

OPTIMAL OPERATORS OF GENETIC ALGORITHM IN OPTIMIZING SEGMENTAL PRECAST CONCRETE BRIDGES SUPERSTRUCTURE

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ABSTRACT

Bridges constitute an expensive segment of construction projects; the optimization of their designs will affect their high cost. Segmental precast concrete bridges are one of the most commonly serviced bridges built for mid and long spans. Genetic algorithm is one of the most widely applied meta-heuristic algorithms due to its ability in optimizing cost. Next to providing cost optimization of these bridge types, the effects of each one of the main three selections, crossover and mutation operators are assessed, and the best operator is determined through the Taguchi experimental design. To validate the functionality of this algorithm, a bridge constructed in the city of Isfahan, Iran (completed in 2017) is optimized, a total of 13% reduction in cost and weight of its superstructure is evident. The efficiency of applying the Taguchi method in determining the type of operators of the genetic algorithm is proved.

Keywords: segmental concrete bridge; optimization; genetic algorithm; Taguchi method

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1. INTRODUCTION

During past decades, optimization methods have been and are being applied to solve large scale and complex structural problems [1, 2]. Due to their high durability and economically advantageous features, pre-stressed concrete bridges, especially those with post-tensioning box girder, are of promising practical applications [3]. Cantilever construction is a common

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procedure applied in pre-stressed concrete bridges [4, 5]. The history of the optimization of pre-stressed concrete bridges goes back to the '60s when Torres et al. [6] made an attempt to minimize bridge construction cost through linear programming. In most of the studies run on the optimization of concrete bridges in the 1960s and 1970s the mathematical methods like linear programming [6, 7], generalized geometric programming and the steepest gradient method [8] prevailed. In recent decades, the meta-heuristic optimization methods like a genetic algorithm (GA), neural networks, particle swarm, and ant colony optimizations have been and are of major concern. Metaheuristic methods are known as efficient tools in solving complicated structural optimization problems [9-12].

In optimization of pre-stressed concrete bridges the GA due to its high capabilities in solving problems with a combination of continuous and discrete variables and nonlinear constraints prevail. The assessments run by [13, 14] on the optimization of pre-stressed concrete bridges and [15] on the optimization of pre-stressed concrete beams are the examples in this context.

There exist many studies on optimization with GA to determine the appropriate operators for each optimization problem. Selection, crossover, and mutation operators are the three main operators of the GA [16-18]. A comparative study of varying operators of the crossover and suggestions for selecting each of them is presented by Eshelman et al. [19]. The one, two, three, and four-point crossover operators in the GA are compared in [20]. A study of the effect of different behavior of crossover operators is run by [21, 22] who found that the combination of crossover operators would improve the results. The assessment run by Picek and Golub [23] on a great number of crossover operators in the GA, found a better performance of uniform and two-point crossover operators. Kazemzadeh Azad and Jayant Kulkarni [24] assessed the sizing and layout optimization of spatial truss structures through a mutation-based GA. They applied the Gaussian mutation operator to devise reproduction operators and the tournament selection mechanism in combination with Gaussian mutation operators for effective search in the design space. They applied the standard deviation (SD) as a criterion in matching mutation operators. A comparative study is run by Cazacu [25] on the performance of three modified classical mutation operators of GA in structural optimization, where the uniform, polynomial, and Gaussian mutation operators are compared to determine their accuracy, reliability, and efficiency. He deduced that all three operators have acceptable performance, but in terms of accuracy, the polynomial mutation and terms of reliability, the uniform mutations perform better. Pulivarti and Birru [26] assessed the influence of process parameters like fineness number, water, fly ash, molasses, bentonite and then the degree of ramming on the results of sand mould properties and optimized them through Taguchi method. They revealed that first, the water content next, the bentonite and degree of ramming constitute the most important parameters affecting the quality characteristics of sand mould properties. A new crossover operator for GA optimization is presented by Hussain et al. [27] where, the GA tool is applied in MATLAB software, and it is found that the convergence rate of their proposed crossover operator is higher than other conventional operators in optimizing the benchmark functions performs better. Castelli et al. [28] developed the definition of crossover distance between populations for n-points crossover. They found that the average distance between a population and the optimum reduces with an increase in the number of crossover points.

There exists no study run on assessing the performance of a variety of genetic operators

in the optimization of segmental precast concrete bridges. Here, for the first time, while presenting an optimal design of these bridges by applying GA and comparing it with the real design [29] of the subject bridge of this study, appropriate genetic operators are evaluated through the Taguchi method.

2. OPTIMIZATION ALGORITHM

In addition to the direct mathematical methods, there exist a great number of other methods for optimization problems categorized as approximation, probabilistic, and meta-heuristic algorithms. The focus of meta-heuristics is on the combination of a heuristic concept with a mathematical planning method. Here, the GA is applied for optimization purposes. GA begins with the introduction of several initial solutions, which are first randomly selected within defined scopes of design variables and next, sorted according to their fitness. The fitness of each solution is determined by the proximity to the optimal solution. In GA, the fittest solutions have more chance to become combined and reproduced. By applying the crossover and mutation operators, the initial solutions are improved to produce new solutions with greater fitness, thus, reduced cost and weight of the superstructure. These new solutions replace older improper solutions. The above process is repeated until the stop criterion (the convergence or the count of iterations) is met [30]. The related flowchart is drawn in Fig. 1.

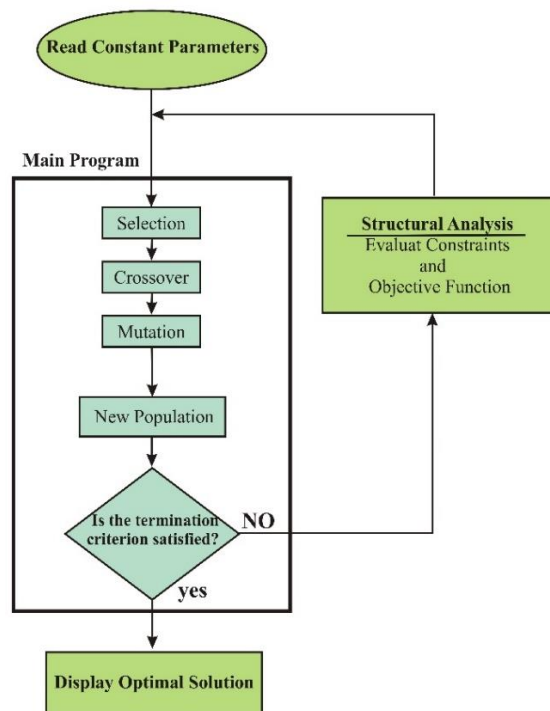


Figure 1. GA flowchart

2.1 Genetic operators

In GAs, during the reproductive stage, the following genetic operators are applied each with an impact a population, the next generation of that population is produced: (1) Reproduction operator, the selection; (2) Mating operator, the crossover; and (3) Mutation operator.

2.1.1 Selection

Based on the survival of the best theory, the best should be selected to generate a better next generation. For this reason, this operator is named the selection. This operator selects several chromosomes from a population for the reproduction of the following methods:

(i) Random: Random selection is the simplest method of selection, where each answer has the same probability of choice, and fitness does not have an effect on selection

(ii) Tournament: In a competitive sense, a subset of the solutions of a community is selected, where the members compete, and only one answer from each subgroup is selected for reproduction.

(iii) Roulette wheel: Here, the criterion of the parents to be selected is their fitness. Better chromosomes have a higher possibility to be selected as parents. Each potential parent is assigned a slice of the circular Roulette wheel, proportional in size to its fitness, that is, the higher the value, the larger the size of the slice.

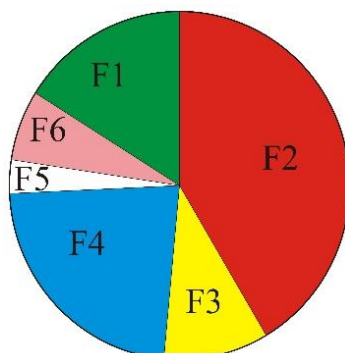


Figure 2. Roulette wheel method

2.1.2 Crossover

The most important operator in the GA is the crossover operator, consisting of a process where the old generations of the chromosomes are combined to generate a new generation. The couples considered at the selection stage as the parent, exchange their genes, and generate new members. The crossover in the GA leads to the loss of genetic diversity or dispersion by allowing each parent to find good genes. This operator consists of three steps: (1) Selecting two strings randomly; (2) Selecting the location for random action; and (3) Replacing, the volume of the two strings.

Among the many types of crossover, here the following three methods are applied:

(i) Single point crossover: for this purpose, one point is selected randomly, the values of which are expressed in Fig. 3.

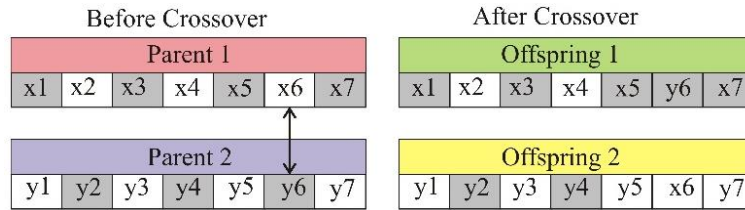


Figure 3. Single point crossover

(ii) Double point crossover: for this purpose, two points are selected randomly, the values of which are expressed in Fig.4.

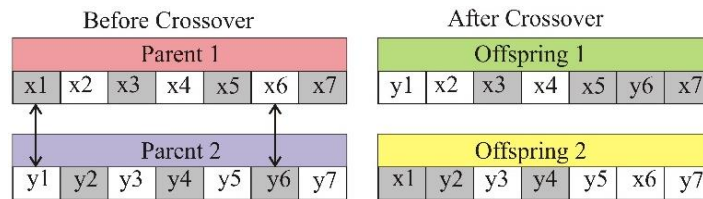


Figure 4. Double point crossover

(iii) Uniform crossover: for this purpose, the data of the first and the second parent chromosomes are copied randomly, Fig.5.

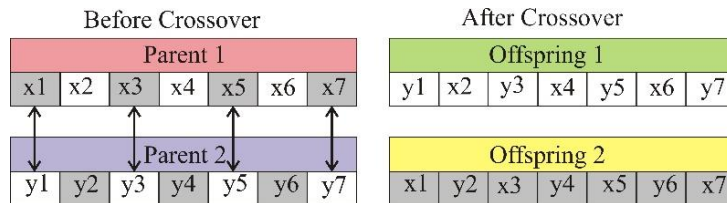


Figure 5. Uniform crossover

2.1.3 Mutation

The mutation is a phenomenon in genetic science that rarely occurs in some chromosomes where the children are endowed with characteristics that are not owned by any of their parents. The contribution of the mutation in the GA is to restore the genetic material lost or not found in the given population, to avoid early convergence of the algorithm to local optimal solutions. In the binary mutations, some genes are randomly selected and converted into zero and one and vice versa. One of the mutation methods is when a number lower than one, named the probability of mutation, a random number is recalled for each gene in a population, and if this random number is less than the probability of mutation, gene mutation occurs, a rare phenomenon in nature. If the characters are continuous numbers, the mutation in the form of positive or negative random variations around the preceding character, Fig. 6.

The main types of mutation operators applied in this study consist of:

(1) in a fixed rate mutation, a certain percentage of chromosomes are mutated, and the count of mutation in each chromosome has a constant value of 10% of the difference between the upper and lower bounds

(2) reduced controlled mutation where the mutation rate decreases with an increase in the count of iterations

(3) in a standard mutation, a certain percentage of chromosomes are selected in the first stage, and then among them, random chromosomes are selected

In general, the contribution of genetic operators in optimization algorithms is to modify their exploitation and exploration capabilities. Some of these operators, like random selection and mutation, enhance the ability to explore the search space, while others, like the crossover, increase exploitation.

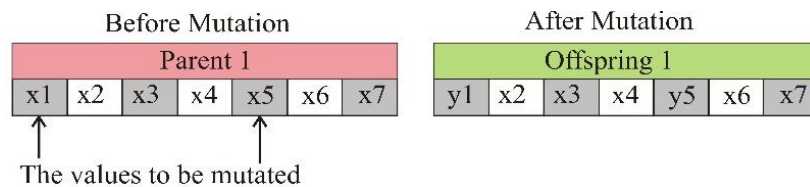


Figure 6. Mutation

2.2 Taguchi method

The Taguchi method (TM) is a robust method where some consistent ideas from statistical experimental design are applied to estimate and improve products, equipment, and processes. The main objective here is to improve product quality by minimizing the effect of diversion causation without eliminating them. The two main tools applied in the Taguchi method consist of the signal-to-noise ratio, to measure the quality and the orthogonal arrays (OA) to check the design parameters' similarities [31] and [32]. The Taguchi design is applied to obtain information like the main effects and interactions among design parameters through the least experiments.

The design (a controllable factor) and noise (an uncontrollable factor) characterize the behavior of a product or process [33]. An OA consist of a table where columns are assigned to factors or their interactions, and rows are assigned to the levels of different factors for a particular experimental trial [34]. The OA refers to the balance of combinations of factors in a sense that one factor is given more or less weight in the experiment than others. In OA effect of each factor is assessed independent of the effects of others in its mathematical sense [35].

3. FORMULATION OF OPTIMIZATION PROBLEM

3.1 Objective function

Here, this function represents the bridge superstructure construction cost. Precast concrete segments and pre-stressing steel cost are the two major components, which should be of concern, mathematically expressed as follows:

$$C_T = C_{PC} + C_{PS} \quad (1)$$

where, C_{PC} and C_{PS} are the costs of precast concrete segments and pre-stressing steel, respectively, calculated through:

$$C_{PC} = UP_{PC} \times V_{PC} \quad (2)$$

$$C_{PS} = UP_{PS} \times W_{PS} \quad (3)$$

where, UP_{PC} is the material, construction and installation cost of precast concrete segments per volume, UP_{PS} is the material and construction cost of pre-stressing steel per weight, V_{PC} is the total volume of concrete, and W_{PS} is the total weight of pre-stressing steel. UP_{PC} and UP_{PS} are estimated at 1220 (USD/m³) and 1500 (USD/ton). These values are based on the project employer's report [29] with respect to the concrete of 40 MPa (5.8 ksi) compressive strength.

The optimal design should satisfy the geometry, serviceability, ductility, and ultimate limit states requirements. To observe the available constraints, the following external penalty approach is applied:

$$C_T = C_{PC} + C_{PS} + Penalty \quad (4)$$

where, $Penalty$ is the constraint violation function expressed as:

$$Penalty = \alpha_p \sum_{i=1}^{n_g} [g_j]^q \quad (5)$$

where, α_p is a constant penalty coefficient, q is a non-negative coefficient, n_g is the count of problem constraints, and g_j is calculated through Eq. 6: where if g_j violates the constraint, it should be considered the same as the constraint; otherwise, it should be assumed zero:

$$\text{if } g_j \leq 0 \Rightarrow [g_j] = \max \{0, g_j\} \quad (6)$$

3.2 Design variables

The cross-sectional dimensions of box girder and the pre-stressing strands count are considered as the design variables in this study and tabulated in Table 1. A longitudinal section of this studied bridge is illustrated in Fig. 7. The bridge is a symmetric three-span bridge with a constant depth. A typical cross-section of the bridge deck and the design variables with the slope of the web assumed as a constant is shown in Fig. 8.

Table 1: Design variables.

No.	Variable	Symbol	Type	Constraints
1	Girder depth in pier (m)	D_0	Continuous	$2.17 \leq D_0 \leq 5.0$
2	Top slab thickness (mm)	t_t	Continuous	$180 \leq t_t \leq 500$
3	Bottom slab thickness in pier (mm)	t_{b0}	Continuous	$180 \leq t_{b0} \leq 500$
4	Bottom slab thickness in mid-span (mm)	t_b	Continuous	$180 \leq t_b \leq 500$
5	Web thickness in pier (mm)	t_{w0}	Continuous	$350 \leq t_{w0} \leq 500$
6	Web thickness in mid-span (mm)	t_w	Continuous	$350 \leq t_w \leq 500$
7	Number of strands per tendon	n	Discrete	$6 \leq n \leq 20$

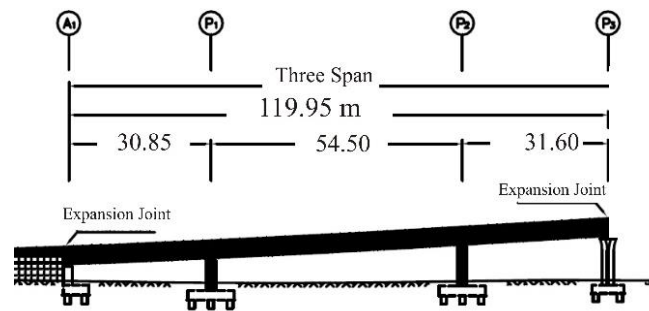


Figure 7. Longitudinal section of the studied bridge [29]

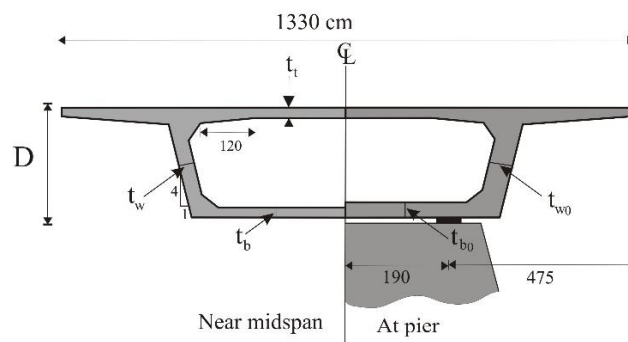


Figure 8. Typical cross-section of deck bridge

3.3 Constant parameters

These parameters consist of span length, deck width, post-tensioned anchorage system, live loads according to AASHTO (2002) [36], superimposed dead loads, and material properties, Table 2. The Class-C anchorage system and 7-wire strands with low relaxation having 12.7 mm (0.5 in) diameter constitute the post-tensioning tendons.

Table 2: Constant design parameters [29]

Constant parameter	Values
Span length (L)	31,55,31 (m)
Deck width (W)	13.3 (m)
The tensile strength of pre-stressing steel (f_{pu})	1890 (MPa)
The yield strength of pre-stressing steel (f_y)	$0.9 f_{pu}$
The yield strength of reinforcement steel (f_y)	400 (MPa)
Unit weight of concrete	$2.5 \text{ (kN/m}^3\text{)}$
Unit weight of Steel	$78.5 \text{ (kN/m}^3\text{)}$
Modulus of elasticity of concrete	$4700\sqrt{f'_c}$
Modulus of elasticity of pre-stressing steel	$1.93 \times 10^5 \text{ (MPa)}$
Modulus of elasticity of reinforcement steel	$2 \times 10^5 \text{ (MPa)}$
Live loads	HS20-44 (Truck and lane load)
Design traffic lane width	3.65 (m)
Barrier load	5 (kN/m)
The thickness of asphalt wearing surface	70 (mm)

In this study, the concrete compressive strength is held constant, equal to 40 MPa (5.8 ksi). The AASHTO HS20-44 (2002) [36] live load, including truckload and distributed uniform load is applied on three lanes. The impact factor applied to the live load is calculated as follows:

$$\text{Impact Factor} = 1.3 - 0.005 L \quad (7)$$

where, L is the span length (m)

Although the pre-stressing strands' count varies, their grouping and layouts are considered similar to that of [37-40]:

Group 1: 13 tendons installed in each flange for the cantilever construction make the total.

Group 2: 4 tendons in each web and two tendons in the top slab constitute the total continuity tendons in tail spans.

Group 3: the total continuity tendons in the center span is 20, installed as 18 tendons in the bottom and two tendons in the top slabs

The longitudinal layout and section of these three group tendons are shown in Figs.9-11.

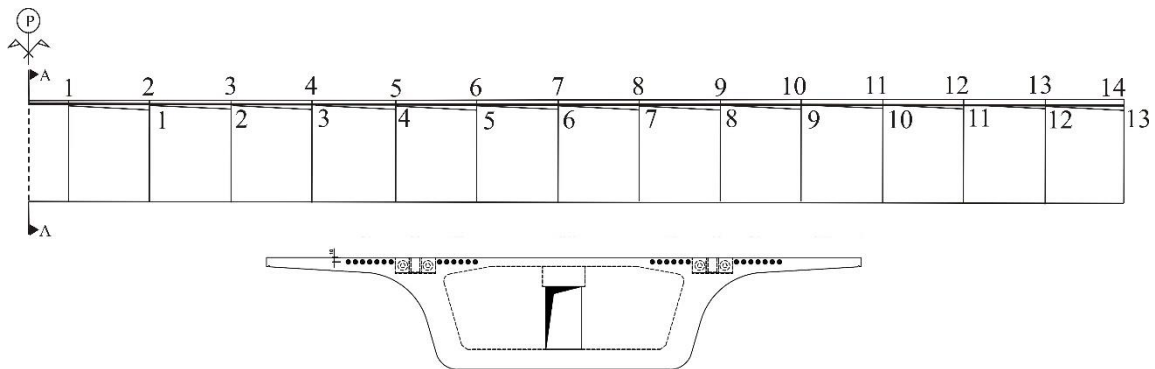


Figure 9. Group1: Cantilever tendon layout

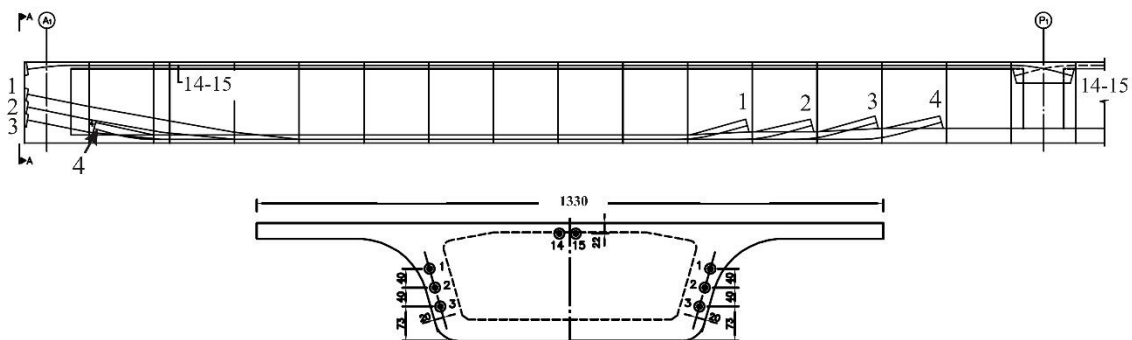


Figure 10. Group2: Tail span continuity tendons

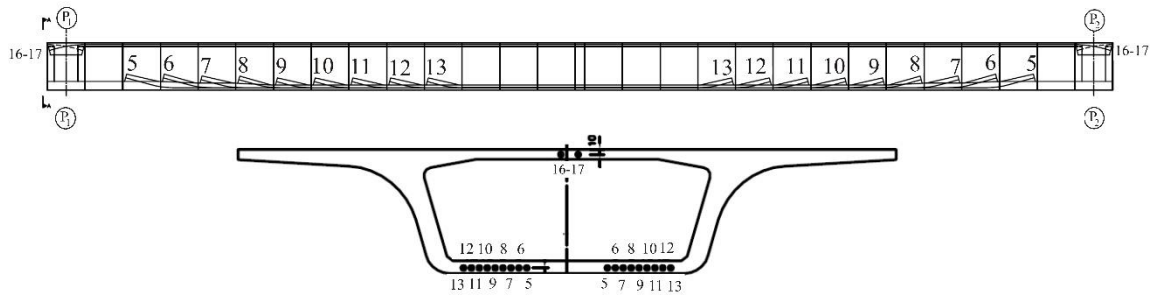


Figure 11. Group3: Center span continuity tendons

3.4 Design constraints

The design constraints like the allowable compressive and tensile stress in all segment installation, completion, operational phases, deflection, and geometrical constraints are based on AASHTO (2002) standard specifications [36].

3.4.1 Allowable stress constraints

These constraints are imposed at the top, and the bottom fibers of the segments in different construction phases expressed as:

$$-0.4f'_c \leq f \leq 0.5\sqrt{f'_c} \quad (8)$$

where f is the stress at any point of the section, and f'_c is the concrete compressive strength (MPa).

Stresses are calculated and controlled in each one of the following five phases:

Phase 1. Cantilever installation of the segments and applying the group1 post-tensioning.

Phase 2. Completion of tail spans by post-tensioning of tendons group 2

Phase 3. Completion of center span, where, the key segment is constructed by applying cast-in-place concrete thus, the left and right-sides of cantilever segments of the center span are connected to each other and, afterwards, 3a and 3b post-tensioning tendons are installed, by which the span construction is completed.

Phase 4. Superimposed dead loads: after post-tensioning of all pre-stressing tendons, like the asphalt and railing loads

Phase 5. Applying live load

The eight critical sections of the mid-bridge and numbering of the sections with respect to the order of the balanced cantilever installation of segments are shown in Fig. 12.

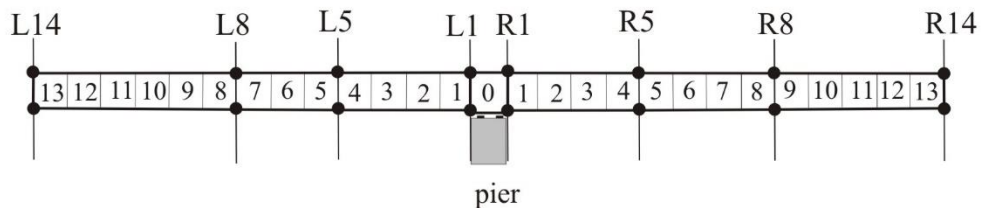


Figure 12. Group3: Center span continuity tendons

The segments are numbered according to the count of the joints between the segments and orientation of each segment with respect to segment zero. As to the symmetric configuration of the bridge and applied loadings, the stresses defined in previous phases are calculated in different sections. In each phase, 32 allowable tensile and compressive strength constraints, that is, 160 constraints constitute the five phases.

3.4.2 Ultimate flexural strength constraints

These constraints, are determined in different sections based on ultimate strength design method:

$$M_u \leq \phi M_n \quad (9)$$

where, M_u is the available bending moment, M_n is the nominal flexural strength of the section, and ϕ is the strength reduction factor equal to 0.9, according to AASHTO (2002).

3.4.3 Ductility constraints

The minimum flexural pre-stressing steel in the critical cross sections are determined through the following equation:

$$1.2M_{cr} \leq \phi M_n \quad (10)$$

where, M_{cr} and ϕM_n are the cracking and ultimate bending moments, respectively.

This design is carried subject to the under-reinforced conditions to provide ductile failure, where, according to AASHTO provisions reinforcing index should not exceed 0.36β . The maximum pre-stressing steel in different sections is defined as:

$$\omega \leq 0.36\beta_1 \quad (11)$$

where, ω is the reinforcing index, and β_1 is the concrete compressive strength factor in case of compressive strength at 40 MPa (5.8 ksi) is 0.75, according to AASHTO (2002).

3.4.4 Serviceability constraints

According to AASHTO (2002), the deflection due to live load shall not exceed 1/800 span length (L), and is calculated by considering the maximum bending moment at the midpoint of the center span subject to live load, expressed as:

$$\Delta \leq \frac{L}{800} \quad (12)$$

where, Δ is the deflection at mid-span and L is the center span length.

3.4.5 Shear constraints

Shear forces should be limited by the allowable shear as follows:

$$V_u \leq \phi V_n \quad (13)$$

where, V_u is the ultimate shear force, ϕ is the shear strength reduction factor equal to 0.9, according to AASHTO (2002), and V_n is the nominal shear strength of the cross-section. The nominal shear strength is the sum of the shear strength of concrete (V_c) and the transversal steels (V_s). If any lack of shear strength is observed in a section, the transversal reinforcement is applied, and the shear constraints based on maximum allowable transverse reinforcement would be expressed as:

$$V_s = \frac{V_u}{\phi} - V_c \leq 0.67\sqrt{f'_c}bd \quad (14)$$

$$V_c = \min\{V_{ci}, V_{cw}\} \quad (15)$$

where, b is the total width of the webs, d is the distance from the outermost compressive zone of the section to the steel centroid, V_{ci} and V_{cw} are the nominal shear strengths of the concrete based on the bending-shear cracking and shear cracking of the pre-stressed beam section, respectively.

3.4.6 Geometry constraints

According to the AASHTO (2002) provisions [36], the minimum top flange thickness should be 1/30 of the clear distance between fillets or webs but not less than 150 mm (6"). This constraint is applicable for the bottom flange, given the difference where the minimum allowable thickness is 140 mm (5.5"). By considering these specifications, the top flange thickness is considered constant, equal to 250 mm (9.8 in), while the bottom flange thickness varies along the span with a minimum value of 180 mm (7.1 in).

There exists no limitation on the depth of the box girder specified in AASHTO (2002) standard. A single cell box would preferably be practical when depth to width ratio $\geq 1/6$, according to AASHTO LRFD (2012) specifications [41]. The minimum depth of the girder section is 2220 mm (85.4 in) that is 1/6 of the top flange width.

4. RESULTS AND DISCUSSION

4.1 Optimization results

After formulating the bridge analysis based on design variables, it is verified through manual calculations for a practical example designed by conventional design procedure. The study bridge is the first piece of the Esteglal Bridge system, which has three continuous openings. These values of the parameters, Table 1 are considered as the variables and the other

parameters are held constant and equal to the design values Table 1. GA is coded in MATLAB and added to the analysis and design codes. The optimization algorithm is run independently for three times.

Initial optimizations are run with different types of operators, which lead to different results. The difference in the results indicates the necessity of determining the optimal combination of the genetic operators; for this purpose, the Taguchi method is adopted to determine the best type of the genetic operators in an optimization algorithm for segmental precast concrete bridges. For each one of the operators, three different types are of concern. The selection operator (A) is divided into three: random(A1), tournament(A2) and Roulette wheel(A3) methods; the crossover operator(B) is divided into three single-point(B1), double-point (B2)and uniform(B3) methods, and the mutation operator(C) is divided into three: fixed rate mutation (C1), controlled mutation (C2) and standard mutation(C3) methods. Here, the OA of L9 is selected through the Taguchi method in Minitab software environment, the outcome of which is shown in Fig. 13.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
	A	B	C				SNRA1	LSTD1	STDE1	MEAN1	CV1
1	1	1	1	161335	151205	168333	104.073	9.06086	8611.6	160291	0.053725
2	1	2	2	145133	129973	129973	102.574	9.07711	8752.6	135026	0.064822
3	1	3	3	157154	166805	162643	104.193	8.48481	4840.7	162201	0.029844
4	2	1	2	126309	147725	158115	103.054	9.69390	16218.4	144050	0.112589
5	2	2	3	163111	157665	154808	103.996	8.34717	4218.2	158528	0.026609
6	2	3	1	166805	168333	167027	104.474	6.71611	825.6	167388	0.004932
7	3	1	3	166805	164191	167027	104.402	7.36340	1577.2	166008	0.009501
8	3	2	1	169640	168112	168333	104.542	6.71638	825.8	168695	0.004895
9	3	3	2	127605	126309	131305	102.168	7.86042	2592.6	128406	0.020191

Figure 13. Data fed in OAs arrays in the Taguchi method

The optimization of each one of the operator's combinations in this figure is run three times, and the cost saving is considered as a qualitative indicator. Taguchi devised the S/N (signal to noise) ratio to quantify the present variation. The term *signal* is the desirable value (mean), and the term *noise* is the undesirable value, the SD. There exist several S/N ratios depending on the types of characteristics: the lower, the better, the nominal the best, and the higher, the better. Since the nature of the objective function is to maximize cost saving, the higher, the better criterion is selected, expressed as [31]:

$$S / N = -10 \log \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{y_i^2} \right) \quad (16)$$

where, y_i is the response for the given factor level combination and n is the count of the responses in the factor level combination.

The columns C1 to C3 in Fig. 13 represent the count of the genetic operator combinations type, and columns C4 to C6 represent the cost savings of the superstructure resulting from three runs of the optimization in comparison with the actual design in U.S dollars. Column C7 represents the S/N ratios; Column C8 represents the SD logarithm; column C9 represents the SD (standard deviations); column C10 represents the means of saving values, and column C11 represent the coefficient of variation generated by the Taguchi method calculated through Minitab software.

The convergence diagrams for the nine combinations are shown in Fig.14, where, the efficiency of the algorithm varies subject to different combinations of genetic operators. The general overview of these diagrams indicates that the algorithm in $A_1B_2C_2$, $A_2B_1C_2$ and $A_3B_3C_2$ states quickly stops at one of the optimal local points and does not achieve global optimal points, indicating the weakness of type 2 mutation operator (controlled). Due to the differences in the combinations of genetic operators function, it is necessary to determine the optimal combination of operators.

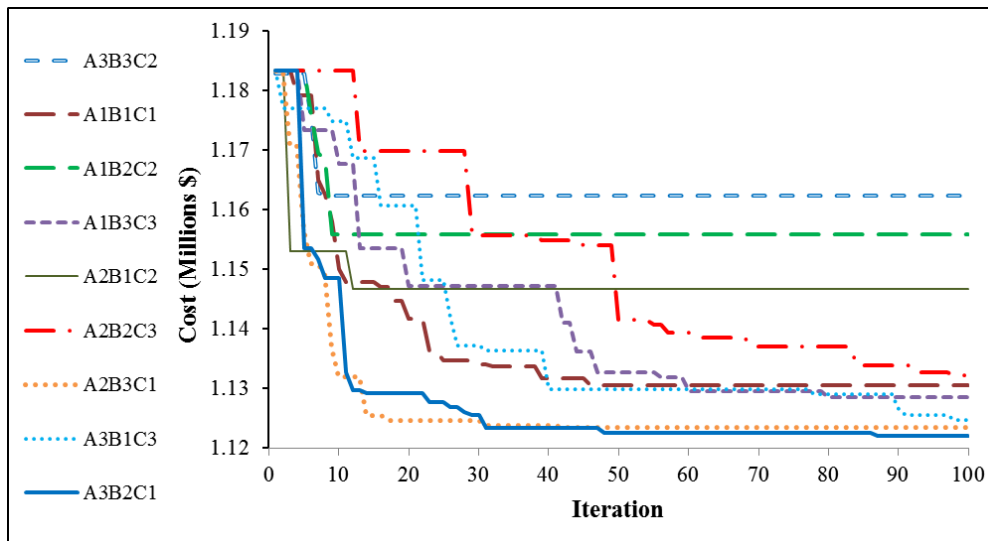


Figure 14. Convergence diagrams for different combinations of genetic operators

After feeding the data to the software and running the calculations of the Taguchi method to maximize the objective function, the saving cost of the superstructure is the yield, Fig. 15.

The average signal to noise ratio is plotted for the different states of selection, crossover, and mutation operators, Fig.15. Because the objective here is to maximize the value of the objective function, in each one of the graphs, the state that represents the larger S/N ratio, is the best.

As observed in S/N ratio diagrams, option 2 of the operator A, option 1 of the operator B and option 1 of the operator C (combining the $A_2B_1C_1$ options) has a larger S/N ratio; therefore, the second type, the tournament selection method, the first-order crossover operator representing the single-point crossover, and the first-order mutations operator with a constant rate, have larger S/N ratios. Consequently, according to the Taguchi method, the combination of operators of tournament selection, single-point crossover, and fixed-rate

mutations is optimal. These results are different from previous studies [13, 14]. Since in different optimization problems, irregularities and complexities vary in different manner, different combinations are selected as optimal genetic operators.

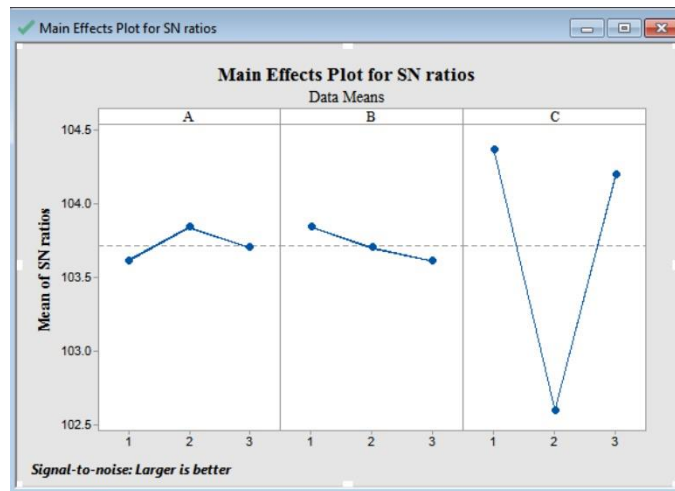


Figure 15. Signal to noise ratios calculated in the Taguchi method

The optimization with the combination of optimal operators introduced by the Taguchi method ($A_2B_1C_1$) is run here. The convergence history diagram of the cost function with optimal GA operators is shown in Fig.16, where the convergence rate of the algorithm has significantly increased with optimal operators, while the resulting savings amount is slightly higher.

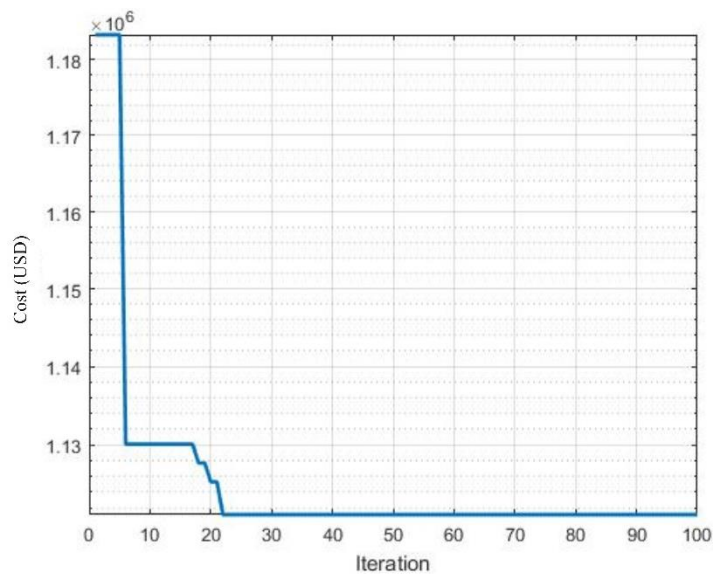


Figure 16. Convergence graph recorded for the best run

For better comparison, the performance of different combinations of genetic operators, the details of the bridge optimization in various performances are provided in Table 3.

Table 3: Results of cost optimization of the subject bridge with different genetic operators

Combination	Selection type	Crossover type	Mutation type	Cost (million \$)	Iteration number of the optimal point	Saving cost (%)	Iteration number of 12% saving
A ₁ B ₁ C ₁	random	single-point	fixed rate	1.131	46	12	46
A ₁ B ₂ C ₂	random	double-point	controlled	1.156	9*	10	-
A ₁ B ₃ C ₃	random	uniform	standard	1.129	80	13	60
A ₂ B ₁ C ₂	tournament	single-point	controlled	1.147	12*	11	-
A ₂ B ₂ C ₃	tournament	double-point	standard	1.132	98	12	98
A ₂ B ₃ C ₁	tournament	uniform	fixed	1.123	42	13	14
A ₃ B ₁ C ₃	Roulette wheel	single-point	standard	1.125	98	13	40
A ₃ B ₂ C ₁	Roulette wheel	double-point	fixed	1.122	87	13	12
A ₃ B ₃ C ₂	Roulette wheel	uniform	controlled	1.162	7*	10	-
A ₂ B ₁ C ₁ (TM)	tournament	single-point	fixed	1.120	81	13	6

*Trapped in the local optimal point

By comparing the results of the final convergence in different states, it is revealed that regardless of the saving value, the convergence rate of the algorithms directly depends on the type of the mutation operator. Comparing the count of iterations of each algorithm in approaching the optimal point, values in column 5, indicates that among the types of mutation operators, the controlled mutation operator has the highest convergence rate, followed by the fixed rate and the standard mutation operators. As observed in Table 4, in A₁B₂C₂, A₂B₁C₂, and A₃B₃C₂ combinations, the algorithm converges into its optimal point at iterations 9, 12 and 7, respectively. Algorithms with a constant rate mutation operator converge at their optimal point at iterations 46, 42 and 87, and algorithms with standard mutations convergence at iterations 80, 98, and 98, respectively. At the same time, comparing the optimal values obtained from different states, column 4, indicate that combinations with a controlled mutation operator, due to a sharp decrease in the mutation rate at higher iterations, lose the ability to release the algorithm from local optimal points, thus all are trapped at the optimal local points. However, algorithms with a constant and

standard rate mutation operator have a lower convergence rate and are released from the local optimal points.

The details of the algorithm implementation are presented with the proposed combination of the Taguchi method in the last row of Table 4. The results indicate that the proposed combination of the Taguchi method, in addition to improving the exploitation capability of the algorithm to be applied and achieving greater savings, has a higher convergence rate, while at iteration six it achieves a 12% saving. It can be deduced that in the optimization of the segmental pre-stressed bridges with high complexities, the combination of genetic operators with higher exploration is better, and the use of higher exploitation operators will stop the algorithm at the local optimal points.

The optimum results for the best runs are tabulated in Table 4. Here, GA is fixed at the bottom flange thickness (t_t and t_b) at its lower bound 180 mm, which is its lowest allowable value. This finding is in agreement with that of Ref. [42].

This proposed optimization procedure yields a total cost saving of \$169,640. The obtained results here indicate a 13% reduction in the construction cost and weight of the superstructure. Due to the high ratio of the unit price of pre-stressing steel in relation to concrete, this optimization leads to a greater reduction in pre-stressing steel than the concrete volume of the segments.

Table 4: Results of cost optimization of the subject bridge with different genetic operators

Design	$D(m)$	$t_t(m)$	$t_{b0}(m)$	$t_b(m)$	$t_{w0}(m)$	$t_w(m)$	n	Weight (kN)	Cost(USD)
Practical example	2.5	0.25	0.45	0.25	0.60	0.40	12	24714	1,290,800
GA based	2.52	0.18	0.335	0.18	0.35	0.35	10	21530	1,121,160
Total reduction								3184	169,640

5. CONCLUSION

In this study, a GA is designed in MATLAB software to optimize the segmental precast concrete bridge with seven variables and about 200 constraints according to AASHTO LRFD and AASHTO standard specifications for assessing the effect of different genetic operators on the efficiency of the optimization algorithm. The subject bridge (completed in 2017 in Isfahan, Iran) is selected as a case study, and the algorithm's efficiencies are calculated and validated with the selection, crossover, and mutation genetic operators. The Taguchi experimental design method is adopted to determine the best combination of operators:

The results are summarized as follows:

- Implementing an optimization algorithm with different types of genetic selection, crossover and mutation operators provides different results with a difference of 4% significance
- Figures and tables of the GA implementation with different operators indicate that the type of mutation operator has a direct effect on the convergence rate of the algorithm. The controlled mutation operator has the highest convergence rate, and the standard mutation operator has the lowest convergence rate

- Comparison of the results of different studies in structural optimization problems indicate that, depending on the number of design variables and the irregularity of the search space, the combination of optimal operators is different
- The optimal combination of the genetic operators is determined through TM. The obtained results indicate that the Taguchi method combination of tournament selection, single-point crossover, and fixed-rate mutations operators is better
- The above combination is controlled by the optimization algorithm, and it improves the initial optimization and greatly increases the convergence rate
- Cost optimization with the optimal combination of genetic operators leads to a 13% reduction in the construction cost and weight of this subject bridge superstructure, mostly due to the reduction in required pre-stressing tendons

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