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NOVEL OPTIMIZATION ALGORITHM FOR COMPOSITE STEEL DECK FLOOR SYSTEMS: PELOTON DYNAMICS OPTIMIZATION (PDO).

Poitras, Gérard J[1,3] , Cormier, Gabriel[2] and Nabolle, Armel S[1]
[1] Département de génie civil, Université de Moncton, Moncton, NB, Canada
[2] Département de génie électrique, Université de Moncton, Moncton, NB, Canada
[3] gerard.poitras@umoncton.ca

Abstract: In structural steel buildings, one of the most common floor systems is composed of concrete-filled ribbed steel decking supported by wide-flange beams and girders. Traditional design approaches for choosing the components of this typical composite floor system are usually based on the experience of the design engineer. Since there are many possible combinations to this problem (over a billion), it is difficult to guarantee that the final design is the most economical one. Different metaheuristic optimization algorithms have been used to address this design problem with different degrees of success. In particular, the efficiency of some of these algorithms is diminished because of their difficulties in dealing with integer numbers representing the components of the composite floor system. For this study, a novel optimization algorithm is presented based on peloton dynamics that occur during bicycle racing. Peloton dynamics are largely attributable to the physical capacity of cyclists, energy saving by the coupling effects of drafting, and the capacity for cyclists to pass others. It also includes cooperation with other cyclists by changing positions inside the peloton, competitors' positions and their relative energy levels. The optimization procedure used is based on strength, serviceability, performance and cost criteria. The concrete slab + steel deck + steel beams floor configuration used in this study meets all the requirements of the Canadian standard for Design of Steel Structures (CAN/CSA S16-09). The algorithm optimizes the size of all structural elements including girders, beams, slab and deck. The performance of the PDO is compared with other optimization algorithms based on the success rate (ability to find the best solution) and computational effort required. Results indicate the PDO performs better than other metaheuristic optimization methods and requires less user input parameters.

1 INTRODUCTION

Structural optimization is now commonly used by designers to reduce costs. Optimized structures such as buildings should minimize the cost while meeting code-specified performance requirements. Optimization methods have gained much attention because of their direct applicability to the design of structures. One of the first optimization methods applied to structures is the Genetic Algorithm (GA) initially proposed by Holland (1975). The GA tries to find a near-optimal solution for structural optimization problems for which traditional optimization algorithms cannot be applied because of the discrete nature of its variables and the complexity of its objective function and constraints. It is a population based optimization method based on the theory of natural evolution, Goldberg (1989). Senouci and Al-Ansari (2009) utilised a genetic algorithm for the cost optimization of composite beams based on the load and resistance factor design (LRFD) specifications of the AISC specifications. The model formulation includes the cost of concrete, steel beam, and shear studs. A parametric study was also conducted to investigate the effects of beam spans and loadings on the cost optimization of composite beams.

The Particle Swarm Optimization (PSO) algorithm is another population based optimization method. This algorithm was first introduced by Kennedy and Eberhart (1995). The PSO algorithm is based on the social behaviour of groups of animals such as bees, insects and birds. When these groups of animals and insects are looking for food, there is normally a leader who influences the other group members. The PSO algorithm operates in a similar manner. The PSO algorithm was used extensively for different types of optimization problems, including design optimization of structures. Poitras et al. (2011) optimized composite and non-composite steel concrete floor systems using a PSO algorithm. The design problem was the cost of a steel floor configuration subject to constraints related to the Canadian S16-09 (2009) design standard. The design output returned the girder and beams sizes, steel deck profile, concrete slab thickness, number of interior beams and the number of steel studs needed per beam for a typical floor bay.

The Simulated Annealing method, Kirkpatrick et al. (1983) is a trajectory heuristic technique that mathematically mirrors the cooling of a set of atoms to a state of minimum energy. It draws an analogy between the cooling of a material (search for a minimum energy state) and the solving of an optimization problem. This type of algorithm uses less computational resources than population based optimization methods since it starts with one feasible solution and just tries to improve it. Rather than drawing its inspiration from biological or physical processes, the Harmony Search (HS) algorithm proposed by Geem et al. (2001) is inspired by an artistic creative process. The HS algorithm is based on the talent of musician searching for harmony and then continuing to refine the tune to achieve an increasingly better state of harmony. Musical harmony is analogous to an optimization solution and a musician's improvisations are analogous to local and global search schemes in optimization techniques. This trajectory based optimization method has been used successfully for a wide variety of practical structural optimization problems. For example, the cost optimization of a composite floor system utilizing the harmony search algorithm was presented by Kaveh and Abadi (2010). The composite floor system consists of a reinforced concrete slab and steel I-beams designed in accordance with LRFD-AISC (2005) method. The objective function is considered as the cost of the structure, which is minimized subjected to serviceability and strength requirements. Kaveh and Ahangaran (2012) presented a HS algorithm model for the cost optimization of composite floor systems using discrete variables. The total cost function includes the costs of concrete, steel beam and shear studs. The design is based on AISC load and resistance factor design specifications and plastic design concepts. The proposed model is compared to the original harmony search, its recently developed variants, and other metaheuristic algorithms. In order to investigate the effects of beam spans and loadings on the cost optimization of composite floor system, a parametric study was also conducted.

Other optimization methods were applied to the optimization of composite floor systems including a Nonlinear Programming Approach (NLP) by Kravanja and Silih (2003) and Klansek and Kravanja (2007), a Charged System Search (CSS) by Kaveh and Behnam (2012), an Ant Colony System (ACS) by Kaveh and Massoudi (2012) and a Multi-parametric MINLP optimization by Kravanja et al. (2017).

The advantages of metaheuristic optimization algorithms over calculus-based optimization algorithms include: not requiring complex gradient derivatives, the ability to perform global search as well as local searches, and can handle discrete variables. However, one of the major disadvantages with these algorithms is that they require algorithm specific parameters for good performance not known beforehand. Furthermore, discrete optimization problems are difficult to solve for many metaheuristic optimization algorithms. Most structural problems consist of finding member components from available standard members identified by discrete values. To overcome some of these difficulties, a new trajectory based method is presented. Thus, this study will focus on a novel approach, the Peloton Dynamics Optimization (PDO) algorithm which requires less setting parameters.

A peloton may be defined as a group of cyclists that are coupled together through the mutual energy benefits of drafting, whereby cyclists follow others riding in sufficiently close proximity. Although the interactions among individual cyclists are in principle very simple, the collective behaviour of the peloton is very complex. One characterization of a peloton is that they employ group and individual tactics and strategies to obtain top position at the finish line. Interactions usually involve only a few individuals at a time, yet may give rise to non-trivial global phenomena.

In competitive cycling, air resistance is by far the greatest force opposing the forward motion of the cyclist on a flat surface. Air resistance can be effectively reduced by riding downstream near another rider. The drafting rider will then benefit from the low-pressure area behind the front rider. By exploiting the reduced power output requirement of drafting, a drafting cyclist's power output is coupled to the rider ahead. Drafting is a major contributor of cyclists' capacity to pass each other, in addition to their inherent physical capacity to accelerate. Cyclists in drafting zones expend less energy than front position cyclists. According to Olds (1998), taking advantage of the energy-saving benefits of drafting, cyclists' energy expenditures/power outputs are coupled, and by alternating peloton positions to optimize energy expenditures, cyclists in groups can sustain speeds at lower power outputs than individuals riding alone. The equalizing effect of drafting is the basis for cyclists' race strategy and tactics. Both on the track and on the road, cyclists often ride in groups, alternating between leading a peloton and moving behind front riders in a peloton. By coupling in this way, the overall external power requirement of cycling is reduced in that at any one time at least some riders are taking advantage of the effect of drafting.

The threshold at which cyclists decouple is identified by the Peloton Divergence Ratio (PDR), Trenchard and Mayer-Kress (2005) :

[1] $PDR = ((MSO_a – MSO_b) / MSO_a) / (D/100)$

where MSO_a is the maximum power output sustainable for a given period of time (in Watts) of cyclist a at any given moment, MSO_b is the maximum sustainable power output of cyclist b at any given moment, assuming $MSO_a > MSO_b$ and ignoring negligible differences in equipment, body mass and volume, etc., and $D/100$ is the percent energy savings due to drafting at the velocity travelled. Maximum sustainable output (MSO) refers to outputs sustainable for specific times to exhaustion as a fraction of VO_{2max} (maximal oxygen consumption), Olds (1998). The difference between the MSO of a stronger front rider in a non-drafting position relative to a weaker drafting rider is equalized by the drafting benefit, Trenchard and Mayer-Kress (2005).

The Peloton Convergence Ratio (PCR) indicates how a weaker rider can sustain convergence by changing from a front position to a drafting position, or repeated alternations of this process and is given by:

[2] $PCR = [P_{front} – P_{front} \times (D/100)] / P_{draft}$

where P_{front} is the power output (in Watts) of the front rider at the given speed and equals the power output required by the drafting rider to maintain the speed set by the front rider if the drafting rider were not drafting, P_{draft} is the maximum sustainable power (MSO) of the drafting rider and $D/100$ is the percentage of energy saved by drafting. Unlike equation [1], the front rider is not required to be stronger than the drafting rider in the PCR equation. It expresses coupling degrees between cyclists of different strengths. The numerator term of the PCR equation gives the required output of the drafting rider while drafting to maintain the speed set by the front rider. Hence, the PCR equation shows whether or not the drafting rider is capable of keeping pace with the speed set by the front rider while exploiting the power reduction benefit of drafting. As long as $PCR \leq 1$, the riders remain coupled and all cyclists within a peloton are at $PCR < 1$ relative to each other.

Olds (1998) derived an equation for a drafting coefficient based on analysis and data given in Kyle (1979). Drafting benefits can be defined as a ratio of cyclists' power requirements in drafting positions to power requirements in non-drafting positions. According to Olds (1998), the drafting coefficient is:

[3] $d = 0.62 - 0.0104d_w + 0.0452d^2_w$

and represents the ratio of the resistance under drafting conditions to where no drafting occurs. The term d_w is the wheel-to-wheel distance (in metres) between the front and the drafting rider. For $d_w \geq 3$ m, d is assumed to be ≈ 1 and no benefit is gained by drafting more than 3 m behind another cyclist. The drafting coefficient applies no matter how many bicycles are in the peloton and regardless of the position of the cyclist in the peloton, Kyle (1979). The value $1\text{-}d$ is equivalent to the energy saved by the drafting rider which is approximately 38% for a drafting cyclist at 40 km/h, thus $d = 0.62$, given optimal wheel spacing and normalized for other lesser factors that may affect the power output of the drafting rider, Martin et al. (1998).

The Peloton Convergence Ratio (PCR) is found according to the equation:

[4] $PCR = [P_{front} – P_{front} x (1 – d)] / MSO_{drafting} = (P_{front} x d) / MSO_{drafting}$

where $P_{front} = MSO_{drafting} x Rv$, Rv is the ratio of the drafting cyclist's current speed to his maximum sustainable speed when not drafting. For this algorithm, $Rv = Vr/Vs_{max}$ where Vr is the race speed and the maximum sustainable speed Vs_{max} of each cyclist is calculated from the power equation found in http://kreuzotter.de/english/espeed.htm. Weaker cyclists can sustain the pace of the strongest rider between PCR = d and PCR = 1 (d < PCR < 1). In this PCR range, these cyclists cannot pass (drafting riders will move toward the front rider but will not pass him). However, if PCR ≤ d, passing can occur (drafting riders will move ahead of the front rider).

The coupling effect is fundamental to the emergence of complex dynamics and observable phase changes in the peloton (Relaxed, Convection Rolls, Synchronization and Disintegrated). These phases represent the predicted behaviour that may be observed in a dynamic peloton simulation, Trenchard (2012).

2 OPTIMIZATION ALGORITHM

An optimization problem can be defined as finding a minimum or maximum for f(X) where f(X) is the objective function value and X is a vector for the independent variables of the function. In the context of this algorithm, the position of a cyclist during a race is a solution of the objective function.

The proposed algorithm is based on data analyzed from mass-start bicycle races. Mass-start track races represent highly controlled conditions for the study of peloton dynamics. Since track topography does not vary, speed data may be used for a reasonable approximation of MSO, Trenchard et al. (2014). All cyclists' maximum sprint speeds are obtained from sprint time trials and top speeds can be applied as benchmark absolute maximal sustainable outputs (MSO).

The three main components of the peloton dynamic optimization algorithm applied here are: (1) Passing rule; (2) Breakaway and (3) Positional changes. Before the iterative process begins, the algorithm only needs two parameters, the number of cyclists Nc and the number of iteration Ni. Cyclists are randomly assigned MSO values between 400 W and 500 W and the percentage of energy saved by drafting D is given a value of 38%, thus d = 0.62 and the race speed was set at 36 km/h. These values were chosen to favour convection rolls among cyclists where PCR < 1. Since the race speed is chosen beforehand, PCR values for all cyclists are calculated at the beginning of the race. Details of the iterative procedure used for the PDO algorithm is as follows:

Step 1: For each cyclist (i.e. k=1, 2, . . . , Nc), random values respecting domain limits of the objective function are generated for each variable. This step represents phase I identified beforehand.

Step 2: A random cyclist k is chosen from the group of cyclists forming the trailing haft end of the peloton. Another cyclist f is chosen ahead of cyclist k and the following passing rule is applied:

[5] $pk_{i+1} = pf_i + rand x (pf_i – pk_i)$ if $PCR \leq d$

[6] $pk_{i+1} = pk_i + rand x (pf_i – pk_i)$ if $d < PCR < 1$

where rand is a random number between 0 and 1, pk_i is the position of cyclist k and pf_i is the position of cyclist f at iteration i. This phase can be related to the convection phase of the peloton and is the most important step of the algorithm.

Step 3: When a paceline is formed, a small group of riders or an individual cyclist have successfully opened a gap ahead of the peloton to take the front position. For this type of action, a cyclist's position is changed according to the equation:

[7] $p_{k+1} = pbest_i + rand x (pbest_i – pj_i)$

where pj_i is the position of a random cyclist j and $pbest_i$ is the front runner of the peloton at iteration i. This breakaway phase can be related with the synchronization and disintegrated phases of the peloton.

Step 4: A change in position of the worst cyclist w in the peloton is implemented according to the following equation

[8] $pw_{i+1} = pbest_i + rand(0,1 \text{ or } 2)$

where pw_{i+1} is the new position of the worst cyclist at iteration i, $pbest_i$ occupies the front position (the best solution) among all cyclists at iteration i and rand(0, 1 or 2) is an integer random number of either 0, 1 and 2. This positional change phase can also be associated with the disintegrated and synchronizing phase of the peloton described beforehand and is only activated after 1/3 of the iterations are completed. The best and worst cyclists (solutions) are identified at the end of each iteration.

Equations 5 through 8 are used for a maximization problem. Implementation for a minimization problem only requires changes in signs for these equations. These steps are repeated for each iteration until the final iteration is reached. The total number of function evaluations in the PDO algorithm is equal to (3Ni - 1/3Ni) only since there is a maximum of three cyclist positional changes per iteration.

3 DESIGN PROBLEM

The layout of the concrete steel deck floor system is illustrated in Figure 1. All girders and beams are pin-connected, the girders are laterally supported by the beams and the beams can be considered laterally supported or not by the steel deck. All design parameters used in the algorithm are given in Table 1. The beam and girder sizes are hot-rolled W shapes found in the Canadian Institute of Steel Construction Handbook (2016) excluding class 4 sections. The steel deck choices were taken from the Canam® Steel deck catalogue (PC3615, PC3623, PC2432) and the steel deck thicknesses considered are either 0.76, 0.91, or 1.21 mm (22, 20 or 18 gauge). Each type of steel deck has six possible slab thicknesses made of either lightweight or normal density concrete. Slab thickness can be 90, 100, 115, 125, 140, 150, 165, 190 or 200 mm, depending on the type of steel deck and concrete slab configuration used.

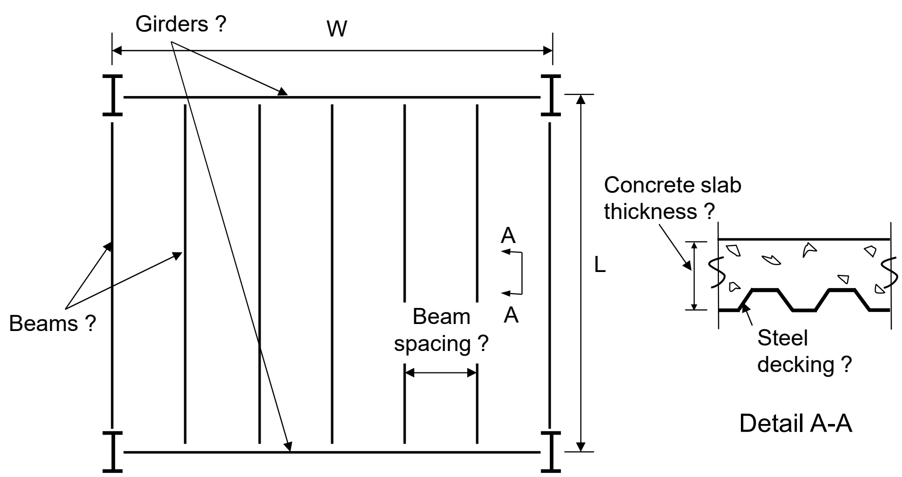

Figure 1. Steel floor system configuration and physical input parameters

Table 1: User inputs required for the concrete steel deck configuration

- Bay width, W (m) and bay length, L (m)	- Limits on the number of interior beams
- Additional dead load, wD (kPa)	- Height limits on the beams and girders
- Live load, wL (kPa)	- Concrete type (normal or light weight)
- Uniform dead loads on edge beams, qD (kN/m)	- Concrete compressive strength, f'c (MPa)
- Uniform live loads on edge beams, qL (kN/m)	- Vibration live load, wLv (kPa)
- Deflexion limits	- Additional vibration dead load, wDv (kPa)
- Laterally supported beams (yes or no)	- Vibration control properties

The user may modify the minimum and maximum number of interior beams (spacing) of the floor layout, reduce the number of possible combinations of girders and beams by limiting the height of girders and beams, use normal density (2400 kg/m^3) or lightweight concrete (1840 kg/m^3) or both. An option for shoring to support the steel deck during the pouring and curing of the concrete slab is given. For vibration consideration, parameters are set by the user for the floor bay in consideration (interior bay or edge bay) and if there are additional bays along its length or its width. Furthermore, other design parameters used are double span and triple span conditions for the steel deck, steel decking ribs are parallel to the girders and perpendicular to the beams, deflection control for beams and girders is applied for live loads only while for the steel deck, construction deflection criteria are also considered. Similar floor configurations were used by Poitras et al. (2011) to test the capacities of a Particle Swarm Optimization algorithm.

The algorithm will provide the north girder size, GN, south girder size, GS, west edge beam size, BW, east edge beam size, BE, the interior beams size, the number of interior beams, NB, the type of steel deck, PC, the height of the concrete slab, tc, and the price of the bay configuration.

3.1 Objective function

The objective function to minimize the cost of the floor system. It is defined as

[9] f_{cost} = c(girders) + c(edge beams) + c(int. beams) + c(deck) + c(slab)

where c( ) represents the cost of each floor component. The cost of each component is calculated from prices given by local construction companies. The prices used for calculating the cost of the floor are presented in Table 2.

Table 2: Prices for various floor components

Components	Price $
Steel	2.86 per kg
Steel deck	2.25 per kg
Steel deck (installation)	5.40 per m^2
Concrete	131 per m^3
Concrete (installation)	5.40 per m^2

3.2 Constraints

The components of the floor system are designed to meet all the requirements of the Canadian National Building Code (2010), the CSA-S16 Limit States Design of Steel Structures standard and the CSSBI_2M standard for composite steel deck for ultimate and serviceability limit states. Floor vibration control is applied according to the Steel Design Guide Series 11 for floor vibrations control, Murray 1997. The ultimate limit state requirements demand that the resistance of the members must be higher than the critical factored internal forces for all load combinations. The serviceability limit state requirements imply that the vertical deformation of each floor components due to construction and live loads is limited to an acceptable amount (i.e. L/360). The objective function is subjected to the constraints represented in Table 3 for all components of the floor configuration. A cyclist represents a solution of the floor system which includes one steel deck, one slab thickness, five steel sections and the number of inside beams. These components are selected individually by the algorithm and their position (values) are modified using Equations 5 through 8 during the iteration process.

Table 3: General design constraints

- Moments (steel deck)	cs_1 : $Mf_{max\,(+)} / Mr_{(+)} \leq 1.0$, $cs_2 = Mf_{max\,(-)} / Mr_{(-)} \leq 1.0$
- Web crippling (steel deck)	cs_3 : $Rf_{int} / Br_{int} \leq 1.0$, $cs_4 = Rf_{ext} / Br_{ext} \leq 1.0$
- Deflection (steel deck and slab)	cs_5 : $\Delta L / \Delta adm \leq 1.0$ (construction), cs_6 : $\Delta L / \Delta adm \leq 1.0$ (cured)
- Total factored load (slab)	cs_7 : $wf_{max} / wr \leq 1.0$ (cured)
- Moment (girders and beams)	cs_8 : $Mf_{max} / Mr \leq 1.0$
- Shear (girders and beams)	cs_9 : $Vf_{max} / Vr \leq 1.0$
- Deflection (girders and beams)	cs_{10} : $\Delta L / \Delta adm \leq 1.0$
- Floor acceleration limit(walking)	cs_{11} : $(a_p /g) / (a_0 /g) \leq 1.0$

3.3 Iteration procedure

The algorithm starts with a user-defined peloton size Nc (i.e. the number of solutions to be evaluated). Random solutions are generated and their components are then verified to determine if they satisfy all the ultimate and serviceability states. The algorithm won't start the optimization process if any of the requirements are not met. This method has been used to simplify the programming of the algorithm as it provides solutions that must respect all the constraints and design criteria firsthand. During the iteration process, the algorithm calculates the cost of each floor configuration (i.e. each cyclist) that satisfies all the imposed constraints. For subsequent iterations, these solutions are adjusted by the algorithm using Equations 5 through 8. The modified solutions are analyzed and compared with the requirements once again before proceeding with the next iteration. If a floor component fails only one constraint, it is rejected and a new solution is sought. The new solution is chosen from an existing one and only one random variable of the solution is changed by applying the same step (step 2, 3 or 4). Floor components are identified by using discrete numbers. Therefore, changes in position are done using integer value only.

4 RESULTS

The preceding PDO algorithm was applied on three steel floor bays. The three examples are,

- a corner bay 6 m x 8 m floor with laterally supported beams;
- an interior bay 10 m x 8 m floor with laterally supported beams;
- an interior bay 10 m x 8 m floor with non-laterally supported beams.

The first example was used to test the capability of the PDO algorithm to find the best corner bay floor configuration that includes these restraints: 200 mm to 650 mm girders (2) and beams (3) with three to six spaces, six different thicknesses of normal density concrete, nine types of steel decks, which gives 161^5 (girders and beams) x 4 (spaces) x 6 (concrete thickness) x 9 (steel deck) = 23.4×10^{12} possible configurations. The design parameters used for this example are shown in Table 4. The additional dead and live loads take into account the load attributed to the adjacent bays and exterior walls.

Table 4. Design parameters used for the corner bay floor configuration

Bay size (mm)	Dead load (kPa)	Live load (kPa)	Additional dead load (kN/m)	Additional live load (kN/m)	Load for vibration criteria (kPa)
Corner bay W = 8000 L = 6000	WD = 1.6 +deck +concrete +steel	WL = 4.8	wD = 10 (north) wD = 6 (south) wD = 4 (west) wD = 6 (south)	wL= 14 (north) wL = 0 (south) wL = 4 (west) wL = 0 (south)	wD=0.5 +deck +concrete +steel wL=0.5
Interior bay W = 10000 L = 8000	WD = 2.0 +deck +concrete +steel	WL = 2.4	wD = 16 (north) wD = 16 (south) wD = 10 (west) wD = 10 (south)	wL = 9.6 (north) wL = 9.6 (south) wL = 6 (west) wL = 6 (south)	wD=0.5 +deck +concrete +steel wL=0.5

The best solution for the corner bay example is a steel floor system consisting of a W530x74 north girder, a W460x52 south girder, a W310x24 west beam, a W310x21 east beam, 4-W310x24 interior beams, a PC-3615x0.76 mm steel deck and a 90 mm concrete slab. The total cost of this floor configuration is $7149. The second-best configuration for this floor is a W530x74 north girder, a W460x52 south girder, a W310x28 west beam, a W310x21 east beam, 3-W310x28 interior beams, PC-3615x0.91 mm steel deck and a 90 mm concrete slab for a total cost of $7180. There is only a difference of $30 between these two floor configurations. This last configuration was only found by the PDO algorithm a few times since the W460x52 beam has a 0.998 solicitation rate whereas the second-best three interior beam configuration has a cost of $7254. This configuration consist of a W530x74 north girder, a W460x60 south girder, a W310x28 west beam, a W310x21 east beam, 3-W310x28 interior beams and a P3623x0.76 steel deck with a 100 mm concrete slab.

Two other interior bay configurations were design using the parameters presented in Table 4. The first bay configuration used beams that were laterally supported by the steel deck while for the other bay configuration, the beams were designed considering they were laterally unsupported. For the interior bay, the most economical floor configuration consists of 2-W610x101 girders, 2-W410x46 edge beams, 3-W310x39 interior beams, a PC-3615x0.91 mm steel deck and a 100 mm concrete slab. The cost of this floor system is $14016. For the same interior bay with laterally unsupported beams, the most economical floor configuration is 2-W610x101girders, 2-W310x79 edge beams, 3-W250x67 interior beams, a PC-3615x0.91 mm steel deck and a 100 mm concrete slab for a total cost of $17448.

Table 5. Design parameters used for the corner bay floor

Bay size (mm)	Floor components	Maximum design ratio	Controlling design parameter
Corner bay	W530x74 north beam	0.975	Mf / Mr
W = 8000 mm	W460x52 south beam	0.998	Mf / Mr
L = 6000 mm	W310x24 west beam	0.929	∆L / 360
	W310x21 east beam	0.845	Mf / Mr
$ 7149	4-W310x24 int. beams	0.911	∆L / 360
	PC-3615x0.76 deck + 90 mm slab	0.751	Mf(+) / Mr(+) (construction)
Interior bay	W610x101 north beam	0.971	Mf / Mr
W = 10000 mm	W610x101 south beam	0.971	Mf / Mr
L = 8000 mm	W410x46 west beam	0.949	Mf / Mr
(laterally supported	W410x46 east beam	0.949	Mf / Mr
beams)	3-W310x39 int. beams	0.907	Mf / Mr
$ 14016	PC-3623x0.91 deck + 100 mm slab	0.737	Mf(-) / Mr(-) (construction)
Interior bay	W610x101 north beam	0.971	Mf / Mr
W = 10000 mm	W610x101 south beam	0.971	Mf / Mr
L = 8000 mm	W310x79 west beam	0.966	Mf / Mr (Ls = 8000 mm)
(laterally	W310x79 east beam	0.966	Mf / Mr (Ls = 8000 mm)
unsupported beams)	3-W250x67 int. beams	0.972	Mf / Mr (Ls = 8000 mm)
$ 17448	PC-3623x0.91 deck 100 mm slab	0.737	Mf(-) / Mr(-) (construction)

Table 5 presents the results obtained for the three floor configurations, the maximum design ratio for each floor components and the controlling design parameter. Most of those ratios are in the high 90% solicitation rate for the girders and beams. For the deck design, a 75% solicitation rate is the highest value obtained. This lower value is expected since they are only fifty-four possible deck + slab configurations. Small changes for this component can result in important design differences where higher design ratios do not exist.

A hundred trial runs were realized for the 8 m x 6 m corner bay configuration to compare the PDO results with other metaheuristic methods (PSO and HS algorithm) as shown in Table 6. For all the trial runs, the number of solutions during the iteration process was fixed at twenty and the total number of iterations was 5000. Since the PSO algorithm is a population base optimization method compared with the trajectory methods for the HS and PDO algorithm, it was expected that the calculation time used by the PSO algorithm was much larger. However, this did not result in a better success rate (6%) since this method requires a higher number of iterations for this application. The HS result shows a better success rate (23%) compared to the PSO algorithm combined with the fastest overall performance since only one solution is changed per iteration. The only algorithm with a 100% success rate for this floor configuration is the PDO algorithm. Furthermore, the PSO and HS algorithm did not find the second-best floor configuration of $7180. Even with 2000 iteration, the PDO algorithm still has a 92% success rate with a total calculation time of 110 seconds.

Table 6. Results from 100 trials, 5000 iterations, 4 interior beams

		PSO (20 particles)	HS (20 harmonies)	PDO (20 cyclists)
Corner bay W = 8000 mm L = 6000 mm **$7149**	Success rate	6%	23%	100%
	Mean	$7473	$7325	$7149
	Worst	$8145	$7683	$7149
	Standard dev.	$191	$157	$0
	Execution time	2030 s	126 s	303 s

5 CONCLUSION

For this work, a new optimization algorithm, the Peloton Dynamic Optimization (PDO) was presented for the design of a steel floor system. The optimization problem was the minimization of the cost of a steel floor configuration. The performance of the PDO algorithm was tested for three steel floor design configurations. For all test cases, the optimum design was consistently found where all components chosen by the algorithm satisfied all design constraints. Despite the fact that over a billion combinations were possible, a small peloton of 20 cyclists is sufficient to find the optimum floor configuration with a very high success rate. It was shown that this new algorithm is more efficient than the PSO and HS algorithms for finding the least cost of a composite floor system. The number of iterations and convergence rate can be improved by making an initial run with a large number of combinations (e.g. two to eight beam spacing) and then, once the preceding results are known, limiting the number of components available (e.g. imposing a fix value for the number of spacing). Further studies are being conducted to apply this method to composite floor systems with studs, to building bracing systems and to develop a real number version of this algorithm.

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