

Advanced Model Of Solar Power Forecasting Systems In Constructions

K.Poornima¹, Sonu Kumar Sah², Ashok Kumar Yadav³, Satya Prakesh Rana⁴

¹Assistant Professor, ^{2,3,4}Research scholar, Department of Civil Engineering, Excel Engineering College, Komarapalayam - 637303

Abstract

In order to advance the field of solar power forecasting, the public, business, and academic sectors collaborated, and the results are reported in this study. Under the direction of the National Centre for Atmospheric Research (NCAR), the project used a value chain strategy to capitalise on team members' visions and advance towards the ultimate objective of enhancing the economics of solar energy deployment. This paper examines the collaborative design process, talks about the outcomes of the project, and offers suggestions for "best practise" solar forecasting.

Keywords

Solar power forecasting, Sunforecasting, atmospheric research, WRF- solar.

Introduction

Energy is essential to the current human society. It is essential to any country's socioeconomic development. Thus, the availability of energy and a nation's level of development are closely related. In countries all around the world, as wealth and economic opportunities increase, so does energy consumption [1]. Thus, the need for energy generation has grown over time. This problem has two important aspects. First off, the current pattern of energy generation is unsustainable because the majority of energy generation units rely on fossil fuels. It endangers human life and is a serious threat to the environment [2-4]. The main component of any nation's economic growth is energy. Energy consumption is therefore a barometer for the country's growth pace. The two primary categories of energy sources are defined as renewable and non-renewable. The scarcity of non-renewable energy resources stems from their protracted replenishment period. Power plants can generate additional power on demand to these non-renewable resources. The foundation of non-renewable energy resources is natural gas, oil, coal, and nuclear power. These natural resources are depleting over time because the sources do not refill. With the exception of nuclear energy, which is frequently referred to as "zero-carbon" or "low-carbon" energy, the majority of renewable energy sources are environmentally harmful [5-9].

Solar Power production (SPG) is the technical term for a power production process that uses solar energy to create electricity. It makes use of solar panels, which are frequently placed atop structures or concentrated in solar farms, to accelerate a process that turns solar radiation into electrical power. In a solar panel, photovoltaic (PV) cells convert sunlight into direct current (DC) power [6-10]. The DC electricity is then changed into alternating current (AC) electricity via an inverter. The electricity is then either used, fed back into the system, or stored in a battery after this process has taken place. The cost of generation is contingent upon the quantity, configuration, and location of the panels; nevertheless, in general, the cost of solar electricity is declining annually [11-14].

The amount of solar energy that reaches the Earth's surface is 1,20,000 TW, or 20,000 more than what the world requires. Therefore, it is crucial to efficiently convert solar energy into electricity and integrate it into the grid so that it may be distributed and used where it is needed. Solar energy is also self-renewing, limitless, and non-contaminating [15-16]. For these reasons, producing electricity from solar energy differs from other methods of energy conversion. In many parts of the world today, renewable energy sources—more especially, solar energy conversion techniques—are more affordable than traditional energy [17]. They stand out for being more affordable and, in many cases, are just as good as traditional sources. Renewable energy is already emerging as the most environmentally and financially viable option due to economies of scale and innovation.

The first stage in harvesting solar electricity is converting the sun's energy, or irradiance, into usable power. Some of this energy is attenuated by clouds and atmospheric particles on its way to the Earth's surface, which reduces the available irradiance depending on the atmospheric conditions. The volatility in solar power availability becomes a crucial aspect as utilities work to preserve grid stability and plan for the next day's unit allocations (Fig 1). Therefore, with the increasing rate of solar power integration into the national electric grid, it is becoming increasingly important to overcome the normal forecasting challenges of this highly variable renewable resource (Fig 2).

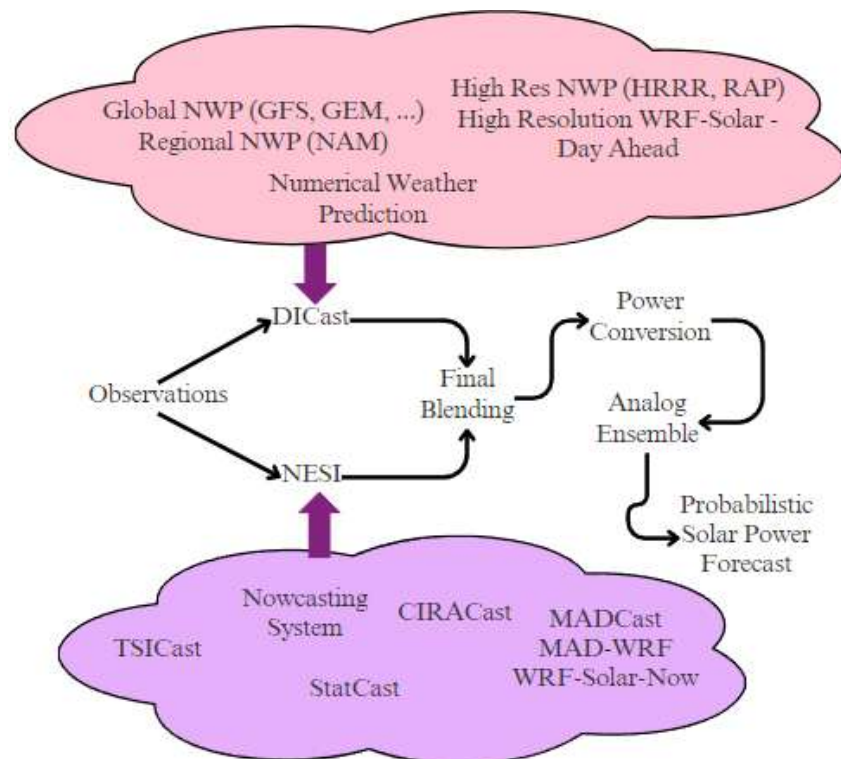


FIG. 1. The Sun4Cast forecasting technology in multiscale predictions.

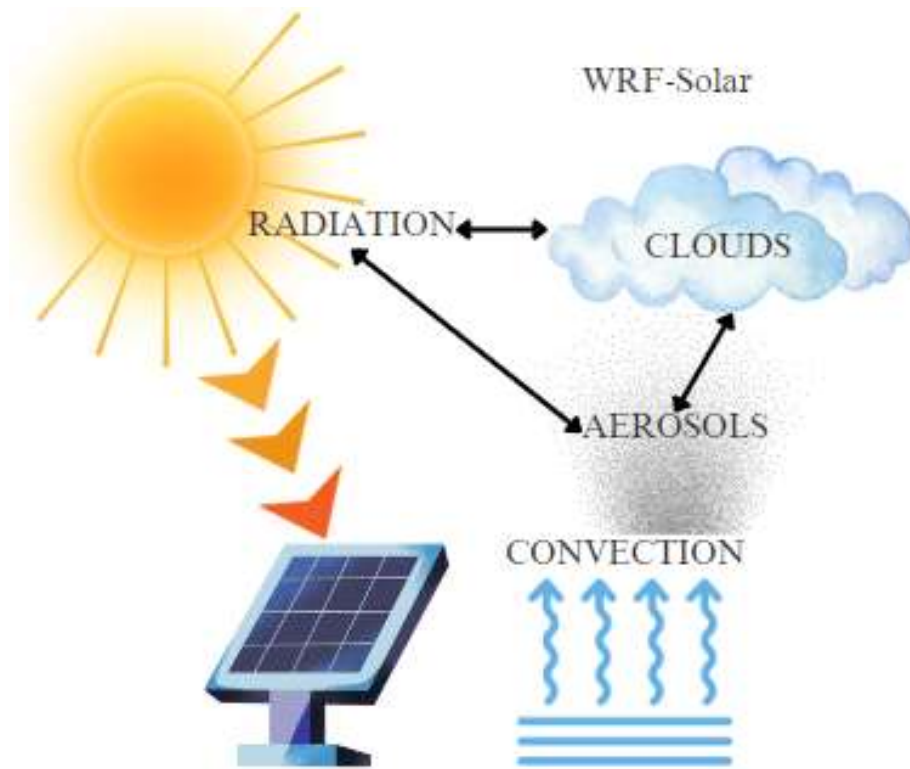


FIG. 2. Diagram showing the WRF-Solar augmentations that now include specific interactions between radiation, clouds, and aerosols.

Materials and methods

In response to the increasing need for specialised forecast products for solar energy applications, the Weather Research and Forecasting (WRF) Model (WRF-Solar) was created. The goal of the research was to enhance WRF-Solar's solar configuration, which is utilised by the DICast and NESI systems. For a wide variety of sites, the ECMWF global model greatly outperformed the GFS-driven WRF Model; this was mostly because of shortcomings in cloud modelling and data assimilation. The initial improvement was to incorporate fluctuations in Earth's orbit eccentricity and obliquity into the solar-tracking algorithm. Diffuse (DIF) and direct normal irradiance (DNI) components from WRF-Solar were introduced in the second upgrade.

The short-range forecasting methods are the Cooperative Institute for Research in the Atmosphere (CIRA) Nowcast, WRF-Solar-Now, MAD-WRF, Multisensor Advection-Diffusion Nowcast, and NESI system, which offers an illumination forecast with a time range of 0 to 6 hours. With its ability to operate on the smallest time scale, TSICast is a ground-based cloud imaging and tracking system that makes it possible to identify

Results and discussion

Forecasting solar radiation

An essential factor that has a direct impact on the SPG is the design and execution of the solar radiation forecasts based on the WT-MTLBO-OELM model, which is covered in chapter 4. Precise estimation of solar radiation is necessary to accurately estimate the energy output of solar energy systems, contingent on the surrounding conditions. The performance of solar irradiation forecasting using WT-MTLBO-OELM, MTLBO ELM, TLBO ELM, ELM, and ANN model has been examined. The LMD-MTLBO-OELM model is used in this section to forecast solar irradiation. The WT-MTLBO-OELM and MTLBO OELM models were contrasted with the suggested model. The forecasted sun irradiation is now more accurate (Fig 3).

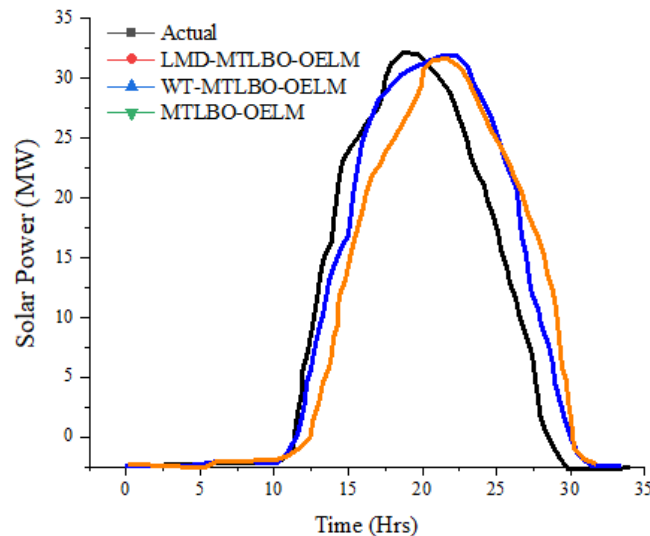


Fig 3: variation of WT-MTLBO-OELM and MTLBO OELM

Analysis of the results

Furthermore, non-parametric tests like the Diebold-Mariano (DM) test (Fig 4) are used to potentially test the suggested model's superiority over competing models. By acknowledging errors related to the anticipated data of each model, the test helps determine how competent a prediction model is in comparison to others.

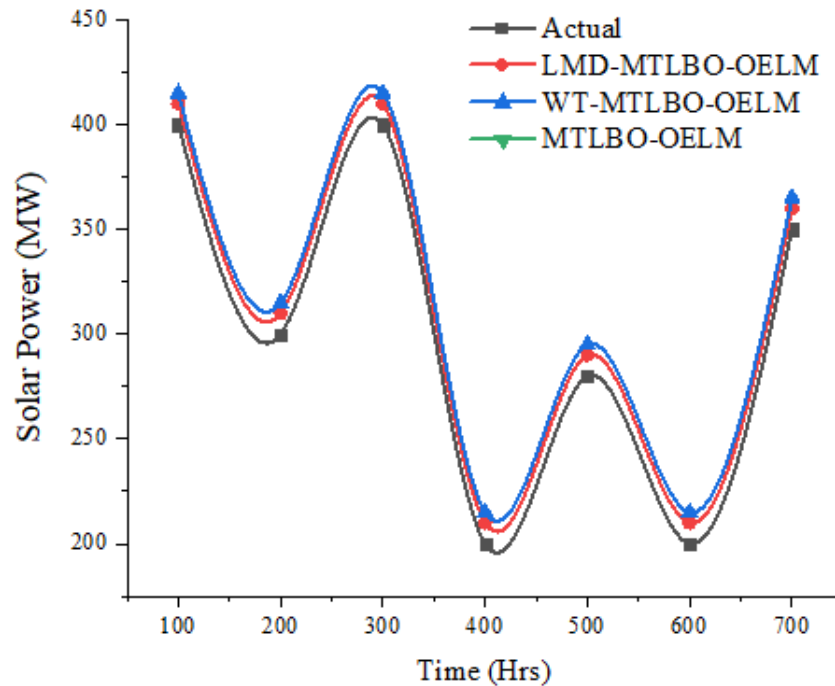


Fig 4: Diebold-Mariano (DM) test

System evaluation and testing. approximately operationalization

Co-implemented with team members, the Sun4Cast system ran from January 2015 to March 2016. The project's partners are dispersed among important geographic areas, which enhances the quality of the results. The Model Evaluation Tools (MET) package (Fig 5) from NCAR serves as the foundation for the verification system, and verification measures of power and irradiance are computed using the METViewer database and display system. The Sun4Cast algorithm creates forecasts beginning at time $t = 0$ by statistically combining NWP estimates to provide a forecast that lasts longer than six hours. When scores are averaged across all partner sites, the blended Sun4Cast and WRF-Solar systems perform better for day-ahead forecasts than operational models

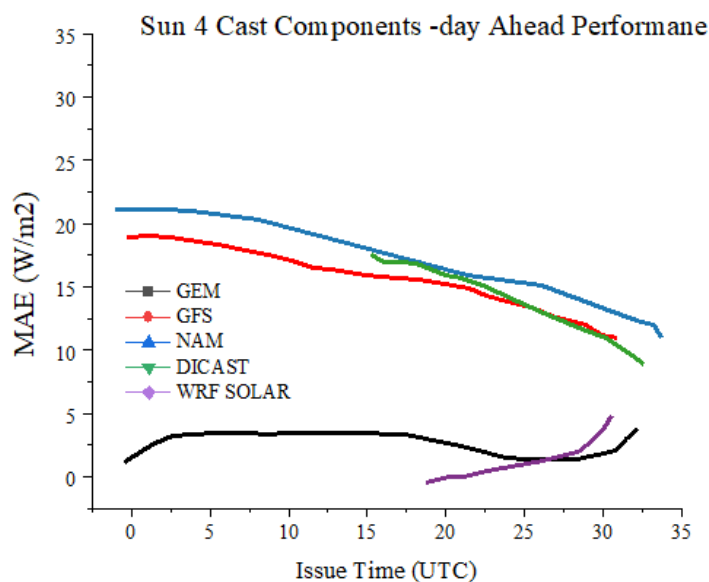


Fig 5 : Sun 4 cast components performance

NOWCAST Evaluating

One reason to look at each nowcast component is because they may all be helpful for a particular forecast horizon (lead time) and set of sky conditions. Figure 6 displays the relative skill of each model when these scores are totaled over the course of the 15-month evaluation period across all regions. The scores were averaged throughout the hourly startup times. It also exhibits proficiency in clear, partly cloudy, and cloudy conditions. In clear conditions, only the combined nowcast NESI and WRF-Solar-Now beat the smart persistence to 45 minutes (0.75 hours). After this, all approaches exceed smart persistence in terms of MAEs; through lead durations of three to six hours, WRF-Solar-Now and CIRACast surpass WRF-Solar-Now and MAD-WRF.

Case Studies NOWCAST

The observations from seven SMUD-owned and -operated pyranometers near Sacramento, California, were compared to the 15-min-average GHI predictions. A comparison was made between the GHI forecasts from many forecast models, including StatCast-Cubist, CIRACast, MADCast, and four variants of WRF-Solar.

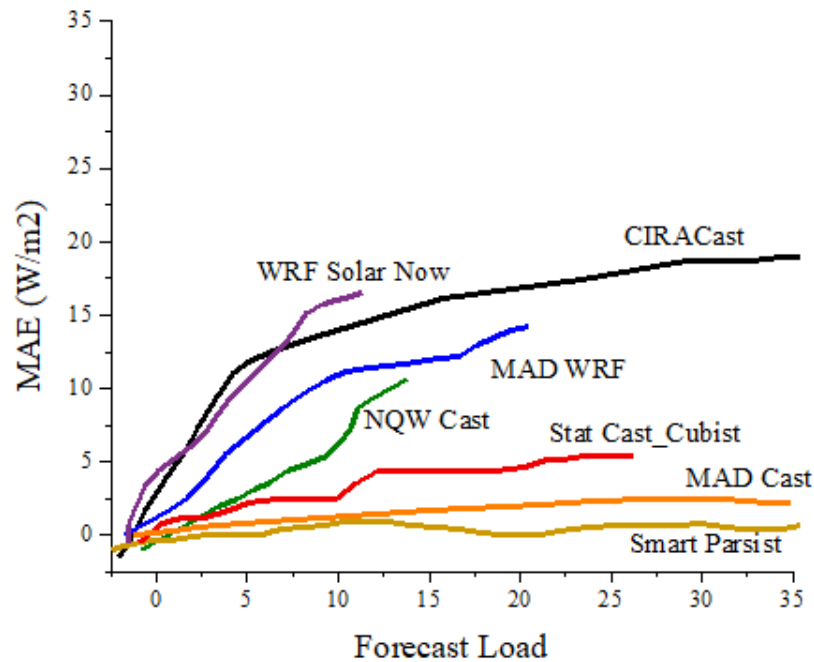


Fig 6: case studies of NOWcast performance

Discussion

All participants in the DOE-sponsored Public-Private-Academic Partnership to Advance Solar Power Forecasting programme contributed to the Sun4Cast Solar Power Forecasting System. The project began with a value chain approach to characterise the problems in order to build a solution that meets industry needs. The result is the solar power forecasting tool Sun4Cast, which has been thoroughly evaluated.

recommendations for forecasting that adhere to best practices. Two of the key goals of the research were to determine the functionality of each component system and to provide recommendations for best practices in the setup of solar power forecasting systems. The following are some specific recommendations:

- Merge different component models or systems. The projections produced by integrated models/systems are consistently noticeably better than those from a single model or technique when the entire time frame is analysed.
- Utilise an adjusted NWP model for the planned application. Making use of WRF-Solar greatly improved the prediction. It has proven especially useful to use high-resolution, high-quality aerosol datasets in conjunction with a shallow cumulus scheme.
- Make use of several NWP models. Better forecasts are produced for time intervals ranging from three hours to the day-ahead forecast and beyond when multiple NWP models are combined.
- Use statistical learning techniques trained on focussed in situ data for short-range forecasting. StatCast, which learns from local pyranometer data, outperformed TSICast, which also uses numerous sky imagers, even at short time scales (15 min–3 h).

Conclusion

Regarding how they see solar power forecasts developing in the future, our utility and ISO partners offered input. "The industry need is still there and will only get larger as more distributed energy is connected to the grid," remarked one partner. According to another, the projections will come from "centralised forecasts generated by the balancing authority (BA), the ISO, and the regional transmission authority (RTO), with multiple applications and varying granularities." It is our collective responsibility as a community to continuously deliver better forecasts in a way that will be useful and enticing to end users. Solar power forecasting using tools like Sun4Cast will offer critical technologies that will improve the economics and enable larger solar power installations as solar power penetration grows.

Competing interests

The authors declare that they have no competing interests.

Consent for publication

Not applicable

Ethics approval and consent to participate

Not applicable

Funding

This research study is sponsored by the institution name. Thank you to this college for supporting this article!

Availability of data and materials

Not applicable

Authors' contribution

Author A supports to find materials and results part in this manuscript. Author B helps to develop literature part.

Acknowledgement

I offer up our fervent prayers to the omnipotent God. I want to express my sincere gratitude to my co-workers for supporting me through all of our challenges and victories to get this task done. I want to express my gratitude for our family's love and support, as well as for their encouragement. Finally, I would like to extend our sincere gratitude to everyone who has assisted us in writing this article.

Abbreviation

SPG	- Solar Power production
PV	- photovoltaic
AC	- alternating current
DC	- direct current

REFERRENE

1. Alessandrini, Stefano. 2022. "Predicting Rare Events of Solar Power Production with the Analog Ensemble." *Solar Energy* 231 (January): 72–77.
2. Chang, Rui, Lei Bai, and Ching-Hsien Hsu. 2021. "Solar Power Generation Prediction Based on Deep Learning." *Sustainable Energy Technologies and Assessments* 47 (October): 101354.
3. D'Isidoro, Massimo, Gino Briganti, Lina Vitali, Gaia Righini, Mario Adani, Guido Guarnieri, Lorenzo Moretti, et al. 2020. "Estimation of Solar and Wind Energy Resources over Lesotho and

- Their Complementarity by Means of WRF Yearly Simulation at High Resolution.” *Renewable Energy* 158 (October): 114–29.
4. Haupt, Sue Ellen, Tyler C. McCandless, Susan Dettling, Stefano Alessandrini, Jared A. Lee, Seth Linden, William Petzke, et al. 2020. “Combining Artificial Intelligence with Physics-Based Methods for Probabilistic Renewable Energy Forecasting.” *Energies* 13 (8): 1979.
 5. Haupt, Sue Ellen, Tyler C. McCandless, Jared C. Lee, Branko Kosović, Stefano Alessandrini, Susan Dettling, Tahani Hussain, and Majed Al-Rasheedi. 2020. “Combining Physical Modeling with Artificial Intelligence for Solar Power Forecasting.” In 2020 47th IEEE Photovoltaic Specialists Conference (PVSC), 2051–53. IEEE.
 6. Huertas-Tato, Javier, Ricardo Aler, Inés M. Galván, Francisco J. Rodríguez-Benítez, Clara Arbizu-Barrena, and David Pozo-Vázquez. 2020. “A Short-Term Solar Radiation Forecasting System for the Iberian Peninsula. Part 2: Model Blending Approaches Based on Machine Learning.” *Solar Energy* 195 (January): 685–96.
 7. Jiménez, Pedro A., Jimmy Dudhia, Gregory Thompson, Jared A. Lee, and Thomas Brummet. 2022. “Improving the Cloud Initialization in WRF-Solar with Enhanced Short-Range Forecasting Functionality: The MAD-WRF Model.” *Solar Energy* 239 (June): 221–33.
 8. Liu, Ye, Yun Qian, Sha Feng, Larry K. Berg, Timothy W. Juliano, Pedro A. Jiménez, Eric Gritmit, and Ying Liu. 2022. “Calibration of Cloud and Aerosol Related Parameters for Solar Irradiance Forecasts in WRF-Solar.” *Solar Energy* 241 (July): 1–12.
 9. McCandless, Tyler, Susan Dettling, and Sue Ellen Haupt. 2020. “Comparison of Implicit vs. Explicit Regime Identification in Machine Learning Methods for Solar Irradiance Prediction.” *Energies* 13 (3): 689.
 10. Shaker, Hamid, Daniel Manfre, and Hamidreza Zareipour. 2020. “Forecasting the Aggregated Output of a Large Fleet of Small behind-the-Meter Solar Photovoltaic Sites.” *Renewable Energy* 147 (March): 1861–69.
 11. Shendryk, Vira, Yuliia Parfenenko, Yevhen Kholiavka, Petro Pavlenko, Oleksandr Shendryk, and Larysa Bratushka. 2022. “Short-Term Solar Power Generation Forecasting for Microgrid.” In 2022 IEEE 3rd International Conference on System Analysis & Intelligent Computing (SAIC), 1–5. IEEE.
 12. Suksamorn, Supachai, Naebboon Hoonchareon, and Jitkomut Songsiri. 2021. “Post-Processing of NWP Forecasts Using Kalman Filtering With Operational Constraints for Day-Ahead Solar Power Forecasting in Thailand.” *IEEE Access* 9: 105409–23.
 13. Tawn, R., and J. Browell. 2022. “A Review of Very Short-Term Wind and Solar Power Forecasting.” *Renewable and Sustainable Energy Reviews* 153 (January): 111758.
 14. Yang, Dazhi, Wenting Wang, Jamie M. Bright, Cyril Voyant, Gilles Notton, Gang Zhang, and Chao Lyu. 2022. “Verifying Operational Intra-Day Solar Forecasts from ECMWF and NOAA.” *Solar Energy* 236 (April): 743–55.
 15. Xie, Yu, Manajit Sengupta, Yangang Liu, Hai Long, Qilong Min, Weijia Liu, and Aron Habte. 2020. “A Physics-Based DNI Model Assessing All-Sky Circumsolar Radiation.” *iScience* 23 (3): 100893.
 16. Pasanisi, F., Righini, G., D’Isidoro, M., Vitali, L., Briganti, G., Grauso, S., Moretti, L., Tebano, C., Zanini, G., Mahahabisa, M. and Letuma, M., 2021. A cooperation project in lesotho: Renewable energy potential maps embedded in a webgis tool. *Sustainability*, 13(18), p.10132.

17. Alharbi, F.R. and Csala, D., 2021. Gulf cooperation council countries' climate change mitigation challenges and exploration of solar and wind energy resource potential. Applied Sciences, 11(6), p.2648.