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## ► To cite this version:

Zhenglei He, Kim Phuc Tran, Sébastien Thomassey, Xianyi Zeng, Changhai Yi. Modeling Color Fading Ozonation of Textile Using Artificial Intelligence. ISSAT International Conference on Data Science in Business, Finance and Industry, Jul 2019, Da Nang, Vietnam. <hal-02268138>

**HAL Id: hal-02268138**

**<https://hal.science/hal-02268138v1>**

Submitted on 20 Aug 2019

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# Modeling Color Fading Ozonation of Textile Using Artificial Intelligence

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**Keywords:** Artificial intelligence, Modeling, Color Fading, Ozonation, Textile

**Abstract** - Textile products with faded effect achieved via ozonation are increasingly popular recently. In this study, the effect of ozonation in terms of pH, temperature, water pick-up, time and applied colors on the color fading performance of reactive-dyed cotton are modeled using Extreme Learning Machine (ELM), Support Vector Regression (SVR) and Random Forest Regression (RF) respectively. It is found that RF and SVR perform better than ELM in this issue, but SVR is more recommended to be used in the real application due to its balance predicting performance and less training time.

## 1. Introduction

Increasingly, textile products with faded effect, worn look or vintage style have gained considerable share of fashion market and are attracting a growing number of consumers' attention [1]. However the faded effect conventionally was achieved by chemical methods which are not only highly water and power consuming, but also leave a heavy burden to the environment.

Ozone is an excellent gaseous oxidant with environmentally friendly property that can be decomposed rapidly to O<sub>2</sub> after using without emitting secondary pollution. In recent years, the study of color fading dyed textile using ozone instead of conventional method has been increasingly reported because of the advancement of ozonation. However the complicated and nonlinear relationship between the applied parameter in ozonation and color fading effects are still not clearly known, in other words, a model that can predict the engineering application effect is rather necessary.

Thus, models for predicting color properties of ozone fading dyed textile using different artificial intelligent techniques of ELM, SVR and RF is comparatively researched in this study.

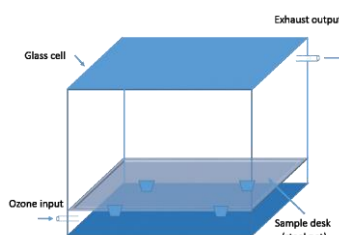


Figure 1. The reactor of ozonation.

experiment.

## 2.2 Methods

Ozone employed in this work was generated by a corona discharge ozone generator, CF-G50 (Guolin, China, fed by ( $\geq 99.9\%$  pure and compressed dry oxygen (1Mpa, 12L/min) from oxygen cylinder) and supplied into the reactor (as shown in Figure 1. which is made of glass). Ozone was continuously fed in and flowed over the ozone gas (used gas would be outputted as exhaust) with  $137 \pm 3$  mg/min at 2L/min. Dyed fabrics were wetted and placed evenly in the reactor before treating by ozone. The fading performance of three colors (blue, red, yellow) of dyed fabrics at different pH (1, 4, 7, 10, 13) and temperatures (0, 20, 40, 60, 80°C) with different water pick-up (0, 75%, 150%) over varied period (0, 5, 10, 15, 20, 25, 30, 35, 40, 45, 50, 55, 60 min) were investigated respectively.

According to Kubelka-Munk theory, it is known that  $K/S$  value indicates the color depth of samples. While  $L^* a^* b^*$  values (or CIELab), an international standard widely used for color measurements, is capable of illustrating the color variation of textile samples. Thus, these values tested by Datascolor 110 spectrophotometer (Datacolor, USA) were used to characterize the color variation of dyed textile in the color fading ozonation.

## 2.3 Artificial Intelligence techniques

As introduced above, it is clear that expected models would be inputting by the color of fabric as well as ozonation parameters of pH, temperature, water content and time, meanwhile outputting four outputs of  $K/S$ ,  $L^*$ ,  $a^*$ ,  $b^*$  values.

### 2.3.1 ELM

ELM is an algorithm for single-hidden layer feedforward neural networks (SLFNs) which randomly chooses hidden nodes and analytically determines the output weights of SLFNs. It tends to provide good generalization performance at extremely fast learning speed [2]. In this study, activation functions of Sigmoid, Sine and Hardim are comparatively analyzed with different number of nodes in the use of ELM.

### 2.3.2 SVR

Support vector machine (SVM) analysis is a popular machine learning tool for classification and regression, first identified

## 2. Experimental

### 2.1 Material

Cotton fabrics ( $3/1$  twill,  $325.7\text{g/m}^2$ , Shunfu, China) dyed by reactive dyes of Blue-RN, Red-2BL and Yellow-2RN (provided by Color Root, China) were used in the

by Vladimir Vapnik and his colleagues in 1992. In particular, multi-output least-squares support vector regression machines (MLS-SVR) toolbox [3] was used in this study with a range of different kernel functions such as Linear, Sigmoid, Polynomial and Radial basis function (RBF).

### 2.3.3 RF

Random Forest is a predictive model composed of a weighted combination of multiple regression trees. In general, combining multiple regression trees increases predictive performance. Multivariate Random Forest (MRF) developed by Raziur Rahman et al [4] were used in this study with an optimization of three parameters in terms of the number of trees in the forest and minimum number of samples in the leaf node as well as the randomly selected features considered for a split in each regression tree node.

## 3 Process modeling

The real samples treated in the ozonation at pH7, 20°C with 150% pick-up for different time from 0 to 60min are demonstrated in Figure 2. Corresponding  $K/S$ ,  $L^*$ ,  $a^*$ ,  $b^*$  values of these samples are provided in TABLE I. It is clear that each sample has obvious difference in terms of color performance with different ozonation parameters.

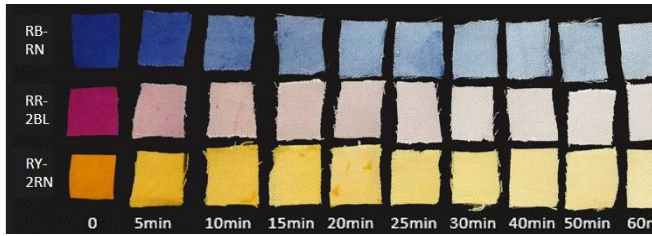


Figure 2. The illustration of real ozone faded cotton samples.

TABLE I.  $K/S$ ,  $L^*$ ,  $a^*$ ,  $b^*$  VALUES OF SAMPLES SHOWN IN FIGURE 2.

		Time(min)									
		0	5	10	15	20	25	30	40	50	60
RB-RN	$K/S$	8.12	3.70	2.17	1.63	1.24	1.17	0.89	0.85	0.66	8.12
	$L^*$	6.13	14.89	21.90	26.12	29.50	29.93	33.44	33.80	36.66	6.13
	$a^*$	-2.86	-4.47	-5.18	-5.68	-5.57	-5.27	-5.25	-5.19	-4.76	-2.86
	$b^*$	4.48	11.38	15.46	16.85	18.83	19.59	21.40	22.16	23.62	4.48
RR-2BL	$K/S$	1.10	0.95	0.70	0.66	0.52	0.57	0.51	0.39	0.39	1.16
	$L^*$	22.66	25.93	29.74	30.26	33.05	31.96	33.79	36.04	36.43	21.68
	$a^*$	-32.59	-37.32	-39.25	-40.16	-41.17	-41.82	-43.19	-42.44	-43.49	-32.39
	$b^*$	12.84	13.69	12.84	12.49	12.05	11.82	12.38	11.23	11.69	13.41
RY-2RN	$K/S$	6.60	3.70	2.90	2.20	1.81	1.58	1.16	1.11	0.87	6.60
	$L^*$	8.02	8.49	9.80	10.82	11.60	13.19	13.96	14.14	15.43	8.02
	$a^*$	20.41	15.35	12.99	11.47	9.59	8.62	7.31	6.52	5.56	20.41
	$b^*$	-17.99	-28.27	-32.09	-37.32	-40.95	-41.58	-47.94	-48.92	-52.39	-17.99

TABLE II. THE MAXIMUM, MINIMUM, AVERAGE AND STANDARD DEVIATION OF OZONATION PARAMETERS.

Parameters	Minimum	Maximum	Average	Std. dev.
Color	0(Blue)	1(Yellow)	0.5(Red)	-
pH	1	13	7	3.463
Temperature	0	80°C	40°C	24.91
Pick-up	0	150%	75%	58.78
Time	0	60min	30min	20.77
$K/S$	0.0975	22.82	7.177406	7.94
$L^*$	0.99	65.27	33.52368	17.61
$a^*$	-58.99	53.68333	-1.81221	32.75

$b^*$	-90.53	88.03545	3.875674	42.34
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TABLE II illustrates the variation including the minimum, maximum, average and standard deviation of inputs as well as outputs in the expected model. K-fold cross validation ( $k=10$ ) based on 459 experimental datasets (75%) were distributed to train and validate all the models above, while 153 datasets (25%) were used to test the models. K-fold cross validation is a popular statistical approach for estimating the predictive models. As  $k=10$  in present study, 459 sets of data would be divided randomly and equally into 10 disjoint folds, 9 folds of it would be split into training subset while the rest 1-fold of dataset would be used as validating subset. This method would be repeated 10 times with varied training and testing dataset at each time. Performance of models would be evaluated by Mean Square Error (MSE) based on the equation (1).

$$MSE = \frac{1}{n} \sum_{i=1}^n (e_i - p_i)^2 \quad (1)$$

where  $e_i$  is the real experimental results, whereas  $p_i$  is the predicted output of specific model.

In present study, the models' construction were carried out using MATLAB R2015b for ELM and MLS-SVR but R studio for MRF respectively on a personal computer (Core i7-4710, 2.5GHz, 16GB RAM).

## 4. Results and discussion

### 4.1 ELM models

ELM models with hidden nodes 1-136 activated by Sigmoid, Sine and Hardim functions are investigated respectively (the validated MSE shown in Figure 3.). It is worth to note that Sigmoid trained ELM models performed similarly to the ones trained by Sine that their MSE both dropped and minimized at with around 50 nodes ( $MSE \approx 0.052$ ) but enhanced dramatically after achieving the minimum MSE. By contrast, validation accuracy of Hardim activated models are minimized at the one with 97nodes ( $MSE \approx 0.069$ ). Meanwhile it is generally stable when the number of node further increased.

The use of activation functions in neural network is to convert an input signal of node to an output signal. As known that the used activation functions were  $Sigmoid(x) = \frac{1}{1+e^{-x}}$ ,  $Sine(x) = \sin(x)$  and  $Hardim(x) = 1$  if  $x \geq 0$ ; 0 otherwise. Among which, the graph of Sigmoid and Sine has something in common which may result in their similar proximity in the ELM models. Hardim performed worse as it is over-saturated.

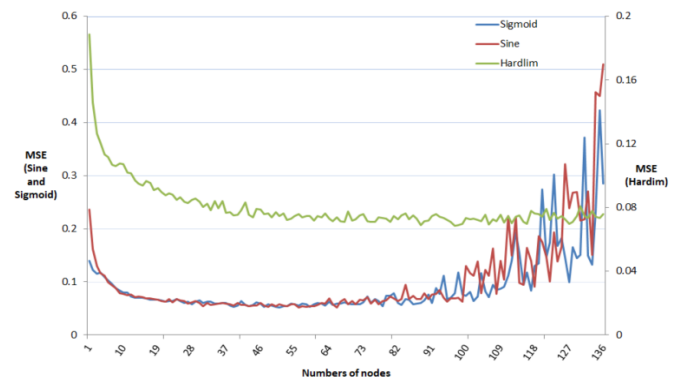


Figure 3. Validation MSE of different trained ELM models.

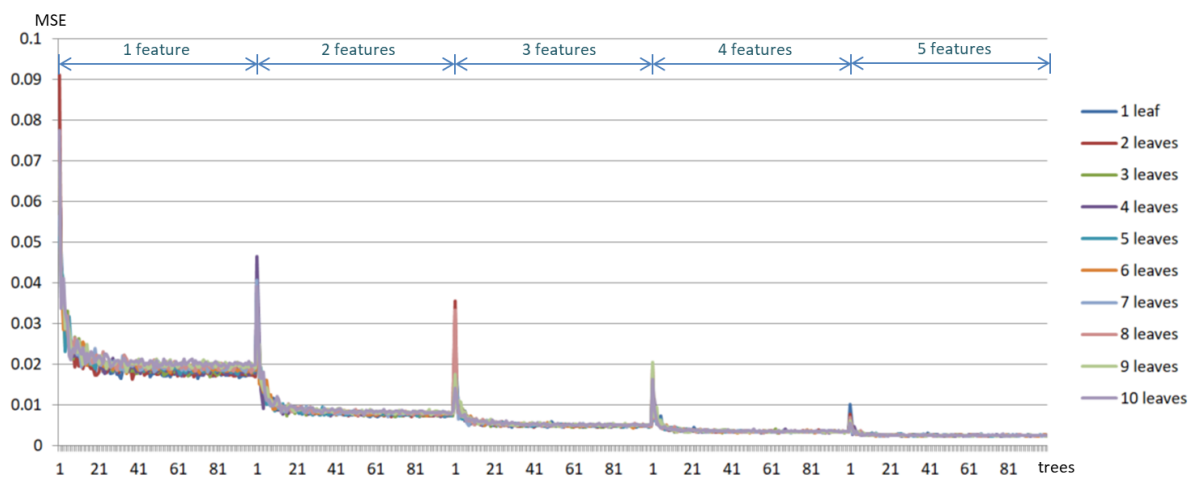


Figure 4. MSE of RF models with varied number of features, leaves and trees

## 4.2 SVR models

Multi output SVR with kernel functions of Linear, Sigmoid, Polynomial and RBF are trained and comparatively investigated using MLS-SVR toolbox [3]. The corresponding validation results of minimum MSE are 0.0539, 0.0095, 0.084, and 0.0047 respectively. In particular, SVR model with kernel function of RBF is the best one performed in this issue when parameters are optimized as  $\gamma = 32768$ ,  $\lambda = 9.7656e^{-4}$  and  $p = 0.125$ .

Kernel function is to transform the data as input into the required form to facilitate a non-linear decision surface to be a linear equation in higher dimensions. It is well known that RBF kernel is recommended to be tried first in a SVR model as the fact that it not only possesses certain similar parameters and behaviors of Linear and Sigmoid, but also has less hyperparameters than Polynomial to complex the model. RBF gained the lowest MSE is more suitable in this case because we have not too much features in model but with comparatively large numbers of observations.

## 4.3 RF models

RF models with different features from 1 to 5 and leaves from 1 to 10 as well as trees from 1 to 100 were trained, and the validated MSE are demonstrated in Figure 4. The number of randomly selected features in each regression tree node is found that plays a very vital role in affecting the models' predicting accuracy in this issue. This is owing to that the constructed model possesses five inputs, namely color of dyed cotton couple with pH, temperature, pick-up and time in ozonation, and the independency of these five factors are obvious clear. As a result, RF models with five randomly selected features optimized in the performance comparison. It is also found that RF models perform steadily when there are more than 30 regression trees in RF. But taking training time and cost into account, the 10 trees forest is sufficient and more recommended to be used in the color fading ozonation of dyed textile predicting model.

However, different from the selected features and trees, minimum number of samples in the leaf node seems to be

preferable to be less (apart from 1 leaf) in this investigation as the average MSE of achieved RF models linearly enhanced when the number of leaf is increased from 2 (0.0081) to 10 (0.0087) though it is relatively uninfluential.

## 4.4 Prediction performance

According to the analysis above, it is known that the ELM models trained with activation function of Sine and Sigmoid with around 50 nodes, and SVR models worked with RBF kernel function as well as the RF with 5 randomly selected features, 10 trees and 2 minimum number of samples in the leaf node are the optimized models in the application of modeling color fading ozonation of dyed textile.

To estimate and compare the optimized models, the prediction test using testing dataset (which has not been used in the training and validation process) is carried out. The prediction performance results are demonstrated in Table III. Generally, ELM models using different training function of Sigmoid (MSE=0.0172) and Sine (MSE=0.0173) does not make any big difference in regard to their prediction performance, but both of it are slightly poorer as compared with SVR and RF models. However, ELM models are the fastest-trained ones in this specific comparison, which means that ELM model is still worth to be used in certain resource limited cases especially while training time is concerned. The most accurate model in this issue is constructed by RF, which can be observed in Table III that leads the minimum testing MSE as only 0.0036. But it is also noted that training RF model requires much longer time than the others (21 seconds, which is over 22 times more than SVR). Therefore, it is important to take the SVR models into account as it achieved the second lowest MSE (0.0043) and it is more acceptable with the correspondingly shorter training time (0.9360s).

The constructed models possess four outputs, namely the chromatic values of  $K/S$ ,  $L^*$ ,  $a^*$ ,  $b^*$  values of ozone faded cotton fabrics. In order to reflect the real prediction performance of each trained model with respect to each single output specifically, the predicted data of models (using testing data) versing real experimental data is illustrated in Figure 5 (a) (b) (c) (d) with respect to each single output of the model.

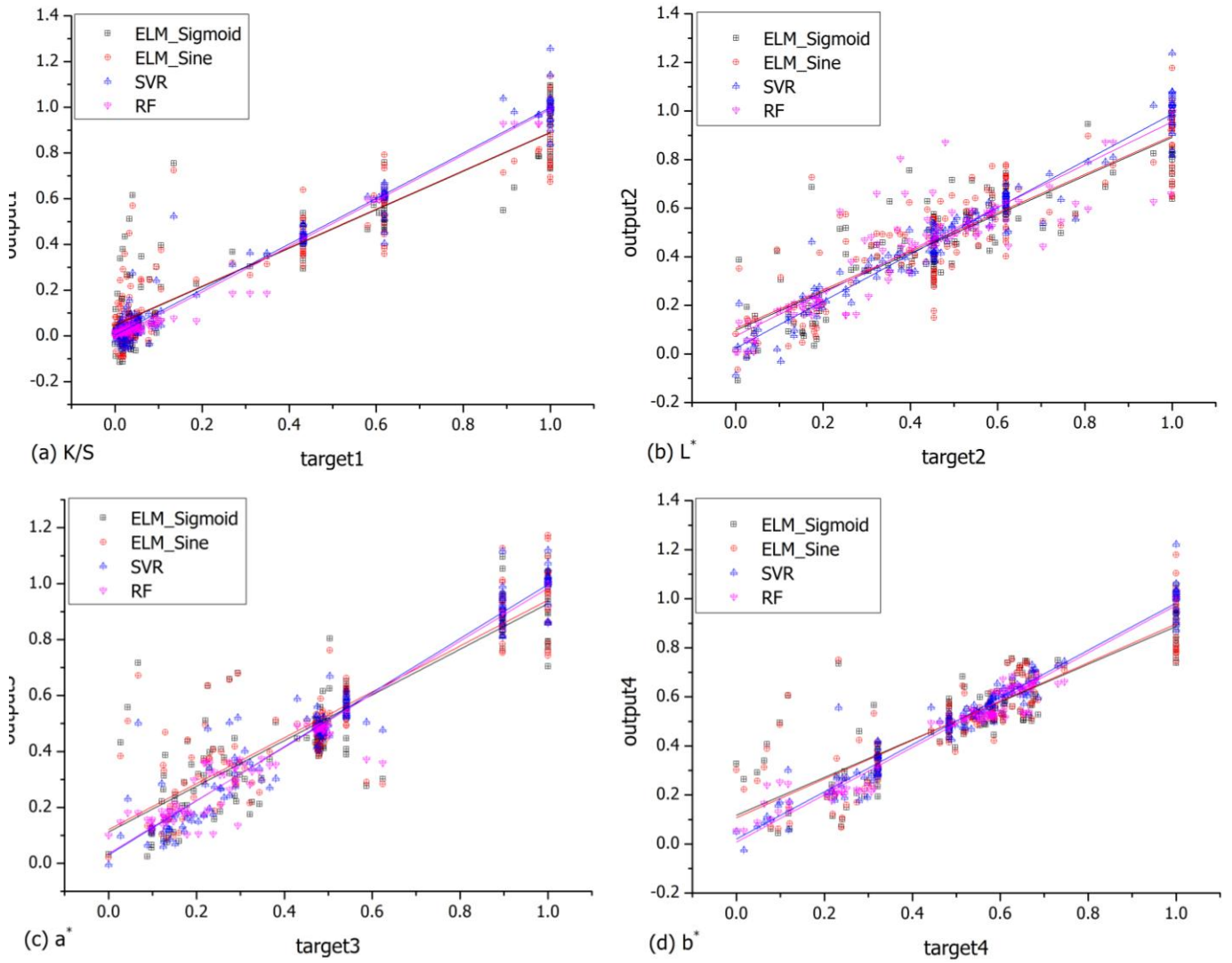


Figure 5. Predicted data outputted by ELM (trained by Sigmoid and Sine respectively), SVR and RF versus experimental data

TABLE III. PREDICTION PERFORMANCE OF OPTIMIZED MODELS.

Parameters	ELM (Sigmoid)	ELM (Sine)	SVR	RF
Training time(s)	0.0312	0.0936	0.9360	21
Average error (%)	0.1527	0.1549	0.1530	0.149
Maximum error (%)	0.3752	0.3700	0.3503	0.302
Minimum error (%)	0.0300	0.0029	0.0304	0.038
Testing MSE	0.0172	0.0173	0.0043	0.0036

TABLE IV. CORRELATION COEFFICIENTS OF DATA IN FIGURE 5.

R <sup>2</sup>	ELM (Sigmoid)	ELM (Sine)	SVR	RF
Target 1 - K/S	0.8474	0.8596	0.9683	0.9954
Target 2 - L*	0.7944	0.7517	0.9442	0.8816
Target 3 - a*	0.7903	0.8048	0.9380	0.9719
Target 4 - b*	0.7778	0.7868	0.9513	0.9731
Average	0.8025	0.8007	0.9505	0.9555

In Figure 5, it is found that the predicted values of models roughly agree with the actual values, although the predictive error maybe comparatively large in certain cases. The

difference of models' prediction performance in terms of MSE and average error are not that significant as shown in Table III (Sigmoid activated ELM=0.0172, Sine activated ELM=0.0173, SVR=0.0043, RF=0.0036), while the distribution of single output prediction is observed that may have a big gap in the real application.

As shown in Figure 5 (a) and (c), certain predicted data of ELM models can be clearly seen that are far different from the real target data, which may result in big mistake in certain single prediction application though the average of four outputs may alleviate the single wrong output. According to the correlation coefficients of predicting data versing real experimental data (demonstrated in Figure 5) listed in Table IV, the testing result reveals that SVR ( $R^2=0.9505$ ) model and RF model ( $R^2=0.9555$ ) are actually more suitable than ELM models ( $R^2=0.8025$  and  $0.8007$  for Sigmoid and Sine activated respectively) in modeling color fading ozonation of dyed textile.

The finding of this investigation indicates that both of SVR and RF are good candidates for making predictions on the



color quality of dyed textile in color fading ozonation as they both have a good agreement between the actual and predicted chromatic values of the textile samples.

## **5. Conclusion**

Color fading ozonation for dyed textile products have specific vintage effect and are going to be increasingly popular in recent years. The effects of ozonation in terms of pH, temperature, water pick-up, time and applied colors on the color fading performance of reactive-dyed cotton are modeled using ELM, SVR and RF respectively in this study. The investigation results show that both of SVR and RF are good to be used in this issue compared with ELM, however, taking the training time as a consideration, SVR model would be more recommended to be applied in the real use.

## **6. Acknowledgement**

The first author would like to express his gratitude to China Scholarship Council for supporting this study (CSC, Project NO. 201708420166).

## **7. Referencess**

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