Journal of Architectural Engineering and Design Management 2016
Special Issue on Offsite Construction

Simulation-Based Optimisation Using Simulated Annealing for Crew Allocation in the Precast Concrete Industry

Abstract
Numerous different combinations of crew alternatives can be deployed within a labour intensive manufacturing industry. This can therefore often generate a large number of possible crew allocation plans. However, inappropriate selection of these allocation plans tends to lead to inefficient manufacturing processes and ultimately higher labour allocation costs. Thus, in order to reduce such costs more sophisticated and innovative allocation systems are required. The main aim of this study is to develop a Simulation-Based Multi-Layered Simulated Annealing ("S_MLSA") system to solve crew allocation problems encountered in labour-intensive parallel repetitive manufacturing processes. The 'Multi-Layered' concept in modelling of crew allocation problems is introduced in response to the problem-solving requirements of different sets of labour inputs such as multi-shifted crews. As part of the methodology used, a process simulation model is developed to mimic a parallel-repetitive processes layout. A Simulated Annealing module is proposed and embedded into the developed process simulation model for a better search for solutions. Also, the Multi-Layered Dynamic Mutation operator is developed to add more randomness to the searching mechanism through the solution space. A real industrial case study data of the precast concrete labour intensive manufacturing systems is used to demonstrate the applicability and practicability of the developed system. From the research findings, the proposed system has the potential to produce more cost effective allocation plans, through reducing process waiting times as compared with real industrial based plans. Also, the main contribution to knowledge is in the application of such innovative systems in the precast concrete industry and the potential impact of reducing production costs and improving process efficiency.

Keywords: Simulated Annealing; Crew Allocation, Parallel Repetitive Processes, Precast concrete Industry, Manufacturing Simulation

Introduction

The precast concrete products industry is labour-intensive in which different skilled labourers are required during the manufacturing process. In this industry, a number of manufacturing system layouts are designed, which involve repetitive parallel production processes. Crews are often required to repeat the same work in different locations of the production facility, moving from one location to another.

Due to the large array of different possible crew allocations to similar parallel or linear repetitive activities of an offsite manufacturing system, this type of allocation is classified as a complex combinatorial problem (Floreza and Castro-Lacoutureb, 2014; Bhoyar and Parbat, 2014). However, the 'classical problem solving' techniques that are widely used in optimising traditional allocation problems cannot be used to obtain optimal solutions for such combinatorial problems (Collet and Rennard, 2007).

Therefore, the lack of appropriate optimisation systems for crew allocations in the precast labour-intensive manufacturing systems suggests the need to develop advanced crew allocation systems. These systems will assist production planners of such manufacturing systems to achieve the most efficient allocation of crews and this will eventually contribute to much reduced labour allocation costs, reducing process-waiting time and subsequently improving the overall productivity.

This study presents an innovative system for crew allocation dubbed "S_MLSA" which is specially developed for the efficient allocation of crews of workers to parallel repetitive labour-driven processes with a focus in the precast concrete industry.

Crew Allocation Problem in the Precast Concrete Parallel Repetitive Processes

A crew allocation problem appears when the formation of any crew involves shared labourers working on parallel or sequential similar/different processes. This type of labour sharing can cause high process-waiting times, low resource utilisations, a disturbed workflow and subsequently high allocation costs. Since a parallel or sequential similar/different processes structure of a manufacturing system is pre-specified, the involvement of shared workers can be required in one or more processes. See Figure 1 for crew allocation in a parallel repetitive processes manufacturing layout:

****

FIGURE 1

****

As presented in Figure 1, the allocation process for a particular operation starts with identifying the minimum requirement of different skilled labourers. A number of crew alternatives are available that can satisfy the minimum labour requirement to work on a process and also provide more than the required output, in terms of providing different types and larger numbers of skilled workers. After selecting the crew of workers, the crew members (crew formation) are recalled from the workers' pool. Delays occur when the worker is required for more than one process at the same time; the status of a utilised worker in the workers pool is an 'engaged' worker. The 'idle' status of the worker can be obtained after releasing him/her from the assigned job back into the pool, at which time the worker can be re-allocated to other operations.

In order to identify the optimal/ near optimal crew allocation plans in repetitive-parallel processes manufacturing systems with reduced allocation cost, an advanced crew allocation system is required. During the allocation process, an objective function is used to evaluate the outcome of applying each allocation plan. The objective function is a mathematical expression that an optimisation procedure uses to select better solutions over poorer solutions (King and Wallace, 2012, pp.61).

Previous Literatures on Crew Allocations in Both Precast Concrete and Construction Industries

In order to reduce waste and improving the quality of construction in a cost-effective manner, offsite manufacturing systems are used as construction components can vary from a complete structure systems or cladding and individual components (Alazzaz and Whyte, 2014). Production of precast components is factory based and follow a well defined manufacturing processes which include intensive crew allocation processes. In this context, the crew allocation problem was investigated by Biruk and Jaśkowski (2008) who used a Petri Nets-based approach to find the optimal project planning and allocation of individual groups of subcontractors to execute repetitive processes. The project duration with a set risk level was the only focus rather than allocation cost. El-Gafy (2006) developed an Ant Colony Optimisation (ACO) algorithm to perform resource allocation in a repetitive activities construction project. This allocation is constrained by the activity precedence, a resource unique skill and multiple resource limitations. Al-Bazi and Dawood (2010b) utilised Process Simulation-based Genetic Algorithms approach to allocate crews of workers to labour-intensive repetitive processes at a precast concrete facility. The crew formation consisted of a number of workers each with multiple skills. Huang and Sun (2009) developed a Genetic Algorithm model for scheduling workgroup-based repetitive or similar activities in a project. Bhoyar and Parbat (2014) presented a new scheduling model for repetitive construction projects with multiple crews. The developed model not only complies with precedence logic and resource crew availability, but also ensures minimum project duration and maximum crew work continuity. However, neither the skills of workers nor the allocation cost is considered. Floreza and Castro-Lacoutureb (2014) proposed a framework for a decision support system to assist contractors in the allocation of crews in labour dependent masonry projects. The activities layout within each masonry project was not of the parallel repetitive type. Nassar (2005) developed a Genetic Algorithm model to optimally assign resources to repetitive construction projects. Although different crew formation options are available for each project activity, only the crew formation size is considered in the optimisation of the overall project duration. Vaziri, Carr and Nozick (2007) developed a solution procedure based on combining Simulation and the Simulated Annealing approach for optimal assignment of resources to tasks when this affects the probability distribution for task duration. Challenges in single-skill labour resource management and scheduling over multiple concurring construction sites are addressed by Lam and Lu (2008).

Although some of the previous works above have shown serious attempts in modelling and solving crew allocation problems in a repetitive-parallel processes environment, the focus of these works was only on optimising project duration, activity scheduling and profitability. However, this work presents a new crew allocation system that optimises costs of resources allocation taking into consideration different crew allocation constraints such as skills of workers, crew formation details and the parallel repetitive layout of manufacturing operations.

Development of the Crew Allocation System: Theoretical Concept

The Architecture of the Crew Allocation System

The “S_MLSA” architecture (Figure 1) comprises a central simulation model, which is integrated with databases, and optimisation (Simulated Annealing) modules such that various possible allocation plans can be generated by simulating the allocation process of crews to production processes (see Figure 2).

****

FIGURE 2

****

The inputs, processes and outputs presented in Figure 2 are introduced and discussed as follows:

- Inputs

The main inputs to the system are: orders (demand) from customers, which includes numbers, sizes, quantities and specifications of precast concrete components, to be produced in each labour-intensive production line at each section; labour information which includes different combinations of crews, workers, crew processing time, and other workers’ related information such as worker skill and costs. The labour information is stored in a relational database using the Structured Query Language (SQL). SQL is a standardised programming language used for managing relational databases. This language enables simulation to access and retrieve these inputs through a developed input integration component. This component is one of the main process components that developed to enable such input integration.

- Process

The core of this module consists of three components; the first component is the process simulation model which is used to mimic the parallel repetitive operations within the manufacturing system. The second component is the 'Simulated Annealing' model that is developed to generate feasible allocation plans, which consist of a set of crews to be allocated to a number of processes. The third component is the input integration module in which inputs defined earlier are provided to the process simulation model. It consists of a number of integration technologies including ActiveX Data Objects (ADO) and Data Access Objects (DAO) technologies.

The process starts by generating and retrieving the formation of each crew from the SQL database for the simulated annealing model in order to generate feasible allocation plans. These plans will then be evaluated by the process simulation model for the purpose of identifying the optimal/ near optimal allocation plan.

The optimisation process is an iterative procedure of progressive improvement in which the proposed Simulated Annealing algorithm generates a feasible allocation plan while the developed process simulation model evaluates the performance of the resultant allocation, and based, on this, the Simulated Annealing algorithm adjusts the decision variables (crew alternatives) and selects the most promising plan. After each iteration, the result of the evaluation in terms of cost and process-waiting time are stored in a database for further analysis.

- Outputs

As shown in Figure 2, a number of key performance indicators such as labour allocation costs, allocation plans for crews, and process-waiting time are considered as outputs. Each set of outputs (possible allocation plan and other key performance indicators) are stored in the SQL database for further analysis. Outputs are designed to identify the most useful key performance indicators that fairly reflect the performance of the developed system. In the next section, solution set representation/ structure and its inputs in terms of Multi-Layered Crew's Vector are discussed.

Solution Set (Multi-Layered Crew's Vector) Representation

A row vector is defined as an ordered collection of n elements, which are called components. In the proposed simulated annealing model different types of decision variables are placed in a multiple rows vector called a Multi-Layered Crew's Vector. The Multi-Layered Crew's Vector has a number of elements (inputs) representing different possible crews of workers based on their shift patterns. A Multi-Layered Crew's Vector structure has been designed to suit this type of problem (Al-Bazi, Dawood and Dean, 2010). Figure 3 shows the proposed vector for the purpose of crew allocation:

****

FIGURE 3

****

In Figure 3, the integer number of each input represents the crew index number of the set of crew alternatives associated with that input. i.e, this number would give the index of a crew that would be used in the solution. Each input has different possible alternatives of crews to be used in the solution. A crew's vector is encoded in a decimal way. The Multi-Layered Crew's Vector length represents the maximum number of processes involved in any labour-driven production facility. The decision variables are the number of sets of crews available to be allocated to each process. To evaluate each crew's vector, a single objective function has been identified and adopted, which minimises the multi-skilled labour allocation costs. Many constraints can be determined which limit production quantities, crew alternatives, and operational hours (shifts).

Objective Function

The objective function below is formulated to evaluate the total resource allocation cost. The costs of physical resources are not considered in this model. Only costs of crews of workers based on their backgrounds/ skills are taken into consideration. The equation used to calculate the objective function is:

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

Where:

n is the number of labour-driven processes

BRC_i is the Busy Resource Cost for allocation i

IRC_i is the Idle Resource Cost for allocation i (this is equivalent to the cost of process waiting time)

$RCPU_i$ is the Resource Cost Per Use for allocation i

The objective function (1) minimises the total resource allocation cost. This cost is the sum of the cost incurred by utilising a resource, loss opportunity cost of not utilising a resource and cost per use which indicates a cost that is incurred once, regardless of the number of units.

Initial Solution Generation

As an initial solution, an individual crew's vector is generated using a random sampling technique. A random sampling technique, 'Monte Carlo', is used to select crew alternatives for each input (i.e process). A random integer number is generated for each input to randomly select the crew alternative for each process. The range of random numbers for each input can be determined using the following constraint:

$$MinCA_{i,s} \leq R_{i,s} \leq MaxCA_{i,s} \quad (2)$$

Where:

$R_{i,s}$ represents a random integer number for each crew's vector i on working shifts

$MinCA_{i,s}$ represents the minimum number of crew alternatives in input i on working shifts

$MaxCA_{i,s}$ represents the maximum number of crew alternatives in input i on working shifts

Constraint 2 ensures that only integer numbers lying between the minimum and maximum number of crew alternatives are generated for the PDM strategy.

Once the individual crew's vector is generated, the objective function is evaluated by processing it into the simulation model, assigning crew numbers associated with this vector to the simulated processes, running the simulation model and obtaining the output costs of labour. The PDM strategy is developed to add the required randomness for the searching process and to suit the type of allocation problem, see the section below for the PDM strategy.

Probabilistic Dynamic Mutation (PDM) Strategy

A PDM strategy is developed to achieve the best random exchanging of inputs for the Multi-Layered Crew's Vector (Al-Bazi, Dawood and Dean, 2010). In this strategy, random variates that are uniformly distributed on the closed interval [0,1] are generated to be attached with each input of the crew's vector. If the input is vacant for a reason then the generated random number will be discarded and attention moves to the next input. A vertical mutation takes place to swap or alternate subsequently n input(s) of the selected crews' vector with its set of alternatives from the multi-layered pool of crews' alternatives after satisfying the condition below:

If the probability of mutating an input is less than or equal to the random number associated with that input then mutation of that input is possible.

The probability of mutation which is equal to the Temperature coefficient 'Temp_Coeff' (explained in the below section) can decide the number of exchanged inputs. Selected inputs can be mutated with their respective 'crew alternatives pool' using Monte-Carlo sampling. This type of mutation strategy can provide an equal chance for all inputs to be exchanged with the opposite alternative inputs. See Figure 4 for the proposed PDM strategy.

****

FIGURE 4

****

Research Methodology

As part of the research methodology, both process simulation technology and simulated annealing approach are used to mimic and then optimise the allocation of crews of workers to parallel-repetitive manufacturing operations.

Process Simulation Modelling: The Modified Decomposition Algorithm

As simulation of the manufacturing system of parallel repetitive production lines is a complex task, therefore, the researchers suggest that dividing this system into a number of sub-systems would make the simulation of each-sub system easier and more manageable. Hence, based on the simulation steps suggested by Banks (1999), a decomposition methodology is introduced to modify/ advance these steps for easier simulation of large-scale systems/ problems.

In using this methodology, a problem is defined and then decomposed into a number of sub-problems in order to facilitate investigation, modelling and analysis of each sub-problem. To produce sub-models, a simulation process of each sub-problem is required. Each sub-problem is then verified to check whether or not the modelling process logic of the sub-problem is conducted correctly. If not, then the simulation process is reviewed and compared with the logic of the sub-problem. After verifying each sub-model individually, a validation process takes place to ensure that the simulated sub-model accurately represents the related part of the real life problem. A validation process is then applied to ensure that the sub-simulation model produces accurate outputs. After verification and validation of each sub-model have been achieved, all simulated sub-problems are combined together to form the whole simulation model. A thorough verification and validation process is used to check whether or not the combined sub-models reflect the entire real world. If not, then each sub-model is reviewed again. Simulation experiments are designed to run by executing the simulation model. All outputs are analysed and interpreted before being documented. See Figure 5:

****

FIGURE 5

****

Simulated Annealing Model Development

Avello, Baesler and Moraga (2004, pp.510) define Simulated Annealing (SA) as 'a meta-heuristic technique that proves to be effective as a solution for a number of problems, amongst them, simulation optimisation problems'. Kirkpatrick, Gelatt and Vecchi (1983) propose that SA form the basis of an optimisation technique to solve combinatorial problems. In addition, Janiak and Lichtenstein (2011, p.23) define SA as 'a random-search technique which exploits an analogy between the way in which a metal cools and freezes into a minimum energy crystalline structure (the annealing process) and the search for a minimum in a more general system". They add that 'it forms the basis of an optimisation technique for combinatorial and other problems'. The temperature term in the simulated annealing is used as a parameter that affects the probability of accepting new solutions. In addition, it controls the level of randomising solution set inputs, which subsequently affects the quality of the new solutions being generated.

Janiak and Lichtenstein (2011, p.23) use an imaginative analogy with a bouncing ball to illustrate the mechanism of finding promising solutions through SA: "SA approaches the global maximisation problem similarly to using a bouncing ball that can bounce over mountains from valley to valley. It begins at a high temperature which enables the ball to make very high bounces and so enabling it to bounce over any mountain to access any valley given enough bounces. As the temperature declines the ball cannot bounce so high and it can also settle to become trapped in relatively small range of valleys".

In the developed model, Simulated Annealing creates a new solution by modifying only one solution with a local move. This modification is applied only on one solution set at a time to mutate its inputs for the purpose of creating new solutions. The optimisation loop performs a random perturbation on design variables, whose manipulation coefficient (probability of mutation) is defined by the system temperature "Temp_Coeff". The system temperature is initially high and cools down as the process evolves to an optimum solution. A number of cooling strategies can be used in order to lower the temperature; see Nouraniy and Andresenz (1998). The next iteration starts with a reduction in temperature calculated by the following equation that was suggested by Preiss (1999):

$$T_{k+1} = \alpha T_k \quad \text{…. (3)}$$

Where:

T_{k+1} is the temperature at the next iteration

$0 < \alpha < 1$ is the temperature reduction coefficient "Temp_Coeff"

k is an index that indicates the iteration step

Equation 3 indicates that a reduction in the next iteration temperature is obtained by multiplying the current iteration temperature by the temperature reduction coefficient, α.

All such random searching methods may only reach a local optimal solution; SA attempts to rectify this by accepting inferior solutions with a certain probability and thus allow the search to escape local optima (Ólafsson and Kim 2002). And hence, the worst solutions are accepted with a probability p = exp (-df/T), where df is the increase in objective function and T_k is the system "temperature" irrespective of the value of the objective function.

Thus, this probability of acceptance is high at the beginning and decreases over the course of optimisation process. Due to the possibility that worse solutions can be accepted, SA's major advantage over other methods is an ability to avoid becoming trapped in local minima. The process finishes when the temperature reaches some determined value or the objective function variation does not suffer relevant changes with perturbations of the variables. The simulated annealing algorithm that was proposed by Busetti (2003) has been tailored to be able to solve the aforementioned crew allocation problem. See Figure 6:

****

FIGURE 6

****

As noted in Figure 6, the process starts by generating an initial inputs set (crews' vector) using Monte Carlo simulation. Before running the simulation module, both initial values of objective function and temperature coefficient are defined. After running the simulation, the resultant objective function value calculated by evaluating inputs in the allocation plan is then compared with the initial objective value. As mentioned earlier, worst solutions are accepted with a probability p = exp (-df/T). If these solutions are rejected then they will be replaced by more promising ones. Inputs of the resulting vector are then manipulated by applying the suggested Probabilistic Dynamic Mutation (PDM) strategy.

As noted from the flowchart above (Figure 6), there are two major processes that take place in the Simulated Annealing algorithm. First, for each temperature, the Simulated Annealing algorithm runs through a number of cycles. The number of cycles is pre-determined by the programmer. As a cycle runs, the inputs are randomised. Only randomisations which produce a better-suited set of inputs are retained.

Once the specified number of runs (training cycles) is reached, the temperature could be lowered. If the temperature is not lower than the lowest temperature allowed, then the temperature is lowered and another run/ cycle takes place. The randomisation process is customised for the crew allocation system by using the PDM strategy.

However, if the temperature is lower than the lowest temperature allowed, the Simulated Annealing algorithm terminates. The core of the Simulated Annealing algorithm is the randomisation of the inputs. This randomisation is ultimately what causes Simulated Annealing to alter the input values that the algorithm is seeking to decrease allocation costs.

The calibration of the temperature parameter slows the process of manipulating and randomising inputs, which the quality of the solution depends on. The randomisation process takes as inputs the previous values of the vector and the current temperature. These input values are then randomised according to the temperature. A higher temperature results in more randomisation, while a lower temperature will result in less randomisation.

Assumptions of the Simulation Model

Commented [DN1]: Should this be part of model development?

A number of assumptions have been set to simplify the modelling process of the precast concrete manufacturing system being investigated. These are:

- High level modelling is applied to simulate the processes involved in the manufacturing system. In this modelling, a group of sub processes/ operations within each process is considered without delving into the details and requirements of each of these sub processes.
- Two working shifts are considered while developing the current prototype.
- An average process time of each crew of workers is considered as a function of crew efficiency.

- A process cannot be started without availability of all crew members.
- First-Come First-Served (FCFS) is adopted as a processing priority rule.
- Each order is processed by the same processing machines.
- Each crew member is intensively involved to carry out the production process.
- Each worker within a crew of workers is responsible to complete their job.
- Breakdowns in any of the shared resources or multi-skilled labourers are not considered.
- The whole responsibility for carrying out a job within a process is handed to the next shift crew of workers when the remaining time of the current working shift is insufficient to finish a process.
- To commence processing, all crew members should be assigned to carry out that process and should be released at once on completion of the process.

Case study

Background

This case study was conducted as part of the ESPCO project that had been funded for the UK precast industry by the British Department of Trade and Industry under technology their initiative program. The ESPCO project (2006-2008) aimed at providing a flight-simulator-like tool to precast concrete companies to help them study cost and schedule trade-offs and identify effects of different concrete mix designs on the production process. One of these precast concrete companies was selected as a platform to test the proposed system due to that fact that its manufacturing system had a parallel repetitive operations layout. This company is one of the largest manufacturers of precast concrete sleepers in the UK. Sleeper components are laid transverse to the rails of train lines, on which the rails are supported and fixed. This is to transfer the loads from rails to the ballast and sub grade below, and to hold the rails to the correct gauge.

In the sleeper manufacturing system, a wide range of different shared resources are utilised including workers, equipment and materials. The concrete sleeper manufacturing system is divided into two main production sections. Each production section consists of two labour-driven production lines. The shared resources are used in each production section. Eight production processes including the curing process are applied on each production line. Two working shifts were selected for analysis (day and night for the first production section and one shift for the second production section). In production section 1, eleven operators and two charge hand workers are used to carry out jobs during the day shift. During the night shift ten operators and two charge hand workers are used to carry out jobs which are left over from the day shift. In production section 2, thirteen operators and four charge hand workers are used in one shift. For both charge hand and operator workers, categories are identified by the production planner according to the accumulated experience record of a worker.

In any of the production lines, a 'reusable mould' is the main resource. This consists of a gang of moulds that can be used to produce either the same or the different types of sleepers. The floor shop layout consists of three zones: the materials zone, the concrete mix zone and the production zone. In the material zone, all steel wire rolls, plastic spacers, pandrols, and other finishing accessories are stored close to the production facility, ready to be used when needed. After usage a number of mechanical resources are placed in this area, Figure 7 gives an animated view of the simulated shop floor.

To develop the simulation model of the above processes, real industrial data were collected from one of the Precast concrete manufacturing companies based in the UK. Onsite visits, structured interviews with the production planner and a number of skilled workers were conducted and different processes times were measured using different work measurement techniques. These studies were presented previously in Al-Bazi and Dawood (2010a) and Al-Bazi, Dawood and Khan (2009) for the developed simulation model presented in Figure 7.

****

FIGURE 7

****

Figure 7 shows four mould beds distributed in two production sections. The progress of seven production processes in two shifts can be identified through process bar indicators designed for each mould. A collection of crews are placed in a pool ready to be assigned to production processes. A monitoring panel is designed to show the production details and the changing of concrete demand at each mould during the production process. A process-waiting time visual panel was developed for graphical display purposes. In addition, components of the total allocation cost as well as the total cost can be seen during the progress of the allocation process.

Verification and Validation of the Simulation Model

Verification of the Developed Simulation Model

Proof Animation was used to verify the developed simulation model. It is a general-purpose, post-processing animator designed for use with a wide variety of simulation tools (Henriksen, 1997). Post-processing means that it runs only after the simulation has terminated. Both a trace file and a layout file must exist for running an animation using Proof Animation. The post-processing approach offers such advantages as the ability to jump the time during the animation playback, to show all or a specific portion of the animation, and to accelerate or decelerate the viewing speed. The proof animation in the form of a 3D model is shown to the production manager and other senior planners to determine whether the simulated model reflects reality or not.

Validation of the Developed Simulation Model

After running the "As-Is" scenario, it was important to determine if the simulation outputs were similar to the real ones. The validation procedure used here estimated the production time for each production line and for both production sections together and checked the convergence of results with the "As-Is" outputs. The inputs to the system were the same as the real life inputs. For example, the same allocation plan including crews of workers and crews' formations was fed into the developed simulation model to check its accuracy. After running a simulation model on a 24 hours basis, the results are compared with reality as shown in Figure 8:

****

FIGURE 8

****

Figure 8 shows that when section 1 was isolated and processes were conducted on line 1, then the simulated value was 19.2503 hours due to the approximation of the forklift speed, while the actual value was 19.25 hours to process the whole line. On the other hand, when section 1 was isolated and processes were conducted on line 2, then the simulated value was 20.7503 hours due to the approximation of the forklift speed, while the actual value was 20.75 hours to process the whole line.

For Section 2, Line 1 was verified for one mould (production line) and the total time of processing a mould was equal exactly to the total hours needed to finish that mould in reality (24.75 hours). Line 2 was treated as an isolated unit (that is, all restrictions imposed by line 1 were removed and a normal operation process was conducted on that line to check the total processing time needed to carry on all processes on it), the total production time for a mould was 24.76 hours while the simulation predicted the same time.

Experimentations: Results Analysis and Discussion

The experimental design consisted of developing a number of allocation plans to be evaluated through simulation. The SA engine suggested a possible set of allocations of crews to processes, which could be considered as initial allocation plans. The best suggestion for allocation plans could be obtained by identifying the best parameters of the allocation system.

In order to improve the searching process for promising solutions, optimisation parameters were set after a number of experiments, as several sets of different probabilities were attempted without any significant effects. The following well-tuned settings were used: the temperature coefficient equal to 70, a decrement of 0.01 and 20 runs per iteration at each temperature. The stopping condition was then satisfied when the lower temperature coefficient was reached. Many key performance indicators were designed to test the performance of the allocation system.

In order to identify the value added by the proposed approach, it was necessary for the new assignment scenario to be compared with the current allocation strategy used in the real world. A comparative study of the collected industrial assignment from the precast concrete company and the optimised solution was conducted. The improvement over current solutions in terms of reducing allocation cost is shown in Figure 9.

****

FIGURE 9

****

Figure 9 shows that two significant cost drops took place after the 1st and 30th iterations. The SA dynamic probabilistic operator successfully explored more promising solution areas in the aforementioned iterations. After 52 iterations, allocation costs tend to have no improvement. The best scenario drove down the allocation cost to £49,062 (existing cost is £51,115), achieving a return of 4.016% (about £2053 per five working days). Other influential factors in allocation costs such as process-waiting time need to be investigated. Manipulating crews by enabling workers to be heavily involved elsewhere according to the required skills produces less idle time for labour. On the other hand, reducing clashes amongst workers is essential to ensure a better flow of work. As an influential factor in the cost reduction process, process-waiting time should be analysed and minimised for a better workflow. The reduction of process-waiting time plays a significant role in reducing IRC_i cost and subsequently the total allocation cost. See Figures 10 and 11 for the process-waiting times achieved by running current and optimal allocation plans.

****

FIGURE 10

****

In Figure 10, adopting the best-case scenario shows a noticeable reduction of 4:22 hours in the total process-waiting time (existing total process-waiting time is 14:37 hours). In the finishing process-waiting time, 2.5 hours are saved per production cycle equal to a total of 5 days (45% time reduction in the finishing time is achieved). The waiting time yielded in the setup and saw-off processes have a slight improvement. These reductions in the setup and saw-off processes resulted in increasing the average waiting time of demould process as a response to the effect of the balancing process and because of the problem of sharing workers. The casting process is considered a critical process as it utilised full/partially shared resources with other processes; therefore, any improvement would reduce their process waiting time. The second production section which is involved in the optimisation of process-waiting time is presented in Figure 11.

****

FIGURE 11

****

In Figure 11, a reduction of 1:53 hours in the total process-waiting time is achieved (existing total process-waiting time is 13:15 hours). In the sawing off production process, 1 hour is saved by adopting the best allocation scenario. The reduction resulted in increasing the average waiting time of the finishing process as a best solution for the workers sharing problem. A slight improvement in a number of processes such as setup and de-mould is achieved. The stress process required fewer workers, which helped in avoiding the problem of sharing workers.

Comparison with the Monte Carlo Technique

In order to evaluate and justify the performance of the proposed model in terms of solution quality and efficiency, a comparison with Monte Carlo sampling was conducted. The Monte-Carlo experiment is designed to start by generating an individual set of solutions solely using a Uniform random number generator. The generator selected a crew from each alternative pool associated with a process. After forming an allocation plan in which a crew of workers was proposed for each process, the simulation engine evaluated the generated allocation plan, with the result being stored in a database. An allocation plan was generated per iteration, which was then evaluated by the simulation engine.

Figure 12 shows the allocation costs yielded through iterations by using Simulated Annealing, and Monte-Carlo Sampling techniques.

****

FIGURE 12

****

In Figure 12, it is shown that the Monte-Carlo model generated random allocation costs with some being close to the minimum allocation cost. Monte Carlo results indicated a better cost reduction than the SA for nearly thirty generations. The best SA achieved at each iteration showed a significant and rapidly improving trend towards the minimum allocation cost. SA was considered to be evolving solutions towards identifying the best allocation plan, while the Monte-Carlo model utilised the 'Trial-Error' concept to hit by chance as minimal an allocation cost as possible. This comparative study has shown the superiority of the proposed SA model.

Conclusion

The crew allocation system presented in the paper has successfully been developed to optimise costs of crews allocation in the precast concrete manufacturing systems of parallel repetitive processes layout, taking into consideration different crew allocation constraints such as skills of workers, and other crew formation details that were not considered in the related previous literature.

The integration of simulation with simulated annealing achieved an optimal/ near optimal allocation of suitable crews of workers to the right processes in parallel repetitive manufacturing processes in the precast concrete industry. The concept of using SA in solving this type of problem and the construction of an innovative crew's vector to accommodate multi-attribute inputs assisted greatly in solving the aforementioned complex-allocation problem. The chosen operators contributed significantly to the search for promising solutions within a very large solution space. The overall structure of the proposed system and the full integration of its components led this system to be considered as an advanced crew allocation system that can be used to solve complex crew allocations in the precast concrete industry or similar type of industries.

The results showed that by applying the proposed allocation system, costs could be saved by over 4% per production cycle. An optimal crew allocation plan reflected a minimal crew allocation cost and reduced process-waiting times in both production lines.

As a further development of this research work, different levels of priority (high, medium, and low) can be defined for each production process and included in a crew's vector layer, especially if they have a significant influence on the overall system performance. The prediction of workers' absences can be considered as one of the influential factors that affect the allocation process, and hence more features could be added to the current system to be able to handle such stochastic situations. The environmental impact of waste and CO2 produced by production processes can also be taken into consideration whilst allocating resources.

References

Alazzaz, F. and Whyte, A. (2014). Uptake of Off-site Construction: Benefit and Future Application. World Academy of Science, Engineering and Technology, *International Journal of Civil, Architectural, Structural and Construction Engineering*, 8(12), pp.2219-2223

Al-Bazi, A. and Dawood, N. (2010a). A Multi-Layer Genetic Algorithm for SolvingCrew Allocation Problem in the Precast Industry. *Proceedings of the 16th International Conference on Automation & Computing*, University of Birmingham, UK, 11 September 2010, pp.214-220.

Al-Bazi, A. and Dawood, N. (2010b). Developing Crew Allocation System for Labour Intensive Industries Using Genetic Algorithms. *Journal of Computer-Aided Civil and Infrastructure Engineering*, 25(8), pp.581-595. Available at: http://onlinelibrary.wiley.com/doi/10.1111/mice.2010.25.issue-8/issuetoc [Accessed 26 Feb. 2017]

Al-Bazi, A., Dawood, N. and Dean, J. (2010). Improving Performance and the Reliability of Off-Site Pre-Cast Concrete Production Operations Using Simulation Optimisation. *Journal of Information Technology in Construction,* 15(2010), pp.335-356. Available at: http://www.itcon.org/papers/2010_25.content.03937.pdf [Accessed 26 Feb. 2017].

Al-Bazi, A., Dawood, N. and Khan, Z. (2009). Development of Hybrid Simulation and Genetic Algorithms System for Solving Complex Crew Allocation Problems. *Proceedings of the CIB W078 Managing IT in Construction*, October, 2009, Istanbul, Turkey.

Avello, E.A., Baesler, F.F. and Moraga, R.J. (2004). A Meta-Heuristic based on Simulated Annealing for Solving Multiple-Objective Problems in Simulation Optimisation. *Proceedings of the 2004 Winter Simulation Conference, R .G. Ingalls, M. D. Rossetti, J. S. Smith, and B. A. Peters, eds.*, pp.508-513.

Banks, J. (1999). Introduction to Simulation. *Proceedings of the 1999 Winter Simulation Conference. P. A. Farrington, H. B. Nembhard, D. T. Sturrock, and G. W. Evans, eds*., pp.7-13.

Bhoyar, S. and Parbat, D.K. (2014). Optimal Scheduling for Repetitive Construction Projects with Multiple Resource Crews. *International Journal of Emerging Technology and Advanced Engineering*, 4(6), pp.302-307.

Biruk, S. and Jaśkowski, P. (2008). Simulation Modelling Construction Project with Repetitive Tasks Using Petri Nets Theory. *Journal of Business Economics and Management*, 9(3), pp.219–226.

Busetti F. (2003). Simulated Annealing Overview. Available at: www.cs.ubbcluj.ro/~csatol/mestint/pdfs/Busetti_AnnealingIntro.pdf [Accessed 26 Feb. 2017].

Collet, P. and Rennard, J.-P. (2007). *Stochastic Optimization Algorithms*. Handbook of Research on Nature-Inspired Computing for Economics and Management', p.28-44.

El-Gafy, Mohamed A. (2006) Resource Allocation in Repetitive Construction Schedules Using Ant Colony Optimization, pp.515-523 Available at: http://www.irbnet.de/daten/iconda/CIB4427.pdf [Accessed 26 Feb. 2017].

Henriksen, J.O. (1997). The Power and Performance of Proof Animation. *Proceedings of the 1997 Winter Simulation Conference, ed. S. Andrado'ttir, E. J. Healy, D. H. Withers, and B. L. Nelson*, pp. 574-580.

Huang, Rong-yau and Sun, Kuo-Shun (2009). A GA Optimization Model for Workgroup-Based Repetitive Scheduling (WoRSM). *Advances in Engineering Software*, 40(3), pp.212-228.

Janiak A. and , Lichtenstein M. (2011) 'Advanced Algorithms in Combinatorial Optimisation'. Projekt współfinansowany ze środków Unii Europejskiej w ramach Europejskiego Funduszu Społecznego, pp. 23-34, Available at: http://www.studia.pwr.wroc.pl/p/skrypty/Advanced%20Informatics%20and%20Control/08_Advanced%20Algorithms.pdf [Accessed 26 Feb. 2017].

King, A.J. and Wallace, S.W. (2012). *Modeling with Stochastic Programming*. Springer Series in ORFE, DOI 10.1007/978-0-387-87817-13,© Springer Science+Business Media New York 2012

Kirkpatrick, S., Gelatt, C.D. and Vecchi M.P. (1983). Optimization by Simulated Annealing. *Science, New Series*, 220(4598), pp.671-680.

Lam, H.-C. and Lu, M. (2008). Simulation-Based Optimized Scheduling of Limited Bar-Benders Over Multiple Building Sites. *Proceedings of the 2008 Winter Simulation Conference, S. J. Mason, R. R. Hill, L. Mönch, O. Rose, T. Jefferson, J. W. Fowler eds*, pp.2353-2360.

Nassar, K. (2005). Evolutionary Optimisation of Resource Allocation in Repetitive Construction Schedules. *Journal of Information Technology in Construction (ITcon)*, 10, pp.265-273.

Nouraniy, Y. and Andresenz, B. (1998). A Comparison of Simulated Annealing Cooling Strategies. *Journal of Physics A: Mathematical and General*, 31(41), pp. 8373-8385.

Ólafsson, S. and Kim, J. (2002). Simulation Optimisation. *In Proceedings of the 2002 Winter Simulation Conference, E. Yücesan, C.-H. Chen, J. L. Snowdon, and J. M. Charnes, eds.*, pp.79-84.

Preiss, B.R. (1999). *Data Structures and Algorithms with Object-Oriented Design Patterns in C++*. John Wiley & Sons. Available at: http://www.brpreiss.com/books/opus4/index.html, [Accessed 26 Feb. 2017]

Vaziri, K., Carr, P. and Nozick L. (2007). Program Planning Under Uncertainty. *Proceedings of the 2007 Winter Simulation Conference. S. G. Henderson, B. Biller, M.-H. Hsieh, J. D. Tew, and R. R. Barton, eds*. pp 2119-2128.