Sizing and Pre-stressing Force Optimization of Pre-stressed Concrete Beam Using Fast Multi Swarm Optimization

R. Frans[1,*)], & Y. Arfiadi[2)],
[1]Civil Engineering Department, University of Atmajaya Makassar, Makassar 90245, Indonesia
[2]Civil Engineering Department, University of Atmajaya Yogyakarta, Yogyakarta 55281, Indonesia
[*]Email: richardfrans.rf@gmail.com

ABSTRACT

Nowadays, pre-stressed concrete is commonly used in many structural constructions, such as bridge and building structures. Cross sectional area of the beam can be smaller if pre-stressed concrete beam is used compared to ordinary reinforced concrete one. In this case, it will have cost saving if we can optimized the structures. However, it must have a good technique for obtaining the optimum cross sectional area of the pre-stressed concrete beam, One of the optimization techniques that give a good result for optimization process is fast multi swarm optimization. In this paper, fast multi swarm optimization was used to obtain the optimum cross sectional area and optimum pre-stressing force of the pre-stressed concrete beam of simply supported condition. This study shows better result compared to the previous research when using similar objective function.

Keywords: sizing optimization; prestressed concrete beam

Article history: received 20 February 2016, last received in revised 15 May 2016

1. INTRODUCTION

The used of pre-stressed concrete structures has some advantages compared to the ordinary reinforced concrete ones. Designing smaller cross sectional area of structural members is one of the important aspects as we can reduce concrete as a based material. Another advantage is that pre-stressed concrete can carry larger loads compared to conventional reinforced concrete members. In addition, when we can optimize the structures to fulfill the design construction criteria, it can also reduce construction cost. In this paper, two variables as objective function for optimization process are considered, i.e., the weight and cost material of pre-stressed concrete beam.

There are many research about optimization of pre-stressed concrete beam that have been done. Evolutionary Operation optimization algorithm (EVOP) was used to optimize I girder beam of bridge structure [1]. Comparative study of optimized pre-stressed concrete beam with optimized conventional reinforced concrete using genetic algorithm where minimum cost as the objective function has been considered in [2]. Evolutionary Operation (EVOP) used as an optimization algorithm to optimize the post tension pre-stressed concrete beam for I girder on bridge structure [3]. Optimization of cross sectional and pre-stressing force using genetic algorithm that utilize β-moment coefficient method developed in [4] for solving continuous beam type has been considered in [5] and [9].

2. PRESTRESSED CONCRETE BEAM

Prestressed concrete structure is a concrete structure in which the internal stresses have been introduced so that the distribution and magnitude of the stresses from external loading are counteracted to a desired degree. In reinforced concrete members the prestressed is commonly introduced by tensioning the steel reinforcement (ACI Committee on Prestressed Concrete). Three different concepts may be applied to explain and analyze the basic behavior of prestressed concrete. The first concept to design the prestressed concrete structures is prestressing to transform concrete into an elastic material. This concept treats the concrete as an elastic material and is probably still the most common to be used by the design engineers [6].

Based on the concept, allowable stress on prestressed concrete follow as:

a. At initial condition (transfer), stress at the top fiber of the prestressed concrete is:

$$-\frac{P_i}{A}+\frac{M_{Pi}Y_t}{I_c}-\frac{M_{DL}Y_t}{I_c}<\sigma_{ci} \qquad (1)$$

while stress at the bottom fiber of the prestressed concrete is:

$$-\frac{P_i}{A}-\frac{M_{Pi}Y_t}{I_c}+\frac{M_{DL}Y_t}{I_c}<\sigma_{ti} \qquad (2)$$

b. At final condition or service condition (after loss of prestressing force), stress at the top fiber is:

$$-\frac{P_e}{A}+\frac{M_{P_e}Y_t}{I_c}-\frac{M_{TL}Y_t}{I_c}<\sigma_{c} \qquad (3)$$

while stress at the bottom fiber of prestressed concrete is:

$$-\frac{P_e}{A}+\frac{M_{P_e}Y_t}{I_c}-\frac{M_{TL}Y_t}{I_c}<\sigma_{t} \qquad (4)$$

where: A = area section of prestressed concrete, P_i = prestressing force at initial condition (transfer), P_e = prestressing force at final condition, I_c = moment of inertia of prestressed concrete, Y_t = distance between central axis to top/bottom fiber, MP_i = moment due to prestressing force on initial condition, MP_e = moment due to prestressing force on final condition, M_{DL} = moment due to dead load condition, M_{TL} = moment due to total load condition (dead load + live load), σ_{ti} = allowable tensile stress at initial condition, σ_t = allowable tensile stress at final condition, σ_{ci} = allowable compression stress at initial condition, σ_c = allowable compression stress at final condition. M_{DL} is used because at initial condition just dead load works (live load has not worked) and M_{TL} is used when prestressed concrete at service condition due to live load have worked (total load).

Equation (1) until (4) are valid for the simply supported beams or statically determinate structures. If the structure is statically indeterminate one, equation (1) until (4) must be modified. One of the method is by using β-moment coefficient proposed in [4].

3. FAST MULTI SWARM OPTIMIZATION

Fast multi swarm optimization is one of techniques that have a good result for optimization process. Fast multi swarm optimization is derived from particle swarm optimization (PSO) which was first proposed by [7]. Theory of particle swarm optimization is based on the behavior of insects or birds swarm. Social behavior consists of individual action and the influence of other individuals within a group. For example, a bird in a flock of birds. Any individual or particles behave in a distributed manner by using its intelligence and also will influence the behavior of the collective group. Thus, if one particle or a bird finding his way or short to get to the food source, the rest of the group will also be able to immediately follow that path although they are far from the location of the group.

The basic equation of particle swarm optimization used to update the position and location of the particle is:

$$v_{i,j}(t+1) = wv_{i,j}(t) + c_1R_1(p_{best,i,j} - x_{i,j}(t)) + c_2R_2(g_{best,i,j} - x_{i,j}(t)) \quad (5)$$

$$x_{i,j}(t+1) = x_{i,j}(t) + v_{i,j}(t+1) \quad (6)$$

where: $v_{i,j}$ (t+1) is updated velocity of particle, $x_{i,j}$ (t+1) is updated location of particle, t represent the iteration-t, $p_{best,i,j}$ is local best location of particle at t-iteration, $g_{best,i,j}$ is global best location of particle at t-iteration. R_1 and R_2 are random number from interval 0-1, c_1 and c_2 are particle acceleration constants, in this paper, $c_1 = c_2 = 2$, and w is positive inertia weight coefficient which is a function ρ_{min} and ρ_{max} as follow:

$$w_{(t)} = \rho_{\max} - ((\rho_{\max} - \rho_{\min}).t / \max t) \quad (7)$$

In PSO, each particle shares the information with its neighbors. PSO combines the cognition component of each particle with the social component of all the particles in a group. Although the speed of convergence is very fast, Once PSO traps into local optimum, it is difficult to jump out of local optimum [8]. Therefore, the addition of a mutation operator to PSO will enhance its global search capacity and thus improve its performance. In order to prevent of falling to a local optimum, a new technique using combination of Cauchy mutation and crossover operation which is called fast multi swarm optimization (FMSO) was introduced [8]. Similar to distributed genetic algorithm, multiple swarm's idea is very useful for speeding up the search. The new information of exchanging and sharing mechanisms of FMSO makes it converge fast to the global optimum.

Whenever the particle converges, it will "fly" to the personal best position and the global best particle's position. Due to this information of sharing mechanism makes the speed of convergence of PSO is very fast. Meanwhile, because of this mechanism, PSO can not guarantee to find global optimum value of function. In fact, the particles are usually converge to local optima. Without loss of generality, only function minimization is discussed here. Once the particles trap into a local optimum, in which $p_{best,i,j}$ can be assumed to be the same as $g_{best,i,j}$, all the particles converge to $g_{best,i,j}$. At this condition, the velocity's update equation becomes:

$$v_{i,j(t+1)} = \omega . v_{i,j(t)} \quad (8)$$

When the iteration in the equation (8) goes to infinite, the velocity of the particle $v_{i,j}$ will be closed to 0 because of $0 \leq \omega < 1$. After that, the position of the particle $x_{i,j}$ will not change, so that PSO has no capability of jumping out of the local optimum. It is the reason that PSO often fails on finding the global minimal value. To overcome the weakness of PSO discussed at the middle of this section, the Cauchy mutation is incorporated into PSO algorithm. The basic idea is that, the velocity and position of a particle are updated not only according to (5) and (6), but also according to Cauchy mutation as follows:

$$x_{i,j(t+1)} = x_{i,j(t)} + (v_{i,j(t)} \exp(\delta))\delta \quad (9)$$

where d denotes Cauchy random numbers.

Since the expectation of Cauchy distribution does not exist, the variance of Cauchy distribution is infinite so that Cauchy mutation could make a particle have a long jump. By adding the update equations of (9), PSO greatly increases the probability of escaping from the local optimum [8].

For crossover operation, for *rand()* < q_c the crossover operation is taken as follows:

$$x_{i,j(t+1)} = (1-\alpha).x_{i,j(t)} + \alpha.p_{best,i,j} \quad (10)$$

$$v_{i,j(t+1)} = rand().(p_{best,i,j} - x_{i,j(t)}) \quad (11)$$

Where, α is random number with 0-1 interval, q_c is crossover rate.

4. RESEARCH METODOLOGY

Considered a pre-stressed concrete beam with simply supported as shown on Fig.1. In this case, there are two variables are optimized, i.e., area section of pre-stressed concrete beam and pre-stressing force. After obtaining the pre-stressing force, the number of pre-stressing tendons is determined. For this problem, the objective function is to minimize the weight and the cost of the material used (concrete + pre-stressing tendon). So, the objective fitness will follow:

$$F = w.c \quad (12)$$

Where, *F* is a fitness value, *w* is weight of the pre-stressed concrete beam, *c* is total cost of material (include concrete and pre-stressing tendon). Table 1 shows the assumption of material properties which used for pre-stressed concrete beam.

Table 1. Material properties

Concrete Density	24 kN/m^3
Steel Density	78.5 kN/m^3
Elastic Modulus of Concrete	25742.96 MPa
f_{ci}	25 MPa
f_c	30 MPa

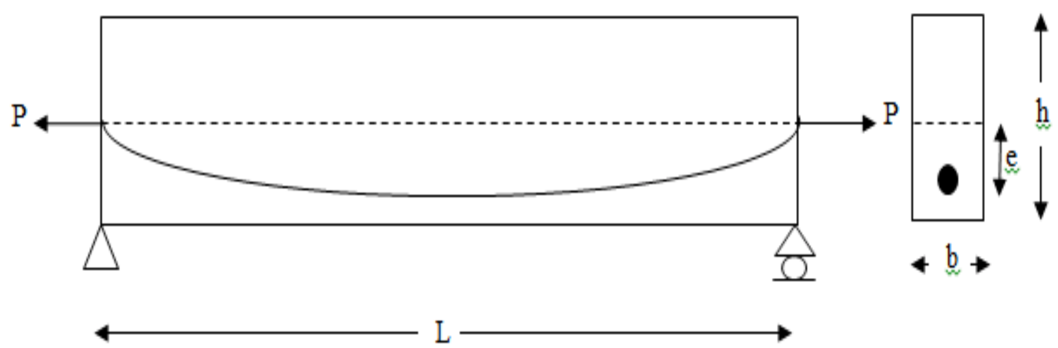

Fig.1. Simply supported of prestressed concrete beam

For loading condition, assumption of dead load and live load are 9.1 kN/m and 5 kN/m, respectively. The dead load is excludes self-weight of the pre-stressed concrete beam. Span length is 15 m. Minimum width of the pre-stressed concrete beam is limited to 0.4 m, so if the width of the beam is more than 0.4 m, it will be penalized automatically. Loss of pre-stressing force due to friction is considered. The cable profile is considered as parabolic curve with no eccentricity at support (hinge-roll). Tendon type that is used in this problem is 7-wire strand with 15.2 mm of diameter and 150 mm2 of area sections. To optimize the problem, sub routine that has developed using *MATLAB R2014a*.

Parameters of optimization using fast multi swarm optimization are:

a. Maximum iteration : 500
b. Number of particle : 25
c. Maximum velocity : 100
d. Crossover rate : 0.8
e. ρ_{max} : 0.9
f. ρ_{min} : 0.4

To ensure the convergence result and to ensure the result is not influenced by the lower and upper bound value, the program was run for four times with difference of lower and upper bound for each run. Table 2 shows the lower and upper bound limit for each run.

Table 2. Lower bound and upper bound value

Run	Lower Bound	Upper Bound
1	0	2000
2	0	1000
3	-10	1000
4	-100	100

5. RESULT AND DISCUSSION

Result of optimization shows that the optimum cross section area of the prestressed concrete beam is 0.5 m x 0.85 m with 1450.7 kN of prestressing force. Total weight of the beam (including concrete and prestressing tendon) is 155.9016 kN. As the validation and comparison, this present study was compared with the previous research which presented in [5].

For comparison, genetic algorithm was performed to optimize the cross section of the pre-stressed concrete beam with minimum limitation of the beam's width is 0.4 m [5]. Loading condition and material properties that is used in [5] is similar to this research. The difference is only on the objective function used. In this paper, the objective function is the weight of the structure and the total cost of material, while in [5] the total cost is used as the objective function. The material price will be taken same as with the material price used as follows: concrete is Rp 1.500.000/m3, and the prestressing tendon is Rp 40.000/kg. Based on this, the total cost obtained after optimization process considered in this paper based on fast multi swarm optimization is Rp 16.340.000, while the result of [5] is Rp 16.649.600. It can be seen that, the total cost considered in this paper is cheaper than the one in [5]. Decreasing of the fitness value (cost of the structure) for each iteration can be seen in Fig. 2 for fast multi swarm optimization.

Fig.2 shows that the finesses at the last iteration are the same for each run for the difference of lower bound and upper bound initial guesses. The iteration number needed to get the optimum solution is as follows: for first run is less than fifty, second run is less than a hundred; while the third and the fourth runs need almost 200 iterations for obtaining the optimum result. This is because the lower and upper bound values of first and second run is positive values and close to the domain area (optimum point); whereas the lower bounds of the third and the fourth runs are negative value and are far from the domain area. However, all four run result in the same optimum solution. Therefore, fast multi swarm optimization can handle the optimization problem of prestressed concrete beam with good level performance.

6. CONCLUSION

The purpose of this present study is to optimize the cross section and prestressing force of prestressed concrete beam by using fast multi swarm optimization of simply supported beam. The objective function is to minimize the weight and the total cost of the prestressed concrete beam. The weight and total cost obtained in this paper are 155.9016 kN and Rp 16.340.000, respectively; while the total cost obtained from previous research is Rp 16.649.600. Based on this result, it can be concluded that this optimization technique has good performance in case of determining the optimum cross section and prestressing force. Although the lower and upper bounds are different, and the number of iteration for obtaining the optimum solution is also different for each run, the optimization results the same optimum values for all runs.

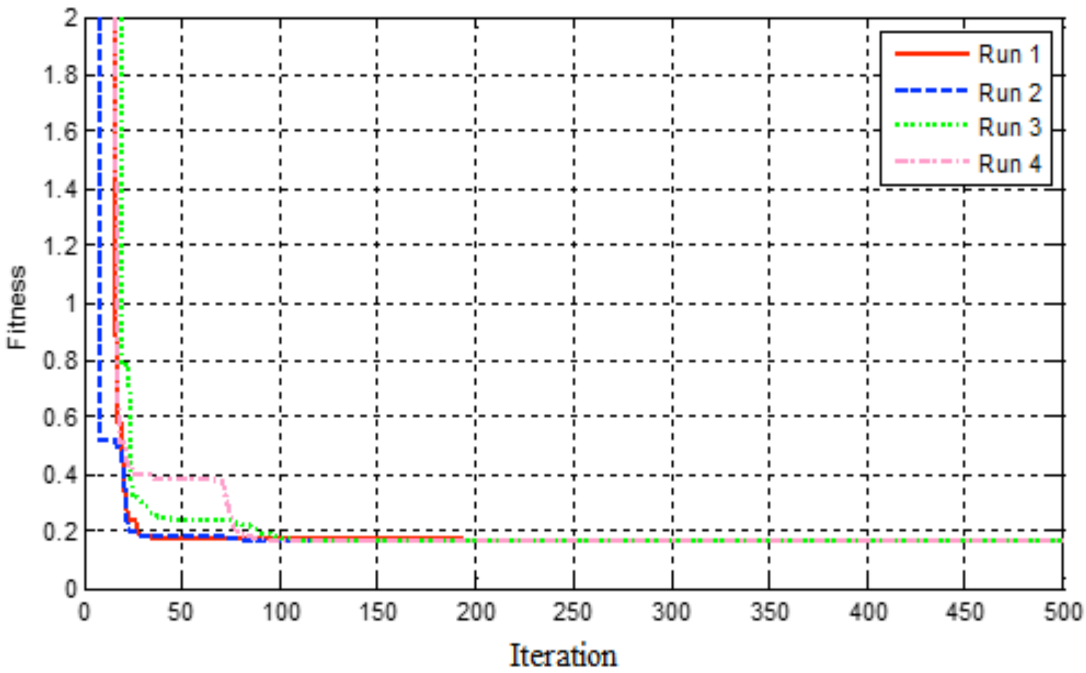

Fig. 2. Fitness value decreasing for each iteration

7. REFERENCES

[1] Rana, S., Ahsan, R., dan Ghani, S.N. (2010). Design of Prestressed Concrete I-Girder Bridge Superstructure Using Optimization Algorithm. IABSEJSCE Joint Conference on Advances in Bridge Engineering-II, pp 211-223.

[2] Alqedra, M., Arafa, M., dan Ismail, M. (2011). Optimum Cost of Prestressed and Reinforced Concrete Beams using Genetic Algorithms. Journal of Artificial Inteligence Vol. 4, 1, pp 76-88.

[3] Ahsan, R., Rana, S., dan Ghani, S.,N. (2012). Cost Optimum Design of Posttensioned I-Girder Bridge Using Global Optimization Algorithm. Journal of Structural Engineering Vol. 138, 2, pp 273-284.

[4] Arfiadi, Y., dan Hadi, M.N.S. (2011). Moment Coefficients for Statically Indeterminate Prestressed Concrete Structures, Asian Journal of Civil Engineering (Building and Housing) Vol 12, 1, pp 39-59.

[5] Zebua, A.W. (2014). Optimasi Ukuran Penampang Beton Prategang Pada Balok Sederhana dan Menerus dengan menggunakan Algoritma Genetika. Tesis : Universitas Atma Jaya Yogyakarta.

[6] Lin,T. Y and Burns,N.H. (1981). Design of Prestressed Concrete Structures:Third Edition. John Wiley & Sons.

[7] Kennedy, J and Eberhart. R.C. (1995). Particle Swarm Optimization. In Proceedings of the 1995 IEEE International Conference on Neural Networks. IEEE Service Center, Piscataway, pp 1942-1948.

[8] Zhang,Q., Li, C., Liu, Y., and Kang, L. (2007). Fast Multi-swarm Optimization with Cauchy Mutation and Crossover Operation. Proceedings of Advances in Computation and Intelligence, Springer-Verlag, Berlin Heidelberg, pp 344-352.

[9] Arfiadi, Y. and Zebua, A.W. (2015). Cross Sections and Prestressing Forces Optimizations of Prestressed Concrete Beams, 11th World Congress on Structural and Multidisciplinary Optimisation , 07th - 12th, June 2015, Sydney Australia, Paper 1163.