Application of the static and dynamic models in predicting the future strength of pozzolanic cements

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***Abstract*—** The objective of this study is to analyze static and dynamic models predicting the future typical compressive strength of Pozzolanic cements. Both classes of models are based on physical and chemical characteristics and on the early strength of this cement type. The models performance was investigated and the superiority of the dynamic models was proved based on different criteria. Based on the dynamic models, the industrial quality control can daily evaluate the reactivity of cement compounds and take preventive or corrective actions if needed in order to maintain a low variance of typical strength.

***Keywords*—**Cement, model, prediction, strength

I. Introduction

BLENDED cements are largely produced and utilized in construction. With these types of cement high performance concrete can be obtained as regards strength and durability under expected environmental conditions. On the other hand, the composite cements due to their lower Clinker/Cement ratio contribute to the reduction of the emitted CO2 per ton of produced cement having a very positive environmental impact. According to the European Norm EN 197-1:2011 [1] several components can be used as main cement constituents, except the clinker: Limestone, natural or artificial pozzolane, fly ash, granulated blast furnace slag and silica fume. The most of these compounds are characterized as pozzolanic or cementitious materials, contributing effectively on the strength development of cement and concrete. Consequently concerning strength development, a binary or ternary mixture of Portland clinker with these components shows a behavior completely different from that of pure Portland cement composed only from clinker and gypsum.

Cement quality is mainly characterized by its stability concerning the compressive strength in mortar and concrete. The stability of 28 days strength of mortar is thought as sufficient indicator of the product quality. In case the cement strength is far from the predefined target, the delay of 28 days of receiving results is enough long and likely the reasons causing strength divergence already have vanished. A second drawback related with this delay is that if the producer does not start any action during this period, a product outside of specifications could be manufactured. Therefore the construction of models predicting the 28-day strength of blended cements is a challenging issue compared to the models predicting the Portland cement strength.

A relatively extended literature exists for models predicting the compressive strength of Portland cement [2] –[11]. No such large bibliography exists for blended cements especially if the constituents contribute drastically in the 28-day strength. Douglas et al. [12] performed an experimental design for mixtures of three components including Portland cement, granulated blast furnace slag and fly ash. Using seven design points, a statistical approach was used to find the equations describing strength development of the ternary systems at 1, 7, 28 and 91 days. For the same ternary mixture Wang et al. [13] applied a simplex-centroid design to study the compressive strengths of mortars at different ages and they found three cubic polynomial models. They also designed ternary diagrams allowing to predict the compressive strengths from the iso-strength contour lines. Kostogloudis et al. [14] developed a multiple linear regression model for predicting the 28-day compressive strength of Portland cement with pozzolana. Except other variables, they utilized the cement insoluble residue and the pozzolanic activity factor to describe the pozzolane effect on the strength. Nehdi et al. [15] used factorial designs to optimize ternary cementitious mortar blends. The ternary mixtures included ordinary Portland cement (OPC) -silica fume (SF) - fly ash (FA) and OPC-SF-granulated blast furnace slag (GBFS). Response surfaces for several properties including compressive strength at 1, 7, 28 and 56 days were obtained for up to 20%, 40%, and 60% replacement levels of OPC by SF, FA and GBFS, respectively. Chen et al. [16] applied the method of the simplex-lattice design for predicting the strength of ternary cementitious systems composed from cement, silica fume and fly ash with constant water to binder ratio and a mass fraction of mineral admixtures not exceeding 30%. With the aid of the optimization theory they optimized the mixture proportioning, using compressive strength as a criterion. Khan [17] investigated the iso-responses for strength, permeability and porosity of high performance mortars composed from cement, fly ash and silica fume, with the aim at developing high performance-low environmental impact concrete. The same author [18] developed analytical models for the strength

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prediction of high performance concrete composed from various binary and ternary combinations of Portland cement, fly ash, slag and silica fume. He derived quadratic response surfaces correlating the compressive strength at 7, 28, 90, 180 days with the proportions of fly ash, slag, silica fume and with the ratio of water to cement. Abd-El Aziz et al. [19] studied the physico-chemical and mechanical characteristics of pozzolanic cement pastes and mortars hydrated at different curing temperatures. Their results indicated that, the pozzolanic cement mortars give higher strength than the Portland cement mortars, especially at curing temperatures above 35 °C. Heikal et al. [20] investigated the characteristics of blended cements containing nano-silica (NS). They considered as control sample a standard mix of Portland (OPC) cement and GBFS. The composite OPC–GBFS–NS cements containing 45 % of GBFS and 3–4 % of NS possess the highest improvement of mechanical properties, hydration kinetics and microstructure of hardened cement pastes and mortars.

The effect of the mentioned pozzolanic or cementitious materials on the compressive strength of concrete has been also investigated and modeled. Several researchers utilized multiple regression models to quantify the impact of the referred materials on the strength [21]-[27]. Another category of research includes modeling based on artificial neural networks (ANN) or fuzzy logic (FL) [28]-[32].

The most of these models are used for design purposes and are based on laboratory experimental data. The predictions are accurate inside their field of application. In case of important change of the value of a parameter not contained in the set of the independent variables, the predictive model could fail. Therefore the most of the models could be called “static”. Tsamatsoulis [33] performed a detailed comparison of static and dynamic models of Portland cements based on regression algorithms. The dynamic models incorporate the uncertainty due to the time variability of non involved factors during the modeling procedure. The main aim of this study is to extend the comparison between static and dynamic models to the class of pozzolanic cements, characterized as CEM IV in EN 197-1 norm. The major difficulty in predicting strength of this cement type is that except clinker at least one other component affecting strength participates. Usually the pozzolanic materials are characterized from elevated variability as concerns their composition, especially in case they are by-products from another industrial process. In the current study natural pozzolane and calcareous fly ash originating from electricity plants are the main constituents of the CEM IV cements. The applicability of such models on the daily quality control was examined in detail. This article is structured as follows: The experimental methods and the applied standards are referred to the first section. Afterwards, the suggested predicting models are developed. The implementation of the models is analyzed in the last section.

II. Experimental

Pozzolanic cements belonging to two strength classes according to EN 197-1:2011 were studied: CEM IV/B (P-W) 32.5 N and CEM IV/B (P-W) 42.5 N. Both cements contain natural pozzolane (P) and calcareous fly ash (W) as main components. The modeling is based on the results of the daily average samples of cement produced in two cement mills (CM) of Halyps plant. The analyses made on these samples were the following:

(i) Residue at 40 μm sieve, R40, measured with air sieving.

(ii) Specific surface, Sb, measured according to EN 196-6.

(iii) Loss on ignition, LOI, and insoluble residue, Ins_Res, of the cement measured according to EN 196-2.

(iv) Oxides analysis (SO_3, CaO, SiO_2, Al_2O_3, Fe_2O_3) measured with X-ray fluorescence.

(v) Compressive strength at 1, 7 and 28 days. The preparation, curing and measurement of the specimens were made according to the standard EN 196-1.

(vi) The cement composition was computed using the results of the steps (iii) – (iv) and the average analysis of the raw materials, by applying the method presented in [34]. In this way the clinker content was calculated.

III. Mathematical Models Predicting Strength

Exclusively plant data of cement produced in the cement mills CM5 and CM6 during height years were utilized. The modeling predicting the 28-day strength was based on more than 1500 data sets of cement fineness, chemical analyses, composition, 1, 7 and 28 days strength. Two categories of models were elaborated: (a) the static ones, wherein for a given data set, the values of the parameters were calculated with multiple linear regression. Afterwards these values were utilized to predict the future strengths, each time the input data were available and (b) the dynamic models, where the parameters were estimated from a moving set of data belonging to past time interval of predefined size, e.g. 3 months, 6 months etc. For all the dynamic models, the latest date of the time interval has two characteristics: (i) the 28-day strength has been measured; (ii) its distance from the date of prediction is the minimum. The dependent and independent variables of static and dynamic models are shown in Tables 1 and 2 respectively.

Table 1. Variables of the static models

	Variable						
Model	Clink (%)	Pz (%)	Ash (%)	$Sb/10^4$ (cm^2/gr)	R40 (%)	Str_1 (Mpa)	Str_7 (Mpa)
Str28_1	+	+	+	+	+	+	
Str28_7	+	+	+	+	+	+	+

Table 2. Variables of the dynamic models

	Model CM5		Model CM6	
Variable	Str28_1	Str28_7	Str28_1	Str28_7
LOI (%)	+			
Ins_Res (%)	+	+	+	+
CaO (%)		+		+
SiO_2 (%)	+	+	+	+
Al_2O_3(%)			+	

Table 2. Cont.	Str28_1	Str28_7	Str28_1	Str28_7
$Sb/10^4$ (cm^2/gr)	+	+	+	+
R40 (%)	+	+	+	+
Str_1 (Mpa)	+	+	+	+
Str_7 (Mpa)		+		+

where Clink, Pz, Ash = clinker, pozzolane, fly ash contents (%) respectively, CaO, SiO_2, Al_2O_3 = the contents (%) of the corresponding oxides, LOI = loss on ignition (%), Ins_Res = insoluble residue (%), Sb = cement specific surface (cm^2/gr), Str_1 and Str_7 = compressive strengths (Mpa) after one and seven days curing correspondingly, Str28_1, Str28_7 = 28-day strength (Mpa) estimated from the respective model.

A. *Static Models*

The models correlating the 28-day strength with 1-day strength (Str28_1) and both 1 and 7 days' strength (Str28_7) were investigated. The models are described by (1):

$$Y = A_0 + \sum_{I=1}^{N} A_I X_I + \sum_{I=1}^{N} A_{II} X_I^2 + \sum_{I=1}^{N} \sum_{J=I+1}^{N} A_{IJ} X_I X_J \quad (1)$$

where X_I, X_J = the independent variables, Y = the dependent variable. The coefficients A_I, A_{II}, A_{IJ} are determined by minimizing the residual error s_{Res} calculated by (2):

$$s_{Res}^2 = \sum_{i=1}^{M} \frac{\left(Y_{calc,i} - Y_{act,i}\right)^2}{M-k} \quad (2)$$

where Y_{act} = actual 28 days strength, Y_{calc} = the calculated one from the model, M = number of data sets, k = number of independent variables. The full set of data involves all results of the two mentioned cement types from 2006 to 2013 for CM5 and CM6. For each CM the model parameters were determined using the data of 2006-2008 by applying multiple linear regressions. With t-test and 95% probability, the non significant parameters were excluded. The statistically significant coefficients (A_I,A_{II}, A_{IJ}) for both models and mills are presented in Tables 3 and 4.

Based on the parameters of the models calculated with data of three full years, a further search was performed as regards the accuracy of future strength prediction. For each CM, the models were applied for the results of 2009 to 2013, using the parameters computed with the 2006-2008 data. The residual errors are presented in Table 5. The last row shows the s_{Res} for the full range of data from 2009 to 2013.

It is clearly observed from the Table 5 that the accuracy of the static models in predicting future strength is deteriorated as long as the time distance between the parameters estimation and the prediction of strength augments. The most probable causes are the changes of the clinker reactivity or other cement constituent contributing to strength and of cement particle size distribution. If these characteristics are not kept relatively stable, then the probability of failure in prediction becomes not negligible.

Table 3. Models Parameters for CM5

Variable	Str_28_1	Str_28_7
Constant	0	0
Clink	0.397	0.316
Ash		0.139
$Sb/10^4$	10.2	1.929
R40	-0.105	
Str_1	3.59	-0.558
Str_7		0.900
Clink·Pz	$5\cdot10^{-3}$	$3\cdot10^{-3}$
Clink·Ash	$8\cdot10^{-3}$	
Pz·Ash		$1\cdot10^{-3}$
Pz· $Sb/10^4$	-0.653	
Ash· $Sb/10^4$	-0.324	-0.263
Clink· R40	$-4\cdot10^{-4}$	-0.012
Ash· R40	$-3\cdot10^{-4}$	
Clink· Str_1	-0.039	
Ash· Str_1	-0.022	-0.02
Clink· Str_7		$-3\cdot10^{-3}$
R40· Str_7		0.026
Num. of data	454	454
s_{Res}	1.811	1.362

Table 4. Models Parameters for CM6

Variable	Str_28_1	Str_28_7
Constant	0	0
Clink	0.248	0.247
Ash		-0.416
$Sb/10^4$	42.6	-30.7
R40	1.404	
Str_1	6.238	0.034
Str_7		3.192
Clink·Pz	0.014	$-2\cdot10^{-4}$
Clink·Ash	$5\cdot10^{-3}$	
Pz·Ash		$-3\cdot10^{-3}$
Pz· $Sb/10^4$	-2.864	
Ash· $Sb/10^4$	-0.403	0.894
Clink· R40	-0.016	0.026
Ash· R40	-0.020	
Clink· Str_1	-0.078	
Ash· Str_1	-0.025	$1\cdot10^{-3}$
Clink· Str_7		-0.029
R40· Str_7		-0.056
Num. of data	169	169
s_{res}	1.572	1.224

Table 5. Residual errors of future application of the models

	Str28_1		Str28_7	
	CM5	CM6	CM5	CM6
2006-08	1.811	1.572	1.362	1.224
2009	2.529	2.529	1.452	1.604
2010	2.195	2.026	1.429	1.426
2011	1.982	3.780	1.401	2.245
2012	3.994	5.087	2.247	2.669
2013	5.979	8.654	3.377	4.545
2009-13	3.452	4.353	1.966	2.415

B. *Dynamic Models*

To improve the predictability of the modeling a second approach was selected by including dynamical characteristics and maintaining the simplicity of implementation. The two models referred in Table 2 were implemented by excluding with t-test the non-significant variables, by omitting the coefficients A_{II}, A_{IJ} and considering movable time horizon as concerns the introduced data. Thus, for each date a new 28-day strength result appears, the models' coefficients are recalculated with the following algorithm:

(i) At date t a new 28-day strength result appears. The specimen was prepared 28 days ago. The production date is in distance t-29 days from the current date t.

(ii) A time interval of T_D days and the samples belonging to the period [t-29-T_D, t-29] are presumed. The dynamic data set consists of this population of samples.

(iii) Using multiple regression the model parameters A_I (I=0 .. N) and s_{res} are computed.

(iv) At date t, the chemical and physical results of the cement produced in the previous day, the 1 day strength of the cement produced 2 days ago and the 7 days strength of cement produced 8 days ago have been measured.

(v) With the set of parameters computed in step (iii) the 28 days strength of cement produced at t-2 and t-8 days are estimated, by applying the models Str28_1 and Str28_7 respectively.

(vi) The procedure is repeated for the date t+t_N, where t+t_N is the date a new 28 days result appears. Consequently $t_N \geq 1$.

(vii) If t_N>1, the future strength of the cement produced in the time intervals [t-1, t+t_N-2], [t-7,t+t_N-8] is computed according to the equation of step (v). Otherwise using the equation computed in step (vi).

(viii) As the time span remains T_D, when a new result is added, the time interval is moved on. Thus the future 28 days strengths are calculated using models applied to data sets of movable time horizon.

(ix) Parameter T_D shall be optimized with one of the two criteria: (a) minimum s_{Res} during modeling and (b) minimum error during the future application of the models. A T_D interval from 90 to 720 days was investigated.

(x) For each date J a set (A_I(J), s_{Res}(J)) is computed from the samples belonging to [J-T_D, J] time interval. Depending on T_D value, the number of the consecutive sets (A_I(J), s_{Res}(J)) is K_{TD} and the number of sets for a date J is N_{TD}(J). The average residual errors, $s_{Res,Aver}$, during modeling is calculated by (3):

$$s_{Res,Av} = \sqrt{\frac{\sum_{I=1}^{K_{TD}} s_{Res}(I)^2}{K_{TD}}} \quad (3)$$

The average number of data sets per T_D, $N_{TD,Av}$ and $s_{Res,Av}$ for the results of both cement mills are presented in Tables 6 and 7.

Table 6. s_{Res} during modeling for CM5

T_D	N_{TD}	Str28_1	Str28_7
		$s_{res,Av}$	$s_{res,Av}$
90	42	1.49	1.06
120	55	1.56	1.12
180	81	1.64	1.22
270	119	1.71	1.30
360	156	1.78	1.35
450	197	1.80	1.36
540	236	1.83	1.52
720	310	1.89	1.58

Table 7. s_{Res} during modeling for CM6

T_D	N_{TD}	Str28_1	Str28_7
		$s_{res,Av}$	$s_{res,Av}$
90	22	1.38	0.94
120	29	1.49	1.02
180	43	1.58	1.12
270	62	1.69	1.20
360	83	1.75	1.25
450	103	1.81	1.29
540	125	1.86	1.31
720	165	1.94	1.36

The following comparison of the two kinds of models is made based on the results of Tables 3, 4 and 6, 7. Increasing N_{TD}, s_{Res} of the dynamic models also increases. Despite the dynamic models are much simpler than the static ones, the residual errors are comparable for N_{TD} = 450 for CM5 and N_{TD}=180 for CM6.

IV. Analysis of Results and Discussion

A. *Prediction of Future Strength with the Dynamic Models*

The worsening of prediction of future strength with the static models was presented in Table 5. The dynamic models have the flexibility to include the tuning parameter TD which needs optimization. The residual errors in predicting the future strength by applying the dynamic Str28_1, Str28_7 models are shown in Table 8 from where the following remarks can be made:

Table 8. s_{Res} during predicting future strength for CM5, CM6.

		Str28_1		Str28_7	
Year	T_D	CM5	CM6	CM5	CM6
2008-13	90	2.26	2.57	2.00	1.93
2008-13	120	2.26	2.21	1.92	1.64
2008-13	180	2.26	2.12	1.76	1.59
2008-13	270	2.23	2.10	1.69	1.50
2008-13	360	2.19	2.16	1.63	1.53
2008-13	450	2.19	2.21	1.61	1.53
2008-13	540	2.19	2.24	1.67	1.54
2008-13	720	2.27	2.42	1.76	1.60

- For CM5 both models show minimum s_{Res} for T_D=360-450 days while for CM6 the minimum is located at T_D=270 days.

ISBN: 978-1-61804-243-9

- The optimum s_{Res} values for both dynamic models are lower than the s_{Res} of the static models for the data sets of 2009-2012 shown in the last row of Table 5. The ratios of $s_{Res,Dyn}/s_{Res,Stat}$ are depicted in Fig. 1 for both models and cement mills from where it is observed that the dynamic models provide a 15-50% lower error than the static ones as concerns the prediction of future strength. The improvement is greater in the case of Str28_1 model.

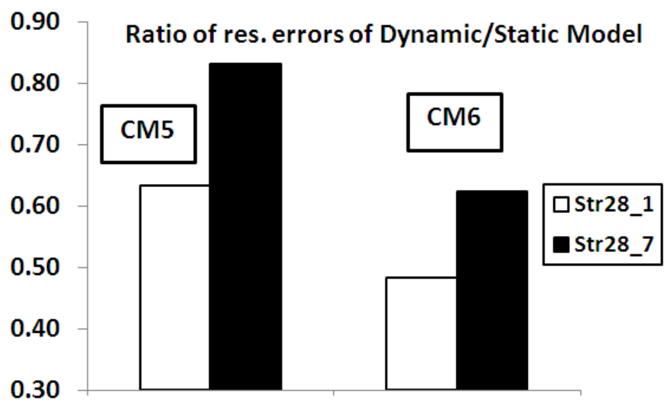

Fig. 1 Ratio of s_{Res} of Dynamic to Static model

- The optimum residual errors computed during modeling and during predicting the future strength were also compared for both models and CM. The ratio of average s_{Res} during prediction and modeling, $s_{Res,Pred}/s_{Res,Mod}$, for dynamic and static models are shown in Fig. 2, from where it is clear that this ratio is much lower in case of dynamic models than this of static models. This is an additional proof that the dynamic models predict the future strength much better than the static ones.

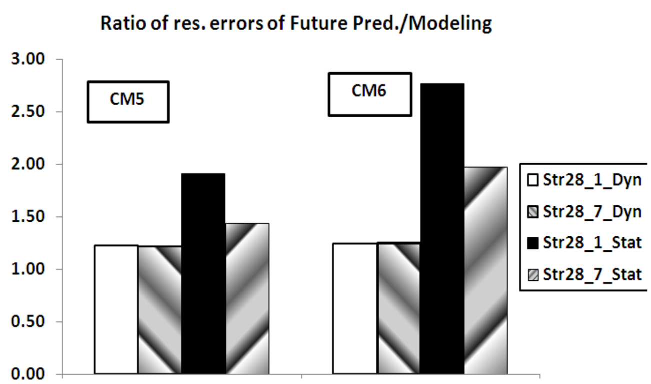

Fig. 2 Ratio of s_{Res} during prediction of future strength and modeling.

To investigate the structure of the distribution of s_{Res} computed during the future strength prediction the following algorithm was chosen.

(i) For the T_D providing an optimum dynamic model, an average number of data sets N_{TD} corresponds.

(ii) Data sets arrays of size N_{TD} were created, which are of movable type: When a next data set is added, the older one is subtracted. The number of consecutive arrays is around equal to K_{TD}.

(iii) For each array I, the $s_{Res}(I)$ was calculated and the distribution was constructed.

(iv) The s_{Res} distributions for the dynamic model Str28_1 for the results of CM5, CM6 are depicted in Figs. 3 and 4 correspondingly. From these two figures it is observed that all the s_{Res} for both CM are lower than the average s_{Res} of static models during strength prediction. The above is a very strong indication of the superiority of the dynamic models in predicting the 28-day strength.

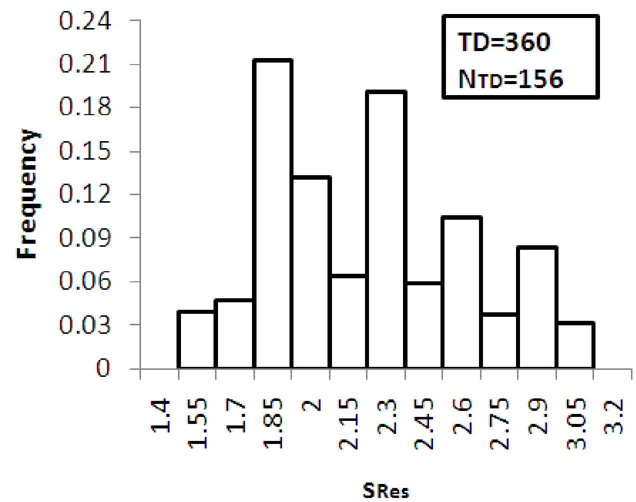

Fig. 3 Distribution of s_{Res} of dynamic Str28_1 model for CM5 results

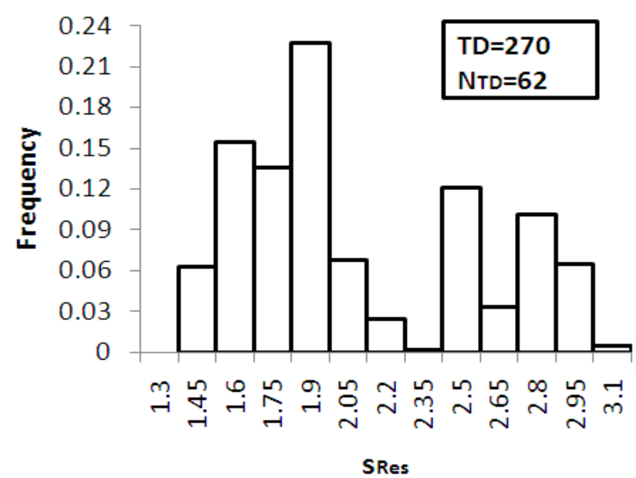

Fig. 4 Distribution of s_{Res} of dynamic Str28_1 model for CM6 results

B. Impact of the chemical, physical cement characteristics on the 28-day strength

The dynamic models predicting the 28-day cement strength are very useful because the impact of each variable can be investigated as function of time. Continuous information can be provided by implementing this model, about the reactivity of the raw materials and the impact of the fineness on the 28 days strength. The traditional Shewhart control charts [35] were proved very helpful in monitoring the cement

ISBN: 978-1-61804-243-9

characteristics as it was analyzed in detail by Tsamatsoulis [9].

For the coefficients A_I of the two dynamical models the average value X_{Aver}, and the standard deviation, σ_X, were calculated. The control charts of the coefficients of variables LOI and SiO_2 for the results of CM5 obtained from the model Str28_1 with T_D=360 days are presented in Figs. 5 and 6. The average values, X_{Aver} and the upper and lower control limits, $X_{Aver}\pm 2\sigma_X$, are also shown.

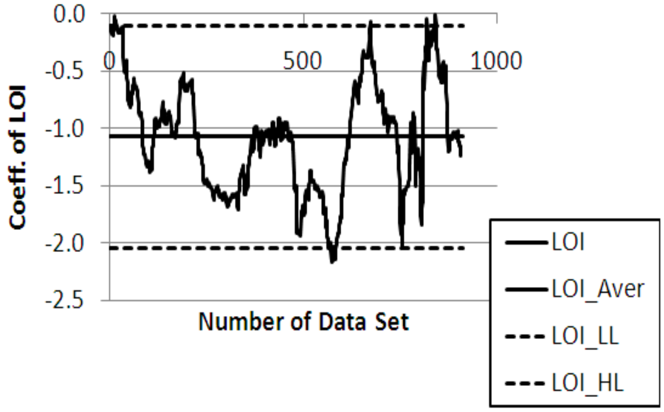

Fig. 5 Control chart of coefficient of LOI variable for dynamic Str28_1 model and CM5 results.

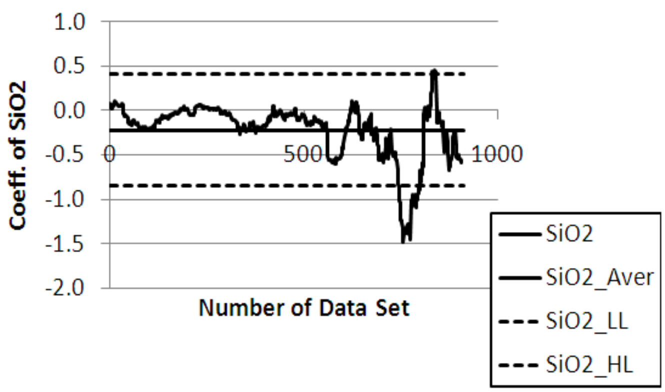

Fig. 6 Control chart of coefficient of SiO_2 variable for dynamic Str28_1 model and CM5 results.

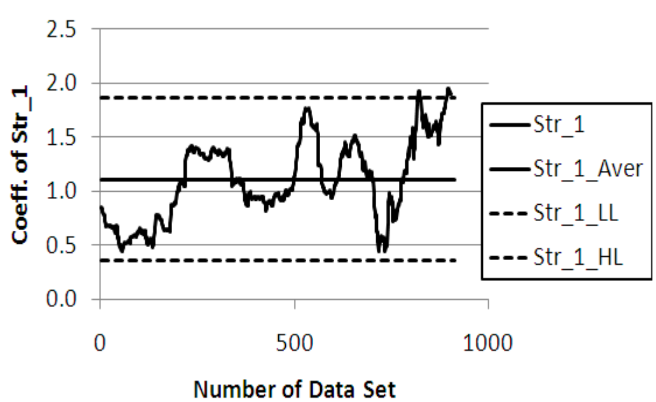

Fig. 7 Control chart of coefficient of Str_1 variable for dynamic Str28_1 model and CM5 results.

The control charts of the coefficients of Str_1 derived from the str28_1 model of CM5 and of the Str_7 derived from Str28_7 model of CM5 with T_D=360 are demonstrated in Figs. 7 and 8.

The average values and standard deviations of all the independent variables of the three dynamic models for CM5, CM6 are presented in Tables 9 and 10 correspondingly.

Table 9. Parameters of the dynamic models for CM5

	Average Values	
T_D	360	360
Coeff.	Str28_1	Str28_7
Constant	46.0	20.6
$Sb/10^4$	3.2	-6.2
R40	-0.26	-0.11
LOI	-1.07	
Ins_Res	-0.09	-0.03
CaO		-0.05
SiO_2	-0.22	-0.01
Str_1	1.11	-0.27
Str_7		1.11
	Standard Deviations	
Constant	12.3	17.0
$Sb/10^4$	10.7	9.7
R40	0.14	0.09
LOI	0.48	
Ins_Res	0.17	0.14
CaO		0.21
SiO_2	0.31	0.27
Str_1	0.38	0.27
Str_7		0.23

Table 10. Parameters of the dynamic models for CM6

	Average Values	
T_D	270	270
Coeff.	Str28_1	Str28_7
Constant	47.5	20.2
$Sb/10^4$	-10.3	-10.7
R40	-0.28	-0.13
LOI	-0.01	0.12
Ins_Res		0.04
CaO	-0.43	-0.09
SiO_2	0.59	
Str_1	1.14	-0.23
Str_7		1.14
	Standard Deviations	
Constant	17.7	34.0
$Sb/10^4$	14.7	11.0
R40	0.31	0.18
LOI	0.32	0.20
Ins_Res		0.41
CaO	0.54	0.51
SiO_2	1.36	
Str_1	0.30	0.49
Str_7		0.29

ISBN: 978-1-61804-243-9

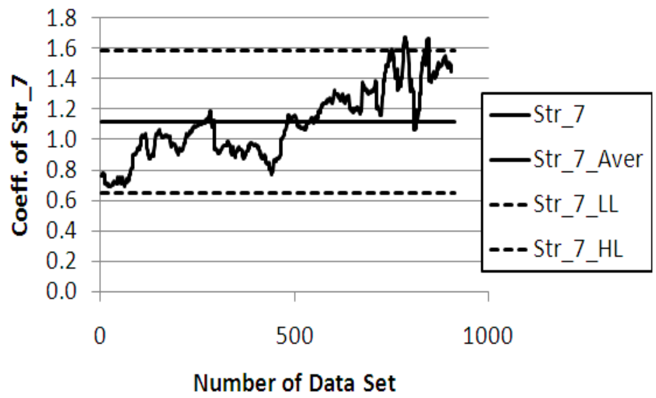

Fig. 8 Control chart of coefficient of Str_7 variable for dynamic Str28_7 model and CM5 results.

C. Uncertainty of the Dynamic Models Parameters

The standard deviations shown in Tables 9, 10 correspond to the optimum T_D in predicting the future strength. A detailed search was made as regards the function between parameters uncertainty and time horizon T_D. The functions between average coefficients, their standard deviation and T_D are shown in Figs. 9 to 12: In Figs. 9, 10 and 11 the statistics of the coefficients of SiO_2, R40 and Str_1 computed from the Str28_1 model are demonstrated. In Fig. 12 the respecting statistics of Str_7 coefficients calculated from the Str28_7 model is also depicted.

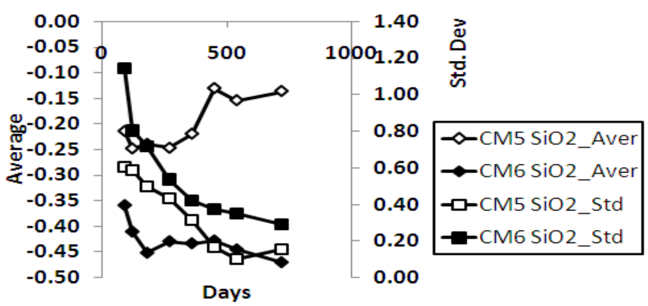

Fig. 9 Average and std. dev. of SiO_2 coefficient of Str28_1 model

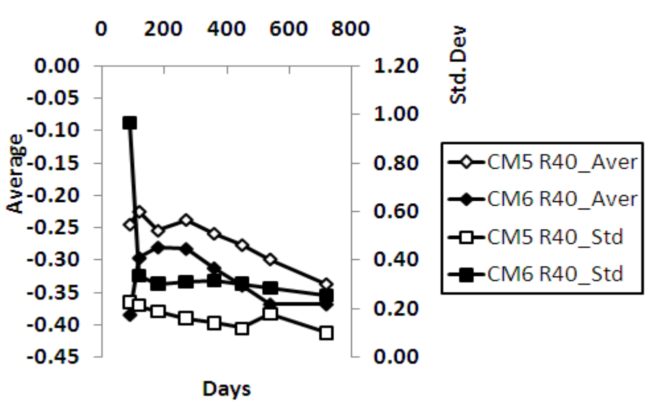

Fig. 10 Average and std. dev. of R40 coefficient of Str28_1 model

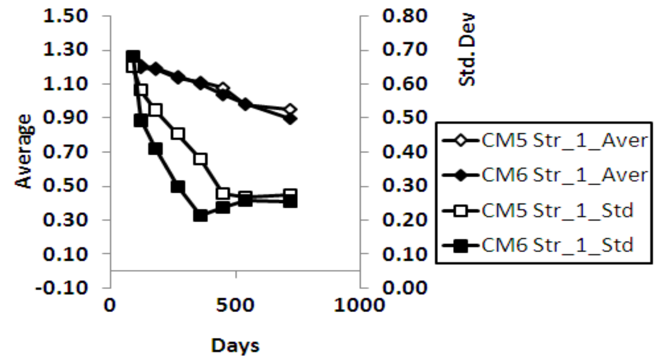

Fig. 11 Average and std. dev. of Str_1 coefficient of Str28_1 model

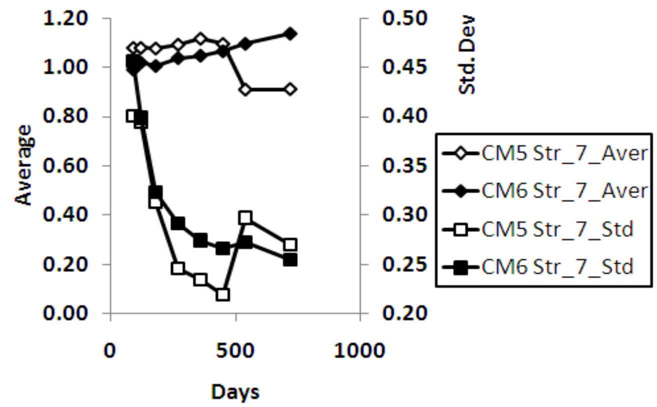

Fig. 12 Average and std. dev. of Str_7 coefficient of Str28_7 model

A big drop of the standard deviations occurs with T_D increasing. Therefore the models with a large T_D provide a more robust estimation of the average value of parameters in long-term.

D. Evaluation of the Reactivity of Cement

The dynamic models constitute a tool to evaluate the reactivity of the different cement compounds, including also the grinding aid. This assessment is shown by the following example. A cement CEM IV B (P-W) 32.5 was selected with Sb = 3900 cm2/gr, R40 = 11.3%, LOI = 3.9%, Ins_Res = 24.8%, SiO_2 = 35.7%, Al_2O_3 = 9%, CaO = 39.9% and Str_1 = 4.5 Mpa produced in CM5 and CM6. The dynamic model Str28_1 for T_D=360 days for CM5 and T_D=270 days for CM6 was applied for all the parameters sets in CM5, CM6 and the average 28-day strength was calculated. The difference of each strength result from this average was computed. The results are demonstrated in Figs. 13, 14.

When the difference is negative, i.e. the strength is lower than the average; the current reactivity of cement compounds is lower than the long – term mean reactivity. The inverse happens in case of positive difference. This analysis is a simple example showing the ability of the dynamic models to contribute in the daily quality control of cement.

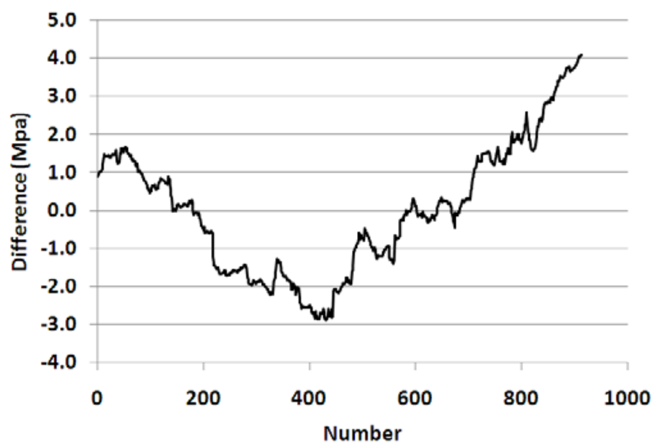

Fig. 13 Application of Str28_1 model for constant composition and fineness in CM5

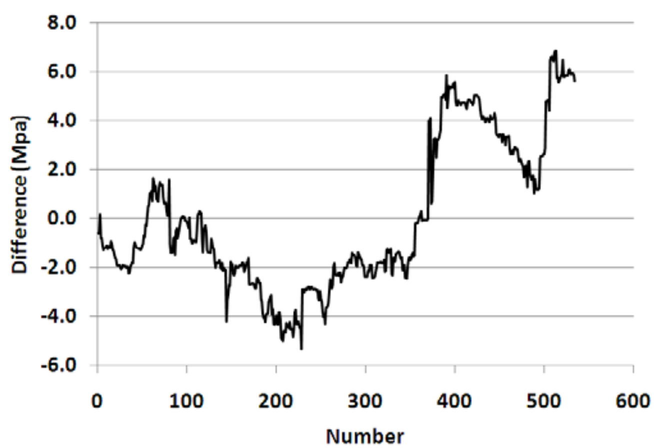

Fig. 14 Application of Str28_1 model for constant composition and fineness in CM6

V. Conclusions

The prediction of the 28-day strength of cements where more than one component contribute in strength development is a challenging issue due to its high importance in the product design, in the daily quality control and in the concrete mix design. The pozzolanic cements belong to this category, where the 28-day compressive strength becomes as a result of the interaction of clinker, pozzolane, fly ash and the cement fineness as well. Two classes of models were developed: (a) the static ones, where based on a predetermined data set, the parameters values were calculated and applied to predict the future strengths and (b) the dynamic models, where the parameters were estimated from a moving set of data belonging to a predefined past time interval, T_D in days. Exclusively industrial data of Halyps cement plant were used.

The future strength predictions obtained by the static models are sufficient only if negligible or small changes to the processes or to the materials reactivity occur. The dynamic models are able to detect such changes due to the continuous calculation of their parameters. The time period T_D was optimized using as criterion the minimum residual error of the future strength prediction. The solutions found were between 270 and 360 days depending on the model applied and the mill.

Independently of the category of model, static or dynamic, two types of models were developed having as independent variables the cement chemical analysis, the fineness expressed as residue at 40 μm and specific surface, and the early strength measured at one and seven days. The static models contain linear terms, the squares and the linear combinations of the above variables whether they are statistically significant. The dynamic models were simplified including only the linear terms. Despite their simpler structure, the dynamic models predict much better the future strength than the static models.

Using the dynamic models the effect of the cement composition, fineness and early strength on the 28-day strength can be investigated as function of time. The continuous implementation of these models and the daily calculation of the coefficients provide this information. On the other hand the uncertainty of the models' coefficients is a monotonic function of T_D. The standard deviation of the coefficients of the models declines, as T_D increases. Consequently the application of the models with large T_D provides a more robust estimation of the average value of parameters in long-term.

The analysis of the two categories of models verified the ability and superiority of the dynamic models against the static ones in predicting the strength of pozzolanic cement. Moreover the implementation of these methods contributes noticeably in improving the cement quality by maintaining a low variance of typical strength. The further improvement of these techniques can follow the next directions.

- Investigation of non-linear dynamic models and possible coupling of the models that include as variables the early strengths at one and seven days, to enhance the predictability.
- Exploitation of the dynamic models to develop robust controllers based on Model Predictive Control (MPD) techniques or other advanced methods.

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