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Uncertainty and sensitivity analysis of time-dependent effects in concrete structures

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Abstract

The purpose of this paper is to propose the method of uncertainty and sensitivity analysis of time-dependent effects due to creep and shrinkage of concrete in concrete structures. The uncertainty and sensitivity analyses are performed using the Latin Hypercube sampling method. For each sample, a time-dependent structural analysis is performed to produce response data, which are then analyzed statistically. Two measures are examined to quantify the sensitivity of the outputs to each of the input variables. These are partial rank correlation coefficient (PRCC) and standardized rank regression coefficient (SRRC) computed from the ranks of the observations. Three possible sources of the uncertainties of the structural response have been taken into account — creep and shrinkage model uncertainty, variation of material properties and environmental conditions. The proposed theory is applied to the uncertainty and sensitivity of time-dependent axial shortening and time-dependent prestress forces in an actual concrete girder bridge. The numerical results indicate that the creep model uncertainty factor and relative humidity appear to be the most dominant factors with regard to the model output uncertainty. The method provides a realistic method of determining the uncertainty analysis of concrete structures and identifies the most important factors in the long-term prediction of time-dependent effects in those structures.
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Keywords: Uncertainty; Sensitivity; Concrete structures; Creep; Shrinkage

1. Introduction

Time-dependent effects of concrete structures result from creep and shrinkage of concrete. Creep and shrinkage are important factors in the design of concrete structures. For example, they affect the setting of bearings of concrete bridges including the size of sliding plates or laminated bearing pads. They also affect the sizing and setting of expansion joints due to time-dependent axial shortening arising from creep and shrinkage effects of prestress force and thereby also affect the secondary moments in prestressed concrete bridges. The creep and shrinkage models which are capable of predicting long-term structural response are specified in design codes such as ACI 209-92 [1], CEB-FIP Model Code 90 [2], etc. However, the application of current code formulations may result in considerable prediction errors stemming from several sources of uncertainty. They predict only mean values and cannot predict the statistical variation. Therefore, a method to deal with the uncertainty involved in the prediction of creep and shrinkage effects of concrete is necessary.

Creep and shrinkage in concrete structures are very complex phenomena in which various uncertainties exist with regard to inherent material variations as well as modelling uncertainties. The study on the uncertainties in creep and shrinkage effects has been continuously an area of significant efforts. Particular attention has given to the problem of creep and shrinkage with uncertainty modelling [3–7] and with the variability in external loads [8,9]. The variation of creep and shrinkage properties is caused by various factors commonly classified as internal and external factors [10]. The change of environmental conditions, such as humidity, may be considered as an external factor. The internal factors include the variation of the quality and the mix composition of the materials used in concrete and the variation due to internal mechanism of creep and shrinkage.

In the prediction formulas of creep and shrinkage of concrete, various kinds of parameters are involved to express the characteristics of concrete under consideration, i.e. the mix proportion of concrete, the shape of the structure, relative humidity, etc. Since it is not possible to remove the statistical

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variation involved in the parameters, it may be necessary to estimate how much the variation of each parameter influences the predicted values. Several different approaches of sensitivity analysis have been developed as numerical tools for reliability assessment of structures [11–15]. Also, a review of different methods for this sensitivity analysis has been provided by Novák et al. [16]. Another example for sensitivity analysis is shown by Tsubaki [17].

The aim of the present study is to propose an analytical approach for the uncertainty and sensitivity analyses of creep and shrinkage effects in concrete structures utilizing the models in the design codes. The present study deals with the uncertainties in the long-term prediction of creep and shrinkage effects, taking into account the statistical variation of both internal and external factors as well as the uncertainty of the model itself. The sensitivity analysis is performed to show the relative importance of individual random variables employed in the creep and shrinkage models. The time-dependent axial shortening of a prestressed concrete girder bridge is analyzed to show the application of proposed method.

2. Uncertainty modelling of creep and shrinkage of concrete

Several material models for shrinkage and creep of concrete have been proposed both in the literature and in the design codes. The most commonly used models in the codes are those suggested by ACI Committee 209 [1] and CEB-FIP MC 90 [2].

2.1. ACI committee 209 recommendations

ACI committee 209 suggests the use of the following equation for prediction of shrinkage strain.

$$\varepsilon_{sh}(t, t_0) = \Psi_1 \frac{(t - t_0)}{f + (t - t_0)} \varepsilon_{sh}^u \tag{1}$$

where, $\varepsilon_{sh}(t, t_0)$ = shrinkage strain at any time t; ε_{sh}^u = ultimate shrinkage strain determined by experiments; f = factor dependent on curing condition (35 for moist cured concrete, 55 for steam cured concrete); t_0 = the age of concrete starting drying (days); t = observation (current) time (days); Ψ_1 = model uncertainty factor for shrinkage model. Creep coefficient is expressed by the following equation:

$$C(t, \tau) = \Psi_2 \frac{(t - \tau)^{0.6}}{10 + (t - \tau)^{0.6}} C_u \tag{2}$$

where, $C(t, \tau)$ = creep coefficient at any time t; C_u = ultimate creep coefficient determined by experiments; τ = the age of concrete at first loading (days); t = observation time (days); Ψ_2 = model uncertainty factor for creep model. In the absence of specific creep and shrinkage data for local aggregates and material conditions, the average values suggested for C_u and ε_{sh}^u are, respectively:

$$C_u = 2.35\gamma_c \quad \text{and} \quad \varepsilon_{sh}^u = 780 \times 10^{-6} \gamma_{sh} \text{ (m/m)} \tag{3}$$

where, γ_c and γ_{sh} represent some correction coefficients.

The coefficients Ψ_1 and Ψ_2 are model uncertainty factors. Information on model uncertainty can be obtained from the work of Bažant and Baweja [6]. The mean value and coefficients of variation of a time-averaged value of Ψ's are estimated. From their study it is found that the coefficients of variation of the creep and shrinkage properties were 55.3% for shrinkage and 52.8% for creep, respectively. The mean values and coefficient of variation of the Ψ factors reported are:

$$E[\Psi_1^*] = 1;\ V_{\Psi_1^*} = 0.553 \tag{4a}$$

$$E[\Psi_2^*] = 1;\ V_{\Psi_2^*} = 0.528. \tag{4b}$$

The coefficients Ψ_1^* and Ψ_2^* are prediction error terms that account for the uncertainty inherent in the theoretical model and the uncertainty of the micro-mechanism of creep and shrinkage that has been neglected. The values in Eq. (4) include several sources of uncertainties and may be written as follows:

$$\Psi_i^* = \Psi_i \Psi_\alpha \Psi_\beta \quad (i = 1, 2) \tag{5}$$

where, Ψ_i = factor due to inadequacy of the prediction formula; Ψ_α = factor due to internal uncertainty; Ψ_β = factor due to measurement errors and uncertainty in the laboratory (or site) environment.

The factors to be used in Eqs. (1) and (2) are prediction model uncertainty Ψ_i, and the coefficient of variations in Eq. (4) must therefore be corrected to include only model uncertainty. The factors in Eq. (5) are assumed independent, and the relation between the coefficients of variation [18] is:

$$(1 + V_{\Psi_i^*}^2) = (1 + V_{\Psi_i}^2)(1 + V_{\Psi_\alpha}^2)(1 + V_{\Psi_\beta}^2) \quad (i = 1, 2). \tag{6}$$

Few data are available for the estimation of V_{Ψ_α}, but the results by Reinhardt et al. [19] indicate that a value between 0.06 and 0.10 is reasonable for test specimens. The coefficient of variation V_{Ψ_β} was estimated as 0.05 by Madsen [4]. In this study, the following corrected values for model uncertainties Ψ_i are obtained from Eqs. (4) and (6):

$$\text{Shrinkage } E[\Psi_1] = 1;\ V_{\Psi_1} = 0.542 \tag{7a}$$

$$\text{Creep } E[\Psi_2] = 1;\ V_{\Psi_2} = 0.517. \tag{7b}$$

2.2. CEB-FIP model code 90

The total shrinkage $\varepsilon_{cs}(t, t_s)$ is calculated from:

$$\varepsilon_{cs}(t, t_s) = \Psi_1 \varepsilon_{cs0} \beta_s (t - t_s) \tag{8}$$

where ε_{cs0} = the notional shrinkage coefficient; β_s = the coefficient to describe the development of shrinkage with time; t = the age of concrete (days) and t_s = the age of concrete (days) at the beginning of shrinkage.

For a constant stress applied at time t_0, the creep strain $\varepsilon_{cc}(t, \tau)$ at any time t is calculated as following equation:

$$\varepsilon_{cc}(t, \tau) = \frac{\sigma_c(\tau)}{E_{ci}} \phi(t, \tau) \tag{9}$$

where, $\phi(t, \tau)$ = creep coefficient; E_{ci} = modulus of elasticity; $\sigma_c(\tau)$ = sustained stress.

The creep coefficient $\phi(t,\tau)$ is calculated from CEB-FIP MC 90 as:

$$\phi(t,\tau) = \Psi_2 \phi_0 \beta_c(t-\tau) \tag{10}$$

where, ϕ_0 = the notional creep coefficient; $\beta_c(t-\tau)$ = the coefficient to describe the development of creep with time after loading.

The coefficients of Ψ_1 and Ψ_2 are model uncertainty factors. An indication of model uncertainty can be obtained also in the work of Bažant and Baweja [6]. The coefficient of variation of the Ψ_i^* factors in total reported by them were 46.3% for shrinkage and 35.3% for creep, respectively. The values for model uncertainties Ψ_i corrected in the same manner as ACI recommendations are therefore obtained as follows:

$$\text{Shrinkage } E[\Psi_1] = 1;\ V_{\Psi_1} = 0.451 \tag{11a}$$

$$\text{Creep } E[\Psi_2] = 1;\ V_{\Psi_2} = 0.339. \tag{11b}$$

3. Method of uncertainty analysis

Simulation is the process of replicating the real world based on a set of assumptions and conceived models of reality. It may be performed theoretically or experimentally. For engineering purposes simulation may be applied to predict or study the performance and/or response of a system or structure. With a prescribed set of values for the system parameter (or design variable), the simulation process yields a specific measure of performance or response. A conventional approach to this process is the Monte Carlo simulation technique. However, in practice, Monte Carlo simulations may be limited by constraints, computer capability and the significant expense of computer runs in time-dependent structural analysis of concrete bridges. An alternative approach is to use a constrained sampling scheme. One such scheme, developed by Iman and co-workers [20–22], is Latin Hypercube sampling (LHS) method. By sampling from the assumed probability density function of the θ and evaluating Y for each sample, the distribution of Y, its mean, standard deviation and percentiles etc., can be estimated.

The LHS method consists of two steps to obtain a $N \times K$ design matrix. The first step is dividing each input variable into N intervals. The second step is the coupling of input variables with tables of random permutations of rank numbers. Every input variable θ_k, $k = 1, 2, \ldots, K$ is described by its known cumulative distribution function (CDF) $f(\theta_k)$ with the appropriate statistical parameters. The range of the known CDF $f(\theta_k)$ of each input variable θ_k is partitioned into N intervals with equal probability of $1/N$.

The representative value in each interval is used just once during the simulation procedure and so there are N observations on each of the K input variables. They are ordered in the table of random permutations of rank numbers which have N rows and K columns. Each row of a table is used on the ith computer run. For such a sample one can evaluate the corresponding value Y_n of the output variable. From N simulations one can obtain a set of statistical data $\{\mathbf{Y}\} = [Y_1, Y_2, \ldots, Y_N]^{\mathrm{T}}$. This set is statistically assessed and thus the estimations of some statistical parameters, such as the mean value and the variance of the response, are obtained. Interested readers are referred to Novák et al. [16] for a more detailed discussion of this sampling method.

4. Method of sensitivity analysis

The results of the Latin Hypercube simulations can be used to determine which of the model parameters are most significant in affecting the uncertainty of the design [23]. Two closely related, but different, measures will be examined in this study. These are partial rank correlation coefficient (PRCC) and standardized rank regression coefficient (SRRC) computed on the ranks of the observations. This method is particularly useful when there are a large number of inputs and several outputs having an associated time history.

Sensitivity analysis in conjunction with sampling is closely related to the construction of regression models which approximate the behaviour calculated by the computer runs. Suppose a model has inputs $\theta_1, \ldots, \theta_K$ and output Y. After making N runs of the model, the multivariate observations $(\theta_{1i}, \ldots, \theta_{ki}, Y_i;\ i = 1, \ldots, N)$ can be used to construct an approximate regression model of the form:

$$\hat{Y} = b_0 + \sum_{j=1}^{k} b_j \theta_j. \tag{12}$$

The constant b_0 and the ordinary regression coefficient b_j are obtained by the usual methods of least squares. The ordinary regression coefficients are the partial derivatives of the regression model with respect to the input variables. However, these ordinary regression coefficients are easily influenced by the units in which the variables are measured. The problem arising with different variables being measured in different units can be eliminated by standardizing all variables used in the regression model as $\theta^* = (\theta - \overline{\theta})/s_\theta$ where $\overline{\theta}$ and s_θ are the usual sample mean and standard deviation, respectively. The previous regression model can be rewritten in the following form:

$$Y^* = \sum_{j=1}^{K} b_j^* \theta_j^*. \tag{13}$$

The coefficient of b_j^* in standardized models is called the standardized regression coefficient. It is a unit free measurement; such coefficients are useful since they can provide a direct measure of the relative importance of the input variables. The larger the absolute value of b_j^*, the more influence the variance θ_j has, while values of b_j^* close to zero indicate little importance for θ_j. After making N runs of the model with varying input, a correlation matrix between the input and output is computed for a given step in the output time history. Let the correlation matrix be represented as follows:

$$\mathbf{C}=\left[\begin{array}{cccc|c} 1 & r_{12} & \dots & r_{1k} & r_{1y}\\ r_{21} & 1 & \dots & r_{2k} & r_{2y}\\ \dots & \dots & \dots & \dots & \dots\\ r_{k1} & r_{k2} & \dots & 1 & r_{ky}\\ \hline r_{y1} & r_{y2} & \dots & r_{yk} & 1 \end{array}\right] \tag{14}$$

where r_{ij}, $1 \le i, j \le k$ is the sample correlation coefficient for the input variables, while r_{yj} is the sample correlation coefficient between Y and θ_j. The value of r_{yj} is computed by the following equation.

$$r_{jy}=\frac{\sum_{i=1}^{n}\theta_{ij}y_i-\sum_{i=1}^{n}\theta_{ij}\sum_{i=1}^{n}y_i/n}{\sqrt{\left[\left(\sum_{i=1}^{n}\theta_{ij}^2-(\sum_{i=1}^{n}\theta_{ij})^2/n\right)\left(\sum_{i=1}^{n}y_i^2-(\sum_{i=1}^{n}y_i)^2/n\right)\right]}}. \tag{15}$$

The inverse matrix $\mathbf{C^{-1}}$ can be written in expanded form as follows:

$$\mathbf{C^{-1}}=\left[\begin{array}{cccc|c} \frac{1}{(1-R_{\theta_1}^2)} & c_{12} & \dots & c_{1k} & -\frac{b_1}{(1-R_y^2)}\\ c_{21} & \frac{1}{(1-R_{\theta_2}^2)} & \dots & c_{2k} & -\frac{b_2}{(1-R_y^2)}\\ \dots & \dots & \dots & \dots & \dots\\ c_{k1} & c_{k2} & \dots & \frac{1}{(1-R_{\theta_k}^2)} & -\frac{b_k}{(1-R_y^2)}\\ \hline -\frac{b_1}{(1-R_y^2)} & -\frac{b_2}{(1-R_y^2)} & \dots & -\frac{b_k}{(1-R_y^2)} & \frac{1}{(1-R_y^2)} \end{array}\right] \tag{16}$$

where the value b_j in $\mathbf{C^{-1}}$ is the standardized regression coefficient (SRC) in Eq. (13); the value R_y^2 is the coefficient of determination from regressing Y on $\theta_1, \dots, \theta_n$, and the value $R_{\theta_j}^2$ is the coefficient of determination from regressing θ_j on Y, $\theta_1, \dots, \theta_{j-1}, \theta_{j+1}, \dots, \theta_k$. The partial correlation coefficient for θ_j and Y is obtained directly from $\mathbf{C^{-1}}$ as:

$$P_{\theta_j,y}=-\frac{c_{jy}}{\sqrt{c_{jj}c_{yy}}}. \tag{17}$$

Therefore the partial correlation coefficient (PCC) can be written as:

$$P_{\theta_j,y}=\frac{b_j/(1-R_y^2)}{\sqrt{\left(1/(1-R_{\theta_j}^2)\right)\left(1/(1-R_y^2)\right)}}=b_j\sqrt{\frac{1-R_{\theta_j}^2}{1-R_y^2}}. \tag{18}$$

The PCC and SRC measure the linear association between variables. When nonlinear relationships are involved, it is often more revealing to calculate the SRCs and PCCs on variable integer ranks than on the actual values for the variables. Such coefficients are the SRRCs and PRCCs.

5. Application to long-term prediction of axial shortening and prestress force in concrete bridges

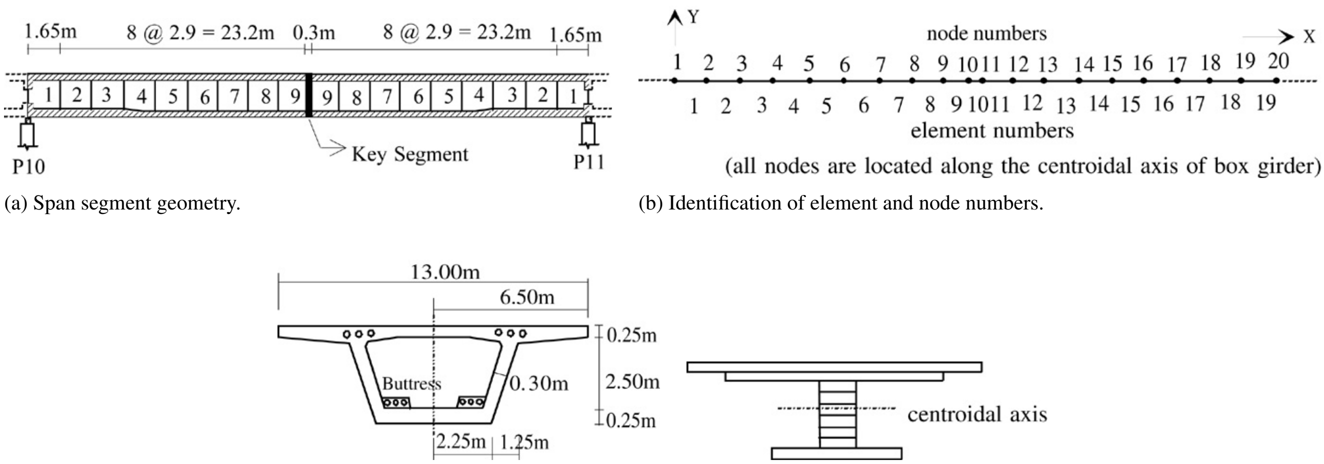
5.1. Description of structure and finite element modelling

Time-dependent effects of a segmentally constructed prestressed concrete girder bridge as shown in Fig. 1 are studied as a practical application of the variability of the response of the bridge. The bridge deck consists of seven continuous spans and each span is 50 m long. The 50 m interior span of the 7-continuous span bridge system is shown in Fig. 2. It is a precast segmental prestressed concrete girder bridge whose typical cross section is also shown in Fig. 2. The interior span of the box girder has nine segments per cantilever (i.e. per half span). The segments are placed symmetrically on both sides of the span. The cantilevers are joined at midspan. The cantilever tendons (top slab tendons) anchored in each segment are stressed at the time of erection of that segment, while the continuity tendons (bottom slab tendons) are stressed after midspan joining as shown in Fig. 2.

Fig. 1. Concrete bridge for practical application.

The finite element analysis method in this study is based on the procedure developed originally by Kang [24] and improved by Oh and Yang [25] for the analysis of segmentally erected prestressed concrete bridges. This procedure involves the time-dependent prediction of deformations and an assessment of prestress losses in such structures under construction stage, and after completion of structures. A box girder of arbitrary plane geometry and variable cross section can be modelled as an assembly of finite elements interconnected at nodal points. Each element is divided into a discrete number of concrete and reinforcing steel layers.

The analytical model for structural analysis consists of 20 nodes, 19 frame elements and 22 prestressing tendons. The cross section is subdivided into 9 layers (Fig. 2). The twenty nodes are located at segment joints along the centroidal axis of the box girder. Nineteen frame elements are used to model the box girder. The elements are prismatic with the cross-section of a point at the mid length of the element. Each cantilever segment and midspan closure segment (key segment) is modelled with one frame element. Twenty-two prestressing tendons are used to model the cantilever and continuity prestressing tendons. Dead load consists of self weight and the design dead load. The design dead load of 29.4 kN/m, is assumed to be applied permanently, which contributes to creep.



(a) Span segment geometry.

(b) Identification of element and node numbers.

(c) Section of typical segment.

(d) Idealized cross section.

Fig. 2. Bridge geometry and analytical model.

Table 1
Statistical properties of basic variables for ACI 209-92 model

Variables	Mean value	Coefficient of variation	Sources
$\Psi_1(\theta_1)$ uncertainty factor for shrinkage	1.0	0.542	Ref. [6]
$\Psi_2(\theta_2)$ uncertainty factor for creep	1.0	0.517	Ref. [6]
$h(\theta_3)$ relative humidity (%)	61.6	0.269	Observed
$f_c'(\theta_4)$ 28 day concrete strength (MPa)	49.2	0.066	Observed
$s/a(\theta_5)$ sand–aggregate ratio	0.41	0.10	Ref. [8]
$S(\theta_6)$ slump (m)	0.15	0.10	Assumed
$c(\theta_7)$ cement contents (kg/m^3)	510	0.10	Ref. [4]

Table 2
Statistical properties of basic variables for CEB-FIP MC 90 model

Variables	Mean value	Coefficient of variation	Sources
$\Psi_1(\theta_1)$ uncertainty factor for shrinkage	1.0	0.451	Ref. [6]
$\Psi_2(\theta_2)$ uncertainty factor for creep	1.0	0.339	Ref. [6]
$h(\theta_3)$ relative humidity (%)	61.6	0.269	Observed
$f_c'(\theta_4)$ 28 day concrete strength (MPa)	49.2	0.066	Observed

5.2. Statistical properties of input variables

Shrinkage and creep model uncertainty factors (Ψ_1, Ψ_2), compressive strength of concrete (f_c'), relative humidity (h), sand–aggregate ratio (s/a), slump (S), and cement contents (c) are assumed to be random variables. All random variables are assumed to be normally distributed. It is also assumed that these variables are independent, which is a simplification. Each random variable is represented by its mean value and coefficient of variation. The numerical values for the mean and the coefficient of variation of input variables are listed in Table 1 for ACI 209-92 model and in Table 2 for CEB-FIP MC 90 model. Model uncertainty factors for prediction models of creep and shrinkage were already examined in Eqs. (7) and (11) in the previous section. The numerical values for relative humidity and compressive strength of concrete were determined using the observed data in the sites. The values for remaining variables were selected on the basis of nominal values of mix design of concrete.

The site for the bridge has four seasons a year. The relative humidity is high in summer and low in winter. The variation of relative humidity is significant over a year. To investigate the distribution of relative humidity, the records from the Meteorological Observatory (about 3 km north of the present bridge) were analyzed statistically and the probability distribution function was ascertained. Also, to investigate the distribution of compressive strength of concrete in 28 days, the results from strength test of concrete cylinders which had been used in construction were analyzed statistically and the probability distribution function was obtained.

5.3. Uncertainty analysis results of the axial shortening of concrete girder

If the values of input variables $\theta_1, \theta_2, \ldots, \theta_K$ are specified, the creep and shrinkage effects or response $Y(\theta_i, t)$ at time t, such as the axial shortening of concrete girder, can be calculated by running a computer program through the deterministic

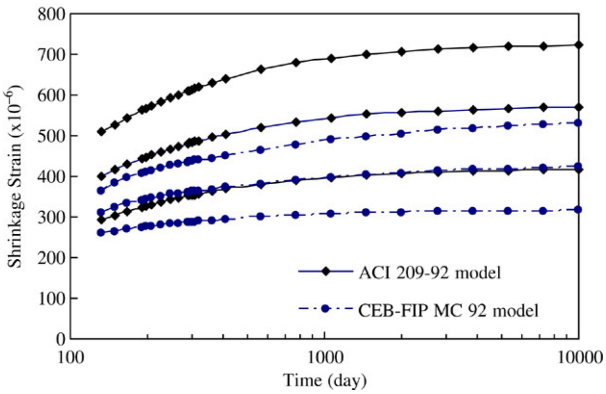


Fig. 3. Comparison of shrinkage prediction.

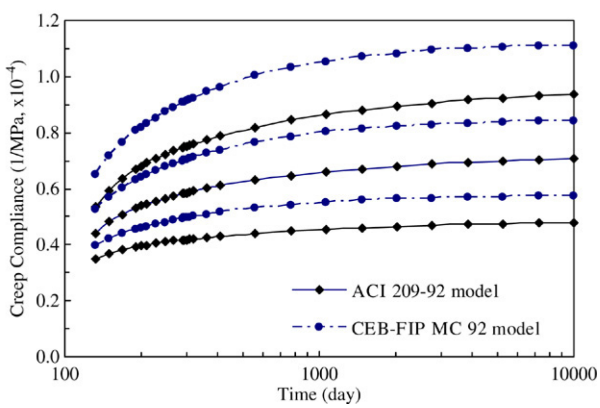


Fig. 4. Comparison of creep compliance predictions.

analysis of the structure. The statistical prediction of axial shortening of concrete girder after continuity tendons are all stressed at midspan has been calculated for 20 samples of parameter θ_i, which represent the number of computer runs.

Each comparison of shrinkage and creep compliance predictions using ACI 209-92 model and those using CEB-FIP MC 90 model is shown in Fig. 3 and Fig. 4. Each curve represents mean value and mean $\pm$ ($2\times$ standard deviation). Shrinkage prediction using the ACI 209-92 model is larger than that using CEB-FIP MC 90 model but creep compliance prediction using ACI 209-92 model is smaller than that using CEB-FIP MC 90 model.

The prediction of axial shortening versus time obtained using ACI 209-92 model is plotted in Fig. 5. The dashed lines in these figures represent $\bar{Y} \pm 2s(t)$, in which $\bar{Y}$ = mean response at age t, and $s(t)$ = standard deviation of the response at age t. As might be expected, the probability band width of structural response widens with time, indicating an increase of prediction uncertainty with time. To assure long-term serviceability it seems reasonable to require that the design of concrete girder bridges should be based on these limits.

5.4. Sensitivity analysis results of axial shortening and prestress force

The sensitivity analysis results of axial shortening of girder using ACI 209-92 model are shown in Fig. 6. For the present problem, the most highly correlated parameters measured by the SRRC and PRCC is the creep model uncertainty factor. The two most important variables are creep model uncertainty factor and relative humidity. The creep model uncertainty factor has positive SRRCs and PRCCs, which indicates that an increase of this variable tends to increase the axial shortening. The relative humidity has negative SRRCs and PRCCs, which indicates that increase of this variable tends to decrease the axial shortening. This effect may occur because increase of

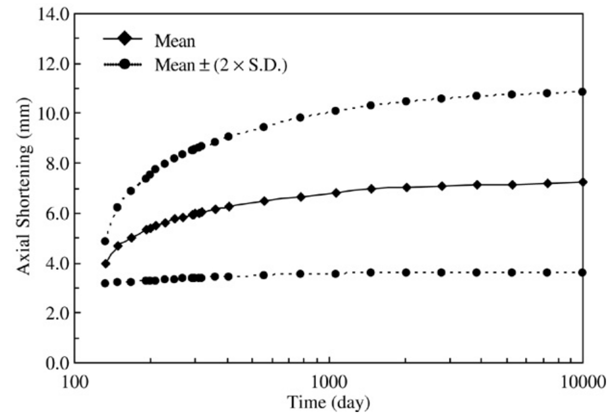


Fig. 5. Prediction of axial shortening using ACI 209-92 model.

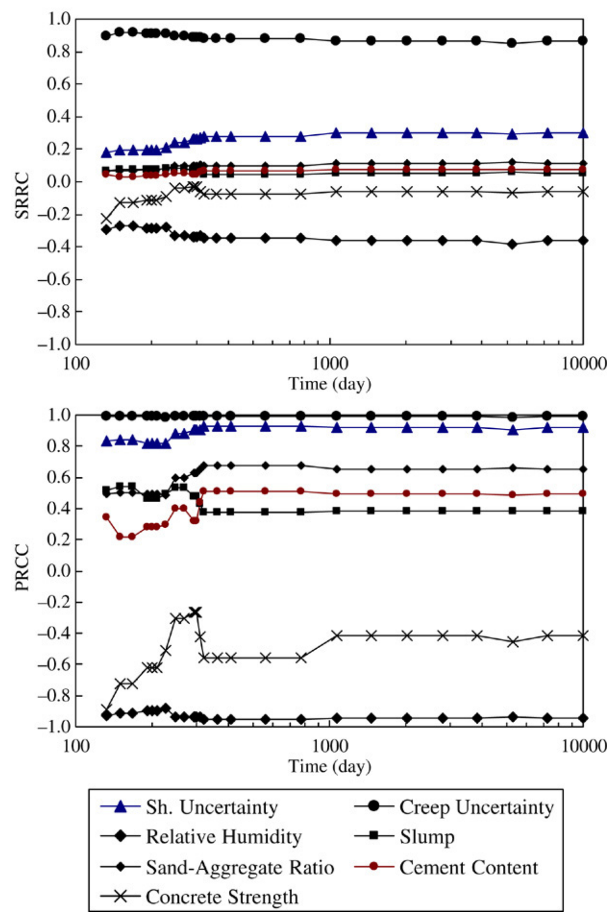


Fig. 6. Sensitivity analysis of axial shortening of girder using ACI 209-92 model.

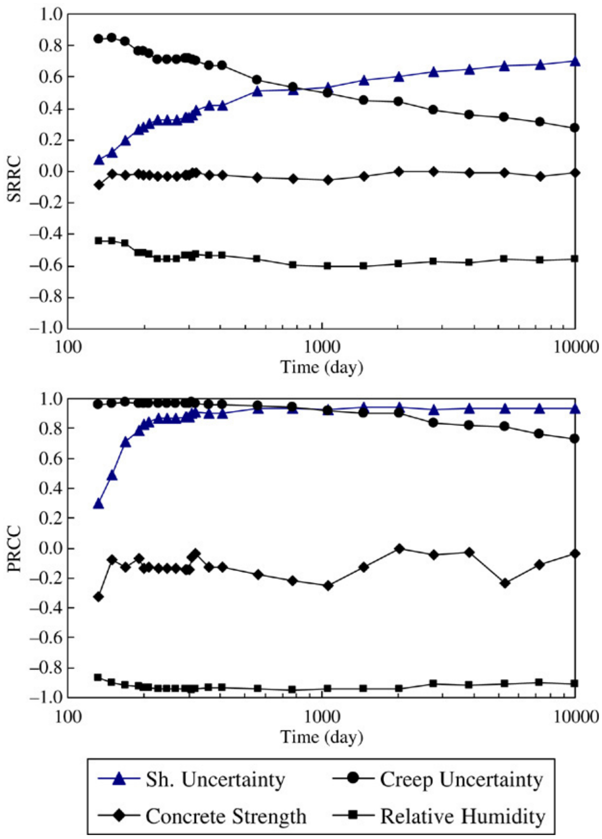


Fig. 7. Sensitivity analysis of axial shortening of girder using CEB-FIP MC 90 model.

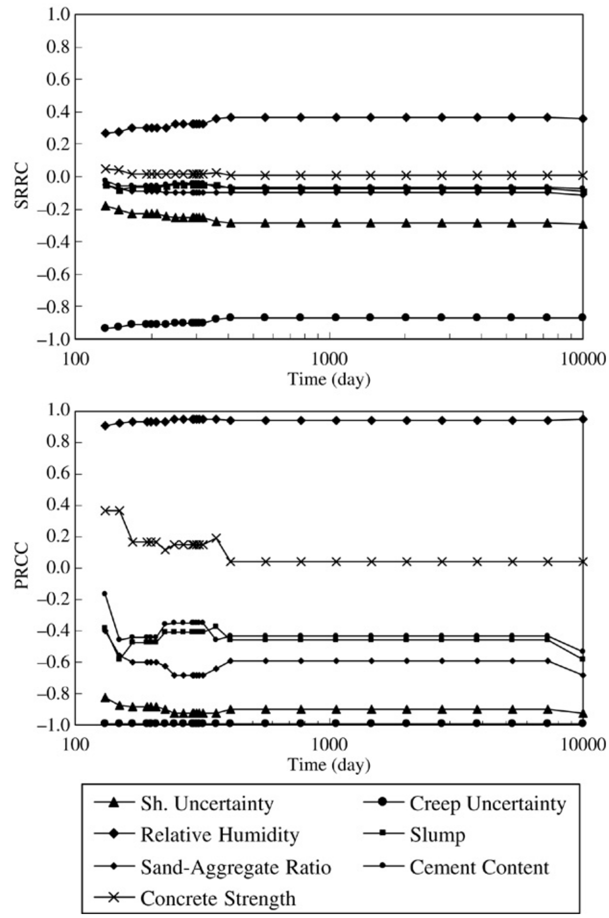


Fig. 8. Sensitivity analysis of prestress force using ACI 209-92 model.

relative humidity tends to reduce the humidity correction factor in ACI 209-92 model and thus decrease the creep coefficient and shrinkage value. The variables of creep model uncertainty factor and relative humidity consistently appear as important variables in the analyses presented in these figures. The variable with the next largest SRRCs and PRCCs is shrinkage model uncertainty factor. It is also seen that the positive correlation is shown for shrinkage model uncertainty factor, which indicates that increasing this variable tends to increase the amount of shrinkage strains. The sensitivity analysis results indicate that axial shortening was inversely correlated with concrete strength and weakly positively correlated with slump, sand–aggregate ratio and cement content.

The sensitivity analysis results of axial shortening of girder using CEB-FIP MC 90 model are shown in Fig. 7. The most highly correlated parameters measured by the SRRC and PRCC is relative humidity. The most important variable at early ages is creep model uncertainty factor. The value of the SRRCs and PRCCs of creep model uncertainty factor decreases gradually with time. The value of the SRRCs and PRCCs of shrinkage model uncertainty factor increases gradually with time. Relative humidity and shrinkage model uncertainty factor are two most important variables at 10,000 days. Creep model uncertainty factor and shrinkage model uncertainty factor have positive SRRCs and PRCCs for axial shortening, while relative humidity and compressive strength of concrete have negative SRRCs and PRCCs for axial shortening.

The sensitivity analysis results of prestress force using the ACI 209-92 model are shown in Fig. 8. For the present problem, the most highly correlated parameters measured by the SRRC and PRCC are the creep model uncertainty factor. The two most important variables are creep model uncertainty factor and relative humidity. The creep model uncertainty factor has negative SRRCs and PRCCs, which indicates that an increase of this variable tends to decrease the prestress forces. The relative humidity has positive SRRCs and PRCCs, which indicates that increase of this variable tends to increase the prestress force. This effect may occur because increase of relative humidity tends to reduce the humidity correction factor in ACI 209-92 model and thus decrease the creep coefficient and shrinkage value. The prestress force has an inverse relation with the creep coefficient and shrinkage value. The variables of creep model uncertainty factor and relative humidity consistently appear as important variables in the analyses presented in these figures. The variable with the next largest SRRCs and PRCCs is shrinkage model uncertainty factor. It is also seen that the negative correlation is shown for shrinkage model uncertainty factor, which indicates that increasing this variable tends to lower the prestress forces. The sensitivity analysis results indicate that prestress force is positively correlated with concrete strength and weakly negatively correlated with slump, sand–aggregate ratio and cement content.

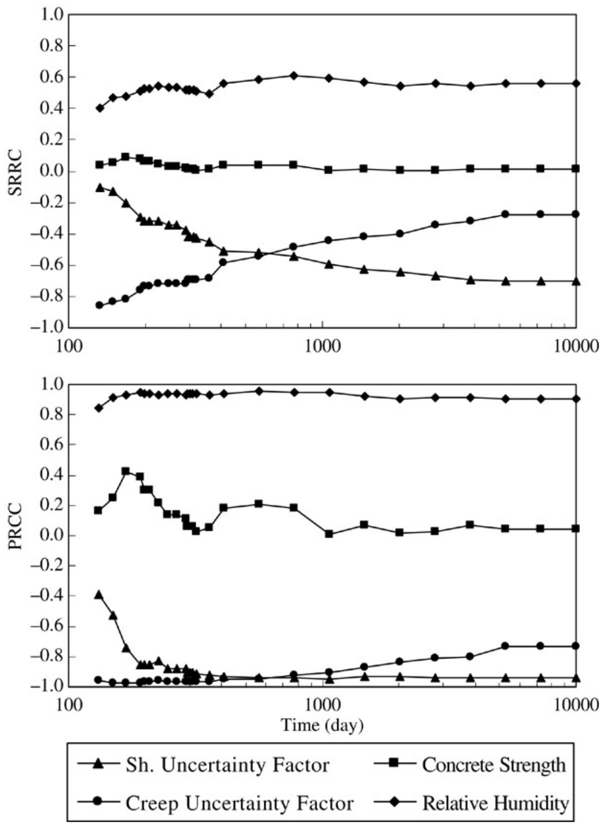


Fig. 9. Sensitivity analysis of prestress force using CEB-FIP MC 90 model.

The sensitivity analysis results obtained for the CEB-FIP MC 90 model are shown in Fig. 9. The most highly correlated variable measured by the SRRC and PRCC is relative humidity. The most important variable at early ages is the creep model uncertainty factor. The value of the SRRCs and PRCCs of the creep model uncertainty factor decreases gradually with time. The value of the SRRCs and PRCCs of the shrinkage model uncertainty factor increases gradually with time. Relative humidity and the shrinkage model uncertainty factor are the two most important variables at 10,000 days. The creep model uncertainty factor and shrinkage model uncertainty factor have negative SRRCs and PRCCs whereas relative humidity and compressive strength of concrete have positive SRRCs and PRCCs.

6. Conclusions

A method of uncertainty and sensitivity analysis to assess the creep and shrinkage effects of concrete structures such as prestressed concrete bridges is proposed. Latin Hypercube simulation technique was used to study the uncertainty of model parameters. The samples are obtained according to underlying probabilistic distributions, and then the outputs from the numerical simulations are translated into probabilistic distributions. The statistical method developed in this study predicts the variability of the long term prediction of time-dependent effects of concrete structures. It provides measures of the expected uncertainty and the distribution of time-dependent effects. The time-dependent effects versus time curves obtained from the numerical example indicate a significant statistical scatter in the predicted long-term axial shortening. The probability band widens with time, which indicates an increase of prediction uncertainty with time.

Also, the proposed method can identify the most influential factors in the long-term prediction of structural response in concrete structures. The coefficients of the regression equations, or response surface equation, are related to the coefficient of determination and can be used to identify the most important model parameters. Numerical results indicate that the creep modelling uncertainty factor and the variability of relative humidity are two most significant factors on time-dependent effects such as axial shortening of girder and prestress force in prestressed concrete bridge. The proposed method can be efficiently used to perform a sensitivity analysis of time-dependent effects of concrete structures.

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