การหาค่าเหมาะที่สุดของวัตถุประสงค์แบบพหุคูณ จากการพัฒนาในอดีตสู่การประยุกต์เพื่ออนาคต

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บทคัดย่อ

การหาค่าเหมาะที่สุดของวัตถุประสงค์แบบพหุคูณ (Multiple objective optimization หรือ MOO) มีความสำคัญอย่างยิ่งในการวิจัยดำเนินการและการตัดสินใจ โดยมีประโยชน์สำคัญกับงานในอุตสาหกรรมในเรื่องของการบริหารทรัพยากรได้อย่างมีประสิทธิภาพ เช่น วัตถุดิบ แรงงาน เครื่องจักร เวลา การเงิน และวิธีการผลิต โดยบทความนี้จะนำเสนอแนวคิดของแบบจำลอง และกระบวนการของการเพิ่มประสิทธิภาพหลายวัตถุประสงค์ โดยมีวัตถุประสงค์เพื่อให้ผู้อ่านเข้าใจเทคนิคการใช้ทฤษฎีการเพิ่มประสิทธิภาพหลายวัตถุประสงค์ ซึ่งในบทความได้ทบทวนวรรณกรรมจากอดีตและยกตัวอย่างกรณีศึกษาการใช้แบบจำลองทางคณิตศาสตร์มาช่วยเรื่องการตัดสินใจปัญหาหลายวัตถุประสงค์ในหลายภาคอุตสาหกรรม เช่น การวางแผนทรัพยากร การปรับปรุงกระบวนการ และการจัดการขนส่ง ซึ่งความรู้ที่ได้จากบทความนี้เป็นประโยชน์และช่วยผู้อ่านบทความสามารถนำความรู้เรื่องการเพิ่มประสิทธิภาพหลายวัตถุประสงค์ไปประยุกต์ใช้กับปัญหารูปแบบอื่นได้

คำสำคัญ: การหาค่าเหมาะที่สุดของวัตถุประสงค์แบบพหุคูณ, การวิจัยดำเนินการ, การตัดสินใจ

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Multiple Objectives Optimization: from development in the past to future of applications

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Abstract

Multiple objective optimization (MOO) is critical in operations research and decision-making. It has crucial benefits for industrial work regarding efficient resource management, such as raw materials, labor, machinery, time, finances, and production methods. This article will present the concept of the model. and the process of multiple objective optimization. The objective is to enable readers to understand techniques for using multiple objective optimization theory. The article reviews the literature and gives examples of case studies using mathematical models to help with multiple objective decision-making in many industrial sectors, such as resource planning process improvement and transportation management. The knowledge gained from this article is valuable and helps the readers apply the knowledge of multiple objective optimization to other types of problems.

Keywords: multiple objective optimization, operations research, decision-making

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1. Introduction

Confronting multiple conflicting goals, such as balancing work, social life, and manufacturing, exemplifies a multiple objectives optimization problem. In the sophisticated realm of mathematics and problem-solving, Multiple Objectives Optimization takes this challenge to a higher level, aiming to discover the best solutions when several competing objectives are simultaneously compared.

This knowledge enables readers to apply these techniques to maximize resource efficiency in managing materials, workforce, machinery, time, finances, and production. Ultimately, this improves decision-making processes and achieves high-efficiency outcomes.

This paper highlights the importance of integrating Multi-Criteria Decision-Making (MCDM) frameworks that are instrumental in enhancing the quality of complex decision-making tasks, including deterministic problem-solving methods. The paper's structure consists of five more main sections: Section 2 provides a literature review of relevant optimization tools and related studies. Section 3 proposes the guidelines for using Multiple Objective Optimization to conflicting objectives. Section 4 presents the Integrating Uncertainty into Models. Section 5 shows the State-of-Art Method which flexibly supports the multiple objective problems and Conclusions and Recommendations
in Section 6.

Multiple Objective Optimization (MOO) refers to applying mathematical programming techniques to optimize solutions where more than one objective function must be improved, either maximized or minimized [1]. This approach is critical for solving problems frequently encountered in industrial plants, which often require balancing conflicting criteria, such as minimizing production costs while maximizing product quality, reducing waste, and cutting transportation costs. By determining and analyzing these problems using the principles of Multiple Objectives Optimization, industries can develop strategies that lead to better resource management and more sustainable operations.

The essence of Multiple Objectives Optimization involves balancing various priorities simultaneously. It is about finding optimal solutions that satisfy multiple conflicting objectives and making decisions that consider all goals rather than focusing on just one.

In a world of trade-offs and competing interests, Multiple Objectives Optimization is a game-changer. It helps making well-rounded decisions that balance different goals, whether maximizing profits while minimizing costs or enhancing efficiency while reducing environmental impact. The Multiple Objective Optimization approach enhances the operational improvement of resource utilization and ensures sustainable practices, making it essential for addressing complex challenges in the industrial sector.

2. Literature review

2.1 Multiple Objective Optimization

2.2 Linear Programming

Linear programming (LP) has been found and used for a long time. In 1939, Kantorovich the Russian mathematician applied LP to approximate the solution for Organization and Planning of Production [2]. Since the late 1940s, many other computational techniques and variations have been devised, usually for specific types of problems or to use with certain types of computing hardware.

In practice, Linear programming (LP) models are fundamental operations research tools that optimize resource allocation in various fields, such as transportation and assignment problems. These powerful models can handle multiple objectives, constraints, and variables within a linear framework. The example of problem-solving using LP is presented in Figure 1.

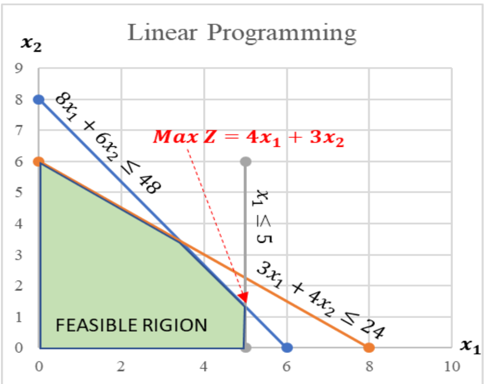

Figure 1 Linear Programming [3]

Any industry limitations are transformed into constrained equations, and a feasible region is created under those constraints. In other words, the possible solution is created within that region.

Several related researchers apply linear programming to solve the problem; Uddin et al. [4] address marketing challenges under uncertainty by incorporating fuzzy goal programming and uncertain parameters for costs, profits, and damage costs, effectively managing multiple conflicting objectives and providing compromise solutions. Similarly, linear programming is utilized in assignment models for resource allocation. Chen's research [5] introduces a circular intuitionistic fuzzy (C-IF) assignment model with a parameterized scoring rule, enhancing decision-making precision in uncertain environments. Furthermore, linear programming underpins network analysis, which is crucial for optimizing the flow of goods, information, or services through networks. Baykasoğlu & Subulan's explore of fully fuzzy linear programming (FFLP) models for reverse logistics network design [6] incorporates risk attitudes using α-cut representations, offering reliable solutions for risk-averse decision-makers validated through comparative analysis under varying uncertainty levels. Additionally, goal programming, a branch of multiple objective optimization, utilizes linear programming to achieve target goals for each objective, as discussed in paper Baky's comprehensive approach [7] highlights the versatility and effectiveness of linear programming in addressing complex optimization problems across various domains.

Linear programming is applied to various special types that support the complex problem characteristics including assignment problems, transportation problems, etc.

2.2.1 Assignment Problems

The assignment model is widely applied across manufacturing, logistics, healthcare, retail, IT, education, and human resources to maximize efficiency or balance workload among agents. This model facilitates allocating machines, workers, or resources to minimize costs while enhancing efficiency. It also involves managing priorities in the industrial production process, reducing production time and expenses while optimizing output quality and workload distribution. The assignment model is presented in Figure 2.

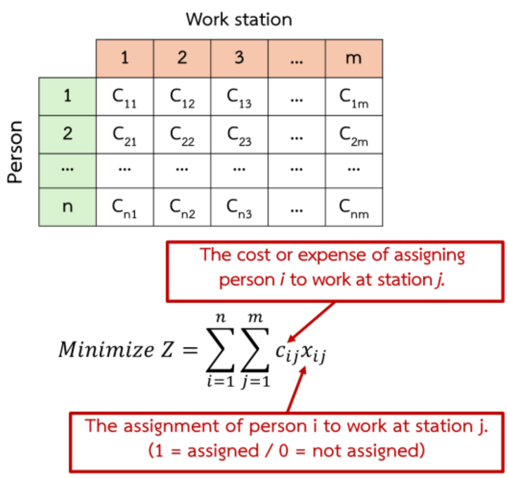

Figure 2 Assignment Model

2.2.2 Transportation Problem

Linear programming equations are pivotal in solving transportation problems by optimizing the distribution of goods from multiple suppliers to multiple consumers while minimizing costs or achieving other specific objectives.

Technology development has led to shorter shipping times and lower unit costs [3]. The application of linear scheduling allows operators to make straightforward logistical decisions to minimize costs, as shown in Figure 3.

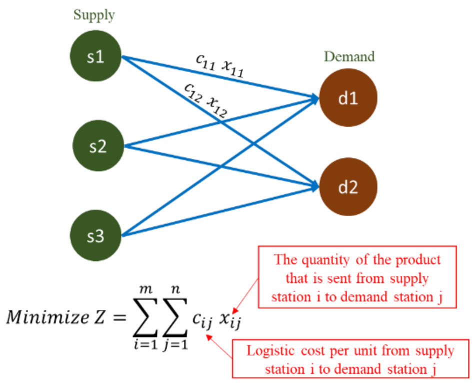

Figure 3 Transportation Problem [3]

In the real world, transporting larger quantities lowers shipping costs per unit. In addition, the speed and risks of shipping have essential implications for shipping prices, which must be considered as well.

Linear programming equations are essential in addressing transportation problems by optimizing the distribution of goods from multiple suppliers to multiple consumers, aiming to minimize costs or achieve specific objectives. For example, Kalaivani & Visalakshidevi [8] have introduced an innovative approach to solving transportation problems using a multi-partite graph combined with game theory. This method transforms the problem into a graphical representation and employs algorithms such as the North-West Corner Rule, the Least Cost Method, and Vogel's Approximation to find optimal solutions. The effectiveness of this method in reducing transportation costs is demonstrated through MATLAB coding, significantly improving cost efficiency.

Linear Programming models are like the highlights of optimization, great for situations where our goals can be represented by linear equations. They help in finding the best outcomes by optimizing a linear objective function.

2.3 Non-linear Programming

When our goals start getting a bit more complex, Non-linear Programming Models step in. These models handle objectives that cannot be neatly represented by straight lines, offering solutions for more intricate optimization problems, whose example is presented in Figure 4. Multiple objective non-linear programming (MONLP) is a particularly practical approach, optimizing multiple conflicting objectives. This is crucial for real-world scenarios that often require consideration of multiple criteria used with various approaches such as iterative methods, dynamic programming, unifying objective functions, compromise programming, and Denovo programming to provide robust solutions.

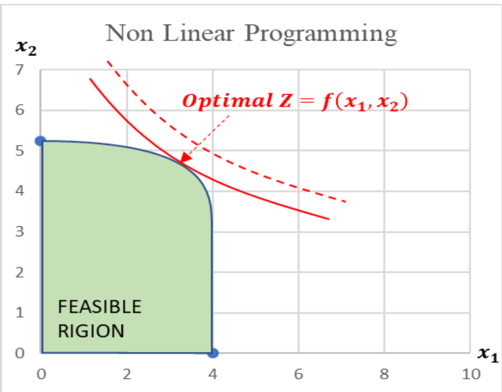

Figure 4 Non-Linear Programming [3]

2.4 Heuristic Models

Heuristic models are suitable for solving problems requiring more explicit guidelines or rules [3]. They rely on experimentation or educated guesses to find optimal solutions. For example, players often use past experiences to make decisions rather than follow strict rules when playing chess. The heuristic models include Genetic Algorithms, Simulated Annealing, Particle Swarm Optimization, Ant Colony Optimization, Tabu Search, and Greedy Algorithms, etc. These models are beneficial for optimizing multiple objectives, especially when the solution space is vast, and help manage goals to achieve balance effectively.

2.5 Equation Transformation

In the article "Bicriterion Linear Programming" by Adulbhan & Tabucanon [9], the authors explain the need to optimize multiple objectives in linear programming when there are conflicting goals. They propose a method to find the best compromise by adding a new linear objective to the existing constraints. This approach allows for finding the optimal solution more efficiently by reducing the number of calculation steps. The mathematical equations (1) can be written as follows:

$$Z = w_1f_1(x) + w_2f_2(x) \qquad (1)$$

The variables in the equation have the following meanings:

Z is the single objective function resulting from the combination of the two objectives. w_1 and w_2 are the weights assigned to the objectives $f_1(x)$ and $f_2(x)$ respectively.

$f_1(x)$ and $f_2(x)$ are the two objective functions that we aim to optimize.

2.6 Key Performance Indicators (KPI)

In terms of performance or objective achievement, it is necessary to determine key performance indicators (KPIs) to determine the level of performance [10]. KPI enables tracking the progress or drop in performance for a given objective, and it can present the work results as the whole organization's functioning [11]. Cosma et al. [12] (2024) use KPI for warehouses, whose KPI definitions are according to the warehouse sustainability, such as withdrawal tasks canceled due to machine errors, Idle times of the stacker crane, etc. Eventually, the warehouse sustainability on seven sides of fourteen weeks is presented in numbers, which means the owner can empirically track the change.

3. Guideline for Using Multiple Objective Optimization

In industrial action, the ultimate goal is the benefits received. However, there is a consideration in terms of sustainability and the environment, which inevitably increases production costs. As a result, the industry has conflicting objectives. It is consistent with solving problems by the MOO. The preliminary utilization and the related works of the MOO are as following.

3.1 The Appropriate Tool

The most crucial thing is choosing the right tool for the problem to generate the appropriate solution. In this study, mathematical models were chosen to support the empirical solution, which can eliminate bias and ambiguity. The related work is that Kengpol & Chanchittakarn [13] improve the hardness of the seawater pump impeller through the centrifugal casting process. It was found that the casting factors influence the hardness in non-linear characteristics, as shown in Figure 5. The impeller manufacturers using centrifugal casting receive the standard impellers and can control the resources required. This is why selecting the appropriate tool is essential. In this case, the casting factors cannot be detected if the linear is used instead of the non-linear one.

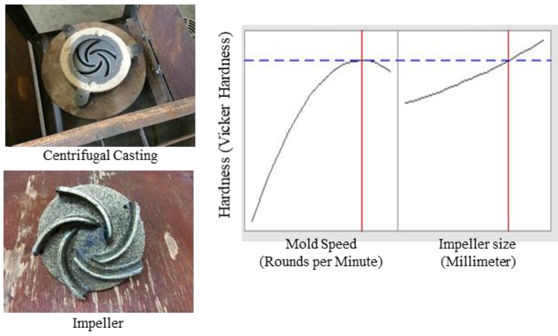

Figure 5 Influential of centrifugal casting to the impeller hardness [13]

3.2 Model Designing

Most real-world optimization problems include constraints that must be satisfied [14]. For this reason, industry models are created for multiple purposes, including forecasting markets for strategic planning, providing a basis for directing investments by financial institutions and governments, and developing contingency plans simultaneously [15]. Nowadays, simulation modeling is well-established in science and engineering. In engineering, simulation modeling helps reduce costs, shorten development cycles, increase the quality of products, and dramatically facilitates knowledge management [16].

The environmental planning, balancing conservation, development, and sustainability goals is crucial. Multiple objectives optimization plays a vital role in finding solutions that protect the environment while meeting the needs of society and the economy.

Navigating the complex landscape of multiple objectives optimization research can feel like solving a Rubik's cube blindfolded. This is the challenge for shaping the future of optimization models. Using a mathematical model through the "Application in the Industry" supports the stakeholders in decision-making, which is reasonable and unbiased.

3.3 Application in the Industry

Using a mathematical model can support stakeholders in making reasonable and unbiased decisions. Beyond being a mathematical concept, multiple objective optimization is a practical tool that applies to diverse fields. Consequently, it is pivotal in critical digital transformation and essential for creating an excellent profile at all relevant job levels in the industry sector, including engineering, business, and environmental domains [17].

In the realm of industry optimization, multiple objective optimization is a powerful tool for designing efficient systems that manage resources effectively. It enables engineers to tackle complex challenges and devise innovative solutions that meet a variety of constraints and goals. For instance, a study by Uddin et al. demonstrates how multiple objective optimization can address challenges under uncertainty [18], incorporating fuzzy goal programming and uncertain parameters for costs, profits, and damage costs. The proposed model effectively manages multiple conflicting objectives and provides compromise solutions.

Additionally, in agriculture, multiple objectives optimization involves mathematical and computational techniques to balance and achieve various conflicting goals in terms of planning and management. The forecasting factors related to crops and agriculture, such as the selling price, quality aspects of crops, and more, can also be optimized using these methods. Research by Kengpol & Klaiklueng [19] also applies ordinal logistic regression and Convolutional Neural Network (CNN) to create a system that classifies lime quality according to Thai Agricultural Standards No. TAS 27-2017. This classifier achieves over 90% accuracy and enhances lime classification compliance with Thai standards.

When industries achieve multiple objectives, it is wise to keep data in a way that tracks changes. As time moves forward, the established model may no longer be suitable. However, self-learning models, known as Artificial Intelligence (AI), are being used as practical tools to support human decision-making.

4. Integrating Uncertainty into Models

Multiple Objectives Optimization is an indispensable tool across various fields, significantly enhancing the ability to navigate complex decision-making processes. In engineering, Multiple Objectives Optimization enables the creation of efficient systems and optimal resource utilization. Similarly, in business decision-making, Multiple

Objectives Optimization facilitates strategic planning that balances profitability, risk, and sustainability, maximizing overall outcomes and driving success. For example, the election of strategic planning or industry models based upon multiple objectives is shown in Figure 6. These empirical solutions help making effective decision under risk.

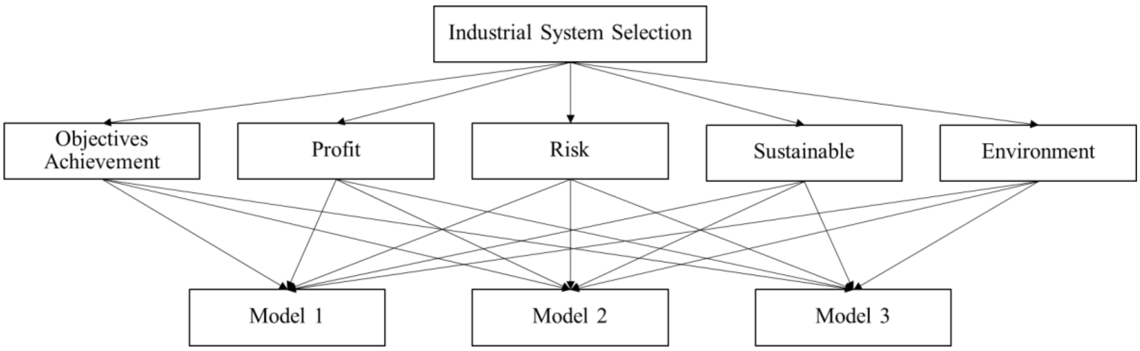

Figure 6 The selection of strategic planning or industry models based upon multiple objectives

When each industrial factor mentioned above is optimized using the appropriate tool, the value of factors is generated and integrated into the Model's Score, and each factor's integrated value is weighted according to the industry's strategy or character, as presented in equation (2).

Model n Score =

$$w_{oa}f(z_{oa})+w_pf(z_p)+w_rf(z_r)+w_sf(z_s)+w_ef(z_e) \quad (2)$$

Where z is the mathematical value of each related factor, which is optimized through linear or non-linear methods, including objective achievement (oa), profit (p), risk (r), sustainability (s), environment (e), etc. For integrating all related factors into the Model n score, z from every factor is normalized using their function, f(z). Variables w are the weights of each related factor that reasonably adjusts each model's equation. Eventually, the scores of all models are summarized and compared to select the best alternative model for the industrial system.

Although equation (2) summarizes the Integrated model factor to be used to find the optimum state for supporting Industrial System Selection, the mentioned factors can have an interaction effect; for example, the change in raw material types in a plastic industry affects the waste disposal cost which is an environmental operation, etc. In this regard, the management can use the design of experiments or appropriate tools to examine the effect of the interaction of interested factors. Therefore, the Integrated model factor equation should be adjusted according to the factor characteristics.

Additionally, the trade-off can occur while decision-making is ongoing. Balancing trade-offs is an art by itself, requiring delicate thinking among competing goals. Researchers constantly explore innovative ways to tackle this problem, from elegant mathematical formulations to creative solutions.

5. State-of-Art Method: Advancements in Multiple Objective Optimization Algorithms

Tabucanon [20] discusses the human ability to make rational decisions using various techniques and technologies, such as Operations Research and Computer Technology, which manage the complexity of decision-making problems. Selecting appropriate models and methodologies for the industry is crucial to ensure effective decision-making. Prioritizing the project's objectives can be achieved by considering the effect of the deviations from set goals [21]. Despite the industry's success in solving its multiple objectives using Multiple Objective Optimization frameworks, significant challenges persist, such as managing and integrating uncertainty into optimization models. In many case studies, nonlinear models are used to solve problems with uncertain variables because they can detect complex relationships between variables and manage uncertain variable data more effectively. This capability is crucial for developing new algorithms and techniques to process variables efficiently.

Nevertheless, in the present advancements, multiple objective optimization models have been used in designing algorithms for artificial intelligence, which expands the capabilities of multiple objective optimization and helps create a robust framework for solving more complex problems. These developments underscore the potential of Multiple Objective Optimization to solve problems and drive innovation and efficiency, enabling the simultaneous achievement of multiple objectives.

In the advancement of artificial intelligence, multiple objective optimization has brought evolutionary algorithms such as Non-Dominated Sorting Genetic Algorithm II (NSGA-II) and swarm intelligence algorithms like Multiple Objective Particle Swarm Optimization (MOPSO) combined with the integration of machine learning techniques. This approach enables the development of computer systems capable of finding optimal solutions to complex multiple objective problems. These advancements are theoretical and practical, as demonstrated in various real-world applications. For instance, Punyota et al. [22] use the Analytic Network Process (ANP) as a multiple objective optimization tool to select suitable vegetarian foods for patients based on chronic diseases, which include high blood pressure, diabetes, and dyslipidemia. Duangsuphasin et al. [23] apply the convolutional neural networks (CNN) and network-in-network (NiN), to select the passion fruits that match various groups of elderly. Delgarm et al. [24] utilize the MOPSO algorithm in conjunction with EnergyPlus software, which is being applied to improve the energy efficiency of buildings in four climate regions of Iran. It can effectively reduce energy consumption. İzgi [25] aims to enhance the performance of Latent Thermal Energy Storage (LTES) systems by improving fin design efficiency. In this regard, ML and MOO improve fin design efficiency and the overall LTES system.

In the future, MOO can support strategies or environments that can change. For example, facing the Covid-2019 pandemic situation of a bicycle parts factory with two objectives that include 1) reducing the spread of the disease by reducing the contact points among employees and 2) using the least cost of production [26]. Eventually, the optimal condition allows the entrepreneur to make the most appropriate factory layout based upon both objectives. Moreover, MOO can be carried out through AI technology, which is hastily processed, practical, and adjustable, supporting the upcoming trend. Additionally, KPI technical, as mentioned in Section 2.6, is recommended to track and predict the achievement of objectives.

In the real world, multiple objective optimizers have made significant progress in terms of accommodating changes in influential surrounding factors. The increasing of restrictions directly affects decision-making. Considering alternatives through the appropriate and up-to-date tools makes more effective decision-making.

6. Conclusions and Recommendations

When selecting the proper model for the real-world industry, the stakeholders face multiple conflicts in their industries. In terms of decision-making, the mathematical model can empirically support the industry's model selection. Therefore, this article proposes the guideline of transforming each factor into a mathematical model that supports the stakeholders in deciding the appropriate model for their industries. The contribution is that presenting how to integrate the conflicting objectives and related factors supports the decision-making and suggests how to measure the achievement of the goals. Linear and non-linear programming are crucial tools to mitigate the problem. Additionally, state-of-the-art tools like artificial intelligence are intelligent multiple objective optimizers that can hastily learn vast amounts of data and adjust the industry's model appropriately.

The advantage of using MOO is that it can accommodate changes in influential related factors, and conflict objectives can be considered together. On the other hand, the disadvantage of the MOO is that the weight of each related factor, in some cases, is transformed from the strategy, which is abstract and difficult to define.

The increasing of restrictions directly affects decision-making. Considering alternatives through the appropriate and up-to-date tools makes more effective decision-making.

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