Chapter 1
A Multi-objective Simulation-Based Optimization Approach Applied to Material Handling System

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1.1 Introduction

Simulation modelling is indeed a powerful industrial engineering technique for studying the functioning, performance and operation of complex systems. As such, it becomes a useful tool for decision makers in various industries. Unlike a mathematical model, simulation can handle a variety of complex factors that are commonly found in real world. More importantly, the accuracy of the performance measures of the complex systems obtained from simulation models is normally higher than that of analytical methods because analytical methods in general involve making unrealistic assumptions for the systems or problems under investigation [1].

In real world, many problems no matter whether they are in the domain of engineering, finance, business or science can be formulated into different forms of optimization problems. These problems are characterized by the requirement of finding the best possible solution(s) that fulfils certain criteria. Most of the real-world optimization problems normally involve multiple objectives rather than one single objective, in which some objectives conflict with others. However, using simulation modelling alone cannot provide us optimal solutions to these optimization problems. Therefore, an optimization algorithm is needed to guide the search process to the optimal solutions. The study reported in this paper demonstrates how a complex real-life multi-objective optimization problem in distribution industry where material handling system (MHS) is involved can be solved by a simulation-based optimization approach that comprises a simulation tool together with a hybrid AIS-based algorithm.

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1.2 Literature Review

Optimization of MHS via Simulation

In the literature, there are a number of studies that dedicatedly contribute to the optimization of MHS via simulation. For example, Elahi et al. [2] studied the General Motors paint shop conveyor system by developing a simulation model. The model works firmly with a decision optimizer incorporating integer linear programming model and dynamic programming model at critical points such as the beginning and end of buffer conveyors in the system in order to regroup batches of different colour cars. Leung and Lau [3] proposed a simulation-based optimization framework that combines the processes of optimization and simulation for solving typical linear optimization problems related to logistics and production operation. The framework integrates an AIS-based algorithm with a simulation tool for the evaluation of optimal system parameters and to reveal the performance of systems. Subulan and Cakmakci [4] made use of ARENA simulation program and Taguchi experimental design method to build a solution model for effectively designing material handling–transfer systems and optimizing the performance of automation technologies in automobile industry. Chang et al. [5] proposed a framework that integrates simulation optimization and data envelopment analysis techniques to find out the optimal vehicle fleet size for a multi-objective problem in automated material handling systems. Lin and Huang [6] extended the optimal computing budget allocation by adding genetic algorithm together with the help of a simulation model for optimizing the vehicle allocation for the automated material handling system in semiconductor industry.

Multi-objective Optimization Problems

Finding the solutions to the multi-objective optimization problems has long been a challenge to researchers because both the Pareto optimality and the diversity of the generated solutions must be simultaneously addressed. Unlike solutions in single objective optimization problems, which can easily be compared according to the value of the objective function, solutions in multi-objective problems cannot directly be compared with each other unless employing classical techniques, such as weighted objective aggregation methods and constraint approaches. Nevertheless, many real-world problems involving complex and nonlinear properties do not readily fit into these classical approaches [7]. Therefore, modern evolutionary algorithms such as genetic algorithm (GA), evolutionary strategy (ES), artificial immune systems (AIS), etc. incorporating the concept of Pareto optimality are proposed and become popular. These methods have been proved to be effective for solving multi-objective optimization problems by finding the approximated Pareto front, for example, NSGA-II [8], SPEA2 [9], micro-GA [10], omni-aiNet [11], NNIA [12], omni-AIOS [13], etc.

1.3 Multi-objective Simulation-Based Optimization Algorithm

This optimization approach adopted in this paper is a modified version of Leung and Lau's work [3], which incorporates a multi-objective optimization algorithm instead of a single objective algorithm. The multi-objective algorithm is named Suppression-Controlled Multi-objective Immune Algorithm (SCMIA) proposed by Leung and Lau [14]. The fundamental of the algorithm was inspired from mechanisms of biological immune system and biological evolution. It was developed by hybridizing the clonal selection principle and immune network theory with the idea from GA. The algorithm makes use of the Pareto dominance for fitness assignment and some common AIS-based algorithm's features for guiding the search process, such as clonal selection and expansion, affinity maturation, antibody concentration, metadynamics and immune memory. The interesting feature of this algorithm is the introduction of an innovative suppression operator, which is used to help eliminate similar antibodies, hence significantly minimizing the number of unnecessary searches and increasing the population diversity. The similarity among antibodies is determined in terms of both the objective space and the decision variable space to ensure that only similar antibodies are eliminated in the suppression operation. Moreover, a modified crossover operator originated from the biological evolution was also developed to help further enhance the diversity of the clone population and the convergence of the algorithm because some good genes from the elite parents can be passed to the offspring for facilitating the search of optimal solutions; otherwise it may take a longer time to converge towards the Pareto front [15] especially in simulation-based optimization context.

The algorithm comprises five immune operators, cloning operator, hypermutation operator, suppression operator, selection and receptor editing operator and memory updating operator, and one genetic operator, crossover operator. Each of them takes responsibility for different tasks for the purpose of finding uniformly distributed Pareto front. The cloning operator generates a number of copies to explore the solution space where better individuals are given more chances for being cloned. The hypermutation operator works on the clones to bring variation to the clone population, hoping for producing better offspring and increasing population diversity. The crossover operator is used to enhance the diversity of the clone population and the convergence of the algorithm. The suppression operator works on the whole population including the mutated clones and parent cells to eliminate similar individuals in order to avoid a particular search space being overexploited. The selection and receptor editing operator works like a director to guide the search towards the promising regions of a given fitness landscape by selecting the best antibodies to form the next generation and allowing the genes of the less fit to be randomly restructured for changing their specificity through the receptor editing process. The memory updating operator works as an elitist mechanism for helping preserve the best solutions that represent the Pareto front found over the search process. Both the selection and receptor editing operator and memory updating operator can help avoid the problem of losing good solutions during the optimization process due to random effects. The algorithm is conducted by applying these heuristic and stochastic operators on the antibody population for balancing both the local and global search capabilities. For the details of this hybrid AIS-based algorithm, one can refer to [14].

1.4 Simulation-Based Optimization Study

In this study, two experiments based on the complex real-life multi-objective optimization problem were conducted to evaluate the performance and capability of the optimization approach. All these experiments were conducted using a computer with Xeon E5-2620 2 GHz CPU with 2 GB RAM, and the optimization algorithm was implemented with Excel VBA, whereas the simulation models were developed by using the FlexSim simulation tool [16].

Performance Metrics

In this study, two performance metrics, namely, error ratio (ER) [17] and spacing (S) [18], were adopted to examine the quality of solution set in terms of the optimality and diversity. However, ER was modified by using reference Pareto front PF_{ref} instead of true Pareto front PF_{true} for computing ER. This was because the PF_{true} could hardly be found in simulation-based optimization, and hence we used the reference Pareto front, that is, the best approximation of the true Pareto front "PF_{ref}", for measuring the optimality of each solution set instead. The PF_{ref} was found by using all of the algorithms used in this research. To achieve this, a Pareto front for each algorithm was firstly generated by running 100 iterations over 20 trials, and then, all the fronts obtained by all the trials of all the compared algorithms were merged together to form a reference Pareto front.

Experimental Setup

The distribution operation of the material handling system (MHS) implemented at the distribution centre (DC) of SF Express (Hong Kong) Limited was studied through the simulation-based optimization approach. Its service network covers almost all areas of Hong Kong, which is mainly served by the DC located in Tin Shui Wai (TSW) in northern New Territories (Fig. 1.1). Its service stores are located in 30 areas of Hong Kong [19].

In this study, we focus on the physical goods flow at the DC, where the items are imported from China and then distributed to all parts of Hong Kong. At the DC, the items received at inbound docks are directly transferred to outbound docks and then

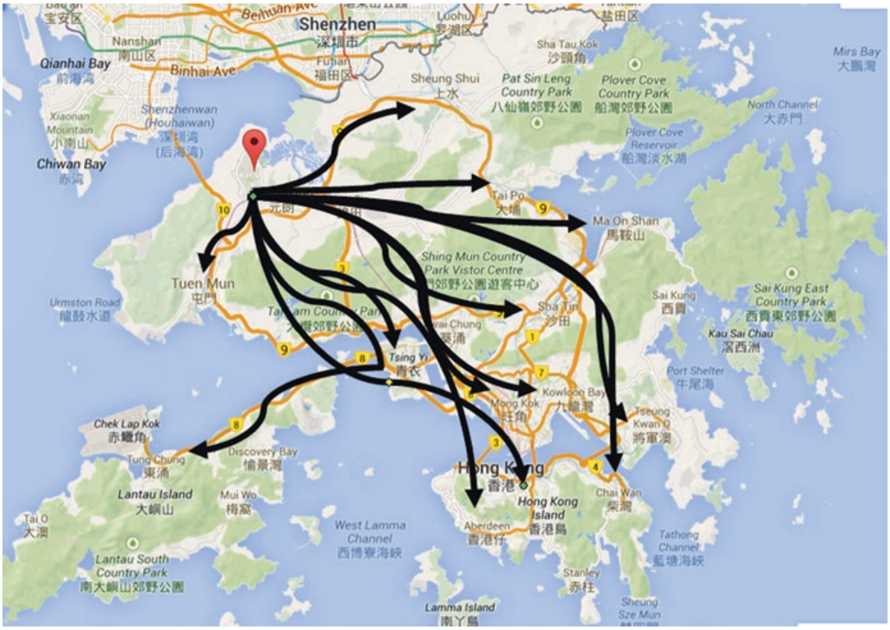

Fig. 1.1 The distribution flow of SF Express's imported goods in Hong Kong

shipped to the final destinations with little material handling in between, such as deconsolidation and sortation. This approach is called cross-docking. To implement cross-docking effectively and efficiently, timely distribution of freight and better synchronization of all inbound and outbound shipments are required by making use of information systems and advanced automated MHS, such as automated conveyor system, warehouse management system, real-time material identification and tracking system (e.g. barcode).

Current Physical Layout and Labour Deployment of the MHS The MHS is a circular shaped automated conveyor system, which comprises a number of interconnected conveyor units. The layout of the MHS is depicted in Fig. 1.2. Each conveyor unit has a programmable logic controller to control the movement (such as speed, direction, etc.) of the items being put on it and to communicate with the central computer. The conveyor system has 4 entrances connecting to 4 inbound docks and 16 exits connecting 30 outbound docks (each outbound dock serves trucks for distributing parcels to one destination).

At each conveyor entrance, seven workers are deployed to unwrap the incoming bulky consolidated parcels uploaded from the big inbound truck (16 tonnes) for facilitating the subsequent sortation process. To enable the distribution process to go well and items to be accurately sorted according to customer requirements, four workers are assigned to each conveyor exit serving two destinations (except two

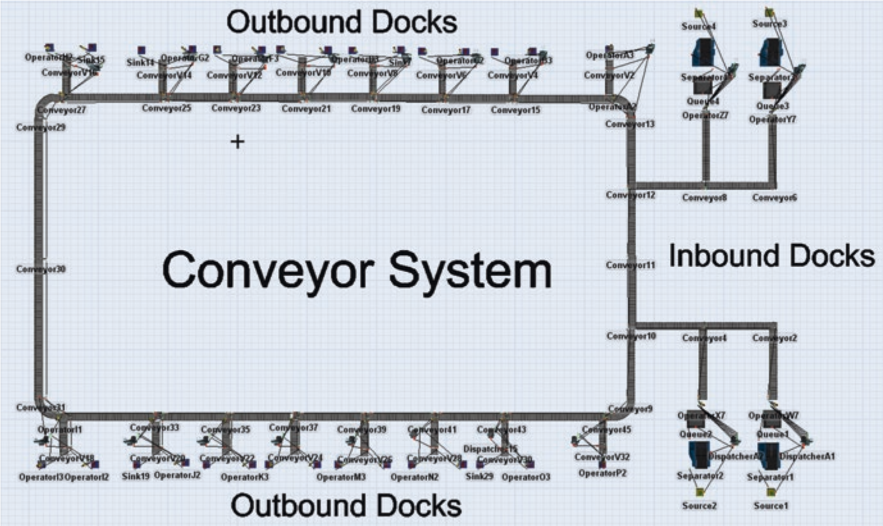

Fig. 1.2 The simulation model of the MHS implemented with FlexSim

exits close to the entrances serving one destination, which require two workers) and equipped a barcode reader for confirming the destination of each small parcel and helping to load the parcel to the small outbound truck (5.5 tons).

Simulation Model The simulation model with specific system configuration and behaviour is implemented with FlexSim (Fig. 1.2). Details of model components and initial model settings (Table 1.1) are as follows:

- Entities are 400 bulky consolidated parcels and 4000 small parcels deconsolidated from the bulky parcels, which are processed through the system causing changes in the system state over time.
- Activities are the deconsolidation of bulky consolidated parcels unloaded from each incoming truck (represented by a source in the simulation model) and the picking of small parcels from the circular conveyor to each outgoing truck (represented by a sink in the simulation model) according to their destinations.
- Item attribute is the product type associated with its destination (one product type corresponds to one specific destination).

Parameter Setting Based on the results of the sensitivity analysis, the parameters of SCMIA were set as follows: SCMIA, initial population size, N = 30; size of active population, N_A = 12; size of the memory population, N_m = 30; maximum number of clones for each cell, max_clone = 6; exponential distribution coefficient, ρ = 0.05; and number of simulation replications per fitness evaluation, $replication$ = 10. To allow a fair comparison among the algorithms compared, the parameters of the benchmarking algorithms were set with similar values and the values suggested by the authors.

Table 1.1 Initial model settings

Item	Value
Conveyor speed	2.5 m/s (limit: 1–2.5 m/s)
Conveyor spacing	1 parcel
Number of workers deployed for each conveyor entrance	7 workers (limit: 1–9 workers)
Number of workers deployed for each conveyor exit (serving 1 destination)	2 workers (limit: 1–4 workers)
Number of workers deployed for each conveyor exit (serving 2 destinations)	4 workers (limit: 1–6 workers)
Handling capacity of worker	1 parcel
Arrival pattern for each source	Uniform distribution with a min. of 5 s and a max. of 10 s
Processing time of deconsolidation process	Normal distribution with a mean of 30 s and a standard deviation of 2 s
Demand for each destination	Uniform distribution with a min. of 220 units and a max. of 280 units

The above model parameters are set based on the real system settings and observation

Antibody Definition An antibody ab that has the direct impact on the system's performance in terms of cycle time (CT) and workers' utilization (WU) is defined as follows: x_1 is taken to be the conveyor speed, x_2 is the number of workers deployed for each conveyor entrance, x_3 is the number of workers deployed for each conveyor exit (serving two destinations), and x_4 is the number of workers deployed for each conveyor exit (serving one destination). Since the objective of the study is to optimize the performance of the MHS by minimizing the system cycle time and maximizing the workers' utilization, the optimization problem can be given by:

$$\underset{\mathrm{ab}\,\in\,\Omega}{\mathrm{Optimize}}\,\vec{f}\left(\mathrm{ab}\right)=E\left[\mathrm{CT},\mathrm{WU},\omega\right] \tag{1.1}$$

Subject to:

$$1 \le x_1 \le 2.5 \tag{1.2}$$

$$1 \le x_2 \le 9 \tag{1.3}$$

$$1 \le x_3 \le 6 \tag{1.4}$$

$$1 \le x_4 \le 4 \tag{1.5}$$

where a set of objective functions $\vec{f}\left(\mathrm{ab}\right)$ to be optimized in objective space are the expected values of the random output variables [CT, WU, ω] that are obtained from running the simulation model, ω is a sample path (i.e. the sequence of random numbers used in a simulation run), and Eqs. (1.2), (1.3), (1.4), and (1.5) define a set of physical constraints.

Experimental Results and Analysis

We conducted two experiments to evaluate the performance of the optimization approach based on the above-mentioned case study, that is, (1) to compare the results of integrating simulation and optimization with the results without using any optimization algorithm and (2) to benchmark SCMIA against two immune-inspired algorithms, MISA [20] and NNIA [12], and two other evolutionary algorithms, NSGA-II [8] and SPEA2 [9], under the same approach. All algorithms were run for 30 generations over 20 trials to obtain the average performance of each algorithm on the same condition.

Simulation Without Optimization vs. Simulation with Optimization The results shown in Table 1.2 are the optimized results obtained by making use of all optimization algorithms studied in this research.

The table shows that the cycle time of the whole distribution system at the DC reduces by about 12–16% and the workers' utilization increases by 40–51% when optimization algorithms are deployed in the simulation process. This proves that the use of the optimizers can enhance the performance in the system's cycle time and the workers' utilization. However, the higher the utilization achieved, the longer the cycle time spent, and vice versa. When comparing SCMIA with other benchmark algorithms, SCMIA is able to produce comparable results in both of the cycle time and the workers' utilization.

Table 1.2 Performance comparison between simulation without optimization and simulation with optimization (the best results are bolded)

	Cycle time (the improvement in % compared with the one without optimization)	Workers' utilization (the improvement in % compared with the one without optimization)
Simulation without optimization	6788.64 s	45.04%
Simulation-based optimization with SCMIA	5775.45 s (14.92%)	65.60% (45.65%)
Simulation-based optimization with MISA	5792.67 s (14.67%)	64.43% (43.05%)
Simulation-based optimization with NNIA	**5685.49 s (16.25%)**	62.83% (39.50%)
Simulation-based optimization with NSGA-II	5687.71 s (16.22%)	63.09% (40.08%)
Simulation-based optimization with SPEA2	5950.84 s (12.34%)	**67.06% (51.11%)**

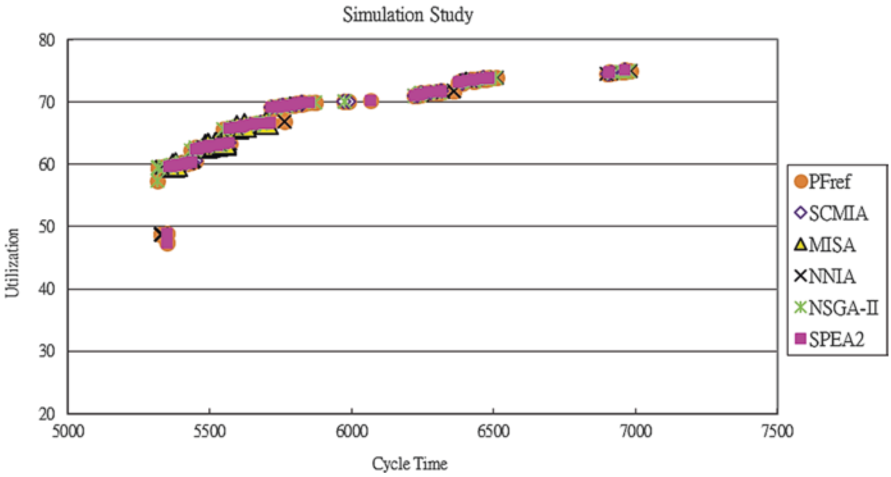

Fig. 1.3 Graphical comparison of the known Pareto fronts generated by the five algorithms

Performance Comparison Between SCMIA and Other Benchmark Algorithms The performance of the algorithms studied was compared by using the graphical representation together with the performance metrics mentioned in section "Performance Metrics". The comparison between the known Pareto fronts shown in Fig. 1.3 suggests that the overall Pareto front patterns generated by the five algorithms are largely similar in which the cycle time ranges from around 5300 s to 7000 s and the workers' utilization ranges from around 50% to 75%. From the figure, it is shown that the higher the utilization achieved, the longer the cycle time spent, and vice versa. This implies that increasing the utilization does not mean that the efficiency of the system can be increased. Therefore, although the optimal solution with 75% utilization while spending almost 7000 s and another case achieving less than 50% utilization while spending only around 5300 s both fall within the reference Pareto front PF_{ref}, the latter case is preferred in practice because the cycle time is much shorter, and hence the efficiency and productivity of the system are much higher. The utilization becoming lower in the latter case is mainly due to the increased values in the decision variables, namely, conveyor speed and number of worker. This implies that in order to further enhance both objectives at the same time for the DC, the company may need to do something other than just changing the system parameters, such as redesigning the layout of the conveyor system.

The performance regarding the optimality and the diversity of SCMIA in this multi-objective optimization problem was then examined. In this experiment, we compared the results of the mean and standard deviation of the 2 metrics over 20 trials obtained by SCMIA with that of the other benchmark algorithms. From the results shown in Table 1.3, we found that SCMIA generally is able to provide the best results in terms of the diversity and the optimality because it generates the low-

Table 1.3 Spacing and error ratio values generated by the five algorithms (the best results are bolded)

	SCMIA	MISA	NNIA	NSGA-II	SPEA2
	Mean (standard deviation)				
Error ratio (ER)	**0.71 (0.12)**	0.83 (0.17)	0.79 (0.18)	0.77 (0.15)	0.74 (0.06)
Spacing (S)	**38.83 (11.82)**	60.79 (53.90)	49.44 (28.22)	51.45 (17.47)	39.00 (35.58)

est values in the metrics of ER (0.71) and S (38.83) and the latter metric is significantly lower than most of the other algorithms. This implies that the generated front is very close to the PF_{ref}. In terms of the stability, SCMIA is also the best one among these five algorithms in error ratio and spacing because it has much lower standard deviations (0.12) and (11.82), respectively, than other algorithms except SPEA2, implying that SCMIA is able to provide a relatively consistent result for each trial.

Discussion Based on the results of the case study, SCMIA generally performs better than other benchmark algorithms especially in the diversity aspect. This is largely attributed to the operators employed in the algorithm. For example, the selection operator incorporates the crowding distance as a measure to select non-dominated antibodies for undergoing the subsequent evolutionary processes so that the antibodies in less crowded regions will have a higher priority to be selected. The cloning operator and hypermutation operator are based on the same measure to generate a number of copies for exploring the solution space and bringing variation to the clone population, respectively, where less crowded individuals are given more chances for cloning and hypermutation in order to hopefully produce better offspring and increase population diversity. The crossover operator helps further enhance the diversity of the clone population and the convergence of the algorithm because some good genes from the active parent can be passed to the offspring. The suppression operator helps reduce antibody redundancy by eliminating similar individuals, hence significantly minimizing the number of unnecessary searches and increasing the population diversity. The memory updating operator takes account of the antibody similarity in terms of both the objective space and the decision variable space to formulate the memory population. As a result, SCMIA is able to generate a well-distributed set of solutions, while it is a good approximation to the reference Pareto front.

The results overall demonstrate the ability of the simulation-based optimization approach to serve as a decision support tool for helping management to effectively and efficiently find near-optimal system operating conditions and parameters such as the number of workers, the speed of various kinds of machines or any other decision variables of interest to fulfil different objectives including cycle time, machine utilization, etc. As a result, significant savings in money, energy, etc. are achieved through the cost-effective and efficient deployment of material handling systems and well-coordinated processing activities based on the optimized results generated from the approach.

1.5 Conclusion

This study applies a multi-objective simulation-based optimization approach incorporating a hybrid AIS-based optimization algorithm SCMIA for evaluating the optimality of the distribution system with respect to the two criteria – system cycle time and workers' utilization through simulation modelling.

Based on the findings of the current undertaking, it is worthwhile to extend the approach to tackle other complex problems involving many objectives to be considered in an efficient and effective manner in the future. Future research could also extend this approach to solve real-world complex business problems with real-world dynamics such as time-varying demand and supply and to solve other large-scale problems with a large number of parameters, operators and equipment involved in order to establish the practical value of the approach in the simulation-based optimization context.

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