*Energies* **2011**, *4*, 1624-1656; doi:10.3390/en4101624

OPEN ACCESS

*energies*

**ISSN 1996-1073**

www.mdpi.com/journal/energies

*Review*

# A Review on Optimization Modeling of Energy Systems Planning and GHG Emission Mitigation under Uncertainty

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*Received: 19 July 2011; in revised form: 1 September 2011 / Accepted: 5 September 2011 / Published: 21 October 2011*

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**Abstract:** Energy is crucial in supporting people's daily lives and the continual quest for human development. Due to the associated complexities and uncertainties, decision makers and planners are facing increased pressure to respond more effectively to a number of energy-related issues and conflicts, as well as GHG emission mitigation within the multiple scales of energy management systems (EMSs). This quandary requires a focused effort to resolve a wide range of issues related to EMSs, as well as the associated economic and environmental implications. Effective systems analysis approaches under uncertainty to successfully address interactions, complexities, uncertainties, and changing conditions associated with EMSs is desired, which require a systematic investigation of the current studies on energy systems. Systems analysis and optimization modeling for low-carbon energy systems planning with the consideration of GHG emission reduction under uncertainty is thus comprehensively reviewed in this paper. A number of related methodologies and applications related to: (a) optimization modeling of GHG emission mitigation; (b) optimization modeling of energy systems planning under uncertainty; and (c) model-based decision support tools are examined. Perspectives of effective management schemes are investigated, demonstrating many demanding areas for enhanced research efforts, which include issues of data availability and reliability, concerns in uncertainty, necessity of post-modeling analysis, and usefulness of development of simulation techniques.

**Keywords:** optimization; GHG emission mitigation; energy systems; planning; uncertainty

## 1. Introduction

Energy is important in supporting people's daily lives and the continual quest for human development [1]. In the past decades, the demand for various energy resources, in both sufficient quantities and satisfactory structures, has been increasing worldwide, along with population expansion, economic development and living standard improvement. At the same time, the depletion of conventional fossil fuels, the limitations of new energy resources/technologies, as well as public concerns over energy-induced environmental issues (particularly GHG emission) have greatly weakened society's capabilities for addressing potential risks and impacts associated with our energy supply [2–5]. Although the "energy crisis" of the 1970s may not return soon, there is international consensus regarding the fact that energy resources can no longer be produced and consumed without addressing the issues of sustainability and a variety of associated problems. Thus, planners and decision makers are facing increased pressure to respond more effectively to a number of energy-related issues and conflicts, as well as GHG emission mitigation within multiple scales of energy management systems (EMSs). This quandary requires a focused effort to resolve a wide range of issues related to EMSs, as well as the associated economic and environmental implications. Consequently, effective planning of EMSs with the consideration of GHG emission mitigation has been a priority for energy-related and environmental professionals, as well as regulatory agencies [6,7].

An EMS contains many processes such as energy exploration and exploitation, conversion and processing, production and consumption, importation and exportation, as well as the associated GHG emissions. These processes are undergoing many dramatic changes stemming from regulation implementation, regional/community development, and economic expansion, which would collectively result in significant effects on energy activities and the associated socio-economic and environmental implications [8]. In addition, the processes are generally complicated with a number of economic, technical, environmental, legislative and political factors. Such factors and their interactions are fraught with uncertainties that cannot be expressed as deterministic values or in a single format [9–11]. The uncertainties have multiple dimensions and layered features, and are thus complex by nature. Such dynamics and uncertainties may lead to a variety of complexities in EMSs decision-making activities. Moreover, a number of regional and global environmental issues are closely connected with energy activities, calling for synthetic management of energy resources, activities and the resulting environmental issues. The development of effective systems analysis approaches under uncertainty to successfully address the above interactions, complexities, uncertainties, and changing conditions is desired, which require a systematic investigation of the current studies on energy systems. Therefore, in this paper, a large number of systems analysis and optimization modeling for GHG emission mitigation and energy systems planning under uncertainty will be discussed in Section 2, advanced mathematical programming methods will be presented in Section 3, and decision supporting tools based on optimization will be discussed in Section 4, followed by a summary discussion and conclusions in Section 5.

## 2. Deterministic Optimization Modeling

Optimization is considered as an effective tool for identifying optimal strategies within complex management systems. Conventionally, a large number of deterministic models were used for both energy systems planning and the associated GHG emission mitigation. These methods posed solid basis for the development of inexact optimization. Particularly, due to the complexities co-existing within energy activities and GHG emission problems, many optimization models were developed in these two areas.

### *2.1. Optimization of Energy Systems Planning*

Over the recent decades, a number of optimization models were developed for aiding in the planning of EMSs under multiple scales [12–28]. The models were widely used for supporting an optimum allocation of energy resources, technologies and relevant services under one or several administrative objectives. For example, Sharma *et al*. proposed a method for the optimal design of a compressed air storage and power generation system [29]. Kavrakoğlu developed a dynamic linear programming model for the planning of energy systems at a national scale [30]. Smith proposed a linear optimization model for the planning of New Zealand's energy supply and distribution system [31]. In view of the close relationships between economic development and energy consumption in Pakistan, Riaz proposed an optimization approach resulting from the joint consideration of a set of production models for five typical energy industries in this country [32]. In order to facilitate the management of energy activities within a free-market economy in a given region, a linear optimization model was proposed by Schulz and Stehfest [33]. Samouilidis *et al*. made a thorough evaluation of the modelling approaches for electricity and energy systems planning [34]. It was based on two linear optimization models, including a global energy system model and an electricity generation subsystem model. Wene and Rydën discussed the adoption of a linear programming model for the planning of community-scale energy systems [35]. Groscurth and Kümmel developed a linear optimization model for evaluating industrial energy-saving potentials in several developed countries such as Germany, USA, The Netherlands and Japan [36]. Kahane made a thorough review on optimization modeling for the management of various energy systems [14]. Kaya and Keyes proposed a multi-level controlling and optimization approach to support the efficient operations of heat and power cogeneration systems [15]. Tiris *et al*. developed a linear optimization model and a multi-attribute value model to coordinate long-term interactions among energy, the economy, and the environment in Turkey [37]. Arivalagan *et al*. presented a mixed integer linear programming (MILP) model to identify economically optimum energy mixes in a processing industry [38]. Schoenau *et al*. developed a model for identifying optimum strategies in small-scale energy systems [18]. Lehtilä and Pirilä proposed a bottom-up energy system optimization model for supporting the formulation of policies related to sustainable energy utilization [39]. For optimally identifying heat and power generating strategies in an industrial factory, a MILP model was proposed by Bojiæ and Stojanoviæ [40]. As stated by Henning, MODEST was developed based on linear programming to minimize the capital and operating costs of energy supply and demand [41]. Heyen and Kalitventzeff proposed an optimization methodology to improve energy-utilization efficiencies in processing industries [42]. Farag *et al*. attempted to develop integrated, reliable, and cost-effective approaches for identifying optimal plans and meeting future energy demands in several utilities [43]. In order to identify the optimum technology and resource mixes for the design of energy-conscious buildings, a numerical multivariate optimization procedure was adopted by Peippo *et al*. [19]. El-Sayed proposed a linear optimization model for the management of energy systems at multiple scales [44]. In order to identify optimization solutions for energy and production in many industries, a global, multi-objective optimization methodology was proposed by Santos and Dourado [45]. A genetic-algorithm based solution method was also proposed. In order to determine an economically optimal energy supply structure based on biomass, a MILP model was proposed by Nagel [46]. Yokoyama and Ito proposed an optimization model for supporting the structural design of energy systems as well as their associated long-term operations [47]. Drozdz developed a linear optimization model for the management of geothermal utilization and conversion [21]. Due to the multiplicity of criteria for judging decision alternatives related to energy management, Koroneos *et al*. advanced a multi-objective optimization model. It was then applied to a real-world case in Lesvos Island, Greece [48]. Ostadi *et al*. developed a nonlinear programming approach for identifying optimal energy consuming patterns/schedules within a typical manufacturing factory [49]. Considering that energy consumption is a very important quality index in most of the manufacturing industries in China, an energy optimization model was developed for minimizing energy consumption based on an energy prediction model and genetic algorithm [27]. Beck *et al*. proposed a modeling approach for supporting the optimal planning of energy networks through combining global optimization and agent-based modeling tools [50]. The approach was demonstrated through a case study of regional electricity generation management in South Africa. Bujak proposed a mathematical model to determine optimal energy consumption quotas for a set of boilers [51]. The model was then applied to multiple-scale steam systems that had a group of liquid- or gas-fired shell boilers.

A number of large-scale modeling systems were also developed and then applied to many locations across the World. For instance, the Brookhaven Energy System Optimization Model (BESOM) was used to identify the optimal mixing patterns of energy resources, technologies and investments in accordance with the minimum system cost [35,52–54]. The Time-stepped Energy System Optimization Model (TESOM) was proposed as a consecutive BESOM-type optimization modeling system for supporting energy management [55]. The Market Allocation Model (MARKAL) was developed as a large-scale, technology-oriented energy-activity analysis model [5,56–65]. Multiple Energy System of Australia (MENSA) was developed to identify the optimal combinations of demand- and supply-side technologies with the objective of the lowest economic cost [66–68]. The Energy Flow Optimization Model (EFOM) was established as an engineering-oriented bottom-up model for energy management systems planning and was widely used in European countries [54,69–76]. There were also a number of software packages, such as Long-range Energy Alternatives Planning System (LEAP), New Earth 21 Model (NE21), National Energy Modeling System (NEMS) and Energy 2020, which were developed to evaluate environmental and economic effects of energy activities [77–84]. Papagiannis *et al*. applied LEAP2006 to a number of European countries [85]. Based on MARKAL, Jiang *et al*. estimated future consumptions of natural gas in three Chinese cities: Beijing, Guangzhou and Shanghai [86]. Nguyen examined the economic and environmental impacts of power production and capacity expansions in Vietnam [87,88]. The production of synthetic natural gas from wood in a Swiss methanation plant was effectively assessed through the adoption of MARKAL by Schulz *et al*. [89]. In Japan, Endo employed MARKAL to analyze the market penetration of fuel cell vehicles [90]. The MARKAL model was also successfully applied to a number of countries and regions for identifying sustainable development strategies and policies in South Africa, India, US, and European countries [60,91–119]. Silversides investigated biomass consumption patterns in a number of provinces of Canada, and evaluated their effects on forest management practices [120]. Huang *et al*. comprehensively investigated public policy discourse, energy systems planning methods, as well as relevant measures towards sustainable energy development in Canada [121]. In order to maximize bio-energy production from Lake Winnipeg, Cicek *et al*. evaluated various policies and technologies related to biomass harvesting in Manitoba [122]. Liebig *et al*. estimated GHG contributions and the mitigation potentials of various agricultural practices in several province of western Canada [123]. For examining the effects of fertilizer management on external energy inputs and GHG emissions, a grazing experiment was conducted in Brandon, Manitoba [124].

### *2.2. Optimization of GHG Emission Mitigation*

At the same time, a number of optimization modeling methods were proposed for supporting the management of GHG emission mitigation particularly through the adoption of renewable energies [54,125–143]. In the middle of the 1970s, Duff (1975) presented an optimization model to design solar thermal energy systems in accordance with the minimum system cost [144]. Leledakis *et al*. evaluated the potential distribution of renewable energy resources for reducing GHG emissions in the region of the Cyclades, a Greek island group in the Aegean Sea [145]. Alidi (1988) argued that the utilization of wood residues as a renewable energy source would probably be limited by two major problems (*i.e.*, (a) the high cost of transportation due to their high volume with respect to their energy content, and (b) the stochastic generation of these materials) and would not definitely lead to GHG emission reduction [146]. In order to further support the management of wood residues as an energy source, he proposed a dynamic optimization model. As an effective method for investigating the role of renewable energy resources for mitigating GHG emissions within many EMSs in Australia, the so-called Australian Energy Policy System Optimization Model (AEPSOM) was used by Islam [125]. Bose and Anandalingam presented a goal programming model to reflect multiple objectives of sustainable energy development, which was then applied to the city of Delhi, India [147]. Lehtilä and Pirilä used an optimization model to support energy-policy formulation for GHG emission mitigation in Finland [39]. Martins *et al*. developed a multi-objective, linear programming model for power generation planning and demand management to reduce GHG emissions [148]. Watson and Ter-Gazarian presented an optimization system to study operational and economic impacts for incorporating renewable power source utilization and GHG emission reduction within a large-scale electricity grid [149]. Badin and Tagore proposed an analysis framework to evaluate costs and impacts that might result from the incremental production, storage, transport, and use of different fuels or energy carriers that could reduce GHG emissions [150]. Özelkan *et al*. proposed a linear quadratic programming model for addressing aggregated multi-criteria decision making problems in order to maximize hydroelectric power generation and to minimize GHG emissions [151]. Gopalakrishnan *et al*. proposed an optimization model for the management of stand-alone energy systems that consisted of windmills, diesel generators and power storage equipment [152]. In order to dramatically reduce the costs of energy storage within hybrid energy-storage systems, a time-dependent model of a stand-alone, solar powered, battery-hydrogen hybrid energy storage system was developed by Vosen and Keller [153]. Based on a bottom-up procedure, an energy-module network, and a dynamic programming method, Bojiæ proposed an optimization modeling system for supporting the management of renewable energies and reduce the usage of high-carbon fuels [154]. Suganthi and Williams developed an optimization model to determine optimum allocation of renewable energies among a number of end-users in India [155]. Iniyan and Sumathy developed an Optimal Renewable Energy Mathematical (OREM) model for renewable energy source utilization and GHG emission mitigation in India [156]. Kong *et al*. adopted a linear programming model to deal with planning problems of the combined cooling, heating and power production systems for minimizing the associated cost and GHG emissions [157]. Chinese *et al*. proposed a nonlinear optimization approach for assessing technical and economic feasibility of various renewable-energy-based GHG reduction schemes in northeastern Italy [24]. Kélouwani *et al*. developed a dynamic simulation-optimization model for supporting the management of stand-alone renewable energy systems with hydrogen storage equipments (RESHS) [158]. In order to investigate efficient ways for green electricity and heat supply in rural Japan, Nakata *et al*. developed an optimization modeling system [159]. In order to identify the desired renewable energy options for electricity generation, Dudhani *et al*. proposed an optimization allocation model. The model was formulated based on linear programming [160]. Dufo-López *et al*. presented a genetic-algorithm-based optimization model for supporting the management of a hybrid renewable electrical system for reducing GHG emissions [161]. Zouliasand and Lymberopoulos employed the Hybrid Optimisation Model for Electric Renewables (HOMER) to optimize the replacement of conventional technologies with the ones based on hydrogen and fuel cells in remote communities of Europe [162]. Based on artificial neural networks, Maøík *et al*. developed an optimization model to manage a number of energy resources and power generation technologies for supporting GHG emission mitigation [163].

More recently, Dalton *et al*. used an optimization modeling system to analyze the technical and financial viability of grid-only, renewable energy sources and grid/renewable hybrid power supply configurations for a large-scale grid-connected hotel in a subtropical costal area of Queensland, Australia [164–166]. Babu and Ashok proposed a nonlinear programming model for electricity loading management, renewable energy utilization, and GHG emission mitigation in India [167]. Kamarudin *et al*. proposed an optimum hydrogen delivery network through the development of a mixed integer linear programming model and a GAMS-based solution algorithm [168]. Bernal-Agustín and Dufo-López employed HOMER for supporting the optimal design of hybrid systems that consisted of many components, such as a photovoltaic generator, batteries, wind turbines, hydraulic turbines and fuel cells under multiple administrative objectives [137]. Østergaard provided a thorough review on a series of criteria for the development of renewable energy systems and GHG emission reduction [143]. Fong *et al*. used a robust evolutionary algorithm to identify optimal energy-conservation strategies within a centralized heating, ventilating, and air conditioning system [169]. An optimization model was proposed by Zhao and Burke for managing fuel-cell based energy systems to reduce GHG emissions [170]. In order to optimally design a small-scale energy system for mitigating GHG emissions, Jewett *et al*. proposed a multi-phase, multi-component model based on simulation and optimization approaches [171]. A multi-agent system was presented by Lagorse *et al*. for supporting energy management with the consideration of several distributed power generation facilities that could lead to GHG emission reductions [172]. Andreassi *et al*. developed an optimization model for the management of power distribution systems to reduce GHG emissions [173]. As the basis for an environmental decision support system, Frombo *et al*. developed a linear programming model for the optimal allocation of biomass resources [174]. Chicco and Mancarella advanced an optimization model for the management of a small-scale, tri-generation system to maximize the combined production of electricity, heat, and cooling power under minimized GHG emissions [175]. Chaturvedi *et al*. used a nonlinear programming model with time-varying acceleration coefficients for supporting power dispatchment among various economic sectors [176]. Ehsani *et al*. proposed a mixed integer linear programming model for the planning of power generation in a purely competitive market [177]. Morais *et al*. proposed a mixed integer linear programming model for optimally scheduling power generation technologies within a renewable micro-grid power system [178].

## 3. Inexact Optimization Modeling

Optimization modeling was often based on a number of mathematical equations to represent a series of interactions between relevant system components, processes, and factors. In most of the conventional methods, the modeling parameters/coefficients were usually specified as deterministic. However, in realistic energy management systems, many parameters/coefficients as well as the irrelations may have uncertain natures with multiple dimensions and layers [9,10,179–183]. Over the past decades, the most common approaches for dealing with uncertainties in optimization modeling included interval, stochastic, and fuzzy-set-based methods as well as their hybrids [9–11,184–188].

### *3.1. Fuzzy Mathematical Programming*

Fuzzy mathematical programming (FMP) was derived through the incorporation of fuzzy set theory within conventional mathematical programming frameworks [189]. Normally, the FMP methods could be classified into two major categories: fuzzy flexible programming (FFP) and fuzzy parameter programming (FPP) [190]. In FFP, the flexibility in the constraints and fuzziness in the system objective, which were presented by fuzzy sets and denoted as "fuzzy constraints and goals", were introduced into the conventional optimization models [191,192]; in FPP, fuzzy parameters were introduced into mathematical programming frameworks that could then be used to formulate various intermediate models based on the detailed specifications and analyses of the specific problem. The uncertain parameters were represented as fuzzy regions where they possibly lie and were regarded as possibility distributions [193]. A general linear programming model can be presented as follows:

$$\text{Min} \, f = CX \tag{1a}$$

subject to:

$$AX \lesssim B \tag{1b}$$

$$X \geq 0 \tag{1c}$$

where $\lesssim$ is a fuzzy $\leq$ symbol. The decision maker can establish an aspiration level, *f*, for the value of the objective function he would like to achieve, and also each of the constraints can be modeled as fuzzy sets. Then, the above model becomes:

$$CX \lesssim f \tag{2a}$$

$$AX \lesssim B \tag{2b}$$

$$X \geq 0 \tag{2c}$$

Then, according to the definition of fuzzy sets, a new decision variable $\lambda$ could be introduced, and the above model can be transformed into:

$$\text{Max } \lambda \tag{3a}$$

subject to:

$$CX \leq f^{+} - (1-\lambda)\cdot\left(f^{+} - f^{-}\right) \tag{3b}$$

$$AX \leq B^{+} - (1-\lambda)\cdot\left(B^{+} - B^{-}\right)] \tag{3c}$$

$$X \geq 0 \tag{3d}$$

$$0 \leq \lambda \leq 1 \tag{3e}$$

where $f^{-}$ and $f^{+}$ are the lower and upper bounds of the objective's aspiration level, respectively; the flexibility in the constraints and fuzziness in the objective can be expressed as membership grades $\lambda$, which is the control variable corresponding to the degree (membership grade) of satisfaction for the fuzzy decision.

On the other hand, fuzzy parameter programming (FPP) involves optimizing fuzzy objective functions subject to a fuzzy decision space delimited by constraints with fuzzy coefficients and fuzzy capacities. It uses fuzzy sets as coefficient values in the objective function and constraints, as well as in the right-hand side of constraints. A general FPP problem can be defined as follows:

$$\text{Min} f = \tilde{C}^{t} X \tag{4a}$$

subject to:

$$\tilde{A}X \mathrel{\tilde{\geq}} \tilde{B} \tag{4b}$$

where $\tilde{C}^{t}$ is the transpose of the *n*-dimensional fuzzy objective vector; $\tilde{A}$ represents the fuzzy constraint coefficient matrix; $\tilde{B}$ is the *m*-dimensional vector of fuzzy right-hand sides; $f$ is the fuzzy objective value; $\tilde{\geq}$ represents fuzzy inequality; and $X_D$ is the set of admissible activity vectors $X$, with $X \in \Re_n$, that fulfill all crisp constraints. There were a number of methods that could be used for solving FPP. One of the most general one could be presented as follows: let $\tilde{C}^{t} = \left(\tilde{c}_j\right)$, $\tilde{A} = \left(\tilde{a}_{ij}\right)$, $\tilde{B} = \left(\tilde{b}_i\right)$, $i = 1,2,...,m$, $j = 1,2,...,n$. For triangular fuzzy sets, fuzzy coefficients, $\tilde{c}_j$, $\tilde{a}_{ij}$, $\tilde{b}_i$ are characterized by triangular membership functions defined as:

$$\mu_C(x)=\begin{cases}0, & \text{if } x\le C_L,\ \text{or } x\ge C_R\\ \dfrac{(x-C_L)}{(C_M-C_L)}, & \text{if } x\in[C_L,C_M]\\ \dfrac{(C_R-x)}{(C_R-C_M)}, & \text{if } x\in[C_M,C_R]\end{cases}$$

A triangular fuzzy number can be denoted as $\tilde{C}=(C_L,C_M,C_R)$, where $C_M$ is the central value (maximum grade of membership), $C_L-C_M$ is the left spread, and $C_M-C_R$ is the right spread. Based on the concept of a level set (α-cut levels), the triangular fuzzy number coefficients can be represented as $c_j(\alpha)=\{c_j,u_{\tilde{c}_j}(c_j)=\alpha\}=\{c_j^L(\alpha),c_j^U(\alpha)\}$. Thus, model (4) can be reformulated as follows:

$$\text{Min} f=\sum_{j=1}^{n}\left[c_j^L \text{ or } c_j^U\right]x_j \tag{5a}$$

$$\sum_{j=1}^{n}\left[a_{ij}^L \text{ or } a_{ij}^U\right]x_j\ge\left[b_i^L \text{ or } b_i^U\right] \tag{5b}$$

$$x_j\ge 0 \tag{5c}$$

Model (5) is a deterministic LP model and can be solved using various combinations of the coefficients to obtain different values for $f_\alpha$ and $x_j(\alpha)$. Then the optimal solution for each $\alpha$ value is defined as follows: $f_\alpha=\left[f_\alpha^L,f_\alpha^U\right]$, and $x_j(\alpha)=\left[x_j^L(\alpha),\ x_j^U(\alpha)\right]$. Thus, optimal solutions for fuzzy-parameter model formulated by (1) and (2) can be obtained as: $\tilde{f}=\{(f_\alpha,\alpha)\}$ and $\tilde{x}_j=\{(x_j(\alpha),\alpha)\}$.

According to Bellman and Zadeh, Negoita *et al.*, Dubois and Prade, and Inuiguchi *et al.*, FMP could deal with the following three types of uncertainties: vagueness, ambiguity, as well as their combination (*i.e.*, FMP with both vagueness and ambiguity) [194–197]. Moreover, there were many extensions of fuzzy set theory to other mathematical programming problems, leading to a number of hybrids, such as fuzzy linear programming, fuzzy robust programming, fuzzy dynamic programming, fuzzy multi-objective programming, fuzzy nonlinear programming, and fuzzy (stochastic) linear programming. Fuzzy linear programming (FLP) is a typical FMP method. Based on these method, there were a large number of applications to environmental and energy management and planning [198–206]. For example, Chen and Sheen introduced a generalized fuzzy mathematical model for energy-load management [207]. Kagan and Adams addressed the problems of electrical power distribution systems by planning under uncertainty through the formulation of a fuzzy mathematical model [208]. In order to examine the potentials energy savings and emission reduction for municipal energy systems, a set of three optimization models with high spatial and temporal disaggregation were adopted by Groscurth and Kress [209]. Borges and Antunes presented a fuzzy multi-objective linear programming approach for tackling the uncertainty and imprecision associated with the coefficients of an input-output energy-economy planning model [203]. Mavrotas *et al.* presented a fuzzy linear programming model, including both continuous and integer variables (which represent energy flows and discrete energy technologies, respectively) for supporting the planning of energy resources in buildings [204]. Mavrotas *et al.* proposed an optimization model to address uncertain parameters in the objective function by introducing Triangular Fuzzy Numbers (TFN) into a general MILP modeling framework [210]. Sadeghiand Hosseini attempted to use FLP for the optimal management of the energy supply systems in Iran [76]. Mazur proposed a fuzzy nonlinear programming model in which a number of fuzzy constraints could be considered [211]. Nguene and Finger proposed an optimization modeling methodology based on fuzzy set theory and strategic choices for enabling decision makers to evaluate and identify optimal policies for energy allocations over different time horizons [212]. Martinsen and Krey introduced a series of fuzzy constraints to identify optimal strategies and compromising policies related to energy management by considering a number of contradictory targets such as minimized economic cost, minimized environmental impacts, and maximized energy-supply safety [213]. Bitar *et al*. used a fuzzy multi-objective mathematical programming model to analyze the tradoffs between the variations of system costs, the emissions of $CO_2$, and the number of potential jobs, as well as the expansion options of thermoelectric power in a specific region [214].

*3.2. Stochastic Mathematical Programming*

Stochastic mathematical programming (SMP) was developed by Beale [215]. Normally, SMP can be viewed as an extension of mathematical programming to decision problems whose coefficients/parameters are not known but can be represented as chances or probabilities. According to Li, the inherent uncertainties in a decision can manifest themselves throughout the model as stochastic elements in the constraint matrix, the RHS stipulations, and/or the objective coefficients [189]. The main advantage of SMP methods is that they do not simply reduce the complexity of programming problems; instead, they allow decision makers to have a complete view of the effects of uncertainties and the relationships between uncertain inputs and the resulting solutions [216–218]. Typically, SMP models can be replaced by suitable deterministic versions (named deterministic equivalents) and then solutions of the deterministic models can be extended to represent the stochastic solutions [219]. Among them, chance-constrained programming (CCP) was often used for reflecting the reliability of satisfying (or risks of violating) system constraints under uncertainty. The CCP methods do not require that all of the constraints be totally satisfied. Instead, they can be satisfied in a proportion of cases under given probabilities [220]. Also, the CCP methods are effective in dealing with uncertainties in elements of RHSs when their probability distributions are available [221]. CCP programming was first formulated by Charnes *et al*., and, thereafter, issues of CCP were widely investigated [222–236]. Also, two-stage stochastic programming and chance-constrained programming are the major two methods. Two-stage stochastic programming (TSP) is effective for optimization problems in which an analysis of policy scenarios is desired and the related data are mostly uncertain. Generally, when uncertainties of some elements in the right-hand sides (B) can be expressed as probabilistic distributions, chance-constrained programming (CCP) can be used to deal with them. In terms of uncertainties in B, consider a general stochastic linear programming (SLP) problem as follows:

$$\mathrm{Max} f = C(t)X \tag{6a}$$

subject to:

$$A(t)X \le B(t) \tag{6b}$$

$$x_j \geq 0,\ x_j \in X,\ j = 1, 2, \ldots, n \tag{6c}$$

where $X$ is a vector of decision variables; $A(t)$, $B(t)$ and $C(t)$ are parameter vectors with random elements defined on probability space T [222,224,226]. To solve this SLP model, an "equivalent" deterministic version can be defined. This can be realized by using a CCP approach, which consists of fixing a certain level of probability $p_i \in [0, 1]$ for each constraint $i$ and imposing the condition that the constraint is satisfied with at least a probability of $1 - p_i$. The set of feasible solutions is thus restricted by the following constraints [224]:

$$\Pr\left\{\left[t \mid A_i(t)X \leq b_i(t)\right]\right\} \geq 1 - p_i,\ A_i(t) \in A(t),\ i = 1, 2, \ldots, m \tag{7}$$

According to Huang *et al.*, these constraints are generally nonlinear, and the set of feasible constraint is convex only for some particular cases, one of which is when $a_{ij}$ (elements of $A_i(t)$) are deterministic and $b_i(t)$ are random (for all $p_i$ values). Under this condition, constraint (7) becomes linear:

$$A_i \leq b_i(t)^{p_i},\ \forall\ i \tag{8}$$

where $b_i(t)^{p_i} = F_i^{-1}(p_i)$, given the cumulative distribution function of $b_i$ (*i.e.*, $F_i(b_i)$), and the probability of violating constraint $i$ ($p_i$). The problem with (6b) can only reflect the case when A is deterministic. If both A and B are uncertain, the set of feasible constraints may become more complicated [227].

At the same time, one of the other SMP is TSP, which can be presented as:

$$\mathrm{Min} f = C(t)X = \sum_{i=1}^{m} C_i X_i + E\left[\sum_{i=1}^{m} D_i Y_{iQ}\right] \tag{9a}$$

subject to:

$$A(t)X \leq B(t) \tag{9b}$$

$$x_j \geq 0,\ x_j \in X,\ j = 1, 2, \ldots, n \tag{9c}$$

In the planning of EMSs under multiple scales, a number of methods based on SMP (particularly the TSP and CCP methods) were developed [237–240]. Craig *et al.* analyzed optimal investment strategies for energy conservation with the consideration of probability distributions for various energy prices [241]. Pena-Taveras and Cambel developed a stochastic nonlinear model for supporting optimal energy system design through the adoption of the Schumpeter Clock Model (SCM) and the Ising Model (IM) [242]. Bakirtzis and Gavanidou employed a stochastic dynamic programming method for facilitating the optimal management of power generation and battery storage in a small autonomous system with both conventional and unconventional energy resources [243]. Goumas *et al.* adopted several computational methods to provide a rigorous analysis for improving the decision-making process related to the optimum exploitation of geothermal energy resources [244]. Gamou *et al.* proposed an optimal unit-sizing method for energy cogeneration systems planning through employing continuous random variables for describing energy demands [245]. Falcão presented an optimization model for allocating mechanical and electrical equipment within an oscillating-water-column (OWC) wave power plant [246]. Beraldi *et al.* proposed a two-stage stochastic integer programming model for the integrated optimization of power generation and trading [247]. Krey *et al*. used a stochastic programming technique to explicitly consider uncertainties associated with energy prices [248]. A two-stage stochastic programming model for short- or mid-term cost-optimal electric power production planning was developed by Nürnberg and Römisch [249]. Krukanont and Tezuka proposed a TSP optimization model for supporting energy allocation in Japan [240]. Beraldi *et al*. proposed a two-stage stochastic integer programming model for integrated optimal management of power production and trading in order to reduce power shortage risks [247]. Kim *et al*. developed a TSP model for optimal designing hydrogen supply chains, which consisted of various activities such as production, storage and transportation [250]. Yang *et al*. proposed a new method for optimal transmission system expansion planning based on CCP with the consideration of several uncertain factors such as the locations and capacities of new power plants as well as demand growth [251]. Arun *et al*. adopted a CCP approach for incorporating uncertain energy resources into a facility sizing and design system [252]. Based on CCP, Held *et al*. explored many effective policies on the utilization of fossil fuel and renewable energy resources in terms of economic investments [253].

### *3.3. Interval Mathematical Programming*

As an alternative approach to deal with uncertainty, interval analysis was advanced by Moore [254]. In interval analysis, the only information that is available for an inexact parameter is the lower and upper bounds that are insufficient for creating distribution or membership functions. Interval analysis was then extended into interval mathematical programming (IMP) (Huang *et al*., [255]). According to Huang *et al*. [256,257], the IMP improved upon the existing optimization methods with the following features: (a) it allowed uncertainties to be directly communicated into the optimization and solution processes;(b) it did not lead to more complicated intermediate models, and thus had relatively low computational requirements; and (c) it did not require distributional or membership information for model parameters since interval numbers were acceptable as uncertain inputs, which was particularly meaningful for practical applications because it was typically much more difficult for planners/engineers to specify a distribution than to define a fluctuation interval. According to Huang *et al*. [216–218], a general IMP model can be written as follows:

$$\text{Min}\, f^{\pm} = C^{\pm} X^{\pm} \tag{10a}$$

subject to:

$$A^{\pm} X^{\pm} \leq B^{\pm} \tag{10b}$$

$$X^{\pm} \geq 0 \tag{10c}$$

where $A^{\pm} \in \left\{R^{\pm}\right\}^{m\times m}$, $B^{\pm} \in \left\{R^{\pm}\right\}^{m\times 1}$, $C^{\pm} \in \left\{R^{\pm}\right\}^{1\times n}$, $X^{\pm} \in \left\{R^{\pm}\right\}^{n\times 1}$, and $R^{\pm}$ denotes a set of interval numbers. At the same time, an interactive solution algorithm has been developed to solve the above problem through analyzing the detailed interrelationships between parameters and variables and between the objective function and constraints. According to the algorithms proposed by Huang *et al*., solutions for model (10) can be obtained through a two-step method, where a submodel corresponding to $f^{-}$ (when the objective function is to be minimized) is first formulated and solved, and then the relevant submodel corresponding to $f^{+}$ can be formulated based on the solution of the first submodel.

In detail, the first submodel can be formulated as follows (assume that $b_i^{\pm} > 0$, and $f^{\pm} > 0$):

$$\text{Min}\, f^- = \sum_{j=1}^{k_1} c_j^- x_j^- + \sum_{j=k_1+1}^{n} c_j^- x_j^+ \tag{11a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{ij}|^+ \, Sign(a_{ij}^+) x_j^- + \sum_{j=k_1+1}^{n} |a_{ij}|^- \, Sign(a_{ij}^-) x_j^+ \le b_i^+, \ \forall i \tag{11b}$$

$$x_j^{\pm} \ge 0, \ \forall j \tag{11c}$$

where $x_j^{\pm}$, $j = 1,2,...,k_1$, are interval variables with positive coefficients in the objective function, and $x_j^{\pm}$, $j = k_1 + 1$, $k_1 + 2,...,n$, are interval variables with negative coefficients in the objective function. Thus, solutions of $x_j^-{}_{\text{opt}}$ ($j = 1,2,...,k_1$) and $x_j^+{}_{\text{opt}}$ ($j = k_1 + 1$, $k_1 + 2,...,n$) can be obtained through solving submodel (11). Then the submodel corresponding to $f^+$ can be formulated as follows (assume that $b_i^{\pm} > 0$, and $f^{\pm} > 0$):

$$\text{Min}\, f^+ = \sum_{j=1}^{k_1} c_j^+ x_j^+ + \sum_{j=k_1+1}^{n} c_j^+ x_j^- \tag{12a}$$

subject to:

$$\sum_{j=1}^{k_1} |a_{ij}|^- \, Sign(a_{ij}^-) x_j^+ + \sum_{j=k_1+1}^{n} |a_{ij}|^+ \, Sign(a_{ij}^+) x_j^- \le b_i^-, \ \forall j \tag{12b}$$

$$x_j^{\pm} \ge 0, \ \forall j \tag{12c}$$

$$x_j^+ \ge x_{j\,\text{opt}}^-, \ j = 1,2,...,k_1 \tag{12d}$$

$$x_j^- \le x_{j\,\text{opt}}^+, \ j = k_1 + 1, k_2 + 2, ..., n \tag{12e}$$

Hence, solutions of $x_j^+{}_{\text{opt}}$ ($j = 1,2,...,k_1$) and $x_j^-{}_{\text{opt}}$ ($j = k_1 + 1$, $k_1 + 2,...,n$) can be obtained through solving submodel (12). Thus, we can have the final solution of $f^{\pm}_{\text{opt}} = [f^-_{\text{opt}}, f^+_{\text{opt}}]$ and $x_j^{\pm}{}_{\text{opt}} = [x_j^-{}_{\text{opt}}, x_j^+{}_{\text{opt}}]$.

Over the past decades, a number of methods were developed based on IMP. For instance, Jansson developed a self-validating method for solving linear programming (LP) problems with interval input data [258]. Urli and Nadean proposed interactive approaches for solving multi-objective linear programming problems with interval coefficients [259]. Matloka investigated the generalization of inexact LP methods and provided a relevant solution algorithm [260]. Xia and Zhang introduced several methods for solving interval nonlinear programming problems and applied them to water pollution control planning [261]. Huang and Baetz proposed an inexact quadratic programming (IQP) method through the introduction of interval numbers into a quadratic programming framework [256,257]. Yeh proposed several inexact linear and quadratic programming models for planning water resource management systems [262]. Sugimoto *et al.* advanced a parallel relaxation method for handling quadratic programming models with interval constraints [263]. Huang and his colleagues proposed several interval-parameter mathematical programming methods as a special group of IMP, and applied them to a number of environmental and energy decision analysis problems in Canada, the US, Japan, Taiwan, and China [255,264–267]. Bass *et al*. presented an inexact multi-objective programming method for the planning of climate change adaptation within a water resources management system [268]. Chi proposed an interval-parameter mixed integer linear programming (IMILP) model for the planning of waste diversion in the city of Regina [269]. Liu developed an inexact chance-constrained mixed-integer linear programming (ICCMILP) approach for the planning and management of a regional energy-environmental system [270]. Huang *et al.* developed an interval-parameter fuzzy stochastic programming for environmental management [256,257]. Chen and Wu presented an interval optimization method for the dynamic response of structures with interval parameters [23]. Noureldin and Hasan examined new opportunities for energy saving inside a Bisphenol-A (BPA) plant through optimal selection of process operating temperatures [271].

## 4. Model-Based Decision Support Tools

There are many potential decision alternatives for the planning of multi-scale EMSs under a variety of changing conditions. Decision makers must systematically evaluate economic and environmental performance of energy technologies, resources and services and choose a desired plan for each sub-sector of EMSs. To facilitate this decision-making process, expert systems and decision support tools can be employed based on scientific modeling tools. In the past decades, a number of research efforts have been directed toward developing such systems for energy management systems planning [203,272–280]. For assisting in decision making of an advisory council in identifying areas of interest for energy research and development, Lootsma *et al*. employed a number of multi-criteria decision analysis methods to develop an expert system [281]. Harhammer and Infanger developed a DSS for operation planning (DSS-OP) to assist decision makers in the planning of multiple scales of energy systems [282]. In order to provide interference analysis for the development of geothermal energy in Mexico, Arellano *et al*. developed a computerized expert system (ANAPPRES V1.0) [283]. Liu *et al*. described a computer-based DSS for evaluating quality of life improvement, as well as technological and environmental impacts of energy planning and consumption [16]. Robin *et al*. proposed a computer-aided DSS for supporting thermal design of buildings [284]. Clarke and Grant adopted a computer-based DSS (EnTrack) for supporting the development of renewable energy resources at a regional level [285]. Georgopoulou *et al*. presented a DSS for assisting decision makers in the promotion of renewable energy resource utilization [286]. In order to support the analysis of energy consumption in various buildings, Kim and Degelman developed a computer-aided interface system [287]. As an effective decision-support tool for energy systems planning, a set of computerized decision-support software was developed by Rylatt *et al*. [288]. A specialized group DSS was designed by van Groenendaal for providing long-term support related to energy policy formulation on the island of Java, Indonesia [289]. Freppaz *et al*. proposed a DSS for supporting forest biomass exploitation and renewable energy production [290]. When planning bioenergy production from biomass, in order to take into account opinions from multiple groups of stakeholders (e.g., biomass resources suppliers, and transportation, conversion and electricity suppliers), a two-level general bioenergy decision system (gBEDS) was developed by Ayoub *et al*. [291]. In order to identify the most appropriate set of energy options for providing sufficient power to fulfill local demands and improve rural livelihoods, Cherni *et al*. developed a new multi-criteria DSS [292]. Yue and Yang established a DSS for strengthening the utilization of renewable energy resources and meeting new international environmental requirements and providing self-sufficient domestic energy supplies in Taiwan [293]. Blanco *et al*. developed a DSS for the planning of micro-hydro power plants in the Amazon region under a sustainable development perspective [294]. Panichelli and Gnansounou presented a GIS-based DSS for supporting the selection of the least-cost bioenergy utilization patterns when there was significant variability in biomass farmgate price and when more than one bioenergy plant with a fixed capacity needs to be placed in a region [295]. In order to enhance the utilization of renewable energy sources, an information decision system was developed by Patlitzianas *et al*. based on an expert subsystem and a multi-criteria decision making subsystem [296]. Aydin *et al*. developed a GIS-based DSS for site selection of wind turbines in Turkey [297]. Frombo *et al*. developed a GIS-based environmental decision support system (EDSS) for optimal planning of forest biomass utilization [298]. Vainio *et al*. proposed a GIS-based DSS for wood procurement management in order to identify wood harvesting alternatives [299]. Several studies were also conducted on both environmental and energy management [300–318].

## 5. Discussions and Conclusions

As extensions of deterministic optimization approaches, a number of inexact ones have been proposed for dealing with uncertainties associated with energy systems planning and GHG emission mitigation. These methods can be broadly categorized into fuzzy mathematical programming (FMP), stochastic mathematical programming (SMP), and interval mathematical programming (IMP). Each of these methods could deal with an individual type of uncertainties that can be expressed as fuzzy sets, probability density function, and intervals. For FMP-based methods, they are effective in address uncertain information that can be expressed as fuzzy sets in both objective functions and system constraints. However, there are quite a number of improvements that could be made upon FMP. Firstly, many methods could be used for determining fuzzy membership functions that might be used in the optimization system (mainly for FPP). These methods are mainly subject to a certain degree of subjectivity. Secondly, for both FFP and FPP, the solution procedures could lead to complicated inter-medium processes. Thirdly, for most of the FPP methods, the increased computational efforts may also lead to system infeasibility. Fourthly, most of the FMP methods could only deal with a specific type of function membership (e.g., triangle forms). At the same time, in terms of SMP-based methods, there are effective in handling uncertainties that can be expressed as probability density functions. However, they are also subject to several disadvantages. Firstly, in practical problems it is difficult in establishing probabilistic distributions of relevant parameters. Secondly, most of these methods are mainly proposed based on assumptions that distributions of relevant parameters are fixed and can be identified. This might lead to system infeasibility when the parameters are dynamic and are associated with intensive variations. Thirdly, the computation requirements of stochastic mathematic programming are relatively high especially for large-scale practical problems. Moreover, regarding IMP-based methods, they could easily deal with uncertainties that can be expressed as intervals. However, they are associated with the following three shortcomings. Firstly, since most of the parameters in IMP are expressed as intervals without any distribution information, it might lead to simplification of real-world problem when some of the parameters could be expressed as probabilistic and/or possibilistic distributions. Secondly, due to the adoption of inter-medium submodels, solution feasibility could sometimes be an inherent problem for large-scale real-world cases. Thirdly, when ranges of the intervals are broad, the optimization model could be infeasible. Accordingly, there are still a number of areas that need further studies, including: (a) studies that could incorporate multiple technologies, multiple resources, multiple sectors, as well as their complex interactions within a general modeling framework, particularly those could be used for supporting the planning of renewable energy management systems; (b) efforts in systematically studying multiple formats of uncertainties (e.g., intervals, fuzzy membership functions, probability distributions, as well as their combinations) in a flexible manner; (c) studies that could effectively deal with issues of diverse data availability and reliability. When sufficient information is available to represent the uncertainties as probability distributions but an interval method is used, valuable probabilistic information will be lost. On the contrary, when a stochastic method is used without sufficient information support, detailed probabilistic distributions might be generated based on unrealistic assumptions, resulting in errors in modeling inputs. In general, such manipulation in uncertain modeling inputs would result in considerable effects on modeling results, reducing the system robustness, and (d) studies that could incorporate post-modeling analysis, and energy simulation/prediction models to improve applicability and robustness of the obtained solutions.

## Acknowledgements

This research was supported by the National Natural Science Foundation of China (51009004). The authors are extremely grateful to the editors and the anonymous reviewers for their insightful comments and suggestions.

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