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CO_2-Optimization Design of Reinforced Concrete Retaining Walls based on a VNS-Threshold Acceptance Strategy

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Abstract

This paper describes one approach to a methodology to design reinforced concrete cantilever retaining walls for road construction, using a hybrid multistart optimization strategic method based on a variable neighborhood search threshold acceptance strategy (VNS-MTAR) algorithm. This algorithm is applied to two objective functions: the embedded CO_2 emissions and the economic cost of reinforced concrete walls at different stages of materials production, transportation and construction. The problem involved 20 design variables: four geometric variables (thickness of the stem and the base slab, as well as the toe and heel lengths), four material types, and 12 variables for the reinforcement set-up. Results first indicate that embedded emissions and cost are closely related, and that more environmentally-friendly solutions than the lowest cost solution are available at a cost increment of less than 1.28%. The analysis also indicated that reducing costs by one euro could save up to 2.28% kg in CO_2 emissions. Finally, the cost-optimized walls require about 4.8% more concrete than the best environmental ones, which need 1.9% more steel.

Keywords: Optimization, CO_2 emission, sustainable construction, retaining walls.

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Introduction

Nowadays there is a growing concern for sustainability. This has led to a change in the otherwise economic approach to resource consumption accounting. In recent years, the tendency has been to use structural optimization criteria to reduce the environmental impact involved in all life cycle stages. Any optimization of design for sustainability should be conducted in accordance with the ISO 14040 standards, which require that an appropriate boundary and scope be set and justified (ISO 1998). Reducing CO_2 emissions is one of the most widely used criteria, since data related to the environmental impact of most construction materials have been compiled by distinct organizations (e.g. Goedkoop and Spriensma 2001; Catalonia Institute of Construction Technology 2009) and, hence, the impact of CO_2 on a given structure can now be computed. The fact that the cement industry produces 5% of the world's greenhouse gas emissions justifies the interest in this approach to the optimal design of concrete structures (Worrell et al. 2001). Early studies show that the construction sector was responsible for 17% of India's greenhouse gas emissions (Parikh et al. 1993), while in Western Europe this sector contributed between 8% and 12% of total emissions (Gielen 1997). Reducing CO_2 emissions by efficiently using and optimizing structural design has added to the progress achieved in low-carbon cement technology research (e.g. Gartner 2004; Yang et al. 2008). Tiwari et al. (1996) analyzed the cost of CO_2 reduction in building construction, and the impact technical changes have on employment and materials used. A modified life cycle assessment methodology was proposed by Itoh and Kitagawa (2003) to evaluate CO_2 emissions in new types of bridges. A recent review of life cycle assessment in buildings suggests that the operational phase alone contributes more than 50% of the total greenhouse gas emissions (Sharma et al. 2011). Therefore, it seems crucial to incorporate design criteria to minimize the embedded CO_2 emissions in reinforced concrete (RC) structures. In this regard, Paya-Zaforteza et al. (2009) conducted an optimization study comparing CO_2-efficiency and the cost design for RC building frames using the well-known simulated annealing algorithm; while in the present study, a new hybrid algorithm will be applied to another sort of RC structure.

Applying optimization techniques to the design of RC structures is deemed both appropriate and feasible since the element design is made more efficient. Generally speaking, there are two methods to approach to structural optimization: exact methods and approximate methods. These methods are efficient when using a few design variables, but computing time becomes prohibitive for larger numbers of variables. A review of non-heuristic structural concrete optimization studies can be found in Sarma and Adeli (1998). Approximate methods include both heuristic methods, whose recent development is tied to the evolution of artificial intelligence procedures, and search algorithms such as genetic algorithms (Holland 1975), simulated annealing (Kirkpatrick et al. 1983), and ant colonies (Dorigo et al. 1996), among others. A thorough review of structural optimization methods was conducted by Cohn and Dinovitzer (1994), who highlighted the gap between theoretical studies and the practical application of optimization methods and confirmed that most research focused on steel structures while only a small fraction dealt with RC structures. With regard to RC structures, early heuristic applications involved the optimization of simply supported RC beams (Coello et al. 1997) and the study of three-dimensional RC frames (Balling and Yao 1997). The authors' research group has applied metaheuristics, namely genetic algorithms, ant colony optimization (ACO), threshold accepting (TA) and simulated annealing (SA) methods, to frame bridges (Perea et al. 2008), bridge piers (Martinez et al. 2010), prestressed concrete precast pedestrian bridges (Marti and Gonzalez-Vidosa 2010), and road vaults (Carbonell et al. 2011). Furthermore, our group has applied a multiobjective SA algorithm to optimize the economic cost, the constructability, the environmental impact, and the overall safety of building frames (Paya et al. 2008).

The economic optimization of geotechnical structures has been subject of a number of studies. Wang and Kulhawy (2008) used a linear programming approach to minimize the cost of spread foundations. Badsudhar et al. (2008) developed a sequential unconstrained minimization technique along with conjugate direction and quadratic fit methods to determine the optimal cost of mechanically-stabilized earth walls made with geosynthetically reinforced elements. Regarding the exact optimization of RC retaining walls, Saribas and Erbatur (1996) applied constrained nonlinear programming to a problem with seven geometric and reinforcement design variables, using the cost and weight of the walls as objective functions. Babu and Basha (2008) described a reliability-based design optimization technique for RC retaining walls, considering parametric uncertainties in soil, concrete, steel and wall proportions, and safety in terms of a reliability index. Concerning heuristic optimization, the SA approach with seven geometric design variables was adopted by Ceranic et al. (2001) to minimize retaining wall costs. However, all these approaches are limited not only in terms of practical lengths for reinforcement and cut-off points, but for minimum spacing requirements as well. Yepes et al. (2008) conducted a parametric study with SA for optimum RC retaining walls from 4 to 10 m in height considering different fills and bearing conditions, and improving the robustness of the previously mentioned approaches by formulating the problem to include 20 design variables: four geometric ones, four material types, and 12 variables for the reinforcement set-up.

To build on the work of Yepes et al. (2008), this paper describes a hybrid methodology using 20 design variables for RC cantilever retaining walls like those common in road construction. The design procedure involved an optimization algorithm applied to two objective functions, namely the embedded CO_2 emissions and the economic cost. The method established for this research implied developing an evaluation computer module that checks all the relevant limit states. Dimensions, materials and steel reinforcement were taken as variables. The CO_2 emissions and cost objective functions were then calculated. A hybrid multistart optimization strategic method based on a TA strategy with restarts (abbreviated herein as VNS-MTAR) was then used to search the solution space to identify a set of solutions with optimized values for the designer. The paper is divided into five parts. First, the optimum design problem is formulated. Second, the structural evaluation module is described. Third, the proposed VNS-MTAR algorithm is explained. Fourth, the results obtained in the numerical experiments are discussed. Finally, conclusions and suggestions for further research are made.

The Optimum Design Problem

In this study, the problem of structural concrete optimization involves a single-objective optimization of either the embedded CO_2 or the cost of the structure. Hence, this optimization aims to minimize one of the two objective functions, f_1 and f_2, of Eq. (1) and Eq. (2) while satisfying the constraints of Eq. (3).

$$\mathrm{CO}_2 = f_1(x_1, x_2, ...x_n) \tag{1}$$

$$C = f_2(x_1, x_2, ...x_n) \tag{2}$$

$$g_j(x_1, x_2, ...x_n) \leq 0 \tag{3}$$

Note that $x_1,x_2,\ldots,x_n$ are the design variables chosen for the formulation. The remaining data necessary to calculate a wall are the parameters of the problem. The bounds and scope of CO_2 emissions and cost modeling include (1) the extraction of raw materials, (2) the transportation of raw materials to the factory, (3) the processing, manufacturing and fabrication of products and machinery, and (4) the emissions equipment involved in the construction processes in order to execute the structural work units (earth removal, formwork, backfill, steel, and concrete). Despite the importance of transporting materials to the construction site, neither the use/maintenance nor the removal/disposal phases for long-lived RC structures are considered in the BEDEC PR/PCT ITEC (Catalonia Institute of Construction Technology 2009) materials database consulted for this study. Although this Institute assumes a standard technology to assess the emissions of each construction unit, the methodology proposed herein is not based on any particular database.

The first objective function quantifies the total amount of CO_2 emissions resulting from the use of materials which involve emissions at the different phases of production, transportation, and construction. As a rule of thumb, the higher the cost, the lower its sustainability. Different structural alternatives may be assessed and compared from an environmental point of view. The present study proposes a CO_2-environmental function to analyze ecological earth-retaining walls, which is expressed as follows:

$$CO_2 = \sum_{i=1,r} e_i \times m_i \quad (4)$$

Note that e_i are the CO_2 unit emissions from the RC wall materials; m_i are the measurements of the construction units (depending on the geometry and reinforcement set-up design variables), while r is the total number of construction units. This objective function is the CO_2 emissions of the structure expressed as the sum of unit CO_2 impacts, multiplied by the construction unit measurements. As specified in Table 1, the values of e_i for concrete, steel and formwork used in the present study were taken from the BEDEC PR/PCT ITEC materials database (Catalonia Institute of Construction Technology 2009). It is important to note that the data do not reflect transportation emissions, which are highly dependent in all case studies.

<<INSERT HERE TABLE 1>>

The second objective function is the cost of the structure as defined in Eq. (5), where p_i are the unit prices; m_i are the measurements of the construction units (concrete, steel, formwork, etc.), and r is the total number of construction units. The cost function includes the cost of materials (concrete and steel) and all the entries required to evaluate the entire cost of the wall per linear meter. Table 1 gives the unit prices considered from the aforementioned database (Catalonia Institute of Construction Technology 2009).

$$C = \sum_{i=1,r} p_i \times m_i \quad (5)$$

The present problem has no solution that includes minimizing the two objective functions simultaneously, since the objective functions are not the same. The constraints g_j in Eq. (3) are all the serviceability limit states (SLSs) and the ultimate limit states (ULSs) that the structure must satisfy, as well as both the geometric and constructability constraints of the problem. It is worth noting that other studies transform constrained into unconstrained problems by means of penalty functions. This study, however, is restricted to feasible solutions only, and therefore penalty functions are not applied.

The Structural Evaluation Module

Considering all the data necessary to define a given structure, the structural evaluation module calculates the stress envelopes and checks all the limit states. Structures that comply with all the limit states are called feasible solutions, and those that do not are called unfeasible solutions. Optimization programs define the structure in terms of design variables, which the optimization algorithm must modify when searching for the optimum structures. Therefore, optimization programs include an evaluation module which requires the structure to be defined in terms of design variables and the coding of all the structural constraints to be satisfied. The design variables and structural constraints considered for this study are described in detail by Yepes et al. (2008). The design variables are the magnitudes subjected to optimization, while the parameters are all the remaining data necessary to compute a given wall. The main advantage of this approach is that it leads to optimal design and automation, i.e., the design variables are determined by the optimization process and not by the engineer.

The analysis includes 20 variables (see Fig. 1). These variables define the geometry, the type of concrete grades and the reinforcement used. Variables include four geometric values (thickness of the stem *b*, thickness of the base slab *c*, length of the toe *p*, and length of the heel *t*), while four other variables represent the stem and base slab concrete along with steel grades. The remaining 12 variables define the reinforcement set-up. Vertical flexural steel includes three reinforcement bars for the main bending of the stem (variables A_1, A_2 and A_3). The lengths of these bars are 100%, 50% and 25% the height of the stem. Compression reinforcement is represented by bars of the total height of the stem (variable A_4). Shear reinforcement in the stem is specified by variable A_7, which is the area of reinforcement from the bottom of the stem up to a height *L*. Longitudinal secondary reinforcement A_5 and A_6 are included in the stem for shrinkage and thermal effects. Bending bars in the base slab include reinforcement variables A_8 and A_9 for the toe and the heel, respectively. Shear reinforcement in the base slab is expressed by reinforcement variable $A_{11.}$ Lastly, reinforcement variable A_{10} corresponds to longitudinal effects in the base slab. This reinforcement set-up is considered to be detailed enough for practical purposes. It is worth noting that some variables are discrete, while others are continuous. The solution space is defined by the set of combinations of values for the 20 variables. No attempt is made to calculate the reinforcement according to the usual design rules. Such common design procedures follow a conventional order to obtain reinforcement bars from flexural-shear ULS and then checking SLS and redefining the design if necessary. This order is effective, yet it ignores other possibilities that heuristic search algorithms do not overlook. In this sense, for example, it is possible to suppress shear reinforcement by increasing flexural reinforcement, which may result in a more economical design.

The parameters of the RC wall are all the magnitudes taken as fixed data, including geometric values, properties of the base soil and backfill, partial coefficients of safety, and durability conditions. The most relevant parameters are the total height of the wall *H* (height of stem *h* plus thickness of the base slab *c*), the backfill slope β, the surcharge load *q*, the internal friction angle of the backfill φ, the permissible base soil stress σ_g, the overturning safety factor γ_{fo}, and the sliding safety factor γ_{fs}. Table 2 provides details of the parameters for the analyzed walls.

<<INSERT HERE FIG. 1>> <<INSERT HERE TABLE 2>>

The structural constraints were established following a standard analysis (Yepes et al. 2008), which includes checks against sliding, overturning and ground stresses. These constraints are all the limit states and the geometric constraints with which the structure and its foundations should comply. Prior to verifying limit states, the earth pressure is calculated, depending on the fill and surface loads and it corresponds to the active state while agreeing with Coulomb's theory. The wall as a structure is calculated per linear meter and includes the service and the ultimate flexure as well as the ultimate shear of different cross-sections of the wall and the base slab, in accordance with the Spanish Concrete Code (Ministerio de Fomento 2008). The durability limit state is checked specifically according to the design value of the service working life. Additionally, a constraint of deflection at the top of 1/150 of the height of the stem was also considered. In this study, a rectangular ground reaction of value σ was established following recommendations by Calavera (2001), and thus departs from more common trapezoidal reactions, but is more consistent with the verification of stress reactions based on a single comparison of stresses. Likewise, and following Calavera (2001), it was checked that a 50% increase in earth pressure does not cause a ground reaction greater than twice the permissible ground stress σ_g. The calculation of the ULS for flexure indicates whether the acting resultants, $N_d – M_d$, are within the ultimate iteration diagram $N_u – M_u$. Moreover, the ULS for shear verifies that the two ultimate values are greater than the factored acting shear. Both flexural and shear minimum amounts of reinforcement, as well as the geometric minimum, are also examined. The SLS for cracking includes compliance with the crack width limitation for the existing durability conditions. The design is checked at each iteration. Neither the vertical inclination of backfill pressure nor the passive reaction on the toe was considered.

A Multistart VNS-Threshold Strategic Algorithm with Restarts

The VNS-MTAR search algorithm developed for this study is a hybrid multistart optimization strategic method based on a variable neighborhood search threshold acceptance strategy. The algorithm is run R times, starting from a set of random starting solutions, and yields a set of local optima, the best of which is the best solution for the algorithm. Multistart algorithms can be used to guide the search from a new solution once a region has been explored. With this approach the diversification strategy, obtained from a random generation, is combined with the intensification given in the improvement phase. In this study a TA method is used as the acceptance rule (Dueck and Scheuer 1990). A worse solution is accepted if its difference from the current solution is smaller or equal to a deterministic threshold, T. The proposed method uses the algorithm given by Medina (2001) to determine the initial threshold T_0 and, after a specified number of iterations, the search is restarted with a reduced initial threshold. This combination has been shown to perform better than other TA approaches with regard to other combinatorial optimization problems (Yepes and Medina 2006).

The basic aim of the variable neighborhood search (VNS) is to avoid entrapments in poor local optima (Mladenovic and Hansen 1997) by means of a systematic change of neighborhood within the search. VNS exploits the following: (i) a local optimum found with a current neighborhood structure is not necessarily so with another; (ii) a global optimum is a local optimum with regard to all possible neighborhood structures; and (iii) for many problems, these local optima are relatively close to each other. Neighborhood structure is a key factor when moving from one solution to its neighboring solution. Unlike many other metaheuristics, the basic schemes of VNS are simple and require few decisions: number and types of neighborhoods to be used, order of their use in the search, strategy for changing the neighborhoods, local search methods and stop condition. Here, a stochastic descent-ascent extension of the VNS, based on a TA approach, is applied to overcome the problem of stopping in local optima. Further modifications and extensions of the proposed method may be developed. This extension can be described as follows:

1. *Initialization*. Select the set of neighborhood structures N_k, for k=1,…, k_{max}, to be used in the search; find an initial solution x; choose a stop condition;
2. *Repeat* the following sequence until the stop condition is met:
    a. Set $k \leftarrow 1$;
    b. Until k=k_{max}, repeat the following steps:
        i. *Shaking*. Generate a point x' randomly from the k^{th} neighborhood of x;
        ii. *Move or not*. If this point is accepted in a threshold acceptance decision rule, move there ($x \leftarrow x$'), and continue the search with N_1 ($k \leftarrow 1$); otherwise, set $k \leftarrow k$+1.

The initial solution is generated by a random selection of values from the variables between the upper and lower bounds. The procedure is repeated until a feasible solution is obtained. In our numerical experiments, seven neighborhood structures were selected. The first one was performed by a random variation of 14 variables; the second was performed by a random variation of 15 variables; and continuing in the same manner, the seventh one was performed by a random variation of 20 variables. Local search was based on a small random perturbation to the values for some of the variables that defined the current solution. Discrete variables were modified in one position of their table of values, and continuous variables were modified in less than ±2 cm for the geometric variables, less than ±5 cm for the bar lengths, and less than ±5 cm^2 for the reinforcement areas. These small random variations were selected to avoid a totally random search in the solution space, and they are justified for practical and constructive purposes. Thus, the proposed VNS-MTAR algorithm can be described as follows:

1. Select a random solution as the record solution.
2. Start with a random initial solution.
3. If the current solution is unfeasible, go to Step (2).

4. Select:
    a. Proposed threshold T_0^*;
    b. Cooling schedule for threshold T;
    c. Linear reduction parameter ζ for initial threshold for each restart;
    d. Number of movements for each restart R.
5. Determine the initial threshold T_0. After S movements, if the success rate is less than 20%, then $T_0=2T_0^*$, but if the success rate is higher than 40%, then $T_0=T_0^*/2$. Otherwise, Step (5) must be repeated.
6. Repeat R times. Update the current threshold T with the cooling schedule. Generate a neighboring solution. Compute the increase in the objective function ΔE. If $\Delta E>-T$, accept the new solution.
7. If there is no improvement in the current solution after Step (6), go to Step (8). Otherwise, set a new initial threshold $T_0'=T_0\cdot \zeta$. Go to Step (6).
8. If the current solution is better than the record solution, the current solution is accepted as the record solution.
9. Until a given condition is met, go to Step (2).

An exponential cooling schedule is used for the threshold T of the form

$$T = T_0 \cdot 2^{(-\upsilon/\alpha)} \tag{6}$$

where α=0.20; υ=the current iteration of each restart; the proposed initial threshold was T_0^*=300; the reduction linear parameter was ζ=0.80; the number of iterations of each restart was R=9,000,000. The schedule variable υ was increased from 0 to 1 during the optimization run of each restart. The local search algorithm was performed R=30 times. The number of starts chosen, R, is the stop condition (Step 9) of the VNS-MTAR algorithm.

The parameters α=0.20 and ζ=0.80 were those established by Yepes and Medina (2006). The remaining parameter setting was selected experimentally among the options in the Pareto front (e.g. Lamberti 2008; Perea et al. 2008). The algorithm should be run as many times as needed to ensure the quality of the minimum value obtained from all runs. A simple modus operandi to estimate the expected behavior of the algorithm "Perform R runs of algorithm and take the best" is to run said algorithm some m times, and compute the average of the m best of Rs. The well-known "bootstrapping" method (Efron 1979) can be used to obtain a random sample of R of these results, chosen independently (with replacement). Finally, the average of the m bests can be obtained. Moreover, using the same data set, the expected best of R' results may be estimated for values R' other than R. Therefore, the number of runs is selected as that which is sufficiently accurate for a given computing time.

Results from Numerical Experiments

The algorithm was programmed in Fortran 95 with a Compaq Visual Fortran Professional 6.6.0 compiler. Typical VNS-MTAR runs of 9,000,000 iterations lasted about 100 seconds for an INTEL Core TM2 Quad CPU Q6600 computer with 2.40 GHz. In order to determine the number of starts, R, as a stop condition, the wall of H=8 m and the CO_2 objective functions were chosen. First, the algorithm was run 50 times. Next, eight series of m=9 samples, with replacements, were extracted from the initial population of 50 solutions; each one of these series corresponded to the results of 5, 10, 15, 20, 30, 40 and 50 runs. Then, the average and the minimum of the m=9 bests were obtained for each series; finally, the differences between these values were calculated. Compared to the best of each series, these differences were: 0.012%, 0.007%, 0.006%, 0.004%, 0.003%, 0.002%, 0.002% and 0.001% (5, 10, 15, 20, 25, 30, 40 and 50 runs, respectively). All this suggests that R=30 runs were sufficient in terms of accuracy and computing time.

Fig. 2 and Fig. 3 show, respectively, the variation in the best values found for the minimum CO_2 emissions and costs for nine wall heights, ranging from 4 to 12 m in steps of 1 m. The minimum emissions and costs increase with increasing wall heights. The average difference between the mean value of the results and the minimum value found after 30 runs is only 0.16% for emissions and 0.13% for costs. Likewise, the average difference between the maximum and the minimum value of the results is no more than 1.49% for emissions and 0.56% for costs. These differences are sufficiently low for practical applications. A parabolic relation may be used to describe the general trend for both the CO_2 emissions (kgCO_2=91.01H^2-236.05H+678.92 with a regression coefficient R^2=0.9999) and the costs (C=35.10H^2-18.74H+191.78 with R^2=0.9999). If the ratio between emissions (kg CO_2) and the total height of the wall was chosen as a functional unit to measure the performance of the functional outputs of the product system according to ISO 14040, then Fig. 2 indicates that the higher the wall, the less efficient it would be.

<<INSERT HERE FIG. 2>> <<INSERT HERE FIG. 3>>

In addition, for each minimum found with the CO_2 objective function, we can evaluate this solution in terms of cost, and vice versa. Thus, the relative average difference is small between the obtained values of 0.92% for the emissions and 0.80% for the costs, optimizing one or the other function. This fact justifies the cost optimization with regard to reducing CO_2 emissions, with an error that is no greater than 1.28%, for the analyzed cases. Alternatively, the best cost solutions increase CO_2 emissions by 1.12%. These findings indicate that solutions which are acceptable in terms of emissions are also viable in terms of cost, and vice versa.

Fig. 4 depicts the relationship between emissions and cost when the objective function is either the amount of CO_2 or the cost. It is possible to observe a linear fit between emissions and cost (kgCO_2=2.28C-479.61 with R^2=0.9995) which indicates that, as a rule of thumb, one euro reduction in the wall cost results in savings of 2.28 kg in CO_2

emissions. This relationship assumes a standard technology in order to assess the emissions of each construction unit. For example, if a different mixture composition is used, an increase or decrease in concrete composition materials results, and such changes should be taken into consideration when calculating the amount of CO_2. Nevertheless, this relationship suggests that solutions which are acceptable in terms of emissions are also viable in terms of cost, while good solutions in terms of cost are also good in terms of emissions, i.e. both objectives yield similar solutions and are rather coincidental. This has already been reported by Paya-Zaforteza et al. (2009) for CO_2-optimization of RC building frames. This is a significant finding since the economic cost of reducing CO_2 emissions is clearly affordable with regard to reducing global warming. Moreover, prices are more sensitive to market cycles, while emissions depend on stricter manufacturing processes. Therefore, it appears that designs based on emissions are more stable and more rational.

In Table 3, the percentage of CO_2 emissions has been quantified depending on the total height of the wall and its work units. It is worth noting that concrete represents, on average, some 40% of the total emissions (Table 3), while reinforcing steel totals about 33%. This implies that reducing the volume of materials also reduces the costs and CO_2 emissions. Further, the relative importance of concrete and steel emissions increases with the height of the wall, ranging from about 59% with H=4 m to about 82% in the case of H=12 m.

<<INSERT HERE FIG. 4>> <<INSERT HERE TABLE 3>>

Finally, it is necessary to determine if the cost-optimized walls and the emission-optimized walls present similar aspects. The characteristics for these walls are compiled in Table 4. Fig. 5 represents the relationship between the variables that define the geometry of the walls (stem thickness, toe length, heel length and base slab thickness) where the emissions are optimized with respect to the cost-optimized walls. Although the cost and CO_2 emissions vary little, the physical dimensions and details of the design for cost and emission optimization vary significantly. The greatest difference is noted in the base slab thickness, being thinner in the ecological walls than in the economic ones. The values of the ratio between the base slab thickness for the ecological and economic walls decline with the heights of these structures. The stem thickness is slightly smaller in the ecological walls. The heel length is smaller in the cost-optimized walls.

<<INSERT HERE TABLE 4>><<INSERT HERE FIG. 5>>

In all cases, the steel of the optimized walls has the greatest elastic limit, 500 MPa, which can be explained by the use of a material with greater mechanical resistance for similar costs and CO_2 emissions. The concrete used in the base slabs has the lowest characteristic resistance, 25 MPa (except in the case of the ecological wall H=7, with 30 MPa). In the stem, all the economic walls were built with 25 MPa concrete; on the other hand, the ecological walls used 30 MPa concrete. In Table 1 it is possible to observe, from an environmental point of view, that the concrete placed in the base slab or in the stem emit the same amount of CO_2. However, the concrete for the stem is relatively more expensive. Regarding emissions, concretes can be grouped as those of 25 and 30 MPa and the others. It is reasonable to think that with the same amount of emissions, the concrete with the higher resistance is preferable, because it will reduce the volume needed. In fact, stem thickness is 3.1% greater on average in the cost-optimized walls than in the ecological ones. Regarding the total volume of concrete, the cost-optimized walls needed 4.8% more concrete than the ecological ones (see Fig. 6), which needed 1.9% kg more steel (see Fig. 7).

<<INSERT HERE FIG. 6>> <<INSERT HERE FIG. 7>>

The CO_2 target function appears more robust and environmentally friendly because prices are more sensitive to variations in market values, while emissions are stricter and dependant on manufacturing processes. This analysis provides solutions for more sustainable structures at an assumable cost and reasonable computer times. These results demonstrate the potential of VNS-MTAR algorithms for the minimum-CO_2 emission design of real earth-retaining RC walls.

Conclusions

In this paper we describe an algorithm based on a variable neighborhood search and a threshold acceptance strategy named VNS-MTAR, which is useful to determine the optimum design of RC cantilever retaining walls. Two objective functions are considered: the CO_2 emissions and cost of the wall at the different stages of materials production, transportation and construction. The VNS-MTAR algorithm combines the variable neighborhood search, the threshold acceptance rule and the restart approach, while a bootstrap technique is used to determine the number of starts as a stop condition. As described in this paper, VNS-MTAR may be considered a new state-of-the-art heuristic for optimizing RC structures. The extensive computational experiments with a set of nine wall heights indicate that the VNS-MTAR is an efficient algorithm for the optimum design of RC cantilever retaining walls used in road construction. The analysis reveals that CO_2 emissions and cost are closely related since the best environmental solutions cost, at the most, only 1.28% more than the best cost solutions. Alternatively, the best cost solutions increase CO_2 emissions by only 1.12%. Thus, the solutions which are acceptable in terms of CO_2 emissions are also viable in terms of cost and vice versa. The optimized walls always use steel with the greatest elastic limit (500 MPa) and concrete with the lowest permitted characteristic resistance (25 MPa) for the base slab. However, when optimizing cost, the emission optimization selects concretes with 30 MPa and 25 MPa for the stem. The volume of concrete needed for cost-optimized walls is, on average, 4.8% higher than the ecological ones, which require 1.9% more kg of steel. To conclude, the methodology, as described herein, is quite flexible and open to further modifications and extensions, so that structural engineers can reduce CO_2 emissions in their RC structural designs. Nevertheless, future studies with the algorithm should include a sensitivity analysis of parameters as well as a comprehensive analysis of additional constraints such as different distributions of ground-bearing pressures and full slip-circle analysis; and additional structures, such as counterfort retaining walls and mechanically stabilized earth walls.

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Notations

The following symbols are used in this paper:

b = stem thickness

c = thickness of base slab

e_i = CO_2 unit emission of RC wall materials

f_1 = CO_2 objective function

f_2 = cost objective function

g_j = structural constraints

h = height of stem

k = number of neighborhood structures

m = number of samples with replacement extracted for the bootstrap

m_i = wall measurement

n = number of design variables

p = toe length

p_i = unit prices

q = surcharge load

r = number of construction units

t = heel length

$x_1,..,x_n$ = design variables

$A_1, \ldots, A_{11}$ = passive reinforcement variables

$A_1+A_2+A_3$ = tension reinforcement of stem

C = total cost of RC wall

D = depth of soil in front of the wall

H = total height of wall

L = height of wall with stirrups

M_d = design bending moment

M_u = ultimate bending moment

N_d = design value of normal force

N_u = ultimate normal force

R = number of runs for the VNS-MTAR algorithm

T = threshold

T^*_0 = proposed initial threshold

T_0 = initial threshold

β = backfill slope

α = half-life for the exponential cooling schedule

φ = internal friction angle of backfill

υ = current iteration of each restart using a VNS-threshold algorithm

σ = rectangular ground reaction

σ_g = permissible ground stress

ζ = linear reduction parameter for initial threshold of each restart

δ = inclination of backfill pressure

γ = unit weight of backfill

γ_{fo} = overturning safety factor

γ_{fs} = sliding safety factor

μ = base friction coefficient

ΔE = objective function increase

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Table 1. CO_2 emissions (kg) and costs (euros –USD in parentheses-) and considered in the analysis. Source: Catalonia Institute of Construction Technology (2009)

Unit	**Emissions**	**Cost**
m^3 of earth removal	13.16	8.37 (11.41)
m^2 of foundation formwork	14.55	27.01 (36.82)
m^2 of stem formwork	31.66	27.20 (37.08)
kg of steel B-500S	3.02	1.13 (1.54)
kg of steel B-400S	2.82	1.11 (1.51)
m^3 of concrete HA-25	224.34	72.99 (99.49)
m^3 of concrete HA-30	224.94	76.67 (104.51)
m^3 of concrete HA-35	265.28	79.62 (108.53)
m^3 of concrete HA-40	265.28	86.61 (118.05)
m^3 of concrete HA-45	265.91	89.70 (122.27)
m^3 of concrete HA-50	265.95	94.02 (128.16)
m^3 of backfill	27.20	27.95 (38.10)

Table 2. Parameters of the reported retaining walls

Parameter	Value
Backfill slope	0º
Surcharge load	10 kN/m^2
Depth of soil in front of the wall	2 m
Unit weight of backfill	20 kN/m^3
Internal friction angle of backfill	30º
Inclination of the backfill pressure	0º
Base friction coefficient	0.577
Permissible ground stress	0.3 MPa
Overturning safety factor	1.8
Sliding safety factor	1.5
EHE safety coefficient for loading	Normal
ULS safety coefficient of concrete	1.50
ULS safety coefficient of steel	1.15
Deflections of the stem limitation	1/150
EHE ambient exposure	IIa

Table 3. Percentage of total emissions (kgCO_2) depending on the total height of the wall and its work units

Emission source	***H* (m)**									Average
	4	5	6	7	8	9	10	11	12	
Earth removal	6.95	5.32	4.27	3.50	2.96	2.60	2.32	2.09	1.91	3.55
Foundation formwork	0.83	0.71	0.63	0.61	0.44	0.38	0.34	0.31	0.29	0.50
Stem formwork	19.72	16.25	13.54	11.27	10.02	8.81	7.81	6.99	6.30	11.19
Concrete in base slab	12.55	13.26	14.35	16.50	13.46	13.31	13.65	14.16	14.68	13.99
Concrete in stem	20.60	23.12	24.68	24.98	27.63	28.80	29.57	30.14	30.61	26.68
Backfill	13.66	13.40	12.92	12.11	11.89	11.43	10.93	10.44	9.95	11.86
Steel in base slab	12.08	12.94	13.68	14.96	15.87	16.22	16.44	16.58	16.66	15.05
Steel in stem	13.61	15.00	15.93	16.07	17.73	18.45	18.94	19.29	19.60	17.18

Table 4. CO_2 emissions and cost-optimized wall characteristics

Measurements			***H* (m)**								
			4	5	6	7	8	9	10	11	12
Stem thickness	(m)	a	0.29	0.40	0.51	0.62	0.78	0.92	1.06	1.22	1.37
		b	0.94	0.95	0.96	0.97	0.98	0.98	0.98	0.99	0.99
Toe length	(m)	a	0.10	0.16	0.27	0.40	0.50	0.74	1.01	1.31	1.65
		b	1.00	1.00	1.04	1.03	0.98	0.99	0.98	0.98	0.98
Heel length	(m)	a	1.57	1.87	2.15	2.42	2.67	2.91	3.13	3.34	3.55
		b	1.01	1.01	1.01	1.01	1.01	1.02	1.02	1.02	1.02
Base thickness	(m)	a	0.34	0.43	0.56	0.75	0.70	0.77	0.88	0.98	1.09
		b	1.03	0.98	0.93	0.88	0.90	0.84	0.85	0.82	0.83
Concrete in stem	(m^3)	a	1.08	1.83	2.79	3.90	5.67	7.57	9.73	12.18	14.93
		b	0.96	0.96	0.98	1.00	0.99	1.00	1.00	1.01	1.01
Concrete in base	(m^3)	a	0.66	1.05	1.63	2.58	2.77	3.51	4.50	5.74	7.18
		b	1.02	0.99	0.93	0.89	0.90	0.85	0.83	0.83	0.83
Steel in stem	(kg)	a	53.0	88.4	134.3	186.8	270.7	361.3	464.2	580.5	711.8
		b	1.00	1.01	1.03	1.05	1.03	1.05	1.06	1.06	1.06
Steel in base	(kg)	a	47.1	76.3	115.4	174.1	242.5	317.5	403.0	498.8	605.3
		b	1.00	1.00	0.99	1.00	1.00	1.00	1.00	0.99	0.99

Note: (a) CO_2 emission-optimized walls characteristics
(b) Ratio between CO_2 and cost-optimized walls characteristics

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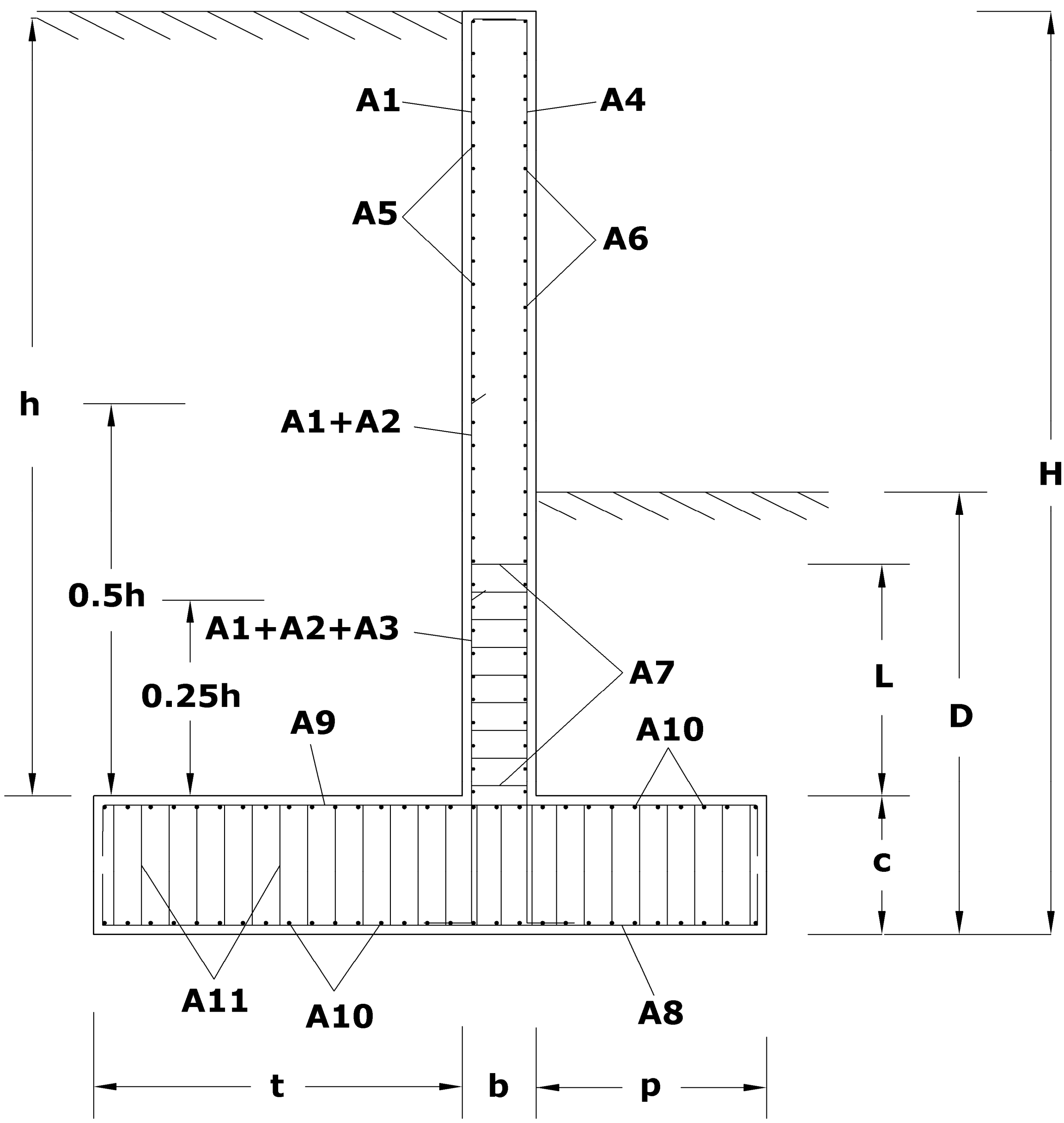


Fig. 1. Variables for the RC cantilever retaining wall

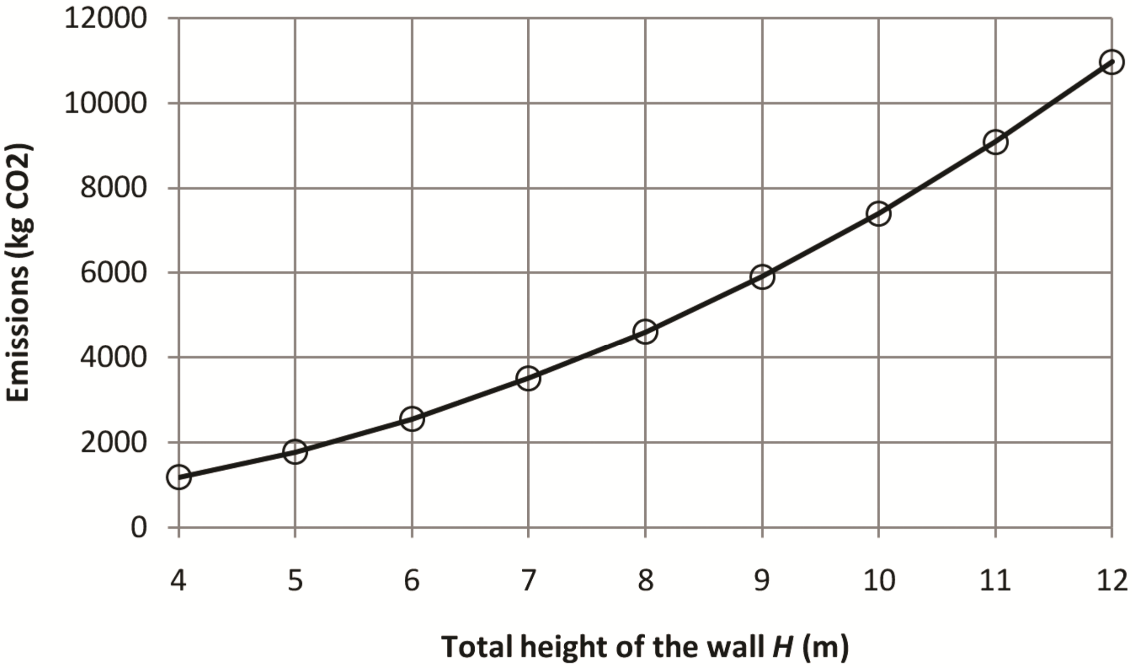


Fig. 2. Variation in the best values for the minimum CO_2 emissions for the walls studied

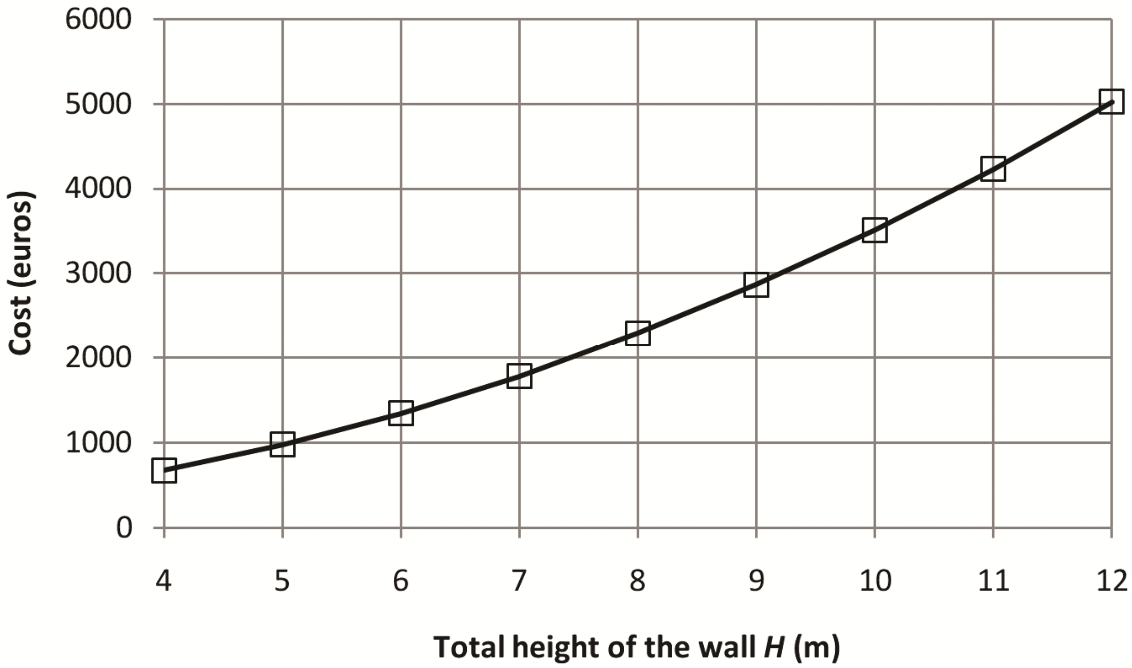
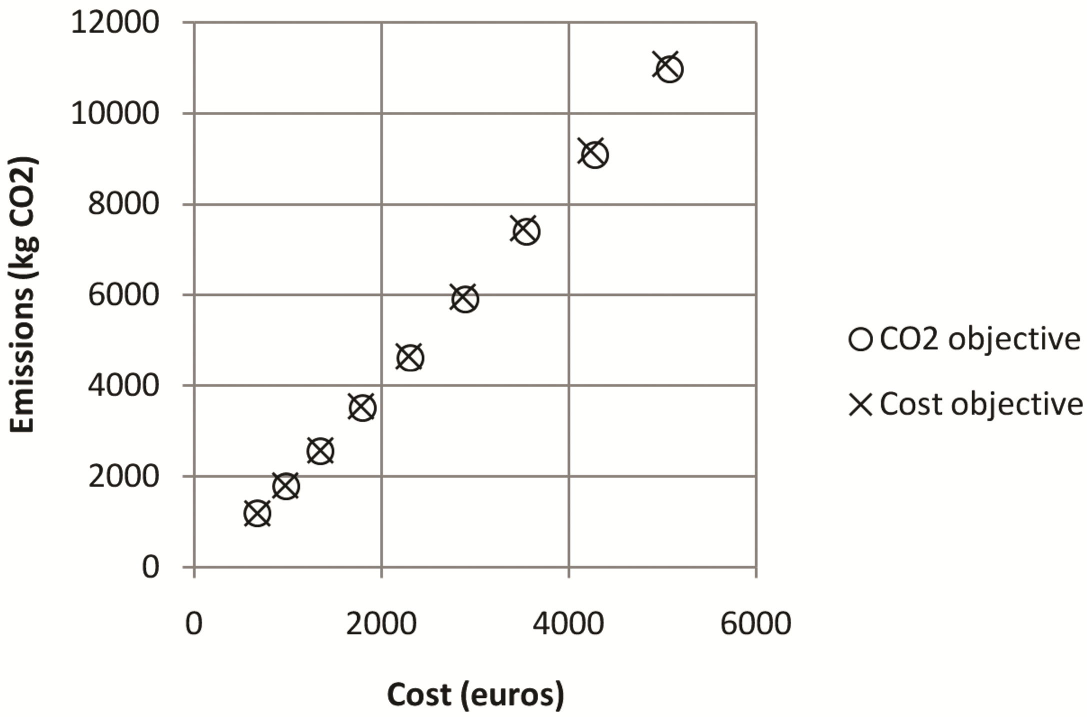


Fig. 3. Variation in the best values for the minimum costs for the walls studied



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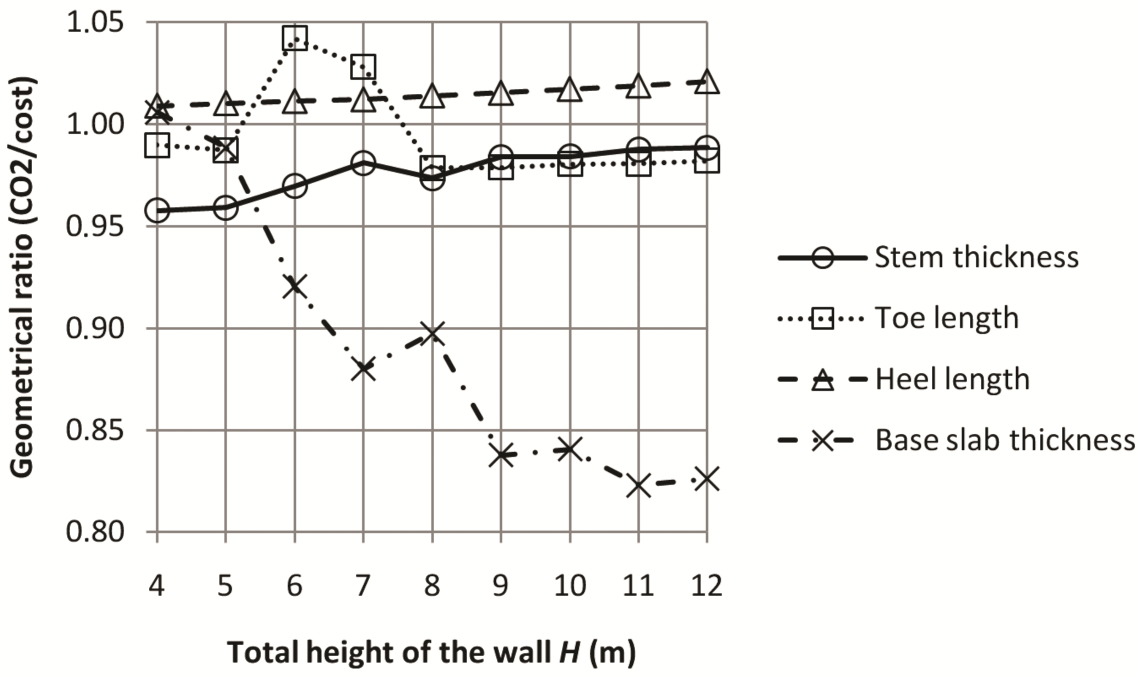

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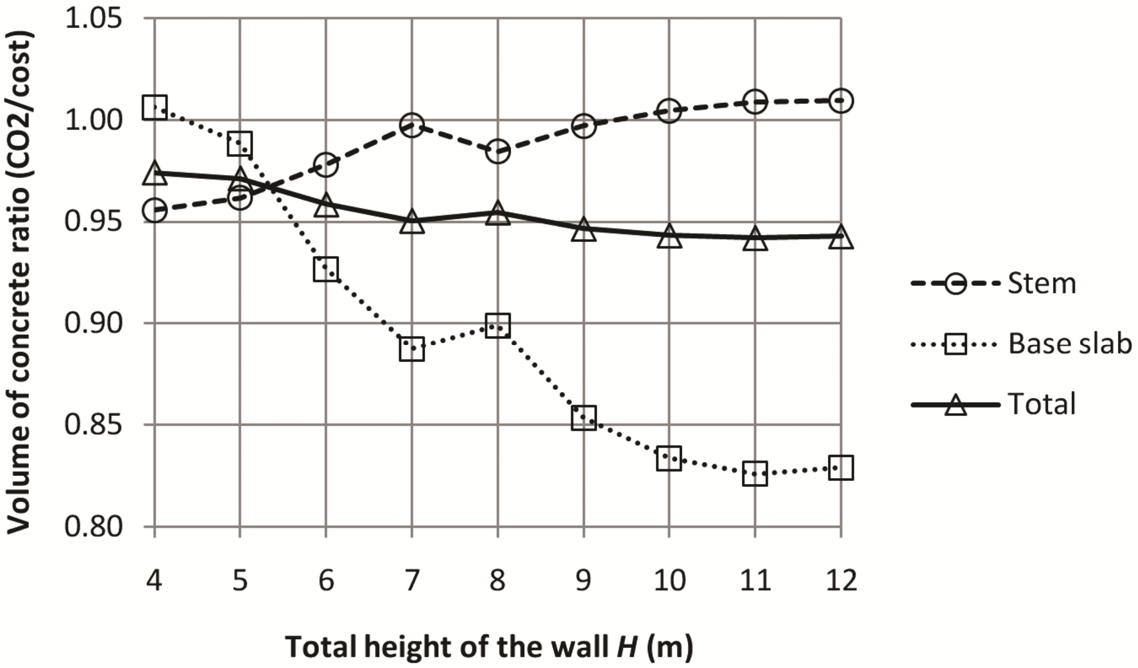

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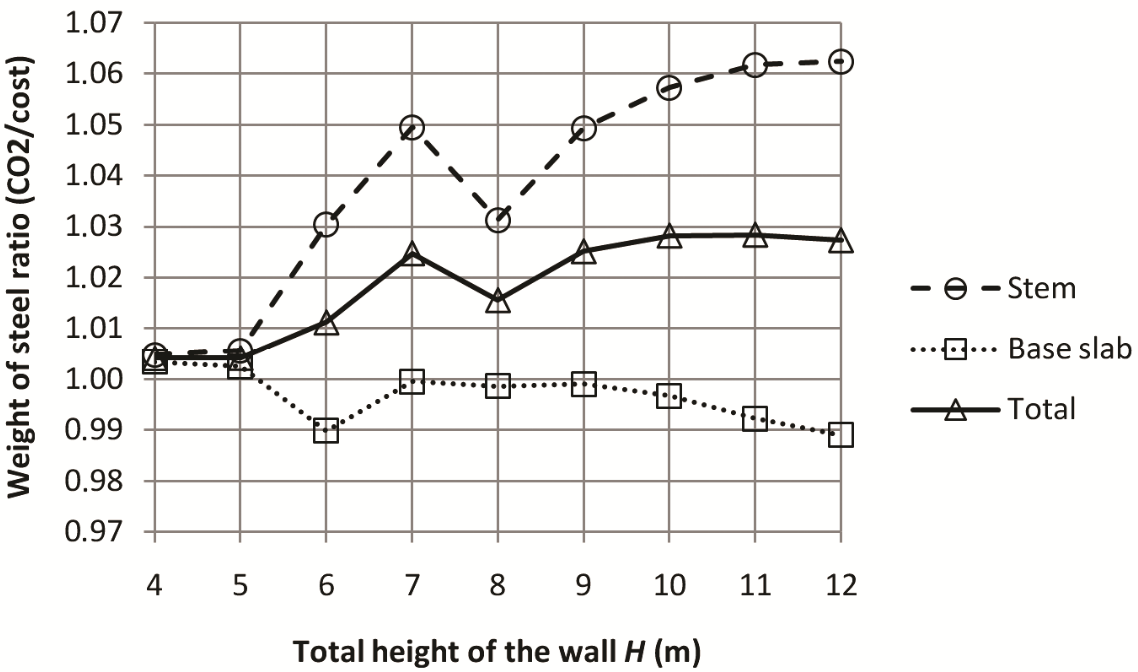

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