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A Synchronized Job Assignment Model for Manual Assembly Lines Using Multi-Objective Simulation Integrated Hybrid Genetic Algorithm (MO-SHGA)

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다목적 시뮬레이션 통합 하이브리드 유전자 알고리즘을 사용한 수동 조립라인의 동기 작업 모델

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The application of the theoretical model to real assembly lines has been one of the biggest challenges for researchers and industrial engineers. There should be some realistic approach to achieve the conflicting objectives on real systems. Therefore, in this paper, a model is developed to synchronize a real system (A discrete event simulation model) with a theoretical model (An optimization model). This synchronization will enable the realistic optimization of systems. A job assignment model of the assembly line is formulated for the evaluation of proposed realistic optimization to achieve multiple conflicting objectives. The objectives, fluctuation in cycle time, throughput, labor cost, energy cost, teamwork and deviation in the skill level of operators have been modeled mathematically. To solve the formulated mathematical model, a multi-objective simulation integrated hybrid genetic algorithm (MO-SHGA) is proposed. In MO-SHGA each individual in each population acts as an input scenario of simulation. Also, it is very difficult to assign weights to the objective function in the traditional multi-objective GA because of pareto fronts. Therefore, we have proposed a probabilistic based linearization and multi-objective to single objective conversion method at population evolution phase. The performance of MO-SHGA is evaluated with the standard multi-objective genetic algorithm (MO-GA) with both deterministic and stochastic data settings. A case study of the goalkeeping gloves assembly line is also presented as a numerical example which is solved using MO-SHGA and MO-GA. The proposed research is useful for the development of synchronized human based assembly lines for real time monitoring, optimization, and control.

Keywords : Job Assignment, Manual Assembly Line, Human Resource Objectives, Multi-Objective Simulation Integrated Hybrid Genetic Algorithm (MO-SHGA)

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1. Introduction

The choice of the right operator at the right operation on an assembly line is essential to achieve the desired results. The use of traditional job assignment objective will be effective only when there is a high level of coordination and cooperation in team members of the manual assembly line. However, traditional job assignment objectives do not consider the factor of coordination and teamwork. In social perspectives, labor must, therefore, be evaluated on the basis of a relationship with each other as well. The less skilled operator usually takes more time than the high-skilled operator to complete an operation. As the operation time increases the energy consumed by machine increases, therefore, the assignment of operators should be such that, there should be minimal variation in skill level otherwise line will be unbalanced with a substantial increase in energy consumption.

This research quantifies and real-time optimizes some novel objectives of teamwork or coordination, deviation in skill level, energy consumption along with some traditional objectives such as throughput, line efficiency, and labor cost. Another important aspect of this research is synchronization of the real system (simulation model) with the theoretical system which evaluates and optimizes the fluctuation in cycle time. Three different type of cycle times are presented here. The cycle time of the real system (simulation model) is called the real cycle time of assembly line. The theoretical cycle time is the maximum operation time in assembly operations. The third is the planned cycle time which is a function of available time for production and demand of products in that period. The performance of assembly lines is perfect only when real cycle time is less than or equal to the theoretical cycle time, and the real cycle time and theoretical cycle time must be less than or equal to planned cycle time in order to deliver the products on time.

To measure the fluctuation in cycle time the relationship among real cycle time, theoretical cycle time and planned cycle time is developed mathematically and included in a model. The formulated mathematical model is solved using real data of goalkeeping gloves manufacturing company. To solve this mathematical model a multi-objective simulation integrated hybrid genetic algorithm (MO-SHGA) is proposed which is capable to perform real-time optimization of a simulation model of assembly lines. Although, there are many algorithms available for the optimization of assembly line problem but it is very difficult to use them for synchronized systems (simulation-optimization models) for real-time optimization because of their search pattern in solution space. Therefore, in proposed model simulation and genetic algorithm have been integrated for real-time optimization of assignment problem.

The performance of MO-SHGA is evaluated by comparing it with standard multi-objective (MO-GA) without simulation using both deterministic and stochastic data settings. The performance of MO-SHGA is found best over the standard MO-GA by achieving the desired objectives with minimum computational time and iterations. The major contribution of this model is the integration of simulation with genetic algorithm to form an approach called HSGA. The SHGA is then applied on synchronized assembly lines to minimize the fluctuation in cycle time. In addition to fluctuation in cycle time it also considers some other novel human resource objective such as team work and skill level. This research paper is organized as follows. The second section is the detailed literature review. Problem formulation and solution methodology are in the third section, fourth is about results and discussion. Finally, the sixth section includes conclusions.

2. Literature Review

An assembly line has been analyzed in terms of line balancing, job assignment and performance improvement. The performance measures of cycle time, line efficiency, production and labor cost have been extensively reported in the literature. Yang et al. [15] presented a multi-objective genetic algorithm for mixed, model assembly to reduce the number of stations, workload and rebalancing variations with constraints of cycle time. Lee et al. [8] proposed an heuristic for minimizing flowtime in the two stage assembly line. Li and Gao [9] examined assembly line problem where production volume and production variety changed in each shift. The objective in this problem was to minimize the labor cost paid in regular and overtime shift and this problem was solved using the branch and bound algorithm.

The integration of human factors with the traditional assembly line is also the major contribution in the production systems. Human factors integration in assembly lines provides more safety to operators and improves the productivity of assembly lines. Kang et al. [7] modelled the human based production with operators having different skills and wages Xu et al. [14] designed assembly and assigned operators considering human factors such as musculoskeletal disorders because this problem may reduce the performance of operator. The major cause of these human factor problems is the repetitive task. Mossa et al. [11] formulated an inter programming model by considering ergonomic factors such as job rotation in case of repetitive tasks and also considered training level of operators for assignment in an assembly line. Michalos et al. [10] investigated the effect of job rotation of operators on production and quality on manual assembly lines and minimized the fatigue level of operators using probability quantification techniques. Özcan [12] considered the stochastic operation time, cycle time and the number of mated station and developed a mixed integer model and solved using chance constrained, piecewise algorithm and simulated algorithm. Bukchin and Cohen [2] analyzed the assembly line for the effect of slow pace operator as a substitute of expert absentees. They proposed the sharing of work with the nearly expert operator and they provided an analytical model to deal with such situation on the assembly line.

The computational power of any algorithm with minimum time is the criteria for the evaluation of its performance over other techniques. There are many heuristics and algorithms for assembly line problems. Yoon and Juhn [16] presented an improved algorithm for assembly type flow shop scheduling to minimize the make span. Mossa et al. [11] introduced a new heuristic and exact method to solve a job assignment problem in manual assembly lines with the objective to maximize the production rate. Ozcan [12] studied the assembly line problem to minimize the number of stations using the multiple colony ant algorithms.

The coordination between operators working on an assembly line is also important. The novelty of this research is the consideration of the human resource objectives such as teamwork and deviation in the skill level of operators on the assembly line. The deviation in skill level also affects the energy so, energy is also considered in this research. The other objectives are throughput, efficiency, fluctuation in the cycle time of the real system (simulation model) from the theoretical (optimization) model. Synchronization of a real system with optimization requires real-time optimization technique. To solve this model a multi-objective simulation integrated hybrid genetic algorithm (MO-SHGA) is proposed which is best suited for simulation-optimization. Although Yu et al. [12] established a lined cell conversion system by reducing operators and improving productivity and to solve this system they used improved exact algorithms. After they got results then their system was evaluated and validated using discrete event simulation. However, in proposed approach, each individual/chromosome is evaluated using simulation.

3. Development of Mathematical Model

3.1 Problem Statement

A manual assembly line consists of set of operations performed by human operators. Due to the variability in skill level and team work among the operators, the performance of assembly lines might be greatly affected and fluctuations in cycle time occur. In order to minimize the fluctuation in cycle time, increase throughput, and minimize the energy consumption, there is need to assign a right operator to right operation. Also, the coordination between consecutive operators is required to achieve maximum team work and minimize deviation in skill levels for maximum throughput of assembly line.

3.2 Model Assumptions

This model is based on some assumptions that are outlined in the following points.

1. Each operation in assembly line is performed by an operator and operators have different skill level.
2. Operators working n assembly level have different relation with each other, some prefer to work together and some don't prefer.
3. Assembly line operates only eight hours per day.
4. Demand of products is known and certain.
5. Planning horizon is one week.
6. There are no machines delays or breakdowns in assembly lines during production phase.
7. Raw material is always available at all operations.
8. Assembly line is balanced i.e. number of stations is already known and operation time at each station is also known.
9. There is no absenteeism of operators, i.e., all operators are available all time of shift on assembly line.
10. For deterministic case, the operation time of a product is known for all operators but for the stochastic model it is generated randomly using distribution.

3.3 Notations

3.3.1 Indices

j	operators	$j = 1, 2, 3 \cdots m$
k	products	$k = 1, 2, 3 \cdots q$
i	operation	$i = 1, 2, 3 \cdots n$
c	chromosome	$c = 1, 2, 3 \cdots u$
o	objective	$o = 1, 2, 3 \cdots z$

3.3.2 Parameters

AC_k	actual cycle time of product "k"
PC_k	planned cycle time of product "k"
t_{ki}	standard time of product "k" at operation "i"
τ_{ijk}	actual time taken by operator "j" at operation "i" of product "k"
HP_i	average power of machine at operation "i"
C	total labor and energy cost
δ	fluctuation in cycle time
AT_k	available production time for product "k"
$CR_{j,j'}$	coordination rating between operator "j" and consecutive operator "j'"
R_{ijk}	relative skill level of operator "j" at operation "i" of products "k"
σ^2	deviation in skill level of operators
ρ	throughput
U	cost of one unit of electricity in kilowatt hours
α_{ijk}	absolute skill level of operator "j" at operation "i" of product "k"
R_{ijk}	relative skill level of operator "j" at operation "i" of product "k"
TC_k	theoretical cycle time of product "k"
f_c	fitness function value of chromosome "c"
PR_j	performance rating of operator "j"
CH_{jk}	labor cost per hour of operator "j" for product "k"
D_k	demand for product "k"
ϕ	percentage fatigue allowance
TW	teamwork
ETC_k	expected theoretical cycle time of product "k"
AAC_k	actual achieved cycle time of product "k"
LF_c	lineraized function value of chromosome "c"
OF	final single objective function
w_o	weight of objective function "o"
BHT_{ki}	bundle handling time of product "k" at operation "i"

3.3.3 Decision Variables

$$Y_{ijk} = \left\{ \begin{array}{ll} 1 & \textit{if worker "j" is assigned an operation "i" of product "k"} \\ 0 & \textit{otherwise} \end{array} \right\}$$

3.3.4 Objective functions

This problem consists of five objectives namely cost, fluctuation in cycle time, throughput, teamwork and deviation in skill level of operators. There are two types of costs. The labor cost and the energy cost, the energy cost is measured by the electricity consumed by the machines.

Minimize

$$C = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{q}\left(\frac{\tau_{ijk}}{60}\times CH_{jk} + \left(\frac{HP_i \times \tau_{ijk}}{1000}\right)\times U\right)\times D_k \times y_{ijk} \quad (1)$$

Equation (1) is the cost function, this objective is the modified form of Sethanan and Pitakaso [13] objective in which cost of energy consumed by different machines in assembly line is added [4].

This model involves the three cycle times : The planned cycle time, theoretical cycle time and actual cycle time of assembly lines. Planned cycle time has been defined by Aziz et al. [1] in Equation (2).

$$PC_k = \frac{AT_k}{D_k} \quad (2)$$

The theoretical cycle time of any assembly line for each product type is given in Equation (3).

$$TC_k = Max\{t_{ki}, t_{k,i+1}, \cdots\cdots\cdots\cdots t_{kn}\} \quad \forall_k \quad (3)$$

In assembly lines if planned cycle time is less than or equal to the theoretical cycle time then demand is fulfilled.

$$ETC_k = Min\{PC_k, TC_k\} \quad (4)$$

Equation (4) shows the expected theoretical cycle time.

$$AC_k = Max\{(\tau_{ijk}, \tau_{i+1,jk} \cdots\cdots\cdots\cdots \tau_{nmq}) \times Y_{ijk}\} \quad \forall_k \quad (5)$$

The actual cycle time of real assembly line is given in Equation (5). The assembly line is restricted to follow the planned cycle time, although the actual cycle time deviates from the theoretical due to the human labor. Equation (6) shows the actual achieved cycle time.

$$AAC_k = Min\{PC_k, AC_k\} \tag{6}$$

The fluctuation in cycle time of assembly line is measured in term of the deviation of actual achieved cycle time from expected theoretical cycle time. Equation (7) shows the fluctuation in cycle time which need to be minimized.

Minimize

$$\delta = \begin{Bmatrix} \left(\overline{(AAC_k - ETC_k)}\right) & AAC_k - ETC_k > 0 \\ 0 & AAT_k - ETC_k < 0 \end{Bmatrix} \tag{7}$$

Equation (8) shows the throughput of production system which is defined as the output per unit time.

$$Maximize \qquad \rho = \overline{\left(\frac{1}{AC_k} \times AT_k\right)} \tag{8}$$

Teamwork on assembly line is measured with the help of coordination matrix which is developed by the line supervisor. In this matrix each operator is rated on the basis of relation with each other. The teamwork is an important objective in human resource management which is shown in Equation (9).

$$Maximize \qquad TW = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{p} Y_{ijk} \times CR_{j,j'} \tag{9}$$

The absolute skill level is the simply ratio of actual operational time of operator to the standard operational time. The Equation (10) shows the absolute skill level of operators.

$$\alpha_{ijk} = \frac{\tau_{ijk} \times Y_{ijk}}{t_{ijk}} \times 100 \tag{10}$$

The skill level of an operator is measured relative to the other operators. Therefore, the relative skill level of each operator is calculated using Equation (11).

$$R_{ijk} = \frac{\alpha_{ijk}}{\sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{q} \alpha_{ijk}} \tag{11}$$

Equation (12) is the desired objective of minimization for the deviation in skill level of operators.

$$Minimize \qquad \sigma^2 = \sum_{i=1}^{n}\sum_{j=1}^{m}\sum_{k=1}^{q}\left(\frac{R_{ijk} - \overline{(R_{ijk})}}{m-1}\right) \tag{12}$$

3.3.5 Constraints

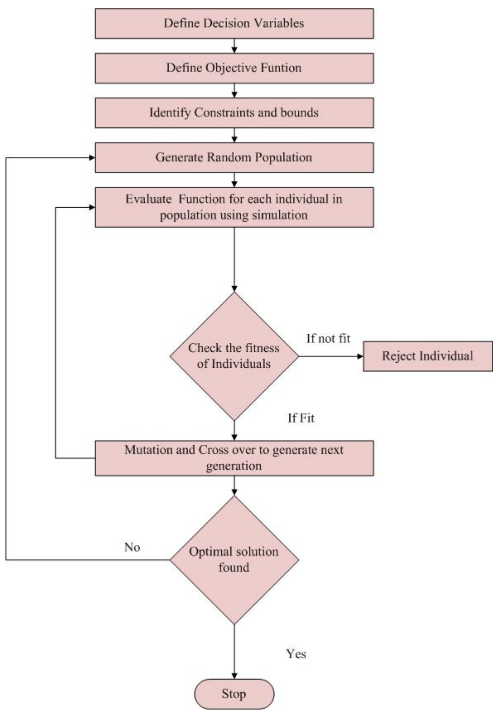
$$\sum_{i=1}^{n} Y_{ijk} = 1 \qquad \forall_k; \forall_j \tag{13}$$

$$\sum_{j=1}^{n} Y_{ijk} = 1 \qquad \forall_k; \forall_i \tag{14}$$

Constraint in Equation (13) shows that each operation is assigned to only one operator and constraint in Equation (14) indicates that one operator can perform one task at a time.

4. Multi-Objective Simulation Integrated Hybrid Genetic Algorithm(MO-SHGA)

In traditional multi-objective algorithm the population is evaluated using mathematical function [5]. However, the multi objective simulation integrated hybrid genetic algorithm is the modified form of multi objective genetic algorithm. In this approach each chromosome or individual is the treated as a simulation scenario and objective functions is evaluated using simulation. <Figure 1> shows the simulation integrated hybrid genetic Algorithm (SHGA) introduced by Imran et al. [6] for cellular manufacturing system for single objective function but this model is the modified version of SHGA which incorporates multi objectives.



<Figure 1> SHGA(Source : Imran et al.[5])

4.1 The Proposed Multi-Objective Approach for MO-GA and MO-SHGA

The proposed multi objective approach is modified form of genetic algorithm in which multiple objectives are converted to a single objective at population evaluation stage. The traditional multi objective algorithm evaluates all functions separately and generates a set of solution called Pareto front. In traditional multi objective problem, the objective to be maximized is changed into minimization objective by changing its sign, but the proposed methodology uses the probability for conversion of the maximization problem into minimization. The fitness value of each individual in a population is computed using equation (15).

$$LF_c = \begin{Bmatrix} \dfrac{f_c}{\sum_{c=1}^{u} f_c} \quad for\ Minimization \\ 1 - \dfrac{f_c}{\sum_{c=1}^{u} f_c} \quad for\ Minimization \end{Bmatrix} \tag{15}$$

and

$LF_c \leq 1$

The importance of each objective can also be defined in the proposed approach. Equation (16) converts the multi objective into single one.

$$OF = \sum_{o=1}^{z} w_o \times LF_c \tag{16}$$

4.2 Model Behavior

The developed mathematical model is analyzed and optimized for two types of behaviors, the deterministic and the stochastic behavior of assembly line.

4.2.1 Deterministic Behavior

In the deterministic behavior all input data is known. The standard operation time of an operation "*i*" of a product "*k*" is computed using equation (17-18)

$$BM_{ijk} = \overline{\tau_{ijk}} \times PR_j \tag{17}$$

The low skilled operator's performance is less than 100 %, while operators with 100% rating have marginal skill level. The performance rating of more than 100% is considered as highly skilled operators.

$$t_{ki} = BM_{ijk}(1+\phi) + BHT_{ki} \tag{18}$$

The nature of operation decides the fatigue level of operators. Gilbreth and Kent [3] suggested a fatigue allowance of 12~15% for normal operations. Bundle handling time also varies operator to operator there it is also included in standard time calculation.

4.2.2 Stochastic Behavior

The collected data is analyzed statically and it is found that process time follows the uniform distribution for each operation performed by any operator. Therefore, for stochastic behavior the operation time taken by each operator is generated using uniform distribution with the following formula.

$$\tau_{ijk} = a + v(b-a) \tag{19}$$

Where "*a*" is the minimum time taken by operator "*j*" on operation "*i*" and "*b*" is the maximum time and "*v*" is random number between zero and one.

4.3 Numerical Example

The data for this numerical example is collected from goalkeeping gloves manufacturing company. Assembly processes of goalkeeping loves consist of seven operations. One operator can operate only one machine, number of available operator is equal to number of operations. Available operators have different skill levels; their skill level also varies operation wise. Also, due to variability in skill level energy consumption by machine also increases as they take different time from standard time of operations. The few operators do not have good relationship with each other so when they are assigned together on consecutive operations that causes disturbance for all other operators. Company is interested in job assignment of operator on assembly line in order to achieve minimum fluctuation in cycle time, maximum throughput, minimum energy and labor cost, minimum deviation in skill level of operators working on the assembly line with highest level of team work among the operators. Demand of each part type from customers is 677,500,345, and 765 units respectively. "*k* = *1*" is to be delivered first then "*k* = *2*" and "*k* = *3*" and so on. Planned lead time for each type of products is five days. Electricity cost per kilowatt-hour is 0.86 $ and power of each machine is 500 Watt. Coordination matrix between operators is given below highest level of coordination scores 10 and minimum score is 0. <Table 1> is coordination matrix which is filled by line supervisor of assembly line of company. Standard time for each operation of each products type is given in <Table 2>. <Table 3> shows the actual time taken by each operator on each operation of all products.

<Table 1> Coordination Matrix

Operators	$j'=1$	$j'=2$	$j'=3$	$j'=4$	$j'=5$	$j'=6$	$j'=7$
$j=1$	0	9	7	9	10	9	6
$j=2$	9	0	6	5	9	5	4
$j=3$	7	6	0	8	8	3	10
$j=4$	9	5	8	0	7	6	9
$j=5$	10	9	8	7	0	7	6
$j=6$	9	5	3	6	7	0	8
$j=7$	6	4	10	9	6	8	0

<Table 2> Standard Operation Time of Each Product

Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	2.590	3.030	3.580	3.220	3.680	3.850	1.530
2	$k=2$	2.650	2.990	3.205	3.650	4.200	3.978	1.823
3	$k=3$	2.330	2.540	2.998	3.760	3.740	3.806	1.754
4	$k=4$	2.986	3.320	2.564	3.245	4.100	3.212	1.897

<Table 3> Actual Operation Times Taken by Each Operator on Each Product

$j=1$								
Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	2.876	3.400	3.654	3.390	3.680	4.200	1.632
2	$k=2$	2.730	3.300	3.120	3.760	4.340	4.000	1.867
3	$k=3$	2.330	2.980	3.000	3.890	4.000	3.760	1.967
4	$k=4$	3.000	3.320	2.564	3.450	4.100	3.321	1.897
$j=2$								
Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	2.876	3.400	3.654	3.390	3.680	4.200	1.632
2	$k=2$	2.730	3.300	3.120	3.760	4.340	4.000	1.867
3	$k=3$	2.330	2.980	3.000	3.890	4.000	3.760	1.967
4	$k=4$	3.000	3.320	2.564	3.450	4.100	3.321	1.897
$j=3$								
Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	3.000	4.000	4.220	3.780	3.454	3.914	1.650
2	$k=2$	2.635	2.456	2.000	3.290	3.500	3.780	2.876
3	$k=3$	3.000	2.765	3.245	4.321	3.000	2.350	2.000
4	$k=4$	2.789	3.975	2.675	4.340	4.230	3.230	1.876
$j=4$								
Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	2.560	4.120	3.998	3.396	3.723	4.000	1.675
2	$k=2$	2.897	3.000	3.335	3.700	3.200	3.978	2.000
3	$k=3$	2.270	3.250	3.000	4.000	4.100	3.654	1.754
4	$k=4$	3.100	3.360	2.680	4.430	4.520	3.453	2.120
$j=5$								
Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	3.000	3.390	3.678	4.200	3.890	3.560	1.870
2	$k=2$	2.987	3.230	3.345	3.760	4.210	4.000	2.100
3	$k=3$	2.598	2.590	3.000	4.120	3.250	3.987	1.997
4	$k=4$	3.000	2.3756	2.987	3.065	4.540	3.346	2.200
$j=6$								
Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	2.786	3.100	3.458	3.214	4.000	3.377	1.543
2	$k=2$	2.687	2.540	2.098	4.100	4.123	4.100	1.500
3	$k=3$	2.360	3.000	3.120	4.000	3.987	4.100	1.876
4	$k=4$	3.000	3.267	2.675	3.320	3.675	3.212	1.897
$j=7$								
Sr #	Products	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
1	$k=1$	3.000	3.200	4.000	3.765	3.879	4.312	1.764
2	$k=2$	2.987	3.000	3.457	4.130	4.320	4.420	2.000
3	$k=3$	3.120	3.100	3.221	3.897	3.880	3.987	1.987
4	$k=4$	3.000	3.570	3.120	3.543	4.340	3.243	1.456

5. Results and Discussion

Two cases of a numerical problem have been solved. First the numerical example is solved using multi objective GA with stochastic and deterministic data. GA converged at 33rd generation for deterministic data and it stopped at 45th generation for stochastic data. Secondly, the same problem is solved using Multi objective SHGA. SHGA-deterministic converged at 25th generation and SHGA-stochastic provided an optimal value at 55th generation.

5.1 CASE I : Deterministic Multi-Objective Simulation Integrated Hybrid Genetic Algorithm (MO-SHGA)

In this case above problem is solved using deterministic data. To solve problem using GA or SHGA we need a genetic representation as shown in <Table 4>. Chromosome 2135476 as shown in <Table 4> means operator number two should be assigned operation "$i = 1$", operator 1, operation "$i = 2$" and so on. Following steps are adopted to solve this problem using SHGA.

1. Settings for SHGA are as follows :
   Population size : 10 Chromosomes; Elitism : 20%; Cross over probability : 0.6; Mutation Probability : 0.2; Selection Method : Stochastic Sampling; Termination Criteria : Repetition of same elite in successive ten generations
2. Random initial population generation
3. Linearization of multi objectives using Equation (15).
4. Evaluation of initial generation using simulation.
5. New generation creation after Elitism, selection, cross over and mutation.
6. Repeat the steps 4 & 5 until termination condition with minimum "*OF*" value.

5.2 CASE-II : Stochastic Multi-Objective Simulation Integrated Hybrid Genetic Algorithm (MO-SHGA)

In stochastic modeling operation times of each operation is uniformly distributed with ± 3 minutes of standard operation time for all operations and each operator has his/her own minimum and maximum time of an operation. To solve this problem same procedure is followed as explained in section 3.3. Both cases of this problem are solved using Microsoft Excel 2013 spread sheet programming with personal computer (PC) with Core™ 2 Duo CPU 3.17GHz processor and 3GB RAM. <Table 5> shows the results and it is clear that fluctuation in cycle time is greatly reduced in SHGA-stochastic setting, this is because of integration of simulation with genetic algorithm. However, in multi-objective genetic algorithm data is not in simulation environment. Therefore, the results may not be realistic ones.

6. Conclusions

This paper presented a multi objective problem of job assignment to manual assembly line. The objectives of the problem are fluctuation in cycle time, throughput and cost (labor, energy). This model also considers two most important human resource objectives such as team work and deviation in skill level of operators which are not paid attention in assignment problems so far. To achieve these objectives a mathematical model is developed. The data for model is collected from goal keeping gloves manufacturing industry. The model is solved by using simulation based hybrid genetic algorithm and Multi objective genetic algorithm. Both algorithms are used for two cases, one for deterministic

<Table 4> Genetic Representation of Chromosome

Operation	$i=1$	$i=2$	$i=3$	$i=4$	$i=5$	$i=6$	$i=7$
Operators	2	1	3	5	4	7	6

<Table 5> Results of Numerical Example

Algorithms	Best individual	Objective Functions				
		Fluctuation in cycle time	Cost	Throughput	Team work	Deviation in Skill level
MOGA Deterministic	2 7 5 1 6 4 3	0.0829	4744068	609	43	21.18
MOGA-Stochastic	1 2 4 7 6 3 5	0.0205	4542624	626	46	21.88
SHGA-Deterministic	2 7 5 1 6 4 3	0.0721	4744068	614	43	21.18
SHGA-Stochastic	1 2 4 7 3 5 6	0.0029	441139.0	624	48	19.58

data and second for stochastic data. Deterministic cases of MO-GA and MO-SHGA are compared with each other and stochastic cases of MO-GA and MO-SHGA are compared with each other and results proved that Stochastic Simulation based hybrid Genetic algorithm provide better results than traditional multi objective algorithm because of dynamic nature of simulation introduced in genetic algorithm while traditional analytical method has stationary behavior so accurate fluctuation in cycle time and throughput is difficult to measure. The results provided by SHGA-stochastic provided minimum fluctuation in cycle time, cost, and deviation in skill level of operators and maximum throughput with highest level of team work. The SHGA is strongly recommended for those performance measures which cannot be measured with analytical formulas. Future work may include an integrated model of job sequencing and job assignment for manual assembly line.

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