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Research Article

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Optimized support vector regression for drilling rate of penetration estimation

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Abstract: In the petroleum industry, drilling optimization involves the selection of operating conditions for achieving the desired depth with the minimum expenditure while requirements of personal safety, environment protection, adequate information of penetrated formations and productivity are fulfilled. Since drilling optimization is highly dependent on the rate of penetration (ROP), estimation of this parameter is of great importance during well planning. In this research, a novel approach called 'optimized support vector regression' is employed for making a formulation between input variables and ROP. Algorithms used for optimizing the support vector regression are the genetic algorithm (GA) and the cuckoo search algorithm (CS). Optimization implementation improved the support vector regression performance by virtue of selecting proper values for its parameters. In order to evaluate the ability of optimization algorithms in enhancing SVR performance, their results were compared to the hybrid of pattern search and grid search (HPG) which is conventionally employed for optimizing SVR. The results demonstrated that the CS algorithm achieved further improvement on prediction accuracy of SVR compared to the GA and HPG as well. Moreover, the predictive model derived from back propagation neural network (BPNN), which is the traditional approach for estimating ROP, is selected for comparisons with CSSVR. The comparative results revealed the superiority of CSSVR. This study inferred that CSSVR is a viable option for precise estimation of ROP.

Keywords: Rate of penetration (ROP); Support vector regression (SVR); Hybrid of pattern search and grid search (HPG); Cuckoo search algorithm (CS); Genetic algorithm (GA)

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1 Introduction

Drilling optimization is the practice of adjusting the operating conditions with a view to reaching the anticipated depth with least possible cost while necessities of personal safety environment, protection, adequate information of penetrated formations and productivity are considered [1]. Rate of penetration (ROP) is one of the paramount parameters which must be considered in drilling optimization. Clearly, a predictive approach to estimating ROP from available data has the potential to improving drilling optimization implementation. Recently, Bourgoyne and Young (1986) presented a mathematical based model for estimating of ROP. This model is a widely accepted model which has the virtue of simplicity [2]. Although this model is advantageous, it possess some shortcomings as it cannot estimate the value of rate of penetration with satisfactory accuracy. Over the last decades, the development of intelligence based approaches for modeling of petroleum-related phenomena has been an area of active research [3–7]. Emergence of these methods has facilitated significant progress in modeling of drilling parameters. In this area, a number of investigators used neural networks as a computational approach to modeling of the ROP [8–16]. Moreover, Bahari et al (2009) renovated the Bourgoyne-Young penetration rate model through employment of the genetic algorithm (GA) to extract the optimal values of the involved coefficient in their equation [17]. Although the aforementioned models have practical results, the quest for the superior approach always exists. In this study, a robust intelligence model based on the support vector regression (SVR) is proposed for prediction of the ROP. Due to high dependency of the SVR performance on fine adjustment of its parameters, employing a potent optimization strategy for this implementation is crucial. Traditionally, a hybrid of pattern search and grid (HPG) search is used for achieving this objective [18–23]. Use of this method is very time consuming and therefore it is essential to employ a potent optimization tool for finding the SVR parameters [24]. In current the study, two optimization tools, namely genetic algorithm and cuckoo search algorithm are adopted to improve the SVR performance.

2 Modeling description

2.1 Support vector regression

SVR is a new estimation technique based on the principal of statistical learning theory [25]. The algorithm estimates unknown values using an optimal linear regression model in a new feature space which is defined by mapping input data from the original space into a higher m-dimensional space.

Consider a given training data in a p-dimensional input vector and one dimensional target vector. The objective is to formulate between input and output data in the following form [25]:

$$f(x) = w^T \varphi(x) + b \tag{1}$$

Where φ is a nonlinear mapping function and w and b are the weighting vector and bias term of the regression equation, respectively. The optimal w and b are determined by minimizing the following risk function using slack variablesas ξ_i, $\xi_i^\star$:

$$R(f) = \frac{1}{2}\,||w||^2 + c\sum_{i=1}^{l}\left(\xi_i \xi_i^\star\right) \tag{2}$$

Subjected to:

$$\begin{cases} d_i - w^T\varphi(x_i) - b \le \varepsilon + \xi_i, & i = 1, \ldots, l \\ w^T\varphi(x_i) + b - d_i \le \varepsilon + \xi_i^\star, & i = 1, \ldots, l \\ \xi_i,\ \xi_i^\star \ge 0, & i = 1, \ldots, l \end{cases} \tag{3}$$

Here, C is a constant parameter which defines the trade-off between flatness and estimation error. Quality of approximation is measured by tube in the loss function. Eq. (3) is solved based on foundation of dual problem formulation and defining Lagrange multipliers, α_i, $\alpha_i^\star \in [0, C]$, and ultimately, the following solution is obtained [25]:

$$f(x) = \sum_{i=1}^{l}\left(\alpha_i - \alpha_i^\star\right) k\left(x_i - x_i^\star\right) + b \tag{4}$$

$k\left(x_i - x_i^\star\right)$ is the called kernel function. In this study, the radial basis function (RBF) is used as a kernel function:

$$k\left(x_i - x_i^\star\right) = \exp\left(-\gamma\left|\left|x_i - x_i^\star\right|\right|^2\right) \tag{5}$$

According to the above brief introduction of the SVR, C, γ and ε are the three main parameters of the SVR method which must be selected during an optimization technique. The accuracy of the SVR model is highly dependent upon the parameter selection. Traditionally, a hybrid of grid search and pattern search were used as an optimization method in many published research studies of the SVR application. In this method, optimization initiates with grid search trying to achieve a region close to the global optimum point. Next, a pattern search is conducted over the narrowed search range surrounding the best point found by the grid search. This combination eliminates the defects of individual employment of grid search as well as pattern search in finding SVR parameters. However, use of HPG is time consuming and also insufficiently accurate in determining the SVR parameters [18–23]. Owing to these restrictions on HPG, it is desirable to introduce the most potent optimization tool for SVR formulation, in order to calculate its parameters are desired. In this study two potent optimization algorithms namely the cuckoo search algorithm (CS) and the genetic algorithm (GA) are introduced in order to select the best SVR parameters.

2.2 Genetic algorithm

GA is an evolutionary algorithm for optimization of the problems inspired by biological evolution based on natural selection theory. The algorithm is started by generating a random population of a set of candidate solution called "chromosomes". Each solution is evaluated based on a fitness function (the function that its global optimum is meant to explore) [26]. Based on fitness score of "chromosomes", they are ranked and then highly-ranked "chromosomes" are selected to be used in the next generation. This process is repeated until a stop condition is satisfied. In order to discover a new solution during each algorithm's iteration, three main processes are accomplished. First, parents that contribute to the next generation are chosen with a selection operation. Second, a crossover operation produces children from parents. Finally, some gene values of "chromosomes" alter in mutation. The mutation increases the performance of the algorithm to a find solution and causes the GA to converge to a global (not local) optimum.

2.3 Cuckoo search algorithm

Cuckoo search (CS) is a new meta-heuristic algorithm based on the parasitic behavior of a bird called

```
begin
    Objective function f(x), x=(x1, ...., xd)^T
    Generate initial population of n host nests Xi (i=1, 2, ...., n)
    while (t<MaxGeneration) or (stop criterion)
    Get a cuckoo randomly by lévy flights evaluate quality/fitness Fi
    Choose a nest among n (say, j) randomly
    if (Fi>Fj), replace j by the new solutions;
    End
    A function (pa) of worse nests are abandoned and new once are built;
    Keep the best solutions (or nests with quality solutions);
    Rank the solutions and find the current best
    end while
    Postprocess results and visualization
end
```

Figure 1: General Pseudo code of cuckoo search algorithm via Lévy flight [27].

"cuckoo" [27]. Some cuckoo types lay their "eggs" in the "nests" of other host birds. These "eggs" can be found by host birds and annihilated or remain in the host nest. Briefly, the CS can be summarized with following three idealizing rules [27]:

– Each "cuckoo" selects a "nest", randomly and lays one "egg" at a time in it.
– The best "nests" with optimal "eggs" will transfer to the next iteration.
– The number of host "nests" is fixed, and the host bird discovers, with a probability, $p_a \in (0, 1)$ the "egg" laid by a "cuckoo". In this case, the host bird can either throw these alien "eggs" away or simply abandon the "nest" and build a completely new nest elsewhere.

Based on above rules, the standard CS algorithm can be explained with pseudo code of Figure 1. Using "Lévy flight" is a novel way to characterize the CS for searching a new "nest". "Lévy" refers to the name of a French mathematician who described a model for the flight behavior of many animals and insects. Yang and Deb (2009) found that random walk style search by "Lévy flight" has a high performance related to a simple random walk in the CS [27].

A "cuckoo egg" represents a solution and a new solution of i^{th} cuckoo is generated with a "Lévy flight" as:

$$x_i^{t+1} = x_i^t + \alpha \oplus \mathrm{Lvy}(s, \lambda), \quad 1 < \lambda \leq 3 \tag{6}$$

where α is the step size scaling factor with a positive value. The sign of product $\oplus$ shows entrywise multiplications, and s is step size drawn from a "Lévy" distribution and can be calculated by [28]:

$$s = \frac{u}{|v|^{1/\beta}} \tag{7}$$

Here, u and v are drawn from normal distribution as:

$$u \sim N\left(0, \sigma_u^2\right), \quad v \sim N\left(0, \sigma_v^2\right) \tag{8}$$

where:

$$\sigma_u^2 = \left\{ \frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}} \right\}^{1/\beta}, \quad \sigma_v^2 = 1 \tag{9}$$

Where Γ refers to gamma function and β is an index defined by user.

However there are some similarities between CS and other nature-inspired optimization algorithms such as the genetic algorithm (GA), and also there are some main differences between them. More details about CS and its comparison with GA can be found in several papers [27–29]. In summary, it can be expressed that the main advantage of CS over the GA, is the application of Lévy flight for enhancing the exploration strategy. Furthermore, the number of parameters for regulating the CS is less than the GA and therefore it potentially enables CS to be more adaptable in optimization problems. Also, the CS has shown great performance to achieve better global optima in many engineering optimization problems [30–33].

2.4 Artificial neural network

Artificial neural networks (ANNs) are popular intelligence learning algorithms inspired by biological neural networks. One of their main applications is the approximation function which is in order to predict unknown values. A common type of ANN is known as back propagation neural network (BPNN). This network consists of three layers, an input layer, a hidden layer and an output layer. The input data are fed into input layer and then they pass on to the hidden layer neurons after multiplying by a weight factor and adding a bias term. In the hidden and output layers, a transfer function is described to let the network learn nonlinear relationships between input and output data. During the learning network, weights and bias are updated and calculation and back- propagation of the error occur to obtain the best fitness function. Details of the back-propagation algorithm and ANNs are thoroughly documented in the literature [34].

3 Data space and inputs selection

In order to construct a potent model for predicting the ROP values, a dataset was provided from a wide geographic distribution in the Persian Gulf. For achieving this essential

Figure 2: The regional location of investigated fields of this study in the Persian Gulf.

Table 1: Formation description of this study.

Main lithology	Code
Sea bed and cement	0
Sand Stone	1
Clay stone	2
Marl	3
Carbonate rocks	4
Evaporate rocks	5

objective, dataset is gathered randomly from daily drilling reports (DDR) of 18 development wells which have been drilled in four Iranian oil fields in the south west of the Persian Gulf. Figure 2 displays a location map of investigated field of this study. There are many parameters that influence the drilling rate including mud properties, drilling and bit parameter, lithology etc. However, only the main parameters that are reported in the DDR are used in this study. The input parameters of this study include mud viscosity, mud weight (MW), pump rate, pump pressure, angle of well deviation, rotary speed, weight on bit (WOB), interval drilled, formation lithology, bit size and tooth wear. Formation, bit size and bit tooth wear are discontinuous parameters and the other data are continuous. According to the documents of the International Association of Drilling Contractors (IADC), the bit tooth wear is a number scaled from 0 to 8 which refers to the condition of the cutting structures of the bit. No loss of the cutting structure is described by zero and complete loss is eight. The bit size is varied from 6 1/8" to 26". Lithology is defined by a series of code numbers from 0 to 5. Table 1 explains the used lithology decryption of this study as per main lithology which presented in the cutting samples. For example when code 3 is used for lithology in this scale, it means most of the drilled cutting samples are marl; however, there are some proportions of other rock types such as anhydrite etc. Table 2 presents a statistical description of input and output data. In total there are 193 data samples and these are divided into two subsets including training (80%) and test data (20%). In order to increase the performance of the model used, all data were normalized linearly in a range of [-1, 1] and after modeling, results were back normalized into the original scale. The normalization removes different units of measurements from data and so, reduces confusion around the model.

4 Results and discussion

In this study, an epsilon-SVR is used for predicting the ROP values from DDR's parameters. The constructed models are evaluated based on statistical criteria which are mathematically defined in Table 3. For training the SVR, a 4-fold cross validation strategy is used. Therefore, training data was broken into four equal sized subsets (folds), randomly. Three subsets are used in the training state and the remaining subset is used as validation data. The training procedure is repeated four times and all validation subsets are used at least once for validation. The performance is described by mean square error (MSE) between output and target data. As mentioned above, two optimization algorithms, namely the cuckoo search algorithm and the genetic algorithm are used for finding the appropriate value of SVR parameters.

In the first stage, the GA algorithm is imbedded in the SVR formulation in order to improve it and find best parameters of the SVR including C, γ and ε. The result with minimum MSE of cross validation has a smaller cost value in the GA and thus, it has a better chance to obtain high quality results in the test state. Finally, the results from the subsets with optimized parameters were combined with others to produce a single approximation. The constraints for regulating the GA are presented in Table 4. Figure 3 depicts the optimal and average fitness values versus the GA iterations. These figures demonstrate that no significant progress is achieved after 20 and 75 iterations for the best and average fitness values, respectively. In the second stage, the CS is coupled with SVR for optimization. Regulation parameters for running the CSSVR are expressed in Table 5. The best and average cost values of the CSSVR are shown in Figure 4. According this figure, it is obvious that

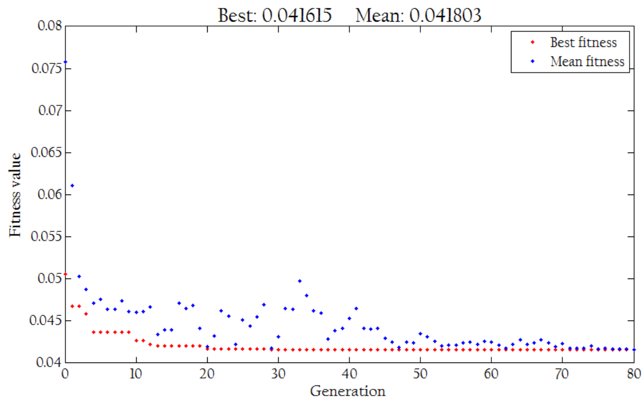

Figure 3: Minimum and mean fitness values of the genetic algorithm.

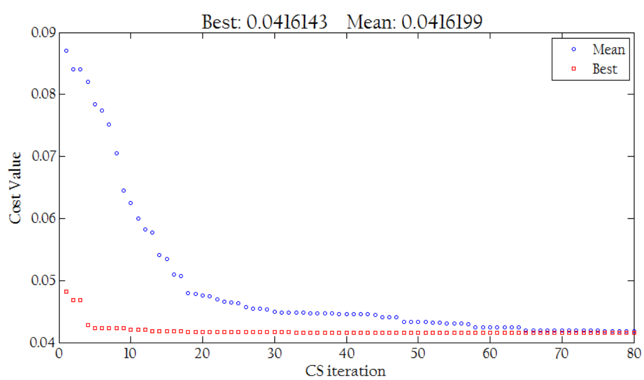

Figure 4: Cost evaluation during the cuckoo search process.

no noteworthy improvement is observed after 13 and 65 iterations for the best and average fitness values. As it is obvious from Figure 3 and 4, the GA is slower than the CS on the convergence rate. The optimal values obtained through the CS and GA for γ, C and ε are tabulated in Table 6.

In order to evaluate the capability of the proposed model, the results of the CSSVR and GASVR were compared with other models. The first model selected for comparison is the SVR models that used an optimized method of hybrid grid search and pattern search. This model was selected owing to its common use in the SVR framework for determining the values of SVR parameters. The second model is a back propagation neural network. The main reason for selecting this model is its successful performance in modeling of ROP which carried out in previous studies [8–16]. Parameters for regulating the running of the BPNN are expressed in Table 7. The cross-plots between predicted value and measure value for BPNN, HPGSVR, GASVR and CSSVR are shown in Figure 5. Also, Table 8 shows the error analysis of CSSVR based on statistical criteria viz. correlation coefficient (R), root mean square error (RMSE), and absolute average relative error (AARE). Figure 6 and 7 show the comparison between GASVR and CSSVR model results and corresponding measured ROP value versus sample number for training data and test data, respectively. The comparative performance among all various methods using the concept of RMSE and R, is illustrated in Figure 8. According to results obtained, all the SVR methods have better results related to the BPNN. Among the SVR methods, evolutionary algorithms create more improvement in the performance of the SVR. The results of CS and GA for SVR optimization are very close to each other, however CSSVR is more successful than GASVR. As is evident from the results, the CSSVR decreases the RMSE of estimation up to 1.4089 (and AARE = 0.3437) which corresponds to an R value of 0.9133 for test data. Finally, cumulative distributive functions (CDF) are estimated for the error between measured and predicted ROP of the test data for all methods. In this analysis, error is the difference between the target and output data. The estimated CDF values of the errors are plotted in Figure 9. According to the results presented in this figure, utilizing the CSSVR decreases the standard deviation (Std) of error values and the proposed model has low error distribution related to other used methods. As seen in aforementioned figures and table, the CSSVR can estimate the ROP with better accuracy.

5 Conclusion

ROP is one of the most critical parameters during drilling optimization practice. In this study, an expert system called support vector regression, improved with an optimization strategy in order to predict the ROP from drilling parameters. The GA and CS are the optimization tools used for achieving the correct value of SVR free parameters. The following results are obtained during this study:

1. The GA and CS algorithms are potent tools for improving the performance of support vector regression.
2. Comparisons between performances of optimization tools indicate the superiority of CS in finding accurate values of SVR parameters.
3. Optimized SVR has better accuracy and robustness in prediction of ROP compared to BPNN.
4. Optimized SVR can be used as a practicable method for the prediction of ROP during drilling optimization implementation.

Table 2: Statistics description of input and output dataset.

Parameter (continues)	Min	Max	Average
Viscosity (sec)	25	78	47.69
MW (pcf)	63	140	78.75
Pump rate (GPM)	100	1200	585.59
Pump pressure (psi)	100	3000	1857.76
Well deviation (degree)	0	90	49.33
Rotary speed (RPM)	0	200	106.28
WOB (klbf)	0	60	21.57
Interval drilled (m)	1	690	184.29
ROP (m/hr)	0.25	12.45	4.19
Parameter (discontinuous)	**Min**	**Max**	**Mode**
Formation	0	5	3
Bit size (in)	6 1/8	26	8 1/2
Bit tooth wear	0	8	1

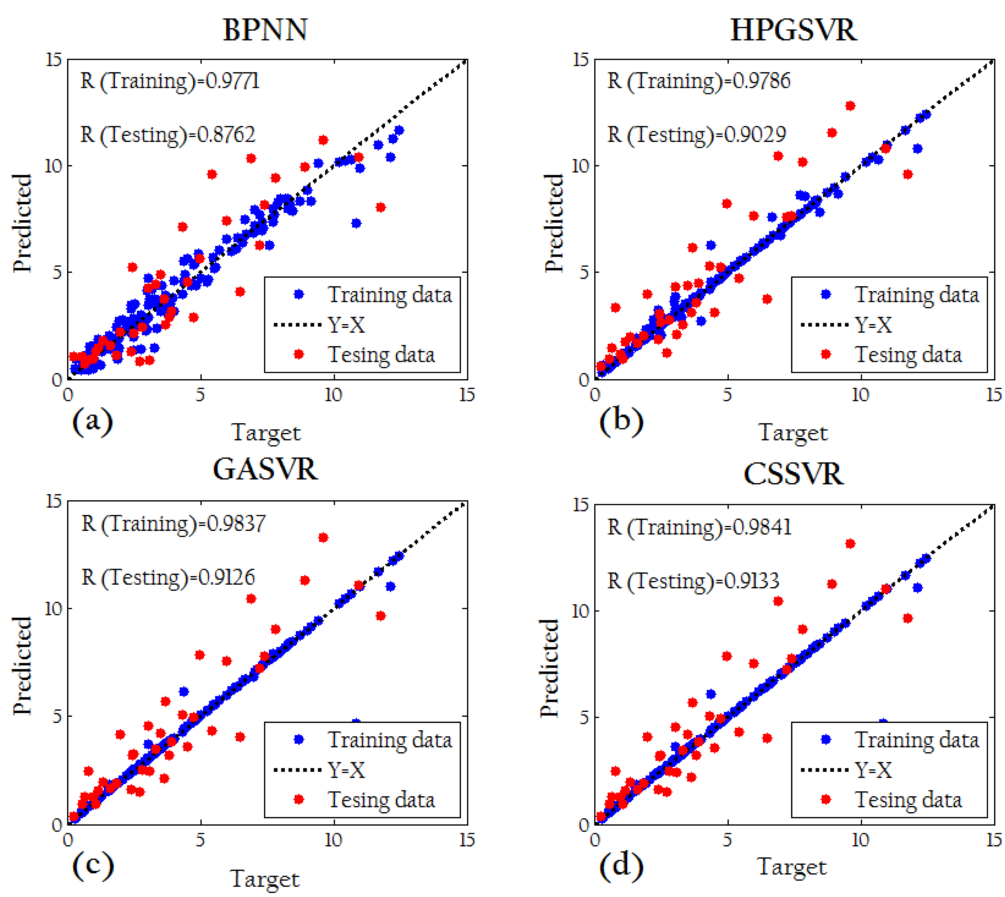

Figure 5: Correlation coefficient between measured and predicted ROP for training data and test data using (a) BPNN, (b) HPGSVR, (c) GASVR and (d) CSSVR.

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Table 3: Definition of the statistical criteria for accuracy evaluation. In this equation y_{obs} is target value and y_{pre} is prediction value.

Criteria	Mathematical expression
Correlation coefficient (R)	$R = \frac{\sum_{i=1}^{n}(y_{obs,i}-\overline{y_{obs}})\cdot(y_{pre,i}-\overline{y_{pre}})}{\sqrt{\sum_{i}^{n}(y_{obs,i}-\overline{y_{obs}})^2\cdot\sum_{i=1}^{n}(y_{pre,i}-\overline{y_{pre}})^2}}$
Root mean square error (RMSE)	$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_{obs}-y_{pre})_i^2}{n}}$
Absolute average relative error (AARE)	$AARE = \frac{1}{n}\sum_{i=1}^{n}\left\lvert\frac{(y_{obs}-y_{pre})_i}{y_{obs,i}}\right\rvert$
Empirical cumulative distribution function (CDF)	$CDF(t) = \frac{1}{n}\sum_{i=1}^{n}\{(y_{obs}-y_{pre})_i \leq t\}$

Table 4: Regulated parameters for run GA.

Parameter/setting	Value/type
Number of initial population	20
Maximum generation	80
Crossover Percentage	0.8
Mutation Percentage	0.3
Elite count	2
Selection function	Roulette
Mutation function	Gaussian

Table 5: Regulated parameters for run CS.

Parameter	value
Number of nests	20
Maximum iteration	80
p_a	0.25
β	1.5

Table 6: Optimal parameters used in various SVR models in this study.

Model	γ	C	ε
HPGSVR	0.382364	6.006760	0.046193
GASVR	0.535640	6.545636	0.000288
CSSVR	0.531139	6.049360	0.000292

Table 7: Regulated parameters for run BPNN.

Parameter/setting	Value/type
Type of network	Back propagation
Back propagation network training function	TRAINBR
Back propagation weight/bias learning function	LEARNGDM
Performance function	MSE
Number of layer	2
Number of neurons in hidden layer	7
Transfer function layer 1	TANSIG
Transfer function layer 2	TANSIG
Net train parameters epochs	400

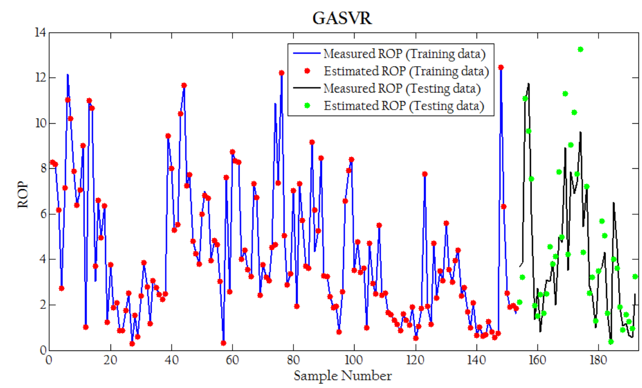

Figure 6: Comparison between measured and predicted ROP for training and testing data using GASVR.

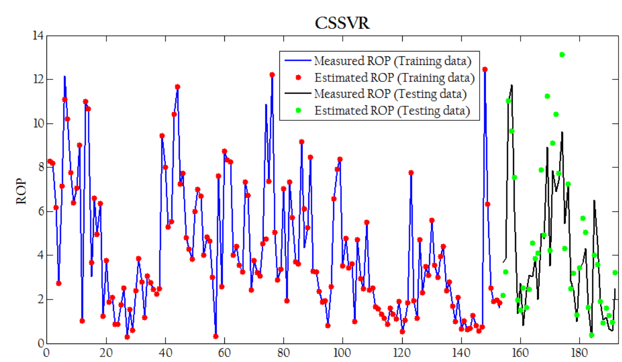

Figure 7: Comparison between measured and predicted ROP for training and testing data using CSSVR.

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Table 8: Comparison between proposed model (CS-SVR) and three different models for ROP estimation.

Model	Allocation	*R*	*RMSE*	*AARE*
BPNN	Training	0.9771	0.6343	0.1799
	Testing	0.8762	1.5820	0.4066
	Total	0.9519	0.9105	0.2205
HPGSVR	Training	0.9786	0.6097	0.0488
	Testing	0.9029	1.5200	0.3795
	Total	0.9569	0.8750	0.1215
GASVR	Training	0.9837	0.5338	0.0112
	Testing	0.9126	1.4220	0.3442
	Total	0.9644	0.7946	0.0782
CSSVR	Training	0.9841	0.5262	0.0104
	Testing	0.9133	1.4089	0.3437
	Total	0.9648	0.7898	0.0781

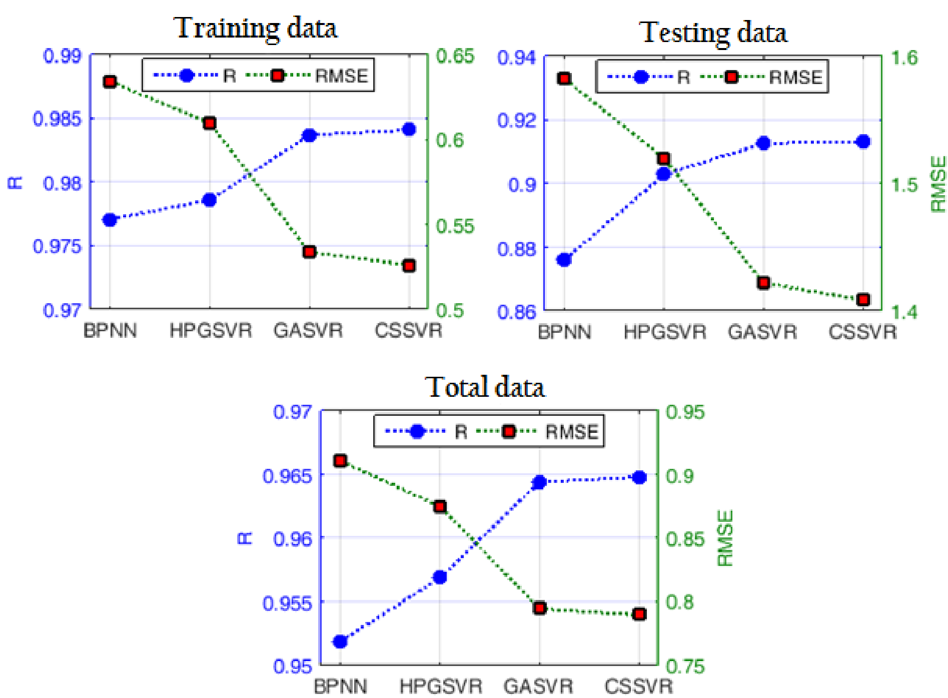

Figure 8: Comparing among different used models in term of R and RMSE for training data, testing data and total data.

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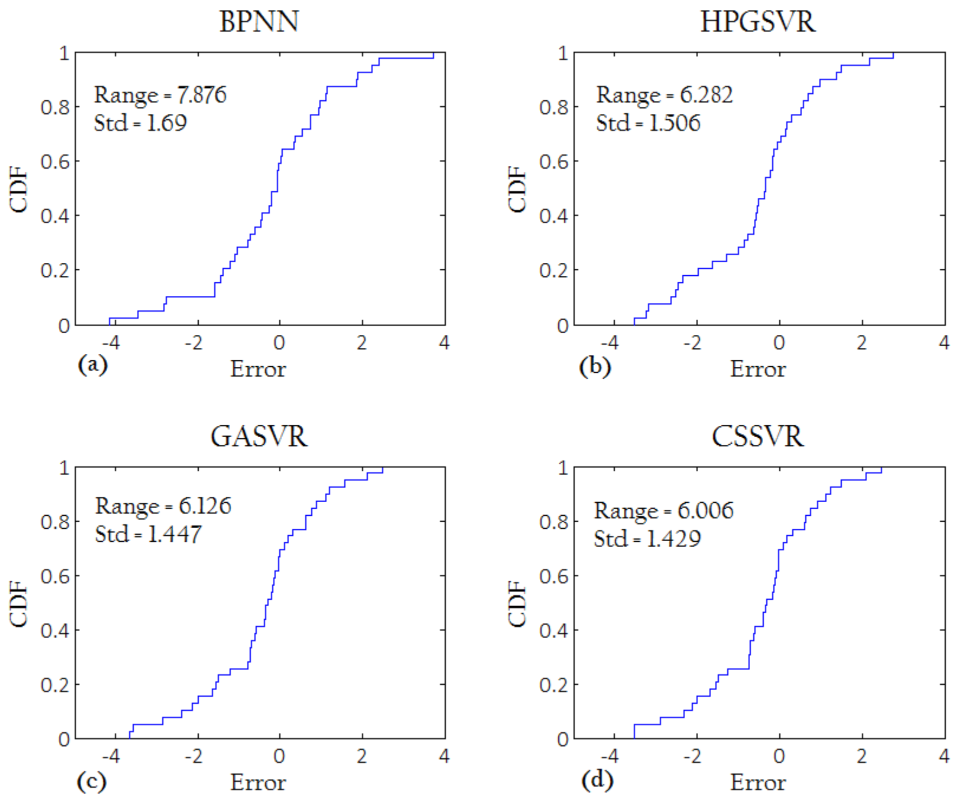

Figure 9: Estimated CDF plot of the error for (a) BPNN, (b) HPGSVR, (c) GASVR and (d) CSSVR.

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