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# A Monte-Carlo-based interval De Novo programming method for optimal system design under uncertainty

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ABSTRACT

In this study, a Monte-Carlo-based interval De Novo programming (MC-IDP) method is developed for designing optimal electricity-allocation system under uncertainty. MC-IDP incorporates Monte Carlo simulation (MCS), interval-parameter programming (IPP), and De Novo programming (DNP) within a general framework. MC-IDP has advantages in (i) constructing optimal system design through introducing the flexibility in the right-hand sides of constraints, (ii) handling uncertainty presented as interval numbers, and (iii) mitigating the influence of decision makers' subjectivity in optimum-path ratio. MC-IDP is then applied to a case study of planning electricity-allocation system involving multiple conflicting objectives, where various scenarios associated with different optimum-path ratios are examined. Results reveal that different scenarios would lead to varied electricity-allocation patterns, pollutant/ greenhouse gas (GHG) emissions, as well as system benefits. Compared to the traditional interval multiobjective programming (IMOP), MC-IDP can achieve higher system benefits and reduce electricity loss; moreover, the maximum benefit for each objective under MC-IDP can be realized at the same time. Findings are useful to decision makers for evaluating alternatives of system designs as well as for identifying which of these designs can most efficiently achieve the desired system objectives in a more sustainable development manner.

## 1. Introduction

### 1.1. Research background

Electricity-allocation planning plays an increasingly crucial role in national and/or regional economic development and human activities owing to the rapid population growth and rising electricity demand (Piao et al., 2014; Kahrl et al., 2016). In recent decades, controversial electricity allocation issues among competing interests have raised wide concern. Optimal electricity allocation is ideally regarded as a linear or non-linear programming problem (Deb, 2014; Colett et al., 2016). Researchers have investigated a variety of approaches to provide managers with optimal solutions (Gjorgiev and Epin, 2013; Hu et al., 2015; Rao et al., 2017). In general, the conventional multiobjective programming (MOP) approaches are primarily concentrated on converting multiple objectives into a single-objective through introducing a set of trade-off optimal solutions (Williams and Kahrl, 2008; Ayuba, 2015). The conventional planning problems using fuzzy interval, and/or stochastic programming mostly focus on optimizing a given system where constraint resources are fixed as deterministic values. In real-world practical problems, however, the constraint resources possess imprecise features which are difficult to be determined precisely. Therefore, it is desired to develop more effective methods for planning system design with multiple objectives and complex uncertainties.

### 1.2. Literature review

#### 1.2.1. De Novo programming

De Novo programming (DNP) has been extensively used for dealing with optimal system design problems (Zeleny, 1990; Kotula, 1997; Chen James and Tzeng, 2009; Wei and Chang, 2011; Chen, 2014; Sarjono et al., 2015). For instance, Kotula (1997) used the DNP technique for controlling and adjusting reservoir design and operation characteristic; Chen James and Tzeng (2009) employed the DNP method as a strategic alliance alternative for achieving optimal resource allocation in supply chain system; Wei and Chang (2011) developed an easy-to

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implement and effective approach for designing their optimal system in which DNP was integrated into optimal system analysis models; Chen (2014) applied DNP to fulfilling optimal resource allocation on integrate circuit design; Sarjono et al. (2015) used DNP for determining the amount of product to be produced by the plate companies to design an optimal system. Generally, DNP is effective for dealing with optimal system design problems. With unknown right-hand resource availability, it intends to seek a portfolio of resource availability level by allocating a budget according to the resource price. In addition, DNP can provide more flexible resource planning schemes because the available system budget can be adjusted based on the variations in resource price.

#### 1.2.2. Inexact De Novo programming

In decision making problems, many system parameters and their interrelationships are often associated with uncertainties presented in terms of multiple formats (Li et al., 2017; Zhalechian et al., 2017). These uncertainties might be multiplied by limited budget and electricity with a maximum system benefit. More robust and effective inexact optimization approaches are desired for aiding in electricity-allocation planning under uncertainty. Previously, a number of methods were proposed for handling these uncertainties in the optimal system design (Chen and Hsieh, 2006; Miao et al., 2013; Saeedi et al., 2015). For example, Chen and Hsieh (2006) advanced a fuzzy multistage De Novo programming model for the optimal system design, in which uncertainties expressed as fuzzy sets were reflected; Miao et al. (2013) proposed an interval fuzzy bi-infinite De Novo programming method for water resources system management, where uncertain parameters were represented as functional intervals; Saeedi et al. (2015) integrated a mixed integer nonlinear programming model into DNP to determine the capacity of recovery facilities in the reverse flow. Among these inexact optimization methods, interval-parameter programming (IPP) approach is effective for handling uncertainties expressed as interval numbers with unknown probability distributions and membership functions. In many real-world problems, uncertainties might hardly be presented as suitable fuzzy membership functions as well as stochastic probability distribution owing to incomplete observed information (Li et al., 2011). Instead, the decision makers can only determine the lower and upper bounds of the system parameters.

#### 1.2.3. Monte Carlo simulation

In DNP problem, one of the significant issues is to determine an optimum-path ratio for achieving optimal system design (Zeleny, 1990). Although a number of researchers focus on seeking optimum-path ratio, the weights in optimum-path ratio are often determined by the subjectivity of decision makers (Miao et al., 2014). Monte Carlo simulation (MCS), as a widely-used tool for solving uncertainty-based system design, is of capability to deal with variability of model coefficient and relative weights for system parameters (Robort et al., 2013; Martín-Fernández et al., 2016; Yu et al., 2017). MCS is applied popularly for its advantages in the simple program structure and objective simulation process (Mavrotas et al., 2015; Runfola et al., 2015; Baležentis and Streimikiene, 2017). For example, Mavrotas et al. (2015) used MCS for robustness analysis in multi-objective mathematical programming where the weights vary one a time, which was different from the weight stability intervals employed in multi-criteria methods; Runfola et al. (2015) implemented MCS to measure relative vulnerability under future climate change scenarios by varying the importance weights; Baležentis and Streimikiene (2017) furthered the application of multi-criteria decision making technique in that the egalitarian weights were supplemented by MCS. Generally, MCS is especially useful for simulating phenomena with significant uncertainty in inputs and systems. Therefore, the application of MCS is meaningful in determining the weights in optimum-path ratio.

### 1.3. Objective

Therefore, the objective of this study is to advance a Monte-Carlo-based interval De Novo programming (MC-IDP) method for addressing the above deficiencies. MC-IDP integrates the techniques of De Novo programming (DNP), interval-parameter programming (IPP), and Monte Carlo simulation (MCS) into a general framework, such that uncertainties expressed as intervals can be effectively tackled. The proposed method cannot only achieve optimal system design, but also mitigate the influence of decision makers' subjective in optimum-path ratio. MC-IDP will then be applied to a case study of electricity-allocation planning, where limited budget will be allocated to multiple competing interests and the objective is to maximize the benefit of each user at the same time. A number of scenarios corresponding to different optimum-path ratios will be examined. Results will be used for (1) designing alternative electricity-allocation patterns, (2) determining which of designs can most efficiently acquire the desired system objective, and (3) coordinating conflict interactions between economic development and environmental protection.

## 2. Methodology

### 2.1. Linear programming

The formulation of standard linear programming of the multiobjective product-mix problem is presented as follows (Katoh et al., 2013; Amin et al., 2016):

$$\text{Max } Z_k = c_k x. \tag{1a}$$

Subject to:

$$Ax \le b \tag{1b}$$

$$x \ge 0 \tag{1c}$$

where $b = (b_1, b_2, \dots, b_m)^T \in R^m$ is the known production levels; $x = (x_1, x_2, \dots, x_n) \in R^n$ denotes $n$ products; the objective of this resource planning model is to maximize the value of the product mix $cx$. Because all components of $b$ are determined as a prior, model (1) can only address the "optimization" of a given system. When the purpose is to design an optimal system, it is essential to extend existed resources instead of finding the optimum in a given system with fixed resources level (Zeleny, 2010). The difficulty arises because such approaches bring about a set of trade-off optimal solutions, instead of a single optimum solution, which is always a sure sign of suboptimality, poor system performance and dissatisfaction (Zeleny, 2010; Lim et al., 2013; Alsyouf and Hamdan, 2017).

### 2.2. De Novo programming

De Novo programming (DNP) is effective for addressing optimal system design problems with unknown right-hand resource availability and maximizing multiple objectives at the same time through adjusting budget level according to the resource price. An DNP model can be formulated as follows (Zeleny, 1990):

$$\text{Max } Z_k(c_k, x) = c_k x \quad k = 1, 2, \dots, q \tag{2a}$$

subject to:

$$Ax \le b \tag{2b}$$

$$pb \le B \tag{2c}$$

$$x \ge 0 \tag{2d}$$

where $b = (b_1, b_2, \dots, b_m)^T \in R^m$ is the $m$-dimensional unknown optimal portfolio vector of resources; $x = (x_1, x_2, \dots, x_n) \in R^n$ is the $n$-dimensional production level vector, which can be assumed as decision