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New Idea of Multi-Objective Programming with Changeable Spaces for Improving the Unmanned Factory Planning

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***Abstract*--Business decision-makers need various decision analyses to meet highly competitive environments. With increasing cost of intensive workforce and lowering marginal-profit products, how to break the limitation of resources and optimally reallocate all of the precious resources is the major issue to create the competitive advantages in the high-technology industry. Moreover, the second industrial upgrading has developed industrial robots in some production processes for providing more value-added production activities. Therefore, this study proposed a new idea of multi-objective programming with changeable spaces (decision space and objective space) named changeable spaces programming extending the concept of De Novo programming. The best production resources reallocation in re-designing the decision space can be considered how to improve the multi-objective of unmanned factory planning in a high-technology firm for achieving aspiration level. This method provides decision analysis planning and not only to reach ideal point but also how achieve aspiration level in resource reallocation/redesign. A numerical example illustrates how to release the *trade-offs* between industrial robots and a workforce subject to constrains of the wafer manufacturing and how stage by stage to improve each objective for closing aspiration level in objective space. Computational results are demonstrated supporting the proposed model is easily implemented with flexible effort in practical.**

I. INTRODUCTION

In developing countries, production-oriented manufacturing is usually followed to take advantage of low costs, especially low labor costs. This business model has been called *original equipment manufacturing* (OEM) [4]; however, today it is facing enormous challenges because of competitive pricing throughout many regions of the world [16]. Therefore, OEM companies need to further reduce production costs. An attractive strategy for doing so is to transform or replace intensive labor with automated systems across an entire manufacturing system. In addition, OEM companies are gradually losing their core competitiveness because of problems such as changes in customer needs, dynamic fluctuations in marketing environments, ill-conceived implementations of traditional semi-automation, and increased production using large batch sizes that limit flexibility [14]. A feasible way to address such issues is via *flexible production,* which would serve as an intermediate step toward the long-term goal of completely automated systems (i.e., the unmanned factory). Flexible production is costly in high-wage countries [12], while throughout the world, implementation of flexible production is challenged by high costs relative to efficiency, new requirements, new standards, failures, and requirements for technology changes during production time [9]. Consequently, industrial upgrades or transformations of technology to robotic automation (the unmanned factory) are developing critical issues for high-tech industries.

Currently, full robotic automation can be found in parts of the automotive industry, where it is used for car body assembly, press tending, painting and coating and to some extent for assembly of engines and power trains. These applications are well established; robot features with respect to installation, programming, integration, maintenance, performance, and functionality are being continuously refined [2].

If the unmanned factory is the goal, then the general path to that goal appears to be the automation of manufacturing by using industrial robots to reduce expenses in the workforce and increase production efficiency. However, in this intermediate period between labor intensive and fully unmanned production, success depends on a balance between the use of laborers and robots. This is rarely easy because decision maker(s) encounter conflicts between the allocation of the workforce to improve production standards and the allocation of robots to automate production. In short, the dilemma is how to effectively and efficiently re-engineer production processes. However, transforming industry requires the automation of industrial robots together with laborers in today’s manufacturing factories. Although the unmanned factory is imperative, there is little literature that addresses how allocations of industrial robots and a workforce can be optimized under available budgets. In other words, while the establishment of an unmanned factory is an ongoing goal, few attempts have been made to identify or evaluate specific paths to that goal.

The purpose of this study is to propose a new idea of multi-objective programming with changeable space programming model [5], [9] based on the basic concept of De Novo programming [6], [13], [17], [18], [19], [20], [21], [22], which deals with *trade-offs* in optimizing the use of industrial robots cooperating with a workforce for achieving the aspiration level in multi-objective space This approach is applied to a wafer manufacturing facility in which we aim to maintain product quality while simultaneously reallocating resources under the total available budget and improving the level of unmanned factory planning. We demonstrate the effectiveness of changeable space programming on no only achieving the ideal point but also achieving the aspiration level of multi-objective space by changing the decision space corresponding to attain a redesign optimal system.

The rest of this paper is organized as follows. Section 2 describes the proposed changeable space programming in terms of a formulation in De Novo programming. Section 3 introduces the background for an unmanned factory, and Section 4 illustrates a numerical example to demonstrate the proposed method. Finally, some remarks and conclusions are presented in Section 5.

II. CHANGEABLE SPACE PROGRAMMING FOMULATION

Usually, a decision model formulated for multi-objective or single-objective programming is limited to fixed constraints that reflect the boundaries of the given system in feasible solutions. This is typically postulated when searching for the optimal solution(s) in the feasible decision space under given constraints or resources. In particular, the traditional optimization methods in multi-objective problem only concerned with the Pareto optimal solutions (or call non-inferior, non-dominated solutions, or effective solutions) within a system rather with the optimality concept itself or on expanding the notions of true optimization [20]. When dealing with a multi-objective decision model (MODM) problem, we usually encounter a situation wherein it is almost impossible to optimize all objectives in a given system. This property is called *trade-offs*, which means that one cannot increase the levels of satisfaction for one objective without decreasing those for another. Though we often apply conventional multi-objective programming to search for non-inferior solutions (i.e., Pareto optimal solutions) or compromise solution, they still need to be transformed into single-objective programming to resolve the solutions preferred by decision maker(s) and to lessen the *trade-offs* when the objective functions conflict with one another.

Because of the *trade-offs* property, we usually cannot find a solution that optimizes all criteria simultaneously within its fixed constraints or resources. Consequently, a method named *De Novo programming* pioneered by Zeleny offers a different viewpoint to the MODM problem for redesigning an optimal system [18]. Zeleny believed that most resources can be ordered from the market or the cooperating partners for a reasonable price so that the only constraint is the total budget required to purchase the required resources [1]. As such, the main difference between De Novo programming and traditional MODM is that De Novo programming determines the resource reallocation of a redesign (or reshape) system. With this system, its objective functions, subject to existing constraints, could eliminate the *trade-offs* and thus achieve an ideal solution (i.e., ideal point) according to the reconstructed decision space [3], [17]. The *trade-offs* are properties inadequately addressed in a given system that can be eliminated through better design, yielding a more optimal system [6], [13], [21]. This is the *optimal portfolio of resources* concept for redesigning or reshaping a given system's resources in the sense of integration, i.e., the levels of individual resources are not determined separately so they will be *trade-offs free* in a redesigned system[20], [21].

To solve this study's resources reallocation problem, such as a multi-objective problem of maximum objective functions can be described as follows [18], [19]

$$\text{Max}\left\{z_k = \boldsymbol{c}_k\boldsymbol{x} \mid k = 1,\ldots,q\right\}$$
$$s.t\ \ \boldsymbol{Ax} \le \boldsymbol{b} \rightarrow \boldsymbol{pAx} \le \boldsymbol{pb} \ \ \rightarrow \boldsymbol{vx} \le B \ \ (B \text{ is total budget}) \qquad (1)$$
$$\boldsymbol{x} \ge 0,$$

where $\boldsymbol{c}_k = (c_{k1},\ldots,c_{kj},\ldots,c_{kn}) \in R^n$ denotes the profit vector of k^{th} objective function in objective set $Z = \left\{z_1,\ldots,z_k,\ldots,z_q\right\}$, $\boldsymbol{x} = \left(x_1,\ldots,x_j,\ldots,x_n\right)^T \in R^n$ denotes the vector of decision variables, $\boldsymbol{A} = [a_{ij}]_{m\times n}$ denotes coefficient matrix for constraints, $\boldsymbol{b} = (b_1,\ldots,b_i,\ldots,b_m)^T \in R^m$ denotes the vector of resources required in numbers, $\boldsymbol{p} = \left(p_1,\ldots,p_i,\ldots,p_m\right) \in R^m$ denotes the vector of resource's unit price in each resources required number, $\boldsymbol{v} = \boldsymbol{pA} = \left(v_1,\ldots,v_j,\ldots,v_n\right) \in R^n$ denotes the vector of unit cost in resources of each variable, $B = \boldsymbol{pb}$ denotes the limited total budget for all resources required. The optimal solution is an objective set $Z^* = \left\{z_1^*,\ldots,z_k^*,\ldots,z_q^*\right\}$, where $z_k^* = \sup\{c_k\boldsymbol{x} \mid \boldsymbol{x} \in X\}$ for $\forall k$. If there exists $\boldsymbol{x}^* = (x_1^*,\ldots,x_j^*,\ldots,x_n^*)^T \in R^n$ such that objective set $Z^* = \{\boldsymbol{c}_1\boldsymbol{x}^*,\ldots,\boldsymbol{c}_k\boldsymbol{x}^*,\ldots,\boldsymbol{c}_q\boldsymbol{x}^*\} = \{z_1^*,\ldots,z_k^*,\ldots,z_q^*\}$, then $\boldsymbol{x}^*$ is the optimal solution in a given system (fixed constraints or resources in decision space).

When a given system that depends on the fixed resources of $\boldsymbol{b}$ reaching the optimal solution of both objectives such as the best quality and the maximal profit purposes in the system [19], [20], [21], it is inappropriate to acquire external resources by any means in the real world for redesigning or reforming the optimized system, which would thereby break through the boundary of fixed resources (see **Fig. 1**).

Based on the concept of a changeable space for achieving the ideal point as shown in **Fig. 2** [5], [10], Tzeng proposed a new thinking of multi-objective programming for decision space and objective space. Firstly, the traditional MODM reaches the front of objective space, i.e., Pareto optimal solution; secondly, De Novo programming [21] is to redesign the given system (i.e., the decision space) and reach the idea point breaking the Pareto optimal solution. How can the most effective in improving changeable spaces from idea point to achieving aspiration level? We extend the basic concept of De Novo programming by Zeleny to propose a new idea of multi-objective programming with changeable spaces in decision space and objective space by expanding competence sets to expand the objective space for achieving aspiration level. The competence sets may consider using such as "decision making trial and evaluation laboratory

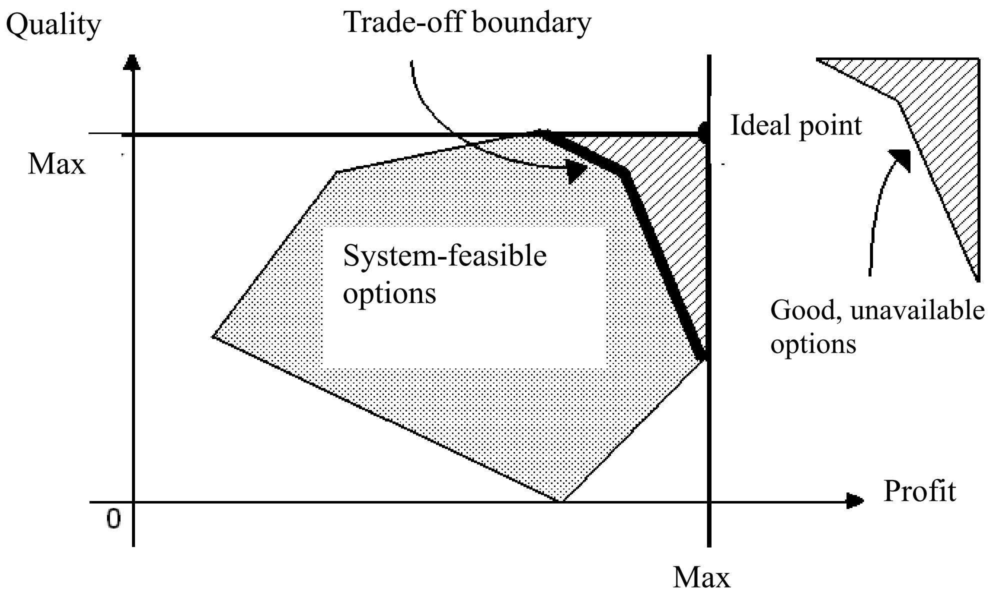

Fig. 1 Trade-offs elimination from a given system (Zeleney, 1995)

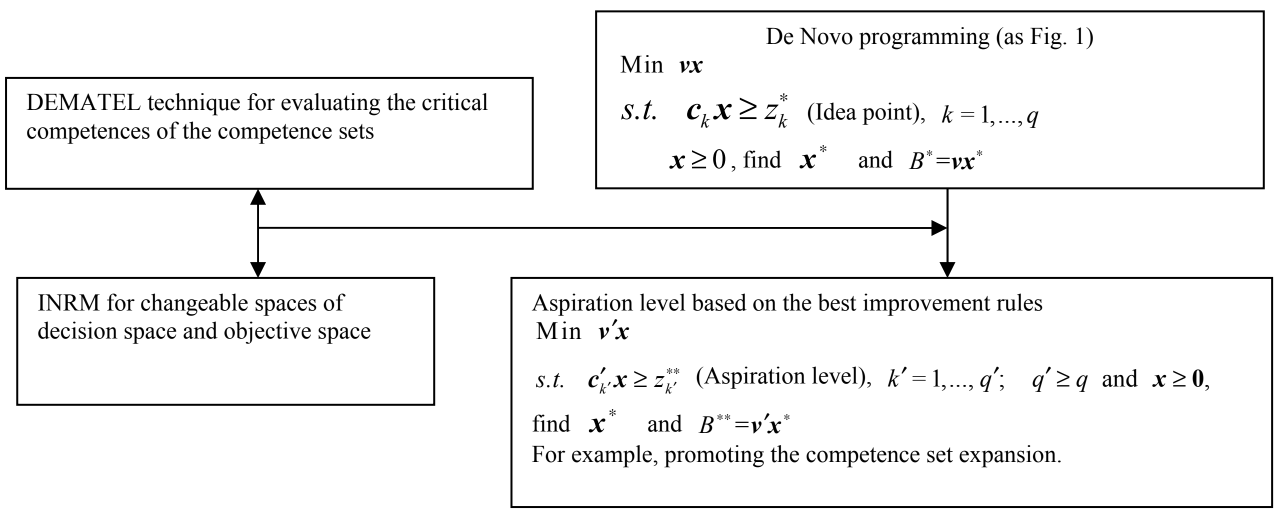

Fig. 2 Aspiration level based on the best improvement rules among inter-relationship

(DEMATEL) technique" to build the influential network relation map (INRM) for changeable spaces of decision space and objective space, i.e., resources, technology, budget, or strategy alliance [6], [13]. Adding to promote the competence sets expansion to help decision maker(s) effectively and easily find the best improvement-rules, such as following relationship (see **Fig.2** and **Fig. 3**).

First stage, considering that Eq. (1) is an optimization problem for a given system, an ideal point, in this case, is not reachable because of the property of *trade-offs* between the multiple objectives. When the purpose is to design an optimal system that corresponds to changeable decision space rather than optimize a given system, we can direct our interest to a consideration of how to formulate the minimum total budget B^* to achieve the ideal point z_k^* and $k = 1,...,q$ by Zeleny [15], [16], [17], [18], [19], [20], i.e.,

$$\text{Min } B = \boldsymbol{vx} \quad (2)$$
$$s.t.\quad \boldsymbol{c}_k\boldsymbol{x} \geq z_k^* \text{ (Ideal point)}, \; k = 1,...,q$$
$$\boldsymbol{x} \geq 0.$$

Solving Eq. (2) to find $\boldsymbol{x}^*$ and $B^* = \boldsymbol{vx}^*$, we yields $\boldsymbol{x}^*$ and $B^* = \boldsymbol{pb}^*$ where the meta-optimum solution in objective set Z^* is identified through $\boldsymbol{x}^*$ and $\boldsymbol{b}^*$. Given the unit prices of resources $\boldsymbol{p} = (p_1,..., p_i,..., p_m)$ and the available budget $B = \boldsymbol{pb}$ and $\boldsymbol{b} = (b_1,...,b_i,\ldots,b_m)^T$

when re-allocating the total budget, B^* ($B^* \le B$, or if $B^* > B$, how improving $B^* > B$ into $B^* \le B$ to change decision space), this results in the re-allocation of the resources portfolio, while also maximizing the values of the objective functions. Consequently, the De Novo programming for locating a solution with conflicting multi-objectives changes the decision space corresponding to the objective space and would lead to a superior system shape from the given one.

Second stage, how change decision stage from the competence set expansion to upgrade technology (innovation/creativity) and improve efficiency for changing the technological coefficients (resource requirement) for achieving aspiration level in objective space based on the best improvement rules.

$$\begin{aligned} &\text{Min } \boldsymbol{v}'\boldsymbol{x}^* \\ &s.t.\ \ \boldsymbol{c}'_{k'}\boldsymbol{x} \ge z^{**}_{k'} \ \text{(Aspiration level)},\ \ k' = 1,\dots,q'; \\ &q' \ge q \ \text{ and } \ \boldsymbol{x} \ge \boldsymbol{0}. \end{aligned} \tag{3}$$

We can find $\boldsymbol{x}^{**}$ and new budget $B^{**} = \boldsymbol{v}'\boldsymbol{x}^{**}$ for achieving aspiration level in objective space (see **Fig. 3**)

However, the ideal point used is not in the ordinary system, and the budget for the redesigned system using De Novo programming is higher than the total available budget [15]. Zeleny suggested an optimum-path ratio β and β' to contract the budget B to a new meta-optimum budget B^* (achieving ideal point) B^{**} (achieving aspiration level) and along the optimal path if a particular budget level B must be enforced. This ratio [18]:

$$\beta = B/B^* \ \text{ and } \ \beta' = B^*/B^{**}, \tag{4}$$

where can be used to construct the ideal system redesigned as in ideal point $\beta\boldsymbol{x}^*$, $\beta\boldsymbol{b}^*$, and βZ^* and $\beta'\boldsymbol{x}^*$, $\beta'\boldsymbol{b}^*$, and $\beta' Z^*$ in aspiration level. Eq. (4) provides an efficient tool for a virtually instantaneous optimal redesign of even large-scale linear systems. This simple and unprecedented ability to make complex MODM problems changeable within the state of optimality, while expanding or contracting the investment or budget B along the optimum-path ratio β and β', is a powerful competitive tool for locating a solution in the new system's decision space. De Novo programming designs the resource portfolio by modifying the slope and intercept of each soft constraint. The new feasible region is optimally modified to satisfy the meta-optimum constraints. The optimal solutions generated can determine the minimum budget necessary to achieve the meta-optimum.

III. UNMANNED FACTORY

Software systems reined in continuous increases in royalty fees over the long term is therefore crucial. This means that new more efficient R&D for new scalable system architecture concepts, open interfaces, and communication concepts will be important drivers in the development of robotic controller systems having the ability to consider time [2]. Moreover, Martinez et al. [11] pointed out that the consideration of time is not the only important benefit but quality must also be considered for the entire system's economy. For instance, the recent substitution of incoming workforce within an unmanned manufacturing environment is being driven by either product quality or the need for a quick process response. The production of industrial robots as a whole,.

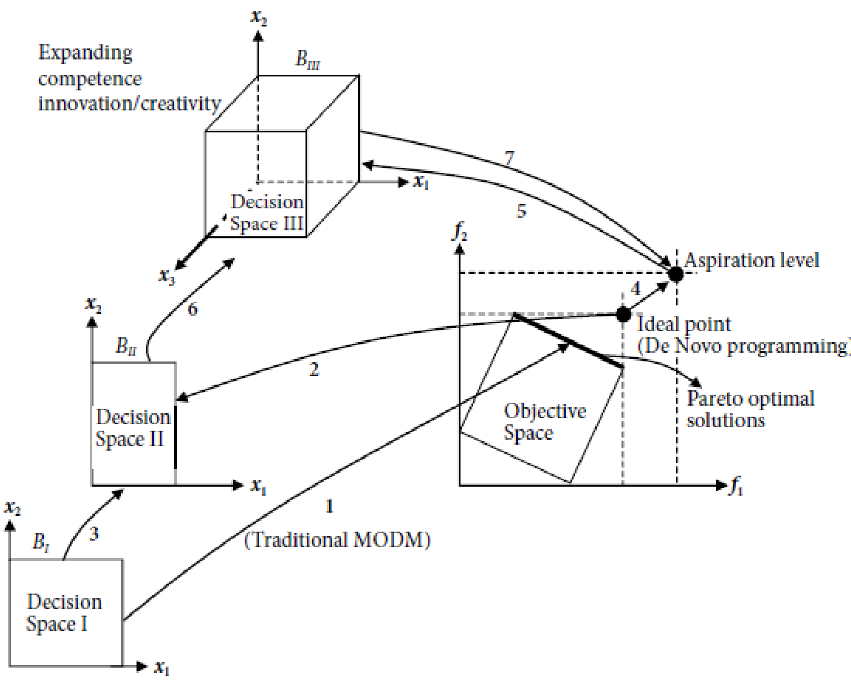

Fig.3 Concept of changeable decision space and aspiration level achievement [9]

however, will require a transition period so the essential workforce can be recruited to manage the indusial robots in the unmanned factory system, with respect to indicators including setup (installation), maintenance, test, and software systems [2], [7]. Moreover, troubleshooting techniques need to be considered for system failures and malfunctions that cause losses in efficiency.

The following section illustrates a numerical example for optimizing system utilization and output quality for industrial robots in cooperation with a workforce.

IV. NUMERICAL EXAMPLE OF UNMANNED FACTORY FOR CHANGEABLE SPACES PROGRAMMING

In this section we offer an empirical example to illustrate the changeable space programming method proposed above for system optimization design. In this example, the decision maker(s) wants to optimize workforce-industrial robots utilization (z_1) and wafer manufacturing quality (z_2) simultaneously in a factory. To resolve both the objective functions and to determine the ideal point of optimal resources reallocation for both, including the number of industrial robots (x_1) and workforce personnel (x_2) for the entire process, the changeable programming method is used. There are two ways to approach the problem. Case 1 assumes a given (and fixed) B, and it explores the *trade-offs* between the individual objective function Z and the corresponding ideal point for redesigning the system; Case 2 releases the B as a changeable decision space to consider at what level of B would Z^* be realizable. Analyzing an optimal path to answer this question will allow us to judge how to reach the performance ideal point of Z^*.

There are five constraints to consider when solving this problem: setup time, maintained time, running test time, system changing, and troubleshooting. The parameter settings are shown in Table 1.

In addition, the unit price for each constraint is allowed to obtain the total budget B is \$232900 on hand. The average profit from the wafer sales that maximizes the utilization of the industrial robots and the workforce (i.e., z_1) will have a \$500 (x_1) and \$100 (x_2) unit price. Moreover, the second objective function (z_2) is to maximize the total wafer manufacturing quality index: 100 points per x_1 and 90 points per x_2, on an index scale from 0 to 100. We assume the same level of importance for both objective functions for simplicity.

$$\begin{aligned}
&\text{Max } z_1 = 500x_1y_1 + 100x_2y_2 \\
&\text{Max } z_2 = 100x_1y_1 + 90x_2y_2 \\
&s.t.\quad 180x_1 + 120x_2 \le 840 \\
&\qquad 90x_1 + 60x_2 \le 480 \\
&\qquad 90x_1 + 90x_2 \le 540 \\
&\qquad 10x_1 \le 50 \\
&\qquad 100x_1 + 50x_2 \le 500 \\
&\qquad y_1 + y_2 = 2 \\
&\qquad x_i \ge 0, \quad \forall i \\
&\qquad y_1,\ y_2 \in \{0,\ 1\}
\end{aligned}$$

Note that the workforce by itself cannot produce wafers without industrial robot support, so the binary variables $y_1,\ y_2 \in \{0,\ 1\}$ construct the additional constraint $y_1 + y_2 = 2$ to guarantee industrial robots-workforce cooperation. Using traditional linear programming techniques, we can easily acquire optimal solutions for $z_1^* = \$1200$ and $z_2^* = 380$, corresponding to the optimal decision variables are $x_1^* = 2$ and $x_2^* = 2$. For De Novo programming, according to Eq. (2), the problem is rewritten as

$$\begin{aligned}
&\text{Min } B = 45200x_1 + 26800x_2 \\
&s.t.\quad 500x_1y_1 + 100x_2y_2 \ge 2100 \\
&\qquad 100x_1y_1 + 90x_2y_2 \ge 560 \\
&\qquad y_1 + y_2 = 2 \\
&\qquad x_i \ge 0, \quad \forall i \\
&\qquad y_1,\ y_2 \in \{0,\ 1\}
\end{aligned}$$

The answer can be solved by simplex method with VBA as B^*=234400 with respect to the optimal solution (i.e., $\boldsymbol{x}^* = (4,\ 2)$), and $Z^* = \{2200,\ 580\}$. The optimal path ratio $\beta^* = 0.993631$ is obtained by (3). The results construct the ideal system redesigning as $\beta^*\boldsymbol{x}^* = (3.974,\ 1.987)$ and

TABLE 1 RESOURCE REALLOCATION OF THE UNMANNED FACTORY

Unit price (p_i)	Constraint (Resources)	Decision Variable x_1	Decision Variable x_2	Resource limitation
50	Setup time	180	120	840
30	Maintained time	90	60	480
100	Running test time	90	90	540
450	System changing	10	0	50
200	Troubleshooting	100	50	500

TABLE 2 COMPARISON OF SOLUTIONS BY DIFFERENT PROGRAMMING METHODS

	Traditional programming	De Novo programming	Changeable space programming
$\boldsymbol{x}$	(2, 2)	(3, 1)	(4, 2)
Z	{1200, 380}	{1600, 390}	{2200, 580}

$\beta^* Z^* = \{2185.921,\ 576.288\}$. For case 1, the β^* will enforce the total budget B remain the same in a given system. However, the $\boldsymbol{x}^*$ must be integer such that we have to round down $\beta^* \boldsymbol{x}^* = (3.974,\ 1.987)$ as $\lfloor \beta^* \boldsymbol{x}^* \rfloor = (3,\ 1)$, and the final results aggregate objective functions $Z^* = \{1600,\ 390\}$.

For case 2 if we can relax or even increase our total budget B^* at 1500 as B^{**}, then the newly ideal redesign system is achieved by changeable space programming that $\boldsymbol{x}^{**} = (4,\ 2)$ and $Z^{**} = \{2200,\ 580\}$. Table 2 shows a comparison of the three programming methods used to solve this problem. The changeable space programming results are superior to those of the other methods.

The changeable space programming also achieves the aspiration level (i.e., aspired point) by releasing the budget (see **Fig. 2**) as a component within the decision space, which eliminates the limitation on a given system. A new frontier for redesigning an optimal system is now within reach by changing the decision and objective spaces.

V. REMARKS AND CONCLUSIONS

In this study, we have proposed changeable space programming based on De Novo programming, demonstrated its application, and compared solutions using different programming methods. By redesigning the system, changeable space programming can achieve the ideal point in the utilization of industrial robots that cooperate with the workforce in a wafer manufacturing factory. The results can serve as a strategic thinking for decision maker(s) who might change their minds (i.e., decision space) concerning how to achieve optimal unmanned factory results in the long term. In addition, the proposed method can be applied to optimize the multiple objective problem examples illustrated in this paper.

The primary benefit of setting up an unmanned factory is the reduction in production time and increased quality while optimizing the cooperation between the industrial robots and the workforce. It is also possible to decrease the operation time (e.g., setup, maintenance, and system change) and efficiently plan work to be undertaken by the unmanned factory. The automatic performance of tasks can be planned to acquire maximum profit as well as maximizing the quality of the manufactured products. Furthermore, since there are no manual operations performed, the incidence of mistakes in operations is reduced with the need for utilization of the workforce.

To realize an unmanned factory system in which the workforce prepares all the materials and work pieces in advance, the decision maker(s) must consider the need for extra storage space, required during the unattended time periods. However, an unmanned factory system operation, such as wafer manufacturing and the construction industry, is difficult to achieve in a short time. Kusuda pointed out that intelligent robots with multi-processing would eliminate this problem; therefore, the upgrade of industrial robots to intelligent robots is imperative in the long term [8].

Further research using the proposed method, that is, changeable space programming, is needed to develop technical innovations for intelligent robots. Parameters such as budget, resources, and technical upgrade can be changed or even expanded within the decision space of decision makers to move beyond the current state-of-the-art. Meanwhile, intensive study of dynamical changeable decision space transition modeling is needed to extend our understanding of how to best redesign optimal systems.

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