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Comparison of accuracy of Epsilon and Quadratic loss function for predicting saturated hydraulic conductivity by SVR and SVR-GA models

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ABSTRACT

Saturated hydraulic conductivity is one of the most effective hydraulic characteristics of the soil processes. One of the methods to measure saturated hydraulic conductivity above water table is applying cased boreholes. Support vector machine is a classifier which uses statistical train theory for classification and regression; and genetic algorithm is a searching technique in optimization problems inspired from the nature and the evolution of the creatures. In this research Epsilon and quadratic loss functions are compared against each other in support vector machine model (SVR) and support vector machine-genetic algorithm model (SVR-GA). These models are developed by the core radial function to predict the saturated hydraulic conductivity to be a suitable replacement for Reynolds analytical solutions in cased boreholes. The data used in this study are consisting of soil moisture percentage, saturated soil moisture percentage, the water table fall versus time, time, size of boreholes and the quantities of saturated hydraulic conductivity of the soil calculated by Reynolds solution. 70 percent of data is used for the train, 20 percent for the test and 10 percent for the validity. In order to analyze the results we have used three different statistical indicators including correlation coefficient (R2), root mean square error (RSME), and normalized root mean square error (NRMSE). Accord-

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ing to the results of SVR-GA model in all three types of flow the coefficient of determination was above 0.99 and root mean square error and mean absolute error were less than 0.02. The results of this research indicate that Epsilon loss function had better accuracy than quadratic loss function but in terms of execution time quadratic loss function is considerably more efficient than Epsilon loss function.

KEY WORDS: GENETIC ALGORITHM, LOSS FUNCTION, SUPPORT VECTOR MACHINE, SATURATED HYDRAULIC CONDUCTIVITY

INTRODUCTION

Although the equations calculating hydraulic conductivity of soil which are including a variety of hydraulic processes are quite accurate but they include a lot of computational stages. On one hand adding different aspects of processes within these equation has increased their accuracy, but it has enhanced the computational load as well. One of the methods to confront increasing computational load is using a meta-model. In other words developing an alternative model instead of the main model which has learnt the relations based on input and output can be more effective in computational efficiency. Applying the appropriate solutions to increase the accuracy of approximated models and efficient use of them can be known as alternative meta-model management. Nowadays the topic of alternative model management has been known as a new field of research and has attracted a lot of attention to it.

Saturated hydraulic conductivity is one of the most effective hydraulic characteristics affecting the soil processes (Reynolds and Topp, 2008). These parameters play a fundamental role in controlling the hydrological processes of underground flows (Reynolds and Elrick, 2005). In order to measure saturated hydraulic conductivity of soil different methods are available according to the soil type and the difference between the levels of underground water wit surface. One of the methods of measuring hydraulic conductivity is borehole method which in known as the falling head lined boreholes permeameter method (Navin *et al.* 2008). Philip has presented an approximately analytical solution for this type of borehole. Philip borehole only studies vertical flows. In the following, Reynolds studied different geometries of flow and various radiuses of tanks and Philip's borehole as well and analyzed them. Due to the high volume of computing in these analyses we can use an alternative model which has been developed by artificial intelligence in order to predict saturated hydraulic conductivity of soil. Artificial intelligence (AI) models has been used in a wide range of fields. AI models are quick, robust, and convenient to use for the prediction and solving complex problems compared with conventional methods which impose more difficulties, time consumption, and high expenses.

Shams Emamzadeh *et al*, (2017) in a study has compared the performance of Multi-Layer Perceptron (MLP) and Radial Basis Function (RBF) in neural networks for estimation of the soil saturated hydraulic conductivity. Amongst the AI models with high accuracy are support vector machine model (SVR) and genetic algorithm- support vector machine combined model (SVR-GA). In this study the prediction of saturated hydraulic conductivity of soil via SVM and SVM-GA model has been calculated using soil moisture percentage, saturated soil moisture percentage, the water table fall versus time, time, and size of the boreholes and the values of saturated hydraulic conductivity of soil calculated by Reynolds solution (Mehmandoust, 2014).

SVM is a collection of training techniques by the machine which is used for classification and or regression and is introduced based on statistical train theory and minimization of loss probability (Kalanaki and Soltani, 2013a; Vapnic, 2010). Genetic algorithm (GA) is a metaheuristic also one of the numerical optimization algorithms which is inspired from the nature and is a good option for the models use regression for prediction. These algorithms are by relying on bio-inspired operators such as crossover, mutation and natural selection. SVM has better efficiency comparing neural networks for flood probability prediction (Liong and Sivapragasam, 2000). Yang Shao and Huang Yuan Fang (Yang and Huang, 2007) used SVM model in order to predict the parameters of hydraulic characteristics of soil and concluded that there was no obvious difference between the predicted results and the observed ones. Navin Twarakawi *et al* (Navin *et al.* 2008) used SVM model to estimate hydraulic parameters of soil, in this study all the parameters which were estimated based on transfer function and via SVM model showed better reliability compared with ROSETTA PTF program.

Kalanaki *et al.* (2013) conducted a comparative study about different Kernel functions and loss functions in support vector machine using SVM_GA combined model in order to predict the refraction rate of the pipes in water distribution network. The findings of this study showed the better efficiency of radial Kernel functions and quadratic loss functions. Krzysztof Lamorski *et al* (Lamorski *et al.* 2011) modelled soil water retention using SVM with the optimized model of genetic algorithm. The findings of the study showed that suing SVM model with the optimized genetic algorithm for soil water retention modelling is better than the prior tested methods. Chen Hai Yan *et al* (Chen *et al.* 2011) used SVR-GA model to predict aquifer hydraulic conductivity and water surface table computation. The findings of their study proved that the model had performed accurate in predicting hydraulic conductivity.

This research aims at assessing and comparing regression support vector machine and hybrid model of genetic algorithm and regression support vector machine (SVR-GA) by Epsilon and quadratic loss functions with the help of the prior study's findings (Asadollah Zade, 2013) which apply Reynolds and Philip methods to predict hydraulic conductivity of soil; and also with developing an artificial intelligence model finds an alternative model for analytical Reynolds model which involves a great deal of computational processes.

MATERIALS AND METHODS

One of the methods of measuring hydraulic conductivity is using boreholes which is known as the falling-head lined boreholes permeameter method (Philip, 1993). The method uses cased boreholes and gives saturated hydraulic conductivity based on the drop in levels of water versus time. In Philip Solution, the walls of the borehole are all covered and permeation occurs only from the floor and vertical. In Reynolds method, the most common and probable types of flow geometry and various radii of tanks for permeameter of boreholes are taken into consideration which consist of: only vertical flow (Philip), only radial flow (permeable wall with the length L and impermeable floor) and a combination of vertical and radial flows where the permeable section has the length L and the radius a. The data used in the model were collected from 27 drilled boreholes in 1 in 1 meter grid with 3 repetitions and for three types of flow including vertical, horizontal and vertical-horizontal flows (radial). Plastic pipes were used to cover the walls of the borehole and the size of the boreholes included three diameter 4, 6 and 8 cm with different lengths (Asadollah Zade, 2013).

HYDRAULIC CONDUCTIVITY

Saturated hydraulic conductivity values used in the models are obtained from Reynolds' approximate analytical solution. These solutions include many equations and long computational steps which require input data such as soil moisture percentage, saturated soil moisture percentage, drop in water levels versus time, time, borehole's size including the borehole's radius and the covered length as well as uncovered length in different considered geometries.

SUPPORT VECTOR MACHINE

Support vector machine is a collection of train methods by machine which is used for classification and regression and is based on statistical train theory and loss probability minimization (Shams Emamzadeh *et al.* 2017; Vapnic, 1995; Kalanaki *et al.* 2013). The function that is used to calculate regression support vector machine is in the form of mapping from the input space of Xi to output space of Yi and is represented by equation (Asadollah Zade, 2013):

$$F(x) = w\ x - b \tag{1}$$

Where W and b represent weight and bias respectively. In regression support vector machine the aim is estimating b and W in order to achieve the best results. In regression support vector machine represents the difference between the actual data and the results data and the variable represents an allowed extent of error that can occur by various factors such as noise (Kalanaki *et al.* 2013; Smola and Scholkopf, 1998). Margin is defined as the ration of and to maximize margin we should minimize. These stages are considered in equations (2) and (3) which are the building blocks of regression support vector machine (Simunek *et al.* 2006; Lamorski *et al.* 2011):

$$\text{Minimize} \ \ \frac{1}{2}||w||^2 + C\sum_{i=1}^{n}\xi_i \tag{2}$$

Subject to:

$$y_i(w^T x_i + b) \geq 1 - \xi_i\,, \qquad \xi_i \geq 0 \tag{3}$$

C determines an exchange between the size of margin and the extent of error in train and controls over-fitting in train. We use Kernel functions because working with above functions can be costly and time-consuming. Kernel function is a linear classifier based on dot product of vectors which is equal to k Kernel function is equivalent to the inner product in the feature space. Therefore, instead of costly calculations in feature space we apply Kernel function. Here W is obtained from equation (Kalanaki and Soltani, 2013a). Finally, the regression support vector machine with the effect of Kernel functions is obtained from equation (Kalanaki and Soltani, 2013a):

$$w = \sum_i (\alpha_i - \bar{\alpha}_i) x_i \tag{4}$$

$$F(x) = \sum_{i=1}(\bar{\alpha}_i - \alpha_i) K(x_i, x) + b \tag{5}$$

One of the most useful basis-functions is Gaussian basis function or radial basis function (RBF) which is shown in equation (Lamorski *et al.* 2011):

$$K(x_i, x_j) = \exp(-\frac{\|x_i - x_j\|^2}{2\sigma^2}) \quad (6)$$

Where Xi and Xj are support vectors and is the bandwidth of the radial basis Kernel function. To minimize the error and other risks we aim at finding a function which is shown in equation (Liong and Sivapragasam, 2000):

$$R_{emp}\,[f] = \frac{1}{l}\sum_{i=1}^{l} c(x_i, y_i, f(x_i)) \quad (7)$$

Function refers to cost function and indicates the penalty for estimate function according to experimental data. Remp represents the experimental error. Loss function determines the penalty of data while estimating. In this study two types of loss functions are utilized which are Epsilon loss function and quadratic loss function. Figure (1) shows the diagrams of these functions.

The values of epsilon and quadratic loss functions are obtained respectively by equations (8) and (9):

$$c(x_i, y_i, f(x_i)) = \begin{cases} |f(x_i) - y_i| - \varepsilon & |f(x_i) - y_i| \geq \varepsilon \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

$$c(x_i, y_i, f(x_i)) = (f(x_i) - y_i)^2 \quad (9)$$

GENETIC ALGORITHM

Genetic algorithm was introduced by John Holland according to evolution theory of Darwin in the early 1970s. The optimization search procedure in genetic algorithm is based on a guided random procedure. The procedure has been inspired from the nature and the evolution of living creatures. In this method each member of the population is shown through a string composed of variables where each variable is called gene and the string composed of genes is called chromosome. In fact, initially for a number of responses which is called population a set of objective parameters are generated randomly. After running numerical simulator program which represents the fitness of the set of data, a fitness value will be attributed to the member of the population. This will repeat for each and every developed member, after calling genetic algorithm operators such as crossover, mutation and selection operators and while retaining the top part of the population, the next generation will be formed and this procedure will continue till one of the stop conditions is satisfied. At the end, the member of the population that has the best fitness value will be selected (Kalanaki and Soltani, 2013a; Kalanaki and Soltani, 2013b).

MODEL DEVELOPMENT

The studies conducted in this research are carried out in the research field of Abureyhan campus of Tehran University which is located in Pakdasht. In order to develop and run SVR model we need to adjust the parameters c, ε and σ in the models engaging Epsilon loss function and the parameters c and σ must be modified in the models involving quadratic loss function. In order to find the most suitable combination of this parameters in SVR model, trial and error method must be used and the combination with the least amount of error and the highest correlation must be selected. It can be mentioned that one of the downfalls of SVR model is finding such a combination using trial and error method. In order to find the best combination GA optimization model was applied. The model was developed and implemented for three kinds of flows introducing input data matrixes which were composed of the combinations of applied variables in Richards and Van Genuchten-Maulem equations and the dimensions of the boreholes and output matrix including the values of hydraulic conductivity calculated by HYDRUS, Kernel and the desired loss function selection and introducing the optimal parameters and the values of correlation coefficient, root mean square error and normalized root mean square error were calculated. Equations (10) to (12) show these relations respectively:

$$R^2 = \left[\frac{[(\sum XY) \frac{\sum X \sum Y}{n}]^2}{[\frac{\sum X^2 (\sum X)^2}{n}][\sum Y^2 \frac{\sum Y^2}{n}]}\right]^{0.5} \quad (10)$$

$$RMSE = \left[\frac{\sum_{i=1}^{n}(P_i - Q_i)^2}{n}\right]^{0.5} \quad (11)$$

$$NRMSE = \frac{\left[\frac{1}{n}\sum_{i=1}^{n}(P_i - Q_i)^2\right]^{0.5}}{\frac{1}{n}\sum_{i=1}^{n} Q_i} \quad (12)$$

Where Pi represents the estimated or stimulated value, Qi is the observed value and n is the number of samples.

In developing GA, the number of the initial population was 20, the combination type was single point, selection rate was 0.5, mutation rate was 0.25 and the number of replications was considered 300. Equation (13) represents the fitness function in genetic algorithm.

$$f = \sum_{i=1}^{n} \frac{|y_{test} - y_{model}|}{n} \quad (13)$$

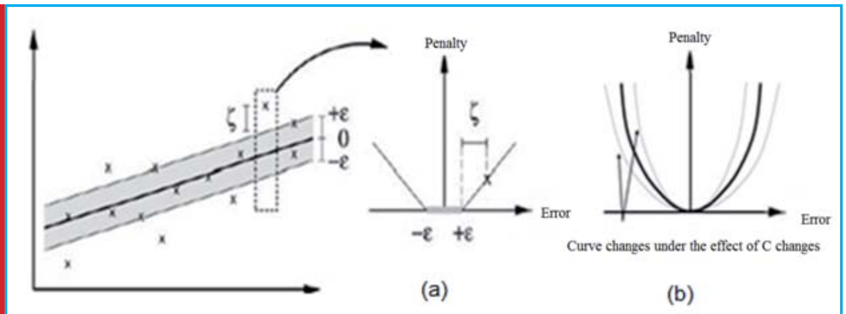

FIGURE 1. (a) Epsilon loss function (b) Quadratic loss function

In the equation above, f represents the average of errors, n is the number of test's data, ytest is the experimental values and y model is the estimated values. Genetic algorithm using a variety of different parameters' combinations converges to a certain extent of error in desired replications. In this study after normalization in order to use Kernel function, 70 percent of data were used for train, 20 percent for test and 10 percent for validation. In order to write and run the codes we have used MATLAB software.

The optimal parameters achieved by the hybrid model were used in Support Vector Machine. Set of chromosomes make up the population. The encoding process of each chromosome in the consolidated SVR-GA model includes ε, C and. A set of chromosomes make up the population (Kalanaki *et al*, 2013; Kalanaki and Soltani, 2013a; Kalanaki and Soltani, 2013b; Smola and Scholkopf, 1998; Shams Emamzadeh *et al.* 2017; Vapnic, 1995; Vapnic, 2010; Yang and Huang, 2007).

RESULTS AND DISCUSSION

The diagram shown in figure 2 represents the convergence of the objective function of genetic algorithm in a horizontal flow at an Epsilon loss function.

The results of the SVR and SVR-GA models with radial Kernel function at Epsilon loss functions are represented in table 1 in three different flows including horizontal, vertical and vertical-horizontal.

The results of the SVR and SVR-GA models with radial Kernel function for quadratic loss functions are represented in table 2 in three different flows including

Figures 3 and 4 represent the diagrams regarding the prediction of hydraulic conductivity by using of SVR model with test and train data for Epsilon and quadratic loss functions in horizontal flows respectively. The longitudinal axis shows the number data and the transverse axis shows the values of hydraulic conductivity.

Figures 5 and 6 represent the diagrams regarding the prediction of hydraulic conductivity by using of SVR-GA model with train and test data for Epsilon and quadratic loss functions in horizontal flows respectively. The longitudinal axis shows the number data and the transverse axis shows the values of hydraulic conductivity.

As it can be seen in table-1 SVR model has accurate and desirable results for three different types of flows (high correlation coefficient and low levels of error) and SVR-GA model also has excellent results (correlation coefficients close to 1 and error percentage close to zero). In SVR model of all three different flows determi-

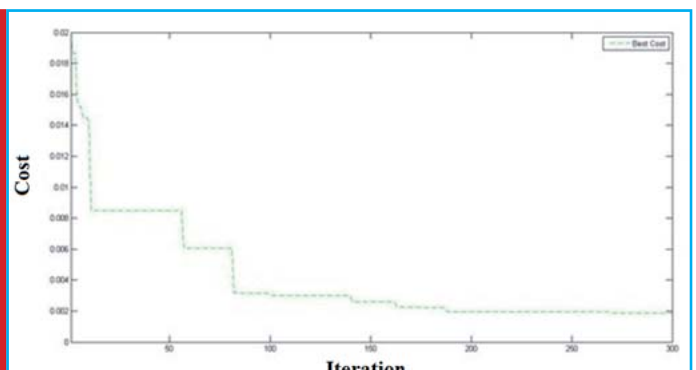

FIGURE 2. The convergence of GA in horizontal flow at epsilon loss function

Table 1. The results of SVR and SVR-GA for epsilon loss function

Run-time (seconds)	ε	c	σ	NRMSE	RMSE (m.s-1)	R2 (%)	Model type		Flow type
97922	0000019/0	70	0004/0	19474/0	09244/0	9786219/0	prediction	SVR	Horizontal flow
				19018/0	13031/0	9591991/0	validity		
93021	00000791/0	5665/72	00021049/0	00175/0	00089/0	9999973/0	prediction	SVR-GA	
				00169/0	00117/0	9999955/0	validity		
92131	000004/0	90	0004/0	15938/0	06601/0	9897919/0	prediction	SVR	Horizontal-vertical flow
				17917/0	09329/0	9780319/0	validity		
90456	00003758/0	1760/48	00001433/0	00292/0	00033/0	9999997/0	prediction	SVR-GA	
				00173/0	00025/0	9999998/0	validity		
103985	0007/0	110	00003/0	16723/0	11536/0	9492773/0	prediction	SVR	Vertical flow
				16578/0	12313/0	9356536/0	validity		
94783	00002245/0	5493/40	00001598/0	01309/0	00995/0	9994702/0	prediction	SVR-GA	
				01271/0	01095/0	9991326/0	validity		

Table 2. The results of SVR and SVR-GA for quadratic loss function

Run-time (seconds)	c	σ	NRMSE	RMSE (m.s-1)	R2 (%)	Model type		Flow type
29217	30	0007/0	45416/0	19230/0	9248/0	prediction	SVR	Horizontal flow
			46718/0	19246/0	9269/0	validity		
23699	3766/155	00029126/0	07426/0	03494/0	9973/0	prediction	SVR-GA	
			06967/0	02133/0	9989/0	validity		
27660	85	00075/0	39274/0	17164/0	9462/0	prediction	SVR	Horizontal-vertical flow
			34866/0	18326/0	9424/0	validity		
21518	1387/132	00021562/0	05838/0	02105/0	9991/0	prediction	SVR-GA	
			08277/0	02385/0	9985/0	validity		
32223	160	0005/0	27422/0	19525/0	8506/0	prediction	SVR	Vertical flow
			26374/0	16398/0	8459/0	validity		
28416	9392/246	00004794/0	09189/0	06917/0	9782/0	prediction	SVR-GA	
			08563/0	02049/0	9977/0	validity		

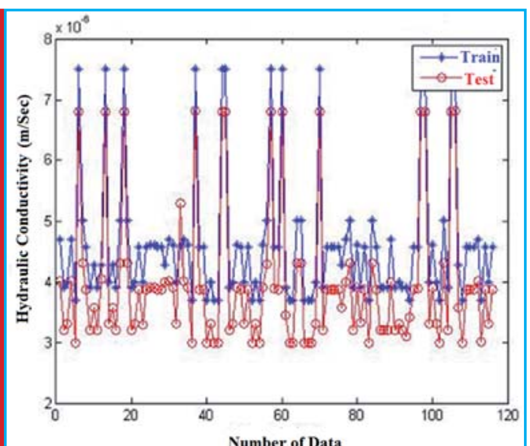

FIGURE 3. The prediction of hydraulic conductivity with test and train data by using of SVR model, with epsilon loss function in horizontal flow

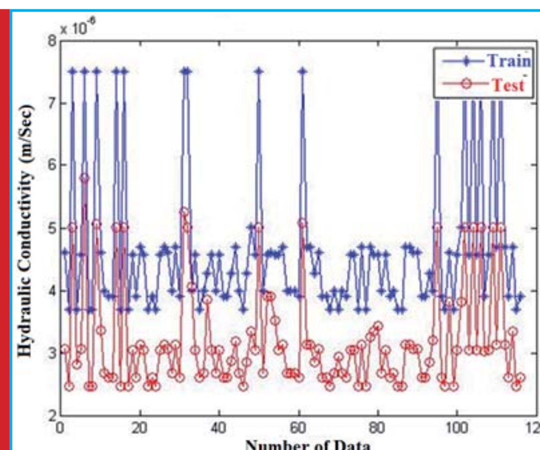

FIGURE 4. The prediction of hydraulic conductivity with test and train data by using of SVR model, with quadratic loss function in horizontal flow

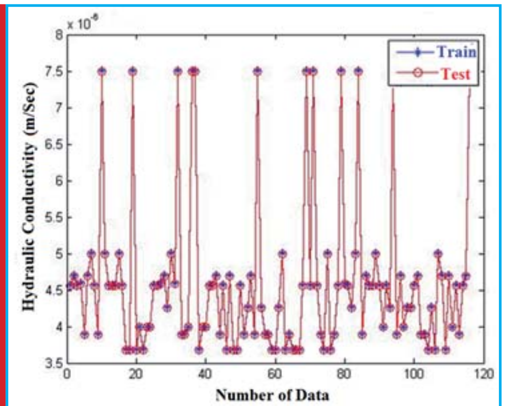

FIGURE 5. The prediction of hydraulic conductivity with test and train data by using of SVR-GA model, with epsilon loss function in horizontal flow

nation coefficient is above 0.93 and root mean square error and mean absolute error are less than 0.2; in the event that SVR-GA model of all the flows determination coefficient is more than 0.99 and root mean square error and mean absolute error is less than 0.02. Thus, hybrid model with epsilon loss function is apparently more efficient. This superiority is shown in Figure 5.

According to the results seen in table 2 for SVR model does not contain good results for quadratic loss function but SVR-GA model shows very desirable results. In SVR model for all three flows, determination coefficient is more than 0.84 and root mean square error and mean absolute error are less than 0.47; in SVR-GA model for all three flows determination coefficient is above 0.97

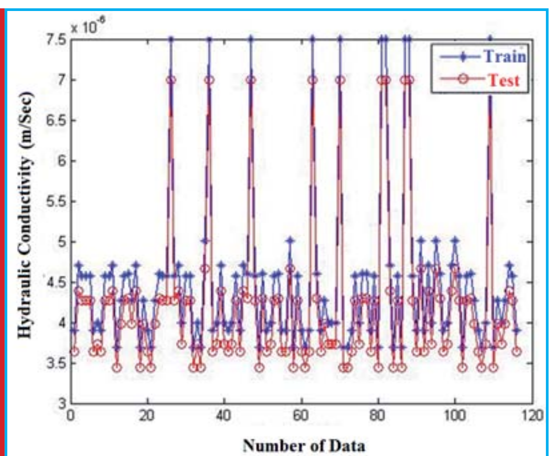

FIGURE 6. The prediction of hydraulic conductivity with test and train data by using of SVR-GA model, with quadratic loss function in horizontal flow

and root means square error and mean absolute error are below 0.1. Therefore, hybrid model is much more efficient as it can be observed. The results obtained from epsilon loss function are more accurate as compared to the results gained from quadratic loss function. The results are demonstrated graphically in figure 6. In both models the results obtained from epsilon loss function were more precise. This procedure is obvious in diagram 3 to 6. But the considerable point is the execution time for epsilon loss function in both models is quite insignificant. According to the findings it can be declared that model hybrid model with epsilon loss function is an appropriate alternative for analytical Reynolds solutions.

Eventually, Results show that epsilon function accuracy is better than the quadratic function, but in terms of run time, quadratic function is superior to epsilon function significantly. Results show that accuracy of epsilon function is better than the quadratic function. Hybrid model with the epsilon loss function is superior. For quadratic loss function, the results of SVR model are not acceptable but SVR-GA model have a very good results. According to the results, we can say that a hybrid model with epsilon loss function very good alternative for the Reynolds analytical solution. The results of epsilon loss function in both models have higher accuracy in comparison with the quadratic loss function, but in terms of run time, quadratic function is superior to epsilon function significantly.

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