Simulation-Based Optimization Methodology for a Manual Material Handling Task Design That Maximizes Productivity While Considering Ergonomic Constraints

Yaar Harari, Avital Bechar, *Member, IEEE*, and Raziel Riemer

***Abstract*—Design of workplaces that include human–machine systems and manual material handling should consider both the productivity of workers and the risk of injury. In this study, a simulation-based optimization methodology for a manual material handling task design was developed. A new formulation of the optimization problem is presented, whose objective is to maximize worker productivity and at the same time not to exceed ergonomic thresholds (which represent injury-risk measures). The workplace and work process were simulated using digital human modeling software (Jack), and the best design was found using a genetic algorithm. The results show that the new formulation of the optimization problem improved the predicted productivity by 105%, compared to the formulation used in previous studies that used a multi-objective function. Meanwhile, the risk of injury did not exceed ergonomic thresholds.**

***Index Terms*—Computational human modeling, ergonomics, human performance, manual material handling task design, optimization.**

I. Introduction

WORK-RELATED musculoskeletal disorders (MSDs) are responsible for 30% of days lost to injury and result in annual costs of \$45–54 billion in the U.S. alone [1], [2].

Therefore, design of workplaces that include human–machine systems (HMS) should consider not only the workers' productivity, but also their risk of injury [3]–[7]. Based on that, the best HMS design should yield maximum productivity while maintaining the injury risk below physiological and biomechanical thresholds.

Several studies have used digital human modeling (DHM) for HMS workplace design, while considering both worker productivity and the risk of injury. Cimino *et al*. [8] proposed a multiple measure-based methodology for the effective ergonomic design of workstations. The authors applied their methodology to a hose pressure test workstation and reduced the work process time by 38% while reducing the oxygen consumption of the worker by 20%. Longo and Mirabelli [9] used DHM to develop an effective assembly line design for heater production that takes into consideration work measurements, line balancing, and ergonomic factors. By manipulating various design configurations (i.e., changing the height of a workstation) better line balancing was achieved, which increased productivity by 47% while improving the working postures of the workers. Battini *et al*. [10] developed a methodological framework to improve productivity and ergonomics in assembly system design, while taking into account technological variables (e.g., work times), environmental variables (e.g., workforce motivation), and ergonomics evaluations. The authors applied their methodology by redesigning a shower enclosure workstation, and increased productivity by 15% while lowering the risk of injury. Shewchuk *et al*. [11] developed a methodology for simulation of workers during physical tasks, considering both the workers' motion and ergonomic assessments. This approach was applied to panelized residential construction and resulted in a software that enables to simulate physical tasks while considering the workers' ergonomics. However, in all of the above studies, the new and improved HMS workplace designs were selected out of a limited number of manually designed configurations with no optimization process. This means that it is very likely that a better solution exists.

To overcome this limitation, several studies have offered frameworks for solving HMS workplace design as an optimization problem. Ben-Gal and Bukchin [12] presented a methodology for workstation design consisting of multi-objective optimization that considered both production and ergonomics features and was applied using the response surface optimization method. The authors demonstrated their methodology by improving a fruit-packaging work process and reduced the process cycle time by 17.5% while improving ergonomic measures by up to 33%. del Rio Vilas *et al*. [13] proposed a general framework for manufacturing workstation design, combining ergonomic and operational considerations. The authors simulated the workplace and process in DHM software and used a

Manuscript received April 15, 2018; revised October 31, 2018, December 5, 2018, and January 22, 2019; accepted February 6, 2019. Date of publication March 12, 2019; date of current version September 14, 2019. This work was supported in part by the Helmsley Charitable Trust through the Agricultural, Biological and Cognitive Robotics Initiative of Ben-Gurion University of the Negev. This paper was recommended by Associate Editor L. Rothrock. *(Corresponding author: Yaar Harari.)*

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Digital Object Identifier 10.1109/THMS.2019.2900294

multi-objective function which combined both ergonomic and operational performance measures. Implementing their methodology resulted in improved work process cycle time and reduced both the workers' risk of injury and their energy expenditure. Ore *et al.* [14] presented an application of HMS design optimization that included human–robot collaboration. The application was demonstrated for a handover task. The tradeoff between the cycle time and the rapid upper limb assessment (RULA) ergonomic measure [15] was investigated. The authors of the current study recently solved the workplace design optimization problem by using DHM and applying a two-step grid search, which comprised a coarse search of the entire solution span and a fine search around the best solution from the coarse search [16].

However, although all of the above studies that address workplace design optimization are innovative and useful, they all combined productivity and risk-of-injury measures into one multi-objective function. Yet, in industry, the common practice is to consider the risk of injury as a constraint (e.g., the compression force on the lower back should not exceed 3400 N [17]). Also, in all of the above studies except one [16], execution of the optimization process and work with the DHM software was conducted manually. This is a very time-consuming process, and therefore the workplaces could not be optimized in a reasonable time [12], [18], [19]. Even in the one study that did offer an automated optimization process [16], the two-step grid search optimization method was computationally inefficient, with the possibility of missing a global optimum.

This study offers a new automated optimization methodology for HMS workplace design, based on a genetic algorithm (GA) using a DHM simulation (Jack) that is a commonly used tool for workplace design [20], [21]. This methodology could be used as a decision-making tool to enhance the capabilities of practitioners (e.g., ergonomists and industrial engineers).

The methodology presented in this study includes a new formulation of the optimization problem, in which the objective of the optimization is to maximize productivity under ergonomic constraints. For demonstration purposes, we solved a case study of a box-conveying task. The ergonomic constraints were thresholds on the compression forces acting on the lower back vertebrae (Lower Back Analysis, LBA; [22]), the worker's oxygen consumption rate (VO_2) for multiple-task work process [23] and the RULA ergonomic measure [15]. The work process cycle time was calculated using time-prediction models from [24], and the productivity was calculated by multiplying the box mass by 1/cycle time.

II. Method

The aim of the proposed methodology is to determine the optimal workplace design by controlling the properties of different entities in the HMS (i.e., shelf and conveyor heights, handled object mass). To demonstrate our methodology, we chose the case study of a box-conveying task, modeled it in Jack, formulated the optimization problem with constraints and solved for the optimal design using a GA.

A. Case Study—Box Conveying Work Process

To demonstrate our optimization methodology, we chose the case study of a box-conveying task, which is common in various industries. An example of such an HMS is a packing house for peppers. Here, boxes of peppers continuously arrive on a conveyor belt. The workers perform the following continuous sequential work process (see Fig. 1):

1) lifting a box from the conveyor;
2) carrying the box in front of the body for three meters;
3) lowering the box onto a shipping platform.

After lowering the box, the workers return to the conveyor to lift the next box. The distance between the conveyor and platform was set at three meters.

Fig. 1. Box-conveying work process at the pepper packing house. (a) Lifting a box from a conveyor. (b) Carrying the box. (c) Lowering the box onto a platform.

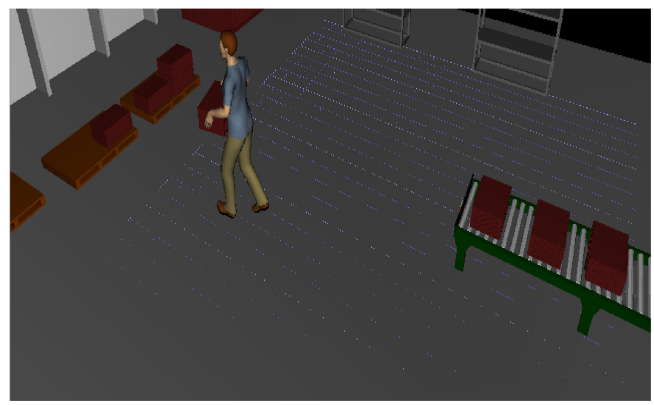

Fig. 2. Box-conveying simulation in Jack.

B. Digital Human Modeling

The work process was simulated using the task simulation builder module in Jack (see Fig. 2). The worker was represented using a virtual male mannequin with a height of 1.75 m and weight of 79 kg. This height and weight represents the anthropometrics of a median male, according to the ANSUR database [25]. The simulation inputs were the mass of the box, the conveyor height, and the platform height. The outputs of the simulation were the joint angles of various body parts of the virtual mannequin, and the compression forces acting on the L5/S1 vertebra joints during the simulation at 30 Hz.

C. Overview of the HMS Workplace Design Methodology

The HMS workplace design optimization methodology consisted of

1) the DHM environment for designing the workplace and simulating the work process (Jack software by Siemens);

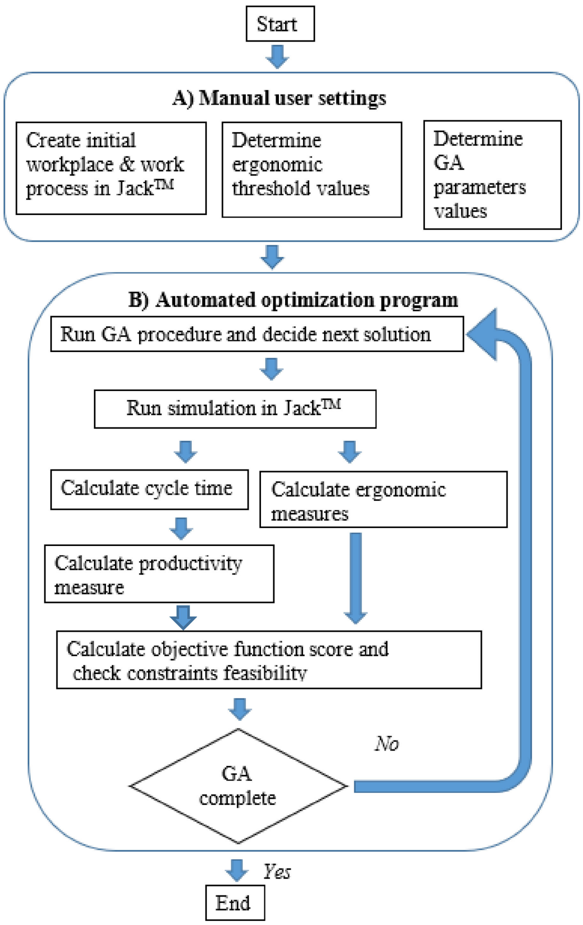

Fig. 3. Overview of the optimization methodology, which is comprised of (a) manual setting of the initial workplace, GA parameters and ergonomic thresholds; and (b) execution of the automated optimization process.

2) an objective function for the worker's productivity;
3) a set of ergonomic constraints which consider physiological and biomechanical injury-risk thresholds;
4) an optimization procedure using the GA method;
5) a main program (in the Python language) that managed and integrated the objective function, the ergonomic constraints, the GA procedure and the Jack software simulation.

The main program received as input the work process to be simulated, the design parameters (e.g., the box mass), the virtual mannequin's anthropometrics (gender, height, and weight), and parameter values for the GA.

For each solution that was generated by the GA procedure, the main program redesigned the workplace and simulated the work process. Then, data were extracted from Jack and the objective function score was calculated. In addition, using the data from Jack, the program checked whether the solution met the ergonomic constraints.

A flowchart of the proposed methodology for optimizing the HMS workplace design is presented in Fig. 3. The optimization process was performed on a Toshiba Satellite P50 PC with an Intel i7-4710MQ processor (6 MB cache, 2.5 GHz, 1600 MHz front-side bus).

D. Development of the Optimization Methodology

Our objective was to maximize productivity while remaining within the ergonomic constraints. The following sections describe the problem formulation and the optimization algorithm code.

1) Objective Function: The productivity measure selected for the objective function was the production rate (PR). The PR is defined as the total mass of boxes transferred per unit time

$$\mathrm{PR} = m/\mathrm{CT} \tag{1}$$

where m is the mass handled per work cycle and CT is the cycle time—the time required to complete the task. The CT was calculated as the total time (min) for completing the lifting, carrying, lowering, and returning tasks

$$\mathrm{CT} = 60/\left(t_{\mathrm{lift}} + t_{\mathrm{carry}} + t_{\mathrm{lower}} + t_{\mathrm{return}}\right) \tag{2}$$

where t_{lift}, t_{carry}, t_{lower}, and t_{return} are the times required to lift the mass from the conveyor, to carry the mass for three meters, to lower the mass onto the platform, and to return to the initial lifting point without carrying the mass, respectively.

t_{lift}, t_{carry}, t_{lower}, and t_{return} were calculated using the time-prediction models from [24] (3)–(8). These models were selected because they consider the influence of the mass of the box and the lifting and lowering heights on the task duration. Furthermore, these models were found to be more accurate for this type of work process than methods-time measurement, which is the time-prediction model in Jack [24]

$$\begin{aligned} t_{\mathrm{lift}} &= 2.099 + 0.0418 * m - 2.211 * \mathrm{LFH} + 1.1658 \\ &\quad * \mathrm{LFH}^2 - 0.117 * \mathrm{LWH} + 0.0752 * \mathrm{LWH}^2 \end{aligned} \tag{3}$$

$$\begin{aligned} v_{\mathrm{carry}} &= 1.2521 + 0.0073 * m - 0.0004 * m^2 - 0.1815 * \mathrm{LFH} \\ &\quad + 0.1077 * \mathrm{LFH}^2 - 0.0966 * \mathrm{LWH} + 0.1389 * \mathrm{LWH}^2 \end{aligned} \tag{4}$$

$$t_{\mathrm{carry}} = \mathrm{dist}/v_{\mathrm{carry}} \tag{5}$$

$$\begin{aligned} t_{\mathrm{lower}} &= 2.1684 + 0.036 * m - 0.1903 * \mathrm{LFH} + 0.0963 \\ &\quad * \mathrm{LFH}^2 - 1.8512 * \mathrm{LWH} + 0.9359 * \mathrm{LWH}^2 \end{aligned} \tag{6}$$

$$\begin{aligned} v_{\mathrm{walk}} &= 1.1015 + 0.0088 * m - 0.0006 * m^2 - 0.0289 * \mathrm{LFH} \\ &\quad + 0.0127 * \mathrm{LFH}^2 - 0.1487 * \mathrm{LWH} + 0.0661 * \mathrm{LWH}^2 \end{aligned} \tag{7}$$

$$t_{\mathrm{walk}} = \mathrm{dist}/v_{\mathrm{walk}}. \tag{8}$$

Above, m is the box mass (kg), LFH is the lifting initial height (m), LWH is the lowering final height (m), dist is the distance between the lifting and lowering stations (m), and v_{carry} and v_{walk} are the carrying and walking velocities, respectively (m/s). In this study, we included a 6 s allowance time between cycles in order for the workers to rest.

2) Ergonomics Measures: The lower back compression force (LBCF), RULA score, and VO_2 were chosen as the ergonomic measures. These measures were selected because each evaluates a different injury-risk factor (RULA evaluates postures, LBCF evaluates forces on the spine, and VO_2 evaluates continuous effort or metabolic rate).

The LBCF was calculated at 30 Hz during the simulation using the LBA tool in Jack [22], and indicated the peak compression force (N) acting on the L5/S1 vertebra joints during the work process simulation. The RULA score was also calculated at 30 Hz during the simulation using our own customized Python code. During the simulation, this code extracted the angles for different body joints and parts (e.g., shoulder, trunk) of the virtual mannequin in Jack. Using the joint angles, the code followed the RULA protocol [15] and determined the RULA score. The RULA measure indicated the highest RULA score during the work process simulation. The VO_2 (ml/min) was calculated using the prediction equations from [23] for a lift–carry–lower process (9)–(14), and indicated the worker's oxygen consumption rate during the work process simulation

$$\begin{aligned} \mathrm{VO}_{2\_L-L} &= -899.1 + 9 * \mathrm{bw} + 184.7 * \mathrm{freq} \\ &\quad + 35 * \mathrm{freq} * \mathrm{dist} + 36.7 * m \end{aligned} \tag{9}$$

$$\begin{aligned} \mathrm{VO}_{2\_L-M} &= -775 + 9.5 * \mathrm{bw} + 53.8 * \mathrm{freq} \\ &\quad + 48.1 * \mathrm{freq} * \mathrm{dist} + 31.3 * m \end{aligned} \tag{10}$$

$$\begin{aligned} \mathrm{VO}_{2\_L-H} &= -771.6 + 8.7 * \mathrm{bw} + 122.9 * \mathrm{freq} \\ &\quad + 32.6 * \mathrm{freq} * \mathrm{dist} + 40.4 * m \end{aligned} \tag{11}$$

$$\begin{aligned} \mathrm{VO}_{2\_H-L} &= -606 + 7.7 * \mathrm{bw} + 77.2 * \mathrm{freq} \\ &\quad + 39 * \mathrm{freq} * \mathrm{dist} + 26.3 * m \end{aligned} \tag{12}$$

$$\begin{aligned} \mathrm{VO}_{2\_H-M} &= -680.4 + 9.7 * \mathrm{bw} + 22.1 * \mathrm{freq} \\ &\quad + 35.3 * \ \mathrm{freq} * \mathrm{dist} + 20.6 * m \end{aligned} \tag{13}$$

$$\begin{aligned} \mathrm{VO}_{2\_H-H} &= -733.9 + 7.9 * \mathrm{bw} + 70.7 * \mathrm{freq} \\ &\quad + 40.1 * \mathrm{freq} * \mathrm{dist} + 26.5 * m. \end{aligned} \tag{14}$$

In VO_{2_X-Y}, *X* is the initial lifting height (*L* for heights below 90 cm and *H* for heights above 90 cm) and the *Y* is the final lowering height (*L* for heights below 80 cm, *M* for heights between 80 and 120 cm, and *H* for heights above 120 cm). bw is the worker's body weight (kg), dist is the distance between the lifting and lowering platform (m), m is the mass of the box (kg), and freq is the number of times the work process is conducted per minute, which was calculated as follows (15):

$$\mathrm{freq} = 1/\mathrm{CT} \tag{15}$$

where CT is the time required to complete the work process in minutes.

3) Optimization Problem Formulation: The aim of the optimization methodology is to find the HMS workplace design in which the productivity is maximal, while the workers do not exceed the ergonomic thresholds. Therefore, we developed an objective function that maximizes the PR, and in which the ergonomic measures are constrained (16)–(20)

$$\mathrm{MAX\ \ PR}, \tag{16}$$

s.t.

$$\mathrm{LBCF} < \mathrm{LBCF}_{cr}, \tag{17}$$

$$\mathrm{RULA} < \ \mathrm{RULA}_{cr}, \tag{18}$$

$$\mathrm{VO}_2 < \mathrm{VO}_{2cr}, \tag{19}$$

$$\mathrm{BM} < \mathrm{BM}_{cr}. \tag{20}$$

Here, LBCF_{cr}, RULA_{cr}, and VO_{2cr} are the ergonomic thresholds for lower back compression forces, RULA score, and oxygen-consumption rate, respectively. BM_{cr} is the maximum box mass that may be handled. In this study, the threshold values were set as follows (21)–(24):

$$\mathrm{LBCF}_{cr} = 3400\mathrm{N}\ \ [17] \tag{21}$$

$$\mathrm{RULA}_{cr} = 5\ \ [15] \tag{22}$$

$$VO_{2cr} = 1000\ \mathrm{ml/min}\ \ [23] \tag{23}$$

$$\mathrm{BM}_{cr} = 23\ \mathrm{kg\ NIOSH\ for\ lifting\ tasks}\ \ [17]\,. \tag{24}$$

The LBCF_{cr} was set at 3400 N since this represents the cutoff value for lower back injury risk [17], based on cadaver studies (e.g., [26], [27]) and biomechanical models (e.g., [28], [29]). The RULA_{cr} was set to 5 since lower values represent a low risk of MSDs [15]. The VO_{2cr} was set at 1000 ml/min (approximately 5 kcal/min) since this represents the cutoff value for prevention of aerobic and muscle fatigue, which is also related to risk of MSDs [30]–[32]. The BM_{cr} was set to 23 kg, which was stated by NIOSH to be the maximal acceptable weight for lifting, regardless of task design [17].

4) Genetic Algorithm: A GA is a biologically inspired optimization method that first examines a generation of solutions. The descendants of the solutions are then examined in the next generation by combining pairs of solutions and by creating random changes in other solutions. We chose a GA since it is particularly suitable for problems with characteristics similar to the problem presented in this study (non-differentiable, discontinuous objective functions, and multiple local minima [16], [33], [34]). In this study, we developed a GA in the Python language. Each solution (a GA chromosome) represented a different HMS workplace design and was comprised of three parameters:

1) the mass of the box to be handled;
2) the height of the lifting platform;
3) the height of the lowering platform.

The box masses ranged between 2 and 23 kg, in increments of 0.5 kg. The lifting and lowering heights ranged between 20 and 160 cm above the floor level, in increments of 2 cm. The following GA parameters values were used:

1) population sizes of 25, 50, 75, and 100 chromosomes per generation;
2) mutation rates of 1%, 5%, 10%, and 15%;
3) total number of generations between 1 and 10, in steps of 1 generation.

Reproduction was implemented using a one-point crossover, and the selection operator was chosen to be the roulette wheel

TABLE I
FOUR CONFIGURATIONS THAT WERE APPLIED FOR SOLVING THE BOX-CONVEYING CASE STUDY

Configuration #	Configuration name	Problem formulation	Optimization method	Time prediction
1	New proposed design	Max productivity and ergonomic constraints (Eq. 16-20)	GA	Time-prediction model from [24]
2	Multi-objective approach	Multi-objective function (Eq. 25)	GA	Time-prediction model from [24]
3	Two-step grid search	Max productivity and ergonomic constraints (Eq. 16-20)	Two-step Grid search	Time-prediction model from [24]
4	Jack's time prediction	Max productivity and ergonomic constraints (Eq. 16-20)	GA	Jack's time-prediction model

Each design configuration represents a different combination of the formulation of the optimization problem, optimization method, and time-prediction model.

technique. Elitism was implemented by passing the top 10% of solutions in each generation to the next one.

E. Analyses

To evaluate the performance of our new methodology for workplace design, the following analyses were performed.

1) Our new formulation of the optimization problem (maximum productivity with ergonomic constraints; configuration #1 in Table I) was compared to that of previous studies (multi-objective approach; configuration #2 in Table I). Both were solved using the GA algorithm, where the multi-objective approach (configuration #2 in Table I) was formulated as follows (25):

$$U = \mathrm{PR}^{-1} * \mathrm{LBCF}^{1} * \mathrm{RULA}^{1} * \mathrm{VO_2}^{1}. \tag{25}$$

2) Our GA procedure (configuration #1 in Table I) was compared to the optimization method from a previous study (the two-step grid search; configuration #3 in Table I), with both solving the optimal design for maximum productivity with ergonomic constraints.
3) It is possible that users will choose to use the time-prediction models currently implemented in Jack (i.e., MTM-1 [35]). Therefore, we will run the optimization methodology using the time prediction models in Jack (configuration #4 in Table I) and analyzes the feasibility of using the methodology with Jack time prediction models.

To perform these analyses, we solved the optimization problem in four configurations. The parameters in each configuration were the formulation of the optimization problem, the optimization method, and the time-prediction model (see Table I).

In this study, we solved the optimization problem using guideline ergonomic thresholds as constraints in the optimization. Yet, it is possible that, due to the preference (of an ergonomist or production engineer) or an updated guideline, the threshold will need to be changed. Therefore, to test the effect of changes in the ergonomic thresholds, a sensitivity analysis was performed. In this analysis, we ran the optimization multiple times (using configuration #1 in Table I) where, in each run, the value of one constraint changed while the values of the other constraints were fixed. The LBCF_{cr} ranged between 1400 and 3400 N in steps of 800 N, the RULA_{cr} ranged between 3 and 7 in steps of 1, the VO_{2cr} ranged between 800 and 1200 ml/min in steps of 100 ml/min, and the BM_{cr} ranged between 4 and 23 kg in steps of 4 kg.

Finally, we investigated the effect of the GA parameters (the number of generations, the number of solutions examined, the mutation rate and the population size) on the PR value of the best solution the GA obtained. This investigation explores whether GAs with different parameter values converge to the same optimal solution. It might also clarify which parameter values are preferable for solving this problem.

III. RESULTS

A. Optimal Solution Obtained Using Different Optimization Configurations

Optimal HMS workplace designs were obtained using three different configurations of the optimization method (see Table II). First, we compared the new formulation of the optimization problem, which maximizes productivity under ergonomic constraints (configuration #1), with the multi-objective approach (configuration #2). With the new formulation of the optimization problem the PR was higher by 105%. The optimal solution of the new formulation of the optimization problem resulted in higher RULA, LBCF, and VO_2 in comparison to the multi-objective approach. Yet, these measures did not exceed injury-risk thresholds, and are therefore likely to be acceptable for safe workplace design.

Comparing the GA (configuration #1) to the two-step grid search (configuration #3) revealed that the optimal design obtained by the GA yielded a PR that was higher by 69% than the two-step grid search.

Since users might wish to apply the methodology using the current time-prediction model implemented in Jack, we ran the methodology using Jack's time instead of the models of [24]. The optimal solution resulted in a box mass of 19 kg, lifting height of 92 cm, and lowering height of 104 cm. This solution resulted in a PR of 77.6 kg/min (using the time models of Jack) or 74 kg/min (using the models of [24]). The RULA score was 4, the LBCF 2514 N, and the VO_2 999 ml/min.

TABLE II
OPTIMAL SOLUTIONS OBTAINED USING THREE DIFFERENT CONFIGURATIONS, WHICH INCLUDE DIFFERENT FORMULATIONS OF THE OPTIMIZATION PROBLEM, OPTIMIZATION METHODS, AND TIME-PREDICTION MODELS

#	Configuration name	Lifting height (cm)	Lowering height (cm)	Box mass (kg)	Production rate (kg/min)	RULA	LBCF (N)	VO_2 (ml/min)
1	New Proposed design	100	116	20	78	4	2251	997
2	Multi-objective approach	112	116	9	38.1	3	1189	813
3	Two-step grid search	100	120	11	46.1	4	1492	982

The GA's shortest time for finding the best solution was 10 min and 24 s. On average, the GA found the best solution in 25 min and 24 s.

B. Relation Between Productivity and Ergonomics Thresholds

The LBCF threshold (constraint) was the limiting factor for values between 1400 and 2200 N, the RULA constraint was the limiting factor for values between 3 and 4, the VO_2 constraint was the limiting factor for values between 0.8 and 1.2 l/min, and the box mass constraint was the limiting factor for values between 4 and 20 kg. Each constraint threshold had a different effect on the PR. The maximum PRs that were obtained from changing each ergonomic constraint threshold, and the constraint values of the optimal solution (configuration #1, Table II) are presented in Fig. 4. The results show that the limiting constraint for our case study was the VO_2 constraint, since it is the only constraint for which increasing its value resulted in an increased PR [see Fig. 4(b)].

C. Investigation of the Genetic Algorithm Configuration

We conducted multiple runs of the optimization program with different GA parameter values (i.e., number of examined solutions, population sizes, mutation rates) and investigated the effects of these GA parameters on the optimal solution (see Figs. 5 and 6). Our investigation revealed the following. The smallest number of solutions evaluated by the GA before finding the optimal solution was 125 [see Fig. 5(d), 25 chromosomes]. The average number of solutions evaluated by the GA before finding the best solution was 305, which is only 5.6% of the 5445 solutions examined by the two-step grid search [24].

Using the hardware detailed in Section II-B, it took approximately five seconds for the automated optimization program to examine one solution. We compared the run-time of the optimization program to the run-time of only the Jack simulation component. The results show that 90% of the optimization run-time was attributed to the simulation in Jack.

The GA's shortest time for finding the best solution was 10 min and 24 s. On average, the GA found the best solution in 25 min and 24 s.

Comparison of the different mutation rates shows that the average number of solutions examined before finding the best solution was 250, 275, 438, and 300 for mutation rates of 1%, 5%, 10%, and 15%, respectively. For the low mutation rates of 1% and 5%, population sizes of 75 and 100 chromosomes evaluated fewer solutions before reaching the best solution [see Fig. 6(a) and (b)]. For the high mutation rates of 10% and 15%, population sizes of 25 and 50 chromosomes evaluated fewer solutions before reaching the best solution [see Fig. 6(c) and (d)]. Analysis of the effect of the number of chromosomes revealed that, for all cases but one, the GA found the optimal solution in less than ten generations [see Fig. 5(b), 25 chromosomes).

IV. DISCUSSION

A. Comparison of the Proposed Design Methodology to Different Design Configurations

In this study, a new formulation of the optimization problem was presented. This new formulation uses an objective function of productivity, and solves the optimization problem with ergonomic thresholds as constraints. This new formulation reflects common practice in workspace design, in which the design objective is to maximize productivity as long as the injury-risk measures' values are below the acceptable thresholds. The formulation in this study is an innovation, compared to previous studies that used multi-objective function formulations to find a design that maximizes productivity and minimizes the risk for injury at the same time [12], [13], [16]. Using our new formulation increased the PR by 105% while not exceeding injury-risk thresholds.

Another advantage of our new formulation of the optimization problem is that it offers a more objective design, since only the PR is considered in the objective function and all the ergonomic constraints must remain under commonly used guidelines. Therefore, it is less susceptible to subjective interpretation.

In comparison to the relatively objective design of the current study, two subjective decisions influenced the optimal design in the previous studies that used the multi-objective function. The first is the formulation of the objective function, which can be selected from a vast number of formulations and may result in different optimal design solutions [36]. Furthermore, even after choosing the function formulation, the weights that are given to the production and injury-risk measures in the objective function represent the user's preference [12]. Thus, changing one's preference for the relative importance of each of the measures (the weights) will result in very different optimal designs [16].

It is possible that users might choose to use the proposed methodology with the time models already implemented in Jack. However, the time-prediction models from [24] and Jack yielded two different design solutions. Jack software time predictions

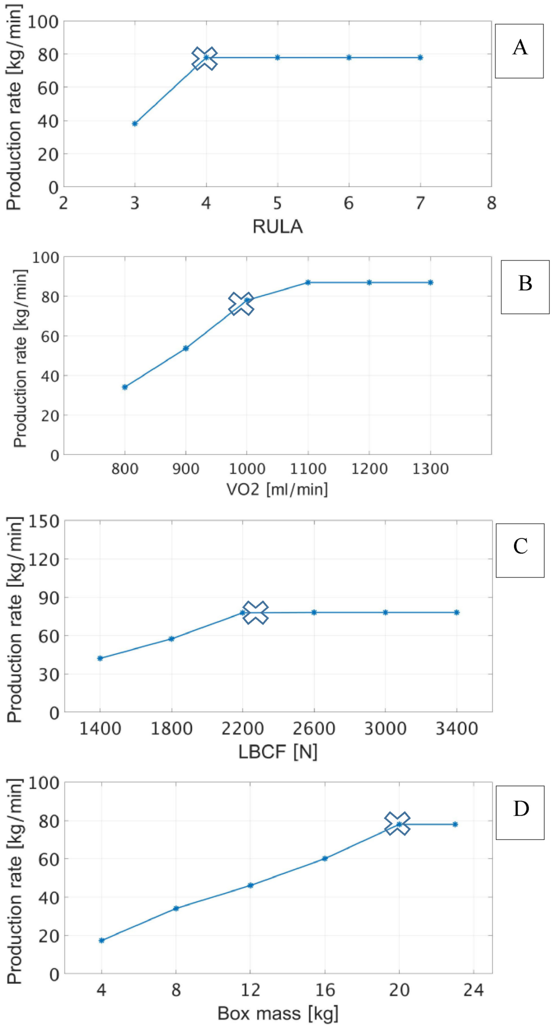

Fig. 4. Production rate as a function of the constraint threshold values. ✕ = values for the optimal solution of the proposed methodology (see configuration #1 in Table II).

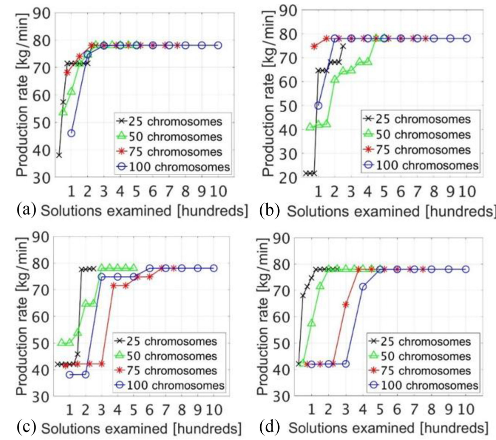

Fig. 5. Best solution achieved versus the number of solutions (in hundreds) examined by the GA, for different population sizes and mutation rates of (a) 1%, (b) 5%, (c) 10%, and (d) 15%.

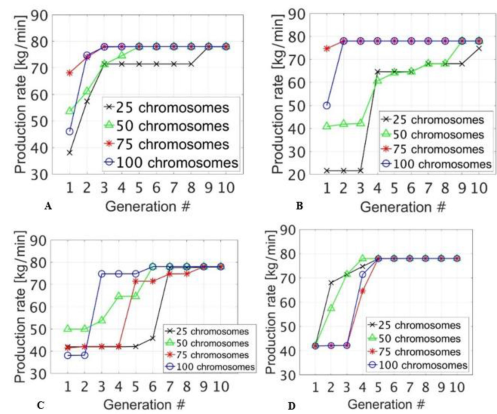

Fig. 6. Best solution achieved for each generation of the GA, for different population sizes and mutation rates of (a) 1%, (b) 5%, (c) 10%, and (d) 15%.

are based on the MTM-1 method [28]. Yet, in the past, we found that the time-prediction models from [24] were more accurate than MTM-1 for predicting the task times in the current case study. Thus, we compared the two workspace design solutions using the time models from [24]. The workplace design obtained with the models from [24] resulted in a 5% higher PR than the solution using the Jack time models. The solution using Jack time models resulted in the same RULA and similar VO_2, compared to the one using the time models from [24], but it resulted in 11.7% more LBCF. Thus, the results show that using the Jack time models might result in a sub-optimal solution, which could decrease the workers' productivity or increase the values of the ergonomic measures.

B. Relationship Between Productivity and Ergonomics

In previous studies, two opposite perspectives have been presented regarding the relationship between worker productivity and ergonomics. One group of researchers suggested that reducing the workers' risk of injury will increase their productivity (e.g., [10], [37]), while others showed that reducing the risk of injury will reduce productivity (e.g., [14], [16]). The results of the current study support the second group, since increasing the ergonomic thresholds (and, as a result, increasing the workers' risk of injury) did increase the productivity (see Fig. 4). However, since several ergonomic constraints were considered, increasing the threshold increased the productivity only in the range of values for which the constraint was the limiting factor. Therefore, while these findings hold for the optimal solution in which the constraints are the limiting factor, it is possible that improving a poor design will improve both the productivity and the ergonomic measures.

The results of the sensitivity analysis emphasized the importance of accurate selection of the constraint thresholds. From the physiological standpoint, while VO_{2cr} of 1000 ml/min is considered an acceptable threshold [23], other studies offered a more conservative threshold of 800 ml/min [17]. The results of the current study show that, if the VO_{2cr} were reduced to 800 ml/min as suggested by [17], the PR would be lower by 20%. On the other hand, allowing 10% more oxygen consumption (i.e., $\mathrm{VO}_{2cr} = 1100$ ml min) would increase the productivity by 12%.

C. Investigation of the Genetic Algorithm Configuration

Common practice in the industry, and in previous studies for HMS workplace design using DHM software, requires an experienced ergonomist or industrial engineer to manually perform the design and simulation run, and calculate the measure values and the objective function score [8], [10], [12], [13], [38]. This is a highly time-consuming task and even for a skilled engineer it takes about 15 min to examine each design [12]. Therefore, there is a need for a method that could solve this type of problem faster.

The optimization problem in this paper is classified as a discrete event simulation-optimization problem [39]. A previous study presented an optimization framework for DHM workplace design using the response surface methodology as the optimization method [12]. In general, this method is suitable for solving this type of problem [26] and is faster than a GA. However, the HMS workplace design problem using DHM may result in several local-optimum solutions in some cases. Therefore, methods such as the response surface methodology could converge to a local optimum and "miss" the global optimum, whereas using a GA increases the probability of avoiding these local optimum solutions and finding a solution near the global optimum within a reasonable time and computational cost [26], [27].

Our results show that, on average, the solution using the GA was obtained after 25 min and 24 s, which is much faster than the previous two-step method (a reduction of 94.6% in computation time). Yet, there is a need for more research into the behavior of this type of objective function and the best optimization algorithm for solving this type of problem. About 90% of the solution time was attributed to the run-time of the simulation in Jack. Therefore, adding more ergonomic constraints to the formulation would probably not have a considerable effect on the solution time. However, changes in the granularity of the workplace design parameters (e.g., changing the platform height in steps of 4 cm instead of 2 cm), or the number of design parameters, will affect the solution time since it will change the number of feasible solutions, and as a result influence the number of simulations in Jack that will be required in order to find the optimal solution.

V. Limitations

The optimization methodology presented in this study is general. Yet, the productivity and injury-risk measures were selected from a vast number of possible measures. Future users of such a methodology could choose to use different measures such as the comprehensive lifting model [40], the comprehensive manual handling limits for lowering, pushing, pulling, and carrying activities [41], the NIOSH lifting index [17], or the maximal acceptable weight [42]. Obviously, using other measures might result in a different optimal workplace design. The time-prediction models used in the optimization methodology [24] were developed based on an experiment in which the range of box masses was 2–14 kg. Thus, using it with box masses up to 23 kg is an extrapolation of the model and might result in an inaccurate time prediction.

VI. Conclusion

This paper presents an innovative framework for formulating workplace design as an optimization problem that maximizes productivity while maintaining ergonomic assessment values below commonly used thresholds. Furthermore, we have demonstrated an automated solution of this workplace design methodology using a GA algorithm. This methodology offers the potential for future development of tools which could be used by practitioners (e.g., industrial engineers and ergonomists). The automation of DHM software could enable a user to evaluate many possible configurations in a relatively short time (5 s to analyze each configuration), in comparison to manual evaluation using the software (approximately 15 min per configuration; [12]).

Using the new formulation of the optimization problem, which maximizes productivity while not exceeding injury-risk thresholds, resulted in a design with higher productivity by 105% than the previously used formulation in which the productivity and ergonomics measures are combined into one objective function.

Applying a genetic algorithm for solving the DHM workplace design optimization enables avoiding local optima. Furthermore, the method found the best design within the specified constraint conditions in a relatively short time.

A. Future Study

The productivity and injury-risk measures used in this study were selected out of a large number of possible measures. A future study should test the influence of other measures on the optimal design. In addition, in many cases, industrial settings are more complex than the case study presented in this study (e.g., there may be multiple workers collaborating; larger number of workstations; larger number of design variables etc.). Therefore, future work should apply this optimization methodology to more complex workplaces and work processes. Furthermore, in this study, we have used the genetic algorithm successfully for solving the optimization problem. Yet, there are many other optimization algorithms (e.g., simulated annealing, gradient descent) that might be even better for these type of problems and should be considered.

Acknowledgment

The authors declare the following interest: the authors have a provisional patent relating to material pertinent to the submitted article #62/648,963.

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