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Correlation between Carbon Steel Corrosion and Atmospheric Factors in Taiwan

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Taiwan has a typical marine climate featuring perennial high-temperature and dampness. This climate, together with the emission of various industrial corrosive waste gases in recent years, contributes a lot to the corrosion of metal materials. In this study, samples of carbon steel exposed to various atmospheres in Taiwan were analyzed to investigate the impacts of atmospheric factors on carbon steel corrosion. Carbon steel samples were collected from 87 experimental stations between 2009 and 2012. Statistical analysis was employed to investigate the correlations between the carbon steel corrosion situations and the atmospheric factors such as concentrations of sulfur dioxide or chloride, exposure time, rainfall, etc. The results indicate that for samples from industrial areas, the sulfur dioxide concentration and exposure time during fall and winter are significantly correlated to the condition of the carbon steel corrosion. However, for samples from coastal zones, the significant correlated factors are chloride concentration and wetting time during winter. The results of this study are useful for the development of carbon steel corrosion prediction models.

Keywords: *Atmospheric corrosion, Environment factors, Carbon steel, Correlation analysis*

1. Introduction

Taiwan, because of its subtropical and tropical location and the surrounding sea, has a typical marine climate featuring perennial high-temperature and dampness. This climate, together with the emission of various industrial corrosive waste gases in recent years, contributes a lot to the corrosion of metal materials. In the light of this, it is necessary to carry out in-depth exploration of atmospheric corrosion of metals here. The investigation and classification of atmospheric corrosion are of critical importance to the safety of metal structures. This study is a correlation research based on investigation data of corrosion factors and local exposure test data for more precise classification of atmospheric corrosion environments for the purpose of the maintenance of safety of major domestic industrial zones and public works. It is a preliminary statistical analysis of survey data [1,2] of carbon steel corrosion at test sites from July 2009 to September 2012.

2. Methodology

The data are archived with Microsoft Excel and analyzed with IBM SPSS and the analysis results are tabulated and summarized into charts. Below is a discussion of the statistical methods used for correlation analysis and regression analysis in the study.

2.1 Correlation analysis

Pearson correlation data are presented in matrices and subjected to statistical correlation analysis in which association between two variables, correlation coefficients, positive and negative interactions, and significance are observed and coefficients will be marked with an asterisk where $p < 0.05$ (significance level $\alpha = 0.05$) or two asterisks where $p < 0.01$ (significance level $\alpha = 0.01$). Eight variables are included as factors that affect corrosion rate of carbon steel, including climate factors such as Time of wetness (TOW), average temperature (TEMP), average wind speed (WS), accumulated precipitation (AP), rainfall hours (RF_HR), Sunshine Hours (SUN_HR), and environmental factors such as chlorides deposit (Cl) and sulfur dioxide deposit (SO_2). It is suggested that these factors are potentially associated with corrosion rate to some extent, therefore this study uses correlation analysis to test and estimate the correlation between the variable groups and its significance.

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Table 1 Descriptive Statistics of the Carbon Steel at Different Exposure Times and Type

Type	Exposure time	Sample	TOW (%)	TEMP (℃)	WS (m/s)	AP (mm)	RF_HR (hr)	SUN_HR (hr)	SO_2 (mg/m^2/day)	Cl^- (mg/m^2/day)	Corr ate (μm/yr.)	Standard Deviation	Corr rate (μm/yr.)
Industry	spring	102	5-81	16-27	1- 4	93-1354	19-680	165-2455	17-1182		26-980	181	184
	summer	106	20-84	24-29	1-4	193-1304	57-270	281-780	10-1140		27-940	166	148
	autumn	97	10-79	14-29	1.5-6	21-2422	1-956	6-755	20-677		26-980	184	144
	winter	107	7-84	11-27	1.5-7	19-1285	16-1083	97-638	3-1973		27-94	148	161
	1-Year	144	18-76	11-26	1-6	455-5662	139-2847	867-3898	13-974		10-889	110	100
Coastal	spring	146	6-88	20-27	2-4	97-1525	14-680	22-2455		1-143	18-908	222	158
	summer	145	21-84	27-29	1-4	193-1791	57-260	282-791		1-116	39-527	91	148
	autumn	135	9-74	17-27	1-6	21-3005	7-1444	73-828		1-243	26-908	167	260
	winter	148	7-84	14-23	2-7	19-1640	11-1402	61-693		1-147	31-673	146	205
	1-Year	147	19-64	11-26	1-5	456-4818	139-2858	862-3898		2-152	41-506	130	78.8

TOW: Time Of Wetness, WS: Wind Speed, AP: Accumulated precipitation, RF_HR: Rain fall hour, SUN_HR: Sunshine-hour

Table 2 Correlation coefficient of the Carbon Steel

Type	Exposure time		TOW (%)	TEMP (℃)	WS (m/s)	AP (mm)	RF_HR (hr)	SUN_HR (hr)	SO_2 (mg/m^2/d)	Cl^- (mg/m^2/d)
Industry	spring	Pearson Sig.	.374**	-.301**	.128	.160	.341**	-.072	.378**	
	summer		.326**	-.446**	-.019	.001	.040	-.052	.479**	
	autumn		.410**	-.138	.221*	.240*	.312**	-.295**	.548**	
	winter		.697**	-.595**	.291**	.650**	.663**	-.499**	.649**	
	1-Year		.427**	-.179*	.045	.062	.213*	-.166*	.742**	
Coastal	spring	Pearson Sig.	.220**	-.200*	-.102	.262**	.279**	-.164*		.437**
	summer		.096	.101	-.256**	.154	.118	-.341**		.364**
	autumn		.377**	.027	-.079	-.099	.050	-.271**		.428**
	winter		.610**	-.543**	.259**	.225**	.302**	-.332**		.430**
	1-Year		.301**	-.156	.049	-.146	-.046	-.125		.506**

**:Correlation is significant at the 0.01 level (2-tailed)
*: Correlation is significant at the 0.05 level (2-tailed)

2.2 Regression analysis

Regression analysis is a method that uses a single variable or multiple independent variables to predict dependent variables. Multiple regression analysis, on the other hand, includes multiple independent variables in a regression equation in order to improve prediction capacity and reduce residuals based on the assumption that dependent variables have a linear relation with criterion variables that can be represented with a multiple linearity regression (MLR) model. It mainly uses least squares method to obtain the optimal coefficient and calculate fitted values with regression line. In this study, MLR is used to identify the relation between carbon steel corrosion rate and environmental factors. The steps to establish a MLR model are as follows [3]:

Ⅰ. Determine criterion variables, identify appropriate predictor(s), and collect data;
Ⅱ. Determine an MLR model, i.e. estimates of various regression coefficients;
Ⅲ. Test the theoretical regression coefficients;
Ⅳ. Determine the fitness of the MLR model;
Ⅴ. Test the hypotheses of the model;
Ⅵ. Make prediction with the MLR model.

3. Results and Discussion

It can be inferred from Table 1 that the dependent variable of the model for analyzing the ranges and average values of carbon steel corrosion is corrosion rate of carbon steel (mm/yr). and Furthermore eight independent variables, i.e. TOW (%), TEMP (°C), WS (m/s), AP (mm),

Table 3 Significance Testing of Atmospheric corrosion and Environment factor

Type	Exposure time	From high to low
Industry	spring	SO_2 · TOW · F_HR · TEMP
	summer	SO_2 · TEMP · TOW
	autumn	SO_2 · TOW · RF_HR · SUN_HR
	winter	TOW · RF_HR · AP · SO_2 · TEMP · SUN_HR · WS
	1-Year	SO_2 · TOW
Coastal	spring	Cl · RF_HR · AP · TOW
	summer	Cl · SUN_HR · WS
	autumn	Cl · TOW · SUN_HR
	winter	TOW · TEMP · Cl · SUN_HR · RF_HR · WS · AP
	1-Year	Cl · TOW

Table 4 Model Summary of the Carbon Steel

Type	Exposure time	R	R^2	$adjR^2$	Standard Deviation	D
Industry	spring	0.517	0.267	0.245	157.4	1.685
	summer	0.520	0.271	0.257	126.8	1.274
	autumn	0.745	0.554	0.535	125.5	1.928
	winter	0.835	0.698	0.686	82.9	1.791
	1-Year	0.784	0.615	0.606	68.8	1.844
Coastal	spring	0.552	0.305	0.285	133.7	1.348
	summer	0.519	0.270	0.254	78.9	1.390
	autumn	0.642	0.412	0.394	129.9	1.681
	winter	0.694	0.482	0.471	106.5	1.399
	1-Year	0.542	0.294	0.284	66.6	1.784

RF_HR (hr), SUN_HR (hr),SO_2 ($mg/m^2/day$) and Cl ($mg/m^2/day$), are used in the analysis.

3.1 Correlation analysis of carbon steel and environmental factors

The corrosion rates data of carbon steel are sorted in accordance with areas, exposure duration and environmental factor related significance coefficient, as shown in Table 2 and Table 3, and explained on the basis of seasons, i.e. Spring (March-May), Summer (June-August), Autumn (September-November), and Winter (December-February), as follows:

3.1.1 Analysis for industrial areas

In spring, the most significant environment-related factors that affect corrosion rate are sulfur dioxide, TOW, RF_HR, and TEMP. In summer, the most significant factors are sulfur dioxide, TEMP, and TOW. In autumn, the factors are sulfur dioxide, TOW, RF_HR, and SUN_HR. In winter, TOW, RF_HR, AP, SO_2, TEMP, SUN_HR, and WS. In a whole year, the most significant factors in industrial areas are SO_2 and TOW.

3.1.2 Analysis for coastal areas

In spring the most significant environment-related factors that affect corrosion rate in association significance order are Cl, RF_HR, AP, and TOW. In summer the most significant factors are Cl, SUN_HR, and WS. In autumn the factors are Cl, TOW, and SUN_HR. In winter TOW, TEMP, Cl, SUN_HR, RF_HR, WS, and AP. In a whole year, the most significant factors in coastal areas are Cl and TOW.

3.2 Establishment of a multiple regression model

The dependent variable (carbon steel corrosion rate) and independent variables (TOW, TEMP, WS, AP, RF_HR, SUN_HR, SO_2 and Cl) in the regression analysis are defined and explained in terms of regression model summary, variance analysis, regression coefficient, and collinearity and the feasibility of the regression predictive model in this study is explained as follows [4,5]:

The regression model summary includes degree of correlation, coefficient of determination, adjusted coefficient of determination and Durbin-Watson test, as shown in Table 4.

3.2.1 Correlation coefficient (R)

The calculated R value in the study is 0.835 in industrial areas in winter and greater than 0.50 for the rest seasons and areas, suggesting that the dependent variable, carbon steel corrosion rate, has a high degree of correlation with the input independent variables; in other words, the correlation between the predicted value and actual value of carbon steel corrosion rate in industrial areas in winter is 83.5%.

3.2.2 Coefficient of determination (R^2)

Coefficient of determination indicates the percentage of variance that is attributable to the multiple regression model in total variance of input dependent. In this study, it is 0.615 (1-year) in industrial areas. It can be said that three predictors (environmental factors) account for 61.5% of the total variance of the corrosion rate, while only less than 30% of the total variance of the corrosion rate can be attributed to the seasons of spring and summer.

Table 5 Regression Statistics and Coefficients Analysis of the Carbon Steel at Industry and Coastal

		Stepwise Regression Variable	Unstandardized Coefficients Beta	Standardized Coefficients Beta	*T* Statistic	sig.	Tolerance	VIF	*F* Statistic
Industry	spring	(Constant)	-108.1		-1.685	0.095			11.09
		SO_2	0.377	0.330	3.715	0.000	0.950	1.052	
		TOW	3.589	0.319	3.603	0.000	0.954	1.048	
		WS	39.8	0.183	2.100	0.038	0.988	1.012	
	summer	(Constant)	1435.6		2.627	0.010			19.13
		SO_2	0.29	0.331	3.184	0.002	0.653	1.530	
		TEMP	-45.7	-0.251	-2.412	0.018	0.653	1.530	
	autumn	(Constant)	-18.179		0.256	0.798			28.62
		SO_2	0.651	0.510	7.102	0.000	0.940	1.064	
		SUN_HR	-0.319	-0.283	-3.949	0.000	0.945	1.059	
		TOW	4.552	0.351	4.778	0.000	0.895	1.117	
		WS	38.276	0.217	2.986	0.004	0.919	1.089	
	winter	(Constant)	-59.462		-2.478	0.015			58.93
		TOW	1.937	0.267	2.865	0.005	0.342	2.926	
		SO_2	0.213	0.380	6.181	0.000	0.782	1.278	
		RF_HR	0.189	0.320	3.390	0.001	0.333	3.002	
		WS	21.094	0.184	2.972	0.004	0.775	1.290	
	1-Year	(Constant) SO_2	3.279		0.115	0.909			74.42
		TOW	0.564	0.683	12.421	0.000	0.910	1.098	
		SUN_HR	1.686	0.202	3.613	0.000	0.878	1.139	
			-0.025	-0.131	-2.454	0.015	0.961	1.041	
Coastal	Spring	(Constant)	627.333		3.699	0.000			15.48
		Cl	2.764	0.385	5.272	0.000	0.925	1.081	
		AP	0.130	0.276	3.712	0.000	0.893	1.120	
		TEMP	-18.788	-0.242	-2.929	0.004	0.722	1.384	
		WS	-29.013	-0.160	-1.988	0.049	0.759	1.317	
	summer	(Constant)	345.047		7.682	0.000			17.37
		Cl	1.291	0.293	3.974	0.000	0.953	1.050	
		SUN_HR	-0.266	-0.287	-3.899	0.000	0.953	1.049	
		WS	-31.969	-0.254	-3.519	0.001	0.997	1.003	
	autumn	(Constant)	265.169		4.285	0.000			22.82
		Cl	1.811	0.360	5.162	0.000	0.931	1.074	
		TOW	3.867	0.322	4.070	0.000	0.723	1.383	
		AP	-0.092	-0.382	-4.543	0.000	0.640	1.562	
		SUN_HR	-0.336	-0.367	-4.335	0.000	0.630	1.587	
	winter	(Constant)	-55.561		-1.905	0.059			44.64
		TOW	3.991	0.528	8.528	0.000	0.939	1.065	
		Cl	1.603	0.276	4.410	0.000	0.919	1.088	
		WS	16.570	0.157	2.579	0.011	0.966	1.036	
	1-Year	(Constant)	35.221		1.622	0.107			
		Cl	1.788	0.462	6.444	0.000	0.953	1.049	
		TOW	1.403	0.201	2.807	0.006	0.953	1.049	30.01

3.2.3 Durbin-Watson test

Durbin-Watson test is a method to determine whether there is autocorrelation of the residuals in a multiple regression analysis. The *D* value is between 0 and 4. Generally speaking, a *D* value around 2 signifies there is no autocorrelation of the residuals. It is found in this study that the *D* value of corrosion rate residuals is about 2 in industrial areas and coastal areas in all seasons, suggesting that there is no autocorrelation of the residuals.

3.3 Regression coefficient

In our regression coefficient analysis, the collinearity analysis of non-standardized coefficient *B*, standardized regression coefficient, *t* test and significance value, tolerance and variance inflation factor is as shown in Table 5.

3.3.1 Standardized regression coefficient:

The standardized regression coefficients listed here are the results of our multiple regression analysis, in which the matrix of independent variable data is standardized first and then *subjected to calculation*. It reflects that the variance of dependent variable with the increase of one independent variable by one unit, i.e. the degree of influence of independent variable on dependent variable. Since the difference between inter-variable variance and mean value can be very significant, it is unable to compare the influence of various variables on the dependent variable by direct application of non-standardized coefficients, it is therefore necessary to carry out standard normalizing transformation of the variables for analysis. The standardized regression coefficients can be directly compared to determine the influence of various variables on the dependent variable.

3.3.2. t test and significance value

The t test of an individual coefficient can be used to determine the importance and contribution of an independent variable to the entire model in a multiple regression model, that is, to determine whether the multiple regression coefficient of an independent variable is too small and can therefore be considered as zero and as the ground to neglect the independent variable. Generally speaking, when the calculated $t > 2$ or $t < -2$ or the significance value < 0.10, the independent variable is a useful or important predictor. The t value is calculated by dividing the regression coefficient with its standard error; the larger the t value, the easier the significant level is achieved. In this study, all t values are at or above the significant level. In industrial areas, the t values of SO_2 and TOW are both > 2, and the t value of SUN_HR is < -2, Therefore they are useful predictor variables. In coastal areas, on the other hand, the t values of Cl and TOW that have a t value are > 2 and those of AP, SUN_HR, WS are < -2 indicating that they are all important predictor variables.

3.3.3 Collinearity of Tolerance and Variance Inflation Factor (VIF)

A collinearity analysis tells us whether there are any collinear data and enables us to evaluate whether the collinearity has impact on the establishment of parameters. Generally we use the tolerance of an variable as the measurement of collinearity, and VIF has a close relation with tolerance, i.e. the greater the variance of regression coefficient, the larger the variance inflation factor (usually 10), *and the serious the collinear problem between the independent variable and other independent variable.* In general, tolerance falls in the range of 0 ~ 1. If the tolerance is small (say, 0.10), then there might be a linear correlation between the variable and other independent variables. In this study, all tolerance values are greater than 0.10 and approximate to 1, and all VIFs are less than 10, suggesting that there is little or no collinearity between independent variables and the linear dependence between independent variables is insignificant in this model.

3.3.4 F test and significance value

F test of *F* statistics is for calculation of the overall significance value. In this study, the calculated significance value is 0.000, suggesting that the independent variables $Z_1 - Z_8$ are effective enough to explain and predict the dependent variable Z_y in the multiple regression analysis.

Table 6 Standardized Regression Model of the Carbon Steel

		Regression Model	R^2	Equation
Industry	spring	$Z_Y = 0.330Z_7 + 0.319Z_1 + 0.183Z_3$	0.25	4.1
	summer	$Z_Y = 0.331Z_7 - 0.251Z_2$	0.26	4.2
	autumn	$Z_Y = 0.510Z_7 - 0.283Z_6 + 0.351Z_1 + 0.217Z_3$	0.54	4.3
	winter	$Z_Y = 0.267Z_1 + 0.380Z_7 + 0.320Z_4 + 0.184Z_3$	0.69	4.4
	1-Year	$Z_Y = 0.683Z_7 + 0.202Z_1 - 0.131Z_6$	0.61	4.5
Coastal	spring	$Z_Y = 0.385Z_8 + 0.276Z_4 - 0.242Z_2 - 0.160Z_3$	0.29	4.6
	summer	$Z_Y = 0.293Z_8 - 0.287Z_6 - 0.254Z_3$	0.25	4.7
	autumn	$Z_Y = 0.360Z_8 + 0.322Z_1 - 0.382Z_4 - 0.367Z_6$	0.39	4.8
	winter	$Z_Y = 0.528Z_1 + 0.276Z_8 - 0.157Z_3$	0.47	4.9
	1-Year	$Z_Y = 0.462Z_8 + 0.201Z_1$	0.28	4.10

Z_1:Standardized TOW Z_2:Standardized Temp Z_3:Standardized WS Z_4:Standardized AP
Z_5:Standardized RF_HR Z_6:Standardized SUN_HR Z_7:Standardized SO_2 Z_8:Standardized Cl
Z_Y:Standardized Corrosion rate

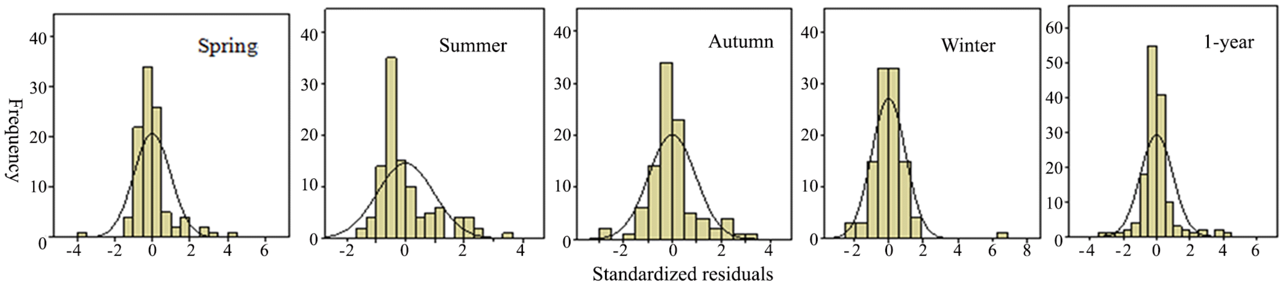

Fig. 1 Standardized residuals frequency distribution histograms (Industry).

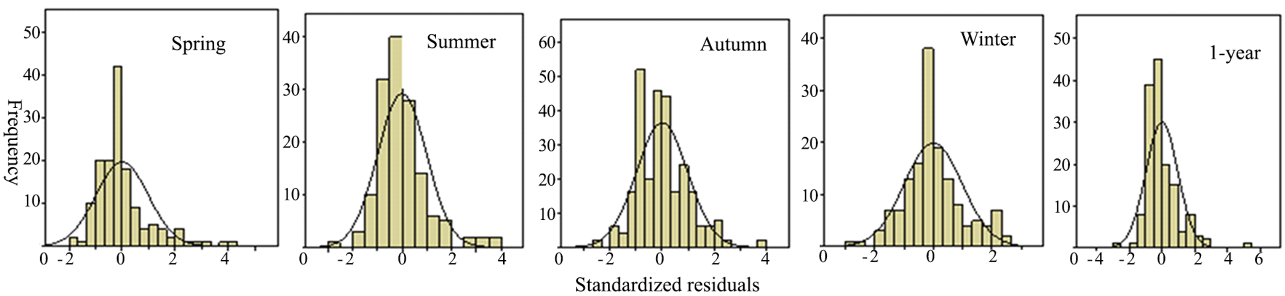

Fig. 2 Standardized residuals frequency distribution histograms (Coastal).

As can be seen from the Table 5, *F*-test of the corrosion rate data in industrial areas and coastal areas yields $P < 0.05$ and significance value =0.000, *suggesting a significant level*; therefore it can be said the eight variables selected on the basis of stepwise regression for prediction are of significant association with corrosion rate.

3.4 Multiple regression models

The output results of the multiple regression analysis and the calculated regression coefficients of variables (TOW, TEMP, WS, AP, RF_HR, SUN_HR, SO_2, Cl) are as shown in Table 6. For example, according to the 1-year standardized model for industrial areas that has SO_2, TOW and SUN_HR as its parameters, it is expected that the corrosion rate will increase by 0.683 with the increase of SO_2 by a unit. Likewise, the decrease of SUN_HR by a unit will give rise to an expected increase of corrosion rate by 0.131. In short, the 1-year model for industrial areas shows that the corrosion rate increases with the increase of SO_2, TOW and with the decrease of SUN_HR.

3.5 Test and discussion of the multiple regression models

Below is a test and discussion of the established multiple regression model of carbon steel corrosion based on the fundamental hypotheses of regression analysis that have been discussed, aiming to determine whether the hypotheses are true:

3.5.1 Standardized residuals frequency distribution histogram

The research data in this study are sorted and summarized using SPSS to generate standardized residuals frequency distribution histograms as shown in Fig. 1 and Fig. 2; the histogram can be used to test whether the observations of samples meet the fundamental hypothesis of normal distribution. The complete fitting of the frequency distribution of residuals with the bell-shape curve (standard normal distribution curve) in the histogram indicates the full normal distribution of standardized residuals of samples. Our study results show it does follow normal distribution pattern.

3.5.2. Normal probability plot of sample residuals

Data from the study are sorted and summarized into the normal probability plot of sample residuals as shown in Fig. 3 and Fig. 4. The better the cumulative probability of sample residuals fits the curve, the better the sample observations fulfill the normality assumption. Our study results show the normality assumption is fulfilled.

3.5.3 Scatter plot of residuals and predicted values

When this scatter plot takes on the appearance of a horizontal random distribution, it indicates that the sample observations meet the assumption of data normality and variance homogeneity. The study results are summarized as shown in Fig. 5 and Fig. 6. It can be inferred from the plot that the residuals and predicted values are distributed randomly, the assumption of variance homogeneity is therefore fulfilled.

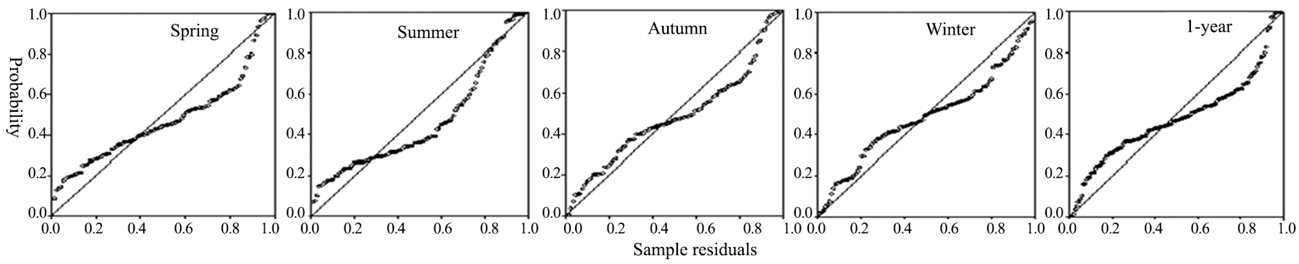

Fig. 3 Normal probablilty plot of sample residuals (Industry).

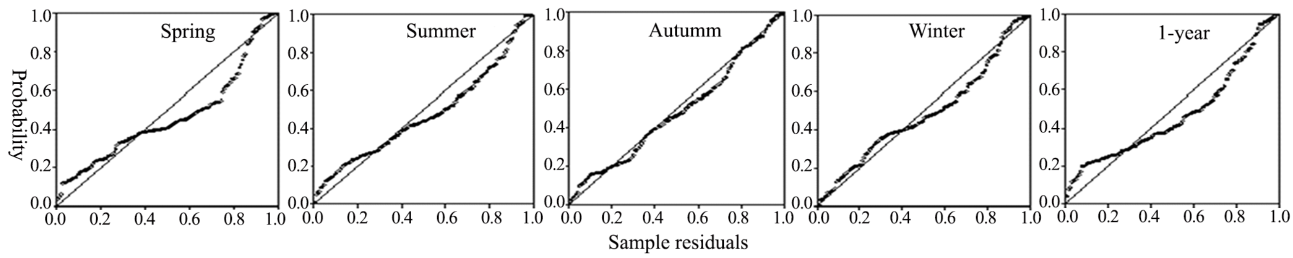

Fig. 4 Normal probablilty plot of sample residuals (Coastal).

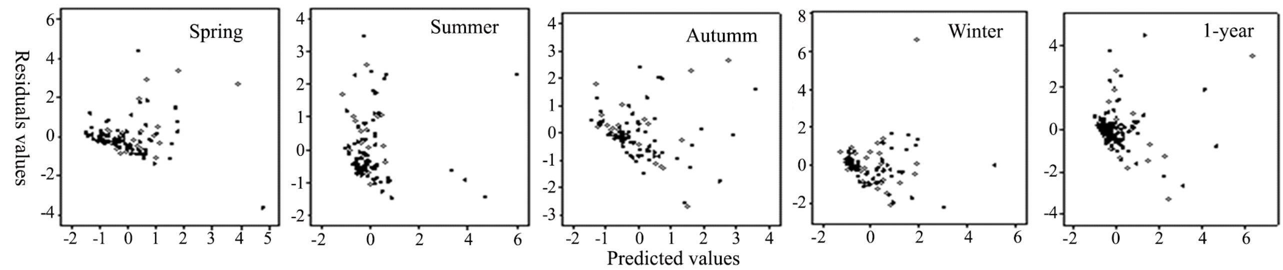

Fig. 5 Scatter plot of residuals and predicted value (Industry).

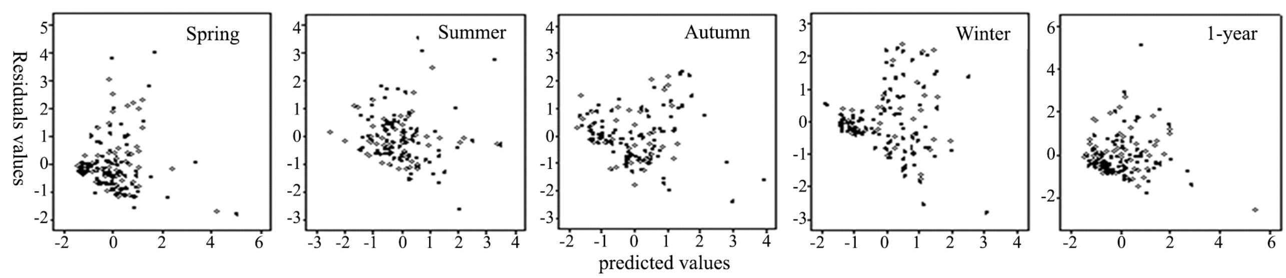

Fig. 6 Scatter plot of residuals and predicted value (Coastal).

3.6 Prediction models of the multiple regression

The above tests show the model has attained significance level and it is determined that the model is appropriate and in line with the fundamental hypotheses of regression analysis and free of any collinearity or autocorrelation problem. Three of the final models, i.e. models for industrial areas in autumn winter and a year, are found to be in line with the fundamental hypotheses. As regards models for coastal areas, the two model for autumn and winter are found to be in line with the fundamental hypotheses. For example: The corrosion rate in industrial areas in autumn is positively correlated with SO_2, TOW, WS (positive coefficient), i.e. the increase of these factors could have positive effect on corrosion rate and could increase the corrosion rate. The corrosion rate in coastal areas in winter is positively correlated with TOW, Cl (positive coefficient) i.e. the increase of these factors could have positive effect on corrosion rate and could increase the corrosion rate.

4. Conclusion

1. The analysis of correlation between carbon steel corrosion and environmental factors reveals that, for the environmental factors in industrial areas, SO_2, TOW in autumn, winter and all year round are significantly correlated with corrosion rate, while the Cl, TOW in winter and all year round are significantly associated with corrosion rate. TOW is highly associated with corrosion rate in both industrial areas and coastal areas in winter.

2. A corrosion prediction relation has been established and verified with statistical tests as appropriate and in line with the fundamental hypotheses of regression analysis and free of collinearity and autocorrelation by virtue of the study results and relevant significance analysis. Three of the final models, i.e. models for industrial areas in autumn, winter and all year round, are found to be in line with the fundamental hypotheses. Regarding models for coastal areas, the two models for autumn and winter were found to be in line with the fundamental hypotheses. The corrosion rate in industrial areas is positively correlated with SO_2, TOW, WS, i.e. the increase of these factors could increase the corrosion rate; the corrosion rate in coastal areas is positively correlated with TOW, Cl, i.e. the increase of these factors could increase the corrosion rate.

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