An approach for quick ergonomic risk evaluation of companies with computer-aided workplaces

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Abstract: - An approach for quick assessment of the exposure to ergonomic risks on computer-aided office workplaces in a company is developed. It includes a checklist considering the following ergonomic dimensions: work organization, displays, input devices, furniture, work space, environment, software and health hazards. By the checklist, data on workplace exposure to ergonomic risk factors are collected. For the calculation of a risk index a neuro-swarm artificial bee colony algorithm has been employed. Based on the risk index three groups of departments are determined: low, moderate and high ergonomic risk departments. Also by this index the departments with significant ergonomic problems and the need for their further detailed study can be determined. This approach is illustrated and validated by a case study. An important advantage of the approach is its easy use and quick ergonomic assessment of companies pointing out departments with high ergonomic risk.

Key-Words: - Computer-aided workplaces; Ergonomic; Risk; Checklist; Neuro-Swarm Model; Artificial Bee Colony Algorithm

1 Introduction
During the last fifteen years, computer work stations have become a necessity in most workplaces. A variety of ergonomic risks have been associated with intensive work using computer-aided workstations. The United States National Institute for Occupational Safety and Health (NIOSH) identified the emerging health and safety issues—such as repetitive stress injuries and ergonomics—of the new office- and computer-centered workplaces [3]. Also in the United States, the National Research Council (NRC) and Institute of Medicine (IOM) recently called for more intervention research to provide scientifically credible evidence to practitioners who are responsible for risk reduction among computer users [19]. The European Framework Directive [1] sets out general principles, procedures, and requirements for occupational health and safety (OHS) legislation in different sectors. Subsequent ‘daughter’ directives conform to the general requirements on, for example, the minimum safety and health requirements for computer work [5] of the Framework Directive. These framework and daughter directives should be made mandatory with their inherent flexibility being incorporated in computer-aided workplaces.

[9] concludes that long hours of computer use are associated with ergonomic problems. It is shown by [6] that prolonged use of computers, while performing work activities in poor ergonomic environments is one major contributing factor to increase causes of neck pain. Studies reported less discomfort when ergonomics were improved or ergonomic information was given [13].

The workplace ergonomic-related risk factors include hours of computer use, sustained awkward head and arm postures, poor lighting conditions, poor visual correction, and work organizational factors [20], [8]. These risks cause problems such as, musculoskeletal disorders (e.g. sustained pain in the neck and upper extremities and regional disorders, such as wrist tendonitis, epicondylitis and trapezius muscle strain), eye discomfort and visual fatigue; and mental stress which are identified as some of the principal risks of computer task-based work [17]. If working tasks are carried out in inadequate conditions, workers with functional limitations may, over time, risk developing further disabilities. Ergonomic complaints have also been found to be associated with psychosocial factors at work [16].

There are a lot of approaches for ergonomic risk assessment of computer-aided office workplaces [4], [21], but for big sized companies with a lot of office workplaces it is difficult to study all of the workplaces. There is a need of an approach for systematic ergonomic risk assessment of whole companies and allocation of departments with high risk for further detailed lower-cost study.
2 Approach Description
An ergonomic risk evaluation approach of companies with office workplaces is proposed (cf. Fig. 1). It includes a checklist (step 1) in which ergonomic dimensions and items/questions are determined. At step 2 data is gathered using this checklist. At step 3, using a neuro-swarm-based model the ergonomic risk is assessed. The departmental ergonomic risk (DER) index, $I_{DER}$ is determined at step 4. Based on $I_{DER}$ the departments are clustered as departments with low, moderate and high ergonomic risk level. Departments with high and moderate risk index are selected for further ergonomic study at step 5. During this step workplaces with high ergonomic risk will be allocated and relevant measures for its reduction will be proposed, for example, the appropriate use of computer workstations can help in reduction of physical discomfort arising from using computers for long hours which is achieved by adjusting the seating and the operator's posture, then adjusting the relation of the user to the keyboard and the screen [22].

2.1 Checklist design
At step 1 of evaluation approach a checklist for quick ergonomic risk assessment of office workplaces in a company is designed. For this purpose a checklist of nine dimensions measured by 15 questions (cf. Fig. 2) is developed. For example, for assessment of checklist dimension environment (D8) two questions shown in Table 1 are used.

| Q12. The lighting on my workplace is suitable to work comfortably (not too bright or too dim, no glare, reflection on monitor). |
| Q13. I find the noise level, temperature and air flow in my office comfortable. |

Table 1: Sample questions for measuring checklist dimension environment (D8)

![Fig. 2: Workplaces ergonomic risk assessment model](image)

2.2 Neuro-swarm-based ergonomic risk assessment model
At steps 3 and 4 a quick ergonomic assessment of company office workplaces and clustering of most risky company departments is carried out. Ergonomic risk assessment aims at identifying ergonomic-related weaknesses of workplaces. The
entire construct of workplace ergonomics can be represented by a single quantitative dependent variable: ergonomic risk index. It is a measure of how closely the features of a workplace match generally accepted ergonomic guidelines. For ergonomic risk assessment an ergonomic index is determined (cf. Fig. 2). For calculation of this risk index, a honey bee-based [10] neuro-swarm optimization [12] algorithm is proposed. It aggregates nine workplace ergonomic dimensions measured by 14 checklist items/questions. The checklist structure is represented as an artificial neural network (p. subsection 2.1) By a modification of the neuro-swarm artificial bee colony algorithm (p. sub-subsection 2.2.1 and sub-subsection 2.2.2) neural network weights are trained using as a target the workplace user satisfaction (checklist dimension D9). Using these weights the responses of workplace users are aggregated to risk indices. Based on risk indices, critical departments with high and moderate risk can be found from a workplace ergonomic viewpoint (cf. Table 2).

Table 2: Scale for assessment of departmental ergonomic risk

<table>
<thead>
<tr>
<th>Rating</th>
<th>Risk level description</th>
<th>Index range [0,100]</th>
<th>Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>minimal harmful ergonomic risk conditions</td>
<td>[0,25]</td>
<td>Green</td>
</tr>
<tr>
<td>Moderate</td>
<td>harmful ergonomic risk conditions</td>
<td>(25,75)</td>
<td>Yellow</td>
</tr>
<tr>
<td>High</td>
<td>very harmful ergonomic risk conditions</td>
<td>[75,100]</td>
<td>Red</td>
</tr>
</tbody>
</table>

2.2.1 Artificial neural network (ANN)
An ANN consists of a set of processing elements (cf. Fig. 3), also known as neurons or nodes, which are interconnected with each other [28].

Output of the ith neuron can be described by:

\[ y_i = f_i \left( \sum_{j=1}^{n} w_{ij} x_j + \theta_i \right) \]  
(1)

Where \( y_i \) is the output of the node, \( x_j \) is the jth input to the node, \( w_{ij} \) is the connection weight between the node and input \( x_j \), \( \theta_i \) is the threshold (or bias) of the node, and \( f_i \) is the node transfer function.

Fig. 3: Processing unit of an ANN (neuron)

The adaptation can be carried out by minimizing (optimizing) the network error function \( \varepsilon \) given by equation:

\[ \varepsilon(w(i)) = \frac{1}{n} \sum_{j=1}^{n} (t_j - o_j)^2 \]  
(2)

where \( \varepsilon(w(i)) \) is the error at the ith training iteration; \( w(i) \) - the weights in the connections at the ith iteration; \( t_j \) - the desired output/target (D8-user satisfaction); \( o_j \) - the actual value of the output node; \( n \) - the number of patterns (data gathered by checklist from workplace users). The optimization goal is to minimize the objective function by optimizing the network weights \( w(i) \).

2.2.2 Artificial bee colony (ABC) algorithm
We selected for optimizing \( \varepsilon(w(i)) \) to use the ABC algorithm [10]. It is a very simple, robust and population based stochastic optimization algorithm. This algorithm has been inspired by honey bees’ intelligent foraging behavior of honey bee swarms, where \( S \) is the size of a single colony. The foraging bees are classified into three categories: employed bee (EB), onlooker bee (OB) and scout bees. Bees that are exploiting a food source represented as an employee workplace are the employed bees. Each food source is a possible solution for the problem with the nectar amount representing the quality or solution or fitness value \( \varepsilon(w(i)) \). If its new fitness value is better than the best fitness value achieved so far, then the bee moves to this new food source abandoning the old one, otherwise it remains in its old food source. By sharing this information with onlooker bees’ good food sources will get more onlooker bees than bad ones. The ith food source position for the dth dimension (network weight) \( w(i) \) or solution is represented \( X_i = (x_{i1}, x_{i2}, ..., x_{id}) \) as. \( F(X_i) \) refers to the nectar amount of the food source located at \( X_i \). Onlooker bee i chooses a food source according to the probability \( p_i \) proportional to the quality of that food source in relation to the quality of all food sources.

\[ p_i = F(X_i) / \sum_{n=1}^{S} F(X_n) \]  
(3)

It then finds a neighborhood food source in the vicinity of \( X_i \) by using:

\[ X_i(t+1) = X_i(t) + \delta_{ij} \cdot u \]  
(4)
where $\delta_{ij}$ is the neighborhood patch size or number of workplaces within the department (department size) for the $j$-th dimension of the $i$-th food source or department workplace, $u \in [-1, 1]$ is a random uniform variable. $\delta_{ij}$ is defined as:

$$\delta_{ij} = x_{ij} - x_{kj}$$

(5)

where $k \in \{1, 2, ..., S\}$ and $k \neq i$. The purpose of scout bees are to search for new food sources near the hive.

This algorithm starts by associating all employed bees with randomly generated food sources (solutions). In each iteration, every employed bee determines a food source in the neighborhood (department’s workplaces) of its current food source (selected department workplace) and evaluates its fitness. A food source which could not be improved through "limit" $L$ trials is abandoned by its employed bee. In a robust search process, exploration and exploitation processes must be carried out together. In the ABC algorithm, while onlookers and employed bees carry out the exploitation process in the search space, the scouts control the exploration process. The algorithm stops when the maximum cycle (C) number (MCN) is reached.

### 2.2.3 Hybrid neuro swarm-artificial bee colony (NS-ABC) algorithm

In NS-ABC algorithm (cf. Fig. 4), the major idea underlying this synthesis is to interpret the weight matrices of the ANNs as solutions, weights or nectar amounts of corresponding food sources, and to change the weights by means of the scout bee finding better food sources. The error, $\varepsilon$ produced by the ANNs using these weights is the fitness measure which guides selection. This leads to the following weights training cycle [27]:

1. Initialize
2. REPEAT
   2.1 move the employed bees (EBs) onto their food source: equation (4) & (5)
   2.2 evaluate EBs fitness: equation (1) & (2)
   2.3 move the onlooker bees (OBs) onto the food source: equation (3), (4) & (5)
   2.4 evaluate OBs fitness: equation (1) & (2)
   2.5 move the scouts for searching new food source: equation (4) and (5)
   2.6 memorize the best food source found so far
3. UNTIL(termination criteria satisfied)

Fig. 4: NS-ABC algorithm

### 3 Case Study

For illustration and validation of approach proposed data was collected from a company with computer-aided office workplaces by using an online checklist of 15 questions (p. Subsection 2.1). The pre-test of the checklist with employees showed that the time for answering the questions took 5-10 minutes. Unclear questions were found and improved. 212 responses were received from employees.

The algorithm was implemented in MATLAB. Each solution $X_{id}$, $i = \{1, 2, ..., S\}$, and $d = 22$ represents the checklist dimensions (network weights) $w(i)$ or solutions, that is, the number of optimization parameters. The control parameters of NS-ABC algorithm are:

- $S = 424$ - the colony size (employed bees plus onlooker bees),
- $i = 212$ - the number of food sources equals half the colony size,
- $C = \{1, 2, ..., MCN=2800\}$ - the hunt for food sources (solutions) is subjected to repeated cycles,
- $L = 150$ - the "limit" number of trials for food source abandonment.

Figure 5 shows the run of the NS-ABC algorithm displaying the training error. The initial convergence was at first to local minima but the algorithm was able to escape these locally optimal points and converge towards the global optimum. This was achieved after roughly 1450 iterations.

Table 3 shows the final weights for each checklist dimension. Here the highest weight value is one and the lowest value is zero. Dimension nine (D9 - satisfaction) was used as targets for training. The weights from training were used to calculate the $I_{DER}$ risk for all departments.

The highest ergonomic risk for the company's departments are health/hazards (D8=0.28) caused by bad display screens (D2=0.25), input devices (D3=0.14) and workspace layout (D5=0.14). On Table 4 are screened company departments with high and moderate risk level (20=95%, 19=91%, 18=86%, 13=84%, 17=79%, 2=76%, 14=73%, 5=69%, 6=55%, 16=41%, 4=36%, 11=32% and 7=30%) for further detailed study. Six departments will not be studied which significantly reduce the efforts, time and costs of ergonomic study.
4 Conclusions
A quick ergonomic risk evaluation approach for identifying high risk departments with computer-aided workplaces in a company was developed. Its checklist contains only 15 items which encourages faster assessment. A hybrid neuro-swarm algorithm trains checklist dimensions and questions weights. The calculation of individual department ergonomic risk indices $I_{DER}$ based on these weights enables the clustering of departments into three categories: low, medium and high ergonomic risk levels. Departmental workplaces with high and medium ergonomic risk are further studied and relevant low-cost measures for reducing the ergonomic risk are recommended.

The advantages of evaluation approach are: (1) significantly reduces the time and errors for ergonomic evaluation; (2) applies modern mathematical model the neuro-swarm ABC algorithm for quantitative ergonomic risk assessment; (3) reduces the load on the evaluating team when dealing with large companies having numerous departments by screening out low and moderate risky departments; (4) makes companies precisely formulate their strategies to redesign and improve their departmental workplaces for employees; (5) higher employee satisfaction resulting in increased company profit.

References:


