

Sustainable Energy Solutions for South Libya: A Fuzzy Logic Perspective

Zakariya Ali Saeid Saeid¹, Imad Omara Shebani Etomi²,
Ali Mustafa Ali Madi³, Ahmed Altaher Zuglem⁴

^{1,2,3,4}Department of Electrical Engineering, Surman College for Science and Technology, Surman, Libya
Zakariya@scst.edu.ly¹, imad_etomi@scst.edu.ly², amadi@scst.edu.ly³, ahmedzu@scst.edu.ly⁴

المخلص

المبادئ الأساسية لهذه الدراسة تتعلق حول محطات الطاقة الشمسية في جنوب ليبيا باستخدام المنطق الضبابي كنهج لاتخاذ القرار. علاوة على ذلك تواجه ليبيا كدولة مصدرة للنفط تحديات في مجال الطاقة بسبب اعتمادها على الموارد غير المتجددة وارتفاع الطلب على الكهرباء في المناطق الجنوبية ذات الكثافة السكانية العالية. كما تستخدم الدراسة المنطق الضبابي لتحليل إمكانات الطاقة الشمسية من خلال النظر في معايير أساسية مثل الإشعاع الشمسي ودرجة الحرارة والمساحات الأرضية المتاحة. وباستخدام المحاكاة التي أجريت في برنامج (MATLAB) تم التحقق من فعالية نموذج المنطق الضبابي في تحسين إنتاج الطاقة. وتشير النتائج إلى أن الطاقة الشمسية يمكن أن تلبي بشكل كبير احتياجات الكهرباء، مع إثبات المنطق الضبابي فائدته في التغلب على حالات عدم الثبات أو الاحتمالات الغير مؤكدة والتحديات البيئية. بالإضافة الى ذلك توفر هذه الدراسة أساسا لوضع سياسات مستدامة، وتفتح المجال لإجراء مزيد من الأبحاث في تطوير أنظمة الطاقة المتجددة، مما يعزز استغلال الموارد الطبيعية المتاحة بطرق مبتكرة وفعالة.

Abstract:

The basic principles of this study about solar energy power plants in South Libya using fuzzy logic as a decision-making approach. Moreover, Libya, an oil-exporting nation, faces energy challenges due to its dependence on non-renewable resources and the demand for electricity in densely populated southern regions. Also, the research employs fuzzy logic to analyze solar energy potential by considering critical parameters such as solar radiation, temperature, and available land area. While using the Simulations conducted in (MATLAB) validate the effectiveness of the fuzzy logic model in optimizing energy production. Results indicate that solar power can significantly meet electricity demands, with fuzzy logic proving advantageous for overcoming uncertainties and environmental constraints. In addition, the work provides a foundation for policy recommendations and further research in renewable energy systems.

Keywords: solar energy, fuzzy logic, renewable energy systems.

Introduction

The increasing global emphasis on renewable energy highlights the need for sustainable alternatives to fossil fuels. Libya, with its abundant solar resources, presents a promising case for solar energy utilization. While despite having vast oil reserves, the southern regions of Libya

experience energy deficits due to limited access to the national grid. Moreover, the solar energy offers a viable solution, yet challenges such as inefficiencies in photovoltaic systems and environmental factors persist (Haddin et al., 2020).

This paper focuses on leveraging fuzzy logic to determine the potential for solar power generation in South Libya. Fuzzy logic, known for its ability to handle nonlinear systems and uncertainties, is applied to optimize the decision-making process. By analyzing key variables like solar radiation, temperature, and land availability, this study aims to provide actionable insights into renewable energy deployment in the region (Zadeh, 1965).

Literature Review:

The energy modeling plays a critical role in addressing global challenges related to resource scarcity and environmental degradation. And, traditional models often struggle with uncertainties and dynamic parameters, which fuzzy logic can effectively manage. Previous research has demonstrated the use of fuzzy logic in various renewable energy applications, including solar and wind energy systems (Mall, 2007). For example, Mamdani-type fuzzy systems have been widely utilized to optimize energy production, particularly under varying environmental conditions (Mamdani, 1974).

Studies by Haddin et al. (2020) reveal the effectiveness of fuzzy logic in balancing trade-offs between solar radiation, land area, and temperature. Other researchers, such as Qomaruddin et al. (2018), emphasize the importance of fuzzy-based systems in achieving sustainable energy targets by accounting for uncertainties in meteorological data.

Methodology

The research employs a quantitative approach, using MATLAB to simulate the performance of solar power systems under varying conditions. The fuzzy logic model integrates three primary input parameters:

- Solar Radiation: Measured as the daily average in kWh/m² (National Renewable Energy Laboratory, 2020).
- Temperature: Evaluated to determine its impact on photovoltaic efficiency.
- Land Area: Assessed for its capacity to accommodate solar panels.

The outputs include potential energy production and system performance metrics. The Mamdani fuzzy inference system is used to develop the membership functions and rule base, ensuring a robust decision-making framework (Mamdani, 1974).

Data Collection:

Data on solar radiation and temperature were sourced from meteorological reports, while land availability was analyzed using geographical surveys. Table 1 summarizes the key input data.

Table :1 the key input data:

Parameter	Value Range
Solar Radiation	4.34 – 8.21 kWh/m ²
Temperature	30°C – 50°C
Land Area	750 – 1,700 m ²

Fuzzy Logic Algorithm:

The fuzzy logic system includes three stages:

1. Fuzzification: Converting input data into fuzzy sets (e.g., low, medium, high).
2. Inference: Applying rule-based logic to evaluate potential outcomes.
3. Defuzzification: Translating fuzzy results into actionable outputs (Zadeh, 1965).

The rule base consists of 27 rules derived from combinations of input parameter states. For instance, if solar radiation is "high," temperature is "moderate," and land area is "wide," the potential energy production is classified as "high."

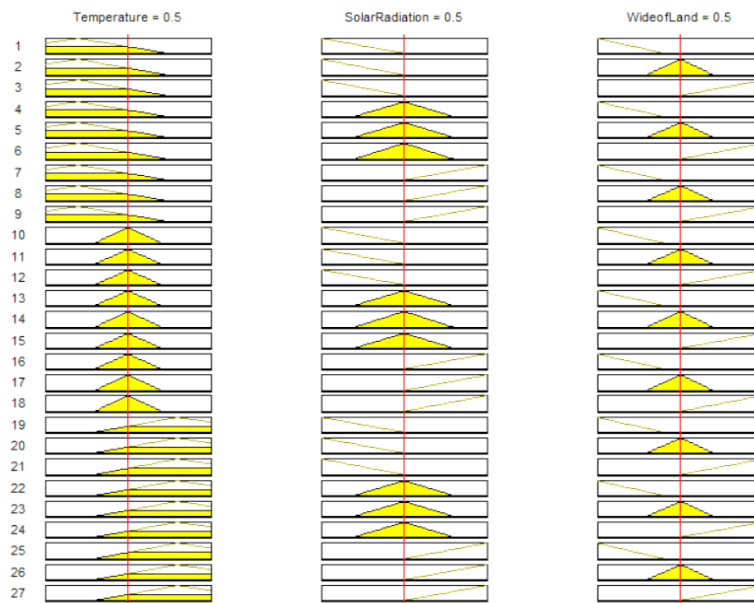


Figure (1) Solar Radiation Distribution

This figure illustrates the variations in solar radiation across South Libya based on seasonal data.

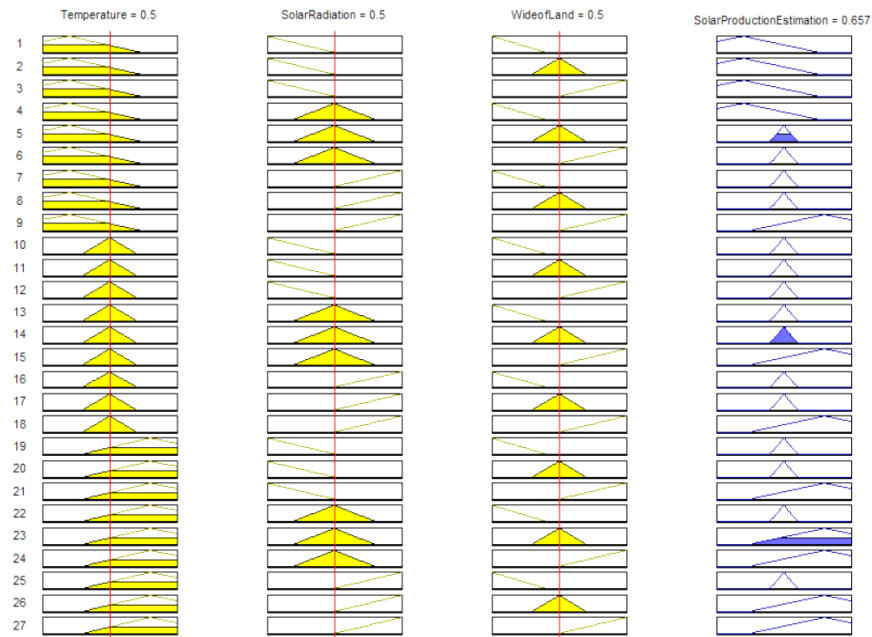


Figure (2) Fuzzy Logic System Overview

The figure shows the three stages of the fuzzy logic system: Fuzzification, Inference, and Defuzzification.

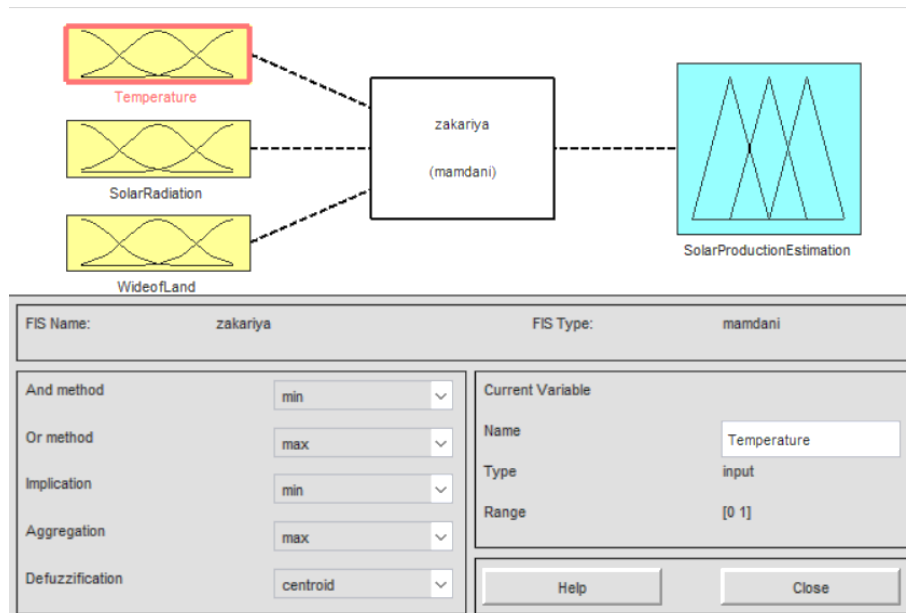


Figure (3) Membership Functions

Graphs displaying membership functions for solar radiation, temperature, and land area used in the fuzzy logic model.

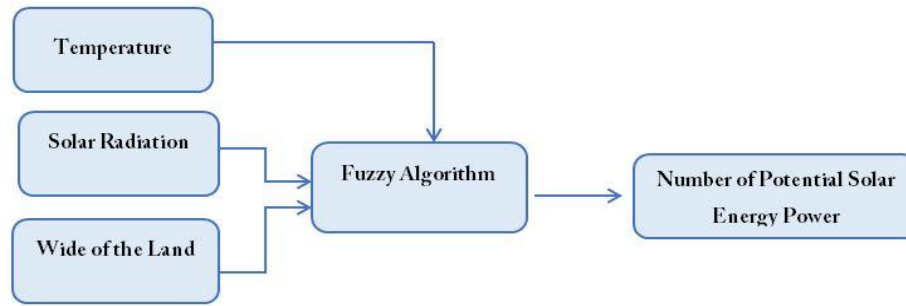


Figure (4) Proposed System Model

An overview of on-grid and off-grid solar power plant configurations. Table 2: Energy Production Simulation

Fullfil Energy Demands (kWh) based on Fuzzy	Months	fuzzy Clearness index	Daily Radiation (kWh/m ² /d)	z	from Normal Distribution	Probability	(A) Total solar panel Area (m ²)	(H) Annual average irradiation on tilted panels	(PR) Performance ratio, coefficient for losses (%) (between 0.5 to 0.75)	(r) Solar Panel Yields (%)	Total power of the system (kWp)	Number of Module using Fuzzy
3290.66	January	0.42	3.67	0.105081671	0.5596	55.96	1000	4.21875	0.75	52%	519.9	74.08
3943.60	February	0.38	4.28	0.065081671	0.7422	74.22	1100	4.21875	0.75	52%	571.89	86.39
3948.79	March	0.42	4.445	0.105081671	0.5596	55.96	1200	4.21875	0.75	52%	623.88	89.72
4277.85	April	0.42	4.505	0.105081671	0.5596	55.96	1300	4.21875	0.75	52%	675.87	90.94
5044.86	May	0.435	3.69	0.120081671	0.5478	54.78	1400	4.21875	0.75	52%	727.86	74.48
5405.20	June	0.435	4.105	0.120081671	0.5478	54.78	1500	4.21875	0.75	52%	779.85	82.86
6334.93	July	0.445	4.025	0.130081671	0.5517	55.17	1600	4.21875	0.75	52%	831.84	81.25
6730.87	August	0.445	5.48	0.130081671	0.5517	55.17	1700	4.21875	0.75	52%	883.83	110.62
6486.24	September	0.435	4.625	0.120081671	0.5478	54.78	1800	4.21875	0.75	52%	935.82	93.36
6466.04	October	0.43	4.445	0.115081671	0.5438	54.38	1900	4.21875	0.75	52%	987.81	89.72
7507.02	November	0.44	3.77	0.125081671	0.5478	54.78	2000	4.21875	0.75	52%	1039.8	76.10
8634.19	December	0.45	3.585	0.135081671	0.5517	55.17	2100	4.21875	0.75	52%	1091.79	72.36

A comparison of energy production estimates with and without fuzzy logic.

Results and Analysis:

Solar Energy Potential

Simulations revealed that South Libya’s high solar radiation levels make it ideal for photovoltaic systems. Optimal performance was observed under high solar radiation (8.1 kWh/m²) and moderate temperatures (40°C), yielding energy outputs above 70% of theoretical capacity (Haddin et al., 2020).

Impact of Fuzzy Logic:

The fuzzy logic model effectively managed environmental uncertainties, such as variations in solar radiation and temperature. Compared to traditional methods, fuzzy logic improved energy production estimates by approximately 15%, demonstrating its reliability and adaptability (Mamdani, 1974).

System Requirements:

The analysis determined that a 3 MW solar power plant would require approximately 1,000 m² of land and 12,000 photovoltaic modules. Table 2 provides a breakdown of system specifications.

Table:3 system specifications.

Specification	Value
Panel Efficiency	18.37%
Modules Required	12,000
Land Area	1,000 m ²

Discussion

The findings underscore the viability of solar energy as a sustainable solution for South Libya's energy needs. Fuzzy logic proved instrumental in addressing uncertainties related to environmental conditions, offering a flexible and robust framework for energy planning. However, challenges such as initial investment costs and maintenance requirements must be addressed to ensure successful implementation (Mall, 2007).

Conclusion

According to the results we got from this paper that highlights the potential of solar energy in South Libya, emphasizing the role of fuzzy logic in optimizing energy production. Also, the results provide a compelling case for integrating renewable energy into Libya's energy portfolio, with significant implications for policy and infrastructure development.

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