Optimal Scheduling of Energy Hubs in the Presence of Uncertainty-A Review

Mohammad Mohammadi[1], **Younes Noorollahi**[2], **Behnam Mohammadi-ivatloo**[3], **Hossein Yousefi**[4], **and Saeid Jalilinasabady**[5]

[1,2,4,5] *Department of Renewable Energies and Environmental Engineering, Faculty of New Sciences and Technologies, University of Tehran, Tehran, Iran*
[3] *Faculty of Electrical and Computer Engineering, University of Tabriz , Tabriz, Iran*
[*] *Corresponding author: m.mohammady@ut.ac.ir*

Manuscript received April 27, 2017; revised June 24: accepted June 25, 2017. Paper no. JEMT1704-1009

Energy Hub is an appropriate framework for modeling and optimal scheduling of multi-energy systems (MES). Energy hub provides the possibility of integrated management of various inputs, converters, storage systems, and outputs of multiple energy carrier systems. However, the optimal management problem in the energy hub is affected by various technical, economic, social and environmental parameters. Many of these parameters are inherently ambiguous and uncertain. Fluctuating nature of renewable energy sources (RES), energy prices in competitive and deregulated markets, the behavior of consumers, inherent variations in the surrounding environment, simplifications and approximations in modeling, linguistic terms of experts, etc. are just a few examples of uncertainties in the optimal management problem of energy hub. Ignoring such uncertainties in the process of modeling and optimization of energy hub leads to unrealistic models and inaccurate results. On the other hand adding these uncertainties leads to increased complexity of modeling and optimization. Therefore, to achieve a realistic model of MES in the form of energy hubs, identifying appropriate methods to address these uncertainties is essential. This paper reviews the different methods for the consideration of uncertainty in optimal scheduling of energy hubs. In this paper, different methods of modeling and optimization of energy hub are reviewed and classified and their strengths and weaknesses are discussed. A classification and review of the various methods that offered in the most recent research of MES in the field of uncertainty modeling are done to identify efficient methods for using in energy hub models.

keywords: *Energy hub; optimization methods; uncertainty modeling; realistic decision-making.*

http://dx.doi.org/10.22109/JEMT.2017.49432

1. INTRODUCTION

Nowadays, economic development, population growth, industrialization and increasing demand have caused energy to become one of the main components of the current human development. The hierarchical structure of generation, transmission, and distribution of energy has been the main framework for demand and supply of energy in recent decades. However, the development of distributed energy resources (DER), particularly RES and local storage systems, leads to non-hierarchical and distributed structures. On the other hand, the advent of efficient technologies, such as combined heat and power (CHP) production, electric heat pumps and fuel cells, leads to the integration of energy infrastructure, such as electricity, natural gas, and district heating networks which create MES [1]. In a multi-energy system, different energy carriers can interact optimally. The existence of various energy carriers and energy infrastructures leads to the complexity of the structure of these systems. On the other hand, optimal performance of such systems requires a comprehensive modeling framework and integrated management.

Energy hub concept has been developed in recent years for integrated management of MES [2]. Planning and management of energy hubs as an effective and efficient method in modeling and utilization of energy systems are essential for ensuring energy security, environmental sustainability, and economic development. However, the energy systems are affected by various technical, economic, social and environmental parameters characterized by uncertainty and high volatility. Therefore, optimal management of energy systems, especially MES, needs to take account the uncertainties in modeling and optimization of the systems. Increased share of renewable resources, deregulation of energy markets and behavior of the different components of the energy system such as producers and consumers, create uncertainty and difficulty in scheduling these systems. Due to

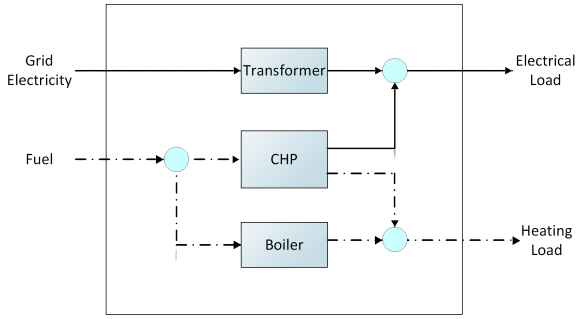

Fig. 1. Example of a simple energy hub.

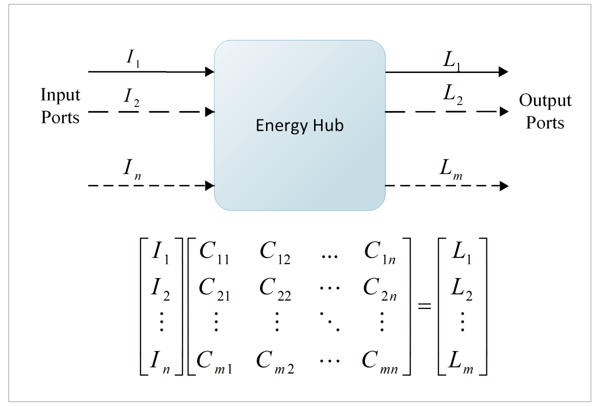

Fig. 2. The matrix model of energy hub concept.

the high cost of the investment in energy infrastructure, the actual planning of these systems is crucial and taking into account the associated uncertainties to reach a real (or close to reality) decision is essential. On the other hand, energy hub operational optimization problem results are under the influence of model input parameters variations and this increase the importance and necessity of uncertainties studying in the process of managing and scheduling of these systems.

This paper reviews the various techniques for taking into account the uncertainties in the planning process and optimal management of the energy hubs. First, an introduction to the concept of energy hub is provided and various methods and models to optimize energy hub are classified and evaluated. The various techniques used in the literature for the consideration of uncertainties in modeling and optimization of energy hub are discussed. As well as, different uncertainty modeling methods that have been used in most recent MES research are reviewed and classified and the advantages and disadvantages of each of them are discussed to determine appropriate techniques for addressing uncertainty in the optimal scheduling of energy hub.

The remainder of this paper is organized as follows. Section 2 provides an introduction to the concept of energy hub and various methods for modeling and optimization of energy hub. Section 3 reviews the different methods used in the literature for modeling uncertainty in energy hub, and efficient methods have been employed in the other MES models. Section 4 includes discussions and general comments about modeling uncertainties in energy hub. The paper is concluded in section 5.

2. ENERGY HUB CONCEPT AND OPTIMIZATION METHODS

Energy hub concept was developed for the first time in "A Vision of Future Energy Networks" (VOFEN) [3] project and aims to get a vision and model of future energy systems. Moving toward MES, non-hierarchical structures, and integrated energy systems are the main goals of this project. Therefore, in order to achieve such structures of energy systems a concept called "Energy Hub" has been introduced as a unit that provides the features of input, output, conversion and storage of multiple energy carriers. Energy hub can be defined as the place where the production, conversion, storage and consumption of multiple energy carriers take place. A common and basic structure for energy hub can be seen in Fig. 1.

In this figure can be seen, an energy hub has different inputs that using various conversion and storage procedures can meet different demands. The energy hub provides the opportunity to use different energy carriers and so demand supply is no longer dependent on the single type of energy carrier. This provides increased reliability of energy supply. By using efficient technologies such as CHP the primary energy usage becomes more efficient, resulting in lower system costs and emissions. On the demand side, by using different inputs and technologies, different demands can be provided in an integrated unit. Different inputs such as electricity, natural gas, and district heating networks, fossil fuels, and RES can be used as energy hub inputs. These inputs inside the energy hub, by conversion technologies such as CHP, boiler, transformer, chillers, fuel cell, electrolyzer as well as storage systems such as electricity and thermal storage systems are qualified for consumption on the demand side. As a result, energy hub can meet different demands such as electricity, heating, cooling, water, hydrogen, chemicals and so on. Therefore energy hub is a comprehensive model of MES and a powerful tool for modeling of such systems. Energy hub with many advantages, such as increased reliability, resilience, productivity and reduced costs and emissions, taking advantage of different energy carriers and different technologies together, also provides the possibility for optimization of MES. Given the existence of different energy carriers, energy conversion, and storage technologies and even presence of responsive demand, these items can be evaluated based on criteria such as cost, emissions, and availability to achieve optimal energy hub structure and performance. Energy hub model is based on a matrix model that can be seen in Fig. 2.

The matrix model of energy hub concept is used to link different energy carriers at the input and output through coupling matrix. Each of the matrix elements represents energy hub interior features include connections, transform coefficients and operating function of various internal components of the energy hub. This matrix provides the possibility of modeling inputs, conversion, storage systems and various outputs in a comprehensive model. Therefore, integrated management and optimization of the MES are provided in the form of energy hub model.

Optimization models related to energy hub can be categorized in different ways. For example, two basic optimization modes can be considered for energy hub as follows:

- Structural optimization: finding the optimal topology and structure of energy hub, based on a specific demand and corresponding objective functions
- Operational optimization: Optimal power dispatch in an

energy hub or optimal power flow in the network of interconnected energy hubs for a given structure of the system

Such concepts for energy hub were presented and formulated by Geidl and Andersson. They have offered a model for optimal power dispatch problem in systems with multiple energy carriers based on energy hub concept [4]. By introduction of the matrix model of energy hub and a dispatch factor for determining the contribution of each converter from different inputs, they submitted an optimization framework for optimal power dispatch problem. The same authors [5], have offered optimal power flow problem between different energy infrastructures, such as electricity, natural gas and district heating networks in the context of interconnected energy hubs for multi-carrier energy systems. Also, the same authors [6] have presented a structural optimization method to find optimal energy hub coupling matrix based on a specific demand and objective functions. Such models were offered in steady-state condition and time-dependent parameters were not considered. Then Geidl [7] has wrapped up the above content. In this research general framework for energy hub modeling has provided for multi-carrier energy system management. Also, multiple energy carrier dispatches and optimal power flow in both operational and structural optimization as well as adding a storage system and taking the time dependency into account have been discussed along with some practical examples.

In general, planning and management of energy hub in the form of an optimal scheduling problem can be divided into two general categories based on the time horizon of the study:

- Short term: operational optimization
- Long term: optimal planning

In the first case, the goal is usually the optimization of the performance and creating an operational program for the various components of energy hub and has a short time horizon from one day to one year. In this case, the smaller time step is not considered and usually, an hour or a quarter of an hour for time steps can be considered to be able to ignore the dynamics and transition of various components of the energy hub. In the second case, the target is usually the optimum structure design of the system; for example finding the optimal size of equipment for a specific demand and considered objective functions. This case has a longer time horizon from one year up to 20-30 years which corresponds to a useful lifetime of the system. In this case, in addition to system operating costs, initial investment costs are also taken into account and the system is evaluated during its lifetime.

Such structures need a comprehensive model and an optimization framework. In energy hub models, the objective is usually minimization of functions such as cost, emissions, primary energy consumption, peak demand or maximizing functions such as profit, the share of RES and customer satisfactions subjected to various operational and structural constraints. A general framework for energy hub optimization models can be considered as the following relationships:

$$
\begin{aligned}
&\text{minimize} \quad f(I_h, F_\alpha, v_{h\alpha k}) \\
&\text{Subject to:} \\
&L_h - C_h I_h = 0 \quad \forall h \in H \\
&G_\alpha(I_h) = 0 \quad \forall h \in H, \forall \alpha \in A \\
&I_{h,min} \leqslant I_h \leqslant I_{h,max} \quad \forall h \in H \\
&I_{h,min} \leqslant v_{h\alpha k} \leqslant I_{h,max} \quad \forall h \in H \\
&, \forall \alpha \in A, \forall k \in k_\alpha \\
&0 \leqslant v_{h\alpha k} \leqslant 1 \quad \forall h \in H \\
&, \forall \alpha \in A, \forall k \in k_\alpha
\end{aligned}
\tag{1}
$$

Where H is the number of energy hubs in a network of interconnected hubs. A is the number of energy carriers. K_α is the number of converters that can use energy carrier as input. With this description can be said that I_h and L_h are input and output matrixes related to the energy hub of h. coupling matrix (C_h) is used to link different energy carriers at the input and output. F_α is the power flow of energy carrier. G is a set of networks equations and constraints. $v_{h\alpha k}$ is dispatch factor that defines the dispatch of an energy carrier to the converters and their sum is equal to 1 for energy carrier. So $\sum_{k \in K_\alpha} v_{h\alpha k} = 1$. Therefore relations (1) to (6) is a simplified representation of the general framework for optimizing energy hubs by varying I_h , F_α and $v_{h\alpha k}$. Obviously, other relationships such as storage equations, reliability indices, etc. can be added to these relationships, but have been neglected here for simplicity.

In general, these relations are in the form of an optimization problem with the objective function, equality and inequality constraints and decision variables. In most cases, due to characteristics of the system, such as nonlinear dependency of the coupling matrix coefficients to inputs, energy hub optimization problem is a nonlinear problem. In the case of a convex objective function and linearized constraints, the problem turns into a convex problem that can be easily solved using numerical methods. A common example of this case is the considering of a linear function for energy costs and assuming constant efficiency for converters of energy hub. But if the objective function is concave (or convex in maximization mode), and/or nonlinear constraints, the problem turns into a non-convex problem and the solution space is no longer convex. Numerical methods can be used in this case as well, but it cannot be ensured that obtained answer is the global optimum solution. So this case requires more advanced optimization methods.

An optimization problem usually refers to a process for finding an optimal solution among a set of possible answers. An optimization problem includes a set of objective functions, constraints of equality and inequality, and decision variables. Convex optimization refers to finding the minimum of a convex function (or a maximum of a concave function) among a convex set of constraints. The main advantage of this type of optimization problems is that the local optimization is the global optimal point. In this method, any optimization algorithm that finds the local optimal point, in fact, has found the global optimal point. Due to the diversity of issues related to optimization in various fields of research, several techniques have been proposed for optimization which in this paper it is not possible to deal with all of them. In this section only dominate algorithms and methods have been discussed that are useful for solving problems related to MES and therefore energy hub. These optimization techniques are discussed as follows:

- Linear programming (LP): LP is a method for finding the minimum or maximum of a linear function on a convex polygon. In the case that objective function and constraints are linear and decision variables are continuous, optimization problem will be a linear problem. Therefore, when the objective function is convex, optimization problem has a unique solution. LP can be considered as the easiest and fastest optimization method and even when there is a large number of variables and constraints the optimization problem can be solved with an acceptable speed. However, in real energy hub model with binary variables and nonlinear relationships, this kind of formulation is less useful [8].

- Nonlinear programming (NLP): If the objective function and/or constraints over a set of unknown real variables are nonlinear, optimization problem becomes a nonlinear problem. As mentioned, due to the structural characteristics of MES most optimization problems related to these systems are nonlinear in nature. Such nonlinear structures have been formulated by Geidl and Andersson [4–6] for optimal dispatch, optimal power flow, and structural optimization of energy hub, respectively. Other examples can be seen in Table 1. The existence of nonlinear terms in the model leads to a reduction of assurance in achieving a global optimal solution and such a problem may be convex or non-convex. Even if be convex, it is still difficult to solve. Some common methods for solving nonlinear programming are general reduced gradient method and sequential quadratic programming [8].

- Integer programming (IP): All or some of the variables are integers. A widely used form of IP is a mixed integer linear programming (MILP). This is similar to linear programming with the difference that in addition to continuous variables, the problem has integer and binary variables. Similar to linear optimization, MILP aimed at finding the minimum or maximum of a linear function over a space with linear constraints, but the existence of discrete variables lead to discrete and non-convex solution space. Therefore solving this kind of optimization problems is more complex than LP requires special methods such as Branch and Bound [8]. In the energy hub by adding the binary control variables, caused by storage systems or describing the state of equipment using discrete steps such as on/off and standby the LP or NLP problems turn to an MILP or mixed integer nonlinear programming (MINLP). It can be said that most of the issues related to energy hubs are NLP or MINLP. To solve such problems in the energy hub so far two groups of methods have been used. Linear equivalents or linear relaxations to convert the NLP and MINLP problems to LP and MILP problems, respectively. The first case involves the assumption of linear relations rather than nonlinear relationships for restrictions; as an example using constant values for the efficiency of converters. A large number of examples from this application can be seen in Table 1. The latter case includes processes for linear approximation of nonlinear relations using different methods such as iterative Branch and Bound, piecewise constant approximation, Taylor expansion, etc. The examples of this case can be seen in [8, 9]. However, such percussive approximations despite the simplification of computing, reduce the accuracy of the model and does not provide a real vision of the system operational conditions. On the other hand solving MILP or MINLP problem in most real systems is difficult and mainly is nondeterministic Polynomial-time hard (NP-hard) [10], that has not polynomial time algorithm. Such problems may need exponential computing time to solve and solving it may greatly increase the computing time. In recent years new methods for solving such optimization problems have been proposed, such as heuristic methods and artificial intelligence-based techniques.

- Heuristic approaches: These methods have been designed to solve the problems that classic approaches are not able to solve them or solving them takes a lot of time. These methods try to solve the problem in a reasonable time and achieving an acceptable solution. This solution is not necessarily the optimal solution for the problem and may be an approximation of the exact solution. Therefore, on some issues, it is difficult to ensure that obtained solution is accurate enough or how much it is important to get an accurate answer. On the other hand, heuristic approaches require a good knowledge of the system. If these methods are designed properly, they are appropriate to reduce the computational load of optimization algorithms and achieving an acceptable solution. The main problems of heuristic algorithms are sticking in a local optimum, premature convergence on these points and dependence on good knowledge of the system. Metaheuristic algorithms have been proposed to solve these problems of heuristic algorithms.

- Metaheuristic approaches: These methods are a generalization of the heuristic approaches which can be applied to a wide range of the problems. These algorithms also are approximation optimization approaches that are capable of getting out of the local optimum. In spite of heuristics, these methods require fewer assumptions and information about the system. Metaheuristic usually divided into two general categories; Trajectory-based or population-based. Trajectory-based metaheuristics also known as single-solution algorithms which are based on a single solution during the search process and focus on improving a solution and usually provide a single solution. Common trajectory-based metaheuristic algorithms, are Tabu search and Simulated Annealing algorithms. Population-based metaheuristics use multiple solutions and they often use population characteristics to guide the search. These algorithms create the initial set of potential solutions and are gradually improving these initial solutions and finally provide a suitable solution for the optimization problem. The most known population-based metaheuristics are Genetic Algorithm and, Ant Colony Optimization, Artificial Bee Colony Algorithm, and Particle Swarm Optimization. Metaheuristic algorithms can be combined with other optimization approaches, which lead to the Hybrid Metaheuristic. Also, multiple metaheuristics can be used in parallel which leads to Parallel Metaheuristic.

- Parallel Computing: A process in which a large problem can be divided into several smaller sub-problems which can then be solved at the same time. Reduction in the computation time, the possibility of resolving the larger issues, and overcoming the limitations of memory are the advantages of this method. Two known examples of these methods are Dynamic Programming and Monte Carlo Simulation.

- Multi-objective optimization: Most optimization methods mentioned above are used to solve single objective problems, while most problems in the real energy hub models are multi-objective problems and usually these objectives are in conflict. Minimizing energy costs while maximizing comfort whilst maximizing renewable energy share while minimizing fuel consumption and emissions are examples of multi-objective optimization problems. Adding more than one objective to an optimization problem adds complexity and optimal decisions need to be taken in trade-offs between two or more conflicting objectives. There are different methods for solving multi-objective problems include Bonded objective, Absolute priorities, Goal Programming, Goal attainment, Weighted sum method, Pareto-based optimization that last three of these are most widely implemented. The main idea behind goal attainment method is to find solutions that satisfy a predetermined objective. A practical example of this approach in the energy hub in order to solve a multi-objective power flow optimization problem in a network of interconnected hubs can be found in [11]. Weighting method is to assign a weight to each of the goals which lead to the creation of an objective function of the sum of previous functions. This method can be considered as the simplest method of solving multi-objective functions. However, this method is applicable only in the convex problems. Also, the difficulty of adjusting the weights and not provided optimal trade-off between conflicting objectives are the disadvantages of this approach. The shortcomings of these methods can be compensated with Pareto-based optimization. The Pareto method is a common method for solving multi-objective problems and identifying suitable trade-off between different objective functions. One solution is Pareto optimal, if improving an objective function, is not possible without degrading the other objective functions. Without any external criteria, all Pareto optimal solutions can be equally acceptable. Therefore, solving the optimization problem requires finding all Pareto optimal solutions. All these optimal solutions are not easy to achieve and so in recent years meta-heuristic methods application for solving multi-objective problems has been increased and a large number of multi-objective metaheuristics have been presented. Some of these methods are non-dominated sorting genetic algorithm (NSGA/NSGA-II), multiobjective simulated annealing (MOSA), and multi-objective Tabu search (MOTS).

As mentioned, these methods and structures have been commonly and widely used in energy hub models, but other specific methods are also used in energy hubs. For example, Arnold et al have used a model predictive control (MPC) method for centralized control [12] and distributed control [13], for a network of interconnected hubs by considering the dynamic of energy storage systems as well as energy prices and demand forecast. Bahrami et al [14] have modeled the interactions between electricity and gas companies with a set of the interconnected hubs as an ordinal potential game in a smart environment. Sheikhi et al [15] have used reinforcement learning (RL) algorithm for optimal management of a residential smart energy hub to reduce energy costs and taking into account the effect of the costumers loads shifting factor on their satisfaction. The summary of models and optimization techniques used in energy hub models can be seen in Table 1.

Almost all the models presented in Table 1 and discussed so far are deterministic models. However, another important part of the optimization approaches is non-deterministic optimization such as stochastic optimization. Another side of realization coin is the complexity of modeling. This means that taking into account the real situation of the system in many cases leads to the complexity of the problem and requires advanced modeling and solving approaches. Lack of attention to actual conditions leads to unrealistic modeling, which results in illusory and inaccurate results. In energy hub models, lower accuracy occurs in two modes. The first mode is modeling simplifications and the second one is ignoring the uncertainties. For example, the efficiency of a CHP is a nonlinear function of its operating point and taking into account this function leads to the complexity of modeling and problem solving is more difficult. In the energy hub models, this efficiency has been usually considered as a constant value. This simplicity leads to a reduction in the accuracy of the model.

In the literature so far, some limited research have been provided to improve the realistic modeling of the energy hub. A new formulation for energy hub has provided in [8] to improve some operational constraints such as minimum operating time after equipment start-up, storage losses and piecewise linear approximation of non-linear efficiency curve. Two limitations of energy hub models, namely the problem of distinguishing the appropriate port for connecting different components (especially RES) and the problem of impossibility of evaluating the bi-directional power flow have been addressed in [16]. In this paper, the authors have used a modified version of the energy hub model by using the graph and network theory to address the above limitations in steady state. The authors in [17] have provided a general heuristic optimization framework to solve optimal power flow problem in the network of the interconnected energy hubs which can be used with all evolutionary methods and provides the possibility of taking a variable function for efficiency into account. The existence of various connections within the energy hub and taking into account all these possible connections leads to an increase in model complexity and difficulty in optimal control of the system. Authors in [18] have provided a method for modeling such a complex energy hub taking into account all the possible connections between system components which lead to increased reliability of demand supply.

As mentioned the latter case that leads to a reduction in the accuracy of the model is ignoring the impact of uncertainties of the input parameters in the optimization process. For example, demand for the future periods is uncertain and taking into account the known demand or a complete forecast of the demand will cause illusory results and will not be considered risks of the changes in demand levels. Other examples include the energy price, weather conditions, RES output, consumer behavior and so on. Energy hub models should consider these uncertainties for achieving a comprehensive and realistic model of the sustainable energy systems in the future. Different approaches for addressing uncertainties is discussed in the next section.

Table 1. A summary of models and optimization techniques used for energy hubs in the literature

References	Objective function	Horizon time	Problem	Solution method	Description	Publish year
[4]	Minimization of energy costs	-	Nonlinear optimization problem	MATLAB optimization toolbox	Optimal power dispatch in EH	2005
[5]	Minimization of energy costs	-	Nonlinear optimization problem	MATLAB optimization toolbox	Optimal Power Flow (OPF) a network of EHs	2005
[6]	Minimization of energy costs	-	Nonlinear optimization problem	MATLAB optimization toolbox	Topological optimization of EH	2005
[19]	Minimization of energy costs	-	Linearized Programming	MATLAB optimization toolbox	Linearized EH optimization problem	2007
[20]	Minimization of energy costs	One day	Nonlinear optimization problem	commercial optimization toolbox	Hydrogen economy consideration in EH	2007
[21]	Minimizing the cost and maximizing the benefit	-	Nonlinear optimization problem	MATLAB optimization toolbox	RES in OPF of a network of EHs	2008
[22]	Minimization of energy costs	-	Nonlinear optimization problem	MATLAB optimization toolbox	Decomposed OPF of a network of EHs	2008
[12]	Minimization of energy costs	One day	Nonlinear optimization problem	MATLAB optimization toolbox	Central controller for a network of EHs	2009
[23]	Minimization of energy costs	-	Nonlinear optimization problem	programming as code in the software AIMMS	Unit commitment in EH	2009
[24]	Minimization of energy costs	One day	Nonlinear optimization problem	MATLAB optimization toolbox	OPF of a network of EHs in the presence of RES and grid exchange	2010
[13]	Minimization of energy costs	One day	Nonlinear optimization problem	MATLAB optimization toolbox	Distributed controller for a network of EHs	2010
[25]	Minimization of energy costs and emissions	One year	Nonlinear optimization problem	Generalized Reduced Gradient (GRG2) algorithm	Planning of EHs	2010
[26]	Minimization of energy costs and emissions	One day	Nonlinear optimization problem	MATLAB optimization toolbox using Particle Swarm optimization to improve optimization Performance	EH modeling for Interconnected power exchange	2011
[27]	Minimization of the total energy costs, total energy consumption, peak load, and emissions	One day	MILP	GAMS optimization solvers	Optimal Operation of Residential EHs	2012
[28]	Minimization of energy costs	One day	MILP	GAMS optimization solvers	RES and PEV Modeling in EH operation	2013
[29]	Minimization of energy costs	One day	Nonlinear Programming		Influence of storage capacity and prediction horizon on the cost optimal operation of EH	2014
[11]	Minimization of energy costs and energy losses	One day	Nonlinear optimization problem	Goal attainment method	Multi-objective optimization of EHs	2014
[30]	Minimization of energy costs	One day	MILP	GAMS optimization solvers	Impact of Energy storage technologies on EH operation	2014
[31]	Minimization of energy costs and temperature deviations	One week	Nonlinear optimization problem	Commercial optimization toolbox	Optimal operation of commercial EHs	2015
[32]	Minimization of energy costs	One day	MILP	GAMS optimization solvers	Optimal operation of agriculture EHs	2015
[33]	Minimization of energy costs and emissions	One day	MILP	GAMS optimization solvers	Optimal energy management of a smart residential EH	2015
[34]	Minimization of energy costs and emissions	One day	MILP	GAMS optimization solvers	Optimal optimization of a network of EHs	2015
[35]	Minimization of system energy costs and the capital cost of the hydrogen refueling station	One year	MILP	GAMS optimization solvers	Hydrogen economy evaluation in a network of EHs	2015
[36]	Minimization of energy costs	One day	Linearizing nonlinear formulation as an MILP	GAMS optimization solvers	internal and external dependency model for assessing the stochastic behavior of the demand side	2015
[37]	Minimization of energy costs	one day	MILP	GAMS optimization solvers	Optimal operation of industrial EHs	2015
[38]	Minimization of energy costs	One day	MILP	GAMS optimization solvers	Considering thermal energy market and DR	2015
[17]	Minimization of energy costs		Nonlinear optimization problem	A general heuristic optimization framework applied by modified teaching learning based optimization (MTLBO) algorithm	OPF of a network of EHs by using a generalized heuristic approach and addressing variable efficiency models	2015
[39]	Maximization of utility companies' profit and to minimization of customers' consumption cost	One day	Ordinal potential game	-	Demand response in the context of smart EHs	2015
[40]	Minimization of energy costs	One day	Non-cooperative game	-	Cloud computing in a network of smart EHs	2015
[41]	Minimization of energy costs	One day	MILP	Branch and Bound solution method in MATLAB optimization toolbox	Optimal operation of a network of EHs and its power exchange with main grid as a prosumer	2015
[42]	Minimization of energy costs and investment costs	Ten years	MILP	GAMS optimization solvers	Optimal planning of network of EHs	2015
[15]	Minimization of energy costs and costumer's dissatisfaction level	One day	Nonlinear optimization problem	Reinforcement learning (RL) algorithm	Optimal energy management of a smart residential EH considering customer's dissatisfaction level	2016
[43]	Minimization of investment and operation costs	15-year	MILP	GAMS	Optimal Wind-integrated hub design	-

3. UNCERTAINTY CONSIDERATION IN MODELING

In general, it can be concluded from the above discussion that an optimization problem is essential to obtain optimal planning and management of the energy hub. Under certain conditions, this optimization problem has an optimal and unique solution. According to the problem condition, this solution can be obtained from different optimization methods. However, for nonlinear, multivariate, and multi-objective functions finding an optimal solution is not an easy task. In these cases, more advanced methods can be used to solve the optimization problem and finding an approximation of the possible optimum solutions. All of these occur in deterministic conditions but when the input variables of the optimization problem are not constant small changes in any of them can change the optimization results.

In an actual environment usually many variables such as demand, the price of energy, solar radiation etc. are not constant and have random and variable behaviors. This random behavior and fluctuating nature, lead to uncertainty in the modeling and ignoring the impact of these uncertainties leads to inaccurate models and illusory results. Therefore the impact of these uncertainties should be considered in the optimization. In general, uncertainties have different resources and hence different types. Each of these types of uncertainties may affect one or more steps of the modeling and optimization processes. Identifying the type of uncertainty helps to the better understanding of their effects on system modeling and performance. The authors in [44] provide a category for a variety of uncertainties that is summarized in Fig. 3.

Variability uncertainty caused by the inherent variations in nature, behavior changes, changes in technology and organization. Knowledge uncertainty is due to limited knowledge about scheduling and making decisions about the system. This type of uncertainty can arise due to the perception of decision makers and planners about scheduling content include system realities, uncertainty, and boundary conditions. On the other hand, knowledge uncertainty can be caused because of the model features such as:

- Lack of knowledge of input parameters
- The uncertainty inherent in the model input data
- Measurement errors
- Insufficient understanding of the processes and system conditions such as physical and dynamic processes
- Simplification and approximations
- Hardware and software errors
- The accumulation of all these

Linguistic uncertainty is caused by the information is expressed by the human that is in linguistic terms and inherently uncertain. Language restrictions in precisely quantifying a parameter (Vagueness), a word that has several meanings and its exact meaning may not clear (Ambiguity), and loss of detail in specification or generalization of some concepts (Under specificity) are some of the linguistic uncertainty items. The decision uncertainty is due to the ambiguity in the definition, quantification and comparing objectives and performance indicators. Procedural uncertainty arises from the imbalance between available resources and time.

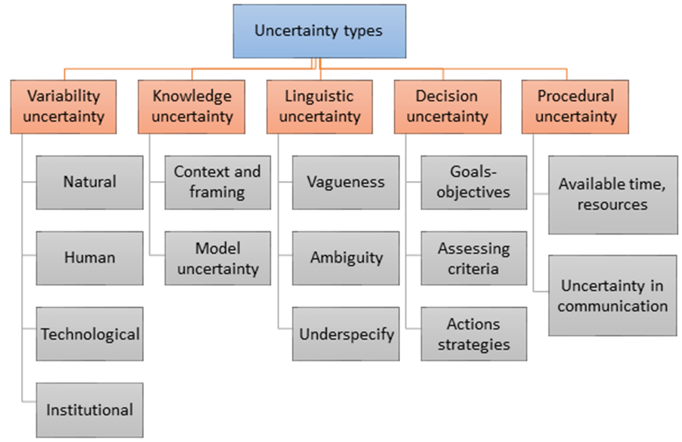

Fig. 3. Different categories of uncertainty.

Accurate recognition of the uncertainties and their impacts increases the accuracy and realizing of the model. However, this uncertainty modeling in a multi-carrier, multi-objective, multi-period and multi-criteria framework is not an easy task. Different methods for addressing and handling of the uncertainties have been presented in the literature so far. The authors in [45,46] have provided a category of uncertainties modeling techniques in the process of decision-making in power and energy systems that is summarized and schematically shown in Fig. 4. The main similarity between them is that all of these methods attempt to quantify the effects of uncertainty on the output parameters and the main difference is in the expression methods of uncertain parameters.

Probabilistic methods use probability density function (PDF) to express uncertainty and are used when sufficient data are available and PDF of uncertain parameters is known. Fuzzy methods use the membership function (MF) to display uncertainty. Unlike previous methods, Information gap decision theory method does not use the PDF or MF and in fact, reveals the error between the parameters values and their predicted values. Robust optimization method uses uncertainty sets to describe the uncertainty and this model actually is used for the worst case. Finally, interval method uses interval values with lower and upper bounds to display uncertainties. In the following sections, each of the mentioned methods and their application in energy hub models is described.

A. Probabilistic approach

Deterministic modeling does not provide a real image of the dynamic behavior of the real world. Dantzig [47] and Beale [48] (1955) provided the stochastic programming model independently that in numerous research have been studied and expanded [49].

Probabilistic methods use statistical distributions such as Weibull distribution for wind speed and the normal distribution for load changes to express uncertainty. A heuristic optimization method known as multi-agent genetic algorithm was used in [50] to solve an economic dispatch problem in a multi-carrier system with integrated energy hubs. In this study, uncertainty related to wind power generation was modeled by Weibull distribution as probability distribution function and performance of proposed method was compared with methods such as GA and PSO. A DR program based on minimizing the cost of a multi-energy system by considering the level of customer satisfaction has

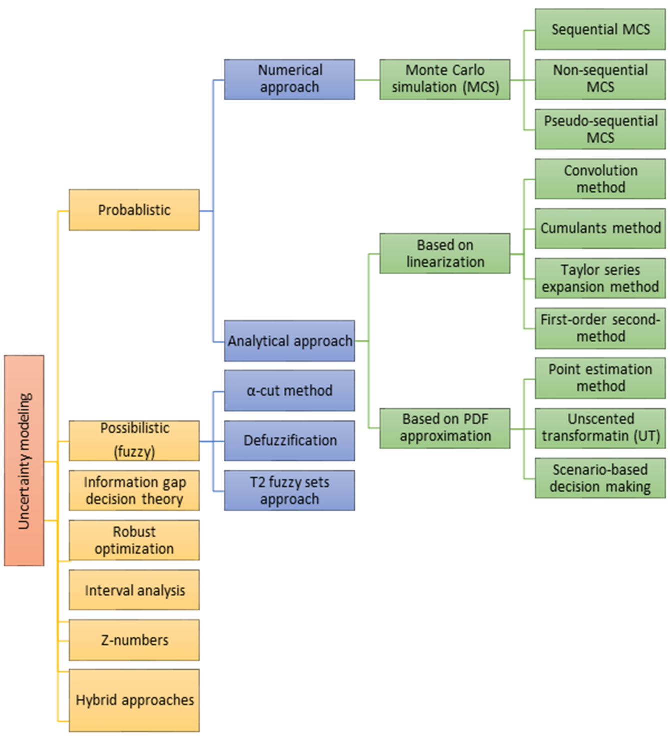

Fig. 4. Uncertainty modeling methods.

been provided in [51]. Uncertainties arising from the behavior of consumers in multi-energy system management is considered. These uncertainties include the percentage of consumers who participate in DR programs, the percentage of consumers who have the ability to switch between different energy carriers and consumers who do not participate in DR programs and may control their demand. A normal distribution has been used to display the uncertainties and producing related scenarios. An optimization model is presented in [52] for a hybrid energy system by considering the various uncertainties based on statistical data. The authors have used binomial distribution for solar and wind power generation uncertainties, a normal distribution for demand and Bernoulli distribution for inaccessibility of production units. The impact of RES on system planning has been evaluated by proposed model in the presence of uncertainty.

Probabilistic methods are usually divided into two main groups: numerical methods and analytical methods. Numerical methods are mainly based on random sampling and Monte Carlo Simulation (MCS) is the most important ones. This method is used when the system size is large or have many uncertain parameters or has a large number of non-linearity. A model for optimal management of energy hub has been provided in [53] under uncertainty and changes in electricity prices. Prices of all input and output energy carriers are regarded as a random variable and MCS considers thousands of possibilities in prices of these carriers. An optimal sizing of a system of interconnected hubs taking into account electric and gas networks physical constraints, reliability indicators and environmental issues has been provided in [54]. The impact of uncertainty in electrical and thermal loads, as well as uncertainty in energy prices, has been studied using Monte Carlo simulations and the performance of interconnected energy hubs system has been proven even in the presence of these uncertainties. A multi-criteria study for ranking different RES at the national level in Scotland has been provided in [55] and the impact of input data uncertainty on the results have been investigated. For this study different technical, economic and environmental criteria have been used that each of these criteria has a wide variation range. To consider this type of uncertainty, the amount of each of these criteria is shown by a statistical distribution and the MCS is used to perform the multi-criteria evaluation. The study showed that the result of ranking extremely depend on uncertain parameters variations. The impact of energy hub on reducing energy costs and increasing profits in the presence of uncertainty of the electricity price has been studied in [56] by using MCS and creating five different scenarios for different levels of uncertainty. In general, it can be said that the MCS is easy to run, flexible, usable in convex and non-convex issues and supports from all types of PDFs. Instead, the number of required simulations increase by increasing the solution space's degree of freedom. So thousands of simulations to get the exact answer is needed and thus the computational load of this method is high.

Analytical methods mainly are based on approximation and use mathematical expressions to display the system's input and the output. The first of these methods are based on linearization and their goal is to make output PDF from input PDF. Methods such as Convolution, Cumulants and Moments, Taylor series expansion and First Order Second moment are in this category. In these methods, mathematical operations such as convolution, calculating the coefficients of expansions and so on are used to get output parameter's PDF from the input parameter's PDF.

All the above methods are common in linearization and this linearization is reliable when the expansion of error is approximated using an appropriate linear function. These difficulties and inaccuracies in linearization process lead to the development of other types of methods. These methods are based on creating a good approximation of input parameter's PDF using the appropriate samples. Point estimate, Unscented Transformation and Scenario-based decision-making methods are in this category. Point estimation method includes the use of sample data to calculate a value as the best estimates and forecasts of a parameter. This method is non-repetitive, simple to use and does not have the problem of convergence. However, this method doesn't provide information about the exact shape of output's PDF and only gives the mean and standard deviation. This method, like other probabilistic methods, needs PDF of uncertain parameters and gives a better answer for non-skewed PDFs. Unscented Transformation method is appropriate to consider the correlation between random variables and is a reliable method to calculate the output of random variables under a set of non-linear transformations. This method is highly functional and its accuracy does not reduce by increasing the number of random variables but its run time depends on the number of random variables and also needs to PDF of input parameters.

Uncertain parameters have numerous realizations which are impossible to consider all of them. However, they can be converted into a number of limited and countable scenarios. This process is the basis for the scenario method. This method converts continuous space to the limited number of discrete scenarios with the related probabilities and so this method enhance computational efficacy. However, the scenario-based approach is an approximate method and requires the statistical information of input parameters. Also in this method size of the model increases if the dimensions of the system are large or the number of components is too high. Among the methods of this group scenario-based method is most widely implemented. The authors in [57] have used discrete statistical distribution to model the uncertainties of demand and the production of the wind and solar power. According to the probability of each state, different scenarios have been provided in the modeling of a real-time dispatching issue and unit commitment for an isolated micro-grid. A scenario-based approach for the consideration of energy price, demand, and wind power generation uncertainties in the optimal management of energy hub has been provided in [58]. In this paper, a multi-objective decision-making model for the consideration of energy costs and associated risks has been developed which provides the ability to make decisions under uncertainty by creating a trade-off between cost and reliability of the system.

A model for mid-term management for an energy hub taking into account uncertainty of wind generation and electricity market with the objective of minimizing costs has been provided in [59]. In this study, Auto Regressive and Integrated Moving Average (ARIMA) and Auto Regressive and Moving Average (ARMA) time series have been used to generate different scenarios. ARIMA method for prediction of the price of electricity and ARMA method for prediction of the wind speed used and the generated scenarios used to model the problem in the framework of a stochastic programming model. By using the mean and variance of input data, ARIMA method can be used to predict future changes in parameters. Usually, the models that use ARIMA method need to be combined with a scenario reduction method. Here, wind speed and price scenarios for electricity production are completely independent of each other and should be considered all the possible combinations of them. Therefore, because of the increased number of scenarios, computing time increases and authors has used a scenario reduction method.
The impact of DER, ESS, and DR on the performance of a commercial energy hub to deal with the uncertainties caused by wind power, energy prices and demand from the operational cost, reliability and emissions points of view have been investigated in [60]. The MCS has been used for the production of uncertainties scenario tree and a large number of generated scenarios have been decreased by using GAMS scenario reduction tool. The study found that in terms of demand uncertainty, the impact of energy storage on the energy hub performance improvement is more than other technologies and in terms of uncertainty in energy prices, the impact of DER and DR and also in terms of wind power generation uncertainty the impact of CHP and heat storage is dominant. In general, the impact of wind power production and energy prices uncertainties on the energy hub operation is greater than the impact of energy demand uncertainty [61]. Authors in [36] have used a scenario-based approach to consider uncertainties in the behavior of consumers who participate in DR programs. Customers that in the form of an energy hub participates in DR programs in addition to shifting or reducing their demand have the ability to switch between different energy carriers. In this paper, some of the demands have been considered as dependent loads which can use different energy carriers to deliver a particular service. Therefore, the management of such loads by consumers to choose between different carriers will lead to uncertainty. The results show that the uncertainty in the random behavior of consumers in the DR program is effective on the share of energy carriers in the demand supply. Increasing the share of loads that are controlled by consumers increases the impact of random behavior of consumers in system performance and leads to increased operating costs of the system.

Table 2. Fuzzy logic based models in energy systems

Fuzzy Approach	Fuzzy Models	Fuzzy Delphi
		Fuzzy regression
		Fuzzy ANP
		Fuzzy AHP
		Fuzzy axiomatic design (FAD)
		Fuzzy gray prediction
		Fuzzy clustering
		Fuzzy expert system (FES)
		Fuzzy linear programming (FLP)
	Hybrid Models	Neuro-fuzzy, adaptive neuro-fuzzy inference system (ANFIS)
		Fuzzy genetic algorithm, neuro-fuzzy GA
		Fuzzy DSS
		Fuzzy DEA, neuro-fuzzy DEA
		Interval Fuzzy linear programming (IFLP)
		Fuzzy-stochastic programming (FSP)
	Multi-criteria Decision Models	Fuzzy VIKOR
		Fuzzy TOPSIS
		Fuzzy support vector machine
		Fuzzy particle swarm optimization
		Fuzzy honey bee optimization
		Fuzzy cuckoo search optimization
		Fuzzy quantum particle swarm optimization
		Fuzzy ant colony optimization

B. Fuzzy approach

As mentioned, because of increased uncertainties in the energy systems, dealing with these uncertainties has become one of the main issues in MES modeling and scheduling. The fuzzy sets approach is an efficient method for dealing with these uncertainties and modeling the real behaviors. On the other hand, energy hub directly interacts with natural processes and human behaviors and so modeling this behavior with certain and determined values is not effective because usually human behavior and natural processes are not predictability deterministic and controllable. Whereas that one of the main applications of fuzzy logic is quantifying of the qualitative and linguistic terms so using this method for expressing the uncertainties helps to achieve the realistic models and extraction more accurate results. Fuzzy sets use the concept of fuzzy membership functions such as triangular, trapezoidal membership functions and Gaussian fuzzy set for uncertainty modeling. Fuzzy logic-based models are used mainly in three ways: fuzzy models, hybrid models and multi-criteria decision models that are shown in Table 2.
Fuzzy models are usually used in order to realize system conditions and characterization linguistic terms. These models have applications such as expressing expert linguistic terms, data capturing, finding the relative importance of variables, resources grouping, data clustering, and predictive purposes. Hybrid models have a variety of applications in energy systems, from designing of control systems to locating and determining of the optimal combination of RES. Multi-criteria models usually have a lot of computing load and have diverse applications such as performance optimization, system control and emissions and financial risks reduction [62].

In this regard, a combination of interval linear programming (ILP) model and fuzzy logic have been presented in [63] to express multiple uncertainties for using in long-term planning and capacity expansion. ILP is an approach for considering uncertainties as interval within the constraints or objective function.

Therefore it has less complexity and computational load but because of the lack of time dependencies consideration, its conformity with actual results and data is less than other methods.

Stochastic methods use probability distributions. The two-stage stochastic method uses a two-step decision-making process that in the first stage a decision is taken based on future events with uncertainty and when it happened, a corrective action is done. But this method requires a clear PDF of the input parameters and sometimes PDF of these parameters are not available or are not accurate or it is not possible to use them in large-scale problems. To solve this problem authors in [64] have used a combination of ILP, two-stage stochastic programming (TSP) and fuzzy logic for optimal planning of a regional energy system that enhances the functionality of the model to deal with uncertainties. Also, TSP has some problems for reflecting the dynamics of the energy system. Multi-stage stochastic programming (MSP) is an extension of the TSP that is able to display the dynamic characteristics. Uncertainties in the MSP are modeled through multi-layer scenario trees that lead to flexibility in decision-making processes and scenarios modeling, especially for the large-scale problems. A combination of interval fuzzy linear programming (IFLP) and MSP has been provided in [65] that uncertainties have been considered by using fuzzy sets, probability distributions and interval values in the framework of an MILP problem. The proposed model has been applied to a case study based on energy and environmental management. The results help to decision makers in the resources allocation, pollution reduction planning and resulting in a trade-off between system cost and environmental requirements under multiple uncertainties. So a combination of fuzzy logic models and stochastic programming have been used for considering the multiple uncertainties in optimal scheduling of energy systems.

Energy storage systems are used to benefit from the excess energy produced by RES at any time. Optimal operation of this complex need for a control strategy to coordinate their performance. Battery charge and discharge control program has been modeled in [66] by using fuzzy logic. In this study, the system has been considered as a set of elements that each element has been assumed as an agent that can control their behavior according to environmental conditions and changes. An optimal operation model for a hybrid system based on fuzzy logic has proposed in [67] which is the combination of PSO and fuzzy theory. In order to control fluctuations and changes in the system, a fractional order fuzzy PID controller has been used to control charging/discharging of battery and production of a diesel generator. The proposed algorithm has high robustness against changes in input parameters and increases system reliability. A fuzzy expert system has been used in [68] to control the output of storage system in the context of a GA-based optimization algorithm and is an example of combining fuzzy theory and GA. This model leads to lower system costs compared using the charging/discharging the battery control based on a threshold.

With the growing penetration of RES in the energy system, output fluctuations of these sources can cause problems such as variations in system voltage and frequency. A method for leveling the renewable energy output changes by using fuzzy control has been presented in [69]. It also controls the power output of PV according to system conditions and taking into account the solar radiation in order to make maximum use of sunlight. As a result, presented fuzzy control make a trade-off between reducing fluctuations and maximizing the use of radiation. A PID controller based on fuzzy logic has been used in [70] to minimize the frequency and voltage deviations in a hybrid system. PID controller alone cannot prove well act under conditions of intermittent wind speed and even adding storage system also doesn't make the system robust against sudden changes in wind speed. But adding a fuzzy controller to the system leads to the successful performance of the system under load and wind speed uncertainty conditions.

Using interval methods along with fuzzy methods have become very popular that describe uncertainty variations in the form of intervals with the upper and lower boundary values. In the literature, several interval methods such as fixed intervals or functional intervals are used to display uncertainty. An interval fuzzy approach has been proposed in [71] to change the boundaries in accordance with the system dynamic and confidence level. In this paper, a scenario-based energy management system for a microgrid has been provided that scenarios are produced using interval fuzzy model and taking into account the uncertainty arising from demand and RES. Fuzzy linear programming (FLP) is an effective method for quantification of ambiguity and uncertainty of information on energy management system that has been developed based on the combination of interval and fuzzy sets but this method for large-scale systems become more complex. Interval linear programming (ILP) makes it easier to address the uncertainties but when the uncertainty level of parameters is high does not provide a reasonable solution. So the combination of these two models is used to benefit from the advantages of both of them. A combination of ILP and FLP has been used in [72] to show the uncertainty in an energy system management problem with the objective of minimizing energy and environmental costs. A hybrid model of ILP and FLP has been presented in [73] that by using Type 2 fuzzy sets increases the amount of fuzziness that can be faced with a higher level of uncertainty and improve the performance of IFLP hybrid model. This method offers a realistic simulation of the energy flow in the system that can be used in decisions related to the capacity expansion and resource allocation. A combination of fuzzy programming models and stochastic linear programming has been presented in [74] that express uncertainties by using probabilistic distribution and Type 2 fuzzy sets. This method without unrealistic simplifications improves the system efficiency and energy security.

In short, it can be said that fuzzy logic has wide applications in modeling and scheduling of energy systems. One of the main applications of fuzzy methods is the modeling and expressing of the uncertainties and ambiguities of energy systems. The use of fuzzy logic to deal with these uncertainties leads to model realization and obtaining more accurate results and also facilitates optimization and decision-making processes. Fuzzy logic controllers are widely used in controlling the power flow of energy systems. As well as hybrid models, including the combination of fuzzy methods, heuristic techniques or multi-criteria decision-making approaches have been used in literature and their number is increasing. The combination of fuzzy models with heuristic techniques despite the complexity of such methods leads to simplicity in using (user-friendly) and the accuracy of these methods. The combination of fuzzy models and methods such as time series, neural networks, and regression are used in prediction models to increase the accuracy of the model. Despite the high potential for application of fuzzy sets in energy hub, however, so far there has not been any research on the use of fuzzy methods in optimal scheduling of energy hub. Therefore, there is a great potential for the use of fuzzy models in the management of energy hub.

C. Information gap decision theory

When there are not sufficient data about the uncertain parameters, PDF or MF cannot be used and methods like Information gap decision theory (IGDT) can be useful. The purpose of this procedure is to reveal the results of the difference between actual and predicted values of uncertainty. In decision-making based on IGDT, two cases occur; risk averse or risk seeker [75]. In the first case (risk averse) the decision-maker is looking for a robust decision against possible errors of uncertain parameters prediction. This decision is created when the objective function be protected against the maximum variations radius of uncertainty. In other words, a forecast of the uncertain parameter is performed and for an authorized range for the objective function, the maximum permissible variation range of uncertain parameters is calculated. Risk seeker case tries to find the minimum variations range of uncertain parameters. This means that for a degree of freedom for the objective function, it find the minimum variation range of uncertain parameters. In other words, decision maker decides in the worst predicted case. Soroudi and Keane [76] have provided a good example of the use of IGDT in optimal management of energy hub. In this study, by taking into account the wind power generation, electrical and thermal loads as uncertain parameters, a prediction of these parameters has been carried out and the maximum allowed variations intervals for this parameter have been calculated in different scenarios. Finally, the necessary measures to achieve a risk-averse management of energy hub have been provided. In [77], risk constrained scheduling of head and power producer is formulated using IGDT considering risk-averse and risk-seeker options.

Other examples of the use of IGDT in energy systems [78], energy markets [79,80], GenCos scheduling [81,82], power distribution network dispatching [83,84], UC [85], self-scheduling [86] and so on can be found in the literature and take into account the proven effectiveness of this method there is a good potential for application of this approach in the management of energy hub.

D. Robust optimization

Robust Optimization (RO) are used when the statistical information of input parameters is insufficient and there is no possibility of extracting PDF of uncertain parameters. In this method instead of PDF, the interval values are used for displaying uncertainty and the problem is solved for the worst case at any interval. Thus, this method is very conservative. In the case of a parameter that is characterized by uncertainty, robust optimization ensures the decision maker that even if there are errors in the prediction of uncertain parameters, the objective function value will remain optimized. A robust optimization has been used in [87] to consider the uncertainty arising from demand and cost (such as emissions tariffs) and the price of electricity and gas in hybrid energy system planning problem for a commercial building. The authors in [88,89] have developed a model for optimal management of a micro-grid based on robust optimization. In this paper, the uncertainty arising from wind power generation and load are displayed as prediction intervals and up and down boundary values have been predicted by a Non-dominated Sorting Genetic Algorithm (NSGA-II) - trained Neural Network (NN). Results of RO-based optimal management have been compared with the results of optimal management based on expected values in terms of performance and reliability of the system in conditions of happening different uncertain events. Results indicate better performance for RO-based optimization. In order to secure the operational model of an energy hub in the face of uncertainties caused by the deviation of the equipment efficiencies from their nominal values, a robust optimization method has been used in [90]. Authors have shown that for securing the model against uncertainties operating costs of the system will rise, but instead, the possibility of complete demand supply grows. As a result, a robust optimization is a conservative approach which increases the robustness of the system against the uncertain parameters, but the result is not always the optimal solution.

E. Interval analysis

Interval method usually is used when we have variations on the interval of uncertain input parameters. In this method, the upper and lower boundary values for output parameters can be obtained by defining upper and lower boundary values for uncertain input parameters. Interval numbers have been used in [91] for considering the uncertainty of the wind power in an operational optimization problem of an interconnected electricity-gas energy system taking into account DR programs. In this study, the power flow problem in the interconnected system has been solved with the objective of minimizing the operating costs. As previously mentioned, ILP is a way to handle uncertainties that are displayed as intervals and without a known statistical distribution or membership functions. In this way, uncertain parameters are displayed by crisp intervals with fixed lower and upper bounds. In the real world, uncertain parameters are changing and these changes are affected by the various parameters and so presenting this changes with fixed intervals does not show the impact of these changes on system performance. An effective way for considering such changes is the functional intervals. In this way, lower and upper bounds are shown as a function of effective parameters and therefore the interval boundaries of uncertainty parameters are variable. An application of the functional intervals method in urban energy system planning, with different primary energy sources, has been provided in [92] to determine appropriate energy resource alternatives. In this paper, the boundary of the electricity price and purchased power have been considered as a function of energy prices. In this model, the intervals have been assumed to be a linear function of a parameter but in many real cases these functions may be non-linear relationships or intervals may be a function of several effective parameters. Therefore, this model can be used for taking into account such uncertainties in energy hubs management. Interval methods, usually are used in the form of hybrid models with other methods for the consideration of uncertainty. In this case, multiple uncertainties can be considered as statistical distributions, membership function, interval values or a combination of them in energy hubs modeling. Examples of the use of this hybrid modeling method can be found in [71,73,74].

Interval optimization is easier to use in engineering systems. Its computational load is less than the stochastic methods and instead of finding the worst case (RO), recognizes the optimal interval of the objective function. But in this method, there is no possibility of taking into account the correlation between uncertain parameters.

F. Z-numbers

The concept of Z-numbers that is related to the reliability of information was introduced by Zadeh in 2011 [93]. As discussed in the previous sections, different methods are used for the uncertainty modeling. However, the Z-number offers a better representation of the uncertainty of the real world. Z-number is displayed as a binary pair Z = (A,B) that first component, A, is a restriction on the value of an uncertain parameter, X, and the second one, B, shows the reliability of A. In fact, A is a restriction on the amount that X can take and B is a prediction of reliability of A and is considered as probability measure of A. This concept represents reliability of input data that can be used in many areas such as decision making, forecasting, risk assessment, economics, engineering, and so on. For example, if we speak about oil prices in the near future. We say that the price of oil in the next year is about $ 40. Expression of this concept by Z-numbers is in the form of Z = (about $ 40, most likely). So, many linguistic terms can be displayed using Z-numbers theory. The Z-number is trying to consider the input information uncertainty and formulation the remarkable ability of the human mind in decision making in the ambiguous and uncertain environment. Therefore, it can be said that the evolution of the uncertainty models is in the form of real numbers, intervals, fuzzy numbers, random numbers, and now is Z-numbers. In fact, can be said that most concepts and numbers in the real world are in the form of the Z-numbers and all of the methods that were used for the realization of the models have been a simplification of Z-numbers concept [93]. One of the main problems associated with Z-numbers is information processing and solving the problems related to them. So many different works have been presented in the literature to simplify the calculation and application of the concept of Z-numbers. The incentive to use Z-numbers, simple examples of its concept, calculations with simple operations and concepts such as Z-numbers ranking have been presented by Zadeh in [93]. The authors in [94] have provided a method for converting the Z-numbers into fuzzy numbers. In this way, the second component of Z-number has been defuzzified to a real value and by multiplying the numeric value by the first component, a fuzzy number is obtained and considered as the representative of Z-number. By using this method, it becomes easier to use Z-numbers in calculations, but the original information of Z-number are lost. The same authors, based on their approach have developed a framework of multiple criteria decision-making in uncertain environments in [95], where the weight of each criterion has been described by using a linguistic term and considered as Z-numbers. Then Z-numbers have been converted to the crisp numbers and evaluation of the alternatives has been done based on this numbers. The authors in [96] have provided a model of analytic hierarchy process (AHP) based on Z-numbers to deal with problems related to decision-making based on linguistic terms. In this study, the weights of criteria have been described as Z-numbers and the proposed method in [94] has been used for converting Z-numbers and then comparing process has been done in the field of real numbers. A model of decision-making in an uncertain environment based on information described by Z-numbers has been provided in [97] and after converting the Z-numbers to fuzzy numbers, the decision has been carried to choose alternatives using a fuzzy measure and within the fuzzy framework. A method for decision making under interval set-valued fuzzy and Z-numbers uncertainties has been presented in [98]. Yager [99, 100] has offered a new methodology and application of Z-number in different fields by using sample distributions and certain assumptions. Also in [101], the issues of continuous Z-numbers calculation and examples of their use in various fields has been discussed. Applications of Z-numbers in calculating with words (CWW) and the issues and problems related to their integration have been offered in [102, 103]. Different ways for evaluation of a Z-number with a reduction in the computational complexity has been presented in [104]. Authors in [105] have provided a method for direct calculating of the discrete Z-numbers to avoid simplifications and data loss of Z-numbers. A model for the integration of LP methods and Z-numbers in the form of a Z-numbers based LP (ZLP) problem has been presented in [106]. In this paper, the reliability of input data in the LP model has been considered as Z-numbers. The authors in [107] have used the Z-numbers for evaluating the effect of system resilience on risk and hazard parameters in a petrochemical unit.

As can be seen, different studies have been carried out on the Z-number concept and efforts for developing the concept and facilitating the calculation of Z-number is ongoing. Z-number is a comprehensive concept for taking into account the uncertainties of the real world and the reliability of input data that improves the accuracy and the ability of the model for decision making in the uncertain environment. Since the energy hub directly faced with the uncertainties of the input data, the use of Z-numbers for more realistic energy hub models is inevitable and by developing and improving the arithmetic of Z-numbers its applications in energy hub models can contribute significantly to realize these models.

4. GENERAL COMMENTS AND SUGGESTIONS FOR RESEARCHERS

As described, several methods have been presented for modeling uncertainties in the literature and these methods have been used in various fields. An overview of various methods for modeling uncertainty in energy systems, the advantages and disadvantages of them, and their application in different energy systems were provided to prove the performance of the different methods in dealing with different uncertainties. Table 3 summarizes the use of these methods in the energy hub. As can be seen, despite the necessity of uncertainty modeling in optimal management of energy hubs, so far very little studies have been done in this area. It represents a weakness in energy hub models in the literature, because of deterministic modeling of the energy hub management problem. At the same time represents a high potential for research in the field of uncertainty modeling in MES in the content of energy hub.

Therefore some of the main uncertainties in energy systems that most commonly mentioned in models and their modeling approaches using a variety of methods are proposed in Table 4. As can be seen, the scenario-based method has many applications in the modeling of uncertainties and even in dealing with multiple uncertainties. The reason is easy applicability of this method and low computational load (with the exception of cases where the number of scenarios is very large) compared to other models. Fuzzy methods have more application in the wind and solar power generation uncertainties modeling. As well as it is a useful method for use in combination with other

Table 3. Summaries of uncertainty modeling applications in energy hub

Uncertainty modeling methods		References
Probabilistic,approaches	Monte Carlo simulation (MCS)	[53, 54, 56]
-	Point estimation method	[108]
-	Scenario-based decision making	[36, 58–61]
Fuzzy approaches	-	-
Information gap decision theory	-	[76]
	-	[90]
Interval analysis	-	-
Z-numbers	-	-
Hybrid approaches	-	-

Table 4. Summary of most popular uncertainty modeling approaches dealing with most common uncertainty types in multi-energy systems

Most common uncertainty types	Probabilistic			Fuzzy	IGDT	RO	Interval	Hybrid
	MCS	PEM	Scenario					
Wind speed	-	-	[57, 59–61, 109–111]	[71, 109, 112]	[76, 85]	[88, 89]	[91]	
Solar radiation	-	-	[57, 111]	[69, 71, 109, 112]	-	[113]		
Load	-	-	[57, 60, 61]	[71]	[76]	[87–89, 113]		
Energy carrier price	[53]	-	[59–61, 110]	-	-	[87]	[92]	
Linguistic terms	-	-	-	[114]	-			
Multiple-uncertainties	[55]	-	[41, 52, 60, 61]	-	-			[63–65, 72, 73, 115, 116]

methods in hybrid models to consider multiple uncertainties. However, fuzzy methods so far have not been applied in the energy hub models. As shown by increasing the number of uncertain parameters, the complexity of the problem increases and the need to use hybrid methods in dealing with multiple uncertainties rises. Obviously, all this kind of uncertainties listed in Table 4 can also appear in the energy hub modeling. Table 4 helps to select the appropriate method for modeling various uncertainty and illuminates the route for enthusiast researcher for modeling energy hub under different and multiple uncertainties.

5. CONCLUSION

In this paper, the importance of addressing the uncertainties in the optimal scheduling of energy hub have been discussed. It is obvious that energy hub, as a concept for integrated management of MES is influenced by several factors that many of these factors are main sources of uncertainties. For example, the growing interest in RES and the increased share of these resources in energy systems due to the fluctuating and uncertain nature of these resources add uncertainties to energy hub models. On the other hand, energy hub has various consumption areas and behavior of consumers in each of these areas is uncertain and leads to uncertainty in the prediction of actual demand of energy hub. On the other side, energy hub for supplying energy demand and selling their excess energy, interact with energy markets such as electricity and gas markets. Due to the structure of these markets, (particularly in competitive and deregulated markets) pricing of energy and the behavior of other market participants are the main sources of uncertainty and so modeling of energy hub can be affected by uncertainties arising from the interaction with these markets. On the other hand, as the energy hubs do not have a limit on the size and can range from a residential building to even an entire city energy system, and so widely associated with environmental and climate issues. Therefore forecasts taken from the environment is also a major source of uncertainty in the energy hub models. Simplifications and approximations in the modeling of energy hub can also lead to unrealistic models and results. These cases are just a few examples of the energy hub interaction with uncertain parameters. Despite the necessity of taking into account the uncertainties in the modeling and optimization of energy hub, most models proposed for energy hubs in the literature have been scheduled in a deterministic environment. This leads to a reduction in the accuracy of these models and unrealistic results as well as ignoring risks arising from variations in uncertain parameters in optimal decision making. Therefore, future energy hub models need to the realistic modeling of multi-energy systems to be able to achieve a realistic and comprehensive model of future sustainable energy systems.

REFERENCES

1. P. Mancarella, "Mes (multi-energy systems): An overview of concepts and evaluation models," *Energy*, vol. 65, pp. 1–17, 2014.

2. M. Geidl, G. Koeppel, P. Favre-Perrod, B. Klockl, G. Andersson, and K. Frohlich, "Energy hubs for the future," *IEEE power and energy magazine*, vol. 5, no. 1, pp. 24–30, 2007.

3. P. Favre-Perrod, "A vision of future energy networks," in *Power Engineering Society Inaugural Conference and Exposition in Africa, 2005 IEEE*, pp. 13–17, IEEE, 2005.

4. M. Geidl and G. Andersson, "Optimal power dispatch and conversion in systems with multiple energy carriers," in *Proc. 15th Power Systems Computation Conference (PSCC)*, 2005.

5. M. Geidl and G. Andersson, "A modeling and optimization approach for multiple energy carrier power flow," in *Power Tech, 2005 IEEE Russia*, pp. 1–7, IEEE, 2005.

6. M. Geidl and G. Andersson, "Operational and structural optimization of multi-carrier energy systems," *European Transactions on Electrical Power*, vol. 16, no. 5, pp. 463–477, 2006.

7. M. Geidl, *Integrated modeling and optimization of multi-carrier energy systems*. PhD thesis, TU Graz, 2007.

8. R. Evins, K. Orehounig, V. Dorer, and J. Carmeliet, "New formulations of the 'energy hub'model to address operational constraints," *Energy*, vol. 73, pp. 387–398, 2014.

9. M. Chehreghani Bozchalui, "Optimal operation of energy hubs in the context of smart grids," 2011.

10. G. J. Woeginger, "Exact algorithms for np-hard problems: A survey," in *Combinatorial Optimization—Eureka, You Shrink!*, pp. 185–207, Springer, 2003.

11. M. La Scala, A. Vaccaro, and A. Zobaa, "A goal programming methodology for multiobjective optimization of distributed energy hubs operation," *Applied Thermal Engineering*, vol. 71, no. 2, pp. 658–666, 2014.

12. M. Arnold, R. R. Negenborn, G. Andersson, and B. De Schutter, "Model-based predictive control applied to multi-carrier energy systems," in *Power & Energy Society General Meeting, 2009. PES'09. IEEE*, pp. 1–8, IEEE, 2009.

13. M. Arnold, R. R. Negenborn, G. Andersson, and B. De Schutter, “Distributed predictive control for energy hub coordination in coupled electricity and gas networks,” in *Intelligent Infrastructures*, pp. 235–273, Springer, 2010.

14. S. Bahrami and A. Sheikhi, “From demand response in smart grid toward integrated demand response in smart energy hub,” *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 650–658, 2016.

15. A. Sheikhi, M. Rayati, and A. M. Ranjbar, “Demand side management for a residential customer in multi-energy systems,” *Sustainable Cities and Society*, vol. 22, pp. 63–77, 2016.

16. J. Wasilewski, “Integrated modeling of microgrid for steady-state analysis using modified concept of multi-carrier energy hub,” *International Journal of Electrical Power & Energy Systems*, vol. 73, pp. 891–898, 2015.

17. A. Shabanpour-Haghighi and A. R. Seifi, “Energy flow optimization in multicarrier systems,” *IEEE Transactions on Industrial Informatics*, vol. 11, no. 5, pp. 1067–1077, 2015.

18. I. G. Moghaddam, M. Saniei, and E. Mashhour, “A comprehensive model for self-scheduling an energy hub to supply cooling, heating and electrical demands of a building,” *Energy*, vol. 94, pp. 157–170, 2016.

19. M. Geidl and G. Andersson, “Optimal power flow of multiple energy carriers,” *IEEE Transactions on Power Systems*, vol. 22, no. 1, pp. 145–155, 2007.

20. A. Hajimiragha, C. Canizares, M. Fowler, M. Geidl, and G. Andersson, “Optimal energy flow of integrated energy systems with hydrogen economy considerations,” in *Bulk Power System Dynamics and Control-VII. Revitalizing Operational Reliability, 2007 iREP Symposium*, pp. 1–11, IEEE, 2007.

21. M. Schulze, L. Friedrich, and M. Gautschi, “Modeling and optimization of renewables: applying the energy hub approach,” in *Sustainable Energy Technologies, 2008. ICSET 2008. IEEE International Conference on*, pp. 83–88, IEEE, 2008.

22. M. Arnold and G. Andersson, “Decomposed electricity and natural gas optimal power flow,” in *16th Power Systems Computation Conference (PSCC 08), Glasgow, Scotland*, 2008.

23. L. M. Ramirez-Elizondo and G. C. Paap, “Unit commitment in multiple energy carrier systems,” in *North American Power Symposium (NAPS), 2009*, pp. 1–6, IEEE, 2009.

24. M. Arnold and G. Andersson, “Investigating renewable infeed in residential areas applying model predictive control,” in *Power and Energy Society General Meeting, 2010 IEEE*, pp. 1–8, IEEE, 2010.

25. E. Fabrizio, V. Corrado, and M. Filippi, “A model to design and optimize multi-energy systems in buildings at the design concept stage,” *Renewable Energy*, vol. 35, no. 3, pp. 644–655, 2010.

26. T. Krause, F. Kienzle, Y. Liu, and G. Andersson, “Modeling interconnected national energy systems using an energy hub approach,” in *PowerTech, 2011 IEEE Trondheim*, pp. 1–7, IEEE, 2011.

27. M. C. Bozchalui, S. A. Hashmi, H. Hassen, C. A. Cañizares, and K. Bhattacharya, “Optimal operation of residential energy hubs in smart grids,” *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1755–1766, 2012.

28. M.-R. Haghifam, S. Pazouki, and S. Pazouki, “Renewables and plug in electric vehicles modeling on electricity and gas infrastructures scheduling in presence of responsive demand,” in *Electric Power and Energy Conversion Systems (EPECS), 2013 3rd International Conference on*, pp. 1–6, IEEE, 2013.

29. F. Adamek, M. Arnold, and G. Andersson, “On decisive storage parameters for minimizing energy supply costs in multicarrier energy systems,” *IEEE Transactions on Sustainable Energy*, vol. 5, no. 1, pp. 102–109, 2014.

30. S. Pazouki and M.-R. Haghifam, “Impact of energy storage technologies on multi carrier energy networks,” in *Smart Grid Conference (SGC), 2014*, pp. 1–6, IEEE, 2014.

31. M. C. Bozchalui, S. A. Hashmi, H. Hassen, C. A. Cañizares, and K. Bhattacharya, “Optimal operation of residential energy hubs in smart grids,” *IEEE Transactions on Smart Grid*, vol. 3, no. 4, pp. 1755–1766, 2012.

32. M. C. Bozchalui, C. A. Cañizares, and K. Bhattacharya, “Optimal energy management of greenhouses in smart grids,” *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 827–835, 2015.

33. F. Brahman, M. Honarmand, and S. Jadid, “Optimal electrical and thermal energy management of a residential energy hub, integrating demand response and energy storage system,” *Energy and Buildings*, vol. 90, pp. 65–75, 2015.

34. A. Maroufmashat, A. Elkamel, M. Fowler, S. Sattari, R. Roshandel, A. Hajimiragha, S. Walker, and E. Entchev, “Modeling and optimization of a network of energy hubs to improve economic and emission considerations,” *Energy*, vol. 93, pp. 2546–2558, 2015.

35. A. Maroufmashat, M. Fowler, S. S. Khavas, A. Elkamel, R. Roshandel, and A. Hajimiragha, “Mixed integer linear programing based approach for optimal planning and operation of a smart urban energy network to support the hydrogen economy,” *International Journal of Hydrogen Energy*, vol. 41, no. 19, pp. 7700–7716, 2016.

36. M. Y. Damavandi, N. Neyestani, G. Chicco, M. Shafie-khah, and J. P. Catalao, “Aggregation of distributed energy resources under the concept of multi-energy players in local energy system,” *IEEE Transactions on Sustainable Energy*, 2017.

37. S. Paudyal, C. A. Cañizares, and K. Bhattacharya, “Optimal operation of industrial energy hubs in smart grids,” *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 684–694, 2015.

38. M. Vahid-Pakdel, S. Nojavan, B. Mohammadi-ivatloo, and K. Zare, “Stochastic optimization of energy hub operation with consideration of thermal energy market and demand response,” *Energy Conversion and Management*, vol. 145, pp. 117–128, 2017.

39. A. Sheikhi, S. Bahrami, and A. M. Ranjbar, “An autonomous demand response program for electricity and natural gas networks in smart energy hubs,” *Energy*, vol. 89, pp. 490–499, 2015.

40. A. Sheikhi, M. Rayati, S. Bahrami, A. M. Ranjbar, and S. Sattari, “A cloud computing framework on demand side management game in smart energy hubs,” *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 1007–1016, 2015.

41. H. Yang, T. Xiong, J. Qiu, D. Qiu, and Z. Y. Dong, “Optimal operation of des/cchp based regional multi-energy prosumer with demand response,” *Applied Energy*, vol. 167, pp. 353–365, 2016.

42. X. Zhang, M. Shahidehpour, A. Alabdulwahab, and A. Abusorrah, “Optimal expansion planning of energy hub with multiple energy infrastructures,” *IEEE Transactions on Smart Grid*, vol. 6, no. 5, pp. 2302–2311, 2015.

43. A. Dolatabadi, B. Mohammadi-ivatloo, M. Abapour, and S. Tohidi, “Optimal stochastic design of wind integrated energy hub,” *IEEE Transactions on Industrial Informatics*, 2017.

44. A. Mirakyan and R. De Guio, “Modelling and uncertainties in integrated energy planning,” *Renewable and Sustainable Energy Reviews*, vol. 46, pp. 62–69, 2015.

45. A. Soroudi and T. Amraee, “Decision making under uncertainty in energy systems: State of the art,” *Renewable and Sustainable Energy Reviews*, vol. 28, pp. 376–384, 2013.

46. J. Yan, Y. Liu, S. Han, Y. Wang, and S. Feng, “Reviews on uncertainty analysis of wind power forecasting,” *Renewable and Sustainable Energy Reviews*, vol. 52, pp. 1322–1330, 2015.

47. G. B. Dantzig, “Linear programming under uncertainty,” *Management science*, vol. 1, no. 3-4, pp. 197–206, 1955.

48. E. M. Beale, “On minimizing a convex function subject to linear inequalities,” *Journal of the Royal Statistical Society. Series B (Methodological)*, pp. 173–184, 1955.

49. G. Dantzig and G. Infanger, “Stochastic programming: The state of the art in honor of george b. dantzig,” 2010.

50. M. Moeini-Aghtaie, P. Dehghanian, M. Fotuhi-Firuzabad, and A. Abbaspour, “Multiagent genetic algorithm: an online probabilistic view on economic dispatch of energy hubs constrained by wind availability,” *IEEE Transactions on Sustainable Energy*, vol. 5, no. 2, pp. 699–708, 2014.

51. N. Neyestani, M. Damavandi, M. Shafie-khah, J. Catalão, and G. Chicco, “Uncertainty characterization of carrier-based demand response in smart multi-energy systems,” in *Power Engineering, Energy and Electrical Drives (POWERENG), 2015 IEEE 5th International Conference on*, pp. 366–371, IEEE, 2015.

52. E. Arriagada, E. López, M. López, R. Blasco-Gimenez, C. Roa, and M. Poloujadoff, “A probabilistic economic dispatch model and methodology considering renewable energy, demand and generator uncertainties,” *Electric Power Systems Research*, vol. 121, pp. 325–332, 2015.

53. F. Kienzle, P. Ahcin, and G. Andersson, “Valuing investments in multi-energy conversion, storage, and demand-side management systems under uncertainty,” *IEEE Transactions on Sustainable Energy*, vol. 2, no. 2, pp. 194–202, 2011.

54. M. Salimi, H. Ghasemi, M. Adelpour, and S. Vaez-ZAdeh, “Optimal planning of energy hubs in interconnected energy systems: a case study for natural gas and electricity,” *IET Generation, Transmission & Distribution*, vol. 9, no. 8, pp. 695–707, 2015.

55. M. Troldborg, S. Heslop, and R. L. Hough, “Assessing the sustainability of renewable energy technologies using multi-criteria analysis: Suitability of approach for national-scale assessments and associated uncertainties,” *Renewable and Sustainable Energy Reviews*, vol. 39, pp. 1173–1184, 2014.

56. M. Zarif, S. Khaleghi, and M. H. Javidi, “Assessment of electricity price uncertainty impact on the operation of multi-carrier energy systems,” *IET Generation, Transmission & Distribution*, vol. 9, no. 16, pp. 2586–2592, 2015.

57. W. Alharbi and K. Raahemifar, “Probabilistic coordination of microgrid energy resources operation considering uncertainties,” *Electric Power Systems Research*, vol. 128, pp. 1–10, 2015.

58. A. Soroudi, B. Mohammadi-Ivatloo, and A. Rabiee, “Energy hub management with intermittent wind power,” in *Large Scale Renewable Power Generation*, pp. 413–438, Springer, 2014.

59. A. Najafi, H. Falaghi, J. Contreras, and M. Ramezani, “Medium-term energy hub management subject to electricity price and wind uncertainty,” *Applied Energy*, vol. 168, pp. 418–433, 2016.

60. S. Pazouki and M.-R. Haghifam, “Optimal planning and scheduling of energy hub in presence of wind, storage and demand response under uncertainty,” *International Journal of Electrical Power & Energy Systems*, vol. 80, pp. 219–239, 2016.

61. S. Pazouki, M.-R. Haghifam, and A. Moser, “Uncertainty modeling in optimal operation of energy hub in presence of wind, storage and demand response,” *International Journal of Electrical Power & Energy Systems*, vol. 61, pp. 335–345, 2014.

62. L. Suganthi, S. Iniyan, and A. A. Samuel, “Applications of fuzzy logic in renewable energy systems–a review,” *Renewable and Sustainable Energy Reviews*, vol. 48, pp. 585–607, 2015.

63. Y. Cai, G. Huang, Z. Yang, and Q. Tan, “Identification of optimal strategies for energy management systems planning under multiple uncertainties,” *Applied Energy*, vol. 86, no. 4, pp. 480–495, 2009.

64. Q. Lin, G. Huang, B. Bass, and X. Qin, “Iftem: an interval-fuzzy two-stage stochastic optimization model for regional energy systems planning under uncertainty,” *Energy Policy*, vol. 37, no. 3, pp. 868–878, 2009.

65. Y. Li, Y. Li, G. Huang, and X. Chen, "Energy and environmental systems planning under uncertainty—an inexact fuzzy-stochastic programming approach," *Applied Energy*, vol. 87, no. 10, pp. 3189–3211, 2010.

66. J. Lagorse, M. G. Simoes, and A. Miraoui, "A multiagent fuzzy-logic-based energy management of hybrid systems," *IEEE Transactions on Industry Applications*, vol. 45, no. 6, pp. 2123–2129, 2009.

67. I. Pan and S. Das, "Fractional order fuzzy control of hybrid power system with renewable generation using chaotic pso," *ISA transactions*, vol. 62, pp. 19–29, 2016.

68. J. P. Fossati, A. Galarza, A. Martin-Villate, J. M. Echeverria, and L. Fontan, "Optimal scheduling of a microgrid with a fuzzy logic controlled storage system," *International Journal of Electrical Power & Energy Systems*, vol. 68, pp. 61–70, 2015.

69. M. Datta, T. Senjyu, A. Yona, and T. Funabashi, "A fuzzy based method for leveling output power fluctuations of photovoltaic-diesel hybrid power system," *Renewable Energy*, vol. 36, no. 6, pp. 1693–1703, 2011.

70. V. Mukherjee *et al.*, "A novel quasi-oppositional harmony search algorithm and fuzzy logic controller for frequency stabilization of an isolated hybrid power system," *International Journal of Electrical Power & Energy Systems*, vol. 66, pp. 247–261, 2015.

71. F. Valencia, D. Sáez, J. Collado, F. Ávila, A. Marquez, and J. J. Espinosa, "Robust energy management system based on interval fuzzy models," *IEEE Transactions on Control Systems Technology*, vol. 24, no. 1, pp. 140–157, 2016.

72. C. Dong, G. Huang, Y. Cai, and Y. Liu, "Robust planning of energy management systems with environmental and constraint-conservative considerations under multiple uncertainties," *Energy Conversion and Management*, vol. 65, pp. 471–486, 2013.

73. L. Jin, G. Huang, D. Cong, and Y. Fan, "A robust inexact joint-optimal α cut interval type-2 fuzzy boundary linear programming (rij-it2fblp) for energy systems planning under uncertainty," *International Journal of Electrical Power & Energy Systems*, vol. 56, pp. 19–32, 2014.

74. L. Jin, G. Huang, Y. Fan, L. Wang, and T. Wu, "A pseudo-optimal inexact stochastic interval t2 fuzzy sets approach for energy and environmental systems planning under uncertainty: A case study for xiamen city of china," *Applied Energy*, vol. 138, pp. 71–90, 2015.

75. M. Kazemi, B. Mohammadi-Ivatloo, and M. Ehsan, "Risk-based bidding of large electric utilities using information gap decision theory considering demand response," *Electric Power Systems Research*, vol. 114, pp. 86–92, 2014.

76. A. Soroudi and A. Keane, "Risk averse energy hub management considering plug-in electric vehicles using information gap decision theory," in *Plug In Electric Vehicles in Smart Grids*, pp. 107–127, Springer, 2015.

77. M. Alipour, K. Zare, and B. Mohammadi-Ivatloo, "Optimal risk-constrained participation of industrial cogeneration systems in the day-ahead energy markets," *Renewable and Sustainable Energy Reviews*, vol. 60, pp. 421–432, 2016.

78. A. Rabiee, A. Soroudi, and A. Keane, "Information gap decision theory based opf with hvdc connected wind farms," *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 3396–3406, 2015.

79. K. Zare, M. P. Moghaddam, and M. K. Sheikh-El-Eslami, "Risk-based electricity procurement for large consumers," *IEEE Transactions on Power Systems*, vol. 26, no. 4, pp. 1826–1835, 2011.

80. M. Kazemi, B. Mohammadi-Ivatloo, and M. Ehsan, "Risk-constrained strategic bidding of gencos considering demand response," *IEEE Transactions on Power Systems*, vol. 30, no. 1, pp. 376–384, 2015.

81. B. Mohammadi-Ivatloo, H. Zareipour, N. Amjady, and M. Ehsan, "Application of information-gap decision theory to risk-constrained self-scheduling of gencos," *IEEE Transactions on Power Systems*, vol. 28, no. 2, pp. 1093–1102, 2013.

82. M. Moradi-Dalvand, B. Mohammadi-Ivatloo, N. Amjady, H. Zareipour, and A. Mazhab-Jafari, "Self-scheduling of a wind producer based on information gap decision theory," *Energy*, vol. 81, pp. 588–600, 2015.

83. A. Soroudi and M. Ehsan, "Igdt based robust decision making tool for dnos in load procurement under severe uncertainty," *IEEE Transactions on Smart Grid*, vol. 4, no. 2, pp. 886–895, 2013.

84. K. Chen, W. Wu, B. Zhang, and H. Sun, "Robust restoration decision-making model for distribution networks based on information gap decision theory," *IEEE Transactions on Smart Grid*, vol. 6, no. 2, pp. 587–597, 2015.

85. A. Soroudi, A. Rabiee, and A. Keane, "Information gap decision theory approach to deal with wind power uncertainty in unit commitment," *Electric Power Systems Research*, vol. 145, pp. 137–148, 2017.

86. A. Soroudi, "Smart self-scheduling of gencos with thermal and energy storage units under price uncertainty," *International Transactions on Electrical Energy Systems*, vol. 24, no. 10, pp. 1401–1418, 2014.

87. K. Akbari, M. M. Nasiri, F. Jolai, and S. F. Ghaderi, "Optimal investment and unit sizing of distributed energy systems under uncertainty: A robust optimization approach," *Energy and Buildings*, vol. 85, pp. 275–286, 2014.

88. E. Kuznetsova, C. Ruiz, Y.-F. Li, and E. Zio, "Analysis of robust optimization for decentralized microgrid energy management under uncertainty," *International Journal of Electrical Power & Energy Systems*, vol. 64, pp. 815–832, 2015.

89. E. Kuznetsova, Y.-F. Li, C. Ruiz, and E. Zio, "An integrated framework of agent-based modelling and robust optimization for microgrid energy management," *Applied Energy*, vol. 129, pp. 70–88, 2014.

90. A. Parisio, C. Del Vecchio, and A. Vaccaro, "A robust optimization approach to energy hub management," *International Journal of Electrical Power & Energy Systems*, vol. 42, no. 1, pp. 98–104, 2012.

91. L. Bai, F. Li, H. Cui, T. Jiang, H. Sun, and J. Zhu, "Interval optimization based operating strategy for gas-electricity integrated energy systems considering demand response and wind uncertainty," *Applied Energy*, vol. 167, pp. 270–279, 2016.
92. Y. Zhu, G. Huang, L. He, and L. Zhang, "An interval full-infinite programming approach for energy systems planning under multiple uncertainties," *International Journal of Electrical Power & Energy Systems*, vol. 43, no. 1, pp. 375–383, 2012.
93. L. A. Zadeh, "A note on z-numbers," *Information Sciences*, vol. 181, no. 14, pp. 2923–2932, 2011.
94. B. Kang, D. Wei, Y. Li, and Y. Deng, "A method of converting z-number to classical fuzzy number," *JOURNAL OF INFORMATION &COMPUTATIONAL SCIENCE*, vol. 9, no. 3, pp. 703–709, 2012.
95. B. Kang, D. Wei, Y. Li, and Y. Deng, "Decision making using z-numbers under uncertain environment," *Journal of Computational Information Systems*, vol. 8, no. 7, pp. 2807–2814, 2012.
96. A. Azadeh, M. Saberi, N. Z. Atashbar, E. Chang, and P. Pazhoheshfar, "Z-ahp: A z-number extension of fuzzy analytical hierarchy process," in *Digital Ecosystems and Technologies (DEST), 2013 7th IEEE International Conference on*, pp. 141–147, IEEE, 2013.
97. R. A. Aliev and L. M. Zeinalova, "Decision making under z-information," in *Human-Centric Decision-Making Models for Social Sciences*, pp. 233–252, Springer, 2014.
98. J. Lorkowski, V. Kreinovich, and R. Aliev, "Towards decision making under interval, set-valued, fuzzy, and z-number uncertainty: a fair price approach," in *Fuzzy Systems (FUZZ-IEEE), 2014 IEEE International Conference on*, pp. 2244–2253, IEEE, 2014.
99. R. R. Yager, "On a view of zadeh's z-numbers," *Advances in Computational Intelligence*, pp. 90–101, 2012.
100. R. R. Yager, "On z-valuations using zadeh's z-numbers," *International Journal of Intelligent Systems*, vol. 27, no. 3, pp. 259–278, 2012.
101. L. A. Zadeh, "Methods and systems for applications for z-numbers," July 29 2013. US Patent App. 13/953,047.
102. R. Banerjee and S. K. Pal, "The z-number enigma: a study through an experiment," in *Soft computing: state of the art theory and novel applications*, pp. 71–88, Springer, 2013.
103. S. K. Pal, R. Banerjee, S. Dutta, and S. S. Sarma, "An insight into the z-number approach to cww," *Fundamenta Informaticae*, vol. 124, no. 1-2, pp. 197–229, 2013.
104. S. Tadayon and B. Tadayon, "Approximate z-number evaluation based on categorical sets of probability distributions," in *Recent Developments and New Directions in Soft Computing*, pp. 117–134, Springer, 2014.
105. R. A. Aliev, A. V. Alizadeh, and O. H. Huseynov, "The arithmetic of discrete z-numbers," *Information Sciences*, vol. 290, pp. 134–155, 2015.
106. R. A. Aliev, A. V. Alizadeh, O. H. Huseynov, and K. Jabbarova, "Z-number-based linear programming," *International Journal of Intelligent Systems*, vol. 30, no. 5, pp. 563–589, 2015.
107. A. Azadeh and M. Zarrin, "Evaluating the impacts of resilience engineering on health, safety, environment, and ergonomics factors by z-number cognitive map in a large petrochemical plant," *Safety and Health at Work*, 2015.
108. M. Moeini-Aghtaie, A. Abbaspour, M. Fotuhi-Firuzabad, and P. Dehghanian, "Optimized probabilistic phevs demand management in the context of energy hubs," *IEEE Transactions on Power Delivery*, vol. 30, no. 2, pp. 996–1006, 2015.
109. Y.-Y. Hong and J.-K. Lin, "Interactive multi-objective active power scheduling considering uncertain renewable energies using adaptive chaos clonal evolutionary programming," *Energy*, vol. 53, pp. 212–220, 2013.
110. G. Díaz, E. Planas, J. Andreu, and I. Kortabarria, "Joint cost of energy under an optimal economic policy of hybrid power systems subject to uncertainty," *Energy*, vol. 88, pp. 837–848, 2015.
111. A. Rabiee, M. Sadeghi, J. Aghaeic, and A. Heidari, "Optimal operation of microgrids through simultaneous scheduling of electrical vehicles and responsive loads considering wind and pv units uncertainties," *Renewable and Sustainable Energy Reviews*, vol. 57, pp. 721–739, 2016.
112. R. Rajkumar, V. Ramachandaramurthy, B. Yong, and D. Chia, "Techno-economical optimization of hybrid pv/wind/battery system using neuro-fuzzy," *Energy*, vol. 36, no. 8, pp. 5148–5153, 2011.
113. C. Wang, B. Jiao, L. Guo, Z. Tian, J. Niu, and S. Li, "Robust scheduling of building energy system under uncertainty," *Applied Energy*, vol. 167, pp. 366–376, 2016.
114. C. Kahraman, İ. Kaya, and S. Cebi, "A comparative analysis for multiattribute selection among renewable energy alternatives using fuzzy axiomatic design and fuzzy analytic hierarchy process," *Energy*, vol. 34, no. 10, pp. 1603–1616, 2009.
115. Y. Cai, G. Huang, Q. Tan, and Z. Yang, "Planning of community-scale renewable energy management systems in a mixed stochastic and fuzzy environment," *Renewable Energy*, vol. 34, no. 7, pp. 1833–1847, 2009.
116. A. Soroudi, "Possibilistic-scenario model for dg impact assessment on distribution networks in an uncertain environment," *IEEE Transactions on Power Systems*, vol. 27, no. 3, pp. 1283–1293, 2012.