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Article

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Regional Energy Supply Planning: Chance Constraint Programming

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ABSTRACT

Regional energy planning under uncertainty is an important concept in energy-economy models which makes the planning outcomes closer to reality and enables the decision maker to select the best decision. Reliability of local energy supply and the possibility of long-term access to resources and emissions reduction is an essential step. In this study, an urban energy demand which is supplied by electricity network is investigated with an optimal combination of alternative energy resources such as solar, wind and natural gas during the next 10 years. The optimal combination of fossil energy as well as renewable energies are determined by goal stochastic programming model. Isfahan province in Iran has been selected as a case study. Empirical results indicate that due to the importance of investment and operation costs, the dominant share of energy supply will belong to natural gas, while the shares of solar and wind energies remain constant in the next decade. In sum, the share of solar and wind energies increases by 8% in 10 years and therefore, it is not necessary to increase electricity supply by the network in order to meet annual increasing demand. CO_2 and NO_x emissions will decrease significantly.

Keywords: Stochastic Programming, Goal Programming, Local Energy Planning, Iran
JEL Classifications: Q43, Q47

Notations	
A	Surface swept by wind turbine blade (m^3)
C_{kj}	Variable costs of production ($/kWh) technologies of annual production
co_{kj}	CO2 emission factor for the generating system at the year,(kg/kW)
Cco_j	Public electric power grid reference CO2 emission factor,(kg/kW)
CNO_j	Public electric power grid reference NOx emission factor,(kg/kW)
D_j	Incremental yearly energy consumption (kWh/year)
d_i^+ d_i^-	Under- and over-achievement of generic objectives
E_{kj}	Yearly generated energy for the generating technology at the year(kWh)

Notations	
$E_{pv,avg}$	Average energy produced by a photovoltaic panel(kWh)
$E_{pv,\min}$	Minimum energy produced by a photovoltaic panel(kWh)
$E_{pv,\max}$	Maximum energy produced by a photovoltaic panel(kWh)
$E_{wind,avg}$	average generation of wind energy by a turbine(kWh)
$E_{\text{wind},\min}$	Minimum wind energy generation by a turbine(kWh)
fc_k	Capacity factor
f_j^- f_j^+	Under- and over-achievement of environmental issue goal, (kg/year)

Notations	
HPY	Time of use of plant (h/year)
I_{kj}	Overnight capital cost for the generating system at the year, US$/year
J	Identification of the year under analysis
K	Identification of electric generating technology (1.solar, 2.wind, 3.gas, 4.steam powerplant)
m+ , m-	Under- and over-achievement of economic issue goal,(US$/year)
NO_{kj}	NOx emission factor for the generating system at the year,(kg/kW)
NP	Number of solar panels
NT	Number of wind Turbine
p_j	Gas power plant capacity(kWh)
Pi	Satisfaction degree
$p_{\min}$	Minimum capacity of gas power plant(kWh)

Notations	
$p_{\max}$	Maximum capacity of gas power plant(kWh)
v_j^3	Wind speed Cubic(s/m)
v_j^- v_j^+	Under- and over-achievement of environmental issue goal, (kg/year)
$a_{k,j}$	($)overnight capital cost coefficient grid
a_{grid}	Overnight capital cost coefficient for ($) Technology kth
ρ	Air density
1-φ	The standard normal cumulative distribution function
(D)σ	Standard deviation demand variable
I_{avg}	Average solar radiation

1. INTRODUCTION

Population growth and urban expansion, as well as increasing energy prices have exacerbated power shortage and changing climatic conditions within municipal energy supply systems. These issues are highly interrelated, not only among each other but also with a variety of social, economic, political, environmental and technical factors (Frei et al., 2003). In regional and urban planning, metropolitan areas must be considered as the regions that require energy planning severely. Dense and high population, goods and services dynamism and centralization of services, commercial and industrial activities have turned these areas to major centers of energy consumption.

Energy consumption has increased diffused pollution in large cities, so that their current development in the near future will be faced with productivity slowdown. With the intensification of pollution issue in large cities efforts for solving this problem were also intensified, which leads to the introduction of systems to replace with existing systems of energy supply in large cities. So energy resource allocation requires a multi-criteria decision approach. Nowadays power systems, regulated or deregulated, are exposed to ever more sources of uncertainty, such as fuel prices, demand fluctuations, as well as transmission constraints. This uncertainty and the increasing demand for power raise new challenges for utility planners, whose goal is to provide reliable power to consumers at the lowest possible cost. (Manickavasagam et al., 2015).

Malik et al. (1994) offer an integer linear programming model to optimize the share of new and traditional technologies in the energy system. Ramanathan and Ganesh (1995) proposed an integrated model using multi-objective planning and hierarchical analysis process according to quantitative and qualitative criteria, which is developed for energy resources allocation. This model has been applied to the household sector in India which three scenarios have been developed and national grid only has been used for lighting. Groscurth et al. (1995) developed a model, in which urban and regional energy system was described as information flow networks. This model is a very flexible tool for minimization of dynamic demand, pollutants pollution and monetary costs in a stochastic framework. Bruckner et al. (1997) in a study about the competition among energy technologies in urban energy systems, proposed a dynamic optimization model to analyze the competition and different technologies for logical use of energy and renewable energies. Gas-fired, medium-size cogeneration units are found to be the best solution (30% primary energy and 2% cost savings) in a cost-benefit comparison with a system providing heat from conventional oil-fired boilers and receiving electricity from the inter-regional public grid. Dentcheva and Romisch (1998) optimized power generation operation under uncertainty using stochastic programming. This study determines least cost combination of local energy resources in order to supply consumers' demand. A dynamic model for the short-term operation and a power production planning model are used to introduce the cost-optimal generation of electric power under uncertain load. Lesourd (2001) gained the cost per unit of photovoltaic energy systems using life cycle cost analysis and compared the results with the cost per unit of energy in conventional power plants. He examined the advantages of photovoltaic power plant and concluded that photovoltaic power plant has a comparative advantage. Cormio et al. (2003) developed an energy planning model considering renewable energy resources and environmental constraints for a region in southern Italy. Their model includes some sections such as initial supply, electricity and heat generation and the ultimate consumer. The optimization process, aiming to reduce environmental impact and economic activities, provides feasible generation settlements that take into account the installation of combined cycle power plants, wind power, solid-waste, and biomass exploitation together with industrial combined heat and power (CHP) systems.

Another study has formulated an energy-economy planning model in Portugal using fuzzy multi-objective planning Borges and Antunes (2003). This approach is illustrated to tackle uncertainty and imprecision associated with the coefficients of an input–output energy-economy planning model, aimed at providing decision support to decision makers in the study of the interactions between the energy system and the economy on a national level. Sadeghi et al. (2006) introduced fuzzy linear programming method for optimization of energy supply system in Iran to indicate the approach of application of FLP for optimization, then they figured out FLP is a flexible method that can be a great competitor for other confronting ways. A fuzzy-random interval programming is used by Cai et al. (2009) for the long-term planning of facility capacity. In this case study, multiple conventional (coal, refinery petroleum products, natural gas and nuclear) and renewable (solar radiation, wind, hydropower) energy resources were allocated to multiple end-users (municipal/commercial, industrial, transportation and agricultural sectors) through multiple facilities. A multi-objective linear programming model is proposed by Ren et al. (2010) in which optimal use of energy resources is specified. This model is developed to analyze the optimal operating strategy of a DER (distributed energy resource) system while combining the minimization of energy cost with the minimization of environmental impact which is assessed in terms of CO_2 emissions. Sensitivity analysis indicates that electricity buy-back, carbon tax, as well as fuel switching to biogas, has more or less effect on the operation of DER systems.

Adeyefa and Luhandjula (2011) propose an up-to-date overview of how vital probability theory and multi-criteria decision analysis are to deal with situations that several objective functions and the stochastic nature of data are under one roof in a linear optimization context. The mathematical formulation of the problem and related solution have been developed by MOSLP model. Sampaio et al. (2013) presented a centralized power supply station in the city, which is a combination of possible technologies, including thermal power plants, hydroelectric power plant, wind systems, and photovoltaic systems with their relevant emission pattern.

Koltsaklis et al. (2015) present a multi-regional, multi-period linear mixed-integer linear programming (MILP) model which combine optimization method with consideration of a Monte Carlo approach (MCA) and demand response. This paper indicates an optimization-based method to address the generation expansion planning (GEP) problem of a large-scale, central power system in a highly uncertain and volatile electricity industry environment. The optimization goal considers the minimization of the total discounted cost by determining optimal power capacity additions per time interval and region, and the power generation mix per technology and time period. Saffari et al. (2016) presented a goal programming model, considering environmental and financial goals to introduce an optimal energy supply by renewable energy (wind, solar and natural gas) and nonrenewable energy in order to meet the electricity demands in Isfahan over 10 years. This model considered the annual electrical consumption, the potential of alternative technologies, the valuable and overnight cost of conventional and new power plants for determining the optimal portfolio of supplied energy. The thermal power plants in Isfahan have produced the sizable portion of energy which has been needed in this city, resulting in a major amount of air pollution (CO_2 and NO_x).

2. DESCRIPTION OF CASE STUDY

This research is concentrated on 2010 statistical year. The electricity supply sector in Isfahan province has been composed of two major power plants, namely Montazeri and Isfahan, with 1600MW and 830 MW actual capacity, respectively as well as Hesa gas power plants with 69 MW capacity in 2010. The major fuel used Natural gas, Gasoil and fuel oil. The nominal capacity share of installed thermal power plants in Isfahan province is 8.6% which put the province in a third place however, the share of gross generation of thermal power plant was 11% that caused the first rank for Isfahan province in this year. Regarding total consumption in 2010, it was 12 TWh with overwhelming majority allocated to industrial sector which was 10745.4 GWh, 17% of total industrial electricity demand in Iran. Emission share of the majority of greenhouse gas such as SO_2, NOx, CO_2 and name a few, was 10% in the mentioned year.

Regarding different dimensions of energy supply including economic costs and environmental dimensions, in this research a general and comprehensive regional energy supply framework has been developed with respect to renewable energy such as wind, solar accompanied by conventional power plants which has supplied the demand for energy in Isfahan. Uncertainty has been considered as a key factor in energy supply provision. The structure of the paper is as follows: In the next section, the details of mathematical model is discussed while in the third section data description is presented. Empirical results and main conclusions form fourth and fifth sections, respectively.

3. METHODOLOGY

Goal stochastic programming approach is one of the most interesting approaches which has been developed in order to include uncertainty as the probable stochastic variables that may change in a predefined domain. The Probable distribution function of uncertain parameters can be different in various circumstances. In order to solve the proposed multi-objective model initially, it is necessary to convert it to a single objective model by using goal programming technique. After allocation of related weight and goal, this technique will be implemented by a decision maker.

Goal programming is one of the available techniques for solving a multi-objective problem. In this method, objectives are transformed into goals by establishing associated targets and are then ranked according to their importance. In the sequence, the goals are transformed into deviations, i.e., variables that represent the distance between the target and the actual attainment of the goal. The preference over the goals may be expressed by deviations in priority levels, often referred to as a preemptive formulation or a "utility function." In a goal programming model, the original objective functions are taken to the constraints and a new objective function written in terms of under- and over-achievement of the considered objectives is minimized. As Sampaio et al. (2013) noted that it is not possible for a goal to be positively and negatively deviated at the same time, d^- and d^+ must be zero, or $d^-.d^+ = 0$.

A general goal programming function that weights (g_i) the under and over achievement of objectives (d^+ and d^-) is described by Eq. (1).

$$\text{MinA} = \left\{g_1\left(d_1^-, d_1^+\right), g_2\left(d_2^-, d_2^+\right), \ldots, g_k\left(d_k^-, d_k^+\right)\right\}$$

S.T

$$f_i(x_j)+d_i^+-d_i^-=b_i, i=1,2,3,\ldots,\mathrm{m} \\ \mathrm{x}, d_i^-, d_i^+\geq 0 \tag{1}$$

Goal programming objective function is shown in Eq. (2). For each decision making, undesirable deviations (positive or negative deviations in achieving the goal) of variables are considered. In objective function, due to heterogeneity, deviations are weighted so that all deviations obtain monetary value (e.g. US$) and a neutral deviation presents null weight, which is desirable in researcher's point of view that it can be different based on decision maker's preferences.

$$\min \sum_{2015}^{2025}\left(g_1 v_j^- + g_2 f_j^- + m_j^-\right) \tag{2}$$

Where

g_1: Related weight for positive deviation from environmental goal which is equal to US$ 0.3925 that is the cost of reducing one kilogram CO_2.

g_2: Related weight for positive deviation from environmental goals which is equal to US$ 5.325 that is the cost of reducing one kilogram NO_x.

As it can be seen, positive deviations from environmental goals are the main weights, since due to the expansion of environmental issues v_j^- and f_j^- are considered as negative environmental effects which lead to destruction and degradation as well as social costs, thus they are defined and minimized in target function. In addition, to create a homogeneous weight of these two variables in target function it has been multiplied by one kg CO_2 and NO_x emission costs, respectively, to compare it easily with other variables and minimize according to currency value. In goal programming, objective function minimizes inappropriate deviations. In this study, economic and environmental goals for Isfahan province in Iran is defined in order to suggest new technology systems and obtain an appropriate portfolio of electricity generation from renewable and non-renewable energy resources to fulfill the required demand. In fact, each of the goals show the current status of power supply system in terms of economic costs and pollutants diffused from power plants in Isfahan province.

Eq. (3) shows an economic goal for E_{kj}, annual generated energy for the kth electric generating at the jth year with Variable costs (c_{kj}) and investment cost (I_{kj}) to meet the incremental yearly energy consumption D_j (kWh/year) at a public electric power grid variable cost, C_{grid}, and overnight capital cost, a_{grid}, repectively. Over-achievement (m^+) and under-achievement (m^-) are the economic targets for the problem.

$$\sum_{j=2015}^{j=2025}\left(E_{kj}.C_{kj}\right)+I_{kj}-\left(m_j^+-m_j^-\right)\leq\left(D_j.C_{grid}\right) \\ +\left(a_{grid}\cdot\frac{D_j}{8760}\right), k=1,2,3,4 \tag{3}$$

Eq. (4) and (5) express environmental goals for the annual energy generation with the respective CO_2 and NO_x emissions considering emission coefficients of such pollutants in year j. The right-hand sides express the incremental annual energy demand at an electric power grid CO_2 and NO_x emission level, respectively.

$$\sum_{j=2015}^{j=2025} E_{kj}.\left(CO_{kj}\right)-\left(v_j^+-v_j^-\right)\leq D_j.\left(CCo_{kj}\right), k=1,2,3,4 \tag{4}$$

$$\sum_{j=2015}^{j=2025} E_{kj}.\left(NO_{kj}\right)-\left(f_j^+-f_j^-\right)\leq D_j.\left(CNo_{kj}\right), k=1,2,3,4 \tag{5}$$

Eq. (6) states that total annual energy produced from new technologies (E_{kj}) must be consistent with total annual energy demand (D_j). To satisfy each of the uncertain limitations in this model with a predetermined probability (e.g. $1-p_i$), $p_i \in [0,1]$. It must be noted that all stochastic variables are considered as normal independent stochastic variables. For example, assume that the mean and standard deviation of stochastic variable $\tilde{D}$ is equal to $\bar{D}$ and σ(D), respectively. We consider 1-φ parameter as standard normal cumulative distribution function which its value can be obtained according to corresponding statistical tables. The parameter p_i is determined according to decision maker opinion and is related to satisfaction degree of each constraint in the model. In this research, $(1-p_i)$ is assumed 95%, energy demand and generation are determined ($E_{wind,avg}$, $E_{pv,avg}$) as the normal stochastic variable with mean and standard deviation (using the standard deviation of 10%, 20% and 30%, respectively).

$$\sum_{j=2015}^{j=2025} E_{kj}\geq\overline{D}_j+\varphi^{-1}(1-p_i)\sigma_{D_j};\ k=1,2,3,4 \tag{6}$$

Eq. (7) to (17) are considered technical, functional and environmental constraints related to corresponding technologies to produce energy. Eq. (7) computes average generation of photovoltaic energy for a solar panel that is equal to 40W power multiplied by the average amount of solar radiation per day (I_{avg} (j)). Average generation of wind power is calculated by Eq. (8). Here, the average generation of wind and solar energy are considered stochastic.

$$E_{pv.avg}(j)=40\times I_{avg}\times 365/1000 \tag{7}$$

$$E_{windavg}(j)=\left(\frac{1}{2}.\rho.v^3(j).A\right).365/1000 \tag{8}$$

Eq. (9) to (11) show the maximum harvested energy for each of the energy production technologies such as photovoltaic systems, wind farms and steam and gas power plants. HPY indicates maximum annual working hours of power plants, which is considered 2960 h/year for solar power plants and 8760 h/year for other types of power plants. FC_k shows the capacity factor of power plants which is considered 0.35, 0.3 and 0.4 for photovoltaic, wind, gas turbine power plants, respectively.

$$E_{kj}\leq NP_j * HPY * \mathrm{FC}_k * (\overline{E}_{pv,avg}(j)+ \\ \varphi^{-1}(1-p_i)\sigma_{E_{pv,avg}});\ k=1 \tag{9}$$

$$E_{kj} \leq NT_J * .HPY * \text{FC}_k * (\overline{E}_{wnd,avg}(j) + \varphi^{-1}(1-p_i)\sigma_{E_{wnd,avg}}); k=2 \quad (10)$$

$$E_{kj} \leq HPY.(P_j) * \text{FC}_k;\ k=3,4 \quad (11)$$

Investment costs for each technology are calculated using Eq. (12) to (14), cost coefficient of overnight capital cost in photovoltaic and wind systems (a_{kj}) is multiplied by the capacity of power plants. Gas turbine and other steam technologies overnight capital costs for their capacity ($P_{k,j}$) are calculated using Eq. (14).

$$I_{k,j} \geq \alpha_{k,j}.NP_j * (\overline{E}_{pv,avg,net}(j) + \varphi^{-1}(1-p_i)\sigma_{E_{pv,avg}}); \quad k=1 \quad (12)$$

$$I_{k,j} \geq \alpha_{k,j}.NT_J * (\overline{E}_{wnd,avg,net}(j) + \varphi^{-1}(1-p_i)\sigma_{E_{wnd,avg}}); \ k=2 \quad (13)$$

$$I_{k,j} \geq \alpha_{k,j}.P_{k,j}; k=3,4 \quad (14)$$

Eq. (15) indicates that photovoltaic panels utilization is limited to minimum 100 and maximum 81630. The number of wind turbines is limited to minimum 1 and maximum 127 turbines which is shown by Eq. (16). The lower and upper bounds of gas turbine power plant capacities are assumed between p_{min} (340 MW) and p_{max} (975 MW) in Eq. (17).

$$100 \leq NP \leq 81630 \quad (15)$$

$$1 \leq NT \leq 127 \quad (16)$$

$$p_{\min} \leq P_j \leq p_{\max} \quad (17)$$

4. DATA DESCRIPTION

4.1. Capital Cost and Demand Forecasting

In order to find the optimal generation, overnight and variable costs in the future years must be predicted for each of the alternative technologies (solar, wind, gas). In addition, given that power plants use subsidized fuel and also according to dollar fluctuations, in order to determine real costs of network, capital cost estimation coefficient is used for steam power plants. In order to estimate the capital used in power plant (fossil and non-fossil), the nominal capacity of power plant can be multiplied by the overnight capital coefficient. Obviously, these coefficients change each year, and in the power plant a different coefficient is considered depending on the type of used technology. According to estimated data by US Energy Information Administration (EIA, 2016), capital cost coefficient for solar and wind technologies with decreasing growth rate in future years are estimated −0.022 and −0.0673 and for steam and gas power plants are estimated 0.02 and −0.0231, respectively (Table 1).

In order to estimate demand parameter, electricity consumption in previous years has been assessed and using these predictions future years are predicted based on Growth formula by Eq. 18.

$$y_t = y_0 \cdot e^{gt} \quad (18)$$

Where y is demand level in year t, y_0 is demand level in the base year, g is the growth rate of demand and t is time. Obviously, this form of scenario is only used to obtain supply level in future years so that it is not considered in terms of prediction accuracy. Since the aim is to provide a reliable prediction, first it is necessary to consider different elements of demand such as price, consumer preferences and substitute goods in calculation then predict by presenting models, which are based on demand theories. Therefore, in order to predict consumption in Isfahan within the next 10 years we use costumers' data and average annual consumption ranging

Table 1: Updated capital cost estimates for electricity generation plants [2012]

Electricity generation plants	Overnight capital cost (US$/kW)	Fixed O&M cost (US$/kW)	Variable O&M cost (US$/kWh)
Steam	3246	37.80	4.47
Natural gas	1023	15.37	0.00327
Photovoltaic	3873	24.69	0.00
Offshore wind	6230	74.00	0.00

Table 2: Annual consumption

Year	Number of costumers	Per capita consumption per subscriber (kWh)	Annual consumption (MWh)	Incremental consumption (MWh)
2015	1057749	4687.516	4634923.199	230881.602
2016	1108317	4681.427	4741339.207	241919.5018
2017	1161303	4675.345	4850198.486	253485.0973
2018	1216823	4669.271	4961557.13	265603.6165
2019	1274996	4663.205	5075472.525	278301.4931
2020	1335950	4657.146	5192003.373	291606.4251
2021	1399819	4651.096	5311209.722	305547.4341
2022	1466741	4645.053	5433153.003	320154.9296
2023	1536862	4639.019	5557896.053	335460.7747
2024	1610336	4632.992	5685503.155	351498.3558
2025	1687323	4626.973	5816040.065	368302.6555

from 2001 to 2013, then we obtain annual electricity consumption of Isfahan. Given that considered growth rate during 2000 to 2013 for subscribers and average annual consumption is 0.0467 and −0.024, respectively, we estimate electricity demand in Isfahan (Table 2).

4.2. Solar Radiation and Wind Forecasting Models

For estimating the potential of photovoltaic and wind energy generation in Isfahan from 2015 to 2025, a time series simulation method is proposed. Time series method is the most commonly used renewable energy system optimization routine, in which time series meteorological station data is processed for developing the feasibility study of hybrid systems. The solar radiation quarterly and wind speed quarterly series are analyzed with ARIMA model ranging from 2007 to 2012 with an adjustment to the first order autoregressive process, as suggested by the auto-correlation function. As prescribed by the ARIMA method, the relevant data are used for model construction and 2013 data are selected for model validation. The time series model and forecast are adjusted using Eviews software.

Table 3: Dickey-Fuller test results for solar radiation

	First quarter	Second quarter	Third quarter	Fourth quarter
ADF test results	1497	−3427.0	9415.0	3971.0
ADF test results	−7605.11	−7789.18	−8593.7	4388.11

Table 4: Dickey-Fuller test results for wind speed

	First quarter	Second quarter	Third quarter	Fourth quarter
ADF test results	−201.0	−9537.0	2445.0	−1746.1
ADF test results	−9834.3	−2767.0	−6965.2	−8286.2

Table 5: Energy generation by each technologies (MWh) considering demand uncertainty

Year	Senario 1			Senario 2	Senario 3
	Solar (k=1)	Wind (k=2)	Gas (k=3)	Gas (k=3)	Gas (k=3)
2015	8158	25380	207150	216960	226780
2016	8065	23217	220920	231200	226700
2017	7903	26807	229550	240220	241480
2018	7823	24310	244760	256050	251090
2919	7906	27830	254390	266220	267330
2020	7917	25088	270990	283390	278050
2021	7908	28568	282060	295050	295780
2022	7895	25640	300230	313830	308030
2023	7882	29094	312740	327000	327440
2024	7871	26030	332540	347470	341260
2025	7928	29476	341200	472710	362410

In order to choose an appropriate model, it is necessary to use some of the tests used in time series analysis. The Dickey-Fuller unit root test for solar radiation and wind speed is performed to determine the stationarity of these variables. As shown in Table 3 for each quarter solar radiation series has a unit root with first-order differencing stationary data.

When applied to the data available for Isfahan from 2007 to 2012, the solar radiation ARIMA models for first to fourth quarter are expressed, respectively, by Eq. (19) to (22),

$$y_t^1 = y_{t-1} - 0.348 y_{t-2} + 0.348 \quad (19)$$

$$y_t^2 = y_{t-1} - 0.471 y_{t-2} + 0.471 y_{t-3} \quad (20)$$

$$y_t^3 = y_{t-1} - 0.2 y_{t-2} + 0.2 y_{t-3} \quad (21)$$

$$y_t^4 = y_{t-1} - 0.425 y_{t-2} + 0.425 y_{t-3} \quad (22)$$

The unit root test for wind speed series is reported in Table 4 which is integrated by first-order differencing.

According to the estimated model, Eq. (23) to (26) describe long-term quarterly model wind speed for the first quarter to the fourth quarter.

$$y_t^1 = 0.052 + 0.392 y_{t-1} + 0.608 y_{t-2} \quad (23)$$

$$y_t^2 = y_{t-1} - 0.515 y_{t-1} + 0.515 y_{t-2} \quad (24)$$

$$y_t^3 = y_{t-1} - 0.715 y_{t-1} + 0.715 y_{t-2} \quad (25)$$

$$y_t^4 = y_{t-1} - 0.272 y_{t-4} + 0.272 y_{t-5} \quad (26)$$

Table 6: Energy generation (MWh) considering solar power plants capacity uncertainty

Year	Senario 1		Senario 2		Senario 3	
	Solar (k=1)	Gas (k=3)	Solar (k=1)	Gas (k=3)	Solar (k=1)	Gas (k=3)
2015	7812	197690	7465	198030	7118	198280
2016	7722	210980	7379	211320	7036	211670
2017	7567	219110	7231	219450	6895	219780
2018	7491	233800	7158	234140	6826	234570
2018	7570	241900	7234	243240	6826	243570
2020	7581	258940	7244	259270	6908	259610
2021	7572	269410	7236	26970	6900	279989
2022	7559	286960	7224	287290	6888	287630
2023	7547	298820	7212	299150	6877	299490
2024	7538	317930	7202	318270	6868	318600
2025	7537	457940	7202	329840	6893	327610

Figure 1: Co_2 emission for each of the optimal portfolio of energy resulting from stochastic parameters (ton). Reference: Researcher's results

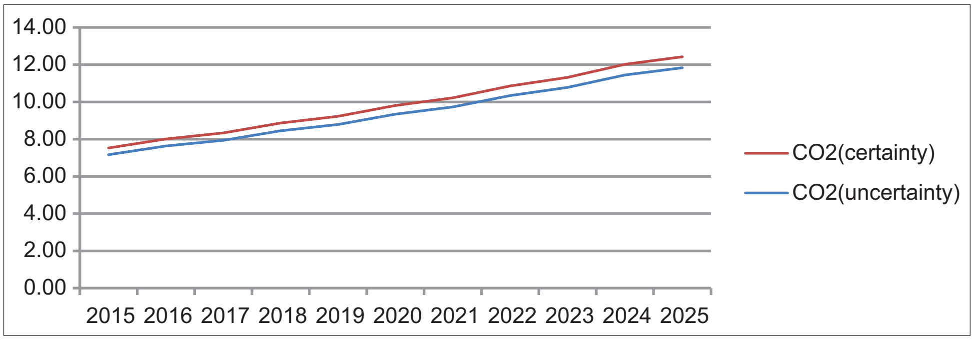

Figure 2: NO_x emission for each of the optimal portfolio of energy resulting from stochastic parameters (ton). Reference: Researcher's results

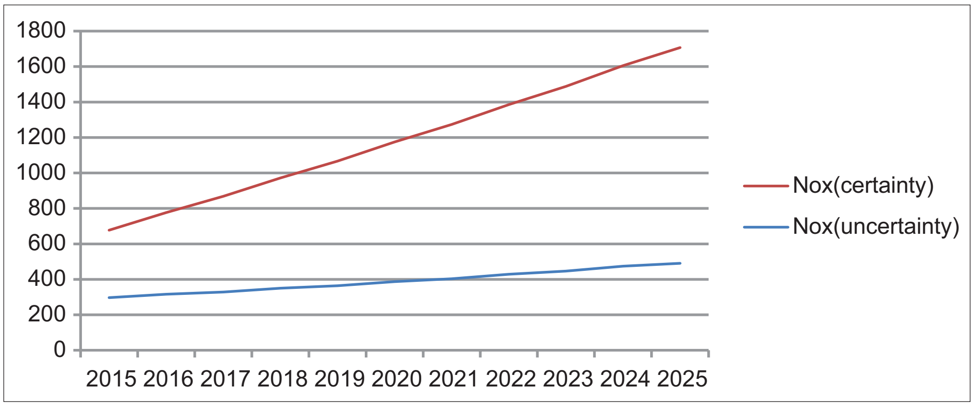

Table 7: Energy production (MWh) considering wind power plant capacity uncertainty

Year	Senario 1		Senario 2		Senario 3	
	Wind (k=2)	Gas (k=3)	Wind (k=2)	Gas (k=3)	Wind (k=2)	Gas (k=3)
2015	24305	198420	23226	199500	22147	200580
2016	22241	211620	21244	212610	20257	213600
2017	25667	219910	24528	221050	23389	222190
2018	23277	234500	22243	235540	21210	236570
2019	26674	243750	25464	244930	24282	246110
2020	24022	259670	22955	260730	21889	261800
2021	27351	270290	26137	271500	24923	272720
2022	24550	287710	23460	288850	22371	289890
2023	27857	299720	26621	300960	25384	302190
2024	24924	218700	23818	319810	22712	320920
2025	28224	172180	26870	331200	25717	197240

Based on the collected data for Isfahan, the electricity demand is predicted until 2025. After obtaining the annual quarterly series, the annual average solar radiation and annual wind speed, the electrical energy produced is estimated by each solar panel or each wind turbine using Eq. (7) and Eq. (8).

5. EMPIRICAL RESULTS AND DISCUSSION

In this section, optimal results of planning are addressed considering stochastic parameters in the first, the second, and the third scenarios with 10%, 20% and 30% standard deviation, respectively. It must be noted that in Tables 6-8 given that variables related to fossil fuel in Isfahan power network are always zero, thus this variable was reported regardless of value, and also considering constant value of wind and solar energy generation in some scenarios, it is addressed in first column of Table 1 to prevent repetitive numbers.

5.1. Demand Sensitivity Analysis

The results of energy planning model for each of the power generation technologies at 95% significance level are presented in Table 5. Obviously, in scenarios 1 to 3 gas energy generation increases and solar and wind energy values remain constant. It can be said that its reason is the high cost of wind and solar energies compared to natural gas. In other words, in proposed model production costs are main drivers that play an important role in energy portfolio selection. The results indicate that with demand uncertainty, the share of natural gas in energy generation exceeds solar and wind energies.

5.2. Sensitivity Analysis of Solar Power Plant Capacity

Average generation of energy produced by solar panels is also considered as the stochastic variable, since solar irradiation at any time of the day has a different value. It can be said that generation

Table 8: Investment costs (Million Dollars)

Year	Demand			Solar			Wind		
	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3	Scenario 1	Scenario 2	Scenario 3
2015	292.0067	316.7571	317.9211	51.98721	51.57059	51.1433	313.783	313.1345	312.486
2016	293.754	319.0273	318.5176	48.24785	47.8544	47.46209	316.1947	315.6787	315.169
2017	299.5055	325.2383	325.3668	49.38557	49.00923	48.63178	322.3065	321.7613	321.2161
2018	309.0638	335.9319	335.395	47.73962	47.37533	47.02199	333.0295	332.5717	332.1133
2019	314.8656	342.1947	342.3122	48.87668	48.62266	48.26177	339.2067	338.7209	338.2355
2020	325.1348	353.6245	353.0722	47.63464	47.28053	46.9286	350.6563	350.2504	349.846
2021	331.5207	360.5502	360.624	48.68538	48.34117	48.99773	357.4981	357.0714	356.6458
2022	342.4764	372.7112	372.138	47.5418	47.20526	46.8686	369.6685	369.3198	368.9616
2023	349.3489	380.1785	380.221	48.52983	48.20066	47.87245	377.0529	376.683	376.3117
2024	360.93	393.0018	392.4153	47.6261	47.30403	46.98312	380.4305	389.5691	389.2637
2025	362.7358	405.6448	395.4618	60.28373	48.21105	47.58763	377.4649	391.6755	378.9079

efficiency of solar panels is variable with solar irradiation change. Obviously, in scenarios 1 to 3 energy generation by photovoltaic panels decreases and generation of energy by natural gas power plants increases, while wind energy generation remains constant because of increasing standard deviations of solar irradiation parameters (Table 6). It is noteworthy that the amount of electricity produced by the network will be zero.

5.3. Sensitivity Analysis of Wind Power Plant Capacity

Regarding Eq. (8), generation of wind energy by each of the wind turbines depends on a cubic value of wind so average energy produced can be considered as the stochastic variable. According to each of the three scenarios, it is clear that as long as wind energy production standard deviations increase, generation of wind energy decreases and generation of electricity by gas increases (Table 7), It definitely by changing scenario the risk of wind energy generation is increasing which is due to capacity changes of wind power plant so the amount of electricity produced from wind power plant are decreasing.

5.4. Pollutants Emission

In order to determine the levels of emissions, the total amount of CO_2 as well as NO_x emissions derived from an optimal portfolio of certain and uncertain are presented in Figures 1 and 2, respectively. As it is shown CO_2 and NO_x emissions are derived for both deterministic and stochastic cases and indicates that in the uncertain conditions pollutant emissions are less than optimal portfolio. It must be noted that NO_x emission decreases significantly, since emission coefficient for this pollutant is more than emission coefficient for the former pollutant (Figure 2).

5.5. Capital Cost

Table 8 presents investment costs for each of the new alternative technologies in defined scenarios. With an increasing standard deviation of demand, total investment costs of new technologies increase, on the other hand investment costs related to wind and solar power plants capacities decrease with increased standard deviations of the parameter.

6. CONCLUSION

Regarding local energy planning issue, a stochastic goal programming model has been used. The empirical results indicate that gas turbine, wind, and solar power technologies will be beneficial alternatives for conventional steam power plants and must be considered as priorities in investment policies. It will initially improve optimal utilization of gas turbine power plants and consequently the optimal share of wind energy is expected to be more than solar energy, and meanwhile steam turbine power plants have no share to fulfill demand. It can be said that advantage of probability distribution assurance method of a random variable is to consider a variable risk in different scenarios. In addition to converting a continuous variable to some discrete parameters, converts model from functional form to parametric form. This method converts the stochastic programming model to a parametric programming model. In this study, the amount of demand, solar radiation, and wind speed are investigated in different scenarios with standard deviations of 10%, 20%, and 30%, respectively. The main findings indicate that:

1. Based on environmental constraints, policy makers should allocate more production between wind and gas power plants when demand is considered as a stochastic variable. As demand grows over the next 10 years, contribution of solar power plant decrease while the amount of wind and gas power plants production increase in the optimal energy production, although in the first scenario the overwhelming allocation goes to gas power plant, a mere 10% and 4% portions are allocated to wind and solar energy, respectively. By changing the scenario of demand from 10% to 20% and 30%, solar and wind power plant production level off while production of gas power plant increases due to the importance of cost.
2. Considering solar power plant capacity as a stochastic variable, its production reaches the lowest point due to an increasing amount of standard deviations of solar radiation parameters and consequently increasing risk of produced photovoltaic energy (Table 6). Consequently, more optimal production is devoted to wind and gas turbine power plants in the first scenario, given the fact that natural gas reserves are an undoubted part in optimal generation basket. It is noteworthy that in the alternative scenarios (increased standard deviation of solar power plant capacity), production of this power plant will continue to decrease, in contrast, the contribution of energy production of gas turbine power plants will increase to meet the demand. In addition, wind power plant remains constant in the alternative scenarios.
3. Similarly, when the capacity of wind power plant is stochastic

(Table 7), in the first scenario, its production will slow down to its lowest level resulting in the concentration of gas and solar power plants generation. Importantly, the order of production contribution by policy maker will be the same as two aforementioned modes with the largest share will be devoted to gas and wind respectively and the smallest share will be allocated to solar energy. It should be noted that in the alternative scenarios, wind power plant production will decrease because of risk increment in the wind energy. Consequently to fulfill demand, gas turbine power plant generation will compensate for the supply and production of solar power plant remains constant due to cost constraints.

It should be noted that with changing from the first scenario to second and third scenarios, the generation of wind and solar power plants stay constant or decline (because of high investment costs) due to risk reduction. In return, gas power plant production share increases. Thus, it can be concluded that in this model, policy makers increase the capacity of solar and wind power plants up to the maximum standard deviation of 10% (first scenario) and by increasing the standard deviation, energy supply will be mostly provided by natural gas power plants. So, cost constraint has a major significant contribution to determine energy production in each power plant compared to the environmental constraint.

Low pollutant emission, lower investment cost and abundance of natural gas are the merits of gas power plants. Regarding wind power plants, it can be said that energy utilization is lower compared to gas power plants but at the same time, it is higher than photovoltaic power plant portion. Regarding photovoltaic power plant, it can be said that although Isfahan province enjoys relatively high radiation, allocating a low portion because of high investment costs. In fact, reduction of CO_2 and NO_x emissions up to 87% show that incremental demand can be met annually by new energy supply system. It can be concluded that despite certain budget and environmental constraint, investment can be directed to renewable energy technologies (Tables 5-8).

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