Effectiveness of Multi Skill Training Program in the Manufacturing Process Using Hybrid Genetic Algorithm

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Abstract. The paper contains the study of Multi skill training to the employees, which includes equalizing the work pressure among the employees and managing the shortage of employees in the manufacturing process. A mathematical model was formed with an objective of minimizing the total expected cost of the employees in the manufacturing process. AHybrid Genetic algorithm was used to stimulate the solutions. The results showed that the multi skill training program yields a better result compared to non-trained employees.

Keywords: Multi skill training, Hybrid genetic algorithm.

INTRODUCTION

The most important thing in the manufacturing process is to balance the workloads among the employees. For example, if we take a car manufacturing process, suppose employee 1 is assigned a work of fixing the wheels to the car and the employee 2 assigned for painting the car, then obviously employee 1 finishes assigned work early compared to the employee 2. This is an unbalanced workload among the employees, which has happened due to reason that the employees are trained for single skill. Such type of issues can be balanced by giving multi skill training to the employees.

As we know that human resource is a key element for success of an organization [1, 2 and 3]. Now a day many organizations are putting an effort to train the employees for multi skill [4] and [5]. As a search for talent increases, optimizing the skills at various levels becomes necessary for stronger performance [6]. These training programs will help in gaining the knowledge about other works related to manufacturing process, which also help in balancing the work pressure among the employees. Another name of multi skill training is a cross training process. Cross training is the process of finding the skills, pattern of a work force. In general, there are two scenarios of cross training, one is full cross training and second is no cross training. There are some intermediate policies such as chaining [7], in which each worker is trained for one or more skills in addition to the normal skills of the home department. The importance of cross training is to provide flexibility for an organized workforce. And it is shown that this flexibility becomes expensive and difficult to maintain [8 and 9]. **Karuppan** showed that cross training decreases productivity and quality [10]. In recent studies, **Easton** used a two stage stochastic model, presented some new results from cross training yielding better result compared to previous literature. They demonstrated that the cross training leads to improved performances compared to other dedicated specialist [11].But there is no literature of multi skill training using Genetic Algorithm.

Genetic algorithm is a tool for solving optimization problems which is developed based on the principal of natural selection. In 1970 John Holland introduced the genetic algorithm for the first time. And he introduced basic principles of genetic algorithm [12]. There after many more literatures are available in [13], [14] and [15] and few reports of the genetic algorithm are available in [16], [17], [18] and [19]. Genetic algorithm has wide range of application due its independent of error free surface. Non differentiable, multimodal, non-continuous, and also NP-Complete problems are solved using genetic algorithm [20]. The multimodal problems are solved with the relative ease using genetic algorithm in [21] and [22]. This is also used in solving nonlinear identification problems [23]. It is also used in the secure communication systems [24] and [25]. Genetic algorithms are also used in scheduling process of multiprocessor systems [26], Nurse scheduling [27] and Doctor Scheduling [28]. The above literature survey shows that there is no work on Employee scheduling using genetic algorithm. Therefore in this paper we are adapting hybrid genetic algorithm(HGA) for employee scheduling with multi skill training program.

A GA hybridized with a local search procedure is called a hybrid genetic algorithm (HGA).
A basic HGA procedure has the following steps.

(1) Define an objective/fitness function, and set the GA operators (such as population size, parent/offspring ratio, selection method, number of crossovers, and mutation rate).

(2) Randomly generate the initial population as the current parent population.

(3) Evaluate the objective function for each individual (chromosome or solution) in the initial population.

(4) Generate an offspring population by using GA operators (such as selection/mating, crossover, and mutation).

(5) Evaluate the objective function of each individual in the offspring population.

(6) Perform a local search on each offspring, evaluating fitness of each new location, and replace the offspring if there exists a locally improved solution.

(7) Decide which individuals to include in the next population. This step is referred to as “replacement" in that individuals from the current parent population are “replaced" by a new population consisting of those individuals from the offspring and/or the parent populations.

(8) If a stopping criterion is satisfied, then the procedure is halted. Otherwise, go to Step 4.

Without Step 6, an HGA is just a GA. Therefore, HGAs have all the properties possessed by GAs. Like GAs, HGAs are a large family of algorithms that have the same basic structure but differ from one another with respect to several strategies such as stopping rules, operators which control the search process, and the local search meme.

Based on previous experiences, in this study, we use a continuous HGA where chromosomes are coded as continuous measurement variables. Suppose there are variables; that is, there are genes in each chromosome. We also make the following assumptions. The (parent) population size is and the offspring population size is also . The type of selection we utilize is random pairing. The blending crossover is utilized and the number of crossover points depends on the number of dimensions of a specific objective function. Random uniform mutation is utilized and the mutation rate is set around or equal to . The type of replacement over both parent and offspring populations is either ranking or tournament. For details on the setting of the GA operators; see, for example[29-33].

MODEL NOTATION

The terms used in the mathematical is given as follows

Indices

i	Particular department
k	Experience level of the employees
r	Regular employees
j	Cross trained employees
T	Temporary employee

Domains

I	Total number of departments
K	Total number of experience levels

Parameters

C_i^r	Cost of regular employee in department i
C_i^c	Cost of cross trained employee in department i
C_t	Cost for a temporary employee
D_i	Random variable for demand for employee in department i
μ_i	Mean demand for employee in department i
S_{min}	Minimum service level required
Q_{min}	Minimum quality level required
μ_k	Relative quality level of employee with experience level k
μ^c	Relative quality level of cross trained employees
n_i^{max}	Maximum number of employees available in department i

Decision Variables

n_i^r	Number regular employees in department i
S_i	Service level in department i
Q_i	Quality level in department i
n_{ik}^r	Number of regular employees in department i of experience level k
n_{ik}^c	Number of cross trained employees in department i of experience level k
n_{ik}	Total number of employees in department i of experience level k
n_i	Total number of employees in department i
$E(shortage)$	Total expected shortage of employees

MODEL DEVELOPMENT

The resulting proposed model is given as follows

$$Minimize = \left[\sum_{k=1}^{K}\sum_{i=1}^{I} n_{ik}^{r}C_{ik}^{r} + n_{ik}^{c}C_{ik}^{c}\right] + E\left[shortage\right]C_{t} \qquad (1)$$

Subject to

$$E\left[S_i\right] \geq S_{\min}, \quad For\, i = 1,2,......I \qquad (2)$$

$$Q_i \geq Q_{\min}, \quad For\, i = 1,2,......I \qquad (3)$$

$$Q_i = \sum_{k=1}^{K}\left(n_{ik}^{r} + n_{ik}^{c}\mu^{c}\right)\mu_k, \quad For\, i = 1,2,......I \qquad (4)$$

$$Q_{\min} \leq 1, \quad For\, i = 1,2,......I \qquad (5)$$

$$n_{ik}^{c} \leq n_{ik}, \quad For\, i = 1,2,......I, k = 1,2,.....K \qquad (6)$$

$$n_i \leq n_{i,\max}, \quad For\, i = 1,2,......I \qquad (7)$$

$$n_i = \sum_{k=1}^{K} n_{ik}, \quad For\, i = 1,2,......I \qquad (8)$$

$$n_{ik} = n_{ik}^{r} + n_{ik}^{c}, \quad For\, i = 1,2,......I, k = 1,2,.....K \qquad (9)$$

$$n_i, n_{ik}^{r}, n_{ik}^{c}, n_{ik} = \text{int}\, egers \qquad (10)$$

$$\mu_1 \leq \mu_2 \leq ....\mu_k = 1 \qquad (11)$$

Calculation of Expected Shortage

For two departments chain i and -1 , the probability that a shortage s occurs in the department i was divided into without multi skill training effect and direct multi skill training effect.

$$P(shortage\, department\, i = s) = P(D_i = n_i + s) + \sum_{T_{i-1=1}}^{n_{i-1}^{c}} P(D_{i-1} \leq n_{i-1} - x_{i-1})\left[P(D_i = n_i + s + T_{i-1}) - P(D_i = n_i + s + T_{i-1} - 1)\right] \qquad (12)$$

Where the first term is for home department and second term is for multi skill trained employees.

The expected shortage of individual department is based on the number of regular and multi skill trained employees given by the mean demand as

$$E(total\, shortage\, department\, i) = \sum_{s=1}^{\infty} P(shortage\, department\, i = s) \qquad (13)$$

The total shortage of all the departments is sum of individuals shortages based on total and multi skill trained employees in each department.

$$E\left[total\ shortage\right] = \sum_{for\ all} \left\langle \sum_{s=1}^{\infty} (shortage\ department\ i = s)s \right\rangle \tag{14}$$

Hence, solving this model by analytical method becomes critical; therefore a heuristic approach was used to solve the entire model.

IMPLEMENTATION OF GENETIC ALGORITHM

Creating an initial population

We randomly create the initial population of the employee chromosomes. Then we check whether primary goal is achieved or not trough minimum working requirements.

Crossover

Main intention of crossover is to combine the good properties of both the parents to yield a new better chromosome [34, 35]. Simple crossover operator is consists of randomly selected crossover point and there after recombines the pair of chromosome in order to form new chromosome.

Mutation

The next stage of the crossover is the mutation process which acts on the pair of chromosomes. Mutation is the important force for revolution although it is infrequent in nature. There are two important mutation process namely inverse mutation and pairwise mutation.

i. *Inverse Mutation:*
   We generate some random positions between (1, n), where n is the number of employees. Let us select two position randomly for mutation, let it be 1 and 5. Then inverse mutation is obtained by reversing the order of the sequence between the positions 1 and 5 as given below

Original string → $\boxed{5\ \ 1\ \ 6\ \ 2\ \ 7}$ 9 4 8 3 10
Mutated string ← $\boxed{7\ \ 2\ \ 6\ \ 1\ \ 5}$ 9 4 8 3 10

ii. *Pair wise Mutation:* We generate some random positions between (1, n), where n is the number of employees. Let us select two position randomly for mutation, let it be 1 and 5. Then pairwise mutation is obtained by interchanging the positions 1 and 5 as given below

Original string → $\boxed{5}$ 1 6 2 $\boxed{7}$ 9 4 8 3 10
Mutated string ← $\boxed{7}$ 1 6 2 $\boxed{5}$ 9 4 8 3 10

Evaluation of Fitness value

The fitness value is calculated using two criteria depending on the solution type.

Criteria 1: If the chromosome is under the feasible solution, then the fitness value is the objective function value.

Criteria 2: If the chromosome is under the non-feasible solution then the fitness value is equal to 1000 iterations.

Chromosome Selection

Chromosomes are selected using Roulette.

Preserving Strategy

The chromosome with high fitness values are replaced by the new chromosomes with the low fitness value and used as initial population for next generation.

Termination Criteria

Once we met the specified number of iterations, we stop the process immediately.

The general flow chart of genetic algorithm is given in the figure 1.

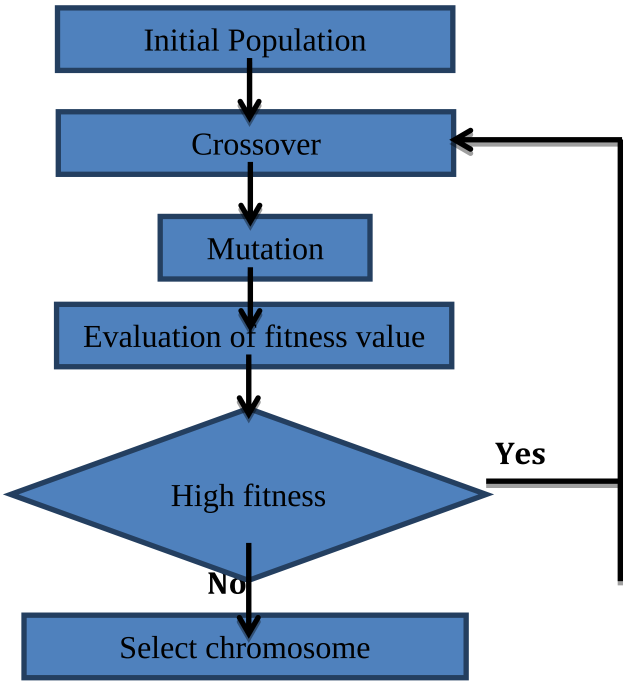

Figure 1: Flow chart of the Genetic Algorithm

NUMERICAL RESULT

To study the proposed model, the researcher considered an industry with two departments. A number of optimizations were performed with a mix of variable, including quality and service level, mean demands as well as maximum available staffing. The data included five based upon experience; <1yr; 1-4yrs; 5-9yrs; 10-14yrs and 15yrs+.

There are two scenarios, namely scenario A and scenario B. For scenario A, there were no constraints on the maximum number of employees available in the department. But the scenario

B has such a constraint. Initially we assume $\mu^c = 1$ for both regular and multiskills trained employees. The comparison of staffing levels and service levels are given in table 1 and table 2 respectively.

TABLE 1: Comparison of staffing levels

	L,H (5,10)	H, L (10,5)	L,L (5,5)	H,H (10,10)
Multi skill trained	17	17	11	18
Non trained	20	20	15	24

TABLE 2: Comparison of service levels

	L,H (5,10)	H, L (10,5)	L,L (5,5)	H,H (10,10)
Multi skill trained	0.752	0.628	0.723	0.596
Non trained	0.626	0.422	0.575	0.438

TABLE 3: Percentage cost saving with multi skill training

	L,H (5,10)	H, L (10,5)	L,L (5,5)	H,H (10,10)
Scenario A	5.2	5.3	5.4	5.5
Scenario B	3.7	4.8	4.5	3.3

Table 1 shows that there is a reduction in staffing level of employees in multi skill training. Table 2 shows that, there is a high service level in multi skill training. The percentage of cost savings over non multi skill training is presented in Table 3.

CONCLUSIONS

In this paper a multi skill training program was given to the employees in to minimize the cost, increase the service level and to balance the shortage of the employees. A mathematical model was framed by setting the objective function and some constraints. An evolutionary algorithm, namely Hybrid Genetic Algorithm was used to find the optimal solutions. The results showed that the multi skill training program reduces the cost by 5.825% for scenario A and 4.225% for scenario B compared to regular (non -cross trained employees).

REFERENCES

[1] Dessler, G. Human Resources Management, 11th ed., Prentice- Hall, Englewood Cliffs, NJ. 2008.

[2] Cascio, W.F. Managing Human Resources: Productivity, Quality of Work Life, Profit, 8th ed., Irwin: McGraw-Hill, New York, NY, 2008.

[3] Draft, R.L. (2008), New Era of Management, 2nd ed., Thomson South-Western, Mason, OH.

[4] Blickstein, S. Does training pay off? Across the Board, 33(6), 16-20, 1996.

[5] Pollitt, D. A flexible workforce for the modern economy: the role of education and training. Education + Training, 43(7), 345- 376, 2001.

[6] Agarwal, N., & Ahuja, V. Creation of the Training-Chart: A Step Forward to Make the Training More Effective. International Journal of Service Science, Management, Engineering, and Technology (IJSSMET), 5(2), 1-18., 2014.

[7] Jordan, W.C., Graves, S.C.. Principles on the benefits of manufacturing process flexibility. Manage.Sci.41, 577–594, 1995.

[8] Hopp, W.J., Van Oyen,M.P. Agile work force evaluation: a framework for cross-trainingandcoordination.IIETrans.36, 919–940, 2004.

[9] Inman,R.R., Jordan,W.C., Blumenfeld,D.E.. Chained cross training of assembly line workers.Int.J.Prod.Res.42,1899–1910, 2004.

[10] Karuppan, C.M.. Labor flexibility: Too much of a good thing? Ind.Manage.48 (5), 13–18, 2006.

[11] Easton, F.F. Cross-training performance in flexible labor scheduling environments. IIETrans.43, 589–603, 2011.

[12] J. H. Holland, Adaption in Natural and Artificial Systems. Cambridge, MA: MIT Press, 1975.

[13] L. Davis, Handbook of Genetic Algorithms. New York: Van Nostrand Reinhold, 1991.

[14] D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Reading, MA: Addison-Wesley, 1989.

[15] Z. Michalewicz, Genetic Algorithms + Data Structures = Evolution Program, 2nd Ed. Berlin: Springer-Verlag, 1994.

[16] D. Beasley, D. R. Bull, and R. R. Martin, “An overview of genetic algorithms: Part I-Fundamentals,” Univ. Comput., vol. 15, no. 2, pp. 58-69, 1993.

[17] D. Beasley, D. R. Bull, and R. R. Martin, “An overview of genetic algorithms: Part 2-Research topics,” Univ. Comput., vol. 15, no. 4, pp. 170-181, 1993.

[18] M. Srinivas and L. M. Patnaik, “Genetic algorithms: A survey,” Computer, pp. 17-26, June 1994.

[19] D. Whitley, “A genetic algorithm tutorial,” Dept. Comput. Sci, Colorado State Univ., Tech. Rep. CS-93-103, Nov. 1993.

[20] M. R. Garey and D. S. Johnson, Computers and Intractability: A Guide to the Theory of NP-Completeness. San Francisco, CA: Freeman 1979.

[21] R. Nambiar and P. Mars, “Adaptive IIR filtering using natural algorithms,” in Workshop on Natural Algorithms in Signal Processing, Chelmsford, Essex, Nov. 1993, pp. 20/1-20/10.

[22] P. B. Wilson and M. D. Macleod, “Low implementation cost IIR digital filter design using genetic algorithms,” in Workshop on Natural Algorithms in Signal Processing, Chelmsford, Essex, Nov. 1993, pp. 4/1-4/8.

[23] R. C. Caponetto, L. Fortuna, G. Manganaro, and M. G. Xibilia, “Chaotic system identification via genetic algorithm,” in 1st IEENEEEE Int. Con$ GAIs in Engineering Systems: Innovations and Amlications, Sheffield, 1. U.K., 1995: pp. 178-174.
[24] L. 0. Chua, K. Eckert, Lj. Kocarev, and M. Itoh, “Experimental chaos synchronization in Chua’s circuit,” Int. J. Bifurcation, Chaos, vol. 2, no. 3, pp. 705-708, 1993.
[25] Lj. Kocarev, K. S. Halle, K. Eckert, U. Parlitz, and L. 0. Chua, “Experimental demonstration of secure communications via chaos synchronization,” Int. J. Bifurcation, Chaos, vol. 2, no. 3, pp, 709-713, 1992.
[26] H. Heidari and A. Chalechale, “Scheduling in Multiprocessor System Using Genetic Algorithm”, IJAST, vol 43, (2012), pp.81-94.
[27] U. Aickelin and K. A. Dowsland, “An indirect Genetic Algorithm for a Nurse-Scheduling Computers & Operations Research, vol. 31, no. 5, (2004) April, pp. 761-778.
[28] Abir Alharbi and Kholood AlQahtani, “A Genetic Algorithm Solution for the Doctor Scheduling Problem”, ADVCOMP 2016: The Tenth International Conference on Advanced Engineering Computing and Applications in Sciences.
[29] D. E. Goldberg, Genetic Algorithms in Search, Optimization, and Machine Learning, Addison-Wesley, Reading, Mass, USA, 1989.
[30] M. Hamada, H. F. Martz, C. S. Reese, and A. G. Wilson, “Finding near-optimal Bayesian experimental designs via genetic algorithms,” The American Statistician, vol. 55, no. 3, pp. 175–181, 2001.
[31] D. G. Mayer, J. A. Belward, and K. Burrage, “Robust parameter settings of evolutionary algorithms for the optimisation of agricultural systems models,” Agricultural Systems, vol. 69, no. 3, pp. 199–213, 2001.
[32] F. Ortiz Jr., J. R. Simpson, J. J. Pignatiello Jr., and A. Heredia-Langner, “A genetic algorithm approach to multiple-response optimization,” Journal of Quality Technology, vol. 36, no. 4, pp. 432–450, 2004.
[33] R. L. Haupt and S. E. Haupt, *Practical Genetic Algorithms*, Wiley-Interscience [John Wiley & Sons], Hoboken, NJ, Second edition, 2004, With 1 CD-ROM (Windows).
[34] Z. Wang, J.-L. Liu, and X. Yu, “Self-fertilization based genetic algorithm for university timetabling problem,” in Proceedingsof the 1st ACM/SIGEVO Summit on Genetic and Evolutionary Computation (GEC ’09), pp. 1001–1004, ACM, Shanghai, China, June 2009.
[35] J. Wang and K. Chu, “An application of genetic algorithms for the flexible job-shop scheduling problem,” International Journalof Advancements in Computing Technology, vol. 4, no. 3, pp. 271–278, 2012.