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RESOURCE OPTIMIZATION IN A DESIGN OFFICE USING GA-BASED SIMULATION

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ABSTRACT
This paper presents a new approach for resource optimization by combining a flow-chart based simulation tool with a powerful Genetic optimization procedure. The proposed approach determines the least costly and most productive amount of resources that achieve optimum profitability. To demonstrate the proposed approach, a case study of a design office was used. A simulation model of the operation in the design office was created with details related to the design projects that flow into the office, employed resources, and the tasks that take places from start to finish of design. Various optimization experiments were then conducted to reveal the consistency and good performance of the proposed approach in determining the best combination of resources that maximize the yearly revenues. Based on the results obtained, Computer Simulation and Genetic optimization proved to be an effective combination with potential for improving productivity, reducing idle time, and saving construction time and cost.

KEYWORDS
Resource Management, Organizational Planning, Simulation, Optimization, Genetic Algorithms, and Computer Application.

1. INTRODUCTION

Efficient management of resources, particularly labor and equipment, is a key factor to the success of any construction or engineering organization. In the literature, various researchers have introduced a number of techniques to deal with individual aspects of resource management at the project level, such as resource allocation, resource leveling, cash flow management, and time-cost trade-off (TCT) analysis. Limited studies, however, have been carried out on modeling overall organizational operations, particularly in design firms. One exception is the work of Karaa et al. (1990) who analyzed the performance of different resource options for an engineering division of a public agency involved in repetitive operations. Focusing on design firms, Hegazy et al. (2000) presented a simple method to model the operations in a design office using discrete-event simulation. The model was then used to conduct various experiments involving different resources combinations.

Resource optimization at the project level has interested many researchers who traditionally used mathematical methods or Heuristic techniques. Mathematical methods, such as Integer, Linear or Dynamic programming have been proposed for individual resource problems. Mathematical methods, however, are computationally non-tractable for any real-life project, which is reasonable in size (Moselhi and Lorterapong 1993; allam 1988), let alone for optimizing resources at the overall company level. The problem with Heuristic methods, on the other hand, is their

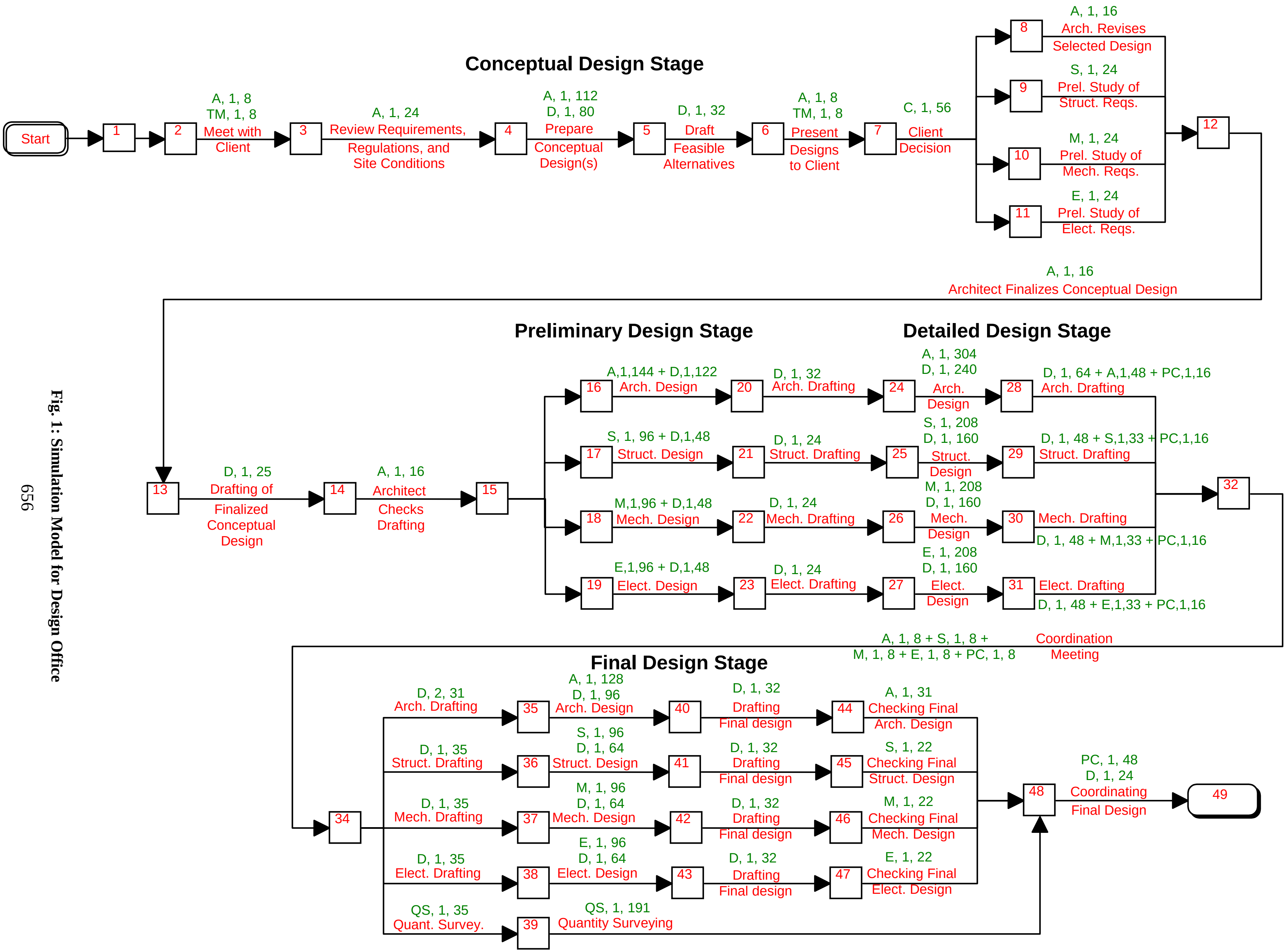

Fig. 1: Simulation Model for Design Office

dependence on experience and rules-of-thumb, rather than rigorous mathematical formulations. Despite their simplicity, heuristic methods perform with varying effectiveness and can not guarantee optimum solutions.

Recent developments in computer science have produced a new breed of tools that are beneficial to be utilized for construction applications. Based on recent advances in artificial intelligence, a new optimization technique, Genetic Algorithms (GAs), has emerged. Simulating natural-evolution and survival-of-the-fittest mechanisms, GAs apply a random search for the optimum solution to a problem. Due to their perceived benefits, GAs have been used successfully to solve several engineering and construction management problems. Applications include optimization of a contractor's markup strategy (Hegazy and Moselhi 1994); steel truss roof optimization (Koumousis and Georgiou 1994); resource scheduling (Chan et al. 1996); time-cost trade-off optimization (Li and Love 1997); optimization of resource allocation and leveling using genetic algorithms (Hegazy 1999); and others (Goldberg 1989, Li and Love 1997).

In addition to GA-based optimization tools, new and easy-to-use simulation systems based on object-oriented programming have recently been introduced. One powerful system, Process V3 (2000), is a general-purpose software for modeling and simulation. The main advantage of this software is its simple flow chart-based modeling, in addition to its object-oriented simulation engine. One advantage of the software is that it applies simulation to traditional activity-on-arrow (AOA) project networks used for scheduling (Hegazy at el. 2000). Using this simulation tool, this research aims at improving resource management at the company level by combining the benefits of simulation and Genetic Algorithms. Resource optimization is demonstrated on an example design office to facilitate manpower-planning decisions.

2. SIMULATION MODEL OF DESIGN OFFICE OPERATIONS

The operations in a typical design office are modeled using the simple flowchart-based simulation software. An actual small-to medium-sized design office is used. The firm has its own staff of architects, structural, electrical, and mechanical engineers, in addition to other support staff for drafting and surveying.

2.1 Process Model

After manually analyzing the office operations in several years, a flow chart model of the firm’s operation was compiled as shown in Figure 1, with the notations described in Figure 2. The model of Figure 1 incorporates the 4 main stages of design development: conceptual design, preliminary design, detailed design, and final design. During simulation, the model works by having flow-objects (representing individual design projects) move along the flowchart. The process starts in the conceptual design stage by initiating activity 2-3 (meeting with client). The start node generates a new flow-object (design project) every 15 days to represent new designs acquired by the firm. After the meeting, a flow-object is generated at node 3 to activate activity 3-4 where the architect reviews client requirements, city By-laws, and site conditions. Ending this activity generates a flow-object that is received at node 4 to start activity 4-5. The process then continues in the same manner, following the flow chart sequence. Each step is activated when its required resources and flow-objects become available. In the process, a design project is completed when activity 48-49 is activated, thus conducting a final design coordination meeting.

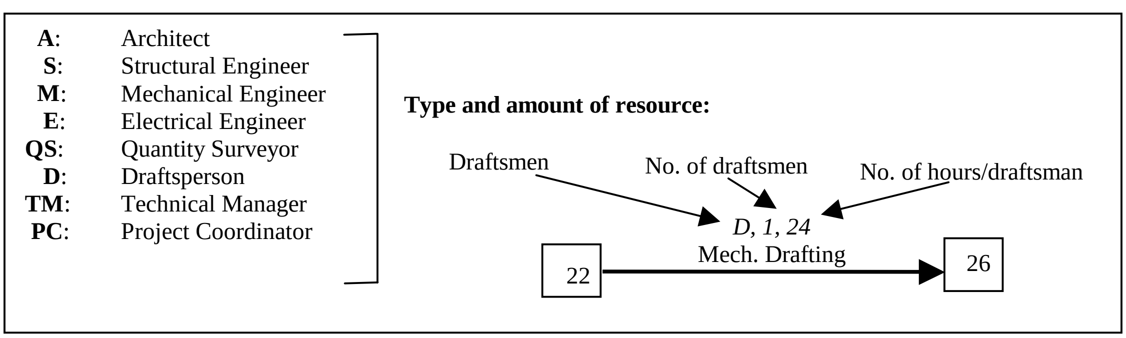

Figure 2: Notation used in the Design Process Model

2.2 Assigning Resources

Once the model was constructed on the software, the next step was to assign resources and work calendars to the process elements. First, various resource categories (architects, structural engineers, mechanical engineers, electrical engineers, quantity surveyors, draftsperson, technical manager, and project coordinator) and their hourly rates were input to the resource sheet of the software (Figure 3). The number of each resource actually employed by the office was specified and was later changed according to the simulation experiments conducted (described later). In general, process steps were assigned appropriate resources, as stated above each arrow in Figure 1. Input and output flow-objects were also set to maintain the logical flow of the model. The nodes of the model were also configured so that more than one project can be processed simultaneously. Since the work strategy of this design office was to assign the majority of resources to existing jobs rather than to new ones, the model was set up to reflect this strategy. Accordingly, in the model, the flowchart activities representing the final design stage were given higher priorities than the activities of the conceptual stage, in case they should compete for the same resource during the simulation. As a general rule in the model, the daily working period for all the resources was set to 8 hours per day, with one and one-half days off per week to account for the yearly vacations and seasonal holidays of the resources in the design office.

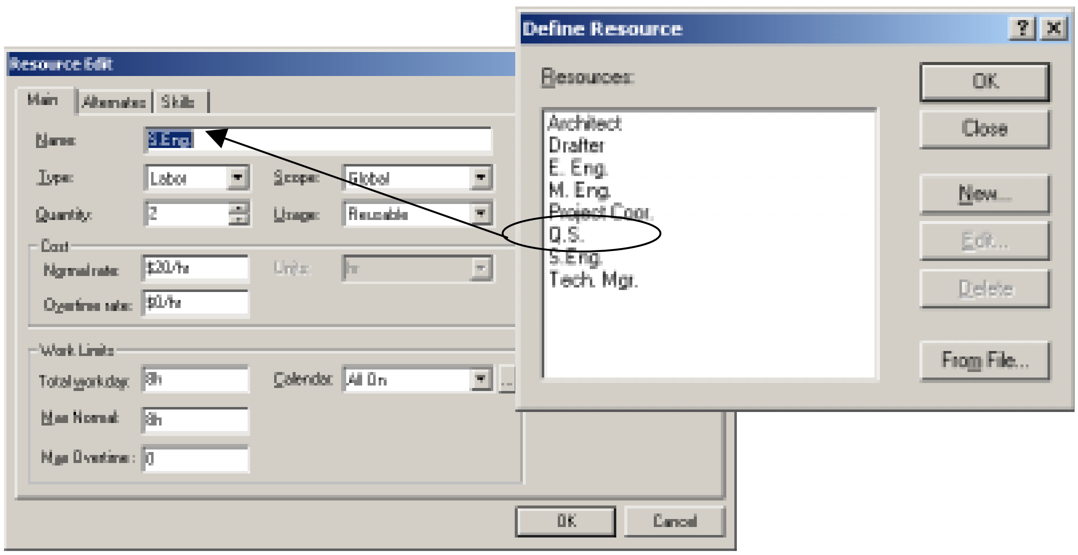

Figure 3: Assigning Resource Properties

2.3 Simulation Run

Once the simulation model was properly configured, the model was run for a user-specified period of simulation time, starting from the first node. The start node generates new flow-objects every 15 days (according to the set rate of acquiring new design projects) that are used with existing resources to meet the requirements of process steps which activate and end by generating other flow-objects. The successor steps are then activated and the simulation process continues in the same manner, following the logic of the model. Whenever a step is activated, its start node counts the number of received flow-objects, and its end node counts the number of generated flow-objects. The object counts provide important information such as the number of completed designs at end of the simulation, in addition to important statistics related to total work hours of resources, idle times, and costs. These quantities become essential indicators of the overall performance of the design office and its resource utilization efficiency.

Initial experimentation with the simulation model was conducted with a resource combination of 17 draftsperson, 5 architects, 4 structural engineers, 4 mechanical engineers, and 4 electrical engineers, in addition to a fixed number of 2 quantity surveyors, one project coordinator, and one technical manager. The model was run to simulate the office operation in 5 years. Accordingly, the number of projects completed was determined along with the effective hours spent by the various resources. A 5-year period was used to overcome the unrealistic start of the simulation when there were no on going projects being designed by the office. The simulation results were then used to calculate the average number of projects completed per year and the average yearly number of hours spent by each resource.

At end of simulation, the resulting number of completed projects is shown in Figure 4. As noticed, the yearly hours spent by architects are much higher than those of engineers. This fluctuation in the resource workload also suggests that the numbers of resources used in this alternative were not properly balanced. Also, it is noted that the workload of the engineers (21679 hrs / 4 engineers / 5 years = 1083 hrs/Year/engineer) is a low workload. Given that each engineer can work for a total of 2002 hours/year (286 days x 7 hrs/day), the work efficiency is then calculated as 1083/2002 = 0.54 and is considered low. This low efficiency requires the office manager to try different levels of resource combinations, by changing the quantity of resources manually.

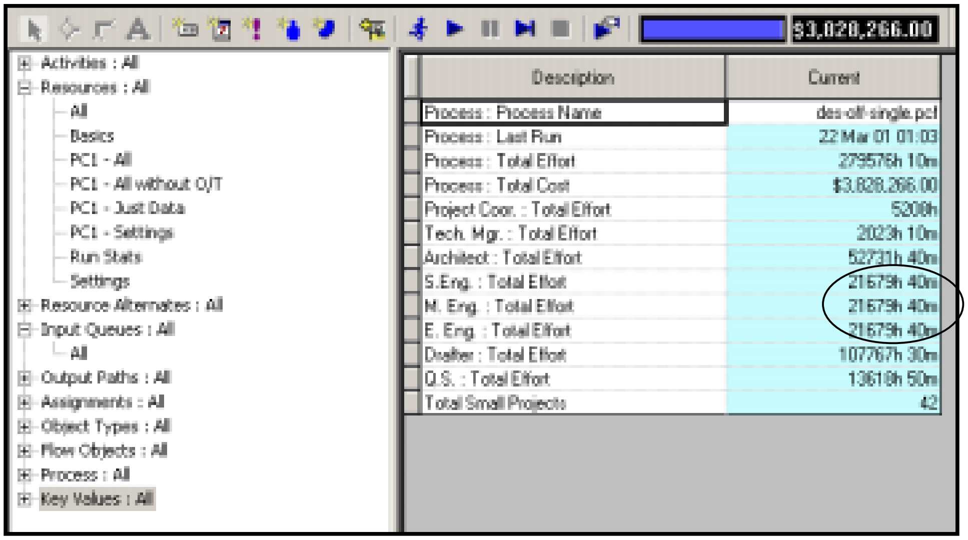

Figure. 4: Results of a 5-Year simulation

3. GA-OPTIMIZED SIMULATION MODEL

The simulation model presented in the previous section is capable of analyzing the office performance given any reasonable set of resources. Normally, a trial-and-error approach is used to experiment with various resource combinations in an attempt to improve the output of simulation-based models. Although the trial-and-error approach might find a reasonable solution (a resource combination that gives high productivity), it can be time consuming and does not guarantee an optimal solution, given the large number of possible resource combinations. For that purpose, Genetic algorithm (GAs), have successfully been used as a powerful search mechanism for optimal solutions in large problem domains such as the one at hand.

3.1 GAs Process

GAs are inspired by the process of natural evolution and the principal of "Survival of the fittest". The procedure begins with the generation of an initial population of random solutions and keeps evolving and searching through this population until an optimum solution is found. Each individual solution is represented by a string-like entity called a chromosome, typically consisting of a number of elements called genes. Each gene represents one of the problem variables (Figure 5). In simulation models, the quantity of each resource to use is a variable to be optimized. With each gene having a certain value for its associated variable, a chromosome encodes a single solution to the problem. Simulating natural processes, an initial population of solutions (can be generated randomly) undergoes evolution in cycles called generations. During the process, a chromosome may persist across many generations or may be replaced in the very next generation, depending on its fitness. During the evolutionary process, population members are married to produce offsprings (through a process of crossover or mutation), which are then tested to see if they are more fit than older population members (Goldberg 1989). The evaluation of each chromosome in this process is quantitatively done by being measured against an objective function (can be cost, production, or both).

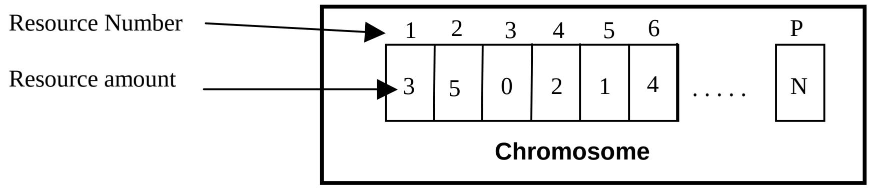

Figure 5: Chromosomal Representation for Simulation Models

3.2 Simulation with GA Optimization

The benefit of using genetic algorithms with simulation models is to search for an optimum set of resources that optimizes both revenues and minimizes cost, under various constraints related to resource availability limits. Implementing the GAs technique to automatically work within the simulation model for the case study at hand involved the following settings:

- **Variables:** Variables are the amount of each resource to use;
- **Objective function:** To evaluate each chromosome, a single objective function that considers the two sub-goals of maximizing revenues and minimizing cost is formulated as follows:

Objective function = Maximize (Revenues / Cost) Ratio

- **Constraints:** Production amount, resource availability limits, and operational hours.
- **Population:** An initial population of 50 was used in all experiments

4. IMPLEMENTING THE GA-OPTIMIZED SIMULATION MODEL

The integration between the simulation tool used (Process V3) and a GA-based tool (Evolver 1998) was implemented using a VBA programming code that uses object linking and embedding (OLE). VBA procedures were coded to control the optimization process. After the system was developed and tested, it was used to optimize the resources for the design office at hand. Before conducting optimization experiments, the variable ranges (used as constraints) were set as follow: Technical Manager (fixed to 1); Architects (1-10), Engineers (1-7), Draftsmen (3-30), Quantity Surveyors (fixed to), and Project Coordinator (fixed to 1). With 8 Hours shift per day as normal work, two optimization experiments were then conducted with different initial resource values, as shown in Table 1.

To evaluate the objective function, revenue was calculated on the basis that each completed project (total number is known after simulation) brings a revenue of $130,000. Accordingly total revenues are calculated as:

Total Revenue ($) = Total number of completed projects (obtained from simulation run) x $130,000

Also, the cost calculation on the other hand, assumes the yearly salary of the various resources as follows:

- Tech. Manager (TM) = $50,000
- Architect (Arch.) = $45,0000
- Structural Engineer (SE) = $45,000
- Mechanical Engineer (ME) = $45,000
- Electrical Engineer (EE) = $45,000
- Draftsman (D) = $35,000
- Quantity Surveyor (QS) = $30,000
- Project Coordinator (PC) = $50,000

Since one Technical Manager and one Project Coordinator and two surveyors were fixed, their salaries add up to $800,000 in the 5-year duration. Accordingly, the office costs for five years simulation period becomes:

Total cost ($)= (No. of Eng. & Arch. x $45,000 + No. of Draftsmen x $ 35,000) x 5 + $ 800,000

Table 1: Results of GAs Experiments for Design Office Operation

			Experiment 1	Experiment 2
Initial Values	Resources	Arch.	3	3
		SE	4	2
		EE	2	2
		ME	2	2
		Draftsmen	16	8
		No. of completed designs	33	31
		Revenue ($)	4,290,000	4,030,000
		Cost ($)	6,075,000	4,225,000
		Revenue/Cost ratio	**0.70**	**0.95**
Optimization Results		**Revenue/Cost ratio**	**1.07**	**1.11**
		No. of completed designs	41	41
		Revenue ($)	5,330,000	5,330,000
		Cost ($)	4,975,000	4,800,000
	Resources	**Arch.**	**4**	**4**
		SE	**2**	**2**
		EE	**2**	**2**
		ME	**2**	**2**
		Draftsmen	**11**	**10**

The same optimum solution was achieved in both experiments, as shown in Table 1. In the first experiment, the maximum Revenue/cost ratio was 1.07 with 41 completed projects, up from the initial Revenue/cost ratio of 0.70 with 33 projects stared with. This result corresponds to optimized resource levels of 1 project manager, 4 architects, 2 engineers for every engineering discipline, 11 draftsmen, 2 quantity surveyors and 1 project co-ordinator. Furthermore, in the second experiment, the GAs optimization resulted in Revenue/cost ratio of 1.1 with 41 projects completed, up from the initial R/C ratio of 0.70 with 31 projects. This result corresponds to an optimized resource levels of 1 project manager, 4 architects, 2 engineers for every engineering discipline, 10 draftsmen, 2 quantity surveyors and 1 project coordinator. Despite of the same number of completed projects in the two experiments, however, the minor difference in the Revenue/cost ratio is due to the probability nature of the GAs technique. It is noted also that due to the nature of GAs, identical results may not be obtained if the experiments are repeated.

The two simulation/optimization experiments were performed using a Pentium II 450 MMX PC, with fixed population size of 50 and 200 offspring generations. The processing time for each 5-year simulation was about 16 hrs. This relatively large processing time could be easily justified, given the remarkable potential savings that result from an optimum solution. One possible improvement is to code the GA procedure in a faster programming language than the VBA language, such as C or C++. The user has the option to turn off the animation feature of the simulation software to reduce processing time. In addition, an overnight run may be a good option to exercise.

5. CONCLUSION

This study presented a simple and powerful approach for resource management, at the company level, using combined simulation and genetic algorithms (GAs). Simulation models were developed in a flowchart-based simulation software that enables the user to build realistic models with relative ease and legible format. These features are convenient for users who are not familiar with simulation theories and help them focus more on the accurate mapping of their process rather than on programming and syntax issues. An example of modeling the operations in a design office is used to show the power and diversity of the proposed GA-optimized simulation approach. The power and simplicity of the proposed approach will hopefully encourage project managers to utilize it in the planning of large infrastructure projects. It can be used to provide the optimum number of resource quantities, workload, and assignment strategies, and accordingly to improve overall productivity.

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