RELIABILITY-BASED DESIGN OPTIMIZATION OF PRESTRESSED GIRDERS BRIDGES

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ABSTRACT

Prestressed concrete girder bridges are popular structures due to their simplicity of fabrication, speed of construction, ease of inspection, maintenance and replacement. Many design factors play an essential role in deciding the members’ dimensions, geometry, weights, and cost. This reflects the importance of developing optimization tools that provide cost-effective design by determining certain design variables to achieve the best measurable objective function under given constraints. However, in order to maintain appropriate safety levels while performing the optimization process, it becomes necessary to adopt a probabilistic approach that considers the uncertainties associated with the basic design variables. In this paper, a reliability-based optimization model, for the design of prestressed girder bridges, is proposed. The proposed model adopts a simulation-based optimization technique. The simulation engine utilizes Monte Carlo analysis, while the optimization engine performs metaheuristic scatter search with neural network accelerator. A case study is provided to investigate the applicability of the proposed model. The implementation of the proposed method will serve bridge engineers who intend to achieve cost-efficient design solutions with guaranteed safety levels reserved in the optimized bridge configuration.

1. INTRODUCTION

Prestressed girder bridges are very common type of bridges constructed all over the world. According to the Federal Highway Administration (FHWA 2000), almost one-quarter of the more than one-half-million U.S. bridges are designed as prestressed girder bridge system (Sirca and Adeli, 2005). This bridge system also represents 40% of the short and medium span bridges built in the United States and Canada (Lounis and Cohn, 1993). Prestressed girder bridges are ideal as short to medium span (60 to 200 ft) highway bridges because of their moderate self-weight, structural efficiency, ease of fabrication, fast construction, low initial cost, long life expectancy, low maintenance, simple deck removal, and replacement (Precast/Prestressed Concrete Institute PCI, 2003).

During the last three decades, much work has been performed in the field of structural optimization as a result of considerable developments in mathematical optimization, advances in computer’s technologies, and the need to perform cost-effective designs (Ahsan et al, 2012). This motivated researchers to apply optimization processes to the design of bridge structures as well, and to develop cost-effective design alternatives. Minimizing the weight of the structure solely through deterministic design optimization can achieve economical solutions; however, the final configuration of the optimized structure might not be entirely safe. In order to identify the best combination between cost reduction and satisfactory safety levels of the optimized structure, reliability-based design optimization should be applied to control the structural uncertainties throughout the design process, which cannot be achieved by deterministic optimization (Chateauneuf, 2007). Hence, safety constraints with respect to every possible mode of failure need to be imposed on the design optimization process.
2. RELIABILITY ANALYSIS

2.1 Loads and Resistance Models

Nowak and Rakoczy (2012) suggested that for dead load, the mean-to-nominal ratio is 1.03 for the factory-made members and 1.05 for cast-in-situ members, with coefficient of variation equal to 0.08 and 0.10, respectively. This study also considered the mean thickness of asphalt equals 3.0 in (75 mm) and coefficient of variation as 0.25.

For live load effect, the bias factors vary with the span length of the bridge. The mean value suggested by Nowak and Rakoczy (2013) was adopted with a coefficient of variation of 0.12.

For the transverse girder distribution factor GDF, a bias factor \( \lambda = 0.98 \) and a coefficient of variation CoV=0.07 was used as suggested by Nowak et al. (2001). For fatigue induced load, the calculated and the measured average stress cycles per vehicle suggested by Laman et al. (1996) were employed in the current study.

For dynamic impact factor of live load, the mean value is less than 0.17 for a single truck and less than 0.12 for two trucks, for all spans. The coefficient of variation of a joint effect of the live load and dynamic load is 0.18, as suggested by Hwang and Nowak (1991) and further verified by Kim and Nowak (1997). As suggested by Tabsh and Nowak (1991), a bias factor of 1.0 and a coefficient of variation of 0.028 for dimensions of concrete members was used.

The statistical parameters (bias factor and CoV) for compressive strength of concrete suggested by Nowak and Rakoczy (2012) were suggested. While, for tensile strength of concrete, the statistical parameters suggested by Lehky et al. (2012) were adopted. The statistical parameters corresponding to the prestressing strands as suggested by Al-Harthy and Frangopol (1994) were adopted. The moment and shear resistance is considered as random variables with stistical parameters as suggested by Nowak and Szerszen (1998). The statistical parameters suggested by Al-Harthy and Frangopol (1994) corresponding to the model coefficient have been used in this proposed model.

2.2 Estimation of Individual Component’s Reliability Indices

The Monte Carlo Simulation technique is used to evaluate the reliability indices with respect to the stress at the top and bottom fibers, of the prestressed bridge girder, measured at different locations (end section, transfer length section, harp point section and at midspan section). Also the reliability indices with respect to fatigue limit state function, ultimate bending and shear are also estimated. Let \( g(\mathbf{X}) = g(x_1, x_2, \ldots, x_n) \) be the limit state function, where \( \mathbf{X} \) is a vector of the basic design random variables. Then the failure state belongs to the region where \( g(\mathbf{X}) \leq 0 \), while \( g(\mathbf{X}) > 0 \) represents the safe region. For every basic variable, a random sample, of values \( x_i \), is generated numerically in accordance with its probability distribution function, using a random number generator. The generated sample values are then substituted in the limit state function. Then, a negative value of the limit state function means failure while a positive value means no failure. This process is repeated many times (large number of samples) in order to simulate the probability distribution of the limit state function \( g(\mathbf{X}) \). Then, the failure probability \( P_f \) can be evaluated as follows:

\[
P_f = P[g(\mathbf{X}) \leq 0] = \lim_{N \to \infty} \frac{N_f}{N}
\]

where \( N \) is the total number of simulations (samples) and \( N_f \) is the number of trials in which \( g(\mathbf{X}) \leq 0 \). The ratio \( N_f/N \) is usually very small and the estimated probability of failure is subjected to considerable uncertainty. As the variance of \( N_f/N \) depends, in particular, on the total number of simulations \( N \), the uncertainty in estimating \( P_f \) decreases when \( N \) increases. The reliability index is then calculated as follows:

\[
\beta = -\Phi^{-1}(1-P_f)
\]

where, \( \Phi^{-1}(\cdot) \) is the inverse of cumulative probability function CPF of the standard normal variables.
2.3 Improved Reliability Bounds For System’s Reliability Assessment

The narrow bounds reliability approach represents adequate technique to predict the probability of failure and corresponding reliability index of complex structural systems, such as bridges (Ditlevsen and Madsen, 2007). Monte Carlo Simulation has successfully been applied to evaluate the system reliability considering lower and upper bounds on structure functions (Huseby et al., 2004). In order to provide very narrow upper and lower limits of the failure probability of a structural system, Ahmed and Koo (1990) derived a set of generalized and improved reliability bounds. In this method, the correlation among failure modes, as well as the absolute value of the probability of failure, have been considered. The method takes into account the effect of intersection of joint failure probabilities. The mean and standard deviation between two correlated modes $Z_i$ and $Z_j$ are as, respectively, obtained from Eqs. 3 and 4:

$$ (Z_i|Z_j) = \mu_i + \eta_{ij} (\sigma_i/\sigma_j)(Z_j - \mu_j) $$

$$ (Z_i|Z_j) = \sigma_j \sqrt{1 - \eta_{ij}^2} $$

where $\eta_{ij}$ is the correlation coefficient between $Z_i$ and $Z_j$. The probability of failure of the first and second modes can be expressed as:

$$ P(Z_1 < 0, Z_2 < 0) = \int_{Z_1=-\infty}^{Z_1=0} \int_{Z_2=-\infty}^{Z_2=0} P(Z_1=U/Z_2=V) \cdot P(Z_2=V) \, dU \, dV $$

$$ P(Z_1 < 0, Z_2 < 0) = \int_{Z_1=-\infty}^{Z_1=0} \int_{Z_2=-\infty}^{Z_2=0} P(Z_2=U/Z_1=V) \cdot P(Z_1=V) \, dU \, dV $$

If a polynomial expression is used, then the double integration in Eqs. 5 and 6 can equivalently be replaced by a single integration. The joint failure probability can be calculated by selecting a suitable range of integration, e.g. $-5\sigma_{z2}$ to 0. For almost all practical applications, the lower limit of $-5\sigma_{z2}$ would yield nearly exact results (Ahmed and Koo, 1990). By substituting $Z_i = \nu$ in Eq. 3, $\eta_{ij}(Z_i/Z_2)$ is obtained. Then from Eq. 4, $\sigma_{ij}(Z_i/Z_2)$ can be calculated. Having the mean and standard deviation, the joint reliability can be estimated as in Eq. 7 and the cumulative distribution function as in Eq. 8:

$$ \beta(Z_i/Z_2) = \mu_i(Z_i/Z_2) / \sigma_i(Z_i/Z_2) $$

$$ \Phi(x) = \int_{-\infty}^{x} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) \, dt $$

Now, the function $f_m(\nu)$ can be calculated as follows:

$$ f_m(\nu) = \left[ \frac{1}{\sigma_m \sqrt{2\pi}} \right] \exp\left(-\frac{(\nu-\mu_m)^2}{2\sigma_m^2}\right) $$

The joint probability can be obtained by applying a suitable integration technique to integrate function $\Phi(\beta), f_m(\nu)$ with respect to $\nu$ (Ahmed and Koo, 1990):

$$ P(m, n) = \int_{-5\sigma_m/\sqrt{2\pi}}^{5\sigma_m/\sqrt{2\pi}} \exp\left[-\frac{(\nu-\mu_m)^2}{2\sigma_m^2}\right] \left[ \int_{-\infty}^{\nu} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) \, dt \right] \, d\nu $$

where,

$$ \beta = \frac{\mu_m + \nu \eta_{mn} \left( \frac{\sigma_m}{\eta_{mn}} \frac{\sigma_m}{\sigma_n} \right) (\nu - \mu_m)}{\sigma_m \sqrt{1 - \eta_{mn}}} $$

Now, for generality, the probability of failure can be written as:
\[ P(Z) = \sum_{i=1}^{k} C_i \]
\[ C_k = P(Z_k) - \sum_{i=1}^{k} \frac{1}{\sum_{m=1}^{k-1} \sum_{n=2}^{m-1} P(Z_kZ_m) \cap Z_n} \]  \( K > 2 \)
\[ L_k \leq C_k \leq U_k \]

where \( L_k \) and \( U_k \) are, respectively, the lower upper bounds of the probability of failure related to the \( kth \) mode.

\[ L_k = P(Z_k) - \sum_{i=1}^{k-1} \frac{1}{\sum_{m=2}^{k-1} [P(Z_kZ_m) \cap \sum_{i=1}^{m-1} P(Z_kZ_m)]} \]  \( K > 2, L_k \geq 0 \)
\[ U_k = \max\{\min(V_k, W_k), 0\} \]
\[ V_k = P(Z_k) - \sum_{i=1}^{k-1} \max(P(Z_kZ_m), P(Z_kZ_n)) \]
\[ W_k = P(Z_k) - \max[P(Z_kZ_i), i = 1, K-1] \]

Rewriting Eq. 14 as:
\[ \sum_{i=1}^{k} L_i \leq P(Z) \leq \sum_{i=1}^{k} U_i \]

3. FORMULATION OF OPTIMIZATION PROBLEM

The unit cost of the superstructure is considered, in this study, as the objective function of the optimization process. For a bridge with total length \( (L) \) and total width \( (W) \), the proposed objective function is defined as follows:
\[ \frac{\text{Unit Cost}}{L + W} = \frac{N_g C_g + C_R V_d + C_c W_R}{L + W} \]
where, \( N_g \) = number of girders, \( C_g \) = cost of precast girder per length (including prestressing and fabrication), \( C_R \) = cost of concrete in deck and diaphragms, \( V_d \) = volume of concrete in deck and diaphragms, and \( W_R \) = weight of conventional reinforcements.

The target of the design optimization process is to assign values to the design variables in order to minimize the objective function within the constraints limits. The design variables considered in this proposed method are: (1) the deck slab thickness, (2) the girder spacing (in other words, the number of girders), (3) amount of prestressing steel (strands), (4) amount of non-prestressing steel (reinforcement), (5) number of diaphragms, (6) size of diaphragm (width and depth), and (7) overhang length (distance from edge of deck to the centerline of exterior girder).

Two types of constraints have been considered:
- Deterministic constraints: which represents the design limitations as specified by the AASHTO LRFD (sixth edition, 2012) code requirements.
- Probabilistic (reliability-based) constraints: which control the individual components reliability indices and the overall system reliability index to be higher than or equal to a specified target reliability indices.

As per the calibration of the AASHTO LRFD specification (sixth edition, 2012), the target reliability of serviceability limit state \( \beta_s = 1.0 \), for fatigue \( \beta_f = 1.0-2.0 \), and for ultimate bending and shear \( \beta = 3.5 \) (Fu, 2013). While for the overall system reliability, Nowak and Szerszen (2000) suggested a value of \( \beta = 3.5 \).

4. SIMULATION-BASED OPTIMIZATION

Simulation is a powerful tool that can be utilized to mimic the performance of real-world systems over time (Law and McComas, 2002). Simulation can obtain the output of a system based on the variations in the input to a system (Fu et al, 2005). In order to obtain optimal or most favourable results using simulation, it would be required to performing large number of replications of trials to investigate different alternatives or solutions (Mawlana and Hammad, 2013). Simulation-based optimization is the process of utilizing a heuristic (or metaheuristic) approach to
guide the simulation analysis without the need to perform an exhaustive analysis of all the feasible combinations of input variables (Carson and Maria, 1997).

![Flowchart of the proposed simulation-based design optimization model](image)

**Figure 1**: Flowchart of the proposed simulation-based design optimization model

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In this paper, a computer-aided model is proposed to interactively link the reliability analysis of prestressed girder bridges to an optimization engine. The OptQuest (the world’s most efficient engine) optimizer is utilized in this proposed model. The optimization technique consists of metaheuristic scatter search assisted by neural network accelerator. The Monte Carlo Simulation MCS has been applied as a simulation technique. The flowchart shown in Figure 1 illustrates the proposed simulation-based optimization model.

4.1. scatter search

Scatter search aims at obtaining a best-case solution for a problem that contains a set of variables (Glover and Laguna, 1997). Let:

- \( Z \) = set of variables that are bounded with upper and lower limits,
- \( L \) = set of lower bounds corresponding to the vector of variables, and
- \( U \) = set of upper bounds corresponding to the vector of variables \( Z \).

\[
\begin{align*}
[l_i, u_i] & \leq z_i \leq u_i \\
z_i &= \frac{u_i - l_i}{2} + l_i \quad \text{for } i = 1, 2, \ldots, n, \quad z_i \in Z.
\end{align*}
\]

If the elements of the population are considerably different from each another, then that population is considered divers. The optimizer uses a Euclidean distance measure to determine how “close” a potential new point is from the points already in the population, in order to decide whether the point is considered or discarded (Laguna, 1997). Scatter search imposes linear constraints on every new solution \( Z \). This allows testing the feasibility of the newly generated population prior to calculating the objective function. The linear constraints can be expressed as follows:

\[
AZ \leq B
\]

For each point, the feasibility test will examine whether the linear constraints considered by the user are satisfied. An infeasible point \( Z \) is made feasible by formulating and solving a linear programming (LP) problem (Laguna, 1997). The LP aims of discover a feasible \( Z^* \) that minimizes the absolute deviation between \( Z \) and \( Z^* \). This can be formulated as follows:

\[
\begin{align*}
\text{Minimize } & d^- + d^+ \\
\text{Subject to } & AZ^* \leq B \\
& Z - Z^* + d^- + d^+ = 0 \\
& L \leq Z^* \leq U
\end{align*}
\]

where \( d^- \) and \( d^+ \) are negative and positive deviations from the feasible point \( Z^* \) to the infeasible reference point \( Z \). When constraints are not specified, infeasible points are made feasible by simply adjusting variable values to their closest bound. That is,

\[
\begin{align*}
\text{If } z_i > u_i, \quad & z^*_i = u_i \quad \text{for } i = 1, \ldots, n. \\
\text{If } z_i < l_i, \quad & z^*_i = l_i \quad \text{for } i = 1, \ldots, n.
\end{align*}
\]

The scatter search will apply iteration process to select improved results. At every iteration, two reference points are chosen to generate four offspring (Glover and Laguna, 1997). Let the parent-reference points be \( Z_1 \) and \( Z_2 \), then the offspring \( Z_3 \) to \( Z_6 \) are generated as follows:

\[
Z_3 = Z_1 + d
\]
\[ Z_4 = Z_1 - d \]
\[ Z_5 = Z_2 + d \]
\[ Z_6 = Z_2 - d \]

where,

\[ d = (Z_1 - Z_2) / 3 \]

The selection of the parent-reference points \( Z_1 \) and \( Z_2 \) is biased by the evaluation of the objective function \( f(Z_1) \) and \( f(Z_2) \) as well as the previous search results.

4.2. neural network accelerator

In order to increase the efficiency and speed of the scatter search process, a neural network is embedded into the optimizer. The neural network role is to “screen out” reference points that are likely to have inferior objective function values as compared to the best known objective function value (Glover and Laguna, 1997). In other words, the neural network is used as a filter model embedded into the optimization system. Such filter will avoid estimating \( f(Z) \) value (corresponding to a newly generated reference point \( Z \)), in cases of low quality results. Form successive iterations, the values of reference points \( Z \) and objective functions \( f(Z) \) are collected. During the search process, the collected data points are then used to train the neural network. The system automatically determines how many data points to collect and how much training is done (Glover and Laguna, 1997).

5. CASE STUDY

The following example demonstrates the applicability of the proposed model where a simple span bridge of 98.5 ft length and 26.5 ft width is considered as shown in Figure 2. The barrier width equals 15.0 in and the thickness of the asphalt surface layer is 3.0 in. The proposed model will, first, perform deterministic analysis and design according to AASHTO LRFD (sixth edition, 2012) to decide about the bridge configuration and also to obtain the nominal values of the basic design variables. Then the probabilistic simulation-based optimization is generated to obtain the optimum solution that minimizes the bridge cost and guarantees the safety levels with respect to every possible mode of failure. The simulation-optimization model was set to conduct 100,000 simulation samples with 100 solutions per sample. Different types of standard precast girders were investigated as shown in Table 1. Concrete compressive strength for the deck and girder is 6 ksi and 8 ksi, respectively.

![Figure 2: the cross section of the bridge considered.](image)

The values of the design variables before and after optimization process are shown in Table 2. The value of the unit cost of the bridge superstructure (objective function), before and after the optimization process, with respect to each girder type, is illustrated in Table 3. The safety levels reserved in the bridge structural configuration, before and after optimization, are expressed in terms of the reliability indices as shown in Table 4. All of these reliability indices are higher than the specified reliability targets which means that the optimization process conducted by the proposed model succeeded to provide economical solutions with assured structural safety.
Table 1: Type and dimensions of girders considered

<table>
<thead>
<tr>
<th>Dimension</th>
<th>AASHTO IV</th>
<th>W54BTG</th>
<th>CPCI 1400</th>
</tr>
</thead>
<tbody>
<tr>
<td>x1</td>
<td>26</td>
<td>26.00</td>
<td>25.60</td>
</tr>
<tr>
<td>x2</td>
<td>20</td>
<td>42.00</td>
<td>21.65</td>
</tr>
<tr>
<td>x3</td>
<td>8.00</td>
<td>6.00</td>
<td>5.91</td>
</tr>
<tr>
<td>x4</td>
<td>0.00</td>
<td>2.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Y1</td>
<td>8.00</td>
<td>6.00</td>
<td>7.09</td>
</tr>
<tr>
<td>Y2</td>
<td>9.00</td>
<td>4.50</td>
<td>5.91</td>
</tr>
<tr>
<td>Y3</td>
<td>23.00</td>
<td>36.00</td>
<td>33.07</td>
</tr>
<tr>
<td>Y4</td>
<td>0.00</td>
<td>2.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Y5</td>
<td>6.00</td>
<td>2.00</td>
<td>3.15</td>
</tr>
<tr>
<td>Y6</td>
<td>8.00</td>
<td>3.50</td>
<td>5.91</td>
</tr>
</tbody>
</table>

Table 2: Values of decision variables before and after optimization process

<table>
<thead>
<tr>
<th>Decision Variables</th>
<th>AASHTO IV</th>
<th>W54BTG</th>
<th>CPCI 1400</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pre-opt.*</td>
<td>Post-opt.**</td>
<td>Pre-opt.</td>
</tr>
<tr>
<td>Deck thickness, in</td>
<td>6.90</td>
<td>8.30</td>
<td>6.90</td>
</tr>
<tr>
<td>Girder spacing, ft</td>
<td>3.33</td>
<td>4.27</td>
<td>3.33</td>
</tr>
<tr>
<td>Number of girders</td>
<td>8</td>
<td>6</td>
<td>8</td>
</tr>
<tr>
<td>Number of strands</td>
<td>34</td>
<td>37</td>
<td>31</td>
</tr>
<tr>
<td>Number of internal diaphragms</td>
<td>2</td>
<td>1</td>
<td>2</td>
</tr>
<tr>
<td>Width of diaphragm, in</td>
<td>12</td>
<td>10</td>
<td>12</td>
</tr>
<tr>
<td>Depth of diaphragm, in</td>
<td>46</td>
<td>44</td>
<td>48</td>
</tr>
<tr>
<td>Area of non-prestress steel in deck, in2/ft</td>
<td>2.80</td>
<td>3.43</td>
<td>2.80</td>
</tr>
<tr>
<td>Overhang length, ft</td>
<td>1.33</td>
<td>1.7</td>
<td>1.33</td>
</tr>
</tbody>
</table>

* Pre-opt. = before optimization, ** Post-opt. = after optimization.

Table 3: Bridge unit cost before and after optimization process

<table>
<thead>
<tr>
<th>Girder Type</th>
<th>Unit cost - $/Sq.ft.</th>
<th>Cost saving</th>
</tr>
</thead>
<tbody>
<tr>
<td>AASHTO IV</td>
<td>165</td>
<td>125</td>
</tr>
<tr>
<td>CPCI 1400</td>
<td>162</td>
<td>122</td>
</tr>
<tr>
<td>W54 BTG</td>
<td>155</td>
<td>118</td>
</tr>
</tbody>
</table>

In order to determine the overall system reliability, the Improved Reliability Bounds IRB method is utilized which requires failure mode analysis to be conducted first. Two possible modes of failure (mechanism) exist. The first mode of failure MF1 occurs when a prestressed girder fails in flexure followed by a flexural failure of the deck slab. The second possible mode of failure MF2 results from girder failure followed by a flexural failure in the intermediate diaphragm. Table 5 illustrates the results of IRB calculated for the optimized bridge configuration with AASHTO IV girders.
Table 4: Reliability indices (safety levels) of the before and after optimization

<table>
<thead>
<tr>
<th>Phase</th>
<th>Reliability index type and location</th>
<th>AASHTO IV</th>
<th>CPCI 1400</th>
<th>W54 BTG</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Pre-opt</td>
<td>Post-opt</td>
<td>Pre-opt</td>
</tr>
<tr>
<td>Top fiber (at transfer)</td>
<td>stress at end section</td>
<td>6.24</td>
<td>5.37</td>
<td>5.96</td>
</tr>
<tr>
<td></td>
<td>stress at transfer length section</td>
<td>6.20</td>
<td>6.04</td>
<td>5.67</td>
</tr>
<tr>
<td></td>
<td>stress at harp point section</td>
<td>4.20</td>
<td>3.89</td>
<td>4.53</td>
</tr>
<tr>
<td></td>
<td>stress at midspan section</td>
<td>4.82</td>
<td>4.37</td>
<td>5.15</td>
</tr>
<tr>
<td>Initial phase (after losses)</td>
<td>stress at end section</td>
<td>2.95</td>
<td>2.70</td>
<td>3.13</td>
</tr>
<tr>
<td></td>
<td>stress at transfer length section</td>
<td>3.11</td>
<td>2.86</td>
<td>3.20</td>
</tr>
<tr>
<td></td>
<td>stress at harp point section</td>
<td>2.84</td>
<td>2.67</td>
<td>2.64</td>
</tr>
<tr>
<td></td>
<td>stress at midspan section</td>
<td>3.02</td>
<td>2.98</td>
<td>2.65</td>
</tr>
<tr>
<td>Top fiber of deck at midspan</td>
<td>section</td>
<td>4.56</td>
<td>4.44</td>
<td>4.58</td>
</tr>
<tr>
<td>Top fiber of girder at midspan</td>
<td>section</td>
<td>4.16</td>
<td>3.99</td>
<td>4.27</td>
</tr>
<tr>
<td>Bottom fiber of girder at midspan</td>
<td>section</td>
<td>3.56</td>
<td>2.52</td>
<td>3.30</td>
</tr>
<tr>
<td>Cracking limit state</td>
<td></td>
<td>3.35</td>
<td>3.45</td>
<td>3.13</td>
</tr>
<tr>
<td>Fatigue at midspan section</td>
<td></td>
<td>5.02</td>
<td>4.66</td>
<td>5.14</td>
</tr>
<tr>
<td>Ultimate bending moment at midspan section</td>
<td></td>
<td>4.11</td>
<td>3.51</td>
<td>3.94</td>
</tr>
<tr>
<td>Ultimate shear at midspan section</td>
<td></td>
<td>4.87</td>
<td>4.76</td>
<td>4.56</td>
</tr>
</tbody>
</table>

Table 5: Results of reliability analysis of system modes of failure (for the bridge with AASHTO IV girders).

<table>
<thead>
<tr>
<th>Failure mode #</th>
<th>Description</th>
<th>Individual mode failure probability $P_f$ (Reliability index $\beta$)</th>
<th>System’s $P_f$ and $\beta_{zyz}$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Girder failure followed by deck failure</td>
<td>$2.24E-04$ (3.51)</td>
<td>$1.20E-05$ 4.224</td>
</tr>
<tr>
<td></td>
<td></td>
<td>$1.506E-05$ (4.17)</td>
<td>$1.24E-05$ 4.216</td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Lower Bound</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td><strong>Upper Bound</strong></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Girder failure followed by internal</td>
<td>$2.24E-04$ (3.51)</td>
<td>$3.00E-6$ 4.526</td>
</tr>
<tr>
<td></td>
<td>diaphragm failure</td>
<td>$5.66E-06$ (4.39)</td>
<td>$3.40E-06$ 4.500</td>
</tr>
</tbody>
</table>

6. CONCLUSIONS

A new methodology for the design optimization of prestressed girder bridges was presented in this paper. A computer-aided model was developed to perform a simulation-based optimization applied to the design of this type of bridges. The proposed model performs a comprehensive reliability analysis, with respect to every limit state function, to assure maintaining satisfactory safety levels of the optimized structure. The simulation engine utilizes the Monte Carlo analysis, while the optimization engine performs metaheuristic scatter search assisted with neural
network accelerator. A case study was conducted to investigate the applicability of the proposed model. Different types of standard precast prestressed girders were considered. A cost saving of around 24% was successfully achieved with satisfactory safety levels reserved in the final optimized structure.

REFERENCES


Nowak, A.S. and Szersen, M.M. (2000), Reliability-Based Calibration for Structural Concrete, Phase 3, PCA R&D Seial No. 2849
