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AN INTEGRATED ANN-EMO APPROACH TO REDUCE THE RISK OF OCCUPATIONAL HEALTH HAZARDS

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Abstract

Workers in labor-intensive units, in general, maximize their earnings by subjecting themselves to high risk of occupational health hazards (RoOHH) due to economic reasons. We present an intelligent system integrating artificial neural network (ANN) and evolutionary multiobjective optimisation (EMO) to tackle this problem, which has received scant attention in the literature. A brick manufacturing unit in India is chosen as case study to demonstrate the working of proposed system. Firing is assessed to be the most severe job among others using an interview method. A job-combination approach is devised which allows firing workers to perform another job (loading/covering/molding) along with firing. The second job not only reduces their exposure to high temperature zone but also helps to compensate for reduced earnings. RoOHH is measured using a risk assessment score (RAS). ANN models the psychological responses of workers in terms of RAS, and facilitates the evaluation of a fitness function of EMO. EMO searches for optimal work schedules in a job-combination to minimize RAS and maximize earnings simultaneously.

1 Introduction

Brick manufacturing (BM) in India is labor intensive and comprises the following major jobs – molding the raw bricks, loading molded bricks to kiln using a pushcart or a pony-cart, stacking molded bricks into the kiln in a particular way, spreading clay sand over the stacks uniformly for superior baking of bricks, firing the kiln that includes pouring the coal into the kiln from the covered holes at the top of the kiln at required intervals and monitoring the fire, and finally unloading the baked bricks from the kiln; we term these processes respectively as molding, loading, stacking, covering, firing and unloading, for ready references in this paper. Firing, the most severe job, involves undue exposure of workers to excessive heat. Each job in a BM unit has its specific earning. Though high earning jobs are usually tedious to perform, yet workers prefer doing such jobs for long hours due to reasons already mentioned, which in turn create health problems. Combining jobs is found to be a way of reducing RoOHH and yet maintaining the good earnings [25]. We, therefore, implement a job-combination approach in the BM unit wherein the firing workers perform another job along with firing job within their prescribed working hours (*WH*) thereby reducing their exposure to high temperature zone while maintaining their earnings to a satisfactory level. Similar to firing workers, molding and other workers go for firing work partially in a job-combination approach which would increase their overall earnings but at the cost of increase in risk of heat stress, however, the risk of musculoskeletal disorder, a recognized OHH in such activities, would reduce to an extent. Firing, molding, and covering jobs require special skills whereas loading is a low skilled job. Therefore it is found essential to train a set of workers to perform different jobs with reasonable skills while implementing job-combination approach.

The temperature inside a brick kiln is about 1200C. Firing workers monitor the fire from the roof of the kiln through a number of covered holes. They pour the coal inside the kiln by opening the holes partially as and when required to ensure the proper baking of bricks. They have high risk of heat stress due to their exposure to high temperature zone. Further if bricks are under-baked or over-baked, the chance of rejection of the whole lot is very high. It further increases the stress level of firing workers. Current guidelines define working environment that causes an increase above 38C (heat stress) as potentially hazardous [1]. However, the effectiveness of these guidelines is limited by the individual variation among employee and variation in work practices [17]. It is also essential to assess the thermal environment of a workplace with good reliability to avoid the underestimation of its dangerousness [5]. Hot conditions give rise to physiological heat strain [3], and cognitive decrements [11, 14, 18]. In general, heat stress decreases workers' performance significantly [19]. In the present work, we assess RoOHH in terms of risk assessment score (*RAS*) of workers for a given job-combination. Risk assessment has been a pertinent area in occupational health and safety [22 , 24]. We make the following observations based on an initial survey using interview method: (1) the workers, in general, are found to maximize their earnings by subjecting themselves to extreme work conditions due to economic reasons, and hence are exposed to greater RoOHH; (2) three factors are identified to be influencing *RAS* of a given job, viz. number of working hours (*WH*), duration of a rest break (*RB*), and number of rest breaks (*NRB*). Many studies have shown the dismal impact of long working hours on workers' performance [9, 15]. The influence of rest breaks have been investigated in reducing the amount of spinal shrinkage while establishing a relationship between duration and frequency of rest intervals (referred to as RB and NRB respectively in this paper) with spinal shrinkage [20]. The importance of frequent, brief rest breaks (5 min rest break to every working hour) has been shown in improving symptoms for workers engaged in strenuous work tasks [12].

Artificial neural networks have gained ample footing in intelligent decision making systems. The data driven approach of the ANNs enables them to behave as model free estimators, i.e., they capture and model complex input-output relationships even without the help of a mathematical model. We, therefore, utilize the function approximation capability of ANN using back propagation neural networks in the evaluation of *RAS*. A back propagation neural network (BPNN) is a multiple layer network with an input layer, output layer and some hidden layers between input and output layers [13]. Its learning procedure is based on gradient search with least sum squared optimality criterion. Calculation of the gradient is done by partial derivative of sum squared error with respect to weights. After having the initial weights specified randomly and presented the inputs to the neural network, each neuron currently sum outputs from all neurons in the preceding layer. The sums and activation (output) values for each neuron in each layer are propagated forward through the entire network to compute an actual output and error of each neuron in the output layer. The error for each neuron is computed as the difference between actual output and its corresponding target output, and then the partial derivative of sum-squared errors of all the neurons in the output layer is propagated back through the entire network and the weights are updated. In course of the back propagation learning, a gradient search procedure is used to find connection weights of the network, but it tends to trap itself into the local minima. The local minima may be avoided by adjusting value of the momentum. This algorithm can be expressed succinctly in the form of a pseudo-code as below.

1. Pick a rate parameter R.
2. Until performance is satisfactory

For each sample input, compute the resulting output. Compute β for nodes in the output layer using

$$\beta = D_Z - O_Z$$

where D represents the desired output and O represents the actual output of the neuron. Compute β for all other nodes using

$$\beta_j = \sum k w_{j \to k} O_k (1 - O_k) \beta_k$$

Compute weight changes for all weights using

$$\triangle w_{i \to j} = r O_i O_j (1 - O_j) \beta_j$$

Add up the weight changes for all sample inputs and change the weights.

The algorithm applies Levenberg-Marquardt (LM) learning rule, which uses an approximation of the Newton's method to get better performance. This technique is relatively faster as demonstrated by [23, 26] while modeling input/output relationships of complex processes using this algorithm. LM approximation update rule is:

$$\triangle W = (J^T J + \mu I)^{-1} J T_e$$

where J is the Jacobean matrix of derivatives of each error to each weight, is a scalar and e is an error vector. If the scalar is very large, the above expression approximates the Gradient Descent method while it is small the above expression becomes the Gauss-Newton method. The Gauss-Newton method is faster and more accurate near error minima. Hence, the aim is to shift towards the Gauss-Newton as quickly as possible. Thus is decreased after each successful step and increased only when step increases the error. Architecture of ANN to evaluate *RAS* is shown in Fig. 1.

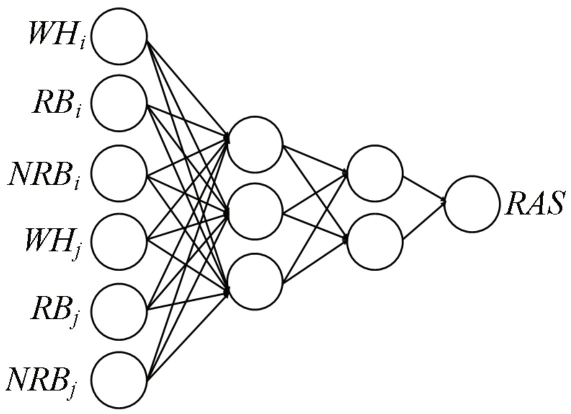

Figure 1. BPNN architecture to evaluate *RAS*

RAS-earning tradeoff (RET) belongs to a class of multiobjective optimization (MOO) problem [27]. There is no single optimum solution in MOO rather there exists a number of solutions which are all optimal – Pareto-optimal solutions – optimal RET solutions in occupational health literature. The curve joining nondominated RET solution points is termed as RET profile. A nondominated RET solution point (SP) represents a point in the feasible region that is not dominated by any other point in the region (it may be noted that if a solution point S^1 is better than S^2 in terms of all objective values, we say that S^1 dominates S^2).The tradeoff between *RAS* and earnings gives workers wide opportunities to work out the best schedule to reduce RoOHH while maintaining their required earnings, and therefore RET analysis is of considerable importance from the view points of both – workers and managers. There are six factors in a given job-combination which assume discrete values in real-life situations; therefore, the problem being tackled in this work, i.e., searching for optimal RET profile for each job-combination, is a combinatorial multiobjective optimization problem – NSGA-II (non-dominated sorting genetic algorithm-II), an EMO technique, solves this problem. MOO is a field reasonably explored by researchers in recent years since 1990 – as a result diverse techniques have been developed over the years [10]. Most of these techniques elude the complexities involved in MOO and usually transform multiobjective problem into a single objective problem by employing some user defined function. Since MOO involves determining Pareto-optimal solutions, therefore, it is hard to compare the results of various solution techniques of MOO, as it is the decision-maker who decides the 'best solution' out of all optimal solutions pertaining to a specific scenario [4]. Evolutionary algorithms (EAs) are meta-heuristics that are able to search large regions of the solution's space without being trapped in local optima [8]. Some well-known meta heuristics are genetic algorithm, simulated annealing, and tabu search. A genetic algorithm (GA) is an evolutionary algorithm [21], and is based on the mechanics of natural selection and genetics to search through decision space for optimal solutions [16]. A string in a genetic algorithm represents a set of decisions (chromosome combination), a potential solution to a problem. Each string is evaluated on its performance with respect to the fitness function (objective function). The ones with better performance (fitness value) are more likely to survive than the ones with worse performance. Then the genetic information is exchanged between strings using crossover and perturbed by mutation. The result is a new generation with (usually) better survival abilities. This process is repeated until the strings in the new generation are identical, or certain termination conditions are met. A genetic algorithm processes a population of solutions in each iteration of its search procedure instead of a single solution, and therefore, the outcome of a GA is also a population of solutions. This unique feature of GA makes it a true multiobjective optimization technique and that is how genetic algorithms transcend classical search and optimization techniques. EMO techniques encompass different versions of multiobjective GAs including NSGA-II, which has been successfully employed to solve many MOO problems in science and engineering [6].

2 Methodology

Ten male workers (mean age: 24 years, average height: 165 cm, average weight: 53 Kg, average job experience: 4 years) are taken for the study. None of these workers report a history of chronic health problems. Specifically, these workers are trained to perform firing job along with one of the following three jobs – molding, loading, and covering, with predefined working hours (*WH*) distribution - resulting in the following three job-combinations - firing-molding, firing-loading, and firing- covering. The risk of OHH for a job-combination is evaluated based on the risk assessment score (*RAS*) of workers using artificial neural networks. It is extremely difficult to evaluate *RAS* for every possible amalgamation of *WH*, *RB*, & *NRB* for each job-combination; therefore, we use artificial neural networks (ANNs) with backpropagation learning, also called backpropagation neural networks (BPNNs), as model free estimators. ANNs evaluate risk assessment score of workers for different values of *WH*, *RB*, and *NRB* for each job-combination. Three ANNs are trained, one for each job-combination, with data set generated as above. The following procedural steps are used for computing *RAS*.

1. We first identify relevant factors that influence *RAS* for a given job, which are *WH*, *RB*, and *NRB*. These factors have a unique subscript number which correspond to job number as mentioned below.

Job	Firing	Molding	Loading	Covering
Job #	1	2	3	4

We get six factors for each job-combination (firing-molding, firing-covering, and firing-loading) considered in the present work, e.g., for firing-covering job-combination, the factors are WH_1, RB_1, and NRB_1 for firing job, and WH_4, RB_4, and NRB_4 for covering job. Range of *WH*, *RB* and *NRB*, for each of the four jobs are illustrated below.

$$WH_i \in \{2, 3, 4, 5, 6, 7, 8, 9, 10\}$$

$$WH_j \in 12 - WH_i$$

where, WH_j is a dependent variable, i = 1 (it refers to job # 1 i.e. firing) and, j = 2, 3, & 4 (these refer to job # 2, 3, & 4 respectively). It is apparent that total working time in a job-combination does not exceed 12 hours. The range of *RB* and *NRB* are same for each of the four jobs as shown below.

$$RB_i \in \{5, 10, 15, 20, 25, 30, 35, 40\}$$

(i =1, 2, 3, 4)

$$NRB_i \in \{1, 2, 3, 4, 5, 6\}$$

(i =1, 2, 3, 4)

2. Feedback from select workers is taken to assess their perceived discomfort for their present state of working in BM units.

3. Sample workers are trained to perform each of the four jobs with reasonable skills for implementing job-combination approach. Specifically, these workers are trained by varying (i) *WH*, (ii) *RB*, and (iii) *NRB*.

4. Recording/analysis of the perceived discomfort of workers in the form of a score, called risk assessment score (*RAS*), is done with respect to variation in (i) *WH*, (ii) *RB*, and (iii) *NRB*. The exhaustive data so collected act as training data for ANNs. Details of this step are as follows. Feedback of each of the ten sample workers is taken in two phases. In the first phase each worker is asked to rate his discomfort echelon for certain pairs of WH_i and WH_j in the feasible range for each of the three job-combinations on a 7 point scale. Each of the linguistic values of the scale, such as, extremely low, low, moderate, high, very high and extremely high, is assigned its equivalent numeric value. In this way an average score is obtained for each of the five pairs of WH_i and WH_j for each job-combination *i-j*, which is referred to as score$_1$. Second phase accounts for rest breaks and number of rest breaks. Each of the sample workers is now asked to rate the reduction in his discomfort level for each of the

four jobs for certain feasible values of RB_i/NRB_i and RB_j/NRB_j. Workers' views are translated into a numeric score in the similar way, which is called score$_2$. *RAS* is obtained simply by subtracting score$_2$from score$_1$ for each set of $WH_i/RB_i/NRB_i$ and $WH_j/RB_j/NRB_j$. It is obvious that WH_i and WH_j contribute positively to *RAS*, whereas higher values of RB_i, RB_j, NRB_i, and NRB_j would cause a decrease in *RAS*. These experimentations allow us to assign a linguistic value of perceived discomfort level (PDL) to different ranges of *RAS* as shown in Table 1.

5. ANN models are trained with available data set for each job-combination.

6. Lastly the accuracy of ANN models is tested and validated with testing data set which has not been used in training.

Sample training data set of ANN models for each of the three job-combinations are shown in Table 2(a), Table 2(b) and Table 2(c) respectively. The wages of workers are based on the job they are doing. In fact workers in a BM unit are paid either contractually or on salary basis – the details follow (local designation of each category of workers is mentioned in bracket). Firing workers (*jalaiye*) monitor the fire in the kiln and ensure proper baking of bricks while adding fuel from the top of kiln through covered holes as and when necessary. Firing being a skilled and tough job is a high earning job – INR 50,000 per month is paid to a set of 6 firing workers. Molding workers (*pathaiye*) are paid INR 360 per 1000 molded bricks. The target output per day is about 50000 bricks – molded by 120 workers (generally 60 couples). Loading workers (*bharaiye*) transport the molded bricks from molding place to kiln using a pushcart or a pony-cart and their earning depends upon the distance travelled. The wages are INR 70 per 800 m distance per 1000 bricks transported. Covering workers cover the stacks of molded bricks in the kiln with clay sand skillfully so that the bricks are baked uniformly in the kiln. INR 18000 per month is paid to a set of 3 covering workers. The following table summarizes per hour earnings of a worker of each category of jobs under consideration.

Job (Job#)	**Earnings/hour (in INR)**
Firing (1)	23.15
Molding (2)	12.50
Loading (3)	19.45
Covering (4)	16.67

Since the proposed system is flexible enough to allow a good amount of rest break (up to 40 minutes) and sufficient number of rest breaks (up to 6), therefore we find it lucid to deduct an amount equivalent to his total rest break time from his earnings/day from the viewpoint of implementability of the proposed system by the owner of the BM unit. The resulting expression for earnings/day (ER_{i-j}/day) is illustrated below for *i-j* job-combination.

$$ER_{i-j}/Day = \left\{WH_i - \frac{(RB_i \times NRB_i)}{60}\right\} \times ER_i + \left\{WH_j - \frac{(RB_j \times NRB_j)}{60}\right\} \times ER_j \quad (1)$$

Now we formally define the RET problem for the first job-combination below.

(i = 1) refers to job # 1 (i.e. firing), and (j = 2) refers to job # 2 (i.e. molding).

$$\text{Min } RAS_{i-j}$$
$$\text{Max } ER_{i-j}/\text{day}$$

Subject to

$$WH_i \in \{2, 3, .., 10\} \quad (i = 1)$$
$$WH_j \in 12 - WH_i \quad (j = 2)$$
$$RB_i \in \{5, 10, 15, 20, 25, 30, 35, 40\} \quad (i = 1, 2)$$
$$NRB_i \in \{1, 2, 3, 4, 5, 6\} \quad (i = 1, 2)$$
$$NRB_i \le \begin{cases} \delta_1, & if\ 7 \le WH_i \le 10 \\ \delta_2, & if\ 3 \le WH_i < 7 \\ 1, & if\ WH_i < 3 \end{cases}$$
$$where\ \delta_1 = \min?\{6, \ (WH_i - 4)\}\ and$$
$$\delta_2 = \{3, \ (WH_i - 2)\}$$

Formulation for the second and third RET problems can be easily obtained from the above one by having (j = 3), and (j = 4) respectively in place of (j= 2).

3 NSGA-II for RET

We employ non-dominated sorting genetic algorithm-II (NSGA-II) in solving RET, a multiobjective optimization problem. NSGA-II has proved its effectiveness in solving many real life MOO problems in terms of convergence of solutions to Pareto-optimal front, and in maintaining diversity of solutions within the population. The NSGA-II algorithm and its detailed implementation procedure can be found in [6, 7]. A brief description of NSGA-II is as follows. NSGA-II uses non-dominated sorting for fitness assignments. All individuals not dominated by any other individuals, are assigned front number 1. All individuals dominated by individuals in front number 1 are assigned front number 2, and so on. Selection is made using tournament between two individuals. The individual with the lowest front number is selected if the two individuals are from different fronts. A higher fitness is assigned to individuals located on a sparsely populated part of the front. Each individual is made to participate in exactly two tournaments, thereby making at most two copies of itself in the selected population. There are N parents in any iteration and crossover is used to generate N new individuals (offspring). This is followed by mutation which is applied on a few randomly selected individuals. In the context of RET problem, a solution in NSGA-II is an array (g_i), where i = 1, 2, . . . 5, which represents an instance of a job-combination (Fig. 2). Here g_1, g_2, g_3, g_4 and g_5 represent WH_i, RB_i, NRB_i, RB_j, and NRB_j respectively.

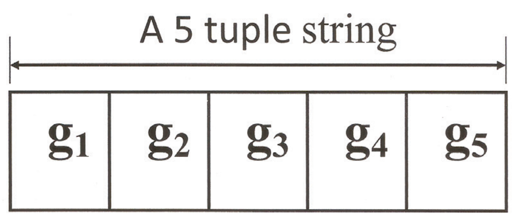

Figure 2. An instance of job-combination schedule

The initial population consists of N solutions, where N strings are selected randomly from the feasible search space. These solutions are referred to as parents. For the crossover, two strings (say, S_1 and S_2) from the population are selected randomly. The offspring O_1 and O_2 are produced as follows: First the working hours of S_1 and S_2 are stored in the respective positions of O_2 and O_1 respectively. The remaining entries of S_1 and S_2 are copied to O_1 and O_2 respectively. To ensure the feasibility of offspring, the number of rest breaks is checked and if it does not satisfy the conditions as mentioned in the formulation part (last paragraph of section 2); its value is reassigned randomly so as to make it feasible. Mutation is performed on randomly selected (r_m*N) individuals from the offspring population wherein the working hours in the selected individual are reassigned randomly, where r_m is the mutation rate.

4 Simulation Results

The design and implementation of the ANN models is far from an exact science. Several design issues need to be finalized carefully to obtain a functional model. The selection of the number of neurons in the two hidden layers is critical for the success of training the ANN model. The ANN attempts to create a function mapping by adjusting the weights in the inner layers. If the number of these neurons is too large, the ANN may be over-trained giving spurious values in the testing phase. If too few neurons are selected, the function mapping may not be accomplished due to under-training. The number of neurons are selected with appropriate experimentation, as there are no standard procedures available for all kinds of ANN training problems. Similarly, the selection of the learning rate and affect the convergence of the network. In the BPNN with LM rule, the learning rate and are continually modified based on the training results. Therefore, only the initial values have to be specified in the model.

As mentioned earlier, three exhaustive training data, one for each ANN, are collected by interview method. Each ANN comprises a three layer network with six inputs i.e., WH_i, RB_i, and NRB_i for job involving the risk of heat stress, and WH_j, RB_j, and NRB_j for second job under consideration, and one output i.e. *RAS*. Fig. 3, Fig. 4 and Fig. 5 illustrate ANN trainings of firing-loading, firing-covering, and firing-molding respectively; the error goal is met very fast in each of three cases as the training curves are steep enough – it takes 139, 53, and 78 epochs respectively to meet the desired goal of 1*e* – 005. It is interesting to note that a significant improvement occurs in a very next epoch (i.e. 136^{th} epoch) in the ANN training of firing work-loading – an accuracy of more than order l*e* –005 is achieved (Fig. 3). However, an appropriate ANN training requires considerable efforts in terms of different sets of hit and trial. After an extensive set of experiments we decide the number of hidden layers as well as number of neurons in hidden layers.

After the training, the weights are frozen and the model is tested for validation. For this purpose, the input parameters to the network are sets of values that have not been used for training the network but are in the same range as those used for training – testing data. This enables us to test the network with regard to its capability for interpolation. ANN results for risk assessment score are thus obtained for the testing data. Then each of the ten sample workers is asked to perform jobs as per each set of the testing data to evaluate the experimental results of *RAS*. The level of agreement between the *RAS* predicted by ANN models and the corresponding actual ones obtained from workers indicates the good performance of the methodology employed in this work.

For training problem at hand the following parameters were found to give rapid convergence of the training network with good performance in the estimation. The first and second layers of the neurons are modeled with a log of the sigmoid function, and the third layer was a purely linear function. Neurons taken in the first and second hidden layers are three and two respectively. Maximum epochs are considered as 250, the error goal was set at 1e-005, and the learning rate for training the ANN is taken as 0.2. The results of the validation of ANN models as described above for BM units are given in Table 3(a) to Table 3(c) for job-combinations tackled in this work.

NSGA-II implementation details are as follows. The procedure is coded in MATLAB 7.0 and run on Pentium (R)-based HP Intel (R) computer with 1.73 GHz Processor and 512 MB of RAM. The crossover rate and the mutation rate are kept as 1.0 and 0.05 respectively. The population size is chosen as 50. Computational experiments are performed to decide these parameters on the basis of faster convergence criteria. The search is set to terminate when nondominated RET profile remains unchanged for three consecutive iterations – a number is suitably decided based on extensive experiments. It takes on an average ten iterations for NSGA-II to search for the best possible RET profile. Results of example runs of NSGA-II follow to demonstrate its performance to solve three RET problems under consideration.

Fig. 6, Fig. 7, and Fig. 8 depict the results for firing-loading job-combination. It can be seen that the initial population is well distributed over the solution space (Fig. 6). Fig. 7 illustrates the intermediate improvements in the RET profile along with different fronts of the population. In succeeding iterations NSGA-II searches for optimal RET profile. Fig. 8 depicts the nondominated RET solution points of the final generation population, which are the best points obtained. These points are shown in bold with bold Pareto front in each of the three cases.

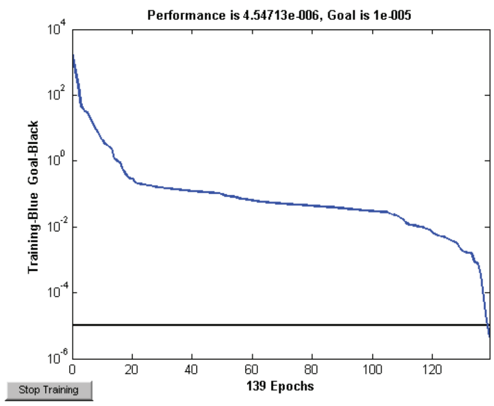

Figure 3. ANN training of Firing-loading

Figure 4. ANN training of Firing-covering

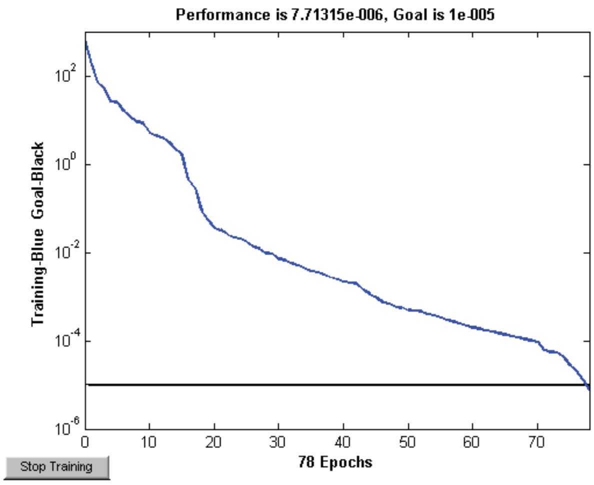

Figure 5. ANN training of Firing-molding

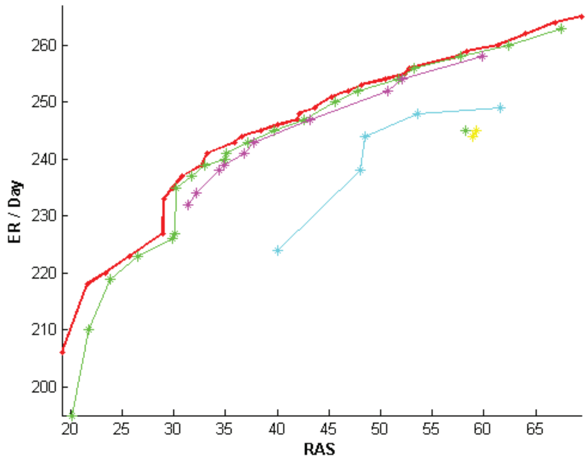

Figure 8. Firing-loading job-combination: RET profile and other fronts of final generation population

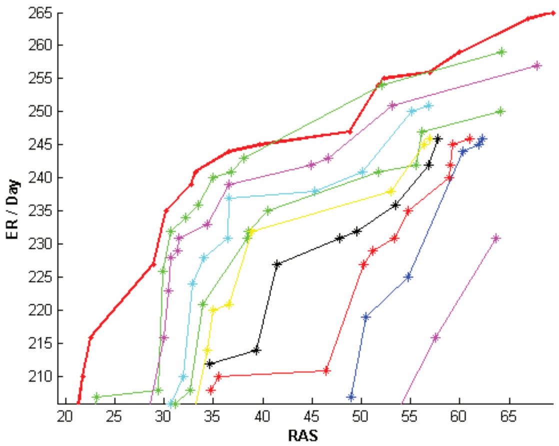

Figure 6. Firing-loading job-combination: Initial population with nondominated RET profile

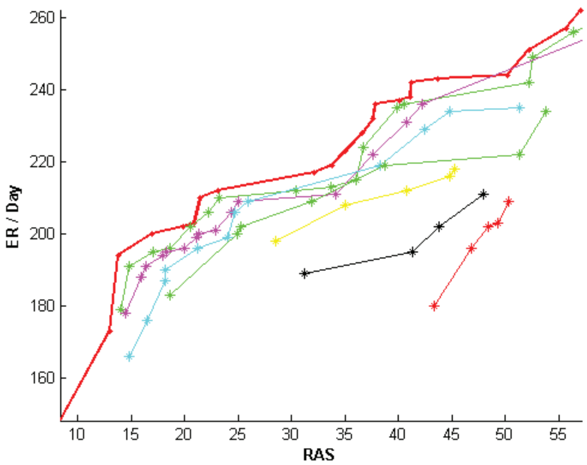

Figure 9. Firing-covering job-combination: Initial population with nondominated RET profile

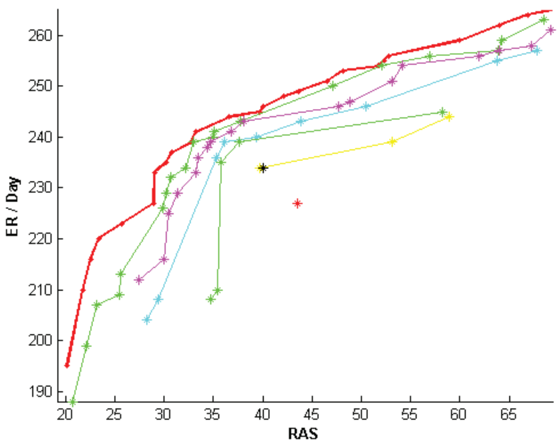

Figure 7. Firing-loading job-combination: Intermediate improvements in the RET profile along with other fronts

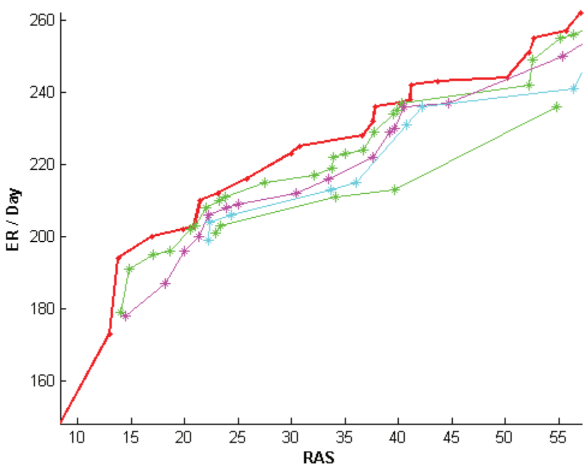

Figure 10. Firing-covering job-combination: Intermediate improvements in the RET profile along with other fronts

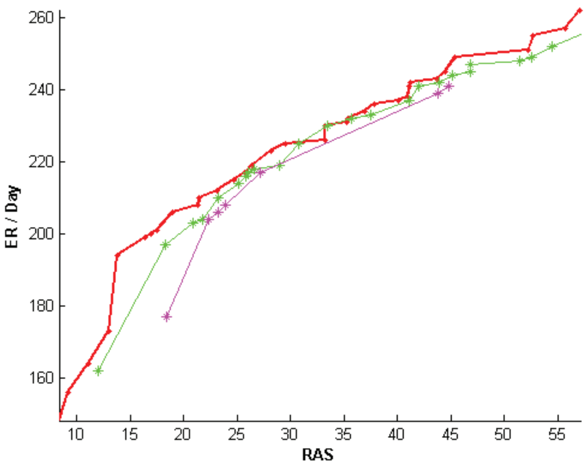

Figure 11. Firing-covering job-combination: RET profile and other fronts of final generation population

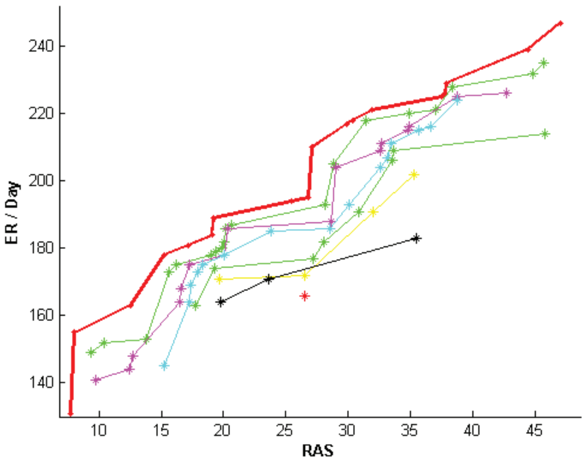

Figure 12. Firing-molding job-combination: Initial population with nondominated RET profile

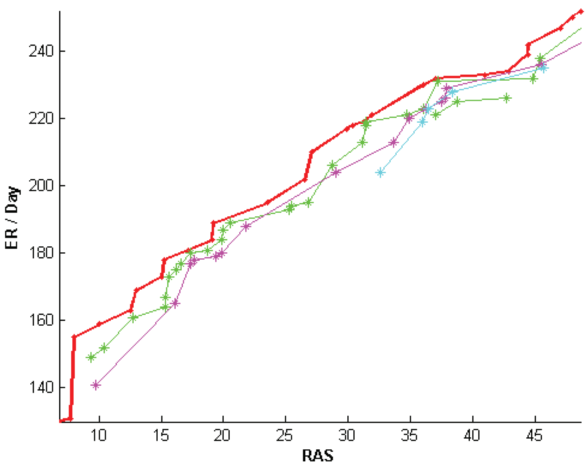

Figure 13. Firing-molding job-combination: Intermediate improvements in the RET profile along with other fronts

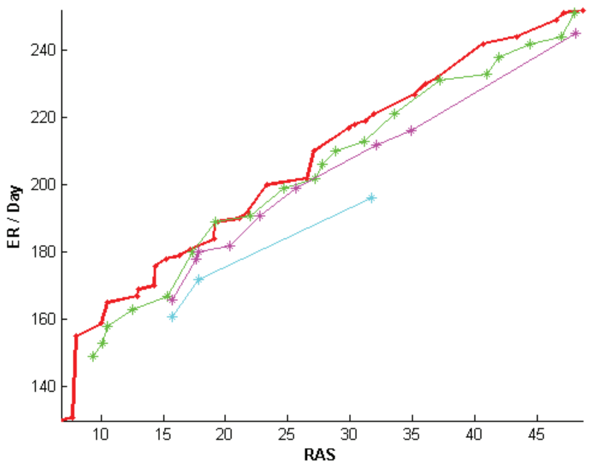

Figure 14. Firing-molding job-combination: RET profile and other fronts of final generation population

Fig. 9, Fig. 10 and Fig. 11 show the initial population, intermediate improvement, and final generation population respectively for firing-covering job-combination – as we move to the final generation population from initial one, we observe a good convergence of solution points to higher fronts. More and more solution points accumulate on the best achieved RET profile which provides more flexibility to the worker and supervisor in choosing a job-combination strategy. The population is well diversified over the solution space in each of the three cases. In other words NSGA-II performs well to solve RET problems under consideration.

Firing-molding is a job-combination wherein firing is combined with the least severe job. This combination allows a worker to do firing work for more number of hours in comparison to previous two job-combinations which may be an important requirement in a BM unit. Fig. 12, Fig. 13 and Fig. 14 represent the NSGA-II fronts for the initial population, intermediate improvements, and final generation population respectively for firing-molding job-combination.

We present the non-dominated solution points appearing on the RET profile of final generation population along with best achieved tradeoff points of *ER*/day and *RAS* in tabular form for each of three job-combinations. PDL values are also shown along with *RAS* in the last column. In general, workers are in safer zone till PDL is *moderate*. Beyond this they fall into higher and higher risk zones as PDL assumes values *high*, *very hig*h, and *extremely high*. Table 4 shows the solution points for firing-loading job-combination. PDL is moderate till 23^{rd} solution point and workers fall into the unsafe zone from 24^{th} solution point onwards. RET solutions provide a huge flexibility to workers and supervisors in terms of choosing the working hours, rest breaks and number of rest breaks. Further the safer zone limits the earnings to INR 256/day (refer to 23^{rd} solution point). If at all a worker is interested to earn more, he or she will have to move to the risky zones. Captivatingly, our proposed system provides the best possible earnings to a worker even in the risk zones. For example say in an extreme case, a worker may choose the last solution point i.e. 29^{th} solution point – this would correspond to a very high earnings of INR 265/day against a *RAS* of 69.37 corresponding to a *high* PDL.

Nondominated solution points of the final generation RET profile for firing-covering job-combination are shown in Table 5. We observe that this combination provides many of the solution points falling into the safer zone. The PDL value is moderate till 32^{nd} solution point out of total 34 points. Hence there is a better flexibility for a worker/supervisor to choose a solution point in the safer zone. The highest earning in the safer zone is limited to INR 255/day against a *RAS* equal to 52.72, and PDL being *moderate* (refer to 32^{nd} solution point).

Table 6 demonstrates the best obtained *RAS*-Earnings tradeoff solution points for firing-molding job-combination. It is interesting to observe that herein we obtain some *very low* values of *RAS* owing to the fact that molding is comparatively less severe job. So firing-molding is a useful combination for workers who are aged and/or having some health issues. We present the comparison of two solution points (17^{th} and 18^{th} both having *low* PDL and minor differences in terms of *RAS* and *ER*/Day) below to illustrate the flexibility with respect to *RB* and *NRB* of firing job. Workers preferring more *RB* over *NRB* for firing job have a choice to opt for 18^{th} solution point, which provides a single rest break of 25 minutes for 6 working hours. Whereas those favoring *NRB* over *RB* can go for 17^{th} solution point, which offers 3 rest breaks each of 5 minutes.

SP	**17^{th}**	**18^{th}**
WH_1	6	6
RB_1	5	25
NRB_1	3	1
WH_3	6	6
RB_3	40	10
NRB_3	1	1
ER/day	200	202
RAS	23.33	26.56

4.1 Comparing JCA with existing situation

For comparison purposes we compute *RAS* in the existing situation in the BM unit at different feasible values of *WH*, *RB* and *NRB* for the jobs that are performed without any combination. We do so specifically for the firing job (job#1).

Case 1: Firing job alone

Worker is doing firing job in the existing system for 12 hours with a single rest break of 15 minutes. The effective working time is 11 hours and 45 minutes.

WH_1	RB_1	NRB_1
12	15	1

We can compute *RAS* using any of the three ANN models employed in this work by substituting WH_i = 12, RB_i = 15, NRB_i = 1, WH_j = 0, RB_j = 0, and NRB_j = 0. *RAS* so obtained is 72.28, which corresponds to *very high* PDL as per Table 1.

Case 2: Firing-loading job-combination

Worker is doing firing job for 10 hours with a single rest break of 10 minutes and a loading job for 2 hours with a single rest break of 5 minutes refer to 29^{th} solution point of Table 4. The effective time is again 11 hours and 45 minutes

WH_1	RB_1	NRB_1	WH_2	RB_2	NRB_2
10	10	1	2	5	1

RAS for this combination is 69.37 and the corresponding PDL is *high*. While comparing the results, *RAS* is higher in job alone case ($72.28 > 69.37$) with an increase in *ER*/day of Rs 7.00. PDL drops down to *high* in job-combination approach from *very high* in job alone case. Thus job-combination approach reduces the *RAS*/PDL and hence RoOHH.

4.2 Global RET solution points

Compilation of non-dominated RET solutions of three job-combinations presents the global RET solution points in Table 7. RET solutions provide a wider flexibility to a worker/supervisor to complete the jobs in the BM unit. To illustrate the importance of global RET solutions, we present the following case, which compare two solution points, 4^{th} and 9^{th}, of Table 7, both belonging to firing-covering job-combination.

NRB_j of 4^{th} solution point is 5 whereas NRB_j of 9^{th} solution point is 3, rest of the values of both the strings are identical. Although PDL of both of these points is same (i.e. *very low*, VL), yet there is a wider choice available to worker/supervisor in terms of *RAS* and *ER*/Day to complete the jobs. If a worker is not young or/and having some health problem, a decision may be taken to choose the 4^{th} solution point which offers five rest breaks for j^{th} job, resulting in much lower *RAS*. However, this option reduces his/her *ER*/Day by INR 17.00.

On the contrary a healthier or/and young worker can go for 9^{th} solution point which would result in higher *ER*/Day.

SP	4^{th}	9^{th}
WH_i	2	2
RB_i	40	40
NRB_i	1	1
WH_j	10	10
RB_j	30	30
NRB_j	5	3
ER/Day	156	173
RAS	9.14	13.00

4.3 Comparison of NSGA-II with enumeration technique

Further, a comparison of NSGA-II with enumeration technique follows. Enumeration technique performs a total of 50176 searches to compute the nondominated solution points for one job-combination whereas NSGA-II takes a maximum of 800 searches for the same. Further, the mean elapse time of a single run of NSGA-II is computed as 3.012 second – a very fast convergence. It is observed that the near optimal nondominated front is attained in 4^{th} or 5^{th} iteration and in the remaining iterations more and more solutions points belonging to this front are explored thereby increasing the size of the nondominated front.

5 Conclusion

An intelligent system is presented to reduce RoOHH of workers in labor intensive manufacturing units. It acts as an advisor to a worker to choose a job-combination and the corresponding values of *WH*, *RB*, & *NRB* to decide his/her occupational risks and earnings suitably. The present work is implemented in a brick manufacturing unit, wherein workers perform firing job, identified to be the most severe job, with other jobs of a BM unit. Job-combination approach ensures that workers' earnings are not compromised to a greater extent. ANN models are effectively used to estimate *RAS* for different job-combinations. Performance of these models is demonstrated by evaluating *RAS* for the testing data and comparing them with experimental results. NSGA-II searches for the optimal *RAS*-earning tradeoff profile. NSGA-II does not place any restriction on the form of inputs (*WH*, *RB*, and *NRB* of two jobs) to evaluate *RAS* and earnings for a given job-combination. The unifying system amalgamating ANNs and NSGA-II in a unique way turns out to be a powerful scheme without losing its simplicity. For complex optimization scenario, it can effectively search for the optimal values of *WH*, *RB*, and *NRB* for minimum *RAS* and maximum earnings.

Brick kiln owners face the problems of putting together and managing large number of workers while considering their health hazards, absenteeism, limited time schedules, and environment uncertainty. Further, the top management faces the problem of monopoly of workers of firing work in BM units, as it is a high skill job. The system presented in this work will alleviate this problem as job-combination approach will make other workers getting trained for firing work. In fact the system will help in 'work generalization' to take over 'work specialization'. Therefore, the feasibility of implementing this system is high as it is beneficial to both – workers as well as owners. In view of these facts, the work presented here forms an important basis to effectively address the issues in health management of workers.

Table 1. Relationship between *RAS* and PDL

RAS (Range *a*-*b*)*	**PDL**	**Abbreviation**
1-6	*Extremely Low*	EL
6-16	*Very Low*	VL
16-35	*Low*	L
35-54	*Moderate*	M
54-70	*High*	H
70-75	*Very High*	VH
75 and above	*Extremely high*	EH
*Range *a*-*b* indicates $a \leq RAS < b$		

Table 2. Sample input data for training ANN

(a)Firing-Loading

WH_1	RB_1	NRB_1	WH_3	RB_3	NRB_3	**Risk Assessment Score (*RAS*)**
10	40	1	2	40	1	62.3
8	40	3	4	10	2	47.8
6	40	1	6	40	1	42.0
4	10	2	8	10	1	34.9
2	10	1	10	10	3	29.9

(b)Firing-Covering

WH_1	RB_1	NRB_1	WH_4	RB_4	NRB_4	**Risk Assessment Score (*RAS*)**
10	10	1	2	10	1	57.6
8	20	2	4	20	2	40.6
6	10	2	6	40	3	27.6
4	20	2	8	20	3	21.4
2	20	1	10	20	2	18.7

(c)Firing-Molding

WH_1	RB_1	NRB_1	WH_2	RB_2	NRB_2	**Risk Assessment Score (*RAS*)**
10	20	3	2	10	1	45.9
8	10	2	4	10	2	35.1
6	20	2	6	40	3	22.0
4	20	1	8	40	3	16.0
2	20	1	10	10	3	13.0

Table 3. Comparison of results of Risk Assessment Score

(a)Firing-Loading

WH_1	RB_1	NRB_1	WH_3	RB_3	NRB_3	**Risk Assessment Score (RAS)**	
						Experimental Results	**ANN Results**
2	10	1	10	20	3	28.6	28.2
4	20	1	8	40	2	32.0	32.1
8	40	2	4	20	2	50.0	49.8
10	10	3	2	40	1	62.0	61.1

(b)Firing-Covering

WH_1	RB_1	NRB_1	WH_4	RB_4	NRB_4	**Risk Assessment Score (RAS)**	
						Experimental Results	**ANN Results**
4	10	2	8	20	3	23.2	22.83
6	20	3	6	10	2	31.2	29.82
8	40	3	4	10	1	37.43	39.16
10	20	1	2	40	1	54.64	57.61

(c)Firing-Covering

WH_1	RB_1	NRB_1	WH_2	RB_2	NRB_2	**Risk Assessment Score (RAS)**	
						Experimental Results	**ANN Results**
2	40	1	10	20	3	9.08	10.45
4	20	2	8	10	2	16.8	16.13
6	20	3	6	40	3	19.6	18.18
10	10	3	2	40	1	45.94	41.46

Table 4. RET solution points: firing-loading job-combination

Solution Points	WH_1	RB_1	NRB_1	WH_3	RB_3	NRB_3	*ER*/Day	*RAS*	PDL
1	2	40	1	10	30	2	206	19.17	L
2	2	30	1	10	35	1	218	21.63	L
3	2	30	1	10	30	1	220	23.35	L
4	3	35	1	9	25	1	223	25.76	L
5	4	35	1	8	25	1	227	28.95	L
6	2	15	1	10	5	1	233	29.03	L
7	3	15	1	9	5	2	235	29.89	L
8	3	15	1	9	5	1	237	30.81	L
9	4	15	1	8	5	2	239	32.72	L
10	4	15	1	8	5	1	241	33.19	L
11	4	10	1	8	5	1	243	35.87	M
12	5	15	1	7	5	1	244	36.62	M
13	4	5	1	8	5	1	245	38.38	M
14	5	10	1	7	5	1	246	40.05	M
15	6	5	2	6	15	1	247	42.00	M
16	5	5	1	7	5	1	248	42.08	M
17	7	5	3	5	15	1	249	43.58	M
18	7	5	2	5	15	1	251	45.27	M
19	8	5	3	4	15	1	252	46.87	M
20	7	5	1	5	15	1	253	48.09	M
21	8	5	2	4	15	1	254	50.46	M
22	8	5	1	4	20	1	255	52.29	M
23	7	5	1	5	5	1	256	52.80	M
24	10	5	4	2	15	1	258	57.47	H
25	8	5	1	4	5	1	259	58.38	H
26	10	5	3	2	15	1	260	61.29	H
27	10	5	1	2	20	1	262	64.03	H
28	10	5	1	2	15	1	264	66.85	H
29	10	10	1	2	5	1	265	69.37	H

Table 5. RET solution points: firing-covering job-combination

Solution Points	WH_1	RB_1	NRB_1	WH_4	RB_4	NRB_4	***ER*/Day**	***RAS***	**PDL**
1	2	40	1	10	30	6	148	8.35	VL
2	2	40	1	10	30	5	156	9.14	VL
3	2	40	1	10	30	4	164	11.11	VL
4	2	40	1	10	30	3	173	13.00	VL
5	2	35	1	10	5	4	194	13.76	VL
6	2	25	1	10	5	3	199	16.44	L
7	3	35	1	9	5	4	200	17.00	L
8	2	25	1	10	5	2	201	17.51	L
9	3	25	1	9	5	3	206	18.99	L
10	4	35	1	8	5	3	208	21.36	L
11	2	5	1	10	5	1	210	21.48	L
12	4	25	1	8	5	3	212	23.12	L
13	4	15	1	8	10	2	215	24.70	L
14	4	5	2	8	20	1	217	25.75	L
15	4	15	1	8	5	1	219	26.40	L
16	5	5	2	7	20	1	223	28.17	L
17	5	5	1	7	20	1	225	29.51	L
18	6	25	1	6	5	2	226	33.20	L
19	6	5	2	6	20	1	230	33.22	L
20	6	5	1	6	20	1	231	35.26	M
21	6	5	2	6	10	1	232	35.33	M
22	6	5	1	6	10	1	234	36.90	M
23	6	5	1	6	5	1	236	37.81	M
24	7	5	3	5	10	1	237	40.07	M
25	7	5	1	5	20	1	238	40.97	M
26	8	15	1	4	20	1	241	41.15	M
27	7	5	1	5	5	1	242	41.18	M
28	8	5	1	4	25	1	243	43.73	M
29	8	15	1	4	5	1	245	44.48	M
30	8	5	1	4	5	1	249	45.40	M
31	9	5	1	3	20	1	251	52.24	M
32	9	5	1	3	5	1	255	52.72	M
33	10	5	1	2	20	1	257	55.72	H
34	10	5	1	2	5	1	262	57.13	H

Table 6. RET solution points: firing-molding job-combination

Solution Points	WH_1	RB_1	NRB_1	WH_4	RB_4	NRB_4	***ER*/Day**	***RAS***	**PDL**
1	2	25	1	10	30	5	130	6.78	VL
2	2	40	1	10	40	3	131	7.70	VL
3	2	40	1	10	5	1	155	8.01	VL
4	2	30	1	10	5	1	159	10.05	VL
5	3	40	1	9	5	1	165	10.53	VL
6	3	30	1	9	5	3	167	12.87	VL
7	3	30	1	9	5	1	169	12.96	VL
8	3	25	1	9	10	1	170	14.29	VL
9	4	40	1	8	5	1	176	14.34	VL
10	4	30	1	8	5	3	178	15.25	VL
11	4	25	1	8	10	2	179	16.31	L
12	4	25	1	8	10	1	181	17.17	L
13	4	5	2	8	25	1	184	19.04	L
14	5	5	3	7	40	1	189	19.15	L
15	5	30	1	7	5	2	190	21.10	L
16	5	25	1	7	10	1	192	21.74	L
17	6	5	3	6	40	1	200	23.33	L
18	6	25	1	6	10	1	202	26.56	L
19	7	5	3	5	40	1	210	27.13	L
20	7	5	3	5	10	1	217	29.92	L
21	9	10	5	3	40	1	218	30.36	L
22	7	5	2	5	10	1	219	31.22	L
23	7	5	1	5	10	1	221	31.93	L
24	8	5	3	4	10	1	227	35.16	M
25	8	5	1	4	15	1	230	36.02	M
26	9	5	3	3	40	1	232	37.07	M
27	10	5	3	2	40	1	242	40.68	M
28	10	5	2	2	40	1	244	43.42	M
29	10	5	3	2	10	1	249	46.60	M
30	10	5	2	2	10	1	251	47.15	M
31	10	5	1	2	10	1	252	48.66	M

Table 7. RET solution points: global RET profile

Solution Points	WH_i	RB_i	NRB_i	WH_j	RB_j	NRB_j	*ER*/**Day**	*RAS*	**PDL**	**Job-combination**
1	2	25	1	10	30	5	130	6.78	VL	FM
2	2	40	1	10	40	3	131	7.70	VL	FM
3	2	40	1	10	5	1	155	8.01	VL	FM
4	2	40	1	10	30	5	156	9.14	VL	FC
5	2	30	1	10	5	1	159	10.05	VL	FM
6	3	40	1	9	5	1	165	10.53	VL	FM
7	3	30	1	9	5	3	167	12.87	VL	FM
8	3	30	1	9	5	1	169	12.96	VL	FM
9	2	40	1	10	30	3	173	13.00	VL	FC
10	2	35	1	10	5	4	194	13.76	VL	FC
11	2	25	1	10	5	3	199	16.44	L	FC
12	3	35	1	9	5	4	200	17.00	L	FC
13	2	25	1	10	5	2	201	17.51	L	FC
14	3	25	1	9	5	3	206	18.99	L	FC
15	4	35	1	8	5	3	208	21.36	L	FC
16	2	5	1	10	5	1	210	21.48	L	FC
17	2	30	1	10	35	1	218	21.63	L	FL
18	2	30	1	10	30	1	220	23.35	L	FL
19	3	35	1	9	25	1	223	25.76	L	FL
20	4	35	1	8	25	1	227	28.95	L	FL
21	2	15	1	10	5	1	233	29.03	L	FL
22	3	15	1	9	5	2	235	29.89	L	FL
23	3	15	1	9	5	1	237	30.81	L	FL
24	4	15	1	8	5	2	239	32.72	L	FL
25	4	15	1	8	5	1	241	33.19	L	FL
26	4	10	1	8	5	1	243	35.87	M	FL
27	5	15	1	7	5	1	244	36.62	M	FL
28	4	5	1	8	5	1	245	38.38	M	FL
29	5	10	1	7	5	1	246	40.05	M	FL
30	6	5	2	6	15	1	247	42.00	M	FL
31	5	5	1	7	5	1	248	42.08	M	FL
32	7	5	3	5	15	1	249	43.58	M	FL
33	7	5	2	5	15	1	251	45.27	M	FL
34	8	5	3	4	15	1	252	46.87	M	FL
35	7	5	1	5	15	1	253	48.09	M	FL
36	8	5	2	4	15	1	254	50.46	M	FL
37	8	5	1	4	20	1	255	52.29	M	FL
38	7	5	1	5	5	1	256	52.80	M	FL
39	10	5	1	2	20	1	257	55.72	H	FC
40	10	5	1	2	5	1	262	57.13	H	FC
41	10	5	1	2	15	1	264	66.85	H	FL
42	10	10	1	2	5	1	265	69.37	H	FL

As the proposed system is general enough to be applied to any labor intensive industrial unit, therefore, as part of future work, one can employ it to solve similar problems of other industrial units. It may also be attempted to investigate the results by having three or more jobs in a job-combination. Further, it would be interesting to experiment with other standard EMO techniques such as SPEA-2or PAES in place of NSGA-II, to search for optimal work schedules in a job-combinations. Results can be compared using metrics to evaluate diversity and cnvergence properties of EMO.

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