Development of Hybrid Simulation and Genetic Algorithms System for Solving Complex Crew Allocation Problems

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ABSTRACT: This paper presents an innovative approach to solving complex crew allocation problems in any labour-intensive industry. This has been achieved by combining simulation with Genetic Algorithm (GA). The integrated system determines the least costly and most productive crews to be allocated on any production processes. Discrete Event Simulation methodology is used to simulate a manufacturing system. A special PROCESS module is developed to overcome limitation of the used simulation software that appears when using normal PROCESS module. A concept of multi-layer chromosome is proposed to store different data sets in multi-layers structure. GA operators were developed to suit such chromosome structure. As a case study, a sleeper precast manufacturing system is chosen to prove the concept of the proposed allocation system. The results showed that adopting Manipulating a number of multi-skilled workers to be allocated among different production processes had a substantial impact on reducing total allocation cost, process-waiting time, and optimising resource utilisation. 3D visualisation is presented.

1 INTRODUCTION

Labour-Intensive Industry requires a substantial number of skilled and semi-skilled labourers to produce industrial products. Labour costs in this industry which are considered as a measure of the economic value of an employee's skill set are increasing rapidly due to high demand on skilled workers and inefficient allocation of them. At present, in most labour-driven process, production managers play a vital role in producing the allocation plan, which is done manually or using simple spreadsheet. The crew allocation problem appears when there is more than one crew of workers ready to be assigned on a process. The second issue is the resulting delay time (waiting time caused by shared labourers of different crews to carry out same job at the same time) which shared workers of a particular crew would cause while being involved in working with another crew on a different process. Crew allocation is hard to manage due to its complexity, especially when it involves huge combinations of crews to carry out jobs in a labour-intensive manufacturing system.

More systematic allocation systems are required to model the distribution and allocation of the skilled worker each according to his expertise. Modelling complexity of different manufacturing systems appears when its systems are having large scale size or a number of repetitive processes besides the combination of working crews. Several different optimisation methods could be used for this purpose, however; genetic algorithms have become one of the most popular search engines. In this paper, a simulation-based Genetic Algorithms model dubbed "SIM_Crew" is developed to serve as a test bed for evaluating the effectiveness and robustness of different crew allocation plans. The remainder of this paper is arranged as follows. In the next section, related work on crew allocation techniques is reviewed. Section 3 addresses the crew allocation system module. Section 4 presents experimentation and computational results followed by results discussion and interpretation. Last section is about conclusions and future investigation.

2 RELATED WORK ON CREW ALLOCATION TECHNIQUES

Several research projects using innovative tools to improve the performance of the precast concrete product manufacturing systems have been conducted: Dohn, et al. 2009 developed an integer programming model for the manpower allocation problem with time windows. Lu, et. al., (2008) presented a computer system called simplified simulation-based scheduling (S3) to solve the problem of skilled labourer scheduling in a multi-project context.

Wang, K., et al. 2007 developed an intelligent resource allocation model using genetic algorithm and fuzzy inference for reducing lateness of orders with specific due dates. Shibghatullah, A. S. et al. 2006 proposed a conceptual framework for developing a bus crew scheduling management system based on Multi Agents System (MAS) paradigm.

Zhang H., et al 2004 developed an optimisation methodology which integrates discrete-event simulation with a heuristic algorithm to optimise dynamic resource allocation for construction scheduling. Orsoni, A. 2004 developed a Decision Support System (DSS) to optimize resources allocation to workgroups in labor intensive industrial and business contexts. Suryadi, H., et al. 2004 described an optimisation-based approach integrating efficiently design, production planning and maintenance models. Guttkuhn R. et al (2003) introduced a discrete event simulation for crew assignment and crew movements integrating train traffic, labour rules, government regulations and optional crew schedules.

Lagerholm, M., et al. 1997 used Potts feedback neural network approach to find good solutions for the airline crew scheduling problems resembling real-world situations. Patel, V. 1997 developed a solution methodology and a software program system for assignment of dual resources (Machines and Workers). An optimized GA based heuristic was developed to solve both dual resource constrained problems. Kataoka, K., et al. 1992 discussed a railway crew allocation problem and proposed a multi-layer gathering model based on the knowledge-based approach to support schedulers on the computer.

3 AN OVERVIEW OF THE CREW ALLOCATION SYSTEM MODULES

The designed crew allocation system in this work consists of four modules, each of them are desgined to be significantly integrated with other modules for a better performance. These modules were: database, simulation, optimisation, and visualisation modules. See figure 1 for the SIM_Crew modules.

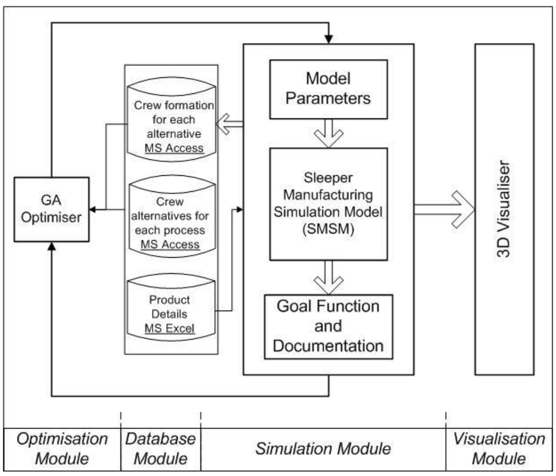

Figure 1: SIM_Crew modules

All those modules are integrated together to form an innovative allocation system. Each of those modules has the ability to support other modules with the required inputs, logic, or decision.

3.1 *Simulation Module*

Simulation and especially Discrete Event Simulation (DES) is used to simulate labour-intensive production processes. All steps and logic details behind constructing the simulation model are developed and prepared. In conjunction with an optimisation module, a simulation model can be thought of as a mechanism that turns input parameters to output performance measures. (Law, A. M. et al. 1991)

It has been noticed that placing of all resources into the current process module, then setting each of them to follow a specific shift pattern trapped the process into an infinite loop. In addition, the PREEMPT shifting rule is the cause of another limitation as this rule was not designed to deal with a Seize module which has seized a number of processes.

This sort of limitation has caused the overflow of the scheduled utilisation to be greater than 1 when designing one or more than working shifts. See figure 2 for the limitation cause of the used simulation software

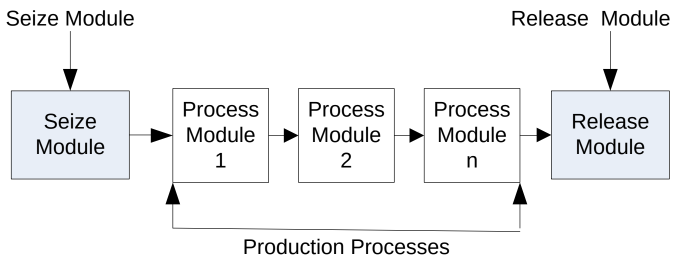

Figure 2: the main cause of shift limitation

3.1.1 The Software Limitation and Development

To overcome this limitaion, a special process model is designed to include more than a resource pool; each resource pool has its own shift calendar. The day shift workers will be placed into the first workers pool and the night shift workers will be allocated into the second shift workers pool and so on. Figure 3 shows the developed TEMPLATE SPECIAL PROCESS module to suit such modeling requirements

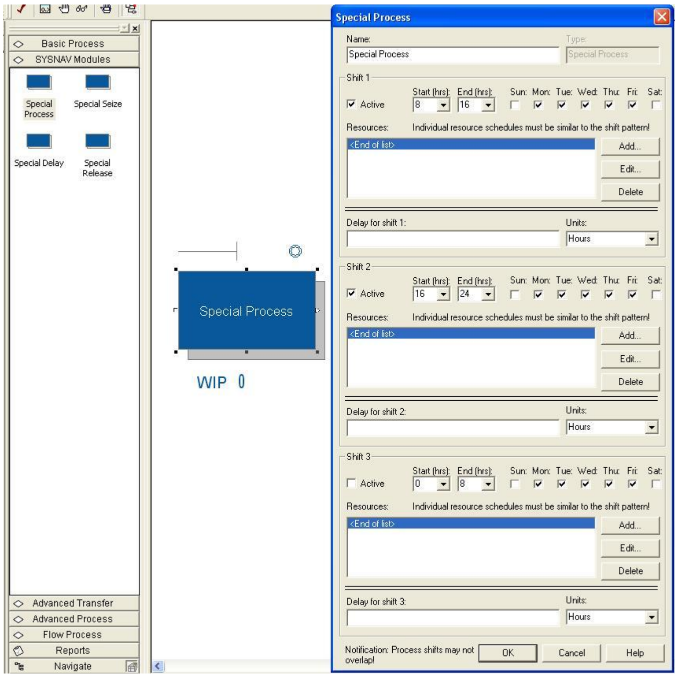

Figure 3: Snapshot of the developed SPECIAL PRCOESS module

3.2 Database Module

The allocation system "SIM_Crew" is designed to be integrated with several different databases. This integration is necessary to retrieve inputs and generate outputs while evolving solutions. Many databases are integrated with the allocation system, some of them used to provide the simulation model with the required inputs, and other databases are used to support the optimisation engine with the required information. For verification purposes, other files are used to accommodate the resulting Genetic Algorithm operators' results. See figure 4 for database integration with SIM_Crew

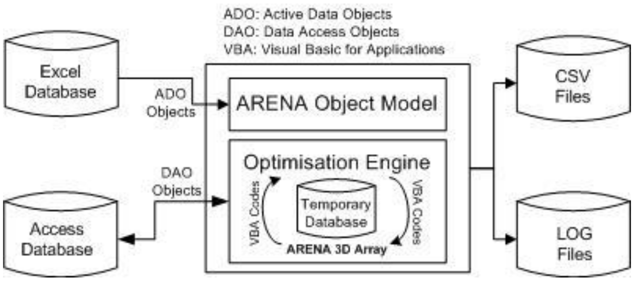

Figure 4: SIM_Crew Database Architecture

The databases can be accessed via Data Access Objects (DAO) or ActiveX Data Objects (ADO). These objects represent the structure of the database and the data it contains. Visual Basic for Applications (VBA) exploits all integration capabilities of automation and it runs within the application. VBA is similar to other Microsoft programming languages included in desktop applications that support ActiveX Automation. With the database integration, the simulation output can be written back to the database. This output can be then customarily formatted and presented to the user to fit their specific analysis perspectives. (Kulvatunyou, B. et al 2001)

3.3 Optimisation Module

Optimisation is needed to orchestrate the simulation of a sequence of system configurations (each configuration corresponds to particular setting of the decision variables). Meta-heuristic algorithms are necessary especially when the system is complex enough to investigate. Meta-heuristic can be defined as a master strategy that guides subordinate models to locate high quality solutions. Further, a meta-heuristic algorithm may employ a single solution or a population of solutions (Hill, R. H. et al. 2001).

Meta-heuristic algorithms such as Genetic Algorithms (GAs) can be used to iteratively generate new and improved sets of allocation scenarios based on the performance estimates provided by the simulator.

3.3.1 Genetic Algorithms

Genetic Algorithm starts with repeating the genetic cycle of manipulating chromosomes from initial random population of chromosomes to generate new generations consisting of "fit" offspring. In the proposed GA algorithm, an initial population is generated using Monte Carlo (MC) sampling technique as a starting solution; decimal coding is applied to suite crew index number (1,…n) where n is number of crew alternatives. Then each individual is evaluated using the simulation engine, the evaluation criterion is an objective function. At the end of each generation, all objective function results should be sorted in an ascending order as costs should be placed at the top of objective function values for further selection. If the convergence condition is satisfied then the required results are obtaine. The process stops when convergence happens. If not, reproduction process is started by preparing the minimum cost from the population size used as next generation starting solution. As a selection strategy, a "Class Interval" selection rule is developed to give a higher chance for promising chromosomes (with minimum costs) to be selected. Each selected pair of chromosomes is then crossed-over to exchange genes between the selected chromosomes. For more randomness, mutation is applied to the crossed-over chromosomes as this process continues until a unique chromosome is obtained.

3.3.2 Chromosome Encoding and Fitness Function

Chromosome can be defined as a vector with a predefined set of inputs. These inputs involve decision variables which are placed in the chromosome.This chromosome has a number of elements (genes) representing the number of variables. A chromosome structure has been designed to suite this type of problem. Figure 5 shows the designed chromosome for crew allocation purposes.

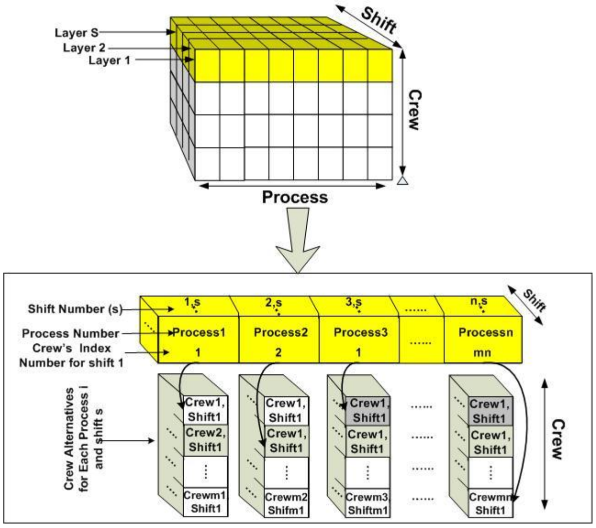

Figure 5: multi-layer chromosome representation for crew allocation problem

In figure 5, each integer number of each gene would give the crew index number of the set of crew alternatives associated with that gene. i.e, this number would give the index of a crew that would be used in the solution. Each gene has different possible alternatives of crews to be used in the solution. A chromosome is encoded in a decimal way. The chromosome length is representing the maximum number of processes involved in any labour-driven production facility.

The decision variables are the number of sets of crews available to allocate on each process. To evaluate each chromosome, a single objective function has been identified and adopted to minimise the labour costs. Many restrictions can be determined which limits production amounts, crew's alternatives, and operational hours (shifts). Initial population can be generated using Monte-Carlo (MC) sampling technique.

The objective function is applied to evaluate the total resources cost. The equation used to calculate such objective function is:

$$f(x_i) = \sum_{i=1}^{n} BRC_i + IRC_i + RCPU_i \qquad (1)$$

Where: n is the number of labour-driven processes; BRC_i is the busy resource cost for set of solution i; IRC_i is the idle resource cost for set of solution i; and $RCPU_i$ is the resource cost per use for set of solution i

As an initial starting point, a population of random solutions (chromosomes) is generated randomly using Monte-Carlo sampling. As one of the random sampling techniques, Monte Carlo is used to select crew alternative for each gene (i.e process). This integer random number is generated for each gene to select randomly the crew's alternative for each process.

In the present model, the user is given the flexibility to input the population size. Once the population is generated, the objective function of each chromosome in this population is evaluated by processing the chromosome into the simulation model, assigning the crew numbers associated with the chromosome to the simulated processes, running the simulation model and obtaining the output costs of labour of that chromosome. GA operators are developed to suite this type of allocation problems. Class Interval selection, Dynamic Probabilistic Crossover, and Mutation Probabilistic Strategies are explained in details as follow:

3.3.3 The Proposed Class Interval Selection Strategy (CISS)

In this proposed selection strategy, the promising chromosomes with least costs will be given a higher chance to be selected. The proposed selection strategy is named class interval strategy. It is developed to provide the promising chromosomes with more chance of selection. The idea is based on the class interval concept which is used in the descriptive statistics. The top of the minimum costs chromosome will be given higher weights than others by calculating the fitness function of each chromosome according to equation (2).

$$Gx_i = Max - f(x_i) \qquad (2)$$

Where: Gx_i: Fitness function of chromosome i; $f(x_i)$: Sorted objective function for top promising chromosomes; Max: The largest cost value in the best promising chromosomes; and m: is the population size

Repetition of any generated chromosome is not allowed as a condition is imposed to violate this repetition, so all generated chromosomes should be unique all over the evolution process. Then as a requirement to construct the chromosome's class interval, a relative fitness function RGx_i is calculated using equation 3.

$$RGx_i = \frac{Gx_i}{\sum_{i=1}^{m} Gx_i} \qquad (3)$$

Where: RGx_i: Relative fitness function of chromosome i.

Cummulative relative fitness function is then calculated as it is useful to determine the desired class width using equation 4.

$$CRGx_i = CRGx_{i-1} + RGx_i \qquad (4)$$

Where: $CRGx_i$: Cumulative Relative fitness function of chromosome i.

Then, the possible interval of occurance for each chromosome is determined in terms of class intervals. The interval associated for each chromosome will represent the chance range of that chromosome to be selected by any generated (0-1) random variate. See figure 6

3.3.4 Probabilistic Dynamic Crossover (PDC) & Mutation (PDM) Strategies

The crossover operation in a conventional GA is based on the exchange of genes between two fixed length chromosomes when coding is applied for chromosomes. To crossver genes in the chromosome, (0-1) variates should be generated for each gene in the multi-layer chromosome. This type of exploration will investigate all active genes (genes occupied by scheduled crew with a shift) for more randomness. A random number is then generated to exchange genes after satisfying a certain condition.

This condition satisfy if the generated random variate is less than or equal to a given probability. In this strategy, random numbers are generated to be attached for each gene at each layer; if the gene is not vacent for a reason then the generated random number will be discarded to skip to the next gene. PDC is developed to achieve the best random exchanging of genes between each pair of chromosomes within a multi-layer chromosome. See figure 6 for PDC strategy. To avoid local maxima and to randomise the searching process, a modified mutation process is developed to swap the gene within a chromosome with its available set of alternatives. In this strategy, (0-1) random variates are generated to be associated with each gene of the chromosome; random variates for vacant genes will be discarded. See figure 6 for the developed probabilistic dynamic crossover

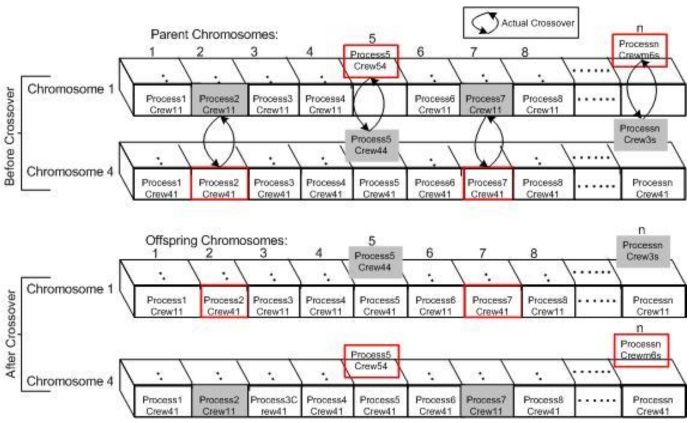

Figure 6: Probabilistic Dynamic Crossover strategy

In PDC, the (0-1) generated random numbers are generated to be associated with each gene at each layer, random number is discarded when gene is vacant (no shift applied to a crew). The probability of crossover can decide how many genes can be swapped with the opposite chromosomes' genes.

Monte Carlo (MC) sampling is then applied to search stochastically for a crew within each assigned pool of crews. See figure 7 for PDM strategy

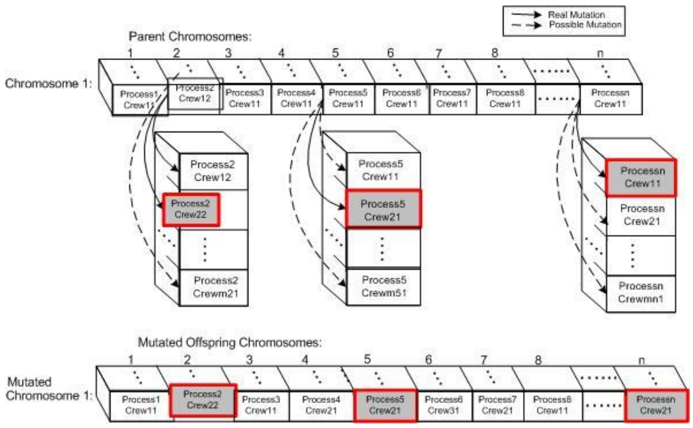

Figure 7: Probabilistic Dynamic Mutation strategy

The selected genes can be mutated with its crew pool "crew's alternative list" using Monte-Carlo sampling.

How Does SIM_Crew Work

The combination of simulation and optimisation can be defined as the process of finding the best set of input variables without evaluating each possibility (Molnár, B. 2004).In the proposed allocation system, the optimisation module is composed of five main processes: initilisation (creating the first generation), evaluation (determining chance of surviving), reproduction (producing offspring), crossover (exchanging chromosomes inherited from parents), and mutation (alternation of genetics encodings inside the chromosomes). See figure 8 for SIM_Crew mechanism

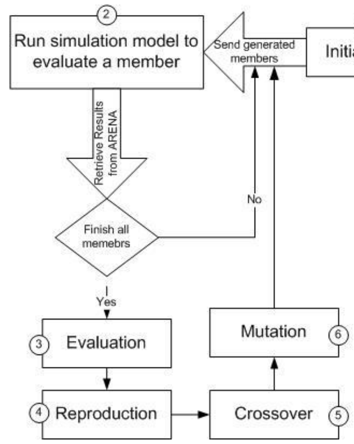

Figure 8: simulation-based GA flowchart

The process of simulation execution starts by evaluating initial generated solutions provided by the initialisation phase, then evaluation, reproduction, crossover, and mutation are repeated until no improvements for two consecutive generations is achieved. The results from all generations are stored in Access database and arranged in a table sorted by objective function, to derive the optimum solution according to GA.

3.3.5 Visualisation Module

The 3D visualisation of the labour-intensive manufacturing system is developed using ARENA 3D player. 3D simulation can be used in all these steps as a communication tool to convey the idea of how a production works and how it performs to avoid costly mistakes as early as possible (Ref: Anttila, M. 2005). Figure 9 shows the 3D visualisation of the manufacturing system.

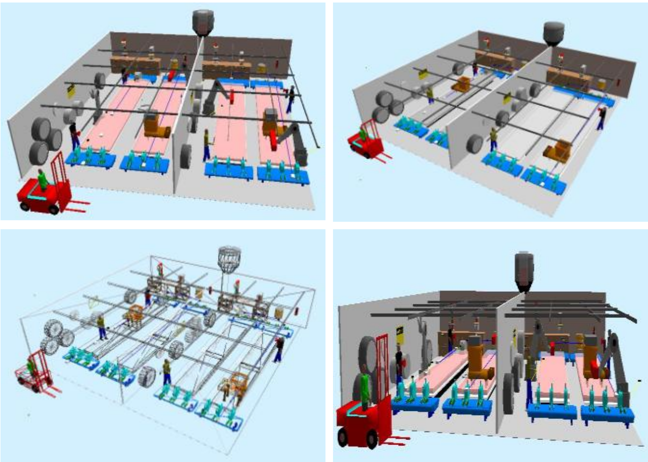

Figure 9: snapshots of the 3D animation of the manufacturing system

4 EXPERIMENTATIONS AND COMPUTATIONAL RESULTS

A case study is used to test and validate the concept of the proposed allocation system. This case study was carried out in one of the major UK precast concrete products manufacturing company. The simulation model is developed after conducting a comprehensive study of the precast manufacturing system.

The simulated manufacturing system consists of four production lines; each production line has eight production processes, at each a shared resource is used.

The developed model is used to allocate possible available crews of workers to production processes, simulate two working shifts, and identify the performance of labour and other related measurements.

The experimental part involves allocating possible crew alternatives available for each production process in order to evaluate allocation cost and optimise both labour utilisation and process-waiting time. In this case study, multi-layers chromosome structure is developed to involve crew alternatives, processes and shift patterns. Two working shifts are accommodated in a multi-layer structure of the developed chromosome. The population size which is found to be stable after 50 generations, (55 were done; each of them had 20 chromosomes). The crossover probability is defined as 0.70 and mutation probability which is defined to be 0.90. Number of processes is defined as 28 processes and 66 resources with two shifts of working at one of the production sections. The stopping condition is satisfied when there is no reduction in the resulting cost for five consecutive generations (100 chromosomes). The best and worst scenario is adopted to compare the resulting key performance criterion obtained using the mentioned scenario and to address some significant relationships between outputs.

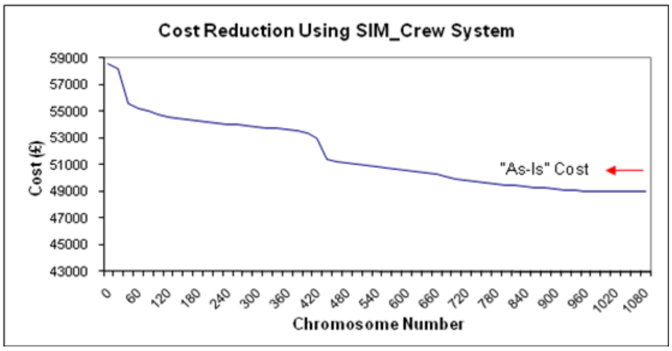

Figure 10: cost reduction using SIM_Crew system

It has been noticed that a significant improvement is achieved in terms of reducing resource allocation cost. GA here shows a significant improvement moving rapidly towards the minimum allocation cost. After 50 generation, no improvement has made in terms of reducing cost and the evolution process is terminated after two consecutive generations with no further improvement. 19% of the “As-Is” allocation cost is saved using the developed allocation system which can be considered as a promising tool to reduced total allocation cost especially in labour-driven production processes. Optimising skilled workers profile was the second concern after allocation cost reduction. The main purpose of such analysis was to identify actual semi skilled workers utilisation profile required to satisfy minimum allocation cost. Best-Worst allocation scenario is adopted for a labour profile utilisaiton balance, See figure 11 for semi-skilled utilisaiton using GA model.

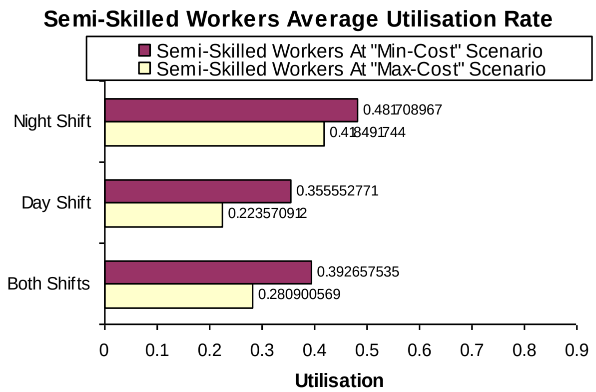

Figure 11: balancing of semi-skilled utilisation profile

In figure 11, best scenario reveals that semi-skilled workers are more required and utilised to carry out jobs for both working shifts. Figure 12 shows the reduction in process-waiting time using worst-best allocation plan scenario

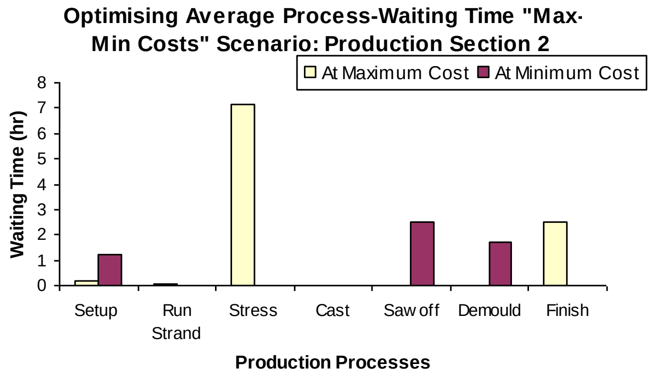

Figure 12: optimising average process waiting time

In figure 12, the resulted average process-time in production section 2 using the proposed allocation system is shown. An average process-waiting time is reduced to guarantee a better flow of work at a particular production section. A better flow of work will diminish worker idle time and subsequently a good work progress can be made.

5 RESULTS DISCUSSION AND INTERPRETATION

The outputs of the SIM_Crew allocation system have been presented in terms of charts as described earlier in section 4. In this section, a detailed interpretation is addressed in order to analyse the behaviour of the outputs. To facilitate the interpretation of results, the behaviour of each output is presented as follows:

GA: In figure 10, a significant cost drops have been noticed after generations 3 and 22. The only interpretation for such behaviour is that the dynamic probabilistic GA operators have found after a while a promising collection of crews for both working shifts which drove the allocation cost down. The slight gradual reduction in allocation cost curve is yielded because there is a slight difference in process times among available alternatives of crew

Utilisaiton Profile: figure 11 show that at best scenario, more semi-skilled workers are required and involved to carry out jobs for both shifts. While worst scenario drive allocation cost high because of less dependency on semi-skilled workers and more about skilled ones.

Process-Waiting Time: The significant reduction in stress waiting time was useful to guarantee a better workflow, see figure 12 A setup process waiting-time has enabled avoiding of any casting process-delay time in which minimum clashes occurred among shared workers.

6 CONCLUSION AND FURTHER INVESTIGATION

It has been concluded that the proposed allocation system SIM_Crew proved an ability to produce minimal crew allocation cost. An optimised balance of labour utilisation is achived, and a process-waiting time is minimised to ensure best work flow. The developed simulation-based GA can provide optimal/ near optimal crew allocation plan to any multi-shift labour-intensive industry. The new concept of using GA in crew allocation process and the developed multi-layer chromosome application has been proven as a sophisticated and advanced technique through this case study. As future works, different levels of priority for each production process can be included when designing the chromosome. Multi-Objective optimisation is still worthy to be modeled in solving this type of allocation problem.

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