IIE Transactions (2002) **34**, 375–391

The ergonomic design of workstations using virtual manufacturing and response surface methodology

IRAD BEN-GAL* and JOSEPH BUKCHIN

The Department of Industrial Engineering, Tel Aviv University, Tel Aviv 69978, Israel
E-mail: bengal@eng.tau.ac.il

Received July 2000 and accepted July 2001

The increasing use of computerized tools for virtual manufacturing in workstation design has two main advantages over traditional methods; first, it enables the designer to examine a large number of design solutions; and second, simulation of the work task may be performed in order to obtain the values of various performance measures. In this paper a new structural methodology for the workstation design is presented. Factorial experiments and the response surface methodology are integrated in order to reduce the number of examined design solutions and obtain an estimate for the best design configuration with respect to multi-objective requirements.

1. Introduction

1.1. *Background*

The design and planning of manual workstations and the determination of proper work methods to be employed are challenging tasks. In order to achieve optimal economic and ergonomic results, a comprehensive study of the task at hand must be conducted and several parameters and constraints have to be considered. Often, this is done using *methods engineering* approaches.

Methods engineering consists of a step-by-step process of project definition; data gathering and analysis; formation of alternative methods and workstation layouts; and evaluation of each alternative. The best fitting alternative is then selected and is designed in detail (Niebel and Freivalds, 1999).

Motion and time study is at the heart of methods engineering. It is intended to determine the standard time for task completion by an experienced well-trained worker and to analyze the worker's motion sequence in order to eliminate unfavorable motions and to maintain efficient ones. Extensive research in the area has yielded a set of principles of motion economy aiming to promote correct utilization of the human body and proper arrangement of the workstation and design of tools and equipment (Barnes, 1980).

Two classes of measures are used to evaluate a given design: (i) economic measures based on completion time and productivity; and (ii) ergonomic measures such as energy exertion, posture analysis and physical loads. In fact, the two classes of measures are associated such that poor ergonomic planning often results in economic damages (e.g., low performance and liability suits).

Current research, which is related to methods engineering and the design of manual workstations, branches into two domains. The first deals with more technical aspects of anthropometric modeling and simulation of human movement (Zhang and Chaffin, 1997; Chaffin, 1997; Zhang *et al.*, 1998). The other domain deals with the development of methodology set to exploit the emerging technologies in design applications such as CAD, Rapid Prototyping and Virtual Reality (Nayar, 1995; Braun *et al.*, 1996; Arzi, 1997; Waly and Sistler, 1999).

Modeling of human motion is an evolving field of research. A simple modeling of the torso and right arm, including four segments with seven degrees-of-freedom (DOF), is presented in Zhang *et al.* (1998). A simulated annealing is used for setting weights to the DOF, which are associated with the relative movements, in order to efficiently resolve the kinematics redundancy. However, as the number of articulations involved increases, the number of DOF becomes almost measureless (Chaffin, 1997). Although it is still a great mystery how the brain resolves this kinematics redundancy, many models attempt to tackle the problem by using some form of optimization method to determine the aperture of each joint in a fixed posture. All these models require very complex, often non-tractable computations and fail to accurately

*Corresponding author

represent the actual dynamic movement of the limb. Any attempt to model dynamic motion by sequencing a series of static frames requires additional dynamic information, such as the intended direction of the motion, and results with a more complex problem (Zhang and Chaffin, 1997). Therefore, one should be careful in selecting an anthropometric model for workstation planning. It is important that the model approximates the human motion as realistically as possible. In particular if the model is used as a basis for an optimization procedure, as done in this paper.

Several attempts have been made to apply computer technology to methods engineering and workstation design. For instance, Braun *et al.* (1996) presented an example of computer-aided planning of a manual assembly workstation using a system called EMMA. The described system was based on AutoCAD and consisted of a database of workstation elements (such as bins and tools) and anthropometric data combined with an MTM-1 analysis module. Six ergonomic measures corresponding to six key principles of workstation design were defined: work area coverage; coverage of the optimal visual area; utilization of left and right hand; balanced motion patterns; degree of control; and quota of sensomotorical motions. Their values were formulated through MTM analysis. In addition, an economic measure was directly derived from the standard assembly-time, thus making an on-line evaluation of any candidate configuration of the workstation. Optimization of ergonomic and economic measures can be achieved through an interactive process of small adjustments to workstation parameters such as bin sizes, arrangement of bins and tools in the workplace, and product design. Since no economic evaluation was associated with the ergonomic measures, Braun *et al.* (1996) proposed to improve both types of measures separately. Therefore, their method focused on finding a good solution relative to both measures rather then finding a strict optimal solution.

Arzi (1997) suggested the integration of more advanced technology in the design process. Technology capable of effectively simulating human movement, rapidly generating workstation prototypes and allowing designers to virtually "step in" to the computer model and examine it using Virtual Reality (VR). The author introduced a framework for Rapid Prototyping (RP)-based system and specified a set of basic modules: Modeling module (the heart of the system); Safety and Health module; Physical Environment module; Anthropometric and Biomechanical Design module; Controls and Display Design module; Task Evaluation module; Time Standards Generation module; and various User Utilities. A preliminary partial RP system was implemented for the redesign of a supermarket cashier workstation. JACK software was used to model alternative configurations of the workstation taking anthropometric and biomechanical aspects into consideration. A simple computer program translated JACK motion commands into MTM-2 vocabulary in order to produce time standards. Results showed an overall improvement in measures for the selected design objectives.

Computer-oriented approaches, such as the above, present a significant improvement over traditional methods. They reduce the required time and effort for constructing physical models, and allow the designer to evaluate more alternatives faster and more precisely. Yet, a step-by-step interactive search for a satisfactory solution remains inefficient because of the limited number of configurations that can be examined, and the small number of conflicting considerations that can be handled. In their survey, Zha *et al.* (1998) briefly reviewed design and simulation approaches in manual assembly layouts, and concluded that those are mostly of sequential and non-intelligent nature and are therefore insufficient for concurrent intelligent design.

A considerably different approach has been represented by Gilad and Karni (1999), who developed the ERGOEX – an expert system suited for professional ergonomists as well as novices. The system receives various data about the worker and the working environment, and generates quantitative and qualitative recommendations based on ergonomic knowledge bases. While an expert system approach may improve significantly the designer's accessibility to accumulated knowledge in ergonomics, it is rather inflexible and is not capable of analyzing fundamental aspects of the design, such as worker's motion and performance time.

In this paper, we follow the work of Nayar (1995), Braun *et al.* (1996), and Arzi (1997) by exploiting computerized applications for the design of manual workstations. In order to overcome the deficiencies pointed out by Zha *et al.* (1998), we suggest a systematic design heuristic based on Fractional Experiments (FE) and Response Surface Methodology (RSM). Fractional experiments are used to generate candidate configurations of a workstation and to build empirical models relating design factors to various objective functions. Based on these models, RSM is utilized to optimize the design factors with respect to economic and ergonomic multi-objective measures.

1.2. *Factorial experiments and response surface methodology*

Design Of Experiments (DOE) is applied to assist an investigator (designer) in gaining information about a particular process or system through experiments. Fundamental questions arise in situations of limited experimental resources, such as, "*which factor affects the system response?*" or "*how to efficiently improve a given system configuration?*" Factorial Experiments (FE) and Response Surface Methodology (RSM) provide a collection of statistical techniques useful for modeling, optimizing and addressing the above as well as other DOE questions.

FE are applied to systems that are characterized by a combination of factor-levels; that is, where each of the control factors is fixed to one out of many feasible levels. FE are often used as *screening experiments*, in which many factors are considered with the purpose of identifying those that have a significant effect on the response (Montgomery, 1997). Screening experiments are useful in early stages of the experimentation, when several discrete factors are tested for their significance. The FE that contains the smallest number of experiments with which k factors can be investigated is the 2^k design. In this design, each of the factors has two levels – "high" and "low" – and therefore the response is assumed to be approximately linear over the range of levels. If the experimenter suspects a higher-order relation between the response and the factors and if experimental resources are sufficient, it is better to consider a higher-order design such as the CCD or the BBD (Montgomery, 1997). Once the experiments are performed, model-fitting techniques can be implemented to portray analytically the relations between the input factors and the response. Regression analysis, which is based on the method of least squares, is probably the most popular method for model-fitting. Least squares can be used for curve fitting without necessarily relying on the assumption that the departure (the differences between the response and the regression model) behaves like white noise (Sacks *et al.*, 1989; Montgomery, 1997). This is important for the design and analysis of computer experiments with deterministic outputs, as performed in this study.

When design factors are continuous, the classical RSM is an efficient method for optimization of the system configuration. In these cases, FE are applied primarily to obtain an empirical response model and improve an initial configuration. Then the RSM can be applied to fine-tune the values of the continuous factors in obtained solutions, following a procedure which is similar to those proposed by Shang (1995) and Ben-Gal *et al.* (1999).

The RSM uses the empirical response model seeking to relate a *response* Y to the values of control factors $x_1, x_2, \ldots, x_n$ where the underlying relationship is unknown. The empirical model is written as:

$$Y = g(x_1, \ldots, x_n; B_1, \ldots, B_n) + \varepsilon, \quad (1)$$

where g approximates an unknown function by a first-order or a second-order polynomial in $x_1, \ldots, x_n; B_1, \ldots, B_n$ are the estimators of the unknown system parameters; and ε represents the experimental error. The estimate of the experimental error is based on high-order interaction effects when using a factorial design with deterministic outputs. In practice, estimators are usually obtained by the method of least squares or maximum likelihood from a set of experiments. The experiments are represented by the design matrix, $\boldsymbol{X}$, whose columns are associated with the system factors and rows correspond to various system configurations.

RSM provides a contour representation of the model by local approximation (a few terms of the Taylor expansion series) over some limited region. The number of unknown parameters depends on the number of factors and on the order of the model (Myers and Montgomery, 1995). Using the smoothness features (differentiability) of the empirical model and the method of steepest descent, the RSM provides a set of adjustments to the factor values (with respect to the direction of the gradient) to improve the system response. In the new region, which is defined by the neighborhood of the improved factor values, a new approximating function is selected and a new direction of improvement is estimated in an iterative manner.

2. The proposed methodology

2.1. *Modeling the design parameters*

The proposed methodology is based on improving an initial workstation configuration, called the *initial solution*. The initial solution may be obtained from an existing workstation or by simulation of Virtual Manufacturing (VM) design tools. A set of system factors (design parameters) has to be defined in order to be modified during the optimization stage.

We recommend choosing factors and conditions that adhere to the following properties. First, they should be suspected of influencing the measures of interest. Second, they should be controllable factors; factors that can be manipulated in reality not only physically, but also from an economical (and/or legal) point of view. For example, there is no reason to model factors representing a new system if the management does not approve purchasing such a system. Third, the specified factors should be easily and accurately modeled by the VM tool. For example, the quality level of a product might be hard to model by a VM tool and therefore should be ignored; on the contrary, factors related to physical measures and locations of entities are simply modeled by the VM tool and easily manipulated during the optimization stages. Finally, it is of interest to include factors that are continuous in nature and, therefore, adequate for RSM optimization. Factors that represent distances, angles, weights, or other characteristics of the task environment are usually continuous and therefore are excellent candidates for the proposed method.

The knowledge regarding which factors to include in the model is system-specific and considered as an art. It is usually based on experience, which is hard to express algorithmically. When such experience does not exist, it is recommended to start the suggested procedure with a large set of candidate factors and use a screening experiment to identify those that have a significant influence on the measures. Further discussion on types of systems that can be represented by a factorial model can be found in Ben-Gal *et al.* (1999).

2.2. *Multi-objective approach to the workstation design problem*

Performance measures that are associated with the workstation design problem are usually characterized as economical or ergonomic measures. Often one can identify the trade-off between these two types of measures. For example, a problematic and inconvenient posture in an assembly workstation can be improved by changing the orientation of the product. Such an action may require additional high-cost equipment as well as changes in the product design, and results in an increase of the cycle time. Jung and Freivalds (1991) presented a trade-off between worker safety and productivity in lifting tasks. They have shown that increasing the load improves productivity, but, on the other hand, increases the worker's risk for musculoskeletal disorders. Hence, one can conclude that both economical and ergonomic measures should be considered in a workstation design while their relative importance should depend on the task performed and the overall objective.

A difference between economical and ergonomic measures is that in economical measures, the relationship between the measure (such as cycle time, number of products and idle time) and the real objective (profitability for example) is relatively clear (although not always). On the other hand, the relationships between ergonomic measures and objectives, such as decreasing risk of injury or improving working conditions, are much less clearer. This might be one reason why many papers in the area of workstation design focus on a single ergonomic aspect of the human operator, such as biomechanical strength, metabolic rate, reach assessment, or time predictions (Feyen *et al.*, 2000). This limitation has been discussed in the literature. Porter *et al.* (1995) as well as Feyen *et al.* (2000) applied for an integrated design tool that minimizes the risk of injuries. Jung and Freivalds (1991) emphasized the importance of considering multiple measures in the design stage due to possible interactions between different measures that may lead to conflicting conclusions if these measures are considered separately.

Once an integrative approach is adopted, the performance measures should be defined. The National Academy of Sciences (Anon, 1998) presents a list of factors that may affect the risk for disorders, such as work procedures, equipment and environment, organizational factors, physical and psychological factors of individuals, non-work-related activities and social factors. In his review Hagberg (1992) divides exposure variables into five categories: posture; motion/repetitions; material handling; work organization; and external factors. Moore and Garg (1995), in analyzing risk factors of distal upper extremity disorder, mention force; repetition; posture; recovery time; and type of grasp as the important factors. Most of the above factors depend both on the work procedures and workstation design. In this research, we deal with the workstation design only. We assume that the structure of the task is already given and aim to provide the most suitable physical environment for doing the job. Accordingly, the measures that are considered here are those that are affected by the workstation design rather than the work orders. Measures such as number of repetitions and exposure time to the risk factor are disregarded in this study. The factors addressed in the following case study (without loss of generality since the proposed approach can be applied with any set of measures) are: (i) the cycle time (economical measure, equals the inverse of the worker's throughput rate); (ii) the metabolic energy consumption according to Garg guidelines, which is a measure to the amount of effort spent on the task (physiological measure); (iii) worker's posture during the task (according to OWAS guidelines) that may indicate risk of injury; and (iv) lifting limitations according to NIOSH guideline (biomechanical). As seen later, these measures (that are widely discussed in Section 3.2) are sensitive to changes in the physical structure of the workstation as represented by the design factors.

In order to combine multiple objectives into a single one, the scaling of each objective has to be determined. In general, the NIOSH report (Anon, 1997) contains limited quantitative information about exposure-disorder relationship between risk factors and musculoskeletal dis-orders. A similar view is presented by the National Acadamy of Sciences (Anon, 1998), reporting that although some statistical results have been obtained regarding the relationship between individual factors and musculoskeletal disorders, they rarely show high predictive value. According to this report, dealing with the combined interaction is much more complicated and much work is still required. In addition, the report states that further research is needed on models and mechanisms that underlie the established relationship between causal factors and outcomes, as well as about the relationships between incremental changes of the environmental load and incremental responses. Hagberg (1992) claims that much has to be done in investigating the exposure-effect relationship between physical exposure and musculoskeletal disorders. Moore and Garg (1995) specify the reasons for the absence of practical physiological, biomechanical, or psychophysical models that relate job risk factors to increase risk of developing upper extremity disorders. They state that dose–response (cause–effect) relationships are not well understood, that measurement of some task variables, such as force, is very difficult in an industrial setting, and that the number of task variables is very large. As a result, most research assumes monotonic or linear risk factor-disorder relationship. McCauley-Bell and Crumpton (1997), who suggest a fuzzy linguistic model for predicting the carpal tunnel syndrome risk, assume a monotonic relationship between the variables and the risk level. Jung and Freivalds (1991), assume a linear relationship between the frequency of doing a task and biomechanical and physiological stress. The only exception is found in the review of Winkel and Westgaard (1992) who raise the fact that sometimes lack of physical exposure (inactivity) may cause a negative effect on the body. Aside from this exception, (which we believe is irrelevant to the environment addressed in our study) they also assume an increasing monotonic relationship between the risk factors and the disorder. Based on the above, we have decided to adopt linear scaling in our case study, while emphasizing that further research has to be conducted to identify precisely the risk factors-disorders relationship.

A basic method to combine multiple objectives into a single one is to use a weighting scheme. Due to the lack of knowledge regarding the factor-risk relationship, one should not expect to find developed weighting schemes in the ergonomics literature. Not surprisingly, the literature reveals that although many recommendations exist for an integrated approach where several measures have to be considered simultaneously, almost none apply a weighting scheme or uses another integrating method. Even those papers that address multiple measures refer to each measure separately, for example those of Laring *et al.* (1996), Gilad and Karni (1999) and Feyen *et al.* (2000), or suggest building an ergonomic profile (Hagberg, 1992) without using any weighting scheme. One approach for setting weights that was found in ergonomics literature is the Analytic Hierarchy Process (AHP) developed by Saaty (1980). The AHP is used by McCauley-Bell and Crumpton (1997), while investigating the prediction of carpal tunnel syndrome, and by Jung and Freivalds (1991). It is a tool for structural collection and analysis of expert opinions, based on a comparison between couples. This tool is suitable for handling a problem with multiple factors, and provides a structural sequence of steps. The general idea of the AHP is that even for an expert it is difficult to compare several factors simultaneously in order to set their weights. Instead, the expert compares a couple of factors each time, and indicates their relative importance. The outcomes of the method are a normalized weighting scheme and a consistency grade of the experts' decisions. In additional, the AHP enables us to combine opinions of experts from different areas (production, manufacturing, ergonomics). Since the major contribution of this study does not lie in the weighting scheme, the weights in the case study were determined arbitrarily. Nevertheless, we recommend that a real application of the proposed approach, a concrete method of combining the performance measures, such as the AHP approach, be used.

2.3. *Outline of the methodology steps*

The suggested heuristic, which applies the new methodology, consists of two parts. The first part is based on factorial experiments and handles discrete search over combinations of factor-levels for improving the initial solution. In the second part, the solution that was obtained earlier is further refined by changing the continuous factors using RSM. The algorithm is illustrated in Section 3.3 by presenting a detailed case study. Its flow chart is presented in Fig. 1 and described in the following steps.

Step 1. Initialization
Given a feasible configuration of the investigated system (either from an existing system or by initial modeling) and a set of performance measures, denote the initial configuration of n design factors by $\mathbf{x}_0$. That is, $\mathbf{x}_0$ is an n-dimensional vector of factor levels (system settings).

Step 2. Modeling and feasibility test
Use a virtual manufacturing tool, such as *eMpower* used here, to model the existing system and check the model validity by simulations. It is assumed that the VM model can be used to evaluate different design configurations accurately.

Step 3. Alternative solutions
Generate a discrete space of M candidate design configurations. Use a screening factorial design where the levels of each factor are selected as follows. Start with the initial design and specify a range for each design factor that contains the current factor level. q discrete points on such range define q possible levels per factor and result in a q^n full-factorial design. For limited experimental resources, a 2^n full-factorial design can be used by assuming a linear response model. Such design is obtained by considering only the endpoints of the factor ranges. Otherwise, the number of the examined systems may be reduced by using Fractional Factorial Experiments (FFE).

Step 4. Simulation and feasibility test
Simulate each of the design configurations. Check the feasibility of each solution, e.g., lack of collisions between environmental objects. Eliminate non-feasible solutions.

Step 5. Analysis
Analyze the performance measures obtained from the simulations. Use a multi-objective function, denoted by $D(\cdot)$, to evaluate the designs with respect to pre-defined performance measures and to select the best system (we use the desirability function suggested by Derringer and Suich (1980), however, different multi-objective functions can be used as well). Denote the best design solution known thus far by $\mathbf{x}^*$. If all design factors are discrete (i.e., qualitative factors or ordinal discrete factors), go to Step 8. If there exist continuous design factors, go to Step 6.

Step 6. Applying optimization RSM techniques to refine the design solution
Apply response surface techniques for model fitting. Check the validity of the model, for example, by using residual analysis. If required, fit a higher-order design

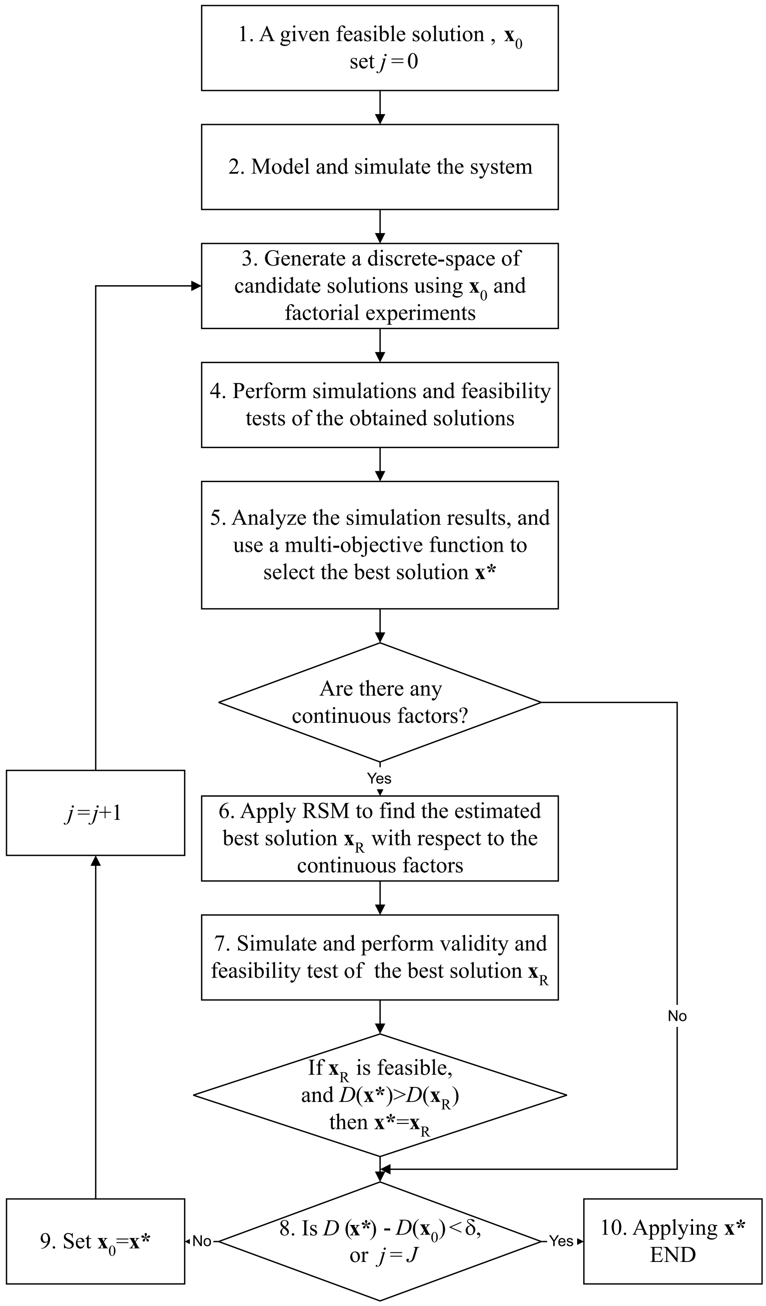

Fig. 1. Steps of the suggested methodology.

such as *Central Composite Design* (CCD). Use the RSM to find optimal factor configurations on a continuous scale that yield the expected best solution. Apply a multi-objective optimization technique. Denote the best design solution obtained from the RSM by $\mathbf{x}_R$.

Step 7. Validation and feasibility test
Simulate $\mathbf{x}_R$ and evaluate its expected multi-objective performance, denoted by $D(\mathbf{x}_R)$. If $\mathbf{x}_R$ is feasible and $D(\mathbf{x}_R)$ is found to be superior than $D(\mathbf{x}^*)$, the expected multi-objective performance of the best design obtained thus far, set $\mathbf{x}^* = \mathbf{x}_R$.

Step 8. Termination condition
If the improvement of the multi-objective performance is smaller than δ, i.e., $D(\mathbf{x}^*) - D(\mathbf{x}_0) < \delta$, or the maximal number of iterations, J, has been obtained, go to Step 10. Otherwise go to Step 9.

Step 9. New search for best design
Set $\mathbf{x}_0 = \mathbf{x}^*$, thus defining the best design configuration found thus far as a new initial solution. Increase the iteration counter by one, i.e., $j = j + 1$, and go to Step 3.

Step 10. Termination
Apply $\mathbf{x}^*$ to the investigated system. END.

3. An illustrative real-life case study

In this section, a detailed case study of an ergonomic design of a workstation is presented. For simplicity reasons, we chose to illustrate the suggested methodology by designing a simple workstation. In particular, we consider a workstation used for packaging of fruits in bins (Elbaz, 1999). Most of the routing and the sorting tasks are fully automated. However, final packaging of the finest quality fruits is performed manually. The most expensive tasks in the process are those involving direct manpower.

The case study is organized as follows: (i) a brief description of the system, the underlying operational processes and the factors are provided; (ii) a detailed description of the performance measures is given; and (iii) a detailed implementation of the suggested methodology is described by using *RobcadMan/eMPower* – a VM software package of Tecnomatix Technologies Ltd.

3.1. *Description of the system*

The workstation for the case study is part of an existing industrial citrus packing house. The main functions in the packing house are as follows:

- Fruit reception.
- Initial cleaning process.
- Fruit classification (according to size and quality).
- Packaging fruit in bins.
- Bin loading for transportation.

The bottleneck of the whole process is the packaging line, which consists of numerous manual workstations. An attempt to replace humans with industrial robots failed in the past, due to low throughput and low quality of the robotic workstations. The worker performs the repetitive task of packing fruits, while staying at the same positions all day long. At the end of the day, many workers are complaining of shoulder aches and lower back aches. The objective of redesigning the packing workstation is dual: to maximize throughput and to create a suitable ergonomic working environment for the workers.

A drawing of the workstation is presented in Fig. 2. The process begins with the arrival of the fruit to the workstation after the classification stage by an upper conveyor, up to the serving shelf. The worker then manually delivers the fruit from the conveyor into the bin until the bin is full. In this stage, the full bin is replaced by a new one, and a new cycle begins. In more detail, the manual work consists of the following four stages:

1. Bin Preparation – the worker walks to a pack of raw material of bins, takes one and prepares the bin by folding its walls. Then the bin is positioned on the working surface.
2. Fruit packing – the main task. The worker, using two hands, takes two pieces at a time and puts it inside the bin. This process proceeds until the bin is full.
3. Bin marking – the worker attaches several tags and a bar code on the outer bin surface.
4. Bin dispatching – the worker closes the bin and pushes it toward the lower conveyor.

As mentioned above, the main task is the fruit packing (stage 2), and in this case study we focus on ergonomic improvement related to this task.

Four design factors are considered. All the factors are location (positioning) factors of the packaging workstation. In particular (see Fig. 2):

- Factor A is the horizontal distance in millimeters between the edge of the serving shelf and the edge of the working surface.
- Factor B is the vertical height in millimeters of the serving shelf.
- Factor C is the vertical altitude in millimeters of the lower edge of the working surface.
- Factor D is the angle in degrees of the slope of the working surface.

3.2. *The performance measures and the objective function*

In this section, we describe the four performance measures that are selected and later integrated using a multi-objective function. The aim is to increase the throughput rate (capacity) of the workstation, as well as to create a

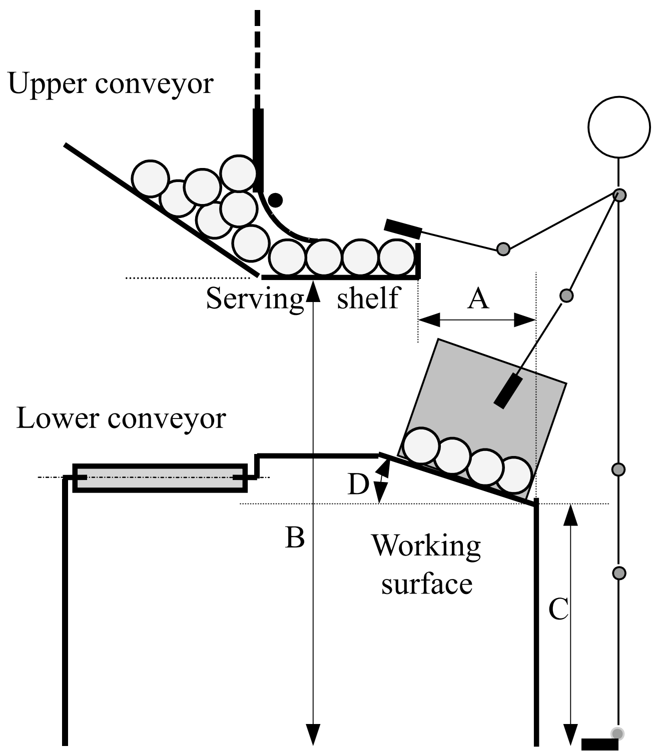

Fig. 2. The packaging workstation.

suitable and adjustable ergonomic environment that accommodates a large percentage of the workers population, as suggested in Niebel and Freivalds (1999). The considered measures are:

• ***Ttask.*** The packaging cycle time (an economical measure) is a measure for the productivity of the workstation, and therefore should be minimized. The task cycle time consists of m individual operations, where the time to perform each operation is denoted by t_i, $i = 1, \dots, m$. The operation times are obtained from the MTM tables stored in the *RobcadMan/eMpower* database. i.e.,

$$Ttask = \sum_{i=1}^{m} t_i \text{ (min/unit)}. \quad (2)$$

• ***Eshift.*** The metabolic energy consumption in a shift according to Garg guidelines (physiological measure). It is used as a measure of the task's difficulty. The objective is to minimize the metabolic energy consumption for an 8-hour shift, measured in Kcal units. The energy consumption rate per each individual operation, denoted by e_i, $i = 1, \dots, m$, is generated by the VM software using the Garg formula (Garg *et al.*, 1978). Eshift is the time-weighted average of the energy consumption rates multiplied by the shift time (480 minutes), i.e.,

$$Eshift = 480\left(\sum_{i=1}^{m} e_i \times t_i\right) \Big/ Ttask \text{ (Kcal)}. \quad (3)$$

One should note that using this measure in the given task is a bit problematic, since the loads involved are relatively light and the relative frequency may not be high enough to significantly load the cardiopulmonary system. Still, we use this measure (as well as all other measures) for demonstration purposes, while noting that in practical implementation its suitability should be carefully examined.

• ***Ptask.*** The worker's posture during the task that may indicate risk of injury. This measure considers the worker's body positions during the packaging task according to the OWAS guidelines (Karhu *et al.*, 1981; Scott and Lambe, 1996). The objective is to shorten operations that require inconvenient body positioning. A good solution requires that during all operations the body position remains in category one. This category, called the *natural position*, insures that no damage is caused to the worker. The Ptask is the time weighted average of the position categories that are denoted by p_i, $i = 1, \dots, m$ and generated by the VM simulator. Thus,

$$Ptask = \left(\sum_{i=1}^{m} p_i \times t_i\right) \Big/ Ttask \text{ (Posture category)}. \quad (4)$$

• ***Wtask.*** The lifting limitations according to the NIOSH guideline (a biomechanical measure). This measure takes into account the upper weight limits that the worker is allowed to carry in each position during the task time. The values are obtained from the *RobcadMan/eMpower* database according the NIOSH lifting equation (Waters *et al.*, 1993). The applicability of the NIOSH formula has several limitations as discussed in Waters *et al.* (1994). One limitation defines the lifting task as "the act of manually grasping an *object* of definable size and mass *with two hands*, and vertically moving the object without mechanical assistance". In this case study, each hand lifts a separate object. However, since both hands operate simultaneously and the two objects are held closely together, it is considered as an applicable lifting task for the NIOSH equation. Furthermore, such a consideration is reasonable since the weight of the objects does not exceed the allowed limit, and the Wtask is employed only as a comparative measure between different postures. In general, one has to look for body positions for which the weight limits are as high as possible, since large values indicate suitable ergonomic positions of the worker. Moreover, the weight limit is important even when the worker carries a weight which is smaller than the limit. The reason is the long run influence of carrying weight on lower back injuries. Hence, the higher the average weight limit during the task, the better. Wtask is the time-weighted average of the weight limits, denoted for each position by w_i, $i = 1, \dots, m$, calculated only for those operations that involve weights,

$$Wtask = \left(\sum_{i=1}^{m} l_i \times t_i \times w_i\right) \Big/ \left(\sum_{i=1}^{m} l_i \times t_i\right) \text{ (Kg)}, \quad (5)$$

where,

$$l_i = \begin{cases} 1 & \text{if operation } i \text{ involves a weight lift,} \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

Assume that the designer has to evaluate K different configurations. Accordingly, T_k, E_k, P_k and W_k denote respectively the Ttask, Eshift, Ptask and Wtask performance measure values for solution $k = 1, \dots, K$, as obtained from the VM simulation. Since many multi-objective functions (and particularly the desirability function used here) require the performance measure values to be between zero and one, we apply the following normalization procedure:

$$\begin{aligned} \tilde{T}_k &= \left(U'_T - T_k\right)/(1.2(U_T - L_T)) \quad k = 1, \dots, K, \\ \tilde{E}_k &= \left(U'_E - E_k\right)/(1.2(U_E - L_E)) \quad k = 1, \dots, K, \\ \tilde{P}_k &= \left(U'_P - P_k\right)/(1.2(U_P - L_P)) \quad k = 1, \dots, K, \\ \tilde{W}_k &= \left(W_k - L'_w\right)/(1.2(U_W - L_W)) \quad k = 1, \dots, K, \end{aligned} \quad (7)$$

where U_T (L_T), U_E (L_E), U_P (L_P), and U_W (L_W) are the upper (lower) limits of the four performance measures respectively and

$$\begin{aligned} U'_{T\backslash E\backslash P\backslash W} &= U_{T\backslash E\backslash P\backslash W} + 0.1\left(U_{T\backslash E\backslash P\backslash W} - L_{T\backslash E\backslash P\backslash W}\right), \\ L'_{T\backslash E\backslash P\backslash W} &= L_{T\backslash E\backslash P\backslash W} - 0.1\left(U_{T\backslash E\backslash P\backslash W} - L_{T\backslash E\backslash P\backslash W}\right), \end{aligned} \quad (8)$$

The rational for such normalization procedure is now explained. In common normalization procedures, the upper (lower) limits are set to the maximal (minimal) values obtained out of all existing solutions. Thus, assigning the grade one to the best-obtained solution and the grade zero to the worst obtained one. This approach is problematic since it assigns the zero grade to the worst obtained solution, as if no worse solution exists. Similarly, the best solution gets the higher normalized value of one, as if better solutions do not exist. Since the current experiment does not cover all the solution space, and it is assumed that better and worse solutions might exist, we increase the range between the upper and lower limits for all the performance measures by 20%, as seen in the dominators of Equation 7. This guarantees that the normalized values of, $\tilde{T}_k$, $\tilde{E}_k$, $\tilde{P}_k$ and $\tilde{W}_k$ are within the range $0.08 - 0.92$.

The next stage is to use a multiple objective function in order to compare alternative design solutions and select the optimal one. Several multiple-response procedures were suggested over the years, for example, by Myers and Carter (1973), Khuri and Conlon (1981), Myers and Montgomery (1995) and Derringer and Suich (1980). The latter method constructs a multiple objective function for each alternative, denoted by D_k and called the desirability function. It reflects the combined desirable grade of the kth solution with respect to all performance measures. The desirability function of solution k is based on the geometric mean of its normalized performance measures, as follows:

$$D_k = \left(\prod_{v=1}^{V} d_{k,v}^{r_v}\right)^{1/\sum r_v} \qquad k = 1, \ldots, K, \tag{9}$$

where $d_{k,v}$ denotes the vth performance measure of solution k; and r_v is the relative importance that is assigned subjectively and respectively to each performance measure. In our example, $v = 4$, $d_{k,1} = \tilde{T}_k$, $d_{k,2} = \tilde{E}_k$, $d_{k,3} = \tilde{P}_k$, and $d_{k,4} = \tilde{W}_k$. Accordingly the desirability function is the following:

$$D_k = \left(\tilde{T}_k^2 \times \tilde{E}_k^2 \times \tilde{P}_k \times \tilde{W}_k\right)^{1/6}, \qquad k = 1, \ldots, K, \tag{10}$$

where, for illustration purpose, the first two performance measures are considered to be twice as important as the last two.

3.3. *Applying the suggested methodology*

Step 1. Initialization

A feasible initial configuration of the packaging workstation is presented in Table 1 and denoted by level 0. The solution is characterized by measures of the four design factors ($n = 4$) and denoted by $\mathbf{x}_0$.

Step 2. Modeling and feasibility test

RobcadMan/eMPower, a virtual manufacturing software package by Tecnomatix Technologies Ltd., is used to model the existing system and its feasibility. It takes about 8 hours to build such a model by a well-trained person. Figure 3 illustrates the graphic interface of *RobcadMan/eMPower* with the modeled workstation.

Step 3. Alternative solutions

Table 1 presents the selected ranges for the four design factors. The initial solution defines the center points for each range. For illustration purpose, a 2^4 full-factorial experiment with 16 different configurations is defined by considering the endpoints of the factor ranges and neglecting higher order response models.

Step 4. Simulation and feasibility test

Table 2 presents 16 configurations that are generated by editing the initial solution model. A few minutes (10–15) are required to generate and run each configuration on a Pentium PC. A validation of the ergonomic constraints is performed on each model and it is found that alternative number 3 is not feasible. An ergonomic report, which is generated by the VM software, is used to calculate the normalized performance measure according to Equations (7) and (8) and the desirability function given by Equation (10). The experiment outputs are shown in Table 2.

Step 5. Analysis

At this stage, the simulation results of alternative solutions are analyzed. The desirability function in Equation (10) is applied to the multiple objectives. The desirability values for each configuration are listed in Table 2. As can be seen from Table 2, no dominant solution (solution which is superior to all other solutions in all performance measures) exists; yet, the initial solution may be improved. The following analysis includes examination of each performance measure separately, evaluation of the multi-objective (desirability) function for all measures simultaneously, residual analysis, and model fitting to confirm the findings.

Ttask. The cycle time per task is considerably affected by changes in the factors' values. There is a large difference of about 17.5% between the best solution (2121 with Ttask = 10.47 seconds) and the worst solution (2212 with Ttask = 12.31 seconds). In a mass production environment, such as in this case, this improvement is

Table 1. The intial values and the selected ranges of the design factors

Parameter	*Factor level*			*Delta*
	0	*1*	*2*	
A (mm)	−300	−330	−270	30
B (mm)	1120	1090	1150	30
C (mm)	600	570	630	30
D (deg)	15.52	12.52	18.52	3

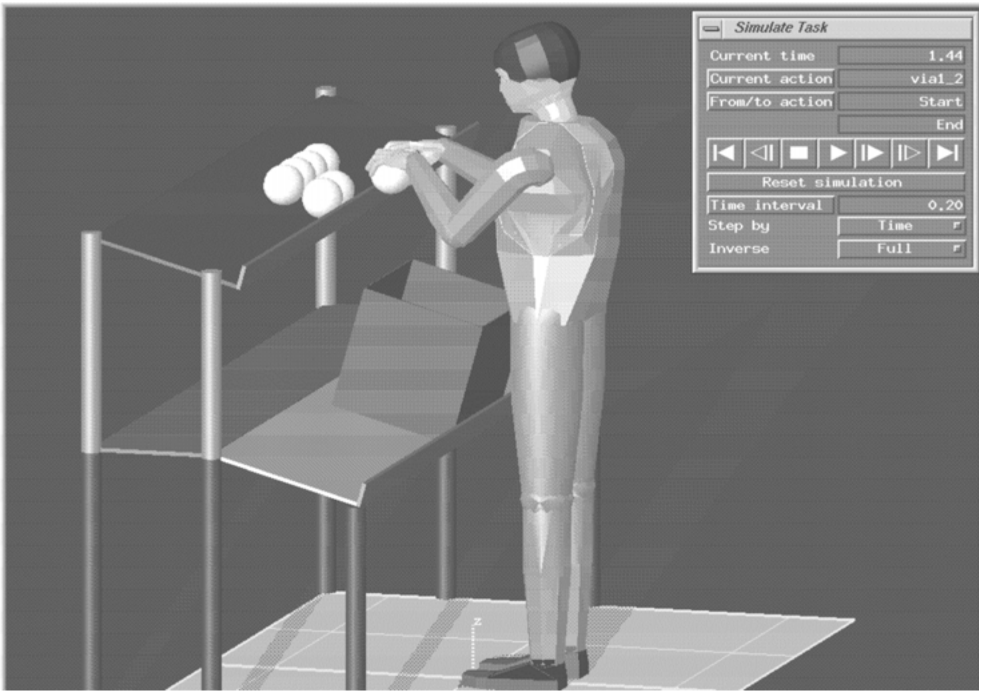

Fig. 3. The examined workstation (the picture is from the *RobcadMan/eMPower* interface).

Table 2. Simulation results of the alternative design solutions

Alternative	*Exp. (ABCD)*	*MTM analysis Ttask (Sec)*		*Garg analysis Eshift (kcal)*		*OWAS analysis Ptask*		*NIOSH 91 analysis Wtask (kg)*		*Desirability*	*Feasibility test*
		Actual	*Norm.*	*Actual*	*Norm.*	*Actual*	*Norm.*	*Actual*	*Norm.*		
0	**0000**	**11.08**	**0.64**	**833.84**	**0.08**	**1.24**	**0.14**	**3.55**	**0.42**	**0.24**	**OK**
1	1111	11.55	0.43	831.76	0.37	1.24	0.09	2.89	0.14	0.26	OK
2	2111	10.82	0.76	833.77	0.09	1.11	0.82	3.67	0.47	0.35	OK
3	2211	–	–	–	–	–	–	–	–	–	No (collision)
4	1211	11.99	0.23	833.61	0.12	1.24	0.12	2.83	0.12	0.15	OK
5	1221	11.49	0.45	832.89	0.22	1.23	0.16	2.75	0.08	0.23	OK
6	2221	11.80	0.31	827.89	0.92	1.14	0.66	3.51	0.40	0.53	OK
7	2121	10.47	0.92	830.63	0.53	1.11	0.82	3.65	0.46	0.67	OK
8	1121	11.24	0.57	829.38	0.71	1.24	0.12	2.82	0.11	0.36	OK
9	1122	11.34	0.52	828.72	0.80	1.23	0.17	2.93	0.16	0.41	OK
10	**2122**	**10.56**	**0.88**	**830.78**	**0.51**	**1.09**	**0.92**	**3.76**	**0.51**	**0.67**	**OK**
11	2222	11.85	0.29	828.97	0.77	1.13	0.70	3.62	0.45	0.50	OK
12	1222	11.69	0.36	832.10	0.33	1.23	0.19	2.87	0.13	0.27	OK
13	1212	12.05	0.20	833.43	0.14	1.24	0.11	3.80	0.53	0.19	OK
14	2212	12.31	0.08	828.86	0.78	1.15	0.61	4.73	0.92	0.36	OK
15	2112	11.02	0.67	832.59	0.26	1.11	0.81	3.79	0.52	0.48	OK
16	1112	11.69	0.36	831.18	0.46	1.25	0.08	3.00	0.19	0.28	OK
Upper limit		12.49	–	834.44	–	1.26	–	4.93	–	–	–
Lower limit		10.29	–	827.30	–	1.08	–	2.55	–	–	–

economically significant. The observation is reconfirmed by the model fitting analysis that follows.

Eshift. The variation in the energy consumption during a work shift among the different solutions is relatively small. The reason is that, energy-wise, the considered task is not a demanding one. A major portion of the energy consumption consists of the Basal Metabolism (the minimal amount of energy needed to keep the body functioning, when no activities are performed at all (Kroemer *et al.*, 1994)) and the energy consumption for basic required body positions. This measure is further considered in this case study for illustration purposes only, whereas in reality it would have been eliminated.

Ptask. The body position category is affected by configuration changes. The back position is found by the VM software to be the most relevant and problematic criterion. For example, during 23.5% of the time, the back position in the initial solution stands on category two, which may harm the worker in the long run. For comparison, in the best solution (2122), the back position stands on category two in only 9% of the task time. Note from Table 2 that factor A has a clear effect on the Ptask value. It is seen that the best solutions are obtained when factor A is fixed on its higher level (the serving shelf is closer to the worker), while the worst solutions are obtained for the lower level. This finding is confirmed by the model fitting analysis as well.

Wtask. The average weight limit in the initial solution is 3.55 kg. The best configuration (2212) has an average weight limit of 4.73 kg, thus an improvement of 33%. Similarly to the Ptask analysis, it is seen that the best solutions are obtained when factor A is fixed on its higher level.

At this stage, the desirability function of each alternative is evaluated. The performance measures are first normalized and the desirability function is then calculated using the relative importance values given in Equation (10). Figure 4 presents the different configurations ranked according to their desirability value. The best solution is configuration 2122 with a desirability value of 0.67. The initial solution is ranked in 13th place with a desirability value of 0.24. It is seen that not only are 12 solutions superior to the initial solution, but also that the initial solution is dominated by three configurations (including solution 2122). In other words, these configurations are superior to the initial solution in *all* objectives and, therefore, are considered better for *any* set of relative importance values.

Finally, a polynomial response fitting is performed with respect to all performance measures. Table 3 is obtained from the *Design Expert* statistical software and presents, for example, such analysis with respect to the Ttask (MTM) measure. The table contains model-fitting measures, including coefficients of determination and the contribution of each term to the model sum-of-squares. The basis for such analysis is the use of higher order interaction effects (that are not included in the model) as an estimate for the experimental error. The required assumption of uncorrelated errors with mean zero and constant variance has to be carefully verified through residual analysis. A normal probability plot of the residuals is presented in Fig. 5 and validates the non-linear response model, given at the bottom of Table 3. This non-linearity results from the significant interaction

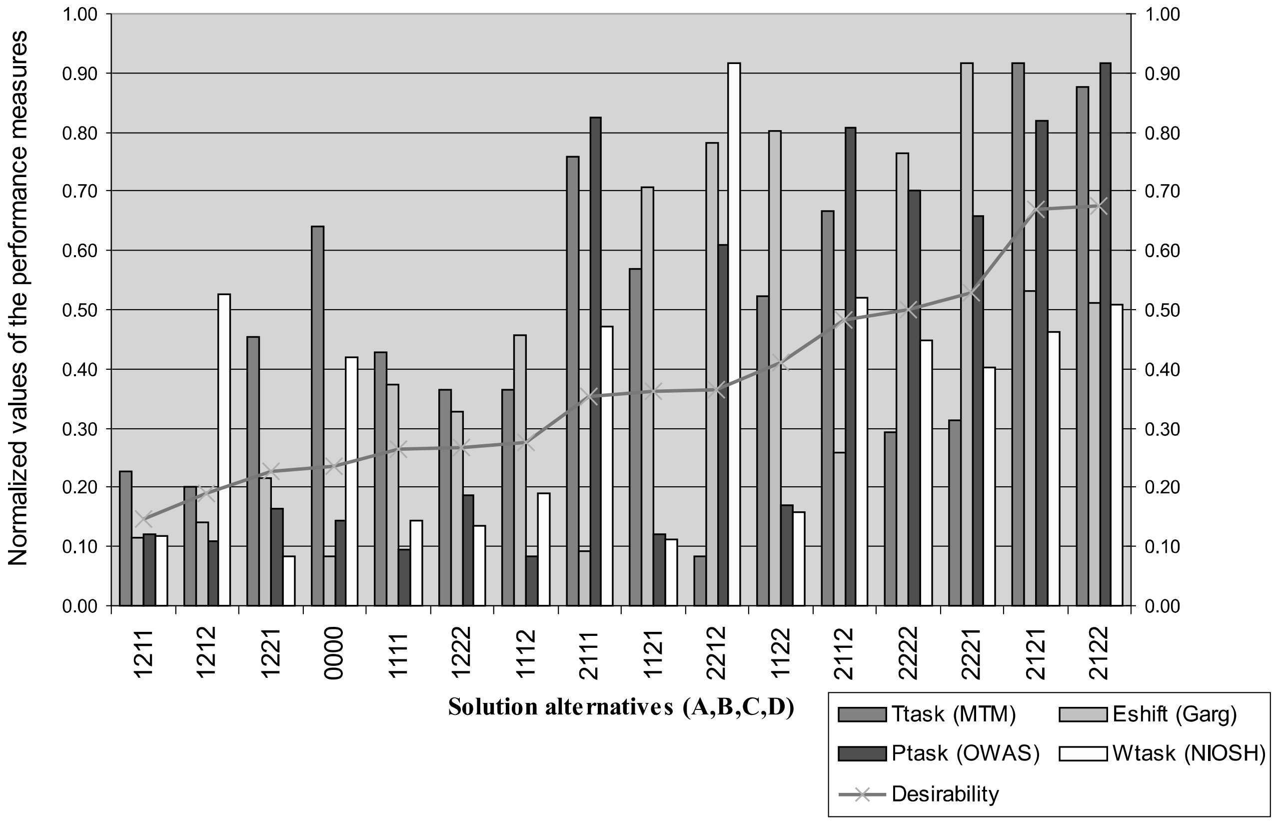

Fig. 4. The different configurations ranked according to their desirability value.

Table 3. Model fitting analysis with respect to the Ttask measure

Factor	*Sum-of-squares*	*DF*	*Mean square*	*Factorial R^2 (*2)*	*Percentage contribution to sum-of-squares (%)*
A	0.24	1	0.24	0.056	5.66
B	2.52	1	2.52	0.592	59.5
C	0.57	1	0.57	0.134	13.4
D	0.055	1	0.055	0.013	1.3
AB	0.85	1	0.85	0.199	20
Full Model	4.17	5	0.83	0.9958	
Residual*[1]	0.018	9	1.958E-003		
Cor Total	4.19	14			

Model fitting measures

Root MSE	0.044	R^2	0.9958
Dep Mean	11.46	Adj R^2	0.9935
C.V.	0.39	Pred R^2	0.9885
PRESS	0.048	Adeq Precision	65.461

Response fitting (in terms of coded factors (+1,−1)):

Expected Ttask (MTM) = 11.50 − 0.13A + 0.42B − 0.20C + 0.061D + 0.24AB

Factor	*Coefficient estimate*	*DF*	*Standard error*	*95% CI low*	*95% CI high*
Intercept	11.50	1	0.012	11.48	11.53
A-shelf_d	−0.13	1	0.012	−0.15	−0.10
B-shelf_h	0.42	1	0.012	0.39	0.44
C-box_h	−0.20	1	0.012	−0.22	−0.17
D-box_angle	0.061	1	0.012	0.035	0.088
AB	0.24	1	0.012	0.21	0.27

*[1] Error estimate is based on high-order interaction effects.
*[2] The factorial R^2 is evaluated by the ratio of the factor sum-of-squares and the total sum-of-squares.

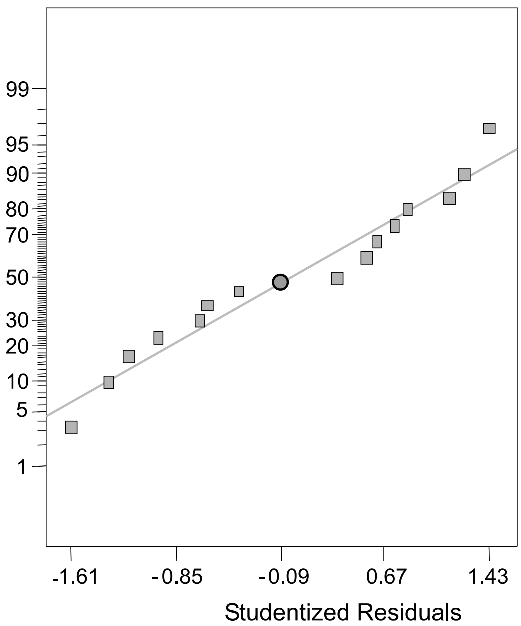

Fig. 5. A normal probability plot of the residuals of the response model for Ttask.

between factors A and B (the horizontal and the vertical distances of the serving shelf). For further discussion on analysis approaches of deterministic simulation models see McKay *et al.* (1979) and Sacks *et al.* (1989).

A similar procedure is repeated with respect to the other three performance measures. Table 4 presents the list of factors with respect to all performance measures in decreasing order of importance. It is found that the vertical distance of the serving shelf (factor A) affects all the measures and that the horizontal height of the serving shelf (factor B) affects all the measures beside the Wtask. The interaction AB is found to affect most measures as well. Figure 6 exemplifies such interaction with respect to the

Table 4. Design factors in decreasing order of significance with respect to all performance measures

Ttask (MTM)	*Eshift (Garg)*	*Ptask (OWAS)*	*Wtask (NIOSH)*
B(−)	AB(+)	A(+)	A(+)
AB(−)	C(+)	AB(−)	
C(+)	A(+)	B(−)	
A(+)	B(+)	C(+)	
D(−)			

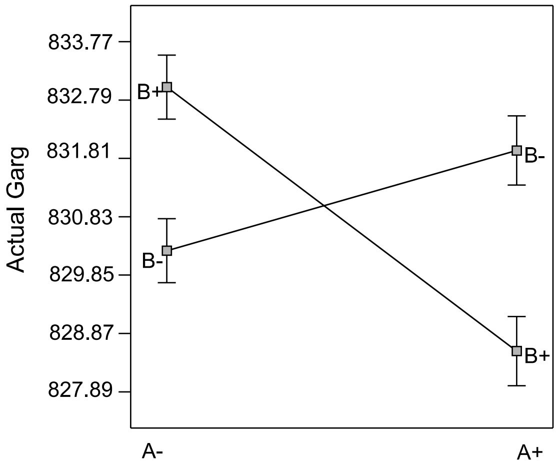

Fig. 6. The interaction between factors A and B with respect to the Eshift PM.

Eshift (Garg) performance measure. The cross of lines clearly indicates that a higher shelf (level B+) should be used if the shelf is closer to the worker (level A−). However, a lower shelf is better if the shelf is distant from the worker.

Since the design factors are continuous, one can refine the best solution found thus far by applying RSM techniques, as explained in the next step.

Step 6. Applying optimization RSM techniques to refine the design solution

In this step, we apply the response surface methodology to find the best solution. We follow the optimization procedure of Derringer and Suich (1980). Table 5 presents the initial conditions of both the performance measure and the design factors that are used by the optimization procedure. We use the extrapolation presented in Equation (7). Thus, with respect to Ttask, Eshift and Ptask, the response gets a desirability grade of one if it is equal (or lower) to the minimum value obtained in previous experiments minus 10% of the observed range. As for the Wtask measure, a desirability grade of one is obtained if the weight limit is equal (or higher) to the maximum value obtained in previous experiments plus 10% of the observed range. The lower and upper weights define the accumulation rate of the desirability grade. Weights of value one imply a linear accumulation rate. The importance column gives the relative importance of each performance measure with respect to the others, as seen in Equation (10). More details regarding the mathematical implication of the weights and the importance can be found in Derringer and Suich (1980). Table 5 also presents the search range for the design solutions. Note that we also allow some extrapolation of the design factor values. That is, the four design factors that were experimented earlier with level values of one or two (in coded terms) are now allowed to vary between 0.8 to 2.2. The reason for such extrapolation is the assumption that one can estimate the response functions over a wider search region by using the responses obtained in a smaller experimental region (Myers and Montgomery, 1995). Such an assumption has to be checked at a later stage by a validation experiment of the best design solution, particularly if such a solution lies out of the experimented range.

The applied desirability RSM method is based on a general non-linear optimization technique that utilizes the steepest ascent algorithm. The initial solution is based on the best solution obtained thus far. Additional starting simplex points are then generated randomly by adding or subtracting a fraction of each of the factor ranges to the initial starting point. A downhill simplex (Nedler-Mead) multi-dimensional pattern search is then applied which converges at either a stationary point or a design space boundary. Convergence is achieved when the distance moved or objective function change is less than a 10^{-6} ratio. Further details on the optimization algorithm can be found in Derringer and Suich (1980).

Table 6 presents nine design solutions sorted in a decreasing order by their desirability grades. For comparison purpose, two solutions from previous steps were added to the table: the initial solution given in Step 1 (denoted in the Table by IS), and the best "discrete" solution obtained at Step 4 (denoted in the Table by DBS).

The best design solution that is obtained by the response optimization procedure (Design No. 1) achieves a desirability grade of 0.736. The design factors and its performance measures are presented in Fig. 7. Note that

Table 5. Search region and definition parameters for the multiple desirability method

Name	*Goal*	*Lower limit*	*Upper limit*	*Lower weight*	*Upper weight*	*Importance*
shelf_d (A)	0.80..2.20	0.8	2.2	1	1	–
shelf_h (B)	0.80..2.20	0.8	2.2	1	1	–
box_h (C)	0.80..2.20	0.8	2.2	1	1	–
box_angle (D)	0.80..2.20	0.8	2.2	1	1	–
Ttask	$\leq$10.29	10.29	12.48	1	1	2
Eshift	$\leq$827.29	827.29	834.44	1	1	2
Ptask	$\leq$1.07	1.07	1.26	1	1	1
Wtask	$\geq$4.93	2.55	4.93	1	1	1

Table 6. Design solution improvement using the RSM

Number	*Shelf_d*	*Shelf_h*	*Box_h*	*Box_angle*	*Ttask*	*Eshift*	*Ptask*	*Wtask*	*Desirability*
1	2.20	1.26	2.20	0.95	10.62	829.98	1.08	3.99	0.736
2	2.20	1.28	2.18	0.81	10.63	829.95	1.08	3.99	0.736
3	2.20	1.38	2.20	0.80	10.78	829.48	1.09	3.98	0.734
4	2.20	1.08	2.20	0.80	10.33	830.76	1.07	3.99	0.732
5	2.20	1.23	2.20	1.40	10.62	830.13	1.08	3.98	0.729
6	2.20	1.29	2.20	1.51	10.73	829.87	1.08	3.99	0.727
7	2.15	1.18	2.20	0.80	10.51	830.28	1.09	3.94	0.726
8	2.17	1.04	2.20	0.80	10.29	830.88	1.08	3.96	0.723
9	2.20	1.24	2.20	1.88	10.69	830.09	1.08	3.99	0.722
:	:	:	:	:	:	:	:	:	:
DBS	2	1	2	2	10.56	830.78	1.09	3.76	0.674
:	:	:	:	:	:	:	:	:	:
IS	0	0	0	0	11.08	833.84	1.24	3.55	0.236

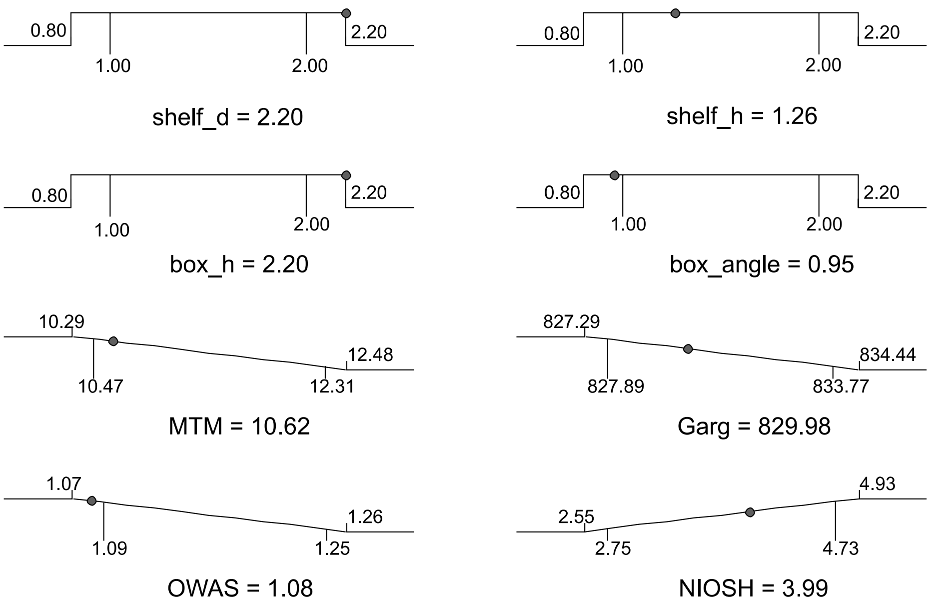

Fig. 7. Design parameters and performance measure values of the best solution.

both the shelf distance (factor A) and the box height (factor C) are set in the edges of the permitted range, thus outside the experimented region. The shelf height (factor B) is set to 1.26, within the experimented range and the box angle (factor D) is set to 0.95 outside, but close to the experimented region. In terms of the performance measures, note that the Ptask (OWAS) is better than the best value obtained earlier, the Ttask (MTM) is close to the best value, while the Eshift (Garg) and Wtask (NIOSH) are smaller than the best values obtained in Step 5.

Finally, Figs. 8 and 9 (a and b) present, respectively, a three-dimensional plot of the desirability response and the contour plots of the MTM and Garg measures with respect to the shelf distance (factor A) and the shelf height (factor B). It can be seen that the desirability response is flat close to the optimal solution, indicating that potentially there are several optimal solutions close to design solution number one.

Step 7. Validation test

The best solution obtained in Step 6 is modeled by the *RobcadMan/eMPower* simulator to validate its expected performance.

Steps 8–10. Termination

At this stage, the termination condition has to be checked. For illustration purposes, only a single iteration is allowed. Therefore, design No. 1 is selected as the best design, denoted by $\mathbf{x}^*$, and the system is reconfigured accordingly.

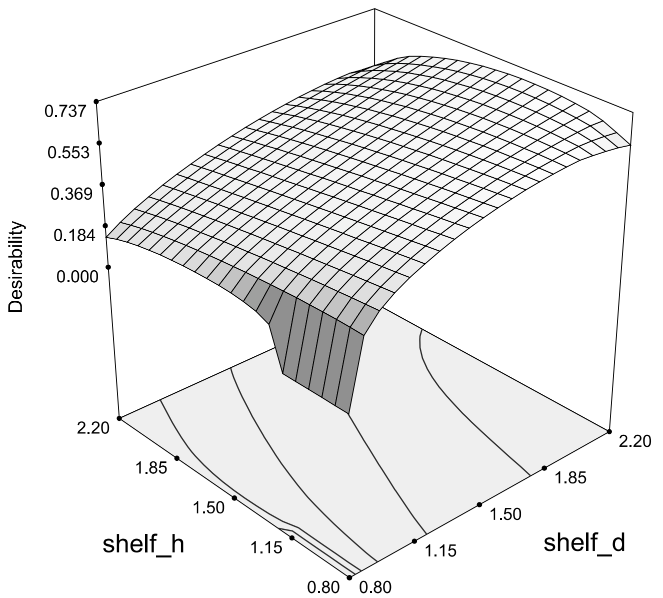

Fig. 8. A three-dimensional plot of the desirability response as a function of factors A and B (box_h = 1.89, box_angle = 0.80).

Remark: In this case study we showed how a real-life working environment could be improved using the proposed methodology. Although only a single iteration was conducted, the final selected configuration was found to be superior to the initial configuration with respect to *all* the objective measures, and consequently obtain a substantially higher desirability grade.

4. Summary

In this paper, a new methodology for workstation design was introduced. The proposed approach was based on Factorial Experiments (FE) and Response Surface Methodology (RSM) and utilized computerized tools for virtual manufacturing and graphical simulation. Computerized tools enable an individual to simulate and evaluate a large number of design configurations with respect to multiple performance measures. However, most of the VM tools that are available in the market focus on modeling and graphical aspects and fail to propose a systematic procedure for the design process. In most cases, they also overlook the effect of interactions among design factors that play a significant role in the design of manual workstations. FE and RSM were used in this work to bridge these gaps by generating a set of alternative design configurations in a systematic manner, and apply educated changes to configuration parameters. Such an approach enables us to reach a satisfactory solution, with respect to both operational and ergonomic measures, within a limited number of examined configurations.

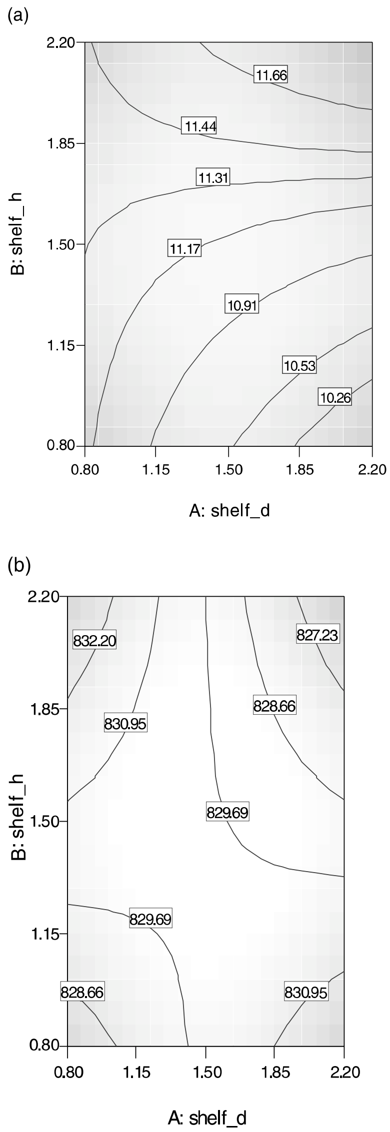

Fig. 9. (a) A contour plot of the MTM measurement for factors A and B; and (b) a contour plot of the Garg measurement for factors A and B. In both figures box_h = 2.20, box_angle = 0.80.

The proposed methodology emphasized the advantages of combining computerized tools such as virtual manufacturing, and statistical design approaches such as RSM. Workstations are often characterized by continuous metric factors, such as height, length and depth, that are well suited to be input factors to RSM. In particular, the case study demonstrated that a dramatic improvement in workstation performances can be obtained by applying the proposed methodology to these factors. The best configuration obtained was superior to the initial configuration with respect to all performance measures and a significant increase in the desirability measure, from 0.236 to 0.736, was accomplished.

The proposed methodology can be applied to different workstation configurations, provided that they can be characterized by a set of design factors. Furthermore, almost any tool for virtual manufacturing and graphical simulation, which contains anthropometric models, can be used for this matter.

References

Anon (1997) Musculoskeletal disorders and workplace factors. Technical Report No. 97–141, US Department of Health and Human Services (NIOSH), Cincinnati, OH.

Anon (1998) *Work-related Musculoskeletal Disorders: A Review of the Evidence*, The National Academy Press, Washington, DC.

Arzi, Y. (1997) Methods engineering: using rapid prototype and virtual reality techniques. *Human Factors and Ergonomics in Manufacturing*, **7**(2), 79–95.

Barnes, R.M. (1980) *Motion and Time Study – Design and Measurement of Work*, John Wiley & Sons, New York, NY, pp. 173–236.

Ben-Gal, I., Braha, D. and Maimon, O. (1999) Probabilistic sequential methodology for designing a factorial system with multiple responses. *International Journal of Production Research*, **37**(12), 2703–2724.

Braun, W.J., Rebollar, R. and Schiller, E.F. (1996) Computer aided planning and design of manual assembly systems. *International Journal of Production Research*, **34**(8), 2317–2333.

Chaffin, D.B. (1997) Development of computerized human static strength simulation model for job design. *Human Factors and Ergonomics in Manufacturing*, **7**(4), 305–322.

Derringer, G. and Suich, R. (1980) Simultaneous optimization of several response variables. *Journal of Quality Technology*, **12**(4), 214–219.

Elbaz, M. (1999) Ergonomic analysis and improvement of working environment via simulation and experimentation. Unpublished work, Department of Industrial Engineering, Tel Aviv University (in Hebrew).

Feyen, R., Liu, Y., Chaffin, D., Jimmerson, G. and Joseph, B. (2000) Computer-aided ergonomics: a case study of incorporating ergonomics analysis into workplace design. *Applied Ergonomics*, **31**, 291–300.

Garg, A., Chaffin, D.B. and Herrin, G.D. (1978) Prediction of metabolic rates for manual materials handling jobs. *American Industrial Hygiene Association Journal*, **39**(8), 661–674.

Gilad, I. and Karni, R. (1999) Architecture of an expert system for ergonomics analysis and design. *International Journal of Industrial Ergonomics*, **23**(3), 205–221.

Hagberg, M. (1992) Exposure variables in ergonomic epidemiology. *American Journal of Industrial Medicine*, **21**, 91–100.

Jung, E.S. and Freivalds, A. (1991) Multiple criteris decision-making for the resolution of conflicting ergonomic knowledge in manual materials handling. *Ergonomics*, **34**(11), 1351–1356.

Karhu, O., Karkonen, R., Sorvali, P. and Vepsalainen, P. (1981) Observing working postures in industry: examples of OWAS application. *Applied Ergonomics*, **12**(1), 13–17.

Khuri, A.I. and Conlon, M. (1981) Simultaneous optimization of multiple responses represented by polynomial regression functions. *Technometrics*, **23**, 363–375.

Kroemer, K.H.E., Kroemer, H.B. and Kroemer-Elbert, K.E. (1994) *Ergonomics: How to Design for Ease and Efficiency*, Englewood-Cliffs, NJ: Prentice-Hall.

Laring, J., Falk, K.J., Kadefors, R. and Ortengren, R. (1996) Computer aided workplace design: an approach to create a tool for the production engineer. *International Journal of Industrial Ergonomics*, **17**, 323–330.

McCauley-Bell, P. and Crumpton, L. (1997) A fuzzy linguistic model for the prediction of carpal tunnel syndrome risks in an occupational environment. *Ergonomics*, **40**(8), 790–799.

McKay, M.D., Conover, W.J. and Beckman, R.J. (1979) A comparison of three methods for selecting values of input variables in the analysis of output from a computer code. *Technometrics*, **21**, 239–245.

Montgomery, D.C. (1997) *Design and Analysis of Experiments*, John Wiley & Sons, New York, NY.

Moore, J.S. and Garg, A. (1995) The strain index: a proposed method to analyze jobs for risk of distal upper extremity disorders. *American Industrial Hygiene Association Journal*, **56**, 443–458.

Myers, R.H. and Carter, Jr., W.H. (1973) Response surface techniques for dual response systems. *Technometrics*, **15**, 301–317.

Myers, R.H. and Montgomery, D.C. (1995) *Response Surface Methodology*, John Wiley & Sons, New York, NY.

Nayar, N. (1995) Deneb/ERGO – a simulation based human factors tool, in *The 1995 Winter Simulation Conference Proceedings*, December 3–6, 1995, Arlington, VA, USA, pp. 427–431.

Niebel, B.W. and Freivalds, A. (1999) *Methods Standards and Work Design*, McGraw-Hill, Boston, MA.

Porter, J.M., Freer, M., Case, K. and Bonney, M.C. (1995) Computer aided ergonomics and workplace design, in *Evaluation of Human Work: A Practical Ergonomics Methodology*, 2nd edn, Wilson, J.R. and Corlett, E.N. (eds.), Taylor and Francis, London, pp. 574–620.

Saaty, T.L. (1980) *The Analytic Hierarchy Process*, McGraw-Hill, New York, NY.

Sacks, J., Welch, W.J., Mitchell, T.J. and Wynn, H.P. (1989) Design and analysis of computer experiments. *Statistical Science*, **4**(4), 409–435.

Scott, G.B. and Lambe, N.R. (1996) Working practices in a perchery system using the OWAS. *Applied Ergonomics*, **27**(4), 281–284.

Shang, J.S. (1995) Robust design and optimization of material handling in a FMS. *International Journal of Production Research*, **33**(9), 2437–2454.

Waly, S.M. and Sistler, F.E. (1999) Ergonomic design using computer animation. *Computers and Industrial Engineering*, **37**(1–2), 293–296.

Waters, T.R., Putz-Anderson, V. and Garg, A. (1994) Applications manual for the revised NIOSH lifting equation. Publication no. 94–110, Department of Health and Human Services (NIOSH), Cincinnati, OH.

Waters, T.R., Putz-Anderson, V., Garg, A. and Fine, L.J. (1993) Revised NIOSH equation for design and evaluation of manual lifting tasks. *Ergonomics*, **36**(7), 749–776.

Winkel, J. and Westgaard, R. (1992) Occupational and individual risk factors for shoulder-neck complains: part II – the scientific basis (literature review) for the guide. *International Journal of Industrial Ergonomics*, **10**, 85–104.

Zha, X.F., Lim, S.Y.E. and Fok, S.C. (1998) Integrated intelligent design and assembly planning: a survey. *International Journal of Advanced Manufacturing Technology*, **14**(9), 664–685.

Zhang, X. and Chaffin, D.B. (1997) Task effects on the three-dimensional dynamic postures during seated reaching movements: an investigative scheme and illustration. *Human Factors*, **39**(4), 659–671.

Zhang, X., Kuo, A.D. and Chaffin, D.B. (1998) Optimization-based differential kinematic modeling exhibits a velocity-control strategy for dynamic posture determination in seated reaching movements. *Journal of Biomechanics*, **31**(11), 1035–1042.

Biographies

Irad Ben-Gal is an Assistant Professor at the Department of Industrial Engineering in Tel Aviv University. He holds a B.Sc. (1992) degree from

Tel Aviv University, M.Sc. (1996) and Ph.D. (1998) degrees from Boston University. Irad is a member of the Institute for Operations Research and Management Sciences (INFORMS) and is the head of the Computer Integrated Manufacturing (CIM) lab at Tel Aviv University. He has worked for several years for various industrial organizations, both as a consultant and as a project manager. His research interests include, quality control, design of experiments and testing procedures, and application of information theory to industrial problems.

Joseph Bukchin is a member of the Department of Industrial Engineering at Tel Aviv University. He received his B.Sc., M.Sc. and D.Sc. degrees in Industrial Engineering from the Technion-Israel Institute of Technology. He is a member of the IIE and INFORMS. Bukchin has been a Visiting Professor at the Grado Department of Industrial and Systems Engineering at Virginia Tech. His main research interests are in the areas of assembly systems design, assembly line balancing, facility design, design of cellular manufacturing systems, operational scheduling as well as work station design with respect to cognitive and physical aspects of the human operator.

Contributed by the Engineering Design Department