A PARTICLE SWARM ALGORITHM FOR MANUAL LIFTING TASKS DESIGN

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PARÇACIK SÜRÜ ALGORİTMASI İLE MANUEL YÜK KALDIRMA İŞLERİ İÇİN TASARIM

Anahtar Kelimeler
Manuel Yük Kaldırma
İş Yeri Tasarımı
Parçacık Sürü Optimizasyonu

Öz

Son yıllarda otomasyonun neredeyse tüm aşamalarda kullanıldığı Endüstri 4.0 konsepti gündemde olmasına rağmen bir çok işletmede yük kaldırma işlemleri hala manuel olarak (elle) yapılmaktadır. İş sağlığı ve güvenliği açısından birçok yasal düzenleme ve çeşitli enstitülerin getirmiş olduğu standartlar çerçevesinde özellikle manuel taşıma işleri için uygun işyeri tasarımı önemli bir problem olarak görülmektedir. Genellikle yapılan kaldırma işi ile ilgili; ağırlık, çalışma ortamı, yük ile ilgili şekil, taşıma kolaylığı vb. bilgiler bilinmekle beraber yükün nereden, hangi açıyla, ne sıklıkla, ne kadar yüksekliğe ve mesafeye taşınacağı yasalar ve mevzuatlar dikkate alındığında iş yeri tasarımı açısından en iyi değerleri bulunması gereken parametreler olarak karşımıza çıkmaktadır. Bu çalışmanın amacı, yapılacak iş için önceden belirlenmiş koşullar dikkate alınarak fiziksel stresi en aza indirecek bir iş yeri tasarımı önermektir. Çalışma alanındaki kısıtlamalar dahilinde yük kaldırma gerektiren işlerde güvenli çalışma alanları tasarlamak için Parçacık Sürüsü Optimizasyon Algoritması kullanılmıştır. Literatürde bulunan NIOSH(ABD Ulusal İş Sağlığı ve Güvenliği Enstitüsü) tarafından sunulan manuel yük kaldırma endeksini en aza indiren iş yeri tasarımı ile ilgili test problemleri çözülmüş ve mevcut çalışmalarla kıyaslanmıştır. Önerilen algoritma, bu tarz problemlerde mevcut yöntemlere kıyasla daha iyi tasarımlar sunmuştur.

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Keywords
Manuel lifting task
Workplace design
Particle Swarm Optimization

Abstract

In recent years although the Industry 4.0 concept, which has been used in almost all stages, is still on the agenda, many lifting operations are still carried out manually. In terms of occupational health and safety, many legal regulations and the standards brought by various institutes, especially suitable for manual transport work is an important problem. Generally related to the lifting work; weight, working environment, load related shape, ease of handling etc. while the information is known, where the load is to be moved, how often, how much height and distance to be taken into consideration, the best values in terms of workplace design are the parameters that should be found when the laws and regulations are taken into consideration. The aim of this study is to propose a workplace design that minimizes physical stress by considering the predefined conditions for the work to be done. Particle Swarm Optimization Algorithm has been used to design safe working areas for jobs requiring load removal within the constraints of the work area. Test problems related to workplace design which minimizes manual load lifting index presented by NIOSH are solved and compared with current studies. The proposed algorithm offers better designs compared to existing methods in such problems.

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1. Introduction

Manual handling of loads (MHL) is a situation that can be encountered in almost everyday life of both home and work. However, if this handling of the loads process is frequently repeated and has become a part of the work, it should be done in a well-designed way to prevent discomfort in the musculoskeletal system. The prevalence and cost of low back pain associated with this work in businesses where handling of loads is frequently applied shows that a better understanding of the occurrence of such painful events is needed. The type of work (eg lifting or lowering), the size of the load on the hands, and the role of variables such as the posture of the worker when performing various tasks, etc. the parameters must be well designed (Anderson et al., 1985). While many discomforts that may occur during the load lifting process can be prevented by ergonomic designs and strategies, the most common disorders in workers are back and low back pain (Fan and Straube, 2016). Especially the blue-collar workers in heavy transportation jobs, frequently expose to the musculoskeletal disorders (Sterud and Tynes, 2013; Andersen et al., 2016, 2017). Therefore, in this study, a workplace design will be proposed to minimize physical stress by taking into account the predetermined conditions for a job.

The sections are listed as follows. In the second part, previous studies that were done review are discussed. In the third part, after the problem is described Particle Swarm Optimization (PSO) used in this study is also described in detail. In the fourth part of the study the implementation of the proposed methodology and calculations are made. In the last section, the results are evaluated and suggestions for future studies are presented.

2. Scientific Literature Review

Singh et al. (2016) stated that the complexity of manual material handling is inherent. Manual material handling jobs at risk of occupational accidents and injuries emphasizes the importance of the application of ergonomics. In general, lifting job factors are classified in the revised NIOSH lifting equation (see Niosh, 2017) for manual load lifting (Waters et al., 1993). Generally, these factors are weight of load, horizontal distance, vertical distance, vertical travel distance, asymmetry angle, lifting frequency, classification of the quality of the load. In addition, the existing workplace design, with pre-designed and physical constraints, where lifting is performed, should also be considered as one of the critical factors. In these circumstances, it is an important strategic advantage to provide employers with flexible workplace design alternatives for load lifting problems (Carnahan and Redfern, 1998). When classical optimization methods address this problem, global solutions can be optimally provided and an alternative solution sets that provide constraints with intuitive approaches can be suggested to the user.

Many biomechanical improvement problems are related to the manual load lifting and the review of these studies will be effective. The most common method used for biomechanical optimization problems is Gradient Based Nonlinear Programming method because the design variables of the problem are not linear generally. Chang et al. (2001) proposed a model for biomechanical simulation of manual load lifting using space temporal optimization. In their study, they developed a new methodology to produce optimum motion models for parasagittal load lifting operations. The proposed model also aims to minimize certain pre-planned conditions. Arjmand et al. (2011) used Response Surfaces Methodology to find the spine loads estimation equation in symmetrical transport works. Eight estimation equations are proposed for spine loads at two disc levels (L4-L5 and L5-S1) and in two postures (flexible and perpendicular). This article has been a guide for identifying low back pain. Batish et al. (2011) conducted an experimental study that included five independent lifting variables and their interactions were evaluated in the Taguchi design. In order to achieve multi-response optimization conditions, the cardiopulmonary responses of the operators and the continuous removal or reductions of the objects have been ensured. Bangar et al. (2012) with Taguchi Parametric Optimization Technique sets the maximum recommended weight limit for manual lifting in the industry. They evaluated various experiments using a number of analytical test problems up to seven design variables. Singh et al. (2014) evaluated the effect of lifting work parameters on heart rate and oxygen uptake during manual lifting operations in different ambient conditions.

In recent years, although many jobs are done with automatic machines, there are some studies showing that this is the exact opposite, although it seems to reduce the manual lifting loads. Kuta et al. (2015), in their study, they observed that workers working in the agricultural sector are experiencing increases in their working conditions due to handling of loads, material handling, milking and tractor riding. Previously the milking process, which is done by hand, is carried out with machines to increase productivity and to make the jobs faster nowadays. Because of the fact that these machines had to be carried by the workers, they have concluded that this technological development turned into a problem that needs to be examined ergonomically.

Construction workers are often suffering from back pain complaints due to load lifting problems. In an existing study, the determination of the safe weight limit of the sand stone block was discussed (Ismaila and Aderele, 2015). In a study related to construction works, there are applications that determine whether the work to be done by using expert systems is risky (Adejuyigbe et al., 2015). Another study in which the expert system is used is the risk assessment of the work-related musculoskeletal disorders (Pavlovic-Veselinovic et al., 2016).

Since the problem of manual handling of load is frequently encountered in daily life, the studies on this subject vary. One of the remarkable studies is the examination of muscle movements during the load lifting process in obese and non-obese individuals (Colim et al., 2015). Also, Sign et al. (2016) conducted a literature review on the application of the NIOSH lifting equation for manual load lifting and discussed the important factors. Furthermore, Lu et al. (2016) presented a study evaluating the effects of NIOSH lifting equation for manual load lifting.

In the literature, the problems of handling of load problems and examination of musculoskeletal system disorders have been studied in various sectors such as market (Rahman and Zuhaidi, 2017), agriculture (Kuta et al., 2015), construction (Ismaila and Aderele, 2015; Adejuyigbe et al., 2015) and blue collars (Lars Louis Andersen et al., 2016; Lars L. Andersen et al., 2018; Jakobsen et al., 2018).

However, there are some deficiencies specially related to workplace design. In this study, various test problems have been studied to overcome this deficiency. The used test problems were proposed by Carnahan and Redfern (1998) firstly. Genetic Algorithm (GA) approach has proposed alternative solutions for 6 different handling of load problem scenarios with physical limits that previously have known (Carnahan and Redfern, 1998). Then, Seckiner and Eroglu (2015) handled the same problem with the Harmony Search (HS) algorithm and presented different workplace design solutions. The aim of this study is to present better alternative workplace designs with a different solution approach by focusing on this problem in the literature. For this, Particle Swarm Optimization algorithm will be utilized in the analysis.

3. Method

3.1. The particle swarm algorithm (PSO)

PSO is a stochastic global optimization approach proposed and developed by Eberhart and Kennedy (1995) originally (Eberhart and Kennedy, 1995; Eberhart et al., 1996; Kennedy, 1997; Engelbrecht, 2007; Kennedy, 2010; Engelbrecht, 2014).

In PSO every individual that states as a particle stands for a potential solution. Each particle in the swarm has a ‘position’ and a ‘velocity’, which is updated both by its own experience (pbest) and by neighbours experience (gbest) in the search space. Moreover, a swarm is similar to population while a particle is similar to an individual (chromosome) analogically to evolutionary computation paradigms (Engelbrecht, 2007; Sulaiman et al., 2014). In other words, every single particle has a circulation in a multidimensional search space, where each particle's position is regulated according to its own experience and neighbours.

PSO starts with a group of random particles and then updates the generations to search for the optimum. Every single particle is updated by the following two ‘best’ values with iterations. The first one is the best solution (goodness) it has reached up to now. The goodness value is kept too. This value is called ‘pbest’. Another ‘best’ value is monitored by the particle swarm optimizer is the best value, acquired until now by any particle in the population. This best value is a global best and called ‘gbest’. The best value is a local best and is called ‘lbest’ when a particle is located in the population like its topological neighbours. Afterwards determine the two best values, the particle’s velocity and positions are brought up to date with following Equation 1 and 2 (Hu and Eberhart 2002).

$$v[\ ] = C1 * rand(\ ) * (pbest[\ ] - present[\ ]) + C2 * rand * (gbest[\ ] - present[\ ]) \quad (1)$$

$$present[\ ] = present[\ ] + v[\ ] \quad (2)$$

Where:

v[ ]=the particle velocity

present [ ]=the current particle (solution)

pbest [ ]= ‘personal best’ which is the personal best position of a given particle, so far

gbest[ ]= ‘global best’ which is the position of the best particle of the entire swarm

rand( )= a random number between 0 and 1

c1 and *c2*= two positive constants called cognitive learning rate and social learning rate.

A global pseudo code for the general PSO algorithm, which is derived from the codes given in presented below (De Castro, 2002):

Initialization: randomly initialize a population of particles.

Population loop: for each particle, do:

Goodness evaluation and update: evaluate the 'goodness' of the particle. If its goodness is greater than its best goodness so far, then this particle becomes the best particle found so far (pbest).

Neighborhood evaluation: if the goodness of this particle is the best among all its neighbors, then this particle becomes the best particle of the whole neighborhood (gbest).

Calculate particle velocity (Eq. 1)

Update particle positions (Eq. 2)

Cycle: repeat Step 2 until a given convergence criterion is met

The algorithm in the study was coded in the MATLAB language and PSO analyses were designed for a standard size of 200 particles, and other algorithm parameters are also selected based on standard recommendations as seen in Table 1.

Table 1. Standard PSO algorithm parameters used in the present study

Parameter	Description	Value
P	Population size number of particles	200
c1	Cognitive trust parameter	0.5
c2	Social trust parameter	0.5
w0	Initial inertia	1.0
wd	Inertia reduction parameter	0.0

All computations were compared Genetic Algorithm (GA) developed by Carnahan and Redfern (Carnahan and Redfern, 1998) and Harmony Search Algorithm (Seçkiner and Eroğlu, 2015). To identify an appropriate approach to be applied to lifting design problem with PSO algorithm is to see task requirements as environmental conditions. Alternative solutions have two goals; to be competitive in goodness evaluation and global best solution within environmental constraints. There is a short description of below the stages in PSO used to solve for the multiple solutions. The development of PSO algorithm used in the study was depened upon the procedure reffered by De Castro (De Castro, 2002).

Stage 1: *Initialization of the environment*. The environmental conditions are set according to five task parameters. These are weight of the load handled (kg), quality of the handle interface (good, poor, fair), the number of lifts needed in the part of operator, maximum and minimum time allowed to perform the lifts and Lifting Index (LI) considered acceptable by ergonomist.

Stage 2: *Establish the initial particle of solution* (Population loop). A huge number of variable design solutions (set to 200 particles) are generated by PSO algorithm. Every single solution is a linear sequence of five real numbers that are defined in Table 2. The sequence shows five constraints for lifting workplace design. After Stage 2, the constraints are randomly assigned to each of the 200 solutions.

Table 2. Design parameters generated by the PSO solutions. Each design solution is represented as a linear array of 5 real values *H, A, V_e, V_s, D.*

Parameter	Definition	Minimum	Maximum
H	Horizontal distance (load to ankles)	25.4 (cm)	63.5 (cm)
A	Asymmetry (between load & sagittal plane)	0 (deg)	135 (deg)
V_e	Vertical distance (hands to floor-end to lift)	0 (cm)	177.8(cm)
V_s	Vertical distance (hands to floor-start to lift)	0 (cm)	177.8(cm)
D[a]	Duration of lifting task	Min (h)	Max (h)

Stage 3: *Goodness evaluation and update*. In this stage, goodness evaluation and update of each solution in the particle is determined. Goodness evaluation is a quantifiable measure of how well the solution satisfy the productivity and safety desires which are consist of the environment conditions. Every solution is consisted of two types of goodness:

3.2 Raw Goodness

Recommended Weight Limit (RWL) is the product of the NIOSH lifting equation (2017). The following Equation 3 defines the RWL:

$$RWL = LoadConstant\ (23\ Kg) \times HorizontalMultiplier \times VerticalMultiplier \times DistanceMultiplier \times FrequencyMultiplier \times AsymmetricMultiplier \times CouplingMultiplier \quad (3)$$

3.3 Standardized Goodness (GS)

As a measurement of RWL to the weight limit determined by LI and weight of the load (W_t). This related value is computed based on the absolute difference value of RWL and the ratio (W_t/LI) (See Equation 4).

$$SG = \frac{1}{1+[SG\times\left|RWL-\left(\frac{Wt}{LI}\right)\right|]} \quad (4)$$

Where:

L: Lifted object weight

Sg: Selection Gradient setS as a constant value (0.1),

RWL: Recommended Weight Limit.

$$LI = \frac{Wt}{RWL} \quad (5)$$

Greater than 1.0 for LI pose lifting tasks, increases the risk for lifting-related cumulative trauma disorders.

4. Computational Results

For the uses of investigate the utility of PSO in the ergonomics design process, different conditions are chosen accoridng to the NIOSH work practices guide as seen from Table 3. These conditions represent typical work environments that include several lifting indices and production demands. A representative example of the workplace environments where the workers perform manual load lifting is given in Figure-1 (Niosh Méthode, 2018).

Table 3. Environmental workplace conditions (t problems) used in the PSO algorithm

Environment	Weight (Kg)	Hand/hand interface	No. of lifts	Time range (h)	Lift index
Condition 1	9.0923	Good	600	0.0 - 2.0	1.0
Condition 2	4.5463	Poor	200	0.0 - 0.6	1.0
Condition 3	18.1447	Poor	900	3.0 - 8.0	2.0
Condition 4	31.8042	Good	300	0.0 - 8.0	2.0
Condition 5	47.7064	Fair	100	0.3 - 3.3	3.0
Condition 6	5.4332	Fair	2400	4.0 - 8.0	1.0

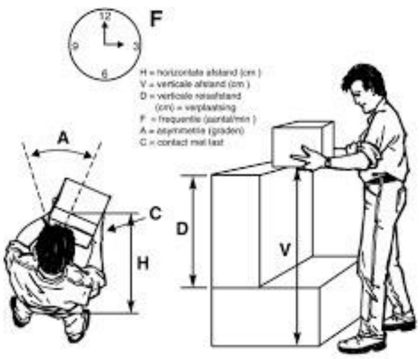

Figure-1 A representative example of the workplace environments

In this study, the environmental design criteria that are used by PSO algorithm are shown in Table 3. Test problem 1 assumes that lifted load is 9.0923 kg, coupling quality constraint is good, the number of performing lift is 600, lifting duration range is between 0- 2 hours and desired LI is 1.0. Test problem 2 assumes that lifted load is 4.5463 kg, coupling quality constraint is poor, the number of performing lift is 200, lifting duration range is between 0- 0.6 hour and desired LI is 1.0. Test problem 3 assumes that lifted load is 18.1447 kg, coupling quality constraint is poor, the number of performing lift is 900, lifting duration range is between 3.0- 8.0 hour and desired LI is 2.0. Test problem 4 assumes that lifted load is 31.8042 kg, coupling quality constraint is good, the number of performing lift is 300, lifting duration range is between 0- 8.0 hour and desired LI is 2.0. Test problem 5 assumes that lifted load is 47.7064 kg, coupling quality constraint is fair, number of performing lift is 100, lifting duration range is between 0.3-3.3 hour and desired LI is 3.0. Test problem 6 assumes that lifted load is 5.4332 kg, coupling quality constraint is fair, the number of performing lift is 2400, time range is between 4.0-8.0 hour and desired LI is 1.0. Each of the six test problems produced from a series of 10 runs. For each run, the developed PSO algorithm worked with 5,000 iterations for 200 particles. In every iteration, the proposed algorithm kept the number of solutions and average standardized goodness for each candidate solution too. The best of run design solutions for each particle discussed and compared with GA and HS algorithm solutions.

4.1. Test Problem 1

Test problem 1 includes a relatively light load lifted 600 times within 2 hours time range. Table 4 contains the solutions evolved from test problem 1. As seen in Table 4, there are several varied offers for manual-lifting design parameters. Despite design parameters have high variability; PSO algorithm could find desired lifting index value in different best combinations. For example, under lift design ♯2, the loads could be grasped with 25.4 cm horizontally away from ankles with the starting height of the lift from 89 cm from the floor. In addition, asymmetry is allowed up to 48.5° movement in the horizontal plane. So that meeting safety and productivity requirements, the design would need that lifts sould be performed at a rate of nearly 6.1 lifts per minute for 96.9 minutes. With these conditions, LI is 1.0 as desired, so #2 is proper design solutions and can be applicable in a real life.

GA has many design solutions from subpopulation evolved. For example, in test problem 1, one of the best solution ranges is such as 25.4-34.0 cm for horizontal parameter, 0-14.2° for asymmetry angle parameter, 63.0-89.4 cm for vertical height parameter, 0-25.4 cm for travelling distance parameter, 5.31 lifts per minutes for repetition rate, and 113 minutes for task duration. As desired, these design parameters provide RWL and LI as 88.95 N and 1.0 respectively. Generally, for test problem 1, suggested design parameters are different, but LI index are equal to 1.0

4.2. Test problem 2

Test problem 2 contains a light load with only 200 total lifts and poor handle interface coupling required. Table 5 contains the best 10 solutions evolved under Test problem 2. For instance, in solution #8 the loads could be grasped with 32.6 cm horizontally away from ankles at the start of the lift; but with a large degree of asymmetry (111°) under the design of #8. The design would need that lifts should be performed at a rate of nearly 6.8 lifts per minute for 29 minutes as a maximum allowable time. As desired, these design parameters provide RWL and LI as 4.5463 kg and 1.0 in return.

In the same manner, the genetic algorithm provides desired RWL and LI in test problem 2. One of the best solution ranges is such as 25.4-28.4 cm for the horizontal parameter, 0-80.6° for asymmetry angle parameter, 32.5-120 cm for vertical height parameter, 0-56.1 cm for travelling distance parameter, 10.8 lifts per minutes for repetition rate, and 19 minutes for task duration. As desired, these design parameters provide RWL and LI as 44.60 N and 1.0 respectively.

Table 4. Design solutions for test problem 1

Particle	Horizontal distance (cm)	Asymmetry angle (deg)	Vertical distance (cm)	Travel distance (cm)	Repetition rate (lifts/min)	Task duration (min)	RWL (Kg)	LI (1)
1	29.2000	11.3000	94.5000	18. 0000	5.9000	101.1000	9.0940	0.9999
2	25.4000	48.5000	89.0000	17 .0000	6.1000	96.9000	9.0927	1.0000
3	25.4000	12.9000	54.4000	33.4000	6.4000	93.7000	9.0927	1.0000
4	27.3000	6.1000	99.6000	4.4000	6.3000	94.8000	9.0928	1.0000
5	25.5000	33.4000	108.0000	7.6000	6.0000	98.9000	9.0927	1.0000
6	27.0000	11.8000	107.8000	1.6000	6.1000	96.9000	9.0928	1.0000
7	25.4000	32.2000	110.3000	5. 0000	6.0000	99.5000	9.0927	1.0000
8	26.6000	45.0000	122.5000	19.2000	5.3000	111.6000	9.0926	1.0000
9	25.5000	7.0000	104.3000	1.7000	6.6000	90.7000	9.0928	1.0000
10	27.9000	25.7000	87.5000	8.6000	6.0000	98.9000	9.0927	1.0000

Table 5. Design solutions for test problem 2

Particle	Horizontal distance (cm)	Asymmetry angle (deg)	Vertical distance (cm)	Travel distance (cm)	Repetition rate (lifts/min)	Task duration (min)	RWL (Kg)	LI (2)
1	47.4000	64.1000	47.9000	89.3000	7.5000	26.6000	4.5463	1.0000
2	45.4000	75.6000	107.6000	6.5000	8.2000	24.1000	4.5463	1.0000
3	34.7000	26.0000	13.6000	47.9000	10.1000	19.7000	4.5463	1.0000
4	26.7000	98.3000	56.5000	52.8000	11.2000	17.7000	4.5463	1.0000
5	32.6000	63.1000	49.3000	34.5000	11.1000	18.0000	4.5463	1.0000
6	42.1000	25.4000	103.5000	17.6000	10.3000	19.4000	4.5463	1.0000
7	43.0000	78.6000	52.7000	6.4000	8.8000	22.5000	4.5463	1.0000
8	42.8000	111.4000	12.0000	18.3000	6.8000	29.0000	4.5463	1.0000
9	39.5000	39.4000	53.2000	67.6000	9.6000	20.7000	4.5463	1.0000
10	36.1000	68.3000	26.4000	15.0000	9.6000	20.8000	4.5463	1.0000

4.3. Test problem 3

Test problem 3 represents a high number of lifts with a moderate load 18.1447 kg and poor handle interface coupling quality. Table 6 contains the best 10 solutions evolved under Test problem 3. At this test problem, LI chosen as 2.0 by the designer different from previous lifting design conditions. In this condition, it is decided to observe design solution #6.

In solution #6 the loads could be grasped with 27.9 cm horizontally away from the ankles at the start of the lift. The amount of asymmetry angle is set as 9.2°. The allowable vertical travel for the load is relatively high compared to the distance permitted

of other solutions. Travel distance is set as 6 cm and the solution requires the operator to lift at an average rate of 2.5 lifts per minute for relatively high duration of 359 minutes. Approximately, these design parameters provide RWL and LI as 9.0724 kg and 2.0 in return.

One of the best solution ranges in genetic algorithm is such as 25.4-25.9 cm for horizontal parameter, 0-77.9° for asymmetry angle parameter, 49.4-103 cm for vertical height parameter, 0-25.4 cm for travelling distance parameter, 2.11 lifts per minutes for repetition rate, and 7.2 hours for task duration.

As desired, these design parameters provide RWL and LI as 89.18 N and 2.0 respectively.

4.4. Test problem 4

Test problem 4 represents a heavier load (31.8042 kg) with fewer repetitions. Especially, horizontal parameter requires closeness from the ankles at the start of the lift. Table 7 presents the best 10 solutions under Test problem 4. In solution #4, the loads are grasped with 25.4 cm horizontally away from the ankles at the start of the lift. The amount of asymmetry angle is set as 4°. The allowable vertical height is 107.6 cm. Travel distance is set as 9.3 cm and in order to meet the production constraints, the solution requires the operator to lift at an average rate of 0.7 lifts per minute for relatively high duration of 400.1 minutes. Approximately, these design parameters provide RWL and LI as 15.9025 kg and 2.0 respectively.

Table 6. Design solutions for test problem 3

Particle	Horizontal distance (cm)	Asymmetry angle (deg)	Vertical distance (cm)	Travel distance (cm)	Repetition rate (lifts/min)	Task duration (min)	RWL (Kg)	LI (3)
1	30.3000	20.3000	98.3000	33.1000	2.1000	428.5000	9.0724	2.0000
2	25.4000	62.4000	111.4000	1.8000	2.3000	386.8000	9.0724	2.0000
3	26.2000	67.0000	63.1000	33.3000	2.2000	396.0000	9.0724	2.0000
4	25.4000	54.6000	55.4000	63.1000	2.1000	409.3000	9.0723	2.0000
5	25.4000	48.8000	34.9000	26.8000	2.5000	346.8000	9.0722	2.0000
6	27.9000	9.2000	128.8000	6.0000	2.5000	359.8000	9.0724	2.0000
7	27.7000	43.5000	102.1000	1.5000	2.4000	370.3000	9.0724	2.0000
8	31.0000	34.2000	76.9000	20.1000	2.3000	377.2000	9.0724	2.0000
9	27.9000	28.0000	60.1000	29.9000	2.7000	325.9000	9.0723	2.0000
10	28.6000	48.1000	43.5000	23.5000	2.0000	442.9000	9.0723	2.0000

Table 7. Design solutions for test problem 4

Particle	Horizontal distance (cm)	Asymmetry angle (deg)	Vertical distance (cm)	Travel distance (cm)	Repetition Rate (lifts/min)	Task duration (min)	RWL (Kg)	LI (4)
1	25.7000	37.7000	70.6000	23.0000	2.5000	117.1000	15.9014	2.0001
2	25.9000	5.6000	81.8000	14.8000	1.1000	259.1000	15.9020	2.0000
3	25.4000	22.0000	88.1000	12.0000	0.7000	415.0000	15.9019	2.0000
4	25.4000	4.0000	107.6000	9.3000	0.7000	400.1000	15.9025	2.0000
5	26.5000	6.7000	76.6000	31.1000	0.7000	426.9000	15.9022	2.0000
6	25.5000	16.3000	93.2000	6.5000	0.7000	384.4000	15.9028	1.9999
7	25.4000	21.3000	84.9000	4.6000	0.8000	372.2000	15.9019	2.0000
8	25.5000	33.3000	75.1000	13.4000	5.0000	59.5000	15.9019	2.0000
9	25.4000	27.3000	90.3000	21.8000	2.7000	108.2000	15.9020	2.0000
10	25.4000	16.0000	89.9000	9.4000	0.8000	369.7000	15.9022	2.0000

One of the best solution ranges in genetic algorithm is such as 25.4-25.7 cm for horizontal parameter, 0-28.4° for asymmetry angle parameter, 68.6-83.8 cm for vertical height parameter, 0-27.9 cm for travelling distance parameter, 0.81 lifts per minutes for repetition rate, and 6.3 hours for task duration. These design parameters provide RWL and LI as 156 N and 2.0 respectively. Both algorithms propose similar lifting design parameters.

4.5. Test problem 5

Test problem 5 represent a heavy load with less repetition (only 100 repetitions). Note that at this condition the designer chooses LI as 3.0 because the task is required to be performed in less than 3.3 hour at a heavy load (47.7064 kg). Table 8 contains PSO design solutions. For example, Solution #1 requires that the load should be at a minimum horizontal distance from ankles at the start of the lift while the amount of twisting permits the operator to turn 46.8°. At the start of the lift under solution #1, the load can be positioned only 89.7 cm above the floor. Travel distance requires 11.2 cm

and the solution requires the operator to lift at an average rate of 3.1 lifts per minute for relatively less duration of 31.5 minutes. Approximately, these design parameters provide RWL and LI as 15.9025 kg and 2.0 respectively.

Genetic algorithm proposes the best solutions such as 25.4 cm for the horizontal parameter, 0-6.1° for asymmetry angle parameter, 44.9-108 cm for vertical height parameter, 0-25.4 cm for travelling distance parameter, 3.31 lifts per minutes for repetition rate, and 1.5 hours for task duration. These design parameters provide RWL and LI as 155 N and 2.0 respectively.

4.6. Test problem 6

Test problem 6 is a repetitive lifting task with a light load. Design solution #5 is discussed to show one of the best lifting design parameters for the test problem in Table 9. Solution #5 allows the operator a great vertical movement and the load can be held up to 25.5 cm horizontally from the ankle joint. In the sagittal plane, the operator can make only 4.3° movement and travel distance can be 7.1 cm.

Table 8. Design solutions for test problem 5

Particle	Horizontal distance (cm)	Asymmetry angle (deg)	Vertical distance (cm)	Travel distance (cm)	Repetition rate (lifts/min)	Task duration (min)	RWL (Kg)	LI (5)
1	26.0000	46.8000	89.7000	11.2000	3.1000	31.5000	15.9022	3.0000
2	25.5000	14.3000	123.6000	1.1000	1.4000	66.8000	15.9021	3.0000
3	25.4000	28.0000	110.2000	2.6000	1.4000	67.1000	15.9019	3.0000
4	25.4000	41.8000	103.7000	14.8000	3.0000	33.3000	15.9020	3.0000
5	25.4000	37.9000	98.4000	3.5000	1.6000	61.7000	15.9021	3.0000
6	26.5000	54.0000	78.3000	13.3000	2.6000	37.3000	15.9022	3.0000
7	25.5000	37.0000	100.5000	4.1000	1.4000	68.1000	15.9022	3.0000
8	26.5000	3.0000	100.1000	24.9000	0.6000	149.1000	15.9021	3.0000
9	26.0000	35.5000	108.3000	3.5000	2.4000	40.2000	15.9021	3.0000
10	25.8000	43.4000	94.0000	29.2000	2.6000	37.5000	15.9022	3.0000

Table 9. Design solutions for test problem 6.

Particle	Horizontal distance (cm)	Asymmetry angle (deg)	Vertical distance (cm)	Travel distance (cm)	Repetition Rate (lifts/min)	Task duration (min)	RWL (Kg)	LI (6)
1	25.4000	11.4000	131.3000	4.9000	5.6000	422.8000	5.4333	1.00
2	25.4000	48.5000	118.7000	12.9000	5.3000	444.5000	5.4329	1.00
3	26.3000	6.7000	133.3000	9.3000	5.5000	431.3000	5.4332	1.00
4	25.5000	64.3000	89.4000	3.3000	5.4000	443.7000	5.4332	1.00
5	25.5000	4.3000	144.1000	7.1000	5.5000	433.7000	5.4334	1.00
6	27.2000	43.6000	101.0000	26.0000	5.3000	447.7000	5.4332	1.00
7	25.6000	48.1000	66.3000	36.5000	5.3000	445.8000	5.4332	1.00
8	25.4000	29.7000	74.2000	2.7000	5.8000	408.9000	5.4333	1.00
9	25.4000	51.6000	130.3000	2.2000	5.1000	462.8000	5.4332	1.00
10	26.0000	31.1000	119.8000	9.5000	5.4000	440.7000	5.4334	1.00

The solution requires the operator to lift at an average rate of 5.5 lifts per minute with approximately 433.7 minutes task duration. By the way, these design parameters provide RWL and LI as 5.4334 kg and 1.0 respectively.

One of the best design solutions from subpopulation of genetic algorithm is such as the load can be held up to 32.25 cm horizontally from the ankle joint an can be positioned 53.3-100 cm above the floor. It tolerates up to 2.9° asymmetry angle at the start of the lift. Design requires the operator to work at an average rate of 5 lifts per minute for nearly 8 hrs.

Comparison of PSO with GA and HS Algorithm in regards to design solutions showed that PSO could proper to solve workplace design problem like as GA and HS algorithm. Actually, PSO gives sufficient design rules similar to GA lifting design solutions.

5. Discussion

The objective of this paper was to prove the application of PSO algorithm to provide ergonomic workplace design and to minimize low back injury that occur in lifting tasks considering NIOSH revised lifting equation. The developed PSO algorithm could provide multiple workplace design solutions with respect to work practices guide. To achieve optimal performance in terms of reducing low back injuries raw goodness and lifting index equations simultaneously solved.

PSO algorithm, as a first attempt to develop and implement a particle swarm algorithm for manual lifting design, provides multiple solution alternatives that different from each other when the user runs at each turn. Applications of GA and Harmony Search Algorithm to the design of lifting tasks article were compared with PSO algorithm. Unlike GAs, PSO has no evolution operators like crossover and mutation. Thus, the evaluation frequency of the PSO was less than the GA, the PSO was computationally more efficient in terms of computational time and memory requirements. But, performance of PSO was similar to HS algorithm.

In conclusion, PSO algorithm was a good method for the lifting task design is a crucial problem that has not achieved the prominence it deserves in the operation research literature.

Conflict of Interest

No conflict of interest was declared by the authors.

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