
390	7/1/2019	0.591667	0.683333	0.725	0.791667

Table 5 TLKM testing data after normalization

Index	Date	Day-3	Day-2	Day-1	Actual
391	7/2/2019	0.683333	0.725	0.791667	0.816667
392	7/3/2019	0.725	0.791667	0.816667	0.808333
393	7/4/2019	0.791667	0.816667	0.808333	0.816667
...	...	...	...	...	...
434	8/30/2019	0.925	0.916667	0.925	0.983333

Then the SVR calculation steps is initialize SVR parameters such as complexity (C) with range 100 - 500, lamda (λ) with range 0.001 - 0.1, epsilon (ε) with range 0.0001 - 0.01, sigma (σ) with range 0.001 - 2 and gamma (γ) with range 0.00001 - 0.001, initial values α_i^*= 0 and α_i = 0 and maximum iteration = 1000.

Table 6 Initial SVR parameters on TLKM data

C	λ	ε	σ	γ
189.24	0.0808435	0.0054658	0.66147	0.00081388

Calculate the data with the initial SVR parameters from the SVR algorithm step 2 to step 6 and the result is:

Table 7 SVR prediction results on TLKM data

Index	Date	Actual	Prediction Results
391	7/2/2019	4250	3400.219
392	7/3/2019	4240	3392.122
393	7/4/2019	4250	3387.042
...	...	...	...
434	8/30/2019	4450	3361.61

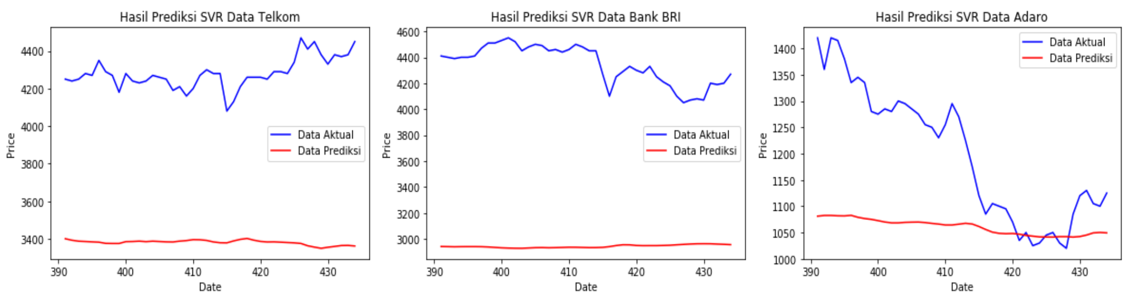

Figure 5. Graph of SVR prediction results on TLKM, BBRI and ADRO data

Next step is calculate MAPE with equation (10) and the result is:

Table 8 Parameters and MAPE of SVR prediction results on stock price data

No	Data	C	λ	ε	σ	γ	MAPE (%)
1.	TLKM	189.24	0.0808435	0.0054658	0.66147	0.00081388	20.97507
2.	BBRI	133.48	0.0973666	0.00285517	1.10745	0.000785962	32.16953
3.	ADRO	151.92	0.0712999	0.00166123	0.285857	0.000787843	11.05048

3.1.2 Calculation of SVR-PSO Algorithm

The SVR-PSO algorithm can be calculated with first step is initialize SVR parameters range (complexity (C) = 100 - 500, lamda (λ) = 0.001 - 0.1, epsilon (ε) = 0.0001 - 0.01, sigma (σ) = 0.001 - 2 and gamma (γ) = 0.00001 - 0.001), maximum PSO iteration = 40, PSO particle population = 40, and kernel using RBF (Radial Basis Function). Then initialize the early particles with equation (12) and set initial velocity = 0. Calculate v_{max} using equation (18) and v_{min} using equation (19). Evaluate the early particle with the SVR algorithm steps as shown in figure 2 and calculate the fitness value using equation (13). The result is:

Table 9 Results of first evaluation using SVR algorithm on TLKM data

Particle	C	λ	ε	σ	γ	MAPE (%)	Fitness
1	366.04	0.02616	0.00344	0.06277	0.00006	23.5623	0.04071
2	114.44	0.04693	0.00193	1.76992	0.00009	23.1653	0.04138
3	391.56	0.09105	0.00217	1.29055	0.00040	21.8698	0.04373
...	...	...	...	...	...	...	...
40	376.36	0.08223	0.00049	1.35092	0.00087	11.3953	0.08068

Set first evaluation result as initial Pbest and set initial Gbest with particle that have the best fitness value. The next step is to enter the PSO iteration with update c_1 and c_2 using equation (14) and (15), update velocity with equation (16), update position using equation (17) and evaluate again with SVR algorithm. Update Pbest and Gbest after get evaluation result. Repeat these steps until the maximum PSO iteration is complete. Then the optimal SVR parameters obtained as below:

Table 10 Optimal SVR parameters using SVR-PSO

No	Data	C	λ	ε	σ	γ	MAPE (%)	Fitness
1.	TLKM	500	0.1	0.0001	0.317283805	0.001	1.35084	0.425379
2.	BBRI	187.56	0.067797	0.0001	2	0.001	1.67819	0.373387
3.	ADRO	100	0.021132	0.0001	0.075305	0.001	2.09733	0.322859

The last step is forecasting using optimal SVR parameters and the result is:

Table 11 SVR-PSO prediction results on TLKM data

Index	Date	Actual	Prediction Results
391	7/2/2019	4250	4122.70393
392	7/3/2019	4240	4166.526
393	7/4/2019	4250	4244.40223
...	...	...	...
434	8/30/2019	4450	4394.67123

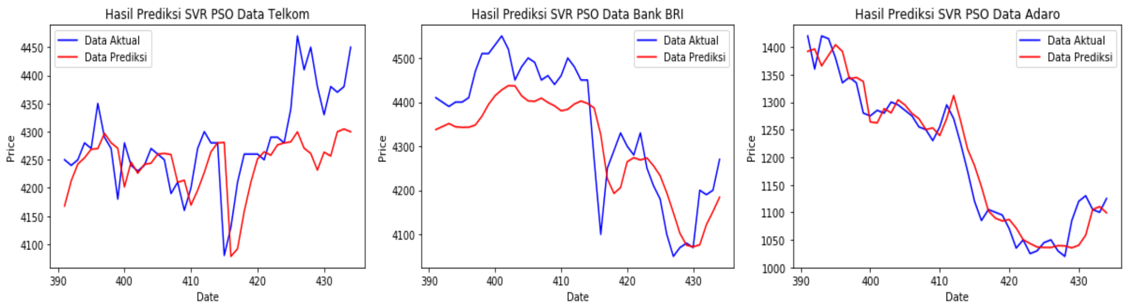

Figure 6. Graph of SVR-PSO prediction results on TLKM, BBRI and ADRO data

3.1.3 Calculation of SVR-WAPSO Algorithm

The first step in calculating the SVR-WAPSO algorithm is initialize SVR parameters range (complexity (C) = 100 - 500, lamda (λ) = 0.001 - 0.1, epsilon (ε) = 0.0001 - 0.01, sigma (σ) = 0.001 - 2 and gamma (γ) = 0.00001 - 0.001), maximum WAPSO iteration = 40, WAPSO particle population = 40, WAPSO maximum iteration = 40, and kernel using RBF (Radial Basis Function). Then initialize the early particles with equation (12), but in this study will use the same early particles as SVR-PSO early particles. Set initial velocity = 0. Calculate v_{max} using equation (18) and v_{min} using equation (19). Evaluate the early particle with the SVR algorithm steps as shown in figure 2 and calculate the fitness value using equation (13) . The result will be the same as in tabel 9.

Set first evaluation result as initial Pbest and set initial Gbest with particle that have the best fitness value. The next step is to enter the WAPSO iteration with update w (weight attribute) using equation (20), update c_1 and c_2 using equation (14) and (15), update velocity with equation (21), update position using equation (17) and evaluate again with SVR algorithm. Update Pbest and Gbest after get evaluation result. Repeat these steps until the maximum WAPSO iteration is complete. The optimal SVR parameters obtained as below:

Table 12 Optimal SVR parameters using SVR-WAPSO

No	Data	C	λ	ε	σ	γ	MAPE (%)	Fitness
1.	TLKM	500	0.1	0.0001	0.316908	0.001	1.35079	0.425388
2.	BBRI	439,349	0.1	0.0001	2	0.001	1.67504	0.373826
3.	ADRO	126,5377	0.022206	0.0001	0.076038	0.000933	2.10111	0.322465

The last step is forecasting using optimal SVR parameters and the result is:

Table 13 SVR-WAPSO prediction results on TLKM data

Index	Date	Actual	Prediction Results
391	7/2/2019	4250	4167.664
392	7/3/2019	4240	4212.306
393	7/4/2019	4250	4242.494
...	...	...	...
434	8/30/2019	4450	4299.882

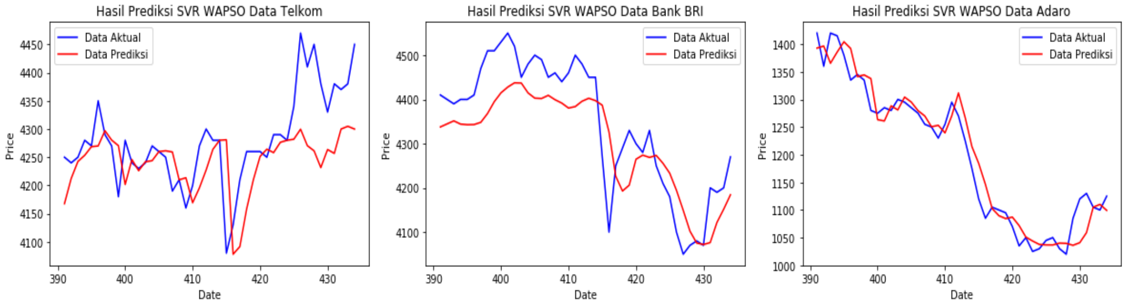

Figure 7. Graph of SVR-WAPSO prediction results on TLKM, BBRI and ADRO data

3.1.4 Calculation of Accuracy

Accuracy can calculate with equation 100% minus MAPE and the result is:

Table 14 Accuracy results

No	Algorithm	Data	MAPE (%)	Accuracy (%)
1.	SVR	TLKM	20.97507	79.02493
		BBRI	32.16953	67.83047
		ADRO	11.05048	88.94952
2.	SVR-PSO	TLKM	1.35084	98.64916
		BBRI	1.67819	98.32181
		ADRO	2.09733	97.90267
3.	SVR-WAPSO	TLKM	1.35079	98.64921
		BBRI	1.67504	98.32496
		ADRO	2.10111	97.89889

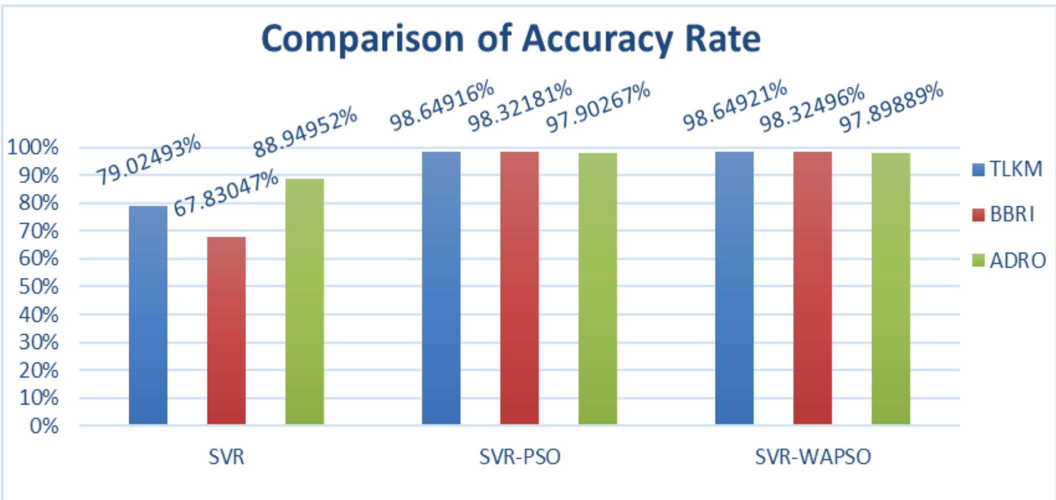

Figure 8. Graph of accuracy rate comparison

3.1.5 Calculation of Kolmogorov-Smirnov

Kolmogorov Smirnov normality test was conducted to determine the distribution of data on the mean fitness value and the result is TLKM PSO data and TLKM WAPSO data not normal, but BBRI PSO, BBRI WAPSO, ADRO PSO and ADRO WAPSO is normal. The following is a graph of the distribution of mean fitness value data:

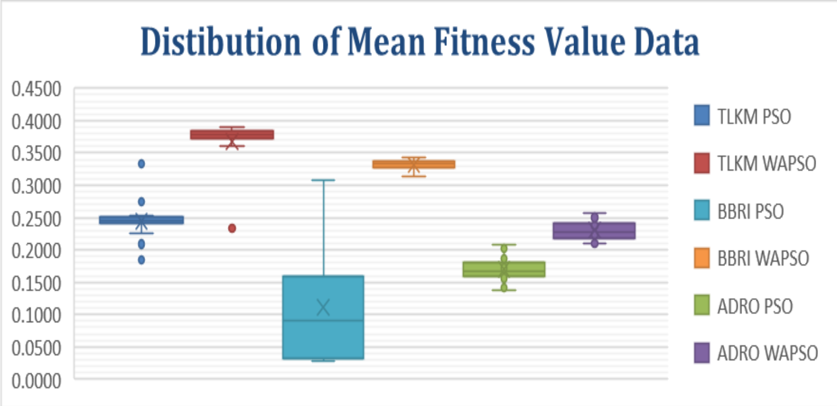

Figure 9. Graph of mean fitness value distribution data

3.1.6 Calculation of Paired Sample t-Test

Paired sample t-test calculated to compare between mean fitness value of SVR-PSO and SVR-WAPSO. In this study use manual calcuation and also use SPSS to calculate it. Based on the results of the normality test, the data to be calculated using the paired sample t-test method are BBRI mean fitness value data and ADRO mean fitness value data. Significant value (α) used is 0.05. The hipotesis is:

H_0: There is no significant difference between the mean fitness value of the PSO algorithm and the WAPSO algorithm in optimizing the SVR parameter.

H_1: There is a significant difference between the mean fitness value of the PSO algorithm and the WAPSO algorithm in optimizing the SVR parameter.

If $T_{cal} > T_{tab}$ or P-value < α (0.05) then there is a difference in significance (H0 is rejected).

If $T_{cal} < T_{tab}$ or P-value> α (0.05) then there is no significant difference (H0 is accepted).

The result calculation with SPSS is below:

Table 15 Paired sample t-test results

Paired Sample t-Test							
		Paired Difference			t	df	Sig. (2-tailed)
		Mean	Std. Deviation	Std. Error Mean			
Pair 1	BBRI_PSO - BBRI_WAPSO	-0.2202	0.0874	0.0138	-15.931	39	$1.15E^{-18}$
Pair 2	ADRO_PSO - ADRO_WAPSO	-0.0597	0.0207	0.0033	-18.275	39	$1.01E^{-20}$

3.1.7 Calculation of Wilcoxon Signed-Rank Test

Calculation of Wilcoxon signed-rank test is applied to TLKM mean fitness value data because the data distribution is not normal so non-parametric statistic test is needed. The hipotesis same with paired sample t-test hipotesis. The rule in Wilcoxon signed-rank test is:

If $Z_{cal} > Z_{tab}$ or P-value < α (0.05) then there is a difference in significance (H0 is

rejected).
If $Z_{cal} < Z_{tab}$ or P-value> α (0.05) then there is no significant difference (H0 is accepted).
The result calculation with SPSS is below:

Table 16 Wilcoxon signed-rank test results

Wilcoxon-Signed Rank Test	
	TLKM_WAPSO - TLKM_PSO
Z	-5.497^{b}
Asymp. Sig. (2-tailed)	$3.85E^{-8}$

3.1.8 Statistical Test Results

Based on calculation of paired sample t-test and Wilcoxon signed-rank test, it can be concluded that the accepted hypothesis is H_1 which states there is a significant difference between the mean fitness value of the PSO algorithm and the WAPSO algorithm in optimizing the SVR parameter. In addition, 2 out of 3 stock data shows that the accuracy of SVR-WAPSO is better. Details of the comparison between SVR-PSO and SVR-WAPSO can be seen in the following table:

Table 17 Comparison SVR-PSO and SVR-WAPSO

No	Comparison Indicators	SVR-PSO : SVR-WAPSO		
		TLKM	BBRI	ADRO
1.	The Best Accuracy	SVR-WAPSO	SVR-WAPSO	SVR-PSO
2.	Test Statistics Method	Wilcoxon signed-rank test	Paired sample t-test	Paired sample t-test
3.	P-Value	$3.85E^{-8}$	$1.15E^{-18}$	$1.01E^{-20}$
4.	Hipotesis Results	H_1 (significantly different)	H_1 (significantly different)	H_1 (significantly different)
5.	The Best Mean Fitness Value	SVR-WAPSO	SVR-WAPSO	SVR-WAPSO
6.	Difference in Mean Fitness Values	0.1230	0.2202	0.0597

3.2 Discussion

In this study used 3 stock price data those are TLKM data, BBRI data and ADRO data with a total of each data is 438 data. The implemented algorithms are SVR, SVR-PSO and SVR-WAPSO to predict the stock price data. SVR algorithm is used to predict time series data. PSO and WAPSO are used to optimize the SVR parameters for high accuracy. The results show that the SVR algorithm is accurate but not highly accurate because high accuracy has a MAPE of less than 10% or an accuracy rate of more than 90%. The results of the SVR-PSO and SVR-WAPSO show accuracy rate more than 90%, therefore these two algorithms can be said to have high accuracy.

Statistical test results using Kolmogorov-Smirnov show that distribution of mean fitness value data in SVR-PSO TLKM and SVR-WAPSO TLKM is not normal, but in BBRI data and ADRO data the distribution of mean fitness value by SVR-PSO or SVR-WAPSO is normal. Paired Sample t-Test is used for BBRI data and ADRO data because the distribution is normal, but TLKM data must use the Wilcoxon signed-rank test because the distribution is not normal. The result of statistic test show that accept H_1 so there is significant difference between the mean fitness value of the PSO algorithm and the WAPSO algorithm in optimizing the SVR parameter. From 3 of 3 data shown that SVR-WAPSO have better mean fitness value.

4. CONCLUSION

The accuracy rate of the Support Vector Regression (SVR) algorithm on TLKM, BBRI and ADRO stock data without parameter optimization is 79.02493%, 67.83047% and 88.94952%. Then the accuracy rate of the Support Vector Regression (SVR) algorithm on TLKM, BBRI and ADRO stock data with parameter optimization using the Particle Swarm Optimization (PSO) algorithm is 98.64916%, 98.32181% and 97.90267%, while the accuracy rate with parameter optimization using the Weight Attribute Particle Swarm Optimization (WAPSO) algorithm are 98.64921%, 98.32496% and 97.89889%. The effect of the weight attribute (inertia weight attribute) on the optimization of the Support Vector Regression (SVR) parameters for stock price predictions is to increase the average fitness value caused by the determination of the new position of the particles that are better and more directed to the optimal position point. The mean increases were 0.1230 (TLKM), 0.2202 (BBRI) and 0.0597 (ADRO).

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