7 Conclusions

We have introduced WIOM, a MIP that helps NAVSUP planners to set reorder points for thousands of maritime and aviation line items under uncertain demand. WIOM seeks to minimize weighted, expected shortfalls from fill rate targets and deviations from legacy solutions under a limited safety stock budget. We adjust an existing closed-form approximation of expected fill rate that better captures multiple expected orders per lead time, and incorporate it into the optimization model. We solve realistic instances of WIOM provided by NAVSUP via both a general-purpose MIP solver and by Lagrangian relaxation. Preference for either method depends on the case and metric used: objective value, computational time, or fraction of budget used.

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Smart Production by Integrating Product-Mix Planning and Revenue Management for Semiconductor Manufacturing

Marzieh Khakifirooz, Jei-Zheng Wu, and Mahdi Fathi

Abstract Semiconductor manufacturing is a capital-intensive industry, in which matching the demand and capacity is the most important and challenging decision due to the long lead time for capacity expansion and shortening product life cycles of various demands. Most of the previous works focused on capacity investment strategy or product-mix planning based on single evaluation criteria such as total cost or total profit. However, a different combination of product-mix will contribute to a different combination of key financial indicators such as revenue, profit, gross margin. This study aims to model the multi-objective product-mix planning and revenue management for the manufacturing systems with unrelated parallel machines. Indeed, the present problem is a multi-objective nonlinear integer programming problem. Thus, this study developed a multi-objective genetic algorithm for revenue management (MORMGA) with an efficient algorithm to generate the initial solutions and a Pareto ranking selection mechanism using elitist strategy to find the effective Pareto frontier. A number of standard multi-objective metrics including distance metrics, spacing metrics, maximum spread metrics, rate metrics, and coverage metrics are employed to compare the performance of the proposed MORMGA with mathematical models and experts' experiences. The proposed model can help a company to formulate a competitive strategy to achieve the first-priority objective without sacrificing other benefits. A case study in real settings was conducted in a leading semiconductor company in Taiwan for validation. The results showed that MORMGA outperformed the efficient multi-objective genetic

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M. Fathi et al. (eds.), *Optimization in Large Scale Problems*, Springer Optimization and Its Applications 152, https://doi.org/10.1007/978-3-030-28565-4_16

algorithm, i.e., NSGA-II, as well as expert knowledge of the case corporation in both revenue and gross margin. An evaluation scheme was demonstrated by comparing the effectiveness of manufacturing flexibility from the multi-objective perspective.

1 Introduction

Manufacturing companies are highly utilizing smart devices such as sensors and wireless technology and getting smart which make manufacturers more sustainable, profitable, productive, and efficient [26]. They are becoming more complex with automation, and computerized processes and systems which lead to big data challenges and how to interpret them and use for the innovative improvement of processes and products [25–27].

Kusiak [27] believes that "Smart manufacturing such as semiconductor, computing, aircraft, energy industries is an emerging form of production integrating manufacturing assets of today and tomorrow with sensors, computing platforms, communication technology, control, simulation, data-intensive modelling and predictive engineering based on cyber-physical systems with artificial intelligence, cloud computing, the internet of things, service-oriented computing, and data science. He considered six pillars for smart manufacturing including manufacturing technology and processes, materials, data, predictive engineering, sustainability and resource sharing and networking. He defined the future of smart manufacturing in ten opinions varying from manufacturing digitization and material-product-process phenomenon to enterprise dichotomy and standardization".

Following Moore's law that the number of transistors fabricated on a wafer will be doubled every 12 or 24 months with lower average selling price [37], the new generation product will dominate prior generations regarding the cost-per-function. This technology migration will accelerate the price decline of prior generation products. The increasingly fierce competition also has commodified chip sales and led to continuous and significant price decline [8, 21]. With continuously advanced functions with reducing average unit cost, semiconductor applications are continuously expanding and penetrating into various segments [28]. Smart integrated circuits (ICs) have been increasingly employed in medical electronics, green energy, car electronics, computers, communication, and consumer electronics. In general, IC product demands can be categorized into make-to-order (MTO) logic ICs and make-to-stock (MTS) memory ICs [20]. Wafer foundry companies generally fabricate logic ICs whereas memory ICs are standard products and normally produced by integrated device manufacturers. In order to search for growth opportunity, integrated device manufacturers have been aggressively snatching foundry business while foundry service companies have been developing manufacturing flexibility to support memory products families. Semiconductor manufacturers are facing challenges to supply a high variety of product by utilizing flexible processes and machines.

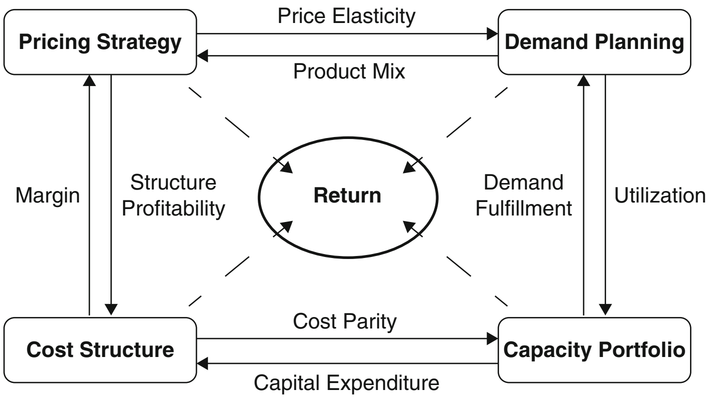

Fig. 1 Conceptual framework of PDCCCR [8, 11]

There are some papers studying the demand and capacity planning in semiconductor industry such as [14, 15, 23, 39, 40]. To respond to increasing demand, manufacturing strategic decisions of the interrelated determinants include pricing strategies (P), demand forecast and demand fulfillment planning (D), capacity planning and capacity portfolio (C_1), capital expenditure (C_2), and cost structure (C_3) that will affect the overall financial return (R) of semiconductor manufacturing companies, as illustrated in the PDCCCR conceptual framework of Fig. 1 [8, 11].

Forecasts of future demands from various marketplaces provide the basis for capacity decisions. However, the demand fluctuation due to shortening product life cycle and increasing product diversification in the consumer electronics era make the demand forecast problem increasingly difficult and complicated. Demand forecast errors cause either inefficient capacity utilization or capacity shortage that will significantly affect the capital effectiveness and profitability of semiconductor manufacturing companies [8].

Conventional approaches for capacity management include capacity transformation and expansion investment from strategic level to operational level [61], new product allocation, intra-company inter- and intra-fab backup [13], inter-company backup [11], outsourcing [12, 47, 52], portfolio selection [10] and productivity enhancement [9]. Most of the approaches have been applied by semiconductor manufacturing companies to meet diverse and increasing demands. However, the capacity planning in the semiconductor industry can be characterized by high capital expenditure in capacity investment, long capacity installation lead times, high obsolescence rates due to rapid technology development, high demand volatility [47, 50]. Indivisibility, irreversibility, and nonconvexity in capacity cost modeling contribute to the additional complexity of the problem [60]. While existing studies have developed robust capacity strategies [15], facility allocation [59], manufacturing execution system [62], and manufacturing flexibilities [42] including product-mix, process, and machine flexibilities provide conservative and asset-lite alternative solutions for short-term capacity dynamics to meet surge demands in the highly uncertain environment.

Empirical studies showed higher performances of plants with higher levels of volume and product-mix flexibility that can be achieved through a mix of flexibility multiple source factors [63]. Although the definition of product-mix flexibility is not unanimous, main features comprise the ability to quickly and economically adjustment of capacity for switches between products [4]. The externally-driven manufacturing flexibility including volume and variety flexibilities were influenced by the capability of internally-driven manufacturing flexibilities such as process and machine flexibilities [18]. In particular, process flexibility is the ability of a single manufacturing plant to make multiple products whereas machine flexibility, a moderating factor to process flexibility, is measured in terms of the capacity lost when multiple products must be produced [2].

Furthermore, most of existing capacity planning models consider single return objective function such as cost, profit, utilization, or the possibility of shortage [1, 45, 49, 64]. Yet, the optimization of a single objective is solved at the expenses of other financial and operating indexes. For example, maximizing profitability may lead to the loss of market share due to abandoning of low-profit-margin-but-high-volume demand.

This study aims to propose a multi-objective capacity planning model to address the product-mix, process, and machine flexibilities, i.e., backups among different product families and technologies to maximize the synergistic benefits of revenue growth, profitability, and wafer outputs, which are critical to evaluating the competitiveness of a semiconductor company. Without loss of generality, the aforementioned model lies in the category of quantity-based revenue management decisions comprising allocations of output or capacity to different segments, products or channels [43]. For dealing with the nature of high combinatorial problem complexity involved in the present problem, this study develops an efficient multi-objective revenue management genetic algorithm (MORMGA) based on bi-vector encoding method for chromosomes representation such as the one in [53] where they modeled and solve the simultaneous multiple resources scheduling problem based on a genetic algorithm with a novel bi-vector encoding method representing the chromosomes of operation sequence and seizing rules for resource assignment in tandem. For validation, this study will propose an evaluation scheme for comparing the multi-objective effectiveness of manufacturing flexibility of the proposed solution with alternative approaches, in which standard multi-objective performance metrics such as distance metrics, spacing metrics, maximum spread metrics, rate metrics, and coverage metrics will be employed. Decision makers can select the beneficial alternatives of product-mix and capacity configuration decisions from a set of nondominated solutions without the need of a priori articulation of preferences among multiple objectives.

The remainder of this paper is organized as follows. Section 2 defines the multi-objective product-mix planning and revenue management for the semiconductor manufacturing systems with unrelated parallel machines and proposes a mathematical model to find the exact solution of the problem. Section 3 proposes an efficient multi-objective genetic algorithm model to solve the problem. Section 4 examines the proposed genetic algorithm with real case data. Section 5 concludes with discussions of contributions and future research directions.

2 Problem Definition

Before describing the problem and solution in detail, some definitions regarding multiobjective optimization are presented [16].

For $F : \Omega \rightarrow \Re^m$, a multiobjective optimization program (MOP) can be represented as follow:

$$\begin{cases} \max F(x) = (f_1(x), \ldots, f_m(x))^T \\ \quad st: \qquad\qquad x \in \Omega \end{cases}$$

where x, Ω, m, and $\Re^m$ are the decision variable vector, the decision space, the number of conflicting objectives, and objective space, respectively.

In an MOP, an objective vector v is said to dominate another one u if and only if $v_i \geq u_i, i \in 1, \ldots, m$ holds with at least one strict inequality. An objective vector is nondominated if no other vectors dominates it, and a solution x is said to be Pareto optimal if its objective vector is nondominated by others. The set of nondominated objective vectors and the set of Pareto optimal solutions constitute the Pareto front (PF) and the Pareto set (PS), respectively. Since it is generally time consuming to obtain a complete PF, in real-life applications an approximation to the PF is required to support decision-making.

In literature of Multiobjective Evolutionary Algorithm (MOEA) based on decomposition, there are three decomposition methods including “the weighted sum”, “the weighted-Tchebycheff”, and “the penalty-based boundary intersection” approaches.

1. The ith subproblem of “the Weighted Sum(WS)” approach is as follow:

$$min\ g^{ws}(x|\lambda_i) = \sum_{j=1}^{m} \lambda_i^j f_j(x).$$

   This method is efficient for solving convex Pareto solutions with Min objective function.
2. The ith subproblem of “the Tchebycheff Approach” (TCH), is as follow:

$$min\ g^{te}(x|\lambda_i, z^*) = max_{1 \leq j \leq m} \left\{ \lambda_i^j |f_j(x) - z_j^*| \right\},$$

   where $z^* = (z_1^*, \ldots, z_m^*)^T$ is the ideal reference point with $z_j^* < min\{f_j(x)|x \in \Omega\}$ for $j = 1, 2, \ldots, m$.

3. The ith subproblem "the Penalty-Based Boundary Intersection" (PBI) approach is as follow:

$$min\ g^{pbi}(x|\lambda_i, z^*) = d_1 + \theta d_2$$

where
$d_1 = \frac{\|(F(x)-z^*)^T\lambda_i\|}{\|\lambda_i\|}$ and
$d_2 = \left\|F(x) - \left(z^* - d_1\frac{\lambda_i}{\|\lambda_i\|}\right)\right\|$. The z^* is the reference point as in $g^{pbi}(x|\lambda_i, z^*)$ and θ is a penalty parameter which should be properly tuned.

In this paper, we use "the weighted sum" Pareto-Based MOEA to find PF.

2.1 Assumptions

The following assumptions are considered as follow:

1. Inventory and backlog are not considered. This study focused on semiconductor wafer fabrication foundry service that is make-to-order without inventory, while backlog will become deferred demand [13].
2. All parameters are known and constant. There are two important reasons to show why deterministic models are reasonable. Firstly, deterministic models are easy to analyze and can serve as a good approximate for the more realistic yet complicated stochastic models. Deterministic solutions are asymptotically optimal for the stochastic demand problem [38]. Secondly, deterministic models are more applicable in practice [5].
3. Prices, cost structures, and demand forecasts are given. This study focused on quantity-based revenue management models, i.e., capacity allocation and configuration [43]. The proposed model can be further applied for examining different pricing strategies, cost management plans, and demand scenario analysis.
4. Long-term capacity expansion decision is formed in advance, and is thus not considered in this model. This problem focused on short-term capacity configuration and allocation decisions.
5. Yield defines at the total number of functional chips produced over number of designed chips.
6. The total capacity over horizon is assumed to be bounded by strategic estimation representing the long-term vision under competitors' behaviour. For example, minimum demand for old technology based products and maximum demand of new technology based products would be an estimate for the accumulated capacity.
7. The model is considered to be solved at-least once over the technology changes on horizon.

2.2 Functions

$\lceil x \rceil$ Ceiling of x is the smallest integer not less than x
$\lfloor x \rfloor$ Floor of x is the largest integer not greater than x
$[x]^+$ max $(x, 0)$

2.3 Superscripts and Subscripts

b product type (i.e., digital, analog, and mixed chips for different devices and speed of processing)
g demand group
i order item (chip/wafer)
j machine area group (i.e., cluster tool)
k, m machine group (an specific machine/tool from area group j is required for fabrication the recipe r for layer n of product type b)
n number of layers (number of fabrication rounds repeat from oxidation to doping)
r machine recipe (a set of instruction that at layer n, machine of type m belong to area j is required to do for fabrication the product type b)

2.4 Sets

$\mathbf{B}^m$ set of product type that can be processed on machine group m
$\mathbf{G}$ set of demand groups
$\mathbf{G}_i$ set of demand groups that belong to order i
$\mathbf{I}$ set of orders
$\mathbf{I}^b$ set of orders that belongs to product type b
$\mathbf{I}_g$ set of orders that belong to demand group g
$\mathbf{J}$ set of machine area groups
$\mathbf{K}$ a sequence of pair machines $\{(k_1, m_1), (k_2, m_2), \ldots, (k_{(K)}, m_{(K)})\}$ that can be exchanged from one to another. The pair machines are sorted in the increasing order of F_{km} / V_{km}
$\mathbf{M}$ a sequence of machine groups that is sorted in the increasing order of F_{km} / V_{km}
$\mathbf{M}^j$ a set of machine groups that belong to area group j
$\mathbf{M}_b$ a set of machine groups where product type b will be processed on
$\mathbf{N}^{bm}$ set of process layers where products type b will be processed on machine group m
$\mathbf{R}^{bmn}$ set of recipe by which product type b will be processed on machine group m through layer n

2.5 Parameters

A_m	average availability of machine group m
B_i	product type of order i
C_b	variable cost of product type b
C_{DL}	unit cost per hour for additional direct labor hours
D_i^{max}	maximum demand of order i
D_i^{min}	minimum (committed) demand of order i, where without loss of generality $D_i^{min} < D_i^{max}$
D_i^{range}	range of demand of order i, where $D_i^{range} = D_i^{max} - D_i^{min} > 0$
E_m	efficiency of machine group m
F	total capacity expansion budget of the planning horizon
F_m	capital expenditure of machine group m written down within the planning horizon
F_{km}	unit cost of exchange from machine group m to machine group k within the planning horizon
G	fixed cost
G_g^{max}	maximum output of demand group g
G_g^{min}	minimum output of demand group g
H	total hours within the planning horizon
H_m	net available capacity of machine group m within the planning horizon
H_{im}	unit loading of order item i per hour when processed machine group m within the planning horizon
H_{bmnr}	unit loading of product type b when processed on the nth layer by using machine group m with recipe r within the planning horizon
J_m	area group attribute of machine group m
K_m	indicating whether machine group m needs to be operated by direct labors ($K_m = 1$) or not ($K_m = 0$)
O_j	max number of a machine that can be acquired at area group j
P_i	unit price of order item i
Q_m^{max}	maximum number of machine group m acquired within the planning horizon
R_{bmnr}	rework rate of product type b when processed on the nth layer by using machine group m with recipe r
S	number of unit loading that the current direct labor level can support
S_{bmnr}	number of unit loading of product type b when processed on the nth layer by using machine group m with recipe r
V_m	capacity ramping-up rate of acquiring machine group m
V_{km}	capacity exchange rate of exchanging from machine group k to machine group m
W_i	wafer-per-hour throughput of order item i

W_{bmr} wafer-per-hour throughput of product type b processed on machine group m using recipe r

Y_{bmnr} yield rate of using machine group m to process product type b on the nth layer with recipe r

2.6 Decision Variables

x_i capacity supported the demand of order i

q_m number of machine group m acquired within the planning horizon

q_{km} capacities exchanged from machine group k to machine group m

2.7 Objective Functions and Constraints

$$\max z_{REV} = \sum_{i \in \mathbf{I}} P_i x_i \tag{1}$$

$$\begin{aligned} \min z_{MAR} = 1 - \tfrac{1}{\sum_{i \in \mathbf{I}} P_i x_i} \Big\{ & \textstyle\sum_{b \in \mathbf{B}} C_b \sum_{i \in \mathbf{I}^b} x_i + \\ & \textstyle\sum_{(k,m) \in \mathbf{K}} F_{km} q_{km} + F_m q_m + G + \\ & C_{DL} \left[\textstyle\sum_{m \in \mathbf{M}} \sum_{b \in \mathbf{B}^m, i \in \mathbf{I}^b} H_{im} x_i - S \right]^+ \Big\} \end{aligned} \tag{2}$$

$$\max z_{OUT} = \sum_{i \in \mathbf{I}} W_i x_i \tag{3}$$

$$\min z_{PEN} = \sum_{(k,m) \in \mathbf{K}} q_{km} \tag{4}$$

$$G_g^{min} \leq \sum_{i \in \mathbf{I}_g} x_i \leq G_g^{max}, \forall g \in \mathbf{G} \tag{5}$$

$$\begin{aligned} \textstyle\sum_{b \in \mathbf{B}^m, i \in \mathbf{I}^b} H_{im} x_i \leq H_m + V_m q_m + & \\ & \textstyle\sum_{(k,m) \in \mathbf{K}} V_{km} q_{km} - \\ & \textstyle\sum_{(m,k) \in \mathbf{K}} q_{mk}, \forall m \in \mathbf{M} \end{aligned} \tag{6}$$

$$\sum_{m \in \mathbf{M}^j} q_m \leq O_j, \forall j \in \mathbf{J} \tag{7}$$

$$\sum_{m \in \mathbf{M}} F_m q_m \leq F \tag{8}$$

$$D_i^{min} \leq x_i \leq D_i^{max}, \forall i \in \mathbf{I} \tag{9}$$

$$q_m \in \left\{0, 1, 2, \ldots, Q_m^{max}\right\}, \forall m \in \mathbf{M} \tag{10}$$

$$q_{km} \geq 0, \forall (k, m) \in \mathbf{K} \tag{11}$$

where

$$H_m = H \times A_m \times E_m, \forall m \in \mathbf{M} \tag{12}$$

$$\begin{aligned} &H_{bmnr} = \tfrac{S_{bmnr}}{W_{bmr} H_{bmr} (1 - R_{bmnr}) Y_{bmnr}}, \\ &\forall m \in \mathbf{M}, b \in \mathbf{B}^m, n \in \mathbf{N}^{bm}, i \in \mathbf{I}^b, r \in \mathbf{R}^{bmn} \end{aligned} \tag{13}$$

$$\begin{aligned} &H_{im} = \textstyle\sum_{n \in \mathbf{N}^{bm}} \sum_{r \in \mathbf{R}^{bmn}} H_{bmnr}, \\ &\forall m \in \mathbf{M}, b \in \mathbf{B}^m, i \in \mathbf{I}^b \end{aligned} \tag{14}$$

The conflicting objectives of the proposed model is to simultaneously achieve three non-commensurable objectives including revenue maximization in Eq. (1), profit margin maximization in Eq. (2), equivalent output in Eq. (3), and penalty in Eq. (4). The flexible formulation in Eq. (2) entails treatment to nonlinearity that also justifies the use of genetic algorithm. In addition, the direct labor cost evaluation reflected the need to incorporate labor flexibility when modeling product-mix planning [22].

The decision model is bounded by strategic constraints (Eq. 5) that revealed long-term vision for the company and considered competitors' actions as discussed in [6]. One reminding example was Intel's decision on retiring commoditized memory products that could benefit Intel with economies of scales while the beginning of microprocessor products had no advantage regarding marginal profit per unit of capacity supplied. In this case, minimum demand for microprocessor products and maximum demand of memory products shall be considered. Setting up the floor of grouping demand for ramping-up new technology and ceiling for old technology is another common strategic constraint.

Capacity allocation and configuration constraints are formulated in Eq. (6) to show the relationship between machine requirement and machine supply by considering the number of steps, throughput rate, rework rate, yield rate, machine hours, number of machines on hand, number of incremental machines, number of planned retrofits, number of retrofits to be done, machine availability, and efficiency as detailed from Eqs. (12) to (14). The effective capacity will consider the loss rates during ramping-up and retrofitting. In semiconductor wafer fabrication, a product will go through complex operations of multi-layer process which comprise a number of machine groups. The portion of convertible machine groups for capacity requirement may differ among different operations. Capacity requirement of different machine groups for each product type may also differ in each operation.

A machine group can be characterized by its capability of processing multiple product types. In particular, a dedicated machine group can support only one product type whereas different product types may share capacity on a flexible machine group. In addition, partial flexible machine groups, namely convertible machine groups, can be converted to support different product types with additional loss on cost and capacity. A machine group can be further characterized by its process technology. Old technology cannot be employed to produce advanced products. There are three ways of increasing capacity for a machine group: acquisition and backup (exchange). By acquisition, a new machine group can be purchased, installed, and ramped up to support future demand. By exchange, when the working time of common machines allocated to a technology increases, the capacity will increase accordingly.

Constraints (7) and (8) specify the limitations of facility spaces (enclosed by the building, land clean room floor space, machine types, categories of manpower, etc.) [7] and annual budget for small-scale expansions, respectively. Constraint (9) defined the boundary of demands. Finally, Eqs. (10) and (11) show nonnegative integer variables for machine acquisition, and retrofit, respectively.

$$\begin{aligned} \max z_{REV} &= \textstyle\sum_{i \in \mathbf{I} \equiv \mathbf{M}} P_i x_i \\ &= \textstyle\sum_{i \in \mathbf{I} \equiv \mathbf{M}} \min \left\{ \frac{V_i}{H_{ii}} q_i, G_g^{max}, D_i^{max} \right\} P_i \end{aligned} \tag{15}$$

$$H_{ii} x_i \leq V_i q_i, \forall i \in \mathbf{I} \equiv \mathbf{M} \tag{16}$$

$$\sum_{i \in \mathbf{I} \equiv \mathbf{M}} F_i q_i \leq F \tag{17}$$

$$q_i \in \left\{0, 1, 2, .., Q_i^{max}\right\}, \forall i \in \mathbf{I} \equiv \mathbf{M} \tag{18}$$

The aforementioned mathematical model is computationally intractable, especially when the problem size increases significantly. When we decompose the problem (1)–(14) by considering the special case where each order item requires distinct and unique machine to process, we have the single-objective problem (15) subject (16)–(18) which is a bounded Knapsack problem, a NP-hard (non-deterministic polynomial) problem [34]. Generally speaking, multi-objective optimization problems are more difficult [33].

Approaches to tackle multi-objective optimization problems can be categorized as priori, interactive, and posteriori ones according to the timing when decision-makers' preferences were introduced [36, 65]. Priori approaches can be transformed to single-objective optimization problems by using weighting or lexicographic methods. However, it is inefficient and hard to elicit decision-makers' preferences when no alternatives are provided in the dynamic planning environment. Interactive methods are neither efficient nor cost-effective when the design spaces are wide-spread in the planning problem. Alternatively, after a limited number of solutions are specified through a posteriori approach, it can be transformed to transform it to an interactive approach to elicit decision-makers preferences on alternatives when corresponding criterion values are determined [19].

Multi-objective genetic algorithms are relatively effective to find the nondominated (Pareto) solution set. In particular, a number of tests on NSGA-II with and without constraint dominances showed its efficiency on solving multi-objective optimization problems with continuous variables [17]. However, the lack of empirical experiments on multi-objective combinatorial problems limits its application to product-mix and capacity configuration planning problems. Added to this, the elitism strategy does not guarantee diversity of nondominated solutions so as to provide decision-makers with informational choices.

3 Multiple-Objective Revenue Management Genetic Algorithm

This study modifies the NSGA-II with constraint handling [17] to develop a multi-objective genetic algorithm (MORMGA) to solve the product-mix and revenue management problem with revenue maximization, profit margin maximization, and equivalent output maximization objectives. MORMGA consider five parameters including generation size (N_g), population size (N_p), global front size (N_s), crossover rate (r_p), and mutation rate (r_m). The generation, denoted by t, represents the number of computation iterations of the GA. It contains (N_p) chromosomes and corresponding solutions that collectively represents a population, denoted as $\mathbf{P}(t)$. Initial chromosomes are randomly generated. The crossover rate represents the ratio of the number of offspring produced in each generation to the population size, whereas only some proportion of the population is being generated by mutation.

The global Pareto solutions can be updated at each generation after the NSGA-II process (Fig. 2). The newly generated Pareto solutions are those with rank one. However, these solutions should be compared with the existing Pareto solutions, since there is no guarantee of non-dominance when the two sets are pooled. In other words, one point in the new set can be dominated by another point in the old set,

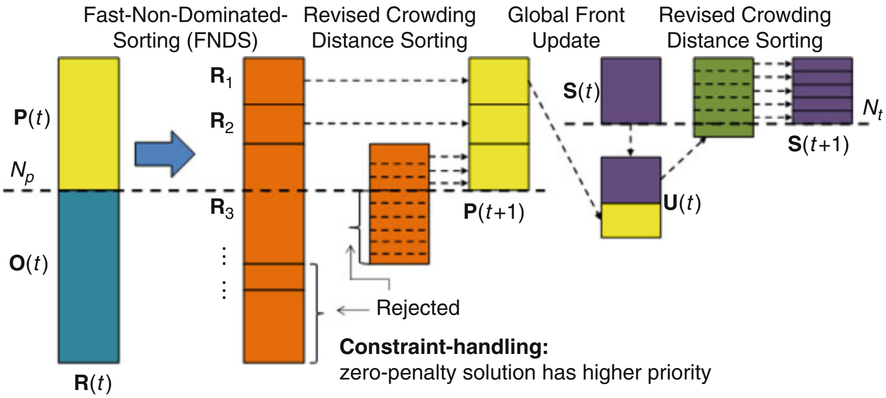

Fig. 2 Revised NSGA-II procedure

while one point in the old set can be dominated by another point in the new set. Therefore, it is possible to pool the two sets into a single population, and then adopt the NSGA-II to find the updated Pareto solutions.

A bi-vector encoding method [53] is embedded in the proposed MORMGA. An allocation vector $\mathbf{A} = [\alpha_1, \alpha_2, \ldots, \alpha_{(\mathbf{I})}]$ contains genes that represent the percentage of individual orders to be allocated. The value of each gene, namely genotype, is encoded as a random key [3], i.e., a real number in [0, 1]. For example, given an order item $i \in \mathbf{I}$ with gene α_i, the corresponding allocation is $x_i := D_i^{min} + \alpha_i D_i^{range}$. The other vector $\mathbf{B} = [\beta_1, \beta_2, \ldots, \beta_{(\mathbf{I})}]$ is a permutation of $[1, 2, \ldots, (\mathbf{I})]$ that contains genes representing the sequence of individual orders to be allocated. The lengths of both vectors equal the number of orders, i.e. $(\mathbf{I})$.

The decoding method utilizes the random key-based representation and priority-based representation to generate feasible order allocations and capacity configuration and to assess objective values of each chromosome. Both repair strategy and penalty objective strategy are embedded. Repair strategy is applied to ensure feasibility of strategic constraints. The constraint-handling version of NSGA-II will deal with the additional penalty objective that represents violation of the capacity constraint.

The worst-case time complexity of decoding method is $O(|\mathbf{M}|^2)$ or $O(|\mathbf{I}|^2)$ depending on the number of orders and machine groups. The level of complexity is reasonable since it is commonly required for capacitated order assignment to traverse all links among orders and machine groups. Consequently, given four objectives and $N_g \gg N_s > N_p$, the complexity of MORMGA is $O(4 N_g N_p N_s)$.

Algorithm 1 Multi-objective revenue management genetic algorithm (MORMGA)

input
Initial parameter setting for MORMGA
Empirical data

output
Pareto optimal solution

begin

Initialize **P**(t)
Evaluate **P**(t) based in the proposed **decoding method**
Generate global Pareto solutions by inserting the rank-one solution with zero penalty value

for $t = 1 : N_g$ **do**

  Recombine **P**(t) to yield **O**(t) by using the two cut-point crossover (r_p) and the partition randomization mutation (r_m) for the allocation vector (random key-based representation) and the partition mapping crossover and the insertion mutation for the sequence vector (permutation-based representation) [52]

  Evaluate **O**(t) based on the proposed **decoding method** and the NSGA-II
  [17]

  $\mathbf{R}(t) \leftarrow \mathbf{R}(t) \cup \mathbf{R}(t)$ – combine parent and offspring population
  $\mathbf{R} \equiv \{\mathbf{R}_1, \mathbf{R}_2, \ldots\} \leftarrow \text{fast} - \text{non} - \text{dominated} - \text{sort}\,(\mathbf{R}\,(t))$ – sort nondominated fronts of $\mathbf{R}(t)$
  $\mathbf{P}(t+1) \leftarrow \varnothing$ and $i \leftarrow 1$

  while $|\mathbf{P}(t+1)| + |\mathbf{R}_i| \leq N_p$ **do**
    $\mathbf{P}(t+1) \leftarrow \mathbf{P}(t+1) \cup \mathbf{R}_i$ – include ith nondominated front in the parent population
    $i := i + 1$ – check the next front for
  end while

  Apply crowding-distance-assignment, i.e. $D_C(a), \forall a \in \mathbf{R}_i$ – calculate crowding distance in $\mathbf{R}_i$

  $\mathbf{P}(t+1) \leftarrow \mathbf{P}(t+1) \cup \mathbf{R}_i[1 : (N_p - |\mathbf{P}(t+1)|)]$ – choose the first $(N_p - |\mathbf{P}(t+1)|)$ elements of $\mathbf{R}_i$

  Sort($\mathbf{R}_i \succ_c$) – sort in descending order using revised crowded-comparison operator ($\succ_c$)

  if a is of zero penalty but b is not
or [it not the reverse case that b is of zero penalty but a is not
and $((a \succ b))$ (week dominance with respect to objective values)
or [$a \sim b$ (non-dominance) **and** $D_C(a) > D_C(b)$ (using crowding distance)])]
then $(a \succ b_c)$
  end if

  $\mathbf{U} \leftarrow \mathbf{S}(t)$ – initialize the joint global Pareto front

(continued)

Algorithm 1 (continued)

```
    for u ∈ P(t + 1) do
        if the penalty objective of u is not zero then
            next u – update with feasible solutions only
        end if
        U ← U ∪ {u} – initialize the joint global Pareto front
        for v ∈ S(t) do
            if u ≻ v then
                U ← U ∪ {v} – check whether v is dominated
            else if u ≺ v then
                U ← U ∪ {u} – check whether u is dominated
            end if
        end for
        Apply crowding-distance-assignment (U) – calculate crowding distance in U
        Sort (U, ≻c) – sort U in descending order of crowding distance
        S(t + 1) ← U [1 : Ns] – choose the first Ns elements of U
    end for
end for
end
```

4 Numerical Results with Real Settings

The proposed MORMGA was examined in an anonymous wafer fabrication foundry company located in Hsinchu Science Park of Taiwan. To ensure confidentiality, data was transformed by reserving comparative results without loss of generality for further explanation. The data comprised 10 products and 72 machine functions. Total product route were 2847 steps, each product had to go through an average about 300 steps. In the same data, three pairs of backups supported machine flexibility. Three working areas spared extra space for small-scale machine acquisition. More details are elaborated in tables 9 to 13 of Appendix. The annual investment limit was $200 million and direct-labor move limit was 198 million steps.

To evaluate and compare multi-objective optimization algorithms, this study adopted conventional performance metrics including the relative average distance (Dav) [46] to the reference front, the percentage of range that the solution set covers the reference front (MS), the space metric used to measure how evenly the solutions are distributed (Tan's spacing, TS) [44], the rate metric (R) [48] which shows the number of non-dominated solutions in the obtained solution set, coverage metric (C) [66] which reflects the dominance relation between two solution sets, and running times (RT) [32, 44].

Algorithm 2 Decoding method

input (including parameters and variables mentioned in the aforementioned mathematical model)

A: An allocation chromosome $[\alpha_1, \alpha_2, \ldots, \alpha_{(\mathbf{I})}]$
B: An allocation chromosome $[\beta_1, \beta_2, \ldots, \beta_{(\mathbf{I})}]$

output

A: A repaired allocation chromosome
$c, q_m, \forall m \in \mathbf{M}$, and $q_{km}, \forall (k, m) \in \mathbf{K}$: Three sets of decision variables
$z_{REV}, z_{MAR}, z_{OUT}$, and z_{PEN}: Three objective values and one penalty value (z_{PEN}) that sums overall exceeding loading.

begin

$x_i \leftarrow D_i^{min} + \alpha_i D_i^{range}, \forall i \in \mathbf{I}$

$\mu_g \leftarrow \sum_{i \in \mathbf{I}_g} x_i, \forall g \in \mathbf{G}$: denotes output of demand group g

Apply **procedure**: prior-repair method to meet strategic demand group constraint
Apply **procedure**: capacity allocation and reconfiguration method
Apply **procedure**: post-repair method to meet capacity constraints and to improve machine utilization

$z_{REV} \leftarrow \sum_{i \in \mathbf{I}} P_i x_i$

$$z_{MAR} \leftarrow 1 - \frac{1}{\sum_{i \in \mathbf{I}} P_i x_i} \Big\{ \sum_{b \in \mathbf{B}} C_b \sum_{i \in \mathbf{I}^b} x_i + \sum_{(k,m) \in \mathbf{K}} F_{km} q_{km} + F_m q_m + G + C_{DL} \big[\sum_{m \in \mathbf{M}} \sum_{b \in \mathbf{B}^m, i \in \mathbf{I}^b} H_{im} x_i - S \big]^+ \Big\}$$

$z_{OUT} \leftarrow \sum_{i \in \mathbf{I}} W_i x_i$

$z_{PEN} \leftarrow \sum_{m \in \mathbf{M}, \nabla_m > 0} \nabla_m$

end

Four numerical tests were performed. Designs of the MORMGA were firstly evaluated. The best MORMGA design was applied thereafter. Secondly, effectiveness of backup and acquisition was examined and compared. After that, complexity effects were evaluated based on four different size problems with the same problem structures. Finally, full-scale test results were presented.

Numerical analysis was performed on a desktop computer equipped with an Intel Core^{TM} Quad CPU Q8400 @ 2.66 GHz and 3.25 GB RAM. The commercial software LINGO 11.0 (LINGO System) was used to generate a reference set of non-dominated solutions by utilizing embedded integer programming (IP) packages. LINGO solved the weighted-sums problem with objectives (1)–(4) subject to (5)–(14) a number of enumerative weight settings. Each problem instance was

Algorithm 3 Prior-repair method to meet strategic demand group constraint

input (including parameters and variables mentioned in the aforementioned mathematical model)

A: An allocation chromosome $[\alpha_1, \alpha_2, \ldots, \alpha_{(\mathbf{I})}]$
B: An allocation chromosome $[\beta_1, \beta_2, \ldots, \beta_{(\mathbf{I})}]$
N: A vector $[\mu_1, \mu_2, \ldots, \mu_{(\mathbf{G})}]$ denoting outputs of demand groups
X: A vector $[x_1, x_2, \ldots, x_{(\mathbf{I})}]$ denoting capacity supported demand (CASD) of orders

output

A: A repaired allocation chromosome
N: A repaired vector denoting outputs of demand groups
X: A repaired vector denoting capacity supported demand (CASD) of orders

begin

for $h = 1$ to $(\mathbf{I})$ where $i = \beta_h$ and $\alpha_i < 1$ **do**

$\Delta_i \leftarrow \min\left\{\left[\max_{g\in\mathbf{G}_i}\left(G_g^{min} - \mu_g\right)\right]^+, (1-\alpha_i)D_i^{range}\right\}$, denotes the increment

$\mu_g \leftarrow \mu_g + \Delta_i, \forall g \in \mathbf{G}_i$

$\alpha_i \leftarrow \alpha_i + \Delta_i / D_i^{range}$

$x_i \leftarrow x_i + \Delta_i$

end for

for $h = (\mathbf{I})$ to 1 where $i = \beta_h$ and $\alpha_i > 0$ **do**

$\Delta_i \leftarrow \min\left\{\left[\max_{g\in\mathbf{G}_i}\left(\mu_g - G_g^{max}\right)\right]^+, \min_{g\in\mathbf{G}_i}\left(\mu_g - G_g^{min}\right), \alpha_i D_i^{range}\right\}$, denotes the reduction

$\mu_g \leftarrow \mu_g - \Delta_i, \forall g \in \mathbf{G}_i$

$\alpha_i \leftarrow \alpha_i - \Delta_i / D_i^{range}$

$x_i \leftarrow x_i - \Delta_i$

end for
end

recognized as "nonlinear integer linear programming" (NILP) and terminated at local optimal solutions. A local optimal solution was collected within various ranges of computation time. Accordingly, a set of reference non-dominated solutions were generated for evaluation purpose. The benchmark mathematical programming solutions were denoted by multiobjective nonlinear programming problems (MONLP) hereafter. The nondominated solutions generated by MONLP were used as reference fronts for aforementioned multi-objective metric calculations. All test

Algorithm 4 Capacity allocation method

input (including parameters and variables mentioned in the aforementioned mathematical model)

$\mathbf{X}$: A vector $[x_1, x_2, \ldots, x_{(\mathbf{I})}]$ denoting capacity supported demand (CASD) of orders

output

$q_m, \forall m \in \mathbf{M}$, and $q_{km}, \forall (k, m) \in \mathbf{K}$: Two sets of capacity-related decision variables
$\mathbf{P}$: An updated loading vector
$\boldsymbol{\nabla}$: A vector $[\nabla_1, \nabla_2, \ldots, \nabla_{(\mathbf{M})}]$ denoting exceeding loading

begin

$\rho_m \leftarrow \sum_{b \in \mathbf{B}^m, i \in \mathbf{I}^b} H_{im} x_i, \forall m \in \mathbf{M}$

$\nabla_m \leftarrow \tilde{\gamma}_m - H_m, \forall m \in \mathbf{M}$

$q_m \leftarrow 0, \forall m \in \mathbf{M}$

$q_{km} \leftarrow 0, \forall (k, m) \in \mathbf{K}$

$\Lambda^F \leftarrow F$, denotes remaining budget for machine acquisition

$\Lambda_j \leftarrow O_j, \forall j \in \mathbf{J}$, denotes remaining quota for installing machines in area j

for $a = 1$ to $(\mathbf{K})$ where $(k, m) \leftarrow (k_a, m_a)$, $\nabla_k < 0$ and $\nabla_m > 0$ **do**

$q_{km} \leftarrow \min(-\nabla_k, \nabla_m / V_{km})$, denotes the maximum capacities that can be exchanged from machine k to machine m without sacrificing those orders which machine k can originally support

$\nabla_m \leftarrow \nabla_m - V_{km} q_{km}$

$\nabla_k \leftarrow \nabla_k + q_{km}$

end for

for $m = 1$ to $(\mathbf{M})$ where $\nabla_m > 0$ **do**

$j \leftarrow J_m$

$q_m \leftarrow \min(\lceil \nabla_m / V_m \rceil, Q_m^{max}, \lfloor \Lambda^F / F_m \rfloor, \Lambda_j)$ denotes the maximum number of machine to be acquired

$\nabla_m \leftarrow \nabla_m - V_{km} q_{km}$

$\Lambda^F \leftarrow \Lambda^F - F_m q_m$

$\Lambda_j \leftarrow \Lambda_j - q_m$

(continued)

Algorithm 4 (continued)

for $a = 1$ to $(\mathbf{K})$ where $(m, k) \leftarrow (k_a, m_a)$, $\nabla_m < 0$ and $\nabla_k > 0$ **do**

$q_{km} \leftarrow \min(-\nabla_m, \nabla_k / V_{mk})$, (incremental machines may yield surplus capacities that can support others)

$\Lambda_k \leftarrow \Lambda_k - V_{mk} q_{mk}$

$\Lambda_m \leftarrow \Lambda_m + q_{mk}$

end for

end for

end

Algorithm 5 Post-repair method to meet capacity constraints and to improve machine utilization

input (including parameters and variables mentioned in the aforementioned mathematical model)

A: An allocation chromosome $[\alpha_1, \alpha_2, \ldots, \alpha_{(\mathbf{I})}]$
B: An allocation chromosome $[\beta_1, \beta_2, \ldots, \beta_{(\mathbf{I})}]$
N: A vector $[\mu_1, \mu_2, \ldots, \mu_{(\mathbf{G})}]$ denoting outputs of demand groups
X: A vector $[x_1, x_2, \ldots, x_{(\mathbf{I})}]$ denoting capacity supported demand (CASD) of orders
P: A vector $[\rho_1, \rho_2, \ldots, \rho_{(\mathbf{M})}]$ denoting loading of each machine group
∇: A vector $[\nabla_1, \nabla_2, \ldots, \nabla_{(\mathbf{M})}]$ denoting exceeding loading

output

A: A repaired allocation chromosome
N: A repaired vector denoting outputs of demand groups
X: A repaired vector denoting capacity supported demand (CASD) of orders
P: An updated loading vector
∇: An updated exceeding loading vector

begin

for $h = (\mathbf{I})$ to 1 **do**

$i \leftarrow \beta_j$ and $b \leftarrow B_i$

$\delta_i \leftarrow \min\left\{\min_{g \in \mathbf{G}_i}\left(\mu_g - G_g^{min}\right), \alpha_i D_i^{range}, \left[\max_{m \in \mathbf{M}_b}(\nabla_m / H_{im})\right]^+\right\}$, δ_i denotes the order quantity reduction to solve the problem of overloading

$\mu_g \leftarrow \mu_g - \delta_i, \forall g \in \mathbf{G}_i$

$\alpha_i \leftarrow \alpha_i - \delta_i / D_i^{range}$

(continued)

Algorithm 5 (continued)

```
        x_i ← x_i − δ_i
        ∇_m ← ∇_m − H_im δ_i, ∀m ∈ M_b
        ρ_m ← ρ_m − H_im δ_i, ∀m ∈ M_b
    end for
    for h = 1 to (I) do
        i ← β_h and b ← B_i
        φ_i ← min{min_{g∈G_i}(G_g^max − μ_g), (1 − α_i)D_i^range, [min_{m∈M_b}(−∇_m/H_im)]^+}, φ_i denotes the order quantity increment to solve the problem of low utilization
        μ_g ← μ_g + φ_i, ∀g ∈ G_i
        α_i ← α_i + φ_i/D_i^range
        x_i ← x_i + φ_i
        ∇_m ← ∇_m + H_im δ_i, ∀m ∈ M_b
        ρ_m ← ρ_m + H_im δ_i, ∀m ∈ M_b
    end for
end
```

ran set generation size $N_g = 2000$, $N_p = 50$ population size, $r_p = 0.6$ crossover rate, and $r_m = 0.3$ mutation rate.

4.1 Designs of MORMGA

Each algorithm design for comparison was the combination of a candidate selection methods and a setting of global front size (N_s). Selection methods included (A) rNSGA-II (the NSGA-II with constrained dominance), (B) NSGA-II (NSGA-II without constrained dominance), (C) exponential ranking roulette wheel selection with multiplier equal to 0.5 [35], and (D) linear ranking roulette wheel selection [41]. Options of the length of tacking list comprised (a) unlimited, (b) 200, (c) 50, and (d) none. Each combination ran 10 replications. Note that the combination A-b represents the proposed MORMGA with $N_s = 200$ whereas A-d is the conventional constraint-handling NSGA-II.

The numerical results showed that selection methods and the global front sizes are determinants to computational performances (significance level = 0.001)

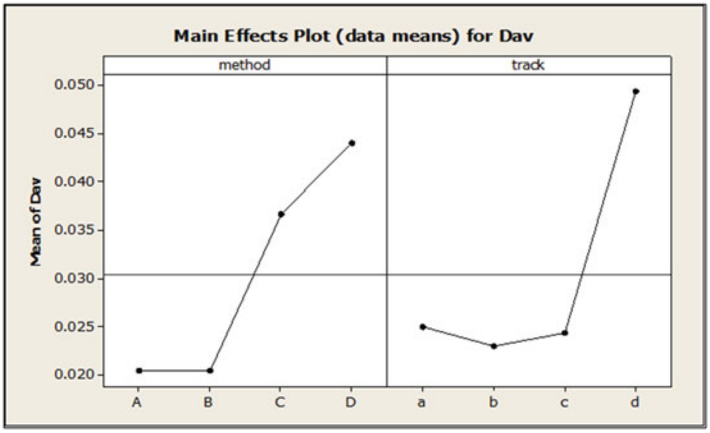

Fig. 3 Results of Davs (lower is better)

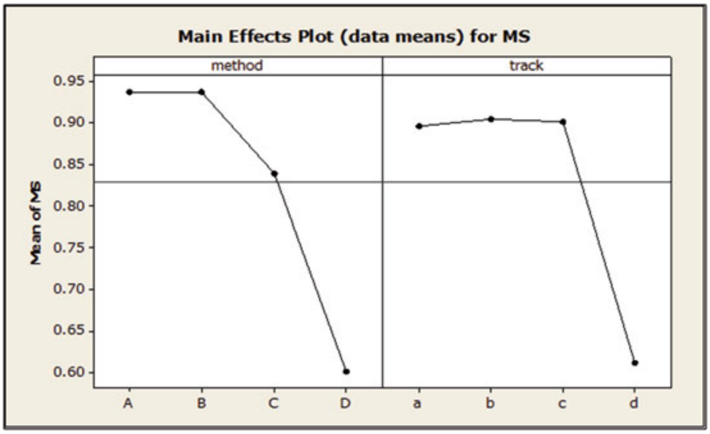

Fig. 4 Results of MSs (higher is better)

(Figs. 3, 4, 5, and 6). Yet, the choices between constrained dominance or not made little differences. Although unlimited number of global fronts outperformed in most of the indexes, it was one of the sources of computational complexity. The decision-makers should perform careful trade-off between solution quality and computational times on the choices of N_s. The following analysis applied rNSGA-II with the global front size $N_s = 200$.

4.2 The Effectiveness of Backup and Acquisition

From the multi-objective perspective, this study proposed a comparison scheme for analyzing the effectiveness of backup and acquisition. Four cases for comparisons

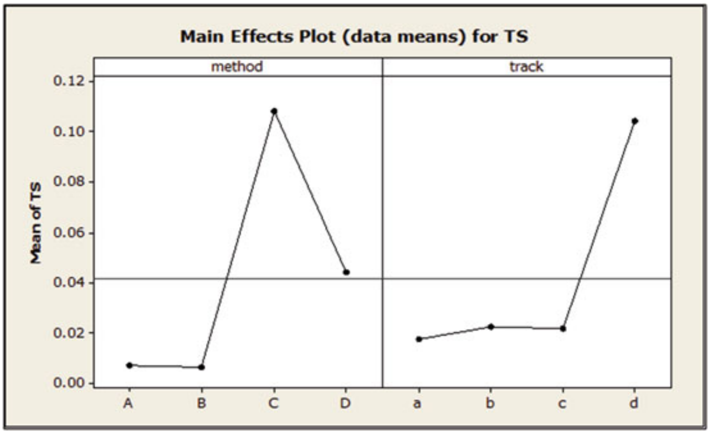

Fig. 5 Results of TSs (lower is better)

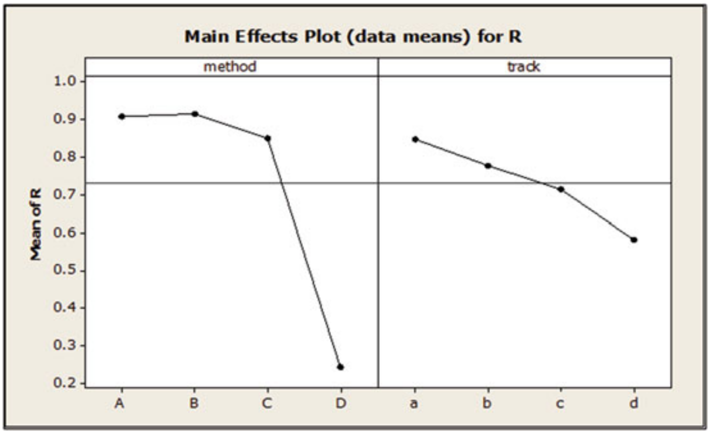

Fig. 6 Results of Rs (higher is better)

were designed as shown in Table 1. Particularly, the case IV was the test problem discussed in the previous section. The case I expressed the situation when neither backup nor acquisition is permitted. Cases II and III represented the situations when merely backup or acquisition is allowed, respectively. Without the option of acquisition, the cases I and II are formulated as multi-objective fractional linear programming models. The complexity sequence of the cases in ascending order is I, II, III, and IV.

The result showed that the running times of proposed MORMGA had little differences among all cases even though theoretically cases III and IV were harder than cases I and II (Table 2). On the other hand, the running times of cases I, II, III, and IV on MONLP were 563, 601, 640, and 732 s, respectively. Case IV took 30% more computational time than case I by using MONLP, i.e.,

Table 1 Design for backup and acquisition comparison

Case		Backup	
		No	Yes
Acquisition	No	I	II
	Yes	III	IV

Table 2 Running times of cases I–IV

Case	N_p	N_g			
		500	1000	1500	2000
I	50	25	50	76	99
	100	57	113	168	225
	150	97	195	290	387
	200	146	293	437	583
II	50	25	51	77	101
	100	57	114	173	229
	150	98	197	296	394
	200	148	299	444	593
III	50	25	51	77	103
	100	57	114	172	230
	150	98	196	295	393
	200	146	293	440	587
IV	50	25	50	82	106
	100	64	127	193	261
	150	112	233	334	463
	200	173	363	516	694

100%ÃŮ(732-563)/563. Regarding the solutions performance, the values of the rate metric increased as the generation size or the population size increased (Table 3). More explorations and more computation times could improve the solutions quality. Almost all values of the rate metric approach one. The Pareto fronts generated by MORMGA were close to the ideal fronts. In addition, the low Tan's spacing values showed that the solutions on the Pareto fronts of MORMGA were diversely distributed (Table 4).

The evaluation of backups and acquisition together with product-mix decisions were demonstrated in Table 5. Clearly, the Pareto fronts of Case IV dominated those of cases I, II, and III due to the highest flexibility whereas Case I was dominated by all other cases because of inflexibility to adjust capacity configuration. It is worthy particularly noting the comparisons between Case II and Case III. None of the solutions in Case II can be dominated by any points in Case III. Since the coverage metric is asymmetrical, we need to compare cases II and III in the converse way. C(II, III) = 1 on MONLP showed that all solutions of Case III were dominated by some points of Case II. On the other hand, The C(II, III) = 0.58 on rNSGA-II showed that more than 50% solutions of Case III were dominated by some points of Case II. In other words, acquisitions were more effective than backups from the multi-objective perspective.

Table 3 Rate metrics of cases I–IV

Case	N_p	N_g 500	1000	1500	2000
I	50	0.935	0.965	0.945	0.970
	100	0.965	0.955	0.950	0.960
	150	0.970	0.960	0.940	0.950
	200	0.960	0.965	0.945	0.960
II	50	1.000	0.990	1.000	0.990
	100	0.985	0.980	0.995	0.990
	150	0.980	1.000	0.995	0.990
	200	0.995	0.995	0.990	0.995
III	50	1.000	1.000	0.990	0.980
	100	0.995	0.990	0.990	0.985
	150	0.990	0.985	0.990	0.985
	200	0.985	0.990	0.990	0.985
IV	50	0.959	0.978	0.976	0.984
	100	0.880	0.980	0.972	0.990
	150	0.967	0.985	0.985	0.990
	200	0.983	0.990	0.990	0.990

Table 4 Tan's spacing of cases I–IV

Case	N_p	N_g 500	1000	1500	2000
I	50	0.0026	0.0038	0.0056	0.0050
	100	0.0027	0.0054	0.0019	0.0002
	150	0.0081	0.0004	0.0002	0.0033
	200	0.0124	0.0080	0.0005	0.0077
II	50	0.0040	0.0102	0.0056	0.0026
	100	0.0015	0.0035	0.0024	0.0024
	150	0.0007	0.0011	0.0052	0.0078
	200	0.0073	0.0013	0.0012	0.0060
III	50	0.0264	0.0022	0.0044	0.0016
	100	0.0010	0.0039	0.0093	0.0049
	150	0.0007	0.0040	0.0025	0.0094
	200	0.0027	0.0024	0.0016	0.0079
IV	50	0.0074	0.0179	0.0013	0.0014
	100	0.0050	0.0033	0.0078	0.0015
	150	0.0027	0.0051	0.0044	0.0014
	200	0.0046	0.0052	0.0012	0.0074

4.3 Examination on Solving Increasingly Larger Problems

Four cases, i.e., Case V–VIII, were designed to examine whether the proposed MORMGA can perform robustly and relatively efficient when the problem size increases. Cases V–VIII were more restricted in group demand constraints than

Table 5 Coverage metrics of cases I–IV (leave blank when value equals zero)

Average C		Case							
		I		II		III		IV	
Case	Model	MONLP	rNSGA-II	MONLP	rNSGA-II	MONLP	rNSGA-II	MONLP	rNSGA-II
I	MONLP		0.04						
	rNSGA-II								
II	MONLP	1.00	1.00		0.01	1.00	0.47		
	rNSGA-II	1.00	1.00			0.43	0.58		
III	MONLP	1.00	1.00				0.02		
	rNSGA-II	1.00	1.00			0.14			
IV	MONLP	1.00	1.00	1.00	1.00	1.00	1.00		0.02
	rNSGA-II	1.00	1.00	1.00	1.00	1.00	1.00		

Table 6 Running times of cases V–VIII

Case	N_p	N_g			
		500	1000	1500	2000
V	50	26	53	80	112
	100	62	126	192	261
	150	106	219	334	449
	200	163	330	497	668
VI	50	35	71	108	146
	100	77	158	237	315
	150	128	257	390	516
	200	187	376	562	749
VII	50	59	121	182	242
	100	125	252	379	509
	150	200	404	602	807
	200	284	570	853	1150
VIII	50	108	234	344	435
	100	224	482	668	907
	150	346	721	1071	1388
	200	493	970	1466	1921

cases I–IV, i.e. maximum quantities were reduced from 60,000 to 40,000. All other settings were not altered except that the number of products increased while the minimum and maximum quantities of each order decreased. Specifically, the order setting of Case V was the same with Case I–IV. Case VI duplicated products of Case V while minimum and maximum quantities of each order were reduced to half of the original setting. The problem size of Case VII and Case VIII were generated by repeating this process based on case VI and case VII, respectively. At the end, there were 80 products in Case VIII that was $2 \times 2 \times 2 = 8$ times the size of Case V. This design enlarged the problem size while keeping the idea nondominated solutions of each case consistent with each other.

The running times gradually increased along with the increments of problem sizes (Table 6). It took around half an hour to complete Case VIII when the generation size and the population size were set as $N_g = 2000$ and $N_p = 200$. Since MONLP was not a specifically designed program for solving the product-mix planning problem, the special problem structure that derived identical idea nondominated solutions was not detected and thus the running times were exponentially increasing from 744, 4,862, 31,808 to 165,269 s along with the doubled-size cases.

The results of multi-objective metrics showed that MORMGA could sustain high performances, i.e. high values of rate metric and low values of Tan's spacing (Tables 7 and 8). One exception in Case VIII was C = 0.193 for $N_g = 500$ and $N_p = 50$ for C = 0.885 for $N_g = 1000$ and $N_p = 50$. The results also supported that decision-makers could determine the quality of MORMGA solutions via corresponding parameter settings.

Table 7 Rate metrics of cases V–VIII

Case	N_p	N_g			
		500	1000	1500	2000
V	50	0.983	0.990	0.962	0.985
	100	0.983	0.985	1.000	0.980
	150	0.990	0.990	0.985	0.990
	200	1.000	0.995	1.000	0.995
VI	50	0.953	0.990	0.990	1.000
	100	0.995	0.975	0.995	0.995
	150	1.000	0.995	0.990	0.990
	200	1.000	0.990	1.000	0.980
VII	50	0.995	0.995	0.960	0.970
	100	0.995	0.980	0.990	0.990
	150	1.000	1.000	0.990	0.995
	200	1.000	1.000	0.980	0.990
VIII	50	0.193	0.885	0.960	0.975
	100	0.965	0.915	0.955	1.000
	150	1.000	0.985	0.990	0.980
	200	0.970	0.970	0.985	0.995

Table 8 Tan's spacing of cases V–VIII

Case	N_p	N_g			
		500	1000	1500	2000
I	50	0.0028	0.0043	0.0040	0.0031
	100	0.0057	0.0008	0.0039	0.0042
	150	0.0066	0.0027	0.0017	0.0059
	200	0.0030	0.0049	0.0035	0.0056
II	50	0.0059	0.0034	0.0022	0.0052
	100	0.0061	0.0026	0.0031	0.0055
	150	0.0005	0.0009	0.0031	0.0001
	200	0.0024	0.0002	0.0006	0.0038
III	50	0.0025	0.0057	0.0034	0.0045
	100	0.0047	0.0056	0.0032	0.0047
	150	0.0056	0.0010	0.0023	0.0022
	200	0.0001	0.0024	0.0011	0.0023
IV	50	0.0101	0.0059	0.0063	0.0046
	100	0.0021	0.0023	0.0031	0.0052
	150	0.0031	0.0003	0.0059	0.0035
	200	0.0030	0.0058	0.0035	0.0063

4.4 Full-Scale Test

The empirical examination compared MORMGA with the expert knowledge of the case corporation, i.e., "Fully load demand with the highest priority first; If demand can not be supported, then manually adjust and negotiate." The real annual plan data included 146 types of product family, 81 machine groups, average 49 machine groups and 7,088 steps for one product. The MORMGA parameters were set as $N_g = 10{,}000$, $N_p = 500$, $N_s = 1000$. The computation completed within 30 min on a mainframe server. The closest nondominated solution generated by MORMGA simultaneously gained 5% revenue and 9.28% margin more than the solution generated by the expert knowledge.

5 Conclusions

This study developed the MORMGA to model and solve the product-mix and revenue management problem for semiconductor manufacturing. The proposed model can help a company to formulate competitive strategy to achieve the first-priority objective without sacrificing other benefits. A GA parameter, the global frontier size, is introduced to provide a number of nondominated solutions for top management to make the final decision. There exists a trade-off between computation efficiency and the number of solutions to evaluate in the light of the quality of the solutions. The convergence and diversity of nondominated solutions are ensured, with satisfactory efficiency for implementation in real settings. An examination scheme is proposed to evaluate the integrated multi-objective product-mix planning and revenue management together with manufacturing flexibilities by using standard multi-objective metrics for validation.

Indeed, the proposed MORMGA can serve as a core computation engine of a decision support system for both demand and capacity planners without the need of a priori articulation of preferences among multiple objectives. Decision makers can select the beneficial alternatives of product-mix and capacity decisions from a set of nondominated solutions. However, a large number of solutions will delay decision-making lead times. In some cases, decision makers may jump into conclusions to prevent from trapping in the complex and lengthy discussions. To enhance decision-making quality, further research can be done in the area of finding efficient interactive models to articulate preferences from a set of nondominated solutions.

In this study commercial version of LINGO 11.0 was used to generate a reference set of non-dominated solutions by utilizing embedded integer programming (IP). Running LINGO to get a group of efficient point for small-size problems is fine.

However, the running time for large scale test problem is high and the proposed MORMGA should be utilized which solve the problems in an efficient time and have a good performance. The future research possibilities are as follow:

- Integrating product mix planing decision support system (DSS) based on experts' opinion with multiple-criteria decision-making (MCDM) techniques [57] such as technique for order preference by similarity to ideal solution (TOPSIS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), elimination et choix traduisant la realité (ELECTRE), the piecewise linear prospect (PLP) theory method, and Analytic Hierarchy Process (AHP), and group decision making for semiconductor [30, 31, 51, 54–56, 58]. Wu and Tiao [57] compare the MCDM methods' ranks with the decision-maker's ranks by utilizing assumed preference utility functions. Testing their results about outperforming interactive MCDM methods such as PLP and AHP in compare to other MCDM method in terms of rank consistency. Also, the performance of the MCDM methods is affected by the percentage of existing efficient solutions which would be a good area of research in product mix planning in semiconductor decision making.
- For product mix planning and decision making based on [57], one could develop:
  - a closed loop learning model to implement decisions suggested by our MORMGA based on selected MCDM methods which are trained and validated as effective methods for the context.
  - measures and models for examining various quantitative Group MCDM (GMCDM) methods and examining with various quantitative GMCDM methods.
  - a closed loop model to integrate distributed and decentralized MCDM decisions in the various contexts of intelligent manufacturing based on training and automatic selections from various GMCDM methods about product mix planning.
- Studying product mix planing and revenue management under uncertain demand and capacity which can be modeled by fuzzy theory [29], Beysian rule [24] and scenario analysis. Moreover, in a case of unpredictable product mix, the capacity planning over horizons is complex problem and we need forecast product mix scenarios which would be a more realistic as a future research.

Acknowledgements This study is supported by the Ministry of Science and Technology, Taiwan (MOST106-2218-E-007-024; MOST104-2410-H-031-033-MY3; NSC-100-2410-H-031-011-MY2; MOST107-2634-F-007-002; MOST107-2634-F-007-009).

Appendixes: Raw Data for Analysis

Table 9 Backup relations

From	To
T19	T22
T42	T39
T58	T61

Table 10 Area information

Area	Max. Add
A	2
B	3
C	0
D	3
E	0

Table 11 Product information

Product	Technology	Unit price	Var. cost	Min. Qty	Max. Qty
P01	I	17,400	4,350	0	7,000
P02	I	0	4,350	300	300
P03	I	14,500	4,060	0	7,000
P04	I	0	4,060	300	300
P05	II	8,700	3,480	0	3,000
P06	II	0	3,480	300	300
P07	II	11,600	2,871	0	3,000
P08	III	15,950	2,900	0	9,000
P09	III	17,400	3,770	0	9,000
P10	III	0	3,770	300	300

Note: P02, P04, P06, and P10 are R&D engineering orders

Table 12 Demand groups

Group technology set	Min. output	Max. output	Max. output (Cases V VIII)
{I, II, III}	15,000	60,000	40,000
{I}	7,000	30,000	10,000
{II}	3,000	30,000	10,000
{III}	5,000	30,000	10,000

Table 13 Machine information

		Cost	Avail.	Avail.		Max.	Amortization	Product Unit Loading Requirement					
Machine	Area	K/M	Time	Eff.	Qty	Add	Price	P01-02	P03-04	P05-06	P07	P08	P09-10
T01	A	1	0.98	0.82	1	0	6,700,000	0.0202	0.0202	–	0.0202	0.0202	0.0202
T02	A	1	0.98	0.82	4	0	6,700,000	–	–	0.0202	–	–	–
T03	A	1	0.92	0.85	8	0	4,966,667	–	–	–	–	0.0295	0.0295
T04	A	1	0.96	0.93	4	0	4,333,333	–	–	–	–	0.0421	–
T05	B	1	0.97	0.92	1	0	533,333	0.0190	0.0190	0.0190	0.0204	0.0211	0.0211
T06	C	1	0.97	0.92	2	0	7,866,667	0.0149	0.0149	0.0149	0.0199	0.0199	0.0199
T07	D	1	0.89	0.87	3	0	35,833,333	–	–	–	–	0.0310	–
T08	A	1	0.94	0.86	5	0	4,900,000	–	–	–	–	0.0216	0.0216
T09	A	1	0.90	0.87	1	0	20,200,000	0.0152	0.0152	0.0152	0.0152	–	–
T10	B	1	0.93	0.94	2	0	2,000,000	–	–	–	0.0513	–	–
T11	B	0	0.99	0.92	2	0	800,000	0.1589	0.1437	0.0988	0.0104	–	–
T12	C	1	0.91	0.96	1	0	73,433,333	0.0082	0.0231	0.0082	0.0878	0.1929	0.1955
T13	C	1	0.91	0.96	3	0	85,700,000	0.0411	0.0411	0.0214	0.0411	–	0.0221
T14	C	1	0.93	0.93	6	0	59,033,333	–	–	–	–	0.0135	–
T15	A	1	0.87	0.85	9	0	5,600,000	0.0472	0.0472	0.0800	0.0472	0.0827	0.0373
T16	A	1	0.87	0.85	4	0	5,600,000	0.0606	0.0606	–	0.0606	0.0392	0.0702
T17	D	1	0.90	0.90	8	0	28,100,000	0.2116	0.1855	0.1597	0.1706	0.0758	0.0758
T18	A	1	0.87	0.93	3	0	25,466,667	0.3159	0.3159	0.3428	0.3154	0.3460	0.0759
T19	A	1	0.87	0.93	4	0	25,466,667	0.0684	0.0704	0.0421	0.0654	–	–
T20	A	1	0.87	0.93	1	0	25,466,667	0.0927	0.0927	0.0415	0.0929	0.0849	0.1155
T21	A	1	0.91	0.87	2	0	40,200,000	0.0100	0.0100	0.0100	0.0100	0.0124	–
T22	D	0	0.95	0.92	3	3	2,233,333	0.0766	0.0766	0.0794	0.0762	0.0386	0.1182
T23	A	1	0.95	0.90	32	2	5,633,333	–	0.0059	0.0092	0.0144	0.1474	0.1484

(continued)

Table 13 (continued)

Machine	Area	Cost	Avail.	Avail.	Qty	Max.	Amortization	Product Unit Loading Requirement					
		K/M	Time	Eff.		Add	Price	P01-02	P03-04	P05-06	P07	P08	P09-10
T24	C	1	0.95	0.96	42	0	34,333,333	0.2439	0.2582	0.2013	0.2675	0.2168	0.2446
T25	A	1	0.98	0.92	3	0	4,000,000	0.0326	0.0326	0.0326	0.0326	0.0481	0.0481
T26	A	1	0.77	0.87	7	0	6,366,667	0.1491	0.1491	0.1228	0.1491	0.1274	0.1716
T27	A	1	0.80	0.87	10	0	7,000,000	0.0529	0.0529	–	0.0529	–	–
T28	A	1	0.72	0.87	10	0	6,233,333	0.0151	0.0151	0.0151	0.0151	0.0151	0.0151
T29	B	1	0.83	0.92	14	0	23,866,667	0.1128	0.0907	0.0667	0.0951	0.1134	0.1209
T30	A	1	0.92	0.87	1	0	17,166,667	0.1336	0.1296	0.0818	0.1322	0.1097	0.1398
T31	A	1	0.92	0.87	11	0	17,166,667	0.0056	0.0056	–	0.0194	–	–
T32	D	1	0.84	0.89	6	0	43,433,333	0.1257	0.1260	0.1005	0.1117	0.0782	0.0785
T33	A	1	0.83	0.87	3	0	16,033,333	0.0383	0.0383	0.0506	0.0479	0.0295	0.0239
T34	A	1	0.97	0.82	5	0	13,233,333	0.0440	0.0459	0.0272	0.0459	0.0359	0.0478
T35	D	1	0.87	0.90	11	0	22,000,000	0.1331	0.1330	0.1108	0.1330	0.1320	0.1320
T36	B	1	0.92	0.94	1	0	24,833,333	0.0285	0.0298	0.0208	0.0290	0.0201	0.0201
T37	B	1	0.89	0.94	1	0	15,500,000	0.0782	0.0782	0.0394	0.1708	0.0421	0.0391
T38	B	1	0.92	0.94	3.5	0	22,633,333	0.0962	0.0722	–	–	–	–
T39	B	1	0.92	0.94	3	3	19,066,667	–	–	0.1010	–	0.1906	0.1845
T40	B	1	0.93	0.94	28	0	10,400,000	0.0119	0.0119	0.0427	0.0119	0.0115	0.0116
T41	B	1	0.92	0.94	1.5	0	24,933,333	–	–	0.0374	0.0374	0.0389	0.0374
T42	B	1	0.91	0.93	8	0	7,633,333	0.0752	0.1176	0.0627	0.1176	0.0755	0.0755
T43	B	1	0.88	0.94	7	0	13,633,333	0.0519	0.0519	0.0660	0.0692	–	–
T44	D	1	0.91	0.92	21	0	16,100,000	0.3136	0.3074	0.2283	0.3062	0.1978	0.1802
T45	D	1	0.92	0.92	1	0	14,966,667	0.0253	0.0253	0.0253	0.0253	–	–
T46	D	1	0.90	0.91	2	0	29,633,333	0.0539	0.0404	0.0269	0.0404	–	–

T47	D	1	0.89	0.90	11	0	21,333,333	0.0258	0.0258	0.0258	0.0187	0.1486	0.1610
T48	A	1	0.95	0.82	3	0	14,800,000	0.0356	0.0356	0.0280	0.0356	–	0.0176
T49	A	1	0.88	0.82	2	0	10,300,000	0.0046	0.0046	0.0046	0.0046	0.0047	0.0046
T50	B	1	0.80	0.97	2	0	5,833,333	0.2229	0.2302	0.2065	0.2302	0.3016	0.2877
T51	B	1	0.87	0.96	10	0	14,300,000	0.0866	0.0866	0.0577	0.0866	–	0.0577
T52	B	1	0.80	0.92	1	0	26,100,000	0.1187	0.1187	0.0960	0.1134	0.1039	0.1017
T53	B	1	0.97	0.90	28	0	6,633,333	0.0798	0.0798	–	0.0795	–	–
T54	B	1	0.96	0.92	2	0	4,933,333	–	–	–	–	0.0784	0.0311
T55	A	1	0.95	0.83	12	1	15,433,333	0.0285	0.0285	0.0273	0.0339	0.0294	0.0294
T56	A	1	0.94	0.82	4	0	11,933,333	0.0202	0.0162	0.016	0.0162	0.0278	0.0278
T57	D	1	0.94	0.87	1	0	23,900,000	0.0339	0.0198	0.0198	0.0198	–	–
T58	D	1	0.89	0.92	13	0	17,466,667	0.0730	0.0730	0.073	0.0730	0.0711	0.0711
T59	D	1	0.93	0.87	1	0	25,633,333	0.0158	0.0158	0.0158	0.0158	–	–
T60	D	1	0.88	0.94	10	0	21,700,000	–	–	–	–	0.1279	0.1279
T61	D	1	0.88	0.87	1	2	40,800,000	0.1529	0.1458	0.0938	0.1431	0.1005	0.1208
T62	D	1	0.85	0.92	5	0	36,000,000	0.0253	0.0253	0.0253	0.0253	–	–
T63	B	0	0.97	0.92	2	0	666,667	–	–	–	–	0.0153	–
T64	A	1	0.91	0.91	10	0	5,166,667	0.1185	0.1185	0.1185	0.1185	0.1661	0.1254
T65	A	1	0.92	0.82	8	0	18,166,667	0.0426	0.0691	0.0703	0.0386	0.0876	0.0520
T66	A	0	0.98	0.97	8	0	1,500,000	0.0229	0.0229	0.0229	0.0260	0.0260	
T67	A	1	0.94	0.87	13	0	7,533,333	0.0689	0.0517	0.0344	0.0517	0.0517	0.0517
T68	A	1	0.99	0.96	21	0	6,666,667	0.1596	0.1596	0.1596	0.1596	0.1596	0.1596
T69	E	1	0.97	0.92	22	0	3,133,333	0.4220	0.3385	0.2575	0.3150	0.1549	0.1549
T70	D	1	0.88	0.91	17	0	17,133,333	0.0877	0.0714	0.0572	0.0715	0.0777	0.0777
T71	D	1	0.90	0.93	12	0	18,833,333	0.2135	0.1932	0.1425	0.1932	0.1347	0.1347
T72	B	1	0.95	0.94	6	0	12,533,333	0.0311	0.0311	0.0311	0.0311	0.0365	–

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