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Application of Information Gap Decision Theory to Practical Energy Problems: A Comprehensive Review

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Abstract

The uncertainty and risk modeling is a hot topic in power system operation and planning. The system operators and planners are decision makers that need to handle the uncertainty of input data of their models. As an example, energy consumption has always been a critical problem for operators since the forecasted values, and the actual consumption is never expected to be the same. The penetration of renewable energy resources is continuously increasing in recent and upcoming years. These technologies are not dispatch-able and are highly dependent on natural resources. This would make the real-time energy balancing more complicated. Another source of uncertainty is related to energy market prices which are determined by the market participants' behaviors.

To consider these issues, the uncertainty modeling should be performed. Various approaches have been previously utilized to model the uncertainty of these parameters such as probabilistic approaches, possibilistic approaches, hybrid possibilisticprobabilistic approach, information gap decision theory, robust and interval optimization techniques. This paper reviews the research works that used information gap decision theory for uncertainty modeling in energy and power systems.

Keywords: Uncertainty, uncertain parameters, information gap decision theory, robustness function, opportunity function, energy.

1. Introduction

The uncertainty of different parameters in power systems has made several operating issues for the system operators and other stakeholders in this area.

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The uncertainty influences the scheduled plans and might create new challenges for the involved decision makers. To resolve the issues mentioned above, various methods and techniques have been studied and utilized to control the outcomes caused by possible uncertainty in the behavior of parameters. Previously implemented techniques are possibilistic technique [1], probabilistic technique [2], hybrid possibilisticprobabilistic techniques [3], robust optimization technique [4, 5], information gap decision theory (IGDT) [6] and interval analysis [7]. The mentioned approaches and techniques are briefly illustrated in Fig. 1. Each approach has specific characteristics and uses different ways to model uncertainty which will be shortly explained in the next section.

Figure 1: Techniques and approaches used for uncertainty modeling [8, 9]

As mentioned before, the primary goal of this paper is to study and investigate the papers that used information gap decision theory in power system studies and reveal unexplored areas. The information gap decision theory models the positive and negative aspects of uncertainty based on the known and unknown information. Positive and negative outcomes that uncertainty may bring are modeled using two functions of information gap decision theory called robustness and opportunity functions. These functions will be comprehensively explained in the next sections. So, summarizing the given descriptions, the rest of the proposed paper can be expressed as follows: Uncertainty modeling techniques and approaches are briefly explained in Section 2. Information gap decision theory and corresponding functions are explained in Section 3. Papers in the field of power system studies in which information gap decision theory has been employed are investigated and reviewed in Section 4. Finally, the conclusions are presented in Section 5.

2. Uncertainty modeling approaches excluding IGDT

The challenges caused by the realization of different uncertain parameters in the power system has encouraged operators to use uncertainty modeling techniques to become ready against possible consequences and make the best decision. Uncertain parameters can be numerous and should be investigated from economic and technical points of view. The well-known ones to be named are energy demand, possible outages of components, the output of renewable generation units and market price. The methods used for modeling mentioned uncertainties are briefly described in this section [8].

2.1. Possibilistic technique

In this technique, the parameters showing uncertain behavior are considered to be X. The system model is assumed to be f and the output variable is considered to be y. To define the membership function of y while the membership function of X is known, α-cut approach is used [10]. Finally, using a defuzzification technique such as centroid technique, max-membership principal, weighted average approach, the fuzzy members are converted to crisp members.

2.2. Probabilistic technique

In this method, we have a multivariate function, $y = f(x)$. Different random parameters are set to be inputs to the system, x, which probability density function is known. y is considered to be the output with an unknown probability density function, and the f is assumed to be the system model. Totally, there are three major probabilistic approaches modeling uncertainty which are: scenario-based technique [11], point estimate technique [12] and Monte Carlo simulation [13].

2.3. Hybrid possibilisticprobabilistic techniques

In the cases that both of possibilistic and probabilistic uncertain parameters are available, hybrid possibilisticprobabilistic techniques are employed to model uncertainty. These techniques are possibilistic-scenario based technique [3] and possibilistic-Monte Carlo technique [14].

2.4. Robust optimization technique

In some cases, the uncertainty is modeled as an uncertainty set. It means that the uncertain parameters always belong to a known uncertainty set. In these cases, the robust optimization technique can be a good a choice to be used for uncertainty modeling. In this approach, the worst possible condition is determined and then using the obtained results, appropriate strategies are taken [15]. The degree of being conservative is adjustable by the decision maker.

2.5. Interval analysis

In this method, the range of uncertain parameters is, and then the upper and lower bounds of the objective function are obtained as the main goal of interval problem [7].

2.6. Z-number

In this approach, The standard deviation from the mean value of a data point is calculated. In fact, it calculates the number of standard deviations below or above the population means a raw number [15].

3. Information gap decision theory (IGDT)

Different methods used for uncertainty modeling were explained in the former section. In this section, information gap decision theory is described in general to give a better and clear view of IGDT application in power system scheduling and planning. At first, some of the papers in various fields except power system scheduling that employed IGDT for uncertainty modeling are summarized.

In [16], information gap decision theory has been employed for uncertainty modeling of biological value persistence or presence in reserve sites. IGDT has been used for investigation of model updating in [17]. Risk-based civil structure design has been carried out using IGDT in [18]. To model the uncertain behavior of a system including unknown events over time, IGDT has been implemented in [19]. In [20], IGDT has been used to solve a spatial search-planning problem including unclear probabilistic info and data. The effectiveness of various uncertainty modeling approaches including IGDT has been evaluated on the uncertainty modeling of ecosystems issues in [21]. IGDT has been used for uncertainty modeling of input data in the neural network in [22]. Using information gap decision theory, environmentally benign manufacturing and design has been studied in [23]. To control and manage water resources including uncertainties, IGDT has been employed in [24].

To obtain the highest possible social welfare by taking various circumstances into account, IGDT has been used in [25]. Using IGDT concept, structural design-codes have been formulated in [26]. Practical utilization of information gap decision theory has been discussed in [27]. Set-models of IGDT are discussed in [28]. Using probability bounds analysis and p-boxes, information gap models are constructed about probability distributions in [29]. Risk-based portfolio management problem in finance has been solved using information gap decision theory in [30]. IGDT has been previously applied to different optimization problems in different fields. For instance, uncertainty-based scheduling problem for selection of appropriate sites for CO2 sequestration has been studied through IGDT in [31].

Unlike other uncertainty modeling approaches, IGDT does not need a great amount of data for uncertainty modeling. In fact, by employing the available data about uncertainty parameter, IGDT informs the operator about the negative and positive results that can be caused by uncertainty to take appropriate and logical decisions which may be safe or risky. IGDT receives the uncertain uncertainty set which may not be such exact. Afterward, IGDT tries to make the system performance consistent against the uncertain parameter while keeping the operational point within the safe region. Sometimes, the uncertainty level of uncertain parameter is such severe that system may not withstand the possible instabilities caused by the mentioned uncertainty. This is one of features of IGDT to assure that system doesnt get into the risky region. Fig. 2 is used to illustrate the safe/risky region of a problem experiencing uncertainty to which IGDT is due to be applied. Sometimes when uncertainty has occurred, operators need to take strategies to handle the condition caused by uncertainty. IGDT is a good tool to evaluate and compare the strategies taken at the times of uncertainty, and the decision maker would be able to evaluate the effectiveness of taken strategies, determine his priorities and evaluate his expected objective function [6].The uncertainty levels determined by IGDT in the safe region are not always free enough to be extended as much as possible. There are usually different factors that may influence the resistance level of system against uncertainty. In fact, IGDT tries to maximize the resistance level of operating system against uncertainty within the safe region while satisfying the other factors that may limit the extension of safe uncertainty set. For example, consider a system participating in energy market power for its energy demand satisfaction. If the market price is due to be uncertain [32], the system operator should increase its operating budget to be robust against the possible increase in price. The budget limitation is the factor that may affect the taken policies against uncertainty and needs to be taken into account. So, for a reasonable amount of increase in budget, the operator expects to obtain the maximum degree of robustness against the market price increase. This IGDT-based problem is a bi-level optimization problem in which the uncertainty set should be maximized and the operational budget should be minimized. The mentioned example is schematically illustrated in Fig. 3. According to this Fig, the uncertainty set (the level of system resistance) is tried to be enhanced as much as possible while the operational budget for controlling the uncertainty is limited.

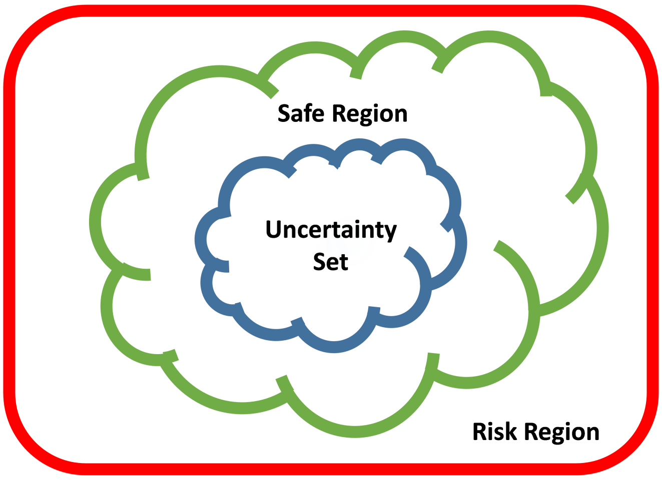

Figure 2: Safe/risk region of uncertainty based problem

3.1. Immunity functions of IGDT

Information gap decision theory includes two immunity functions namely robustness and opportunity functions which are depicted in Fig. 4. Immunity functions can be used by relevant decision makers to model positive and negative outcomes of uncertainty. In fact, these functions are known as major and significant parts if IGDT since operator decisions and actions for handling uncertainty are based on these functions. Predicting possible results and outcomes of uncertainty, robustness and opportunity functions facilitate evaluation of various conditions and help operators take the best strategies at times uncertainty is occurred [28, 29]. As it can be seen from Fig. 4, robustness function of IGDT is usually employed to model negative impacts of uncertainty toward which system should be resistant. On the other hand, as shown with positive sign in Fig. 4, opportunity function is used to assess the benefits possible to be obtained from uncertainty.

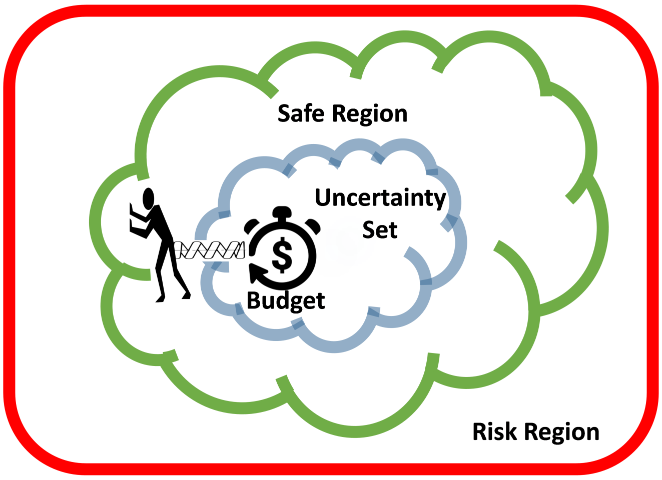

Figure 3: Graphical explanation of IGDT

Figure 4: The robustness and opportunity functions of IGDT

3.1.1. Robustness function

In order to address negative aspects uncertainty, robustness function is used. The parameter modeling this function is α. The greatest level of uncertainty that can be handled through the taken strategies is determined by this function [6]:

$$\hat{\alpha} = \max_{\alpha} \{\alpha : \ maximum\ total\ cost\ which\ is\ not\, higher\ than\ a\ specified\ cost\,\} \tag{1}$$

It can be concluded from the explanation given above that a greater value of $\hat{\alpha}$ is desired.

3.1.2. Opportunity function

Benefits and positive outcomes that can be achieved through uncertainty are modeled by opportunity function [6]:

$$\hat{\beta} = \min_{\beta} \{\alpha : \; minimum\ total\ cost\ which\ is\ less\ than\ a\ specified\ cost\,\} \tag{2}$$

It can be concluded from the explanations given above that a smaller value of $\hat{\beta}$ is desired.

3.2. Structure of IGDT

Information gap decision theory is mainly composed of three parts: system model, operation requirements and uncertainty modeling.

3.2.1. System model

The relationship between inputs and outputs is expressed by system model. Based on IGDT, system model can be expressed by $y(q, l)$ in which q is decision variable and l is uncertainty parameter. For example, in an economic problem with the objective function cost and market price as the uncertain parameter, system model can be expressed by $C(q, l)$ in which $C(q, l)$ is the cost function as the system model, q is decision variable and l is market price [6]. In fact, IGDT uses uncertainty set to strengthen objective function against the uncertainty of input parameters.

3.2.2. Operation requirements

Information gap decision theory includes two main functions namely robustness function $\hat{\alpha}(q)$ and opportunity function, $\hat{\beta}(q)$. Each one of mentioned functions is used to simulate positive and negative aspects of uncertainty, and then according to the achieved results, the appropriate decisions and strategies are taken by the operator of the system. In fact, the robustness function expresses how resistant the system is against the increase of uncertain parameter. In simple words, robustness functions determine how much more money should be paid to avoid further harmful outcomes. Lets consider the same economic problem with market price uncertainty. Based on the robustness function, the maximum resistance is desired while the total cost of the system should not exceed a predefined value. Mathematical formulation of this example is expressed by equation (3) [6].

$$\hat{\alpha}(C_r) = max\alpha\{\alpha : max(C(q, l)) \leq C_r\} \tag{3}$$

C_r is the defined cost that maximum total cost of system cannot exceed. On the other hand, opportunity function of information gap decision theory is used to determine how the system can benefit from the possible reduction of the uncertain parameter which is the positive effects of uncertainty. In the same example, a possible reduction of market price can bring economic benefits to the system. To befit from this positive outcome as much as possible, opportunity function is used which mathematical formulation is presented in the following [6]:

$$\hat{\beta}(C_o) = min\beta\{\alpha : min(C(q,l)) \leq C_o\} \tag{4}$$

C_o is the defined cost that minimum total cost of the system cannot be more than this cost. Its noteworthy that in the equation mentioned above, C_o is lower than C_r.

3.2.3. Uncertainty model

Many various info-gap models are available for uncertainty including envelope-bound models, energy-bound models, Minkowski-norm models, Slope-bound models, Fourier-bound models, Hybrid info-gap models, combined info-gap models, a non-convex info-gap model: Pendulum-like systems, A non-convex info-gap model: Linear system with uncertain coefficients, discrete info-gap models. The whole uncertainty models along with their relevant mathematical formulation are presented in Table 1. As it can be observed, different uncertainty models with specific features and formula are available. One of the most popular models (approved by analyzing the employed models in literature gathered in Table 2) is envelope bound model which is illustrated in Fig. 5 [33]. According to the uncertainty model of envelope bound model presented in this Fig, the uncertainty set given as the input in IGDT method is tried to be maximized. By having the uncertainty set maximized, the mots possible resistance level can be obtained for the operating system against uncertainty. Also, under such a condition, the most possible benefits can be achieved while the requirements are satisfied.

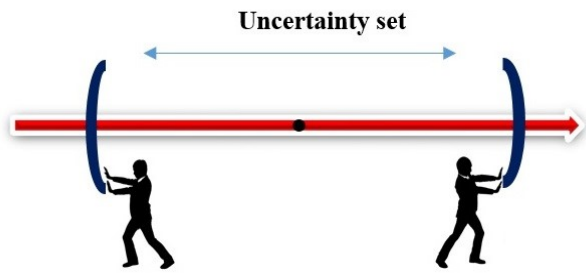

Figure 5: Uncertainty model of envelope bound of IGDT

Table 1: Uncertainty models existing in IGDT literature

Model		Mathematical form	Description
Envelope-bound models		$U(\alpha, \tilde{u}) = \{u(t) : \lvert\frac{u(t) - \tilde{u}(t)}{\varphi(t)}\rvert \leq \alpha\}, \alpha \geq 0$	$u(t)$ is uncertain parameter and $\tilde{u}(t)$ is the nominal value of uncertain parameter
Energy-bound models	Scalar functions	$U(\alpha, \tilde{u}) = \{u(t) : \int_0^\infty [u(t) - \tilde{u}(t)]^2 dt \leq \alpha^2\}, \alpha \geq 0$	$u(t)$ is uncertain scalar function and $\tilde{u}(t)$ is the nominal function
	Vector functions	$U(\alpha, \tilde{u}) = \{u(t) : \int_0^\infty [u(t) - \tilde{u}(t)]^r V[u(t) - \tilde{u}(t)]dt \leq \alpha^2\}, \alpha \geq 0$	$u(t)$ is uncertain vector function, $\tilde{u}(t)$is the nominal vector function and V is known positive definite
Minkpwski-norm models		$U_r(\alpha, \tilde{u}) = \{u : \lVert V^{\frac{1}{2}} (u - \tilde{u}\rVert_r \leq \alpha)\}, \alpha \geq 0$	$u$is uncertain parameter and $\tilde{u}$ is nominal value of uncertain parameter
Slope-bound models		$U(\alpha, \tilde{u}) = \{u(t) : \lvert\frac{du(t) - \tilde{u}(t)}{dt}\rvert \leq \alpha\Psi(t)\}, \alpha \geq 0$	u is uncertain vector function, $\tilde{u}$ is the nominal vector function and Ψ determines the envelope of uncertain variation of the slope
Fourier-bound models		$U(\alpha, \tilde{u}) = \{u(y) = \tilde{u} + c^T W c \leq \alpha^2\}, \alpha \geq 0$	u is uncertain vector function, $\tilde{u}$ is the nominal vector function and W is a known , symmetric, positive matrix
Hybrid info-gap models	Continues random variable	$U(\alpha, \tilde{p}) = \{p(x) : p(x) \in \rho, \lvert p(x) - \tilde{p}(x)\rvert \leq \alpha\Psi(t)\}, \alpha \geq 0$	x is random variable, $p(x)$ is probability density function of x and $\tilde{p}$ is the best known of $p(x)$
	Discredit random variable	$U(\alpha, \tilde{p}) = \{p : p \in \rho, (p - \tilde{p}^T V (p - \tilde{p}) \leq \alpha^2\}, \alpha \geq 0$	Mp is probability distribution of random variable and $\tilde{p}$ is the best known prediction of the probability distribution of random variable
Combined info-gap models		$U(\alpha, \tilde{u}) = \{u(t) : \lvert u(t) - \tilde{u}\rvert \leq \alpha\Psi(t), \int_0^\infty [u(t) - \tilde{u}]^2 dt \leq \alpha^2\}, \alpha \geq 0$	$u$is uncertain parameter and $\tilde{u}$ is nominal value of uncertain parameter
Discrete info-gap models		$\Pi^k = \{\pi \pm e^i, \forall\pi \in \Pi^{k-1}, i = 1, ..., J\}, k = 1, 2, ...$	J is number of options, π is preference vector and Π^k is set of preference vectors differ from the nominal by no more than k single preference changes

4. Risk-based energy problems solved by IGDT

As one of the interesting tools for uncertainty modeling in the field of the power system, IGDT has been utilized to model the uncertainty of different parameters in the power system. In this section, the cases and problems to which IGDT has been applied are classified and summarized. For more clarification, the cases are classified into three groups: cases with market price as the uncertain parameter, cases with generation or consumption power as the uncertain parameter and cases with price and generation or consumption power as the uncertain parameter. It should be noted that one of appropriate solutions to uncertain behavior of input data and info in the scheduling and planning of power systems is implementation of energy storage systems. Various technologies of storage systems have been employed in energy systems to mitigate the negative impact of uncertainty. As an example, CAES has been implemented to cope with stochastic nature of uncertainties like wind [34, 35] and demand [36] and etc. Additionally, pumped hydro storage (PHS) has been also implemented in research papers to handle the uncertainties like the uncertainties of streamflow [37],solar systems [38], wind units [39, 40, 41], loads [42] and forecasts [43]. Storages systems inducing CAES and PHS has specific operational processes. According to the research done in ref [44], under uncertainties, the PHS has been selected as the best storage technology followed by CAES.

4.1. Risk-based problems with the uncertainty of market price

After restructuring in the electricity industry, the notion of the energy market has been redefined in the recent years. In fact, distribution companies are not the only resources to supply energy demand and consumers have been enabled to participate in energy markets to procure their energy demands. Market prices are defined according to the supply and demand curves which makes the final price be an uncertain parameter. Large consumers can participate in energy markets to meet its energy demand. Bilateral contracts and pool markets are available options for large consumers to supply its demand. Employing robustness and opportunity functions, various energy procurement strategies have been provided for large consumers to take appropriate decisions while participating in energy market [45, 46, 47]. It should be noted that in addition to the energy market, distributed generation units have also been used to supply some parts of energy demand. In a day-ahead market with uncertain hourly prices, uncertainty modeling of price is vital. Therefore, Variance-covariance matrix of IGDT has been utilized in [48] to obtain robust strategies for the participation of large consumer in the energy market. Using the obtained robustness curve against procurement cost, the operator has been enabled to take the right procurement decision. Electric utilities are responsible for meeting hourly energy demand of consumers. The same problem has been studied through immunity functions of IGDT in the presence of load management programs in [49].These utilities can join energy markets in upper levels to supply energy demand requested by related retailers. The total benefit of mentioned utilities is provided through participation in the electricity market and selling the procured energy to the relevant retailers. To maximize the utilities benefit, the uncertainty of market price should be taken into account to avoid utility facing unstable conditions. This problem has been investigated in the presence of responsible and non-responsible loads in [50] to determine appropriate participating strategies to maximize utilities total benefit. Due to the larger values of exchanged energies in energy markets, common residential consumers cannot participate in the mentioned markets. So, some of these consumers join together and a retailer who is representative of joined consumers, participates in the energy markets to procure energy demand of consumers. Robust participation of retailers owning distributed generation units in energy markets has been investigated in [51] in which IGDT has been employed to obtain risk-averse and risk-taking strategies according to which retailer participates in energy markets. To efficiently used energy carriers and not waste released heat from the output of generation units in power systems, combined heat and power systems can be used instead of conventional generation systems generate electric power and heat. Efficient utilization of energy carriers in these units can result in higher efficiency up to 80 % for these systems. In [52], large consumers with co-generation systems like combined heat and power systems have been participated in the energy market to supply its energy demands. Uncertainty modeling of energy market price for the large consumer has been carried out through information gap decision theory in [52]. In the competitive energy market, consumers with fewer energy demands do not provide their energy demands from energy market. Instead of them, retailers do participate in the power market. Retailers purchase energy at a variable price form pool market and sell it to the consumers at a fixed price. The retailer is looking for increasing its benefit from participation in the energy market. To do this, retailer attempts to consider possible uncertainties of market price to have robust performance. This uncertainty modeling is done by IGDT in [53]. The same problem has been investigated in [54, 55] with the difference that instead of retailers, generation stations participate in the energy market and using robustness and opportunity functions, optimal bidding strategies are obtained to maximize stations profit. A retailer who purchases energy from different sources and then sells it to the end-users should make a good balance between the purchased power and the power due to be consumed to gain the expected profit. Taking into account this issue, a novel reliability-based optimization framework has been developed in ref [56] in which IGDT and two-point estimate methods have been employed to model the uncertainties of wholesale price and rivals price, respectively. After deregulation in the energy market, generation companies are seeking to maximize their profit through optimal incorporating distributed generation units. Produced power by these units is presented in power market and therefore, uncertainty modeling of market price at which generation company sells its produced power is done by IGDT in [57, 58]. Also, similar to the problem solved in [57], a bi-level optimization problem is investigated in [59] in which bilateral contracts are taken into account by generation company to reduce the risk of participation in energy market as much as possible. It should be noted that the uncertain parameter making energy market risky is market price which uncertainty is modeled by IGDT in [59]. Generation companies have different generation resources which can be either renewable or non-renewable. In the case of non-renewable ones, different types of fuels are burned which leads to environment pollutants. In fact, generation company participates in three electricity, emission and fuel markets in which price of electricity, emission and fuel are considered to be uncertain. These uncertainties are modeled using IGDT in [60]. Robust performance of a thermal generation company has been investigated in [61]. Thermal generation company presents its generation in day-ahead and subsequent adjustment markets which price uncertainties is modeled using ellipsoid bound uncertainty model in [61]. In [62], risk-based bi-level problem of a utility has been investigated. Gained profit due to participation of utility in wholesale market plus the income gained from contracted demand of retail side of utility results the total profit of utility. Uncertainty of prices at which retailer procures demanded energy from pool market is modeled using IGDT in [62]. As a distributed generation unit, compressed air energy storage system (CAES) can participate in energy market to presents power in various time periods and therefore gain benefit. CAES attempts to forecast market price but none of forecasts in each field are perfect. So, an uncertainty modeling is necessary. Therefore, using IGDT, uncertainty modeling of market price is done for CAES in [63]. A novel IGDT-based optimization model is developed for a microgrid in accordance with game theoretical approach in ref [64] to optimize the energy provision of the microgrid operator subject to uncertainty of wholesale prices. A hub energy based microgrid system equipped to different energy facilities has been optimally scheduled under different uncertainties in ref [65]. In detail, the uncertainty of demand and wind forecasts have been modeled through a scenario-based method while the uncertainty of electricity price within the mentioned system has been modeled using IGDT. In [66], info-gap decision theory has been employed to model uncertainty-based performance of a distribution system which operator is faced with fluctuating prices of market price. Using information gap decision theory, a competition based biding problem has been solved in [67]. As one of important energy sectors, smart homes equipped to smart facilities have been optimally scheduled under uncertainties within the research papers. These systems can rely one smart energy equipment to optimally satisfy end-users requirements while controlling the possible uncertainties. In detail, ref [68, 69] has developed an optimization model according to which apartment smart buildings capable of purchasing power from different sectors like market has been optimally scheduled and IGDT concept is employed to assess risk-involved performance of apartment smart building toward market price uncertainty. Within studied papers, impact of thermal storage has been investigated through having different cases been studied. Similar, smart home equipped to smart energy technologies has been optimally configured in ref [70] under uncertainty of market price. To handle the mentioned uncertainty in the studied smart home equipped to smart facilities to efficiently use the available energies, robustness and opportunity functions of IGDT have been employed to provide the appropriate operating strategies.

4.2. Risk-based problems with the uncertainty of generation/consumption

As mentioned in former sections, different parameters in power systems can have uncertain behavior. In addition to the market price which was comprehensively discussed in previous section, load and generation can also have uncertain performance. In this section, risk-based performance of energy systems with load or generation as their uncertainty parameter has been reviewed. In fact, when we talk about uncertainty of generation in power system, the main focus is on renewable resources like wind, photo-voltaic and etc. using free available wind in the air, wind turbine generates clean electric power. Because of that wind speed in all the times is not constant, therefore, output of wind turbine will not be stable and will change appropriate with wind speed which will have negative impact on the generation-load balance of system. In order to solve such problems, uncertainty modeling is necessary. Efficient utilization of clean energies like solar has turned to be an essential topic in the research papers. Solar radiation can be used in different forms for different purposes like generating electricity. Ref [71] has proposed an optimization model based on IGDT to optimize uncertainty-based performance of a solar power plant equipped to thermal storage in which solar radiation is absorbed as much as possible to be used for electricity generation while IGDT methodology is employed to model the uncertain pattern of mentioned radiation. To consider the uncertainties of both wind units and PV systems, information gap decision theory has been employed in ref [72] in which demand response and storage models have been developed to enhance the system performance within the mentioned uncertainties. Security-involved unit commitment problem has been solved subject to uncertainty of load in ref [73] in which novel storage model has been developed and IGDT methodology is employed to model the load uncertainty. In another study, linear relationships have been presented in ref [74] to model linear form of unit commitment problem in which the uncertainty demand has been taken into account with IGDT. In [75], the transmission network reinforcement using series reactance is investigated with considering uncertainty of wind generation in which Uncertainty modeling is carried out by IGDT. The same problem has been investigated without considering security constraints in [76] where demand response program has been used to improve economic performance of system. In a similar research in ref [77], wind-based energy system has been planned under wind units uncertainty. Uncertainty of wind units has been modeled by IGDT in long term subject to security constraint like voltage stability index to assure safe performance of system. Taking into account power flow constraints in the scheduling of energy sectors can make the results more real and accurate. So, a novel optimization model based-on mathematical bases has been presented in ref [78] to optimize performance of an integrated heat and power energy sector under different uncertainties. In detail, the studied system is equipped to different energy resources like combined heat and power systems, boiler units and other resources and to consider the uncertainties of market price, renewable units and electric demand, respectively, robust optimization, scenario-based method and IGDT are employed. The results depicted that implementation of mentioned methods can help the operator to take appropriate decisions against uncertainties. Similarly, smart hub energy systems in distribution networks have been optimally scheduled subject to technical imitations like power flow constraint under different uncertainties in ref [79]. To model the uncertainties of upstream network price, renewable units and electrical demands of smart hubs, interval optimization, scenario-based method and IGDT are respectively employed. Because of large scale renewable generation, wind farms with several wind-turbines should be prepared for each ramp event of wind turbines. Wind-turbine ramp events can make network unstable and therefore, prediction of such mentioned events are vital. But, as said before, none of predictions are always perfect. So, using information gap decision theory, uncertainty of wind power ramp prediction has been modeled in [80]. Optimal power flow problem in the presence of wind generation uncertainty has been evaluated in [81]. Also, optimal power flow problem under uncertainty offshore wind farms has been investigated in [82] where HVDC technology has been used to connect onshore AC network to the offshore wind farms. In addition to the power generation for direct consumption of consumers in demand sides, generation units allocate some percentage of their generation capacity for reserve generation. Depending on that participation in reserve market is beneficial are not, generation units injects reserve power to the transmission network. Uncertainty of presented reserve by generation units to the transmission line is investigated through IGDT in [83]. Finally, uncertainty modeling of wind generation in a power system with DC model has been done in [84] in which energy storage system has been employed to mitigate disturbing effects caused by uncertainty of wind generation.

Load uncertainty of power systems has been always one of major challenges that system operators have been faced. Various load forecasting methods and techniques are available but, in order to take the forecasting tolerances into account, uncertainty modeling should be done. In [85], uncertainty based performance of an on-grid hybrid energy system with electrical and thermal energy demands has been investigated. Electrical load of mentioned hybrid system is considered to be uncertain. Using robustness and opportunity functions of IGDT, uncertainty modeling is done and appropriate power procurement strategies are obtained to be used by system operator. Taking into account the uncertainty of responsive loads participation in demand response programs (considered as reserve providers), IGDT-based optimization framework has been developed in ref [86] in which IGDT methodology has been employed to provide the decisions-making strategies. In order to improve economic performance and reduce total operation cost of hybrid system, the same problem has been investigated in [87] in the presence of demand response program. Load uncertainty problem has been investigated in [88] in which risk-based expansion planning of transmission line has been evaluated under uncertain behavior of load. In ref [89], a novel optimization framework has been presented for uncertainty-based energy management of an islanded microgrid in which IGDT methodology has been implemented to consider the uncertainties of renewable units generation and energy demand. In [90], uncertainty modeling of transmission line overload has been assessed using IGDT in which robust performance of power system has been obtained for the cases line experiences overload. Sometimes, distribution systems may experience some outages which are harmful for structure of the whole system. In thus condition, restoration strategies become more important. Factors influencing restoration strategies are uncertainty of some parameters in power systems which should be molded using uncertainty modeling approaches. In [91], uncertainty of load and output power of distributed generation units have been modeled using IGDT to improve restoration results of power system in the cases of outages. Similarly, an IGDT-based optimization model has been presented for load restoration in ref [92] in which the uncertainty of load has been modeled with IGDT to ensure the maximum tolerable load increment. In ref [93], an industrial continuous heat treatment furnace based on air source heat pump is optimally scheduled to supply heating demand under extreme temperatures. IGDT method is employed to model the uncertainty of heating demand and provide risk-averse and risk-seeking strategies. In ref [94], to solve the electricity pricing and dispatch issues that retailer of local generation unit may deal with, a novel uncertainty-based optimization framework based on bi-level programming has been developed in which the scenario-based method and IGDT have been respectively employed in the upper level and lower level problems to model the related uncertainties.

4.3. Risk-based problems with the uncertainty of price and generation/consumption

Problems with generation/load and price as the uncertain parameter were investigated in previous sections. Here, the problem with both price and generation/load uncertainties are evaluated.

In [95, 96] a risk-based multi-objective optimization model has been presented for generation and transmission planning problems in which electrical load in total investment cost of the system have been considered to be uncertain parameters for which uncertainty modeling has been done using IGDT. In former sections, output uncertainty problem of renewable generation units like the wind was completely discussed. In studied papers, the only generation of the wind turbine was considered to be the uncertain parameter for which uncertainty modeling was done. In [97], in addition to generation, owner of the wind turbine is faced with the uncertainty of market price. Therefore, using information gap decision theory, uncertainty modeling has been for both outputs of the wind turbine and market price to be robust against possible fluctuation of each mentioned uncertain parameters. In a deregulated energy market, small consumers purchase their energy from a retailer. The retailer is responsible for supplying the energy demanded by consumers through available resources. The retailer can either participate in the energy market to purchased energy, or he can use local distributed generation units to generate power locally. There exist two challenges for the retailer in both cases: in the first case, the uncertainty of market price and in the second case, the uncertainty of local units output can make problems for the retailer. So, to handle such mentioned problems, retailer attempts to model uncertainty of market price as well as local units output to have robust performance in the energy market and maximize his benefit [98]. Using the melody search algorithm and Powell heuristic approach, non-convex transmission expansion planning problem is solved in [99] in which electrical load and market price are both considered to be uncertain parameters of the system. Therefore, employing robustness and opportunity and robustness functions of information gap decision theory, uncertainty modeling is done and relevant, appropriate strategies are obtained. In a deregulated power system, operator of the system (DNO) is due to supply demanded energy by consumers through available energy resources. In addition to the types of energy resources, DNO is due to choose, the uncertainty of electrical demand as well as the uncertainty of market price are challenging for DNO. So, employing IGDT which needs less info in comparison with other uncertainty modeling techniques, uncertainty modeling of electrical demand and market price are done in [100]. As mentioned in [100], DNO is faced with different uncertainties. In [101], in addition to the uncertainty of electrical load and market price, uncertainty modeling of wind generation has also been done by information gap decision theory, and consequently, optimal decision-making strategies are obtained for DNO to take the best possible decisions.

4.4. summary of reviewed papers

For more clarification, studied papers in the field of IGDT are classified according to various bases in Table 2. Analyzing the following Table, useful info about the uncertain parameter (which uncertainty is modeled) in each paper, the type of uncertainty model (employed among different models of IGDT), types of programming and problem in each paper which are derived from deep analyzing the papers and planning period can be obtained.

paper	Uncertain parameter			Uncertainty model	Programming	Problem	Planning period(Short-term/Mid-term/Long-term)		
	Price	**Power**[1]	**Both**				**SH-T**	**M-T**	**L-T**
[45]	*			Envelope-bound	MINLP	Operation	*		
[46]	*			Variance-covariance matrices	MINLP	Operation	*		
[47]	*			Envelope-bound	MINLP	Operation	*		
[48]	*			Envelope-bound	MINLP	Operation	*		
[49]	*			Envelope-bound	MINLP	Operation	*		
[50]	*			Envelope-bound	MINLP	Operation	*		
[51]	*			Envelope-bound	MINLP	Operation	*		
[52]	*			Envelope-bound	MINLP	Operation	*		
[53]	*			Envelope-bound	MINLP	Operation		*	
[54]	*			Envelope-bound	MINLP	UC	*		
[55]	*			Variance-covariance matrices	MINLP	UC	*		
[56]	*			Envelope-bound	MINLP	Operation	*		
[57]	*			Envelope-bound	MILP	OPF	*		
[58]	*			Envelope-bound	MINLP	UC	*		
[59]	*			Envelope-bound	MINLP	UC	*		
[60]	*			Envelope-bound	MINLP	UC	*		
[61]	*			Fourier-bound models	MINLP	UC	*		
[62]	*			Envelope-bound	MINLP	UC	*		
[63]	*			Envelope-bound	MINLP	Operation	*		
[64]	*			Envelope-bound	MINLP	Operation	*		
[65]	*			Envelope-bound	MINLP	Operation	*		
[66]	*			Envelope-bound	MILP	OPF	*		
[67]	*			Envelope-bound	MINLP	Operation	*		
[68]	*			Envelope-bound	MILP	Operation	*		
[69]	*			Envelope-bound	MILP	Operation	*		
[70]	*			Envelope-bound	MINLP	Operation	*		
[71]		*		Envelope-bound	MILP	Operation	*		
[72]		*		Envelope-bound	MINLP	OPF	*		
[73]		*		Envelope-bound	MILP	UC	*		
[74]		*		Envelope-bound	MILP	UC	*		
[75]		*		Envelope-bound	MILP	Operation	*		
[76]		*		Envelope-bound	MINLP	UC	*		
[77]		*		Envelope-bound	NLP	Planning			*
[78]		*		Envelope-bound	MINLP	Operation	*		
[79]		*		Envelope-bound	MINLP	Operation	*		
[80]		*		Envelope-bound	MINLP	UC	*		
[81]		*		Envelope-bound	MINLP	OPF	*		
[82]		*		Envelope-bound	NLP	OPF	*		
[83]		*		Envelope-bound	MINLP	OPF	*		
[84]		*		Envelope-bound	MIQCP	OPF			*
[85]		*		Envelope-bound	MIP	Planning			*
[86]		*		Envelope-bound	MINLP	UC	*		
[87]		*		Envelope-bound	MIP	Planning			*
[88]		*		Envelope-bound	MINLP	Planning			*
[89]		*		Envelope-bound	MILP	Operation	*		
[90]		*		Envelope-bound	MINLP	OPF	*		
[91]		*		Envelope-bound	MINLP	OPF	*		
[92]		*		Envelope-bound	SOCP	Operation	*		
[93]		*		Envelope-bound	NLP	Operation	*		
[94]		*		Envelope-bound	MILP	Operation	*		
[95]			*	Envelope-bound	MILP	Planning			*
[96]			*	Envelope-bound	MINLP	Planning			*
[97]			*	Envelope-bound	MINLP	Operation	*		
[98]			*	Envelope-bound	MINLP	Operation	*		
[99]			*	Envelope-bound	MINLP	Planning			*
[100]			*	Envelope-bound	MINLP	Operation			*
[101]			*	Envelope-bound	MILP	Operation	*		

1-Generation/Consumption

Table 2: Summary of reviewed papers in the field of IGDT

5. Conclusion

The uncertainty as one of the major challenging issues for system operators has been broadly studied by many researchers. Since some parameters in power systems have uncertain nature and according to the fact that the forecasts are not always exact, therefore uncertainty modeling is a vital issue in power system studies. As investigated in this paper, many different risk modeling techniques are available that can be used for uncertainty modeling in power systems with various structures and conditions. Each risk modeling techniques has its unique features that differentiate these techniques from one another. It can be concluded that the approach that needs less info in compared with other methods is information gap decision theory. The information gap decision theory involves two main immunity functions that are robustness and opportunity functions. Robustness functions are used to model robustness degree of system faced with uncertainty against the possible increase of risk. On the other hand, opportunity function can be used to determine how benefits can be achieved from possible 'good behaving' of the uncertain parameter.

The untouched research areas are uncertainty modeling of participation of demand response as well as plug-in hybrid electric vehicles aggregators in energy markets, risk-based designing and planning problems of multi-carrier energy systems and micro-grids, security-based designing problem of substations, load growth uncertainty modeling, uncertainty modeling of power plants as well as line availability, uncertainty based designing problem of transmission towers under different weather conditions, disturbance uncertainty modeling in transient stability problems and etc.

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