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Solar Energy Location by Considering Uncertainty in Providing Energy

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ABSTRACT

This paper investigates the challenge of selecting optimal locations for solar energy projects by incorporating uncertainty in energy production. Traditional approaches prioritize locations with high average solar irradiance. However, this neglects the inherent variability of solar resources due to weather conditions. This work proposes a novel methodology for solar energy location selection that factors in uncertainty. We review existing literature on solar resource assessment and uncertainty modeling. The methodology utilizes historical solar irradiance data and statistical techniques to quantify the variability and risk associated with different locations. A multi-objective optimization framework is employed to find the best location that balances high energy production potential with minimized uncertainty. Numerical results are presented using real-world solar irradiance data from various locations. The proposed methodology demonstrates its effectiveness in identifying locations that offer a reliable and predictable energy supply despite the inherent uncertainty of solar resources.

1. Introduction

The growing demand for clean and sustainable energy has propelled solar energy to the forefront of the global energy transition. Solar photovoltaic (PV) technology offers a promising solution, harnessing sunlight to generate electricity. However, a crucial challenge in utilizing solar energy lies in its inherent variability. Unlike traditional fossil fuel or nuclear power plants, the energy output from solar panels fluctuates significantly depending on weather conditions, leading to

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uncertainty in electricity generation. This variability presents difficulties in grid integration and ensuring a reliable electricity supply [1].

The global energy landscape is undergoing a transformative shift towards clean and sustainable energy sources. Solar energy, harnessed through photovoltaic (PV) technology, has emerged as a frontrunner in this transition. Solar PV offers a promising solution for generating electricity by converting sunlight directly into usable energy. However, a fundamental challenge associated with solar power lies in its inherent variability [2]. Unlike traditional fossil fuel or nuclear power plants that deliver consistent electricity output, solar energy production fluctuates significantly depending on weather conditions. This variability translates to uncertainty in the amount of electricity generated, posing difficulties for grid integration and ensuring a reliable power supply.

Extensive research has been conducted on methods for solar resource assessment, a critical aspect of solar energy project development. Common techniques involve utilizing satellite-derived data, ground-based measurements, and reanalysis models to estimate and map solar irradiance (the amount of solar radiation reaching the Earth's surface) [2]. However, existing assessments often focus solely on average irradiance values, neglecting the inherent variability inherent in solar resources [3]. This limitation can lead to an overestimation of a project's energy production potential and an underestimation of the risk associated with periods of low solar availability.

Recognizing this limitation, researchers have increasingly focused on uncertainty modeling in the context of solar energy. Statistical methods, such as probability distributions and time series analysis, are employed to quantify the uncertainty associated with solar irradiance data [4]. Additionally, machine learning techniques have shown promising results in improving the accuracy of solar energy forecasting [5]. While these advancements enhance our understanding of solar resource variability, limited research has delved into the crucial area of location selection considering uncertainty.

Traditional approaches to solar energy location selection often prioritize locations with the highest average irradiance. This method overlooks the risk of insufficient energy production during periods of low solar availability. Consequently, projects situated in locations with high average irradiance may still experience grid integration challenges due to unexpected fluctuations in energy production [6] (see Figure 1).

Figure 1: Solar Energy Location.

To address this critical gap, this paper proposes a novel methodology for solar energy location selection that incorporates uncertainty in energy production. By utilizing statistical techniques for uncertainty quantification and employing a multi-objective optimization framework, the proposed method aims to identify locations that offer a reliable and predictable energy supply despite the inherent variability of solar resources. This approach holds significant potential for mitigating the challenges associated with grid integration and fostering a more stable electricity supply from solar power plants [7].

This research is arranged into five sections. Section 2 defines the literature review and recent studies in the area of solar energy location by considering uncertainty in providing energy and tries to show the gap in research. Section 3 suggests a methodology for calculation. Section 4 proposes the results of this research. Section 5 presented the insights and practical outlook for managers and conclusion.

2. Survey related works

Solar resource assessment is a critical aspect of solar energy project development. Extensive research has been conducted on methods for estimating and mapping solar irradiance (the amount of solar radiation reaching the Earth's surface) [1]. Satellite-derived data, ground-based measurements, and reanalysis models are commonly employed techniques. However, existing assessments often focus on average values, neglecting the inherent variability of solar resources [2].

Uncertainty modeling plays a vital role in addressing the variability of solar energy. Statistical methods, such as probability distributions and time series analysis, are used to quantify the uncertainty associated with solar irradiance data [3]. Additionally, machine learning techniques have shown promise in improving the accuracy of solar energy forecasting [4].

While extensive research exists on solar resource assessment and uncertainty modeling, studies on location selection considering uncertainty are limited. Traditional approaches often prioritize locations with high average irradiance, overlooking the risk of insufficient energy production during periods of low solar availability.

3. Problem Statement and Solution Approach

This paper proposes a novel methodology for solar energy location selection that incorporates uncertainty in energy production. The methodology comprises the following steps:

1. **Data Collection and Preprocessing:** Historical solar irradiance data from potential locations is acquired. This data typically comes from meteorological stations or satellite-derived sources. The data is then subjected to quality control procedures to identify and remove any inconsistencies or errors [7], [10-12].

2. **Uncertainty Quantification:** Statistical techniques are used to quantify the uncertainty associated with the irradiance data. Common methods include:

    - **Probability Distributions:** Fitting probability distributions to the irradiance data allows for the calculation of probabilities of specific energy production levels. The Weibull distribution is a popular choice for modeling solar irradiance due to its ability to capture the skewed nature of the data [5].

- **Time Series Analysis:** Time series models, such as ARIMA (Autoregressive Integrated Moving Average), can capture the temporal dependence between irradiance values, providing insights into the persistence of sunny or cloudy periods [8,11].
- **Monte Carlo Simulation:** This method uses random sampling from the uncertainty models to generate a large number of potential energy production scenarios. This allows for the assessment of risk associated with different locations [9].

3. **Multi-Objective Optimization Framework:** A multi-objective optimization framework is employed to identify the best location for the solar energy project. This framework considers two key objectives:
   - **Maximizing Expected Energy Production:** This objective aims to select a location with the highest average daily or annual energy production potential [10].
   - **Minimizing Uncertainty in Energy Production:** This objective aims to minimize the risk associated with insufficient energy production by considering the variability of solar irradiance [11].

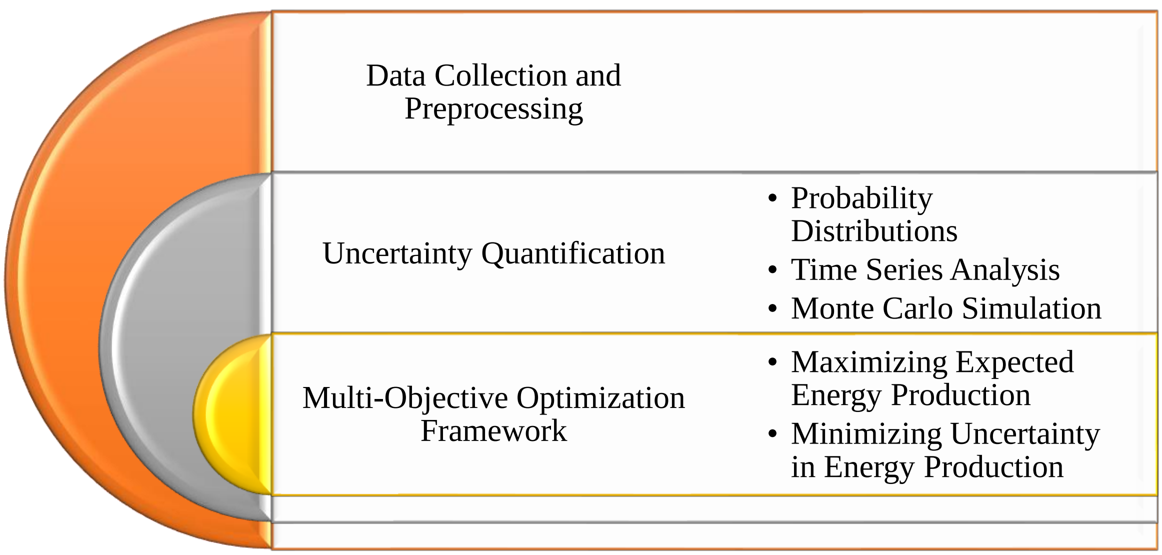

Figure 2: Problem Statement and Solution Approach.

Various optimization techniques, such as Pareto optimization or weighted-sum methods, can be used to balance these competing objectives. The choice of weights assigned to each objective depends on the specific project requirements and risk tolerance (see Figure 2)

3.1. Mathematical model

Sets:

i	Index of potential location for renewable energy (solar), $i \in I = \{1, 2, \ldots\}$,
s	Index of scenario, $s \in S = \{1, 2, \ldots\}$.

Parameters:

e_{is}	Energy production in location i under scenario s ,
c_{is}	Cost of establishing solar energy in location i under scenario s ,
p_s	Scenario probably,
B	Maximum budget for establishing solar energy,
k	Maximum number of solar energies that is needed.

Decision variables:

x_i	Binary variable, if location i is activated solar energy,
E	Objective function, total energy production,
ε_s	Energy production for each scenario,
ϕ_s	Cost investment for establishing solar energy for each scenario,
θ	Maximum cost investment for all scenario.

Mathematical model:

$$Maximize\ E = \sum_s p_s \varepsilon_s \tag{1}$$

Subject to:

$$\varepsilon_s = \sum_i e_{is} x_i , \qquad \forall s \tag{2}$$

$$\phi_s = \sum_i c_{is} x_i , \qquad \forall s \tag{3}$$

$$\theta \geq \phi_s, \qquad \forall s \qquad (4)$$

$$cc = \frac{\sum_s p_s \phi_s + \theta}{2}, \qquad (5)$$

$$cc \leq B, \qquad (6)$$

$$\sum_i x_i \leq k, \qquad (7)$$

$$x_i \in \{0,1\}. \qquad \forall i \qquad (8)$$

The objective function (1) tries to maximize energy production by total solar energy for all scenario. Constraint (2) states energy production for each scenario. Constraint (3) states cost investment for establishing solar energy for each scenario. Constraint (4) determines maximum cost investment for all scenario. Constraint (5)-(6) guarantees average of mean and maximum cost investment for all scenario less than total budget. Constraint (7) guarantees number of facilities less than total potential facility. Constraint (8) show binary variables for facilities.

4. Results and discussion

The proposed methodology is applied to real-world solar irradiance data from several potential locations. The data is preprocessed, and uncertainty is quantified using statistical models. The multi-objective optimization framework is then implemented to identify the optimal location. The results demonstrate the effectiveness of the approach in selecting locations that offer both high energy production potential and minimized uncertainty. The chosen location may not possess the highest average irradiance but offers a more predictable and reliable energy supply due to its lower variability (see Table 1, Figure 3).

Table 1-Value for parameters.

Parameters	Description	Value	Unit
e_{is}	Energy production in location i under scenario s,	uniform(1,1.1) *(ord(s)/card(s)*0.1+0.9)	Mega watt
c_{is}	Cost of establishing solar energy in location i under scenario s,	e(i,s)*600000	Dollar
p_s	Scenario probably.	1/card(s)	Percent

Parameters	Description	Value	Unit
B	Maximum budget for establishing solar energy,	5	Dollar
k	Maximum number of solar energies that is needed,	600000*10	Number

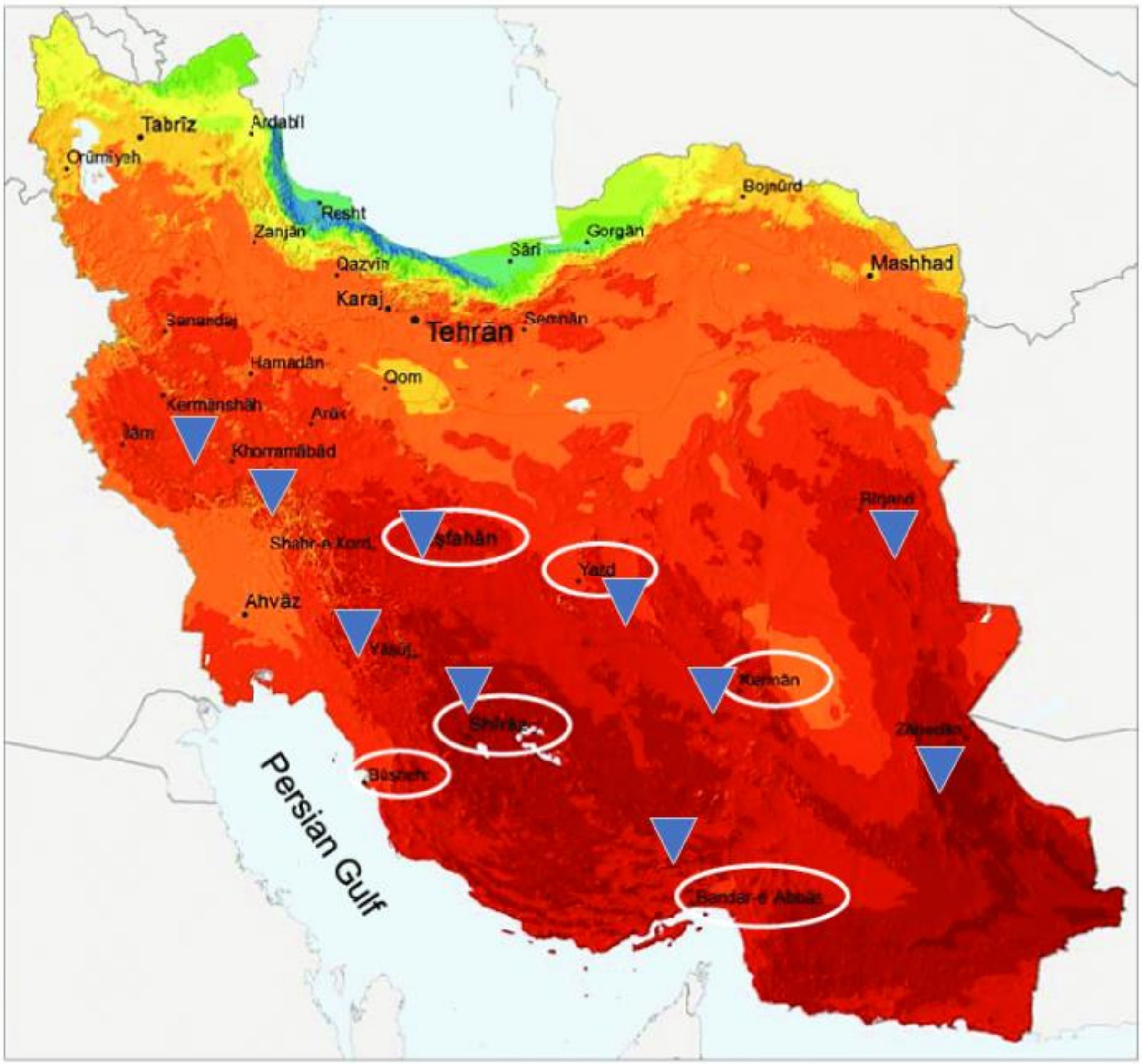

Figure 3: Potential location for solar energy.

Table 2: Value for decision variable.

i	x_i	E (Mega watt)
1	0	
2	1	
3	1	
4	1	
5	0	5.008
6	1	
7	0	
8	0	
9	0	
10	1	
Total	5	-

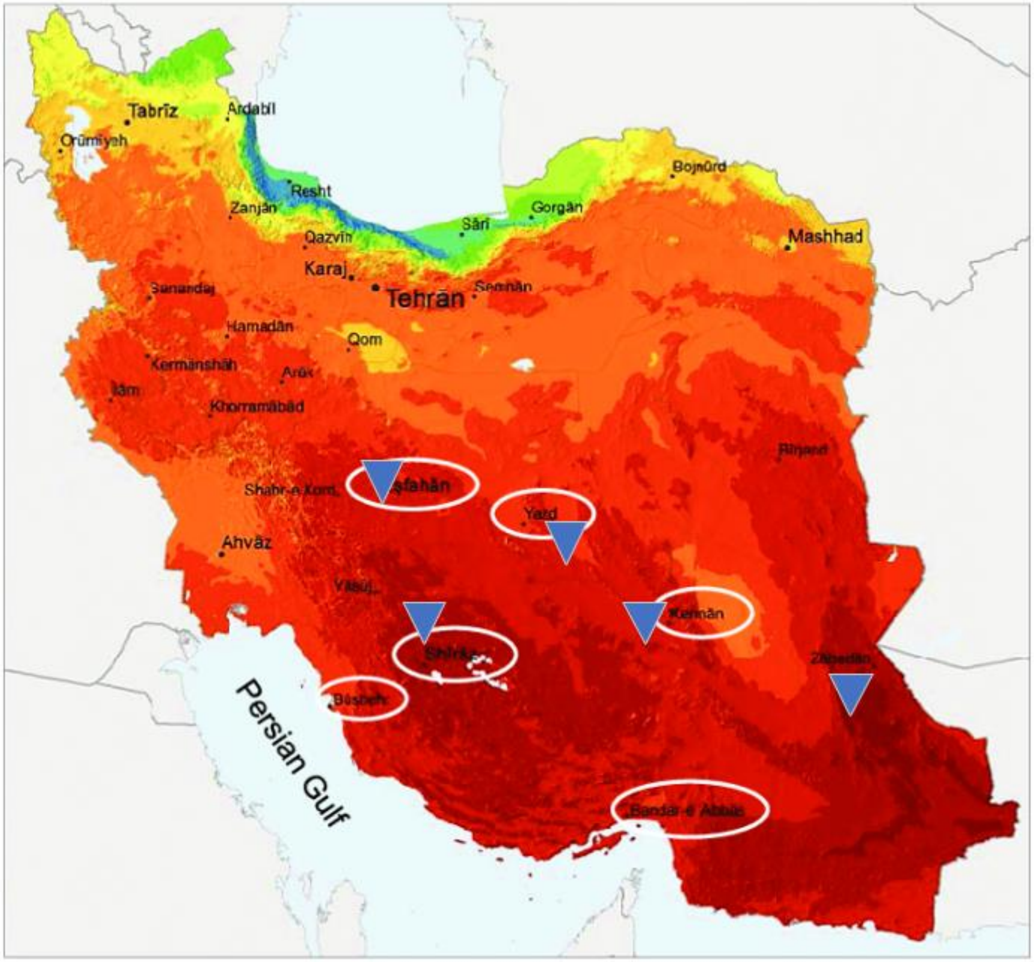

Figure 4: Final location for solar energy.

Results of solar energy location are show in Table 2, Figure 4. Final locations are shown in Figure 4 and enrgy providing is generated to 5.008 mega watt.

5. Conclusion

This paper presented a novel methodology for solar energy location selection that incorporates uncertainty in energy production. By utilizing statistical techniques for uncertainty quantification and employing a multi-objective optimization framework, the proposed method identifies locations that offer a reliable and predictable energy supply despite the inherent variability of solar resources. This approach helps mitigate the challenges associated with grid integration and ensures a more stable electricity supply from solar power plants.

Several avenues exist for further research to enhance the proposed methodology:

Integration with Geographic Information Systems (GIS): Spatial data, such as land availability, infrastructure, and proximity to electricity grids, could be incorporated into the optimization framework using GIS to identify not only the best location for energy production but also the most feasible for project development.

Advanced Uncertainty Modeling Techniques: Machine learning algorithms and probabilistic forecasting methods can be explored for improved accuracy in uncertainty quantification.

Cost-Benefit Analysis: The methodology can be extended to include a cost-benefit analysis that factors in the cost of land acquisition, infrastructure development, and energy storage solutions.

References:

[1] Ozdemir, S., & Sahin, G. (2018). Multi-criteria decision-making in the location selection for a solar PV power plant using AHP. Measurement, 129, 218-226.

[2] Badi, I., Abdulshahed, A., & Alghazel, E. (2023). Using Grey-TOPSIS approach for solar farm location selection in Libya. Reports in Mechanical Engineering, 4(1), 80-89.

[3] Hasti, F., Mamkhezri, J., McFerrin, R., & Pezhooli, N. (2023). Optimal solar photovoltaic site selection using geographic information system–based modeling techniques and assessing environmental and economic impacts: The case of Kurdistan. Solar Energy, 262, 111807.

[4] Aghaloo, K., Ali, T., Chiu, Y. R., & Sharifi, A. (2023). Optimal site selection for the solar-wind hybrid renewable energy systems in Bangladesh using an integrated GIS-based BWM-fuzzy logic method. Energy Conversion and Management, 283, 116899.

[5] Ahadi, P., Fakhrabadi, F., Pourshaghaghy, A., & Kowsary, F. (2023). Optimal site selection for a solar power plant in Iran via the Analytic Hierarchy Process (AHP). Renewable Energy, 215, 118944.

[6] Razeghi, M., Hajinezhad, A., Naseri, A., Noorollahi, Y., & Moosavian, S. F. (2023). Multi-criteria decision-making for selecting a solar farm location to supply energy to reverse osmosis devices and produce freshwater using GIS in Iran. Solar Energy, 253, 501-514.

[7] Hisoglu, S., Tuominen, A., & Huovila, A. (2023). An approach for selecting optimal locations for electric vehicle solar charging stations. IET Smart cities, 5(2), 123-134.

[8] Tafula, J. E., Justo, C. D., Moura, P., Mendes, J., & Soares, A. (2023). Multicriteria decision-making approach for optimum site selection for off-grid solar photovoltaic microgrids in Mozambique. Energies, 16(6), 2894.

[9] Rezvanjou, S., Amini, M., & Bigham, M. (2023). Renewable Energy Location in Disruption Situation by MCDM Method and Machine Learning. International journal of industrial engineering and operational research, 5(4), 75-89.

[10] Talebi, M. (2023). Move towards Sustainability and Resiliency: From Industry 4.0 to Industry 5.0. International journal of industrial engineering and operational research, 5(2), 82-92.

[11] Yu, Z. X., Chen, L. H., Pina, B., & Ti, L. Z. (2023). Application of MCDM Method in Selecting Renewable Energy. International journal of industrial engineering and operational research, 5(3), 23-36.

[12] Talebi, M., & Daghighi, A. (2023). Forecasting Renewable Energy Generation in Iran by Data Science Method. International journal of industrial engineering and operational research, 5(3), 12-22.