GEOSPATIAL AI-BASED APPROACH TO ASSESS THE SPATIOTEMPORAL SUITABILITY OF ONSHORE WIND SOLAR FARMS IN IRAQ

By

MOURTADHA SARHAN SACHIT ALMUSHATTAT

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfilment of the Requirements for the Degree of Doctor of Philosophy

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DEDICATION

To the soul of my parents who have taken great pains to growing me up

And

To my teachers who providing me with best education

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfilment of the requirement for the degree of Doctor of Philosophy

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Chairman : Associate Professor Helmi Zulhaidi bin Mohd Shafri, PhD
Faculty : Engineering

Nowadays, Renewable Energy (RE), such as wind and solar, play a vital role in meeting the increasing demand for electricity and ensuring a low-carbon future. Unfortunately, the efficiency of wind and solar plants depends on the spatially and temporally fluctuating nature of their renewable resources. These fluctuations have prompted planners and decision-makers to shift toward hybridizing such energies in an effort to make electricity generation more stable. Wind-solar hybrid plants have posed new challenges in evaluating suitable sites that meet the requirements of both types of energy. As a result, site selection models for hybrid power systems (wind-solar) have received wide attention in recent years as being a critical planning problem that needs accurate decision-making.

In the existing literature, the site suitability assessment of dual-energy systems (wind-solar) is frequently addressed as a Spatial Decision-Making (SDM) problem involving numerous climatic, economic, and environmental criteria. In most cases, the input factors are considered constant. However, most of these factors, such as wind speed and solar radiation, change over time. Besides, criteria are often subjectively or objectively weighted, generating biased and non-generalizable solutions. To overcome these challenges, the current research aims to develop a SpatioTemporal Decision-Making (STDM) model based on Geospatial Artificial Intelligence (GeoAI) to locate onshore wind-solar hybrid plants. The presented model seeks to fill in the existing gaps by considering the dynamic nature of decision criteria and formulating novel, more reliable global weights.

To achieve the research goal, a four-stage methodology was drawn. A system of spatial evaluation criteria was first designed based on literature statistics and expert judgments supported by content validity analysis. Second, eXplainable Artificial Intelligence (XAI) was introduced to formulate novel global weights for those criteria. In this context,

global geospatial data for 13 conditioning factors were collected, and 55,619 inventory samples of wind and solar stations worldwide were prepared to train three machine learning (ML) algorithms, namely Random Forest (RF), Support Vector Machine (SVM), and Multi-Layer Perceptron (MLP). SHapley Additive exPlanations (SHAP) algorithm was applied to interpret the results of the superior model and elicit the criteria weights. In a separate third step, a new temporal criterion was developed based on temporal complementarity assessment between wind and solar resources. Pearson's correlation coefficients were utilized to explore the synergistic patterns between the time-series dataset of wind speed and solar radiation across Iraqi territory. Finally, spatial, temporal, and exclusion criteria were incorporated along with AI weights into a unified STDM model using multiple overlay analyses in a GIS environment.

The outcomes of the criteria design demonstrated that 13 factors, with an excellent Kappa value of 0.76, would form valuable content for evaluating the spatial suitability of wind and solar farms. The results indicated the superiority of the RF algorithm in both wind and solar modeling, with an overall accuracy of 90% and 89%, a kappa coefficient of 0.79 and 0.78, and an area under the curve of 0.96 and 0.95, respectively. The XAI-based importance analysis revealed higher weights for technical and economic criteria than for other environmental and social criteria. Top weights were given to the criteria of wind speed and proximity to cities (0.373 and 0.149, respectively) in locating wind farms, and the criteria of proximity to cities and air temperature (0.180 and 0.149, respectively) in locating solar farms. The southwestern regions and some eastern parts of Iraq exhibited significant temporal synergistic patterns spanning more than 6 months of the year that influence spatial decision-making. Our spatiotemporal model identified three hotspots over Iraq—South Dhi-Qar, West Diyala, and East Wasit—with a total area of 3,632 km^2. The hotspots revealed exceptional suitability scores exceeding 0.8, meeting both the spatial and temporal constraints. The reported spots have the technical potential to generate electricity from wind turbines and solar PV cells at rates of 11.88–12.58 MW and 81.31–89.51 MW, respectively.

Overall, this research has led to the development of a new GeoAI-based STDM model that can find the best places to put wind-solar systems with great accuracy and consistency. Analyses of transferability, sensitivity, and uncertainty show that the GeoAI-based STDM model is more reliable than one-dimensional solutions. The advantage of the proposed model is not only to identify the technically, economically, and environmentally appropriate sites but also to ensure that they boast temporal synergistic patterns between renewables for stable power supplies around the clock. Consequently, the need to rely on energy storage systems will decrease, leading to reduced investment costs.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Doktor Falsafah

PENDEKATAN BERASASKAN KECERDASAN BUATAN GEOSPATIAL BAGI MENAKSIR KESESUAIAN SPATIOTEMPORAL BAGI LADANG ANGIN SOLAR DI DARATAN DI IRAQ

Oleh

MOURTADHA SARHAN SACHIT ALMUSHATTAT

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Kini, Tenaga Boleh Diperbaharui (RE), seperti angin dan solar, memainkan peranan yang penting dalam memenuhi permintaan yang meningkat terhadap tenaga eletrik dan memastikan masa hadapan rendah karbon. Malangnya, keberkesanan loji angin dan solar bergantung kepada sifat turun naik masa dan ruang bagi sumber boleh diperbaharui mereka. Turun naik tersebut telah mendorong perancang dan pembuat keputusan untuk beralih kepada menghibrid tenaga tersebut supaya penjanaan tenaga eletrik menjadi lebih stabil. Loji hibrid angin solar telah menimbulkan cabaran baharu dalam menilai tapak yang sesuai bagi memenuhi keperluan bagi kedua-dua jenis tenaga. Akibatnya, model pemilihan tapak bagi sistem kuasa hibrid (angin-solar) telah menerima perhatian yang meluas sejak kebelakangan ini sebagai masalah perancangan yang kritikal yang memerlukan pembuat keputusan yang tepat.

Dalam literatur yang sedia ada, penilaian kesesuaian tapak bagi sistem dual tenaga (angin-solar) sering digarap sebagai masalah Pembuat Keputusan Spatial (SDM) yang melibatkan pelbagai kriteria iklim, ekonomi, dan persekitaran. Dalam kebanyakan kes, faktor input dianggap sebagai konstan. Walau bagaimanapun, kebanyakan faktor tersebut, seperti kelajuan angin dan radiasi solar berubah dari masa ke semasa. Di samping itu, kriteria tersebut kerap digarap secara subjektif dan objektif, penjanaan yang berat sebelah dan penyelesaian tanpa boleh digeneralisasikan. Bagi mengatasi cabaran tersebut, penyelidikan ini bertujuan untuk membangunkan model Pembuat Keputusan SpatioTemporal (STDM) berasaskan Kecerdasan Buatan Geospatial (GeoAI) bagi mengesan loji hibrid angin solar di daratan. Model yang dibentangkan bertujuan untuk mengisi jurang dengan mengambil kira sifat dinamik kriteria keputusan dan memformulasikan beban global yang novel, lebih reliabel.

Bagi mencapai matlamat penyelidikan, pendekatan empat peringkat telah dilaksanakan. Satu sistem kriteria penilaian spatial pertamanya telah direka bentuk berdasarkan statistik literatur dan pertimbangan pakar yang disokong oleh analisis validiti kandungan. Kedua, Kecerdasan Buatan Boleh Dijelaskan (XAI) telah diperkenalkan bagi memformulasi beban global novel bagi kriteria tersebut. Dalam konteks ini, data geospatial global bagi 13 faktor penyesuaian telah dikumpul, dan 55,619 sampel inventori angin dan stesen solar di seluruh dunia telah disediakan bagi melatih tiga algoritma pembelajaran mesin (ML), iaitu Hutan Rawak (RF), Mesin Vektor Sokongan (SVM), dan Perseptron Pelbagai Lapis (MLP). Algoritma Penerangan Berdaya Tambah SHapley (SHAP) telah diaplikasikan bagi menginterpretasikan keputusan model superior dan mendapatkan beban kriteria. Dalam langkah ketiga yang berasingan, kriterion temporal baharu telah dibangun berasaskan penaksiran komplementariti temporal antara sumber angin dan solar. Koefisien korelasi Pearson telah dimanfaatkan untuk menyelidiki pola sinergistik antara dataset siri masa kelajuan angin dan radiasi solar merentasi wilayah Iraq. Akhirnya, kriteria spatial, temporal, dan penyisihan telah diinkorporasikan bersama dengan beban AI ke dalam model STDM disatu menggunakan analisis tindihan atas berbilang dalam persekitaran GIS.

Dapatan bagi reka bentuk kriteria memperlihatkan bahawa 13 faktor, dengan nilai Kappa 0.76 yang sangat cemerlang, berupaya untuk membentuk kandungan yang berharga bagi menilai kesesuaian spatial bagi ladang angin dan solar. Dapatan memperlihatkan keunggulan algoritma RF dalam kedua-dua permodelan angin dan solar, dengan masing-masing ketepatan keseluruhan 90% dan 89%, koefisien kappa 0.79 dan 0.78, dan kawasan di bawah lengkungan masing-masing 0.96 dan 0.95. Analisis kepentingan berasaskan XAI menunjukkan beban yang lebih tinggi bagi kriteria teknikal dan ekonomi daripada kriteria persekitaran dan sosial yang lain. Beban teratas telah diberikan kepada kriteria kelajuan angin dan kedekatan pada bandar (masing-masing, 0.373 dan 0.149) dalam mengesan ladang angin dan kriteria kedekatan pada bandar dan suhu udara (masing-masing, 0.180 dan 0.149) dalam mengesan ladang solar. Wilayah barat daya dan beberapa bahagian timur Iraq memperlihatkan pola sinergistik temporal yang signifikan menjangkau lebih daripada enam bulan tahun berkenaan yang mempengaruhi pembuat keputusan spatial. Model spatialtemporal kami mengenal pasti tiga kawasan panas di Iraq—Selatan Dhi-Qar, Barat Diyala, dan Timur Wasit—dengan keseluruhan kawasan 3,632 km^2. Kawasan panas memperlihatkan skor kesesuaian yang luar biasa melebihi 0.8, memenuhi konstrain kedua-dua spatial dan temporal. Kawasan yang dilaporkan tersebut mempunyai potensi teknikal untuk menjana tenaga eletrik daripada turbin angin dan sel PV solar, masing-masing pada kadar 11.88–12.58 MW dan 81.31–89.51 MW.

Keseluruhannya, penyelidikan ini telah membawa kepada pembangunan satu model STDM berasaskan GeoAI baharu yang dapat menyediakan tempat yang paling baik untuk meletakkan sistem angin solar dengan ketepatan dan ketekalan yang mantap. Analisis keterpindahan, sensitiviti, dan ketidaktentuan menunjukkan bahawa model STDM berasaskan GeoAI adalah lebih reliabel daripada penyelesaian matra tunggal. Manfaat model yang disyorkan ialah ia tidak sahaja dapat mengenal pasti tapak yang sesuai secara teknikal, ekonomik dan persekitaran tetapi ia juga memastikan bahawa ia mengutarakan pola sinergistik temporal antara bekalan tenaga stabil yang boleh diperbaharui sepanjang masa tersebut. Akibatnya, keperluan untuk bergantung kepada sistem penyimpanan tenaga akan menurun, yang membawa kepada pengurangan kos pelaburan.

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AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
AT	Air Temperature
AUC	Area Under the Curve
BL	Boolean Logic
BWM	Best Worst Method
CI	Cloud Index
CMIP	Coupled Model Inter-comparison Project
CSP	Concentrating Solar Power
CVI	Content Validity Index
DT	Decision Tree
E	Elevation
EWM	Entropy Weighting Method
EZI	Exclusion Zones Index
GCM	General Circulation Model
GHI	Global Horizontal Irradiation
GIS	Geographic Information System
GPS	Global Positioning System
HadGEM2-AO	Hadley Centre Global Environment Model version 2 Atmosphere Ocean
I-CVI	Item-level Content Validity Index
IMS	Iraqi Meteorological Stations
KNN	K-Nearest Neighbors
LC	LandCover

LULC	Land Use/Land Cover
MCDM	Multi Criteria Decision Making
MERRA	Modern-Era Retrospective Analysis for Research and Applications
ML	Machine Learning
MLP	Multi-Layer Perceptron
ND	Natural Disasters
PC	Proximity to City
PCC	Pearson's Correlation Coefficient
PD	Population Density
PG	Proximity to Grid
PR	Proximity to Road
PV	Photovoltaic
QSL	Quality, Similarity, and Latest
RCP	Representative Concentration Pathway
RE	Renewable Energy
RF	Random Forest
RI	Random Index
RMSE	Root Mean Squared Error
ROC	Receiver Operating Characteristic
RS	Remote Sensing
S	Slope
S-CVI	Scale-level Content Validity Index
SDM	Spatial Decision Making
SHAP	SHapley Additive exPlanations
SR	Solar Radiation
SRTM	Shuttle Radar Topography Mission

SSS	Solar Spatial Suitability
STDM	SpatioTemporal Decision-Making
SVM	Support Vector Machine
T	Tolerance
TCI	Temporal Complementarity Index
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
VIF	Variance Inflation Factor
WD	Wind Density
WLC	Weighted Linear Combination
WS	Wind Speed
WSC	Wind Shear Coefficient
WSS	Wind Spatial Suitability
WSSS	Wind-Solar Spatial Suitability
WSSTS	Wind-Solar SpatioTemporal Suitability
XAI	eXplainable Artificial Intelligence

CHAPTER 1

INTRODUCTION

1.1 Background

Energy is an essential factor connected to the quality of life. Energy demand is increasing due to population growth, urbanization, and rapid industrialization in many parts of the world (Karunathilake et al., 2020; Shahbaz & Lean, 2012). Energy systems that are based on fossil fuel resources (e.g., oil, gas, and coal) affect the economies of any country because such resources have limited reserves (Sbia et al., 2017). Moreover, greenhouse gas releases from burning fossil fuels are the prime driver of global warming above pre-industrial levels (Mensour et al., 2019). As a result, researchers and industry practitioners have become interested in solving this problem, and recent years have witnessed considerable interest in utilizing alternative energy sources.

Renewable energy (RE) has become a significant source of electricity in recent years to meet the growing energy demand and contribute to undermining climate change (Rediske et al., 2020). In particular, wind and solar energy systems are the most mature and popular green energy sources being explored globally due to their cleanliness degree, availability, capacity factor, and construction cost compared to other clean energy sources (Adedeji et al., 2020; Bajpai & Dash, 2012; W. Chen et al., 2017). According to the -2°C climate target, worldwide wind and solar PV should develop from about 3.5% and 1%, respectively, of total electricity generation in 2015 to 36% and 22%, respectively, in 2050 (Solaun & Cerdá, 2019). The challenges of providing huge lands for such investments on the one hand, and the temporal and spatial fluctuations of wind and solar resources on the other hand, prompted planners to shift towards the hybridization of RE systems in an attempt to make electricity generation more stable and less expensive (Saraswat et al., 2021). Wind-solar hybrid systems obtain efficiencies higher than that could be obtained from a single power source (Amer et al., 2013). However, as they are quite complex due to multiple generation systems, exploring suitable sites that meet standard operating conditions for both types of energy (wind and solar) poses new challenges for researchers and decision-makers (Khare et al., 2016).

The site suitability assessment for wind-solar hybrid power generation projects has been one of the most challenging tasks in recent years (Dhunny et al., 2019). This task aims to determine optimal locations for constructing a wind-solar hybrid plant in a study area. The complexity of siting wind-solar systems is the contribution of many factors in the decision process, including technical, economic, and social aspects, as well as natural disasters (W. Chen et al., 2017). In this context, Multi-Criteria Decision Making (MCDM) techniques have been undertaken as a well-known approach in sustainable energy planning since they provide solutions to issues involving multiple and conflicting objectives (Strantzali & Aravossis, 2016). In MCDM, a set of predefined alternatives are evaluated against a set of decision criteria, and then the former is ranked using the latter according to different evaluation techniques (Amjad & Shah, 2020). Commonly, diverse groups of decision-makers are invited to participate in resolving MCDM issues, and each group presents different criteria and judgments, which must be addressed in a framework of mutual understanding and compromise (Zhou, Ang, and Poh 2016). Various MCDM methods have been developed to deal with the complexity of site selection for hybrid power generation projects. The most common methods are Analytic Hierarchy Process (AHP), Fuzzy methods, and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) (Koc et al., 2019; Mohsin et al., 2019; Shao et al., 2020).

Recently, the rapid developments of Artificial Intelligence (AI) have contributed to introducing Machine Learning (ML) models as an alternative approach for decision-making and solving site problems. ML is a computational method that provides systems with the ability to automatically learn and improve performance from experiments (Mohri et al., 2018). It uses statistics and algorithms to develop models that mimic the way humans think (Al-ruzouq et al., 2019). ML models, which have the ability to learn from large data sets, seek to efficiently perform a specific task without using explicit instructions (Han et al., 2022). Generally, ML uses two types of techniques: supervised learning to address classification and regression issues and unsupervised learning to solve clustering problems (Al-ruzouq et al., 2019). Supervised learning algorithms have demonstrated their ability to handle complexity and non-linearity in many site suitability analyses (Kalantar et al., 2021). AI algorithms have been successfully applied to address location suitability, spatial prediction, and hazard susceptibility in different fields (Al-Abadi, 2018; Al-ruzouq et al., 2019; Al-Ruzouq et al., 2021; Almansi et al., 2021; Di Napoli et al., 2020).

Geospatial technologies such as Geographic Information Systems (GIS) and Remote Sensing (RS) are the most common tools used to support spatial analysis due to their ability to handle different data formats (Tarife et al., 2020). GIS, a computer system, is designed to manage and analyze spatial and RS data and is capable to capture, store, and present geographical information (Hassaan et al., 2020; Jahangiri et al., 2016). It is also an indispensable tool in spatial decision-making (SDM), where georeferenced data has an important role (Sun et al., 2020). Essentially, GIS visualizes raw, irrelevant data in a meaningful way when integrated with expert perceptions and/or AI outcomes, saving planning time and cost and achieving informed solutions (Barzehkar et al., 2020). Thus, by combining MCDM, ML, and GIS approaches, a unique and cohesive framework is possible that can handle complex spatial planning problems (Saraswat et al., 2021). AI algorithms, driven by GIS and RS technologies, are currently emerging among the most appropriate approaches for mapping spatial suitability (Al-Ruzouq et al., 2021).

1.2 Problem Statement

As an essential component of the climate change mitigation strategy, the development of wind and solar energy systems enjoys widespread governmental and popular support in various world countries, including Iraq (M. Li et al., 2022). However, the failure to explore suitable sites for implementing these projects may result in reduced efficiency of power plants or even outage in the future. Therefore, site selection for hybrid power systems (wind-solar) is a critical planning problem that needs accurate decision-making due to the difficulty of its assorted factors.

In recent years, several studies have addressed the site suitability assessment of wind-solar farms as an SDM problem involving multiple criteria such as climatic, economic, environmental, and other relevant factors (Asadi & Pourhossein, 2019; Obane et al., 2020; Saraswat et al., 2021). In most of the applied SDM methods, input factors are considered constant. However, most of these factors are of a dynamic nature over time, such as wind speed and solar radiation. Furthermore, criteria are often weighted subjectively or objectively. Subjective weighting is criticized for bias, while objective weighting is not generalizable (Zardari et al., 2014). In other separate works, the assessment of temporal suitability through exploring complementarity patterns between wind and solar resources across time-series datasets is considered (Gallardo, Ríos, et al., 2020; Kapica et al., 2021; H. Zhang et al., 2018). Nevertheless, complementarity studies have neglected criteria with a spatial dimension.

According to the aforementioned challenges, there is an urgent need to introduce a hybrid AI-based assessment model that takes into account the spatial and temporal aspects of decision-making criteria. The target spatiotemporal model can employ real-world experiences (in-situ wind and solar plants) to formulate global weights that are more reliable, generalizable, and free of subjective judgments. The difficulty of the problem is the processing part of the time-series dataset of primary renewable resources: wind speed and solar irradiation. Existing models usually process only raster data, whether continuous or discrete. Therefore, historical datasets are needed to be adapted so that they can be handled spatially along with other factors in a single decision-making model. Another challenge is to train ML algorithms on a global scale to derive the importance of various conditioning factors. The advantage of the improved spatiotemporal model is not only a better understanding of sites that are technically, economically, and environmentally suitable for the deployment of hybrid systems but also that the site has temporal synergistic patterns between renewable resources to ensure stable energy output around the clock. Consequently, the need to rely on energy storage systems will decrease, leading to reducing investment costs.

1.3 Motivations behind This Research

With the fact that our planet is at stake, researchers' efforts are accelerating in an unprecedented way to harness and plan RE. In particular, wind and solar energy are receiving the bulk of the attention due to their abundance around the world, and they are almost negligible impact on the environment. However, their efficiency depends on the spatially and temporally variable nature of wind speed and solar radiation resources. This fluctuation has prompted planners and policymakers to shift towards hybridizing such energies in an effort to make electricity generation more stable. Meanwhile, the investigation of site suitability for wind-solar hybrid plants has become more complicated due to the increasing number of technical, economic, and environmental indicators that must be considered to meet the requirements of both types of energy. Furthermore, for the deployment of wind turbines alongside solar panels to be meaningful, further evaluation is required to confirm that the candidate sites possess promising temporal synergistic patterns among the resources under consideration.

The aforementioned challenges, on the one hand, and the accelerating penetration of AI in various fields, on the other hand, have prompted us to think of formulating intelligent solutions that would implement a spatiotemporal assessment to explore the appropriate locations for wind-solar stations. Moreover, the lack of relevant comprehensive investigations covering developing countries such as Iraq is another motivation for this research.

1.4 Research Objectives

The master aim of this thesis is to develop a decision-making model that would work efficiently for the spatiotemporal assessment of dual-energy systems (wind-solar) based on ML and apply it to the case of Iraq. For the main goal to be practical, it has to be split up into specific objectives as follows:

1. To investigate multiple spatial evaluation criteria and exclusion constraints that impact selecting optimal sites for wind-solar farms.
2. To develop reliable and generalizable ML-based global weights for decision criteria that would work best in SDM models of wind and solar systems.
3. To develop a temporal complementarity map between wind and solar resources covering the entire Iraqi territory to be used as a novel temporal factor in the site suitability assessment for hybrid RE plants.
4. To integrate the SDM model augmented by global weights and the developed temporal complementarity factor into a SpatioTemporal Decision-Making (STDM) model for comprehensive planning of wind-solar energy projects.

1.5 Research Questions

Some of the most exciting questions that we can't yet answer but will address in this study include:

1. What evaluation criteria and exclusion constraints influence the site suitability analysis for wind-solar hybrid plants? How can valid content be designed for these indicators using robust statistical methods?
2. What are the challenges of SDM models currently applied to assess the land suitability of wind-solar systems? Which correction and extra factors can be used to get better results?
3. Unbiased and generalizable weights contribute to informed decision-making. How can ML algorithms and real-world experiences of wind and solar plants worldwide be harnessed to formulate robust global weights for SDM models of hybrid power farms? Do weights based on real-world experiences have transferability to other geographic locations?
4. Temporal complementary patterns between wind and solar resources are necessary for more stable energy production. How are these synergistic patterns distributed spatially across Iraqi territory?

5. What GIS approach can be employed to combine temporal and spatial evidence into a thorough spatiotemporal index? How does the developed temporal complementary factor affect the results of the ML-based SDM model for wind and solar stations across the study area?

1.6 Research Hypothesis

The main endeavor of this research is to develop a comprehensive methodology to explore the spatiotemporal suitability of hybrid power systems. Accordingly, our basic hypothesis is:

"The efficiency and reliability of optimal site selection models to host wind-solar hybrid farms can be increased when spatial and temporal aspects of the decision criteria are integrated."

Spatial aspects, on the one hand, are referred to as technical, economic, environmental, and social factors with a spatial dimension, which will be designed in the first objective of this study. On the other hand, temporal aspects, refer to the dynamic nature of the core renewable resource criteria, which we seek to include in this research by developing the temporal complementarity factor between wind speed and solar radiation. The integration of spatial and temporal factors into a comprehensive spatiotemporal decision-making model would not only shed light on development sites that are technically, economically, and environmentally appropriate, but also ensure the availability of renewable resources around the clock and thus more stability of electricity output.

For the purposes of incorporating different criteria, this study proposes adopting new global weights that would overcome the challenges of subjective and objective weights. In light of this, the following sub-hypothesis can be put in:

"Harnessing real-world expertise of wind and solar plants around the world formulates unbiased and generalizable weightings for decision criteria." The global weights will be free of biases as they do not rely on the subjective judgments of experts. Its generalizability stems from its reliance on capturing the presence and contribution of spatial criteria in RE projects around the world.

1.7 Scope of This Thesis

The scope of this thesis is to design a decision support system based on ML to perform a country-level spatiotemporal suitability assessment for wind-solar hybrid plants. This thesis does not propose a new method of decision-making. More precisely, this thesis aspires to provide an operational tool based on what is already known from decision-making methods and ML algorithms. This unique tool can potentially consider the spatial and temporal aspects of renewable resource criteria. ML-based global criteria weights are a new contribution to the proposed tool workflow. The RE sources targeted in this thesis are onshore wind energy and onshore solar photovoltaic (PV) energy. The entire Iraqi territory was chosen as a study area.

1.8 Thesis Limitations

Although this thesis endeavors to consider various aspects of a spatiotemporal decision support system, it has some limitations as follows:

1. This study has not considered the micro-site assessment, which refers to identifying the layout of the energy unit through the techno-economic comparison. Instead, the current work has focused on the macro-site assessment that covers natural resources, topography, proximity to major infrastructure, and environmental and social criteria over vast areas. It is noteworthy that the macro-site assessment is a significant basis for micro-site assessment and power project construction. Therefore, the results of the current work will pave the way for future research work at the micro-level.
2. The second limitation relates to the data applied in the study. The lack of adequate data based on ground measurements is a common problem in site suitability assessment studies, particularly in developing countries. In this work, therefore, we use some open-access data available from reliable sources. However, the uncertainty associated with the scarcity of site-measured data can be mitigated through field verification of open-access data.
3. The assessment results will not be appropriate for siting offshore wind farms, concentrating solar power plants, or rooftop solar PV systems. However, the proposed STDM model can be adapted to consider the assessment criteria related to these RE types. It is worth noting that Iraq lacks beaches that can accommodate the installation of offshore wind turbines. Moreover, the country is still young in solar energy technology. Thus, the current work directions for assessing the onshore wind and solar PV systems are best suited for the applications of the study area at present.

1.9 Thesis Organization

The thesis is divided into the following five chapters:

Chapter 1: Introduction

This chapter gives a general study background, problem statements, and specific research objectives. Moreover, the chapter highlights the research questions, the scope of the study, and the thesis limitations.

Chapter 2: Literature Review

This chapter overviews the available models and discusses several relevant and essential studies. It provides a comprehensive review of the methodologies applied in the context of a spatial suitability assessment and temporal complementarity assessment.

Chapter 3: Materials and Methodology

This chapter describes the various steps required to implement the proposed methodologies, including data acquisition and processing, design of experiments, and training and evaluation of models.

Chapter 4: Results and Discussion

This chapter discusses the outcomes of the experiments carried out under the specific research objectives and offers a body of proof regarding the validity and dependability of the models for real-world use.

Chapter 5: Conclusions and Recommendations

This chapter summarizes the significant research findings and offers recommendations and suggestions for future work.

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