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Computational Intelligence for Corrosion Rate Prediction of Refinery Cooling Water Plant

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Abstract. In order to predict the corrosion rate of refinery cooling water plant effectively, this paper proposes a novel model, which combines the Restricted Boltzmann Machines (RBM) and Support Vector Regression (SVR). The SVR has been confirmed the effectiveness for corrosion rate prediction, but it has not been used to predict the corrosion rate of the refinery cooling water plant. Moreover, by the aid of Deep Learning (DL) approaches that can model high-level abstractions in the data, the hybrid model is implemented by integrating the RBM with SVR to predict the corrosion rate of the refinery cooling water plant. The proposed model can reduce the dimensionality of data space and preserve the effective features of refinery cooling water plant. Compared with only using SVR model, the combination of the RBM and SVR model can achieve higher prediction accuracy and more efficient and effective. Prediction accuracy is evaluated using the actual Industrial data. According to the comparison results, the hybrid model proposed was better than the previous models in predicting the corrosion rate of the refinery cooling water plant. The hybrid model proposed is a promising and practical methodology for realtime tracking of corrosion in refinery cooling water plant system. The factory can use the hybrid model to schedule maintenance process that leads to risk reduction of structure failure and maintenance cost.

Keywords: corrosion rate prediction, deep learning, refinery cooling water plant, restricted boltzmann machines (RBM), support vector machine (SVM), support vector regression (SVR)

1 Introduction

In the oil and gas industry, the corrosion rate is complex because several factors (physical, chemical and/or mechanical) may take place [1]. In order to obtain the corrosion rate of chemical equipment, multidisciplinary expertise and numerous observations from inspections and laboratory tests reports are required. However, many factors affect the corrosion rate performance. A key factor is not ever losing tracking of the perspective because of the evidence analyzed. Meanwhile, corrosion is a highly nonlinear problem influenced by complex characteristics and models for predicting the corrosion rate of steel currently lack a theoretical basis. It is difficult to develop a theoretical model that is capable of describing the relationship among all of these factors and the associated corrosion rates due to the lack of good understanding of factors that affect the corrosion process. Many of the better known factors that affect the corrosion of steel structure. Therefore, an accurate model for predicting corrosion based historical data is needed [2].

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In order to solve this problem, a variety of methods can be used to predict future data based on the historical data of the system [1-4]. A majority of these approaches have been proposed for analysis, especially for the collected data, on which the corrosion rate prediction is based. Nowadays, Machine learning (ML) and artificial intelligence (AI)-based approach have attracted a great deal of scientific attention and have successful used in civil engineering such as modeling of pier scour [5]. For instance, Wen et al. [6] applied a single support vector regression (SVR) model for predicting the corrosion rate of 3C steel in five different seawater environments. AI approaches, especial artificial neural networks (ANNs) and fuzzy logic methods have been widely used in the fields of corrosion rate prediction and have been proven as a much better approach for corrosion rate prediction [4, 7-9].

Although the AI-based models have proven moderately effective for solving prediction problem, one of the critical problems is how to select an appropriate model and fine-tune the model parameters, which plays an important role in good generalization performance and prediction accuracy for future use [10], [11]. To overcome the drawback and enhance the accuracy, ensemble approaches appear to be promising solutions for the above situations. Hybrid approaches that combine multiple AI models and optimization algorithms have been proposed to enhance the prediction accuracy of single AI models [12].

Recently, Deep Learning (DL) approaches are becoming increasingly popular in Artificial Intelligence [14]. DL that also known as deep structured learning or deep machine learning is a class of machine learning algorithms that employ a cascade of many layers of nonlinear processing units for transformation [13]. Each successive layer uses the output from the previous layer as input. DL is a branch of machine learning based on a set of algorithms. Compared with the previous AI technology, DL attempts to model high-level abstractions in the data by using multiple processing layers, with complex structures, and composed of multiple non-linear transformations [7, 15-16].

The main idea of this paper describes a novel approach to predict the corrosion rate, which consists of the Restricted Boltzmann Machines (RBM) [17] and Support Vector Machine (SVM). The RBM model proposed, which is one of the DL models, can find the correlational structure of the data by encoding the original data. However, various data modalities will typically have a very different statistical property that makes it difficult to model them using the previous AI technology. The model proposed satisfies the above desiderata. RBMs are unsupervised learning models with bipartite connections between adjacent layers of hidden units [17].

The key idea is to learn over the space of all inspections data. We can fill the missing data by sampling from the conditional distributions over them given the observed ones. For example, we use a data set of influential factors to learn a joint distribution. Compared with the shallow models, this approach can capture the very different statistical properties of the inspections data.

In this work, we propose a novel approach which combines the RBM model and SVR (RBM+SVR), to enhance the use of the inspections data, and to overcome the mentioned limitation of the shallow models. Firstly, we employ the Restricted Boltzmann Machine as a generative model as opposed to unroll the network and fine-tuning it as an autoencoder. Secondly, after the representation of inspections data, we utilized the SVM to model complex statistical relationships between inputs and outputs. The overall flowchart of our model is shown in Fig. 1.

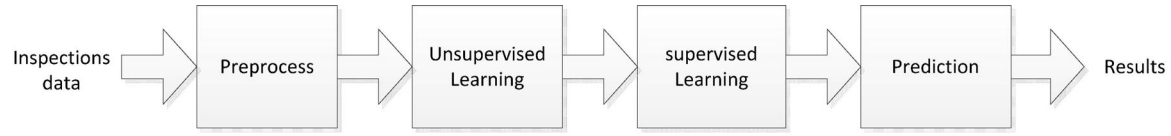

Fig. 1. The flow chart of corrosion prediction model based on the deep learning

The main advantage of RBM+SVR is able to the capability for learning from specific predefined patterns. Other advantages of RBM+SVR are the following:

- Learning capacities. The RBM+SVR can learn from previously identified input and output maps. That is called “Supervised Learning”. Each example may consist of one or more input signals also output signals.
- Generalization. The RBM+SVR are able to generate knowledge, in other words, RBM+SVR may produce reasonable results for data inputs when these are not available for training process.
- No linearity. The DBM+SVR can resolve any problem represented by patterns.

- Adaptability. A trained RBM+SVR to operate in a specific environment re-trained to face any change in the operation conditions.

Typically, the RBM+SVR can provide a specific output for each data input. It parameters is adjusted by comparing the specific weight of each output to the RBM+SVR output until a balanced weighting is reached. Each training instance is described as a list of attribute-value pairs, which constitute a conjunctive description of that instance [3].

After the RBM+SVR training is completed, the RBM+SVR is capable to produce responses to new data inputs that are not considered. This property to recognize new data is called "Generalization" as mentioned above [13]. The "trained" models will not check with "the data for training" again. In this way, the RBM+SVR behave as a functional summary of "data for training" [18]. Due to analogy with a biological brain, a RBM+SVR exhibit similar characteristics. For example, that is able to learn from experience, generalize previous cases to "new cases", elimination of characteristic essentials from irrelevant inputs, etc. These advantages justify the spread of this type of technology in several technical areas.

2 Backgrounds

2.1 Refinery Cooling Water Plant

Corrosion is a common deterioration that reduces the service life of Refinery Cooling Water Plant system. The detection and evaluation of corrosion is importance to the safe operation of Refinery Cooling Water Plant system. An appropriate detection and evaluation approach of corrosion could help to have access to high-level information about health status of refinery cooling water plant and to manage the refinery cooling water plant efficiently. However, corrosion is a highly nonlinear problem influenced by complex characteristics and models for predicting the corrosion rate of refinery cooling water plant lack a theoretical basis. Many of the better known factors affect corrosion of refinery cooling water plant, like PH, heterotrophic bacteria, hardness of water, phosphor, suspended matter, NH4+ and so on. Therefore, It is one of the most challenging problems in oil refinery, mainly due to system complexity such as [4], [19-20]. Many approaches for detection and evaluation of the refinery cooling water plant have been proposed in the literature such as the rate of corrosion, corrosion potential, equipment thinning and so on [21-23]. Compared with these approaches, the most commonly corrosion evaluation criterion of the refinery cooling water plant is Fe2+ and Fe3+ which are corrosion products in solution, because Fe2+ and Fe3+ are easily and economically detected.

2.2 Restricted Boltzmann Machines (RBM)

The Restricted Boltzmann Machines (RBMs) has been used effectively in modeling distributions over binary-valued data. Recent work on Boltzmann machine models and their generalizations to exponential family distributions have allowed these models to be successfully used in many application domains.

A Restricted Boltzmann Machine is an undirected graphical model with stochastic visible units $v \in \{0,1\}^D$ and stochastic hidden units $h \in \{0,1\}^F$, with each visible unit connected to each hidden unit. The model defines the following energy function $E : \{0,1\}^{D+F} \to R$:

$$E(v,h,\theta) = -\sum_{ij} W_{ij} v_i h_j - \sum_{ij} b_j v_i - \sum_{ij} a_j h_j \tag{1}$$

where $\theta = \{a,b,W\}$ are the model parameters. The joint distribution over the visible and hidden units is defined by:

$$P_\theta(v,h) = \underbrace{\frac{1}{Z(\theta)}}_{Partition\ function} \exp(-E(v,h;\theta)) = \frac{1}{Z(\theta)} \prod_{ij} \underbrace{e^{W_{ij} v_i h_j}}_{potential\ functions} \prod_{ij} e^{b_i v_i} \prod_{j} e^{a_j h_j} \tag{2}$$

Since the RBM has the shape of a bipartite graph, with no intra-layer connections, the hidden unit activations are mutually independent given the visible unit activations and conversely, the visible unit

activations are mutually independent given the hidden unit activations. That is, for visible units and hidden units, the conditional probability of a configuration of the visible units v, given a configuration of the hidden units h, is:

$$p(h \mid v) = \prod_j p(h_j \mid v) \tag{3}$$

The individual activation probabilities is given by:

$$p(h_j - 1 \mid v) = \frac{1}{1+\exp(-\sum_i W_{ij} v_i - a_j)} \tag{4}$$

where σ denotes the logistic sigmoid. The visible units of RBM can be multinomial, although the hidden units are Bernoulli. In this case, the logistic function for visible units is replaced by the softmax function

$$p(v \mid h) = \prod_i p(v_i \mid h) P(v_i = 1 \mid h) = \frac{1}{1+\exp(-\sum_j W_{ij} v_i - a_j)} \tag{5}$$

The Restricted Boltzmann machines is trained by maximum-likelihood estimation (MLE), which maximizes the product of probabilities assigned to some training set $D = \{v(1), v(2), \ldots, v(N)\}$ that is the set of independent identical distribution. The function is as follows:

$$L(\theta) = \frac{1}{N} \sum_{n=1}^{N} \log P_\theta(v^{(\theta)}) - \frac{\lambda}{N} \|W\|_F^2 \tag{6}$$

Where $\theta = \{a, b, W\}$ is the estimation of the parameters. Using the function 2-3 to get the derivation as follows:

$$\frac{\partial L(\theta)}{\partial W_{ij}} = E_{p_{data}}\left[v_i h_j\right] - E_{p_\theta}\left[v_i h_j\right] - \frac{2\lambda}{N} W_{ij} \tag{7}$$

2.3 Support Vector Regression

The Support Vector Machine (SVM) is a supervised learning model, used to analyze data, recognize patterns, and classification. It is based on the statistical learning theory [24]. In a high-dimensional or infinite-dimensional space, the SVM is employed to construct a hyperplane or set of hyperplasia, which can be used for classification, regression, or other tasks. Intuitively, a good separation is achieved by the hyperplane that has the largest distance to the nearest training data point of any class (so-called functional margin), since in general the larger the margin the lower the generalization error of the classifier. Then, the new samples are mapped into the same space and predict to a class, based on which side of the hyperplane they fall into.

Support Vector Machine can also be used as a regression method, maintaining all the main features that characterize the algorithm (maximal margin). As the SVM for classification, the Support Vector Regression (SVR) make use of the same principles. It is only a few minor differences. Firstly, the output of the SVR is a real number, which is very difficult to predict the information at hand, because it has infinite possibilities. In the case of regression, a margin of epsilon is set in an approximation to the SVM that would have already requested from the problem. Besides this fact, there is also a more complicated reason [24]. The algorithm is more complex, therefore it can be taken in consideration. However, the main idea is always the same between SVR and SVM: to minimize error, individualizing the hyper-plane which maximizes the margin, keeping in mind that part of the error is tolerated. Training the original SVR means solving regression or SVR [25]:

$$\text{Minimize } \frac{1}{2}\|\omega\|^2$$

$$\text{Subject to } \begin{cases} y_i - <\omega, x_i> - b \le \varepsilon \\ <\omega, x_i> + b - y_i \le \varepsilon \end{cases}$$

where x_i is a training sample with target value y_i. The inner product plus intercept $<\omega, x_i> + b$ is the prediction for that sample, and ε is a free parameter that serves as a threshold: all predictions have to be

within an ε range of the true predictions. Slack variables are usually added into the above to allow for errors and to allow approximation in the case the above problem is infeasible.

The kernel functions transform the data into a higher dimensional feature space to make it possible to perform the linear separation. For example, kernel functions are as follows:

$$k(X_i, X_j) = (X_i, X_j)^d$$

$$k(X_i, X_j) = \exp(-\frac{\left\| X_i - X_j \right\|}{2\sigma^2})$$

They are able to fit a continuous function to data. This is particularly useful when the predicted variable is continuous.

3 Machine Learning Based on RBM+SVR Approach

Until now, despite the RBM+SVR model has been great success in many Artificial Intelligence tasks [26-27], it is still not used to predict the corrosion rate of the refinery cooling water plant system. Therefore, further study is needed to investigate its prediction accuracy and model applicability [31]. The RBM+SVR approach is implemented as Fig. 2. This work includes two steps. First step, the main idea of the RBM is to represent inspections data by "Unsupervised learning", which the detail of is showed in Table 1.

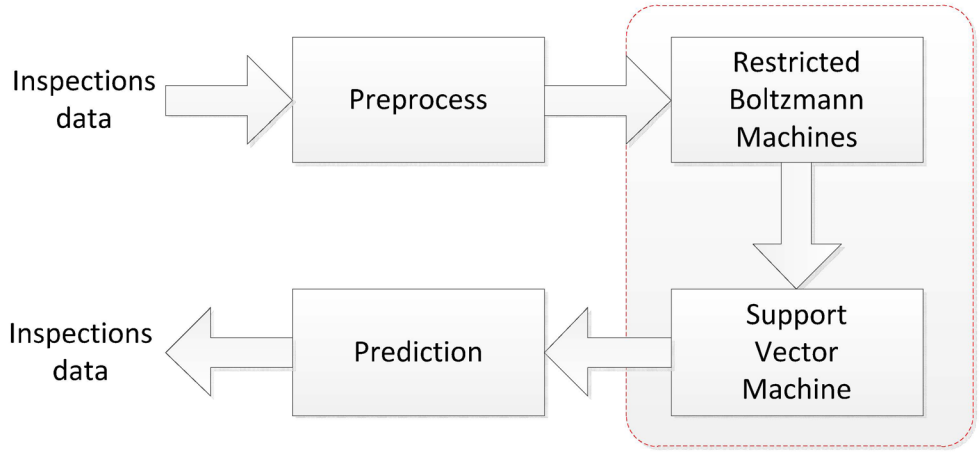

Fig. 2. Flow chart corrosion prediction model based on the RBM

Table 1. RBM algorithm

Restricted Boltzmann Machines model
Input: v_i is i th training data, h_j is jth layer of RBM.
Output: w_j is the weight of j th layer.
1. Choose a sample data as the observed variable, and then randomly initialize parameters w_j.
2. As function 2-3, update hidden variables. Set h_j as 1 or 0, compute $P(h_j = 1 \mid \mathrm{v})$. Then for v_i 、 h_j, compute $P(v_i h_j) = v_i * h_j$
3. Based on h status, compute v by function 2-5. Based on v_1 and function 2-1, compute h_1, $P(v_{1i} h_{1j}) = v_{1i} * h_{1j}$
4. Update the weight of w_{ij} as $w_{ij} = w_{ij} + L * P(v_i h_j)$
5. Choose another sample, repeat 1-4 steps.

After this step, RBM is to learn over the space of all inspections data. Missing inspections data can then be filled-in. Second step, once all inspections data are transformed to the new vector, which clearly presents correlational structure of the data. The χ^2 distance is computed to measure the similarity

between each pair of the inspections data F and $F^{'}$ (n is the size of inspection items):

$$dist_{x^2}(F,F^{'}) = \sum_{i-1}^{n} \frac{(F_i - F_i^{'})^2}{F_i + F_i^{'}}$$

Then, the kernel function based on this distance is used for SVR to train:

$$K_{x^2}(F,F^{'}) = e^{-\frac{1}{D} dist_{x^2}(F,F^{'})}$$

where D is the parameter for normalizing the distances. Here D is set to the average distance of all the training data. Finally, the kernel matrix is fed to SVR.

4 Application of the RBM+SVR Approach

4.1 Data Collection from Refinery Cooling Water Plant

Literature indicates that accuracy of an AI model depends on its parameters set in advance [28-29]. In practice, identifying the best model parameters is an optimization problem. In order to obtain accurate solution for predicting the corrosion rate of the refinery cooling water plant system, the RBM+SVR prediction model must be optimized, including the regularization parameter by training data [32]. To accomplish this, a significant amount of historical and current correlated data from Refinery Cooling Water Plant must be collected. The data of corrosion inspection with Refinery Cooling Water Plant are supplied by Lanzhou Petrochemical Company, which are listed in Table 2.

Table 2. Corrosion inspection data with Refinery Cooling Water Plant

Categories	Criterion	Units	Signal	Value
PH	GB/T 6904	/	Input	8.1-8.6
Cl2	GB/T 14424	mg/L	Input	0.2-1.0
oil	HJ 637	mg/L	Input	below 10.0
heterotrophic bacteria	HG/T 4207	num/L	Input	blow 100000
hardness of water	Q/SY LS1324	mg/L	Input	400-1200
phosphor	GB/T 6913	mg/L	Input	4-8
suspended matter	GB/T 14415	mg/L	Input	blow 30
NH4+	Q/SY LS1326	mg/L	Input	blow 10
Cl-	GB/T 15453	mg/L	Input	blow 500
Turbidity	GB/T 5750.4	NTU	Input	blow 35
concentration times	/	/	Input	3-6
conductivity	GB/T 6908	μs/cm	Input	400-3000
SO42	Q/SY LS1327	mg/L	Input	blow 500
calcium hardness	Q/SY LS1325	mg/L	Input	blow 800
alkalinity	GB/T 15451	mg/L	Input	100-350
potassium	GB 10539	mg/L	Input	blow 40
COD	GB/T 15456	mg/L	Input	blow 20
Fe2+/Fe3+	GB/T 14427	mg/L	Output	blow 1

Note. COD is Chemical Oxygen Demand.

The dataset is divided randomly into a training data set and a testing data set containing 80% and 20% of dataset, respectively. This follows the standard machine-learning paradigm that the amount of learning data should be much larger than the amount of test data. The objective is to avoid the over fitting and under fitting problems [30].

4.2 Data Preprocessing and Data Modeling

As shown in Table 2, the range of values for each element is different. A normalization function is applied to standardize some of the data. The normalization function is $x_{norm} = \frac{x - x_{\min}}{x_{\max} - x_{\min}}$. The

standardized data range is 0 to 1.

We trained the RBM model and studied the output of each feature layer. It is found that the feature of the fourth layer is used as the input variable of SVM, by which the prediction result is the best. Therefore, in this experiment, the characteristics of the fourth layer are used as the classification vector, which is reduced 8 dimensions

For SVR, we take the kernel function into account, which could affect the outcome. In this paper, all parameters are set the default values. Four kinds of kernel functions are involved in our experiment, including the linear, poly, rbf, fourier. The results show that the rbf kernel mentioned in the third part is better than others. The penalty factor *C* in SVR is of importance to predict the results. The larger the *C* is, the greater the likelihood of overfitting becomes. The smaller the *C* is, the greater the likelihood of underfitting becomes. In this paper, the value of *C* is optimized by cross validation. The *C* is set 3 in our SVR finally.

4.3 Validation of the RBM+SVR Approach

The corrosion inspection data of refinery cooling water plant come from Lanzhou Petrochemical Company. There are totally 300 groups of data in our experiment. The dimension of every data series is 17. The training set for this task consists of 240 groups of data, and the testing set consists of 60 groups of data. The data is shown in Table 2.

The following measures are employed to evaluate the prediction accuracy of the proposed model. The calculation formulas for these measures as follows:

The average relative error (MAPE) is a statistic measure, which is useful for evaluating the performance of predictive models because it gives relative values. The MAPE is effective for identifying the relative differences between models because it is unaffected by the size or unit of actual and predicted values. The MAPE can be calculated using equation:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y - y^{'}}{y}\right|$$

The root mean square error (RMSE) is computed to find the square error of the prediction compared to actual values and to find the square root of the summation value. The RMSE is thus the average distance of a data point from the fitted line measured along a vertical line. This tool efficiently identifies undesirably large differences. The RMSE is determined as equation:

$$\mathrm{RMSE} = \sqrt{\frac{1}{\mathrm{n}}\sum_{i=1}^{n}(y^{'} - y)^2}$$

A correlation coefficient (CC) is a number that quantifies a type of correlation and dependence, meaning statistical relationships between two or more values in fundamental statistics:

$$R = \frac{\sum_{i=1}^{n}(y_i - \overline{y})(y' - \overline{y}')}{\sqrt{\sum_{i=1}^{n}(y_i - \overline{y})^2 \sum_{i=1}^{n}(y' - \overline{y}')^2}}$$

indices are employed, where y_i and $y_{\mathrm{i}}^{'}$ are actual and predicted outputs respectively, $\overline{y}$ and $\overline{y}^{'}$ are average of actual and predicted outputs respectively.

4.4 Comparison of Our Approach with MRM, BP-ANNS, SVR and RBM+SVR

We apply different types of Artificial Intelligence approaches to predict corrosion rate of refinery cooling water plant respectively. The efficacy of the baseline machine learners and the model proposed are assessed using the data of corrosion inspection with the Refinery Cooling Water Plant system, which is supplied by Lanzhou Petrochemical Company. Experimental results are shown in Table 3. The partly experimental results of RBM+SVR approach. We can see that the RBM+SVR outperform other approaches.

Table 3. The partly predicate of corrosion rate among the RBM+SVR model and the others

	Actual Value Fe^{2+}/Fe^{3+}(mg/L)	RBM+SVR Fe^{2+}/Fe^{3+}(mg/L)	SVR Fe^{2+}/Fe^{3+}(mg/L)	BP-ANN Fe^{2+}/Fe^{3+}(mg/L)	MRM Fe^{2+}/Fe^{3+}(mg/L)
1	0.17	0.15	0.14	0.26	0.03
2	0.62	0.62	0.61	0.57	0.40
3	0.44	0.44	0.44	0.45	0.12
4	0.32	0.33	0.27	0.31	0.30
5	0.33	0.34	0.34	0.30	0.50
6	0.28	0.29	0.28	0.25	0.25
7	0.15	0.16	0.15	0.17	0.12
8	0.59	0.58	0.61	0.67	0.44
9	0.15	0.15	0.18	0.12	0.38
10	0.60	0.58	0.62	0.62	0.56

Fig. 3 compares the prediction performance when using the test data for the corrosion rate of the Refinery Cooling Water Plant system, which included the multiple regression model (MRM), Back propagation neural networks model (BP-ANN), Support Vector Regression (SVR). Analytical results showed that, for predicting corrosion rate, RBM+SVR models are better than the SVR, BP-ANN, and MRM models.

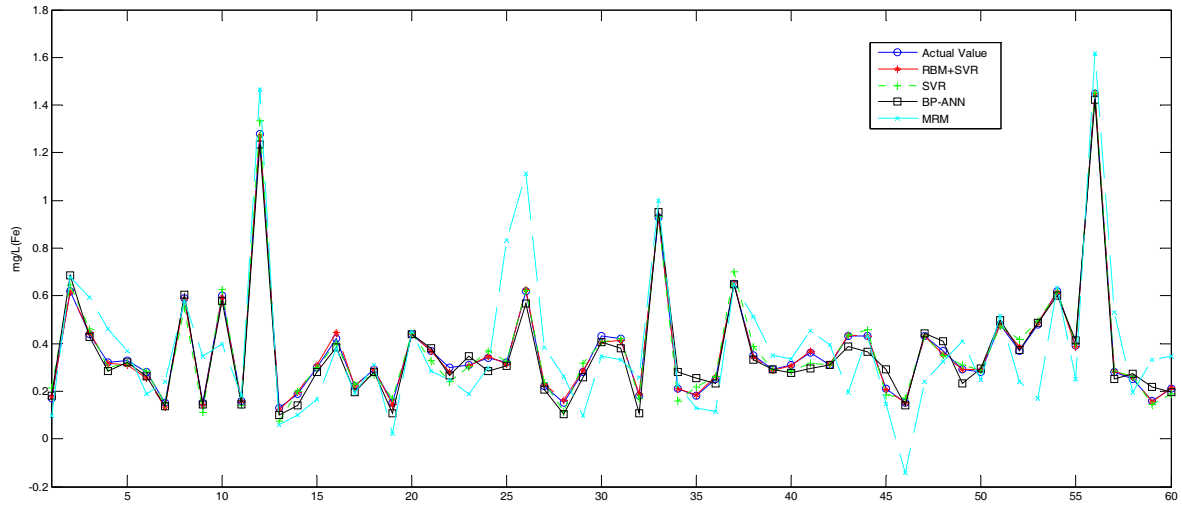

Fig. 3. The predicate of corrosion rate among the RBM+SVR model and the others

Moreover, in order to evaluate the RBM+SVR approach, we compare our approach with RBM+SVR, SVR, BP-ANN, and MRM models. It can be seen that the performance of our proposed RBM+SVR approach is better than other methods in average relative error and correlation coefficient. As shown in Table 4.

Table 4. Precision comparison of forecast results for three models

Model	MAPE (%)	CC(%)	RMSE(%)
MRM	14.42	0.943	0.156
BP-ANN	3.46	0.974	0.084
SVR	2.54	0.965	0.071
RBM+ SVR	1.08	0.981	0.008

Multiple regression model is only suitable for normal distribution and complete data. Especially, it is not fit for nonlinear data. BP-ANN model has some defections, first of all, the structure of the network is hard to fix. secondly, it is easy to get in local optimization. The SVR model introduces structured minimum to avoid the local optimum. However, SVR is significantly dependent on the data which is as input. Deep learning is a form of self-expression. It can automatically get the correlation and remove the correlation. So, we use deep learning model RBM to reduce dimensions and correlation among the inputs.

The test analysis showed that RBM+ SVR model can obtain the better result.

5 Conclusion

This paper introduced a novel approach for corrosion rate prediction, which is used for the Refinery Cooling Water Plant corrosion direct assessment based on Restricted Boltzmann Machines and Support Vector Regression. The Restricted Boltzmann Machines can be used to successfully learn good generative models. This procedure readily extends to learn Boltzmann machines with the corrosion inspection data, provided the distributions are in the exponential family. It makes better representations and creates models to learn these representations from the corrosion inspection data. Then these representations are fed to Support Vector Regression to predict. Based on this approach, the influencing factors that affected the corrosion rate of Refinery Cooling Water Plant are identified and the Corrosion rate of Refinery Cooling Water Plant was accurately predicted. The contribution of this study lies on the investigation of AI models for predicting corrosion rate. Accuracy in predicting corrosion rate can be improved. The findings of this study provide civil engineers with a promising and practice methodology for tracking of corrosion Refinery Cooling Water Plant system.

The factors influenced the prediction accuracy of corrosion rate are too many to include in our work. And the corrosion inspection data is not enough to satisfy the our mode training. In the future, we will improve the model from the next two aspects. First, we will improve the activation function of the deep RBM, in order to better adapt to our data characteristics. Secondly, we will introduce adaptability into SVR, in order to improve the prediction accuracy and be better applied it to the industrial production process.

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