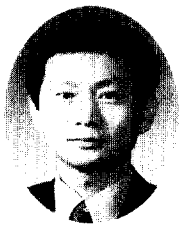
프리스트레스트 콘크리트 박스 거더 교량의 시간에 따른 변형의 확률 해석 및 민감도 해석

Uncertainty and Sensitivity Analysis of Time-Dependent Deformation in Prestressed Concrete Box Girder Bridges

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요 약

프리스트레스트 콘크리트 박스 거더 교량의 장기거동의 정확한 예측은 시공중 및 완공후의 사용성 확보를 위해서 매우 중요하다. 이러한 장기거동은 콘크리트의 크리프와 건조수축 등의 확률특성에 따라 크게 영향을 받는다. 따라서, 본 논문에서는 프리스트레스트 콘크리트 박스거더 교량에서의 크리프와 건조수축 효과의 불확실성 및 민감도 해석에 관한 연구를 수행하였다. 콘크리트의 크리프와 건조수축효과의 불확실성은 입력인자의 변동성을 고려하여 산출한다. 불확실성 및 민감도 해석은 Latin Hypercube 샘플링 기법에 의해 수행하며, 각 샘플에 대하여 시간 의존적 구조해석을 하여 그 결과를 통계학적으로 분석한다. 본 연구에서는 각 입력인자의 구조해석 결과에 대한 민감도를 정량화 하기 위하여 3가지 즉, RCC, PRCC 와 SRRC 상관계수를 사용하여 민감도 해석을 수행하였다. 현재, 주로 교량설계시 사용되는 ACI 모델, CEB-FIP모델과 도로교 표준시방서 모델의 민감도 분석을 수행한 결과, 크리프 모델 자체의 불확실성과 상대습도가 시간에 따른 변형에 가장 중요한 영향 인자인 것으로 나타났다. 본 연구에서는 장기거동에 영향을 미치는 주요인자를 도출하는 합리적인 해석기법을 정립하였으며, 이로부터 좀 더 합리적인 모델 정립에 유용한 토대가 될 것으로 사료된다.

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1. Introduction

Creep and shrinkage are important factors in the design of PSC box girder bridge. For example, they affect the setting of bearings and the size of sliding plates or laminated bearing pads. They also affect the size and setting of expansion joints due to time dependent axial shortening by prestress force. Therefore, the creep and shrinkage models which are capable of predicting long-term structural response are specified in the design codes such as ACI 209 model[1], CEB-FIP model[2] and the model in Korea Highway Bridge Specifications[3]. However, the application of current code formulations may result in considerable prediction errors stemming from several sources of uncertainty[4,5,6]. The sources of uncertainty, both internal and external, in the prediction of creep and shrinkage effects are listed in Ref. 7.

The aim of the present study is to provide and discuss results from the analyses of creep and shrinkage effects in PSC box girder bridges using the models in the design code. The study deals with 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 presented in order to show the relative importance of individual random variables employed in the various models.

2. Model Uncertainties

The variation of creep and shrinkage phenomenon is caused by various factors. As the external factors, the change of environmental conditions, such as humidity, may be considered. The internal factors, on the other hand, are the variation of the quality and the mix composition of the materials used in concrete and the variation due to the internal mechanism of creep and shrinkage.

This study investigate the uncertainty in the shrinkage and creep functions or the model uncertainties related to choosing one specified set of shrinkage and creep model. The influence of varying concrete and environmental parameters have been taken into account. Loads, geometrical parameters, and steel parameters are assumed to be deterministic and known.

Several material models for shrinkage and creep of concrete have been proposed both in national and in international codes. The amount of information on the input parameters such as environmental conditions and concrete composition varies considerably from model to model. The details of the assumptions and expression of the recommendations are different and will not be expressed here in detail.

2.1 ACI Model

Model uncertainties can be taken into account by applying a random model uncertainty factor to each term : shrinkage and creep. The formula for shrinkage is then

$$\varepsilon_{sh}(t, t_0) = \Psi_1 \varepsilon_u^s S(t, t_0) \tag{1}$$

where Ψ_1 is the model uncertainty factor. The model uncertainty for the creep function is assigned in a similar way and the formula for the creep strain is then

$$\phi(t, \tau) = \Psi_2 \phi_u C(t, \tau) \tag{2}$$

in which $S(t, t_0)$ and $C(t, \tau)$ are the hyperbolic functions referred in Ref. 1.

An indication of model uncertainties can be obtained from the work of Bazant and Baweja[8]. The mean value and coefficients of variation of a time averaged value of Ψ's are estimated in which the test data are compared with the predicted curve at discrete times, usually one or two time points per decade in the logarithmic time scale. They found that the coefficient 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

$$E[\Psi_1]=1 \quad ; \quad V_{\Psi_1}=0.553$$
$$E[\Psi_2]=1 \quad ; \quad V_{\Psi_2}=0.528 \qquad (3)$$

The coefficients Ψ_1 and Ψ_2 are present only in the probabilistic analysis. They are prediction error terms that account for uncertainty inherent in the theoretical model, the uncertainty of the micromechanism of creep and shrinkage that has been neglected, and other causes of uncertainty. Due to the way in which the statistics of the Ψ-factors are determined, they reflect three sources of uncertainty and each Ψ is consequently written as

$$\Psi_i=\Psi_i^{*}\ \Psi_\alpha\ \Psi_\beta \qquad (i=1,2,3) \qquad (4)$$

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

The factors to be used in Eq.(1) and (2) are Ψ_i^{*}, and the coefficient of variations in Eq.(3) must therefore be corrected. The factors in Eq.(4) are assumed independent, and the relation between the coefficients of variation[9] is

$$(1+V_{\Psi_i}^{\ 2})=(1+V_{\Psi_i^{*}}^{\ 2})\ (1+V_{\Psi_\alpha}^{\ 2})\times(1+V_{\Psi_\beta}^{\ 2}) \qquad (i=1,2,3) \qquad (5)$$

Scant data are available for the estimation of V_{Ψ_α}, but the results by Reinhardt et al.[10] indicate that a value between 0.06 and 0.10 is reasonable for test specimens. Since the test results were hand-smoothed and the laboratory test conditions were well conditioned, the coefficient of variation V_{Ψ_β} was estimated as 0.05 by Madsen[11]. In the present study, the following corrected values are obtained from the foregoing information and Eq. (6) is therefore used.

$$\text{Shrinkage}\quad E[\Psi_1]=1\ ;\ V_{\Psi_1}=0.542$$
$$\text{Creep}\quad E[\Psi_2]=1\ ;\ V_{\Psi_2}=0.517 \qquad (6)$$

2.2 CEB-FIP Model

Detailed formula of creep and shrinkage of CEB-FIP model is referred in Ref. 2.
Model uncertainty is accounted for by applying a random model uncertainty factor to each shrinkage and creep term. The formula for shrinkage and creep are then

$$\varepsilon_{cs}(t,t_s) = \Psi_1\,\varepsilon_{cs0}\,\beta_s(t-t_s) \qquad (7)$$
$$\phi(t,\tau) = \Psi_2\,\phi_0\,\beta_c(t-\tau) \qquad (8)$$

An indication of model uncertainty can be obtained also in the work of Bazant and Baweja[8]. The coefficient of variation of the Ψ factors they reported were 46.3% for shrinkage and 35.3% for creep, respectively. The following corrected values obtained from the foregoing information are therefore used.

$$\text{Shrinkage}\quad E[\Psi_1]=1\ ;\ V_{\Psi_1}=0.451$$
$$\text{Creep}\quad E[\Psi_2]=1\ ;\ V_{\Psi_2}=0.339 \qquad (9)$$

2.3 Korea Highway Bridge Specification Model

The model in Korea Highway Bridge Specifications is based on CEB-FIP model published in 1978. Model uncertainty is accounted for by applying a random factor to each shrinkage and creep term in the same manner as ACI model and CEB-FIP model. The formula for shrinkage and creep are then ;

$$\varepsilon_{sh}(t,t_0) = \Psi_1\,\varepsilon_{sh0}\,S(t,t_0) \qquad (10)$$
$$\phi(t,\tau) = \Psi_2\,C(t,\tau) \qquad (11)$$

where $S(t,t_0)$ and $C(t,\tau)$ are expressed in detail in Ref. 3. An indication of model uncertainty can be obtained in the work of Bazant and Panula[12]. The coefficient of variation of the Ψ factors reported by them were 28.6% for shrinkage and 24.6% for creep, respectively. The following corrected values obtained from the foregoing information are therefore used.

Shrinkage $E[\Psi_1]=1$; $V_{\Psi_1}=0.269$

Creep $E[\Psi_2]=1$; $V_{\Psi_2}=0.226$ (12)

3. Method of Uncertainty Analysis

The situation addressed by this paper is the following. There is a variable of interest, Y, that is expressed as functions of other variables $X_1, \cdots, X_k$. These functions may be quite complicated and defined by the finite element analysis program for time-dependent analysis of PSC box girder bridges.

To determine the stochastic response characteristics of complex system with a large number of random parameters, Latin Hypercube sampling(LHS) method developed by Iman and co-workers[13,14,15] is introduced. By sampling from the assumed probability density function of the X's and evaluating Y for each sample, the distribution of Y, its mean, standard deviation, percentiles etc., can be estimated.

The general expression of a equation for analytical model is as follows.

$$Y = f(\boldsymbol{X},\ t) \quad (13)$$

where, Y = output variable at time t

$f(\cdot)$ = deterministic analytical system

$\boldsymbol{X} = [X_1, X_2, \cdots, X_K]^T$

the vector of input variables assumed to be random ones

Every input variable X_k, k=1, 2, ⋯, K is described by its known cumulative distribution function(CDF) $F_{X_k}(X)$ with the appropriate statistical parameters. The sample $\{X\}_n$ of input variables, n=1, 2, ⋯, N(N being the number of sample equal to the number of simulations) is selected in the following way. The range of the known CDF $F_{X_k}(X)$ of each input variable X_k is partitioned into N disjunct intervals S_{kn}. Each interval is characterized by the probability p_{kn} defined as

$$p_{kn} = P(X_k \in S_{kn}) \quad (14)$$

and

$$\sum_n p_{kn} = 1 \quad (k=1,2,\cdots K) \quad (15)$$

In the case of intervals of equal probability, it holds that $p_{kn}=1/N$. Each interval is represented in the sample by the representative parameter which is taken at the centroid of the interval. The representative parameter is obtained as

$$F_{X_k}^{-1}\left(\frac{m_{nk}-0.5}{N}\right) \quad (k=1,2,\cdots,K) \quad (16)$$

where, $F_{X_k}^{-1}(\cdot)$ = the inverse of CDF

m_{nk} = the rank number of the interval used in the n th simulation for input variable X_k.

The representative parameter is used just once during the simulation procedure and so there are N observations on each of the K input variables. N observations on each of input variable X_k are associated with a sequence of integers (rank number of intervals) representing a random permutation of integers 1, 2, ⋯, N. They are ordered in the table of random permutations of rank numbers which has N rows and K columns. The rank numbers of intervals used in the n-th simulation are represented by the n th row in the table. For such a sample one can evaluate, using Eq.(13), the corresponding value y_n of the output variable. From N simulations one can obtain a set of statistical data $\{y\}=[y_1, y_2, \cdots, y_n]^T$. This set is statistically assessed and thus estimations of some statistical parameters are obtained.

4. Approach to Sensitivity Analysis

Once the input has been selected and computer runs are completed in a simulation study, it is necessary to quantify the sensitivity of the output to each of the inputs. Three closely related, but different, measures will be examined in this study. These are rank correlation coefficient(RCC), partial rank correlation coefficient(PRCC) and standardized rank regression coefficient(SRRC) computed on the ranks of the observations[16].

A useful index that measures the importance of the input variables is the RCC, computed by

$$r_{jy} = \frac{\sum_{i=1}^{n} x_{ij} y_i - \sum_{i=1}^{n} x_{ij} \sum_{i=1}^{n} y_i / n}{\sqrt{\left[\sum_{i=1}^{n} x_{ij}^2 - (\sum_{i=1}^{n} x_{ij})^2 / n\right]\left[\sum_{i=1}^{n} y_i^2 - (\sum_{i=1}^{n} y_i)^2 / n\right]}} \quad (17)$$

where r_{yj} = the RCC of the input X_j and model output Y ; x_{ij} and y_i = the ranks of input X_j and the corresponding model output, respectively, for the i'th LH sample.

Suppose a computer model has inputs $X_1,\cdots,X_k$ and output Y. After making n computer 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.

$$\mathbf{C} = \left[\begin{array}{cccc:c} 1 & r_{12} & \cdots & r_{1k} & r_{1y} \\ r_{21} & 1 & \cdots & r_{2k} & r_{2y} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ r_{k1} & r_{k2} & \cdots & 1 & r_{ky} \\ \hdashline r_{y1} & r_{y2} & \cdots & r_{yk} & 1 \end{array}\right] \quad (18)$$

where r_{ij}, $1 \le i$, $j \le k$ is the sample correlation coefficient between inputs X_i and X_j, computed on their ranks, while r_{yj} is the rank correlation coefficient.

Let the symmetric matrix $\mathbf{C}$ be partitioned into submatrices as indicated by the dashed lines within the $\mathbf{C}$ matrix as shown in Eq.(18), where C_{11} is $k\times k$, C_{12} is $k\times 1$ and $C_{21} = C_{12}^T$, since $\mathbf{C}$ is symmetric. Both the SRRCs and the PRCCs can be derived directly from $\mathbf{C}^{-1}$. The $k\times 1$ vector of SRRCs is found as $B = C_{11}^{-1} C_{12}$. Furthermore, if Y is regressed on $X_1,\cdots,X_k$, the model coefficient of determination, R_Y^2 is found as $C_{21} C_{11}^{-1} C_{12}$. This information allows $\mathbf{C}^{-1}$ to be written as follows.

$$\mathbf{C}^{-1} = \begin{bmatrix} [C_{11} - C_{12} C_{21}]^{-1} & -B/(1-R_y^2) \\ -B^T/(1-R_y^2) & 1/(1-R_y^2) \end{bmatrix} \quad (19)$$

The diagonal elements of $[C_{11} - C_{12}C_{21}]^{-1}$ contain the coefficients of determination, $R^2_{X_j}$, corresponding to regressing X_j on Y and the remaining X's. Specifically, the diagonal elements are $1/(1 - R^2_{X_j})$. Therefore, $\mathbf{C}^{-1}$ can be written in expanded form as follows.

$$\mathbf{C}^{-1} = \left[\begin{array}{cccc:c} \frac{1}{(1-R^2_{X_1})} & \cdots & c_{1k} & \frac{-B_1}{(1-R_y^2)} \\ \cdots & \cdots & \cdots & \cdots \\ c_{k1} & \cdots & \frac{1}{(1-R^2_{X_k})} & \frac{-B_k}{(1-R_y^2)} \\ \hdashline \frac{-B_1}{(1-R_y^2)} & \cdots & \frac{-B_k}{(1-R_y^2)} & \frac{1}{(1-R_y^2)} \end{array}\right] \quad (20)$$

where B_j is the SRRC for X_j. And PRCC for X_j and Y is expressed directly from $\mathbf{C}^{-1}$ as

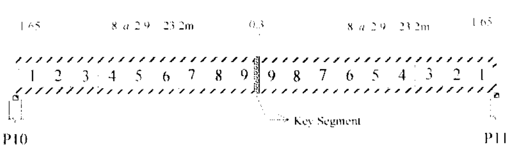
$$P_{X,y} = -\frac{c_{jy}}{\sqrt{c_{jj}\, c_{yy}}} \qquad (21)$$

5. Application to Prestressed Concrete Box Girder Bridges

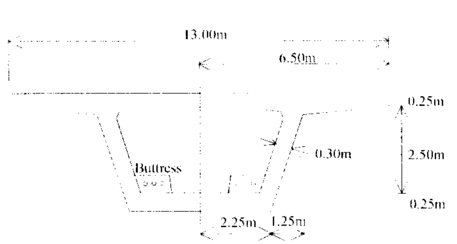
5.1 Description of Structure

The long term deformation of a PSC box girder bridge under construction in Korea is studied as a practical application of the variability of the response of the bridge. The 50m interior span of the 7-continuous span bridge system is analyzed(Fig. 1). It is a segmentally constructed precast PSC box girder. The interior span of the box girder has 9 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.

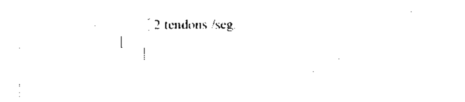
The analytical model for structural analysis consists of 20 nodes, 19 frame elements and 22 prestressing tendons. The cross section is subdivided into 10 layers. The time steps for numerical integration are increased in log scale.



(a) Segment geometry

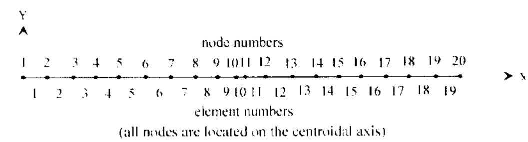


(b) Section of segment



(c) Distribution of cantilever tendons (T1-T9)

(d) Distribution of continuity tendons (B11-B14)



(e) Identification of element and node numbers

Fig. 1 Analytical model

5.2 Statistical Properties of Input Parameters

Each input parameter is represented by its mean value and the coefficient of variation(COV). The numerical values for relative humidity and compressive strength of concrete were determined using the available data. Model uncertainty factors for prediction models of creep and shrinkage were examined previously. The numerical values for the coefficient of variation of input variables are listed in Table 1 for ACI model and in Table 2 for KHBS model and then in Table 3 for CEB-FIP model.

Table 1 Statistical properties of basic variables (ACI model)

Variables		Mean value	COV
Ψ_1	uncertainty factor for shrinkage	1.0	0.542
Ψ_2	uncertainty factor for creep	1.0	0.517
h	relative humidity (%)	61.6	0.269
σ_{ck}	28 day concrete strength(kg/cm^2)	499	0.066
s/a	sand-aggregate ratio	0.41	0.10
S	slump (cm)	15	0.10
c	cement contents (ton/m^3)	0.51	0.10

Table 2 Statistical properties of basic variables (KHBS model)

Variables		Mean value	COV
ψ_1	uncertainty factor for shrinkage	1.0	0.269
ψ_2	uncertainty factor for creep	1.0	0.226
h	relative humidity (%)	61.6	0.269
σ_{ck}	28 day concrete strength(kg/cm^2)	499	0.066

Table 3 Statistical properties of basic variables (CEB-FIP model)

Variables		Mean value	COV
ψ_1	uncertainty factor for shrinkage	1.0	0.451
ψ_2	uncertainty factor for creep	1.0	0.339
h	relative humidity (%)	61.6	0.269
σ_{ck}	28 day concrete strength(kg/cm^2)	499	0.066

To investigate the distribution of relative humidity(h), the records from the Meterological Observatory of Seoul(about 3km north of present bridge) were analyzed statistically and probability distribution function was ascertained. Also, to investigate the distribution of compressive strength of concrete in 28 days (σ_{ck}), the results from strength test of concrete cylinders which had been used in construction were analyzed statistically and probability distribution function was ascertained.

The K-S goodness-of-fit test[9] was applied to fit each distribution function. The best-fitting distribution function for σ_{ck} and h were analyzed under the assumption of normal distribution. In this study, a two sided tolerance limit factor is used to give a 95% probability value. Experimental CDF vs. theoretical CDF for concrete strength and relative humidity is shown in Fig. 2 and in Fig. 3, respectively. The maximum difference between the experimental CDF and theoretical CDF for concrete strength is 0.178, which is less than the critical difference value D_c of 0.187. The maximum difference between the experimental CDF and theoretical CDF for relative humidity is 0.071, which is less than the critical difference value D_c of 0.073. Thus, the test is satisfied at 5% significance level and the plots show a good agreement between two CDFs, respectively. Subsequently, the theoretical analysis models for concrete strength and relative humidity were set up and applied to the present problem.

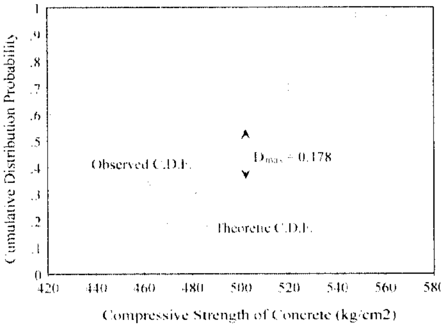


Fig. 2 K-S test for compressive strength of concrete

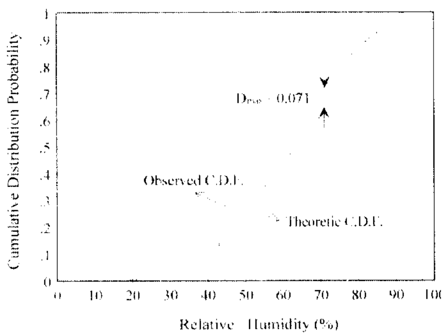
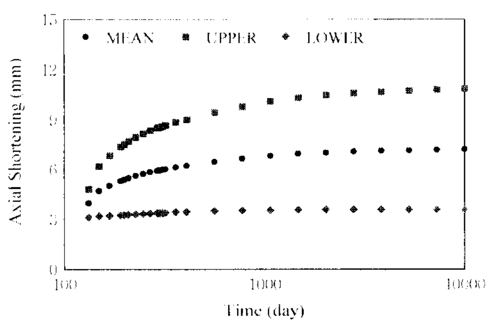


Fig. 3 K-S test for relative humidity

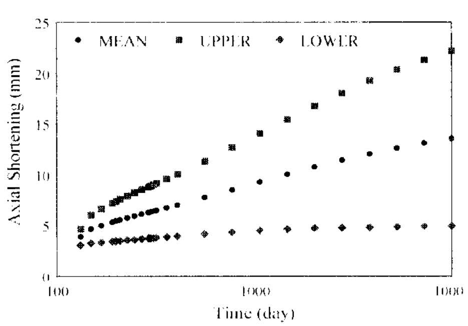
5.3 Statistical Analysis of Deformation

If the values of input variables $X_1, \cdots, X_K$ are specified, the creep and shrinkage effect or response $Y(X_i, t)$ at time t, such as the axial shortening, can be calculated by running a computer program for the deterministic analysis of structure through finite element method. Finite element analysis method for PSC box girder structural system is referred in our study[17,18]. The statistical predictions have been calculated for 20 samples of parameter X_i, which represents the number of computer runs. The normal probability plots of the responses obtained in the individual runs of the creep and shrinkage analysis program for the structures showed that the probability distribution of the response is approximately normal. In this case, therefore the distribution of structural response is considered to be normal. The predictions of axial shortening versus time obtained for present numerical example are plotted in Fig. 4.

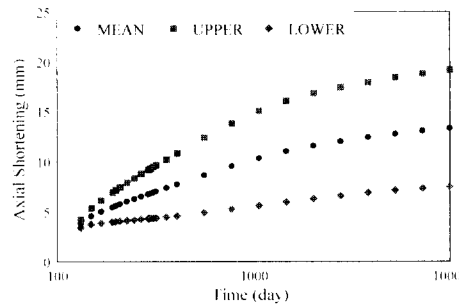
The lines in these figures represent $\overline{Y}(t) \pm 2s(t)$, in which $\overline{Y}(t)$ = mean response at age t, and $s(t)$ = standard deviation of the response at age t. These values represent the 95% confidence limits for the results, i.e., the limits that are exceeded with 2.5% probability on the plus side and 2.5% on the minus side. As might be expected, the probability band width of structural response widens with time, indicating an increase of prediction uncertainty with time. To assure good long term serviceability it seems reasonable to require that the design of box girder bridges should be based on these limits.



(a) ACI model



(b) CEB-FIP model



(c) KHBS model

Fig. 4 Predictions of the axial shortening

5.4 Sensitivity Analysis Results

The results of LH simulations are used with RCC and SRRC, and PRCC to determine which of the model parameters are most significant in affecting the uncertainty of the design.

The sensitivity analysis results obtained for ACI model are shown in Fig. 5. For present problem, the most highly correlated parameters measured by the RCC, SRRC and PRCC is the creep model uncertainty factor. The two most important variables are creep model uncertainty factor and relative humidity. Creep model uncertainty factor has positive RCCs, SRRCs and PRCCs, which indicates that increasing of this variable tends to increase the axial shortening. Relative humidity has negative RCCs, SRRCs and PRCCs, which indicates that increasing of this variable tends to decrease the axial shortening. The variables of creep model uncertainty factor and relative humidity consistently appear to be important variables in the analyses presented in these figures. The variable with the next largest RCCs, SRRCs and PRCCs is shrinkage model uncertainty factor.

The sensitivity analysis results obtained for CEB-FIP model are shown in Fig. 6. The most important variable at early ages is creep model uncertainty factor. The values of the SRRCs of creep model uncertainty factor decrease 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 for axial shortening, while relative humidity and compressive strength of concrete have negative SRRCs for axial shortening.

The sensitivity analysis results obtained for KHBS model are shown in Fig. 7. For present problem, the most highly correlated parameters measured by the SRRC is relative humidity. The two most important variables are relative humidity and creep model uncertainty factor. The variable with the next largest SRRCs is shrinkage model uncertainty factor.

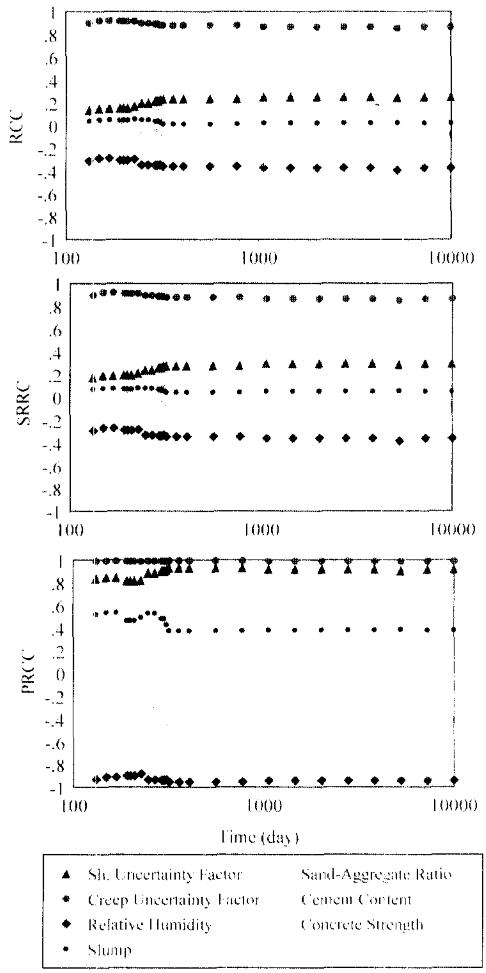


Fig. 5 RCC, SRRC and PRCC of axial shortening (ACI model)

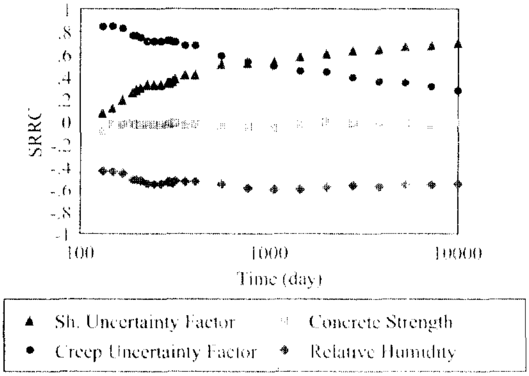


Fig. 6 SRRC of axial shortening for CEB-FIP model

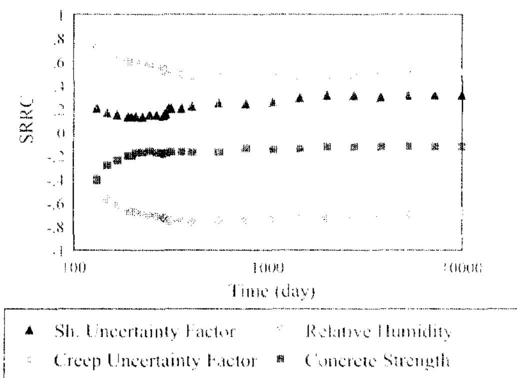


Fig. 7 SRRC of axial shortening for KHBS model

6. Conclusions

The purpose of the present paper is to propose a method of uncertainty and sensitivity analysis to assess the creep and shrinkage effects of PSC box girder bridges. To achieve the goal, Latin Hypercube simulation technique was used to study the uncertainty of model parameters. The samples are obtained according to underlying probabilistic distributions, and then output from the numerical simulations are translated into probabilistic distributions. To conduct sensitivity analysis on the realizations of input vectors, a rank transformation was applied to the input and output variables. Rank transformation is a procedure that replaces raw data with their corresponding ranks for a robust regression analysis. Multiple linear regression on the ranks is then performed to obtain relationships between input and output variables. Coefficient of the regression equations, or the response surface equation, are related to the coefficient of determination and can be used to screen influential model parameters. The following conclusions have been drawn from this study.

(1) The uncertainty in the prediction of creep and shrinkage effects was analyzed using sampling method. The sampling approach reduces the probabilistic problem to a series of deterministic structural creep analysis problem for various samples of random parameters.

(2) The curves of time-dependent effects versus time obtained for the numerical example represent a significant statistical scatter in the predicted long-term deformation. The probability band widens with time, which indicates an increase of prediction uncertainty with time. To achieve a reliable design from the viewpoint of long-time serviceability, the statistical scatter must be taken into account in design.

(3) A statistical method developed in this study predicts the variability of the long term response of a structure. It provides measures of the expected uncertainty and the distribution of time-dependent effects.

(4) The proposed method can be efficiently used to perform a sensitivity analysis of time dependent effects. The present study indicates that the creep modeling uncertainty factor and the variability of relative humidity are two most significant factors on time dependent effects.

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References

1. ACI 209R-92(1992), "Prediction of Creep, Shrinkage and Temperature Effects in Concrete Structures", ACI Manual of Concrete Practice-Part 1.
2. CEB-FIP Model Code for Concrete Structures(1990), Comite Euro-International Du Beton(CEB).
3. Korea Ministry of Construction and Transportation(1996), *Korea Highway Bridge Specifications* (in Korean).
4. Floris, C., Marelli, R. and Regondi, L.(1991), "Creep Effects in Concrete Structures: A Study of Stochastic Behavior", *ACI Materials Journal*, Vol.88, No.3, May-June, pp.248-256.
5. Diamantidis, D., Madsen, H. O. and Rackwitz, R.(1983), "On the Variability of the Creep Coefficient of Structural Concrete", *Materials and Structures*, Vol.17, No.100, pp.321-328.
6. Bazant, Z. P. and Xi, Y.(1993), "Stochastic Drying and Creep Effects in Concrete Structures", *Journal of Structural Engineering*, ASCE, Vol.119, No.1, Jan. pp.301-322.
7. Bazant, Z. P.(1988), *Mathematical Modelling of Creep and Shrinkage of Concrete*, John Wiley & Sons.
8. Bazant, Z. P. and Baweja, S.(1995), "Justification and Refinement of Model B3 for Concrete Creep and Shrinkage 1. Statistics and Sensitivity", *Materials and Structures*, **28**, pp.415-430.
9. Ang, A. H.-S. and Tang, W. H.(1975), *Probability Concepts in Engineering Planning and Design*, Vol. 1, Basic Principles, Wiley, New York.
10. Reinhardt, H. W., Pat, M. G. and Wittmann, F. H.(1982), "Variability of Creep and Shrinkage of Concrete", *Symposium on Fundamental Research on Creep and Shrinkage of Concrete*, M. Nijhoff, The Hague, pp.75-94.
11. Madsen, H. O. and Bazant, Z. P.(1983), "Uncertainty Analysis of Creep and Shrinkage Effects in Concrete Structures", *ACI Journal*, Vol.80, March-April, pp.116-127.
12. Bazant, Z. P. and Panula, L.(1980), "Creep and Shrinkage Characterization for Analyzing Prestressed Concrete Structures", *PCI Journal*, Vol.25, No.3, pp86-122.
13. Iman, R. L. and Conover, W. J.(1980), "Small Sample Sensitivity Analysis Techniques for Computer Models, with an Application to Risk Assessment", *Communications in Statistics*, A9 pp.1749-1842.
14. Iman, R. L., Helton, J. C. and Campbell, J. E.(1981), "An Approach to Sensitivity Analysis of Computer Models : Part I -

Introduction, Input Variable Selection and Preliminary Variable Assessment", *Journal of Quality Technology*, Vol.13, No.3, July, pp.174-183.
15. Iman, R. L., Helton, J. C. and Campbell, J. E.(1981), "An Approach to Sensitivity Analysis of Computer Models : Part II-Ranking of Input Variables, Response Surface Validation, Distribution Effect and Technique Synopsis", *Journal of Quality Technology*, Vol.13, No.4, Oct., pp.232-240.
16. Helton, J. C., Rollstin, J. A., Sprung, J. L. and Johnson, J. D. (1992), "An Exploratory Sensitivity Study with the MACCS Reactor Accident Consequence Model", *Reliability Engineering and System Safety* **36**, pp.137-164.
17. Oh, B. H. and Yang, I. H. (1998), "Effects of Material Characteristics on the Time-Dependent Behavior of Prestressed Concrete Box Girder Bridges Constructed by Free Cantilever Method", *KCI Journal*, Vol. 10, No. 1, pp.179-188. (in Korean)
18. Yang, I. H. (1998), "Probabilistic Prediction of Time-Dependent Behavior of Prestressed Concrete Box Girder Bridges", Ph. D Thesis, Seoul National University.

ABSTRACT

The reasonable prediction of time-dependent deformation of prestressed concrete(PSC) box girder bridges is very important for accurate construction as well as good serviceability. The long-term behavior is mostly influenced by the probabilistic characteristics of creep and shrinkage. This paper presents a method of statistical analysis and sensitivity analysis of creep and shrinkage effects in PSC box girder bridges. Three possible sources of the uncertainties of structural response have been taken into account - model uncertainty, parameter variation and environmental condition. The statistical and sensitivity analyses are performed by using the numerical simulation of Latin Hypercube sampling. For each sample, the time-dependent structural analysis is performed to produce response data, which are then statistically analyzed. The probabilistic prediction of the confidence limits on long-term effects of creep and shrinkage is then expressed. Three measures are examined to quantify the sensitivity of the outputs of each of the input variables. These are rank correlation coefficient(RCC), partial rank correlation coefficient(PRCC) and standardized rank regression coefficient(SRRC) computed on the ranks of the observations. Three creep and shrinkage models - i. e., ACI model, CEB-FIP model and the model in Korea Highway Bridge Specification - are studied. The creep model uncertainty factor and the relative humidity appear to be the most dominant factors with regard to the model output uncertainty.
Keywords : uncertainty, sensitivity, prestressed concrete(PSC) box girder bridge, creep, shrinkage, deformation, axial shortening

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