POLİTEKNİK DERGİSİ

JOURNAL of POLYTECHNIC

ISSN: 1302-0900 (PRINT), ISSN: 2147-9429 (ONLINE)
URL: http://dergipark.org.tr/politeknik

Analysis and modeling of photovoltaic arrays for sustaining power generation in geostationary satellite solar panels using machine learning

Sabit uydu güneş panellerinde güç üretiminin sürdürülebilirliği için fotovoltaik dizilerin makine öğrenimi kullanilarak analizi ve modellenmesi

Yazar(lar) (Author(s)): *İbrahim ÖZ[1], Mehmet BULUT[2]*

ORCID[1]: 0000-0003-4593-917X

ORCID[2]: 0000-0003-3998-1785

To cite to this article: Öz İ., Bulut M., “Analysis and Modeling of Photovoltaic Arrays for Sustaining Power Generation in Geostationary Satellite Solar Panels using Machine Learning”, ***Journal of Polytechnic***, *(*): *, (*).

Bu makaleye şu şekilde atıfta bulunabilirsiniz: Öz İ., Bulut M., “Analysis and Modeling of Photovoltaic Arrays for Sustaining Power Generation in Geostationary Satellite Solar Panels using Machine Learning”, ***Politeknik Dergisi***, *(*): *, (*).

Erişim linki (To link to this article): http://dergipark.org.tr/politeknik/archive

DOI: 10.2339/politeknik.1377988

Analysis and Modeling of Photovoltaic Arrays for Sustaining Power Generation in Geostationary Satellite Solar Panels using Machine Learning

Highlights

- *The study concentrates on modeling satellite solar panels using artificial neural networks.*
- *A non-linear time series neural network with feedback is proposed.*
- *A significantly enhanced and more efficient modeling of solar panels is attained.*

Graphical Abstract

Geostationary satellite solar panels are vital energy sources for space-borne systems. Understanding their power generation and accurately modeling performance is crucial for satellite design, manufacturing, and operation optimization. This study explores how solar panel power fluctuates in response to varying conditions on geostationary satellites. A method employing neural networks was presented to effectively model this power variability over time. Non-linear autoregressive neural networks with exogenous inputs were employed, utilizing both single-input and six-input configurations with feedback. The comprehensive analysis yields a Mean Squared Error (MSE) of 0.0477 and a regression value of 0.9999, indicating exceptional performance. These results validate a strong correlation between predicted and actual power values, underscoring the accuracy of our neural network-based approach in capturing the dynamics of solar panel power generation on geostationary satellites. Satellite operators can employ this technique to monitor and forecast solar panel-generated power effectively.

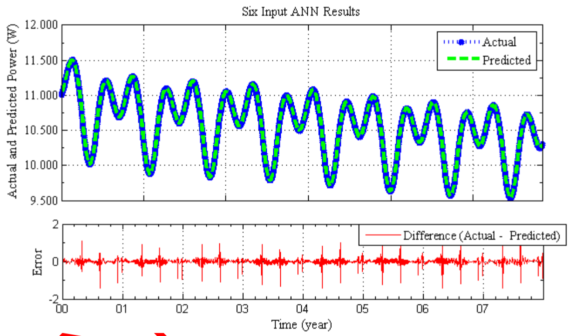


Figure. *The solar panels' predicted and actual power generated using 6- inputs over 8 years.*

Aim

Explores how solar panel power fluctuates in response to varying conditions on geostationary satellites.

Design & Methodology

Employ non-linear autoregressive neural networks with exogenous inputs, utilizing both single-input and six-input configurations with feedback

Originality

Neural network-based approach in capturing the dynamics of solar panel power generation on geostationary satellites

Findings

Analysis yields a Mean Squared Error (MSE) of 0.0477 and a regression value of 0.9999, indicating exceptional performance.

Conclusion

Results validate a strong correlation between predicted and actual power values, underscoring the accuracy of our neural network-based approach in capturing the dynamics of solar panel power generation on geostationary satellites. Satellite operators can employ this technique for effective monitoring and forecasting of solar panel-generated power.

Declaration of Ethical Standards

The author(s) of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Analysis and Modeling of Photovoltaic Arrays for Sustaining Power Generation in Geostationary Satellite Solar Panels using Machine Learning

Araştırma Makalesi / Research Article

İbrahim ÖZ[1], Mehmet BULUT[2]

[1] Enerji Piyasası Düzenleme Kurumu, Ankara, Türkiye
[2]Elektrik Üretim A.Ş Genel Müdürlüğü, Ankara, Türkiye

(Geliş/Received : 18.10.2023 ; Kabul/Accepted : 01.09.2024 ; Erken Görünüm/Early View : 16.01.2025)

ABSTRACT

Geostationary satellite solar panels are vital energy sources for space-borne systems. Understanding their power generation and accurately modeling performance is crucial for satellite design, manufacturing, and operation optimization. This study explores how solar panel power fluctuates in response to varying conditions on geostationary satellites. We present a method employing neural networks to model this power variability over time effectively. To achieve this, we employ non-linear autoregressive neural networks with exogenous inputs, utilizing both single-input and six-input configurations with feedback. Our comprehensive analysis yields a Mean Squared Error (MSE) of 0.0477 and a regression value of 0.9999, indicating exceptional performance. These results validate a strong correlation between predicted and actual power values, underscoring the accuracy of our neural network-based approach in capturing the dynamics of solar panel power generation on geostationary satellites. Satellite operators can employ this technique for effective monitoring and forecasting of solar panel-generated power..

Keywords: Solar air collector, conical spring, fuzzy logic, modeling, outlet temperature, thermal efficiency.

Sabit Uydu Güneş Panellerinde Güç Üretiminin Sürdürülebilirliği için Fotovoltaik Dizilerin Makine Öğrenimi Kullanılarak Analizi ve Modellenmesi

ÖZ

Sabit uydu güneş panelleri, uzay tabanlı sistemler için hayati enerji kaynaklarıdır. Enerji üretimlerini anlamak ve performanslarını doğru bir şekilde modellemek uydu tasarımı, üretimi ve operasyon optimizasyonu için çok önemlidir. Bu çalışma, sabit uydulardaki değişen koşullara yanıt olarak güneş paneli gücünün nasıl dalgalandığını araştırmaktadır. Zaman içindeki bu güç değişkenliğini etkili bir şekilde modellemek için sinir ağlarını kullanan bir yöntem sunulmuştur. Bunun için, hem tek girişli hem de geri beslemeli altı girişli konfigürasyonlardan faydalanan, dışsal girişlere sahip doğrusal olmayan otoregresif sinir ağları kullanıldı. Gerçek bir uydu analizine yönelik kapsamlı çözüm olarak, 0,0477'lik Ortalama Karesel Hata (MSE) ve 0,9999'luk bir regresyon değeri sağlar ve bu olağanüstü performansa işaret etmektedir. Bu sonuçlar, tahmin edilen ve gerçek güç değerleri arasında güçlü bir korelasyonu doğrulayarak, sabit uydularda güneş paneli güç üretiminin dinamiklerini yakalamada sinir ağı tabanlı yaklaşımımızın doğruluğunu göstermektedir. Uydu operatörleri, güneş paneli tarafından üretilen gücün etkili bir şekilde izlenmesi ve tahmin edilmesi için bu tekniği kullanabileceklerdir..

Anahtar Kelimeler: Güneş enerjili hava kollektörü, konik yay, bulanık mantık, modelleme, çıkış sıcaklığı, termal verim.

1. INTRODUCTION

Presently, Photovoltaic (PV) solar array systems stand as the prevailing method for generating power in satellite. The cornerstone of any satellite lies in its electrical power system, as it serves as the lifeblood for all onboard subsystems. The PV array, comprised of solar panels linked in series and parallel, fulfills the entire power demand, thereby sustaining the spacecraft's mission throughout its operational life. While solar PV cells represent the most dependable power generation system for aerospace applications, the aerospace industry often leans towards the more cost-effective Si-based solar cells to offset satellite launch expenses. Notably, the inaugural solar-powered satellite, Vanguard 1, embarked on its journey into space on March 17, 1958 [1]. These PV arrays encompass various solar panel substrates, strategically housing solar cells in series and parallel configurations to meet power requirements. This adaptability in solar panel design facilitates their integration into a multitude of mission profiles and space environments. Progressive strides in solar array technology have embraced the optimization of structural platforms, lightweight substrates, innovative distribution systems, and high-efficiency photovoltaics. An array of technical solutions now caters to missions spanning from interplanetary voyages to low Earth orbit endeavors [2].

**Sorumlu Yazar (Corresponding Author)*
e-posta : mehmetbulut06@gmail.com

In the demanding space environment of geosynchronous orbit (GEO), spacecraft surface materials contend with harsh conditions characterized by the flow of electrons exhibiting a wide energy distribution. Consequently, satellites can accrue negative charges reaching tens of thousands of volts relative to the surrounding space plasma. These electric fields may trigger localized discharges, or arcs, compromising satellite operations [3]. To address this, comprehensive spacecraft charge analyses, employing tools like the Multi-Purpose Spacecraft Charge Analysis Tool, have been undertaken for large GEO satellites. These analyses yield the expected count of electrostatic discharges over a 15-year orbital period, serving as the basis for primary electrostatic discharge (ESD) evaluations in future solar cell coupon ESD tests. In this context, solar panel substrate design is pivotal for fixed satellites. The process involves calculating the total solar array area, eclipse duration, voltage, and power output, considering worst-case scenarios aligned with satellite power requisites. Various solar panel distribution mechanisms are assessed based on their merits and drawbacks [4,5]. Furthermore, understanding the potential and requirements of photovoltaic arrays in catering to the unique demands of spacecraft missions across diverse celestial bodies is paramount. Whether stationed in Earth's orbits, the dusty terrains of Mars and the Moon, the searing climates of Venus and Mercury, or amidst the distant Gas Giants, each environment presents distinct challenges for solar-powered spacecraft. Therefore, not all existing photovoltaic technologies have been fully optimized to navigate this array of conditions [6, 7].

As satellite power demands continue to escalate, the fusion of emerging thin-film PV technologies such as Copper Indium Gallium Selenide (CIGS) cells or gallium-arsenide (GaAs) cells with Gossamer distribution technologies holds the potential to significantly augment power availability for spacecraft [8]. Changes in temperature and radiation significantly influence solar energy production in solar PV cells. An increase in radiation at a constant temperature leads to a rise in both voltage and current output. Conversely, elevated temperatures at a consistent irradiance level diminish power output from the PV array. Mathematical models produce diverse curves mapping the I-V and P-V characteristics of the PV array [9].

Telecommunication satellites in geostationary orbit (GEO) often bear sizable communication antennas and external attachments. These appendages cast varying shadows on the solar arrays. This phenomenon exerts a pronounced adverse impact on solar array power generation and the management of spacecraft payload capacity. Simulation across varying lighting conditions should be performed to accurately forecast array power changes and solar cell performance [10].

The exploration of neural style transfer performance in deep learning models is a well-established subject in both academic and industrial realms. Studies primarily target the improvement of quality and performance, as highlighted in the reference Comparison of Neural Style Transfer Performance of Deep Learning Models [11].

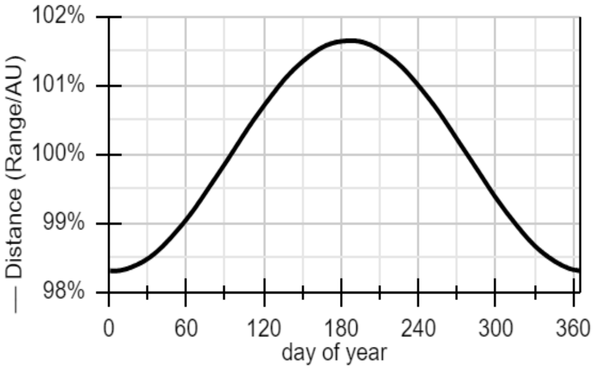
One application of Artificial Neural Networks (ANN) involves predicting the monthly average soil temperature for the upcoming year. This prediction relies on meteorological parameters encompassing historical monthly averages collected over an extended period. Five distinct artificial neural network estimation models, including feed-forward neural networks and Levenberg-Marquardt algorithm-based networks, have been devised to estimate soil temperatures at various depths: five, ten, twenty, fifty, and one hundred centimeters. The comparison reveals that estimations generated by artificial neural network models outperform those from regression models. The study 'Estimating Soil Temperature With Artificial Neural Networks Using Meteorological Parameters' provides insights into this evaluation[12]. Furthermore, the application of artificial intelligence in detecting and diagnosing faults in thermal images of solar panels has been proven effective, as discussed in the reference Deep Learning Based Fault Detection And Diagnosis in Photovoltaic System Using Thermal Images Acquired by UAV [13]. Experimental studies in the literature have demonstrated that temperature significantly influences the performance of photovoltaic (PV) panels, impacting current, voltage, power output, and electrical efficiency, as outlined in the reference Experimental Investigation of The Efficiency of Solar Panel Over Which Water Film Flows [14].

Space solar cell technologies are relentless in their pursuit of heightened solar cell efficiency and adaptability to specific mission environments. Consequently, assessing the performance of photovoltaic arrays throughout their operational lifespan becomes imperative to gauge their suitability for past and future missions. The present study encompasses the simulation of solar panels that are used by artificial intelligence tools to predict power output based on environmental parameters. This holds the potential to enhance the utilization of photovoltaic arrays for space applications. In this article, geostationary satellite solar panels as sources of power generation was analysed. Additionally, employing neural networks to model power generation were investigated. Furthermore, the research findings and discussions that originate from the models are comprehensively summarized and discussed.

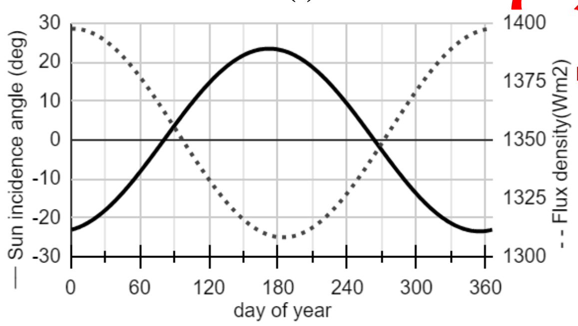
2. GEOSTATIONARY SATELLITE SOLAR PANELS FOR POWER GENERATION

Geostationary satellite solar panels are designed to harness solar energy in space and provide electrical power to satellites. The power generation characteristics of geostationary satellite solar panels depend on a range of factors that evolve over time. These factors include the distance to the Sun, sun incidence angle, panel orientation, temperature variations, and the solar cells' efficiency and degradation rates. Understanding these factors is decisive for assessing and optimizing the longterm performance of solar panels in geostationary satellites [6].

Three-axis body-stabilized satellites typically employ flat solar panels. These panels can be rotated to optimally intercept solar energy, thereby maximizing electric power generation. For instance, 60 m^2 flat solar panels can produce about 9 kW of power on geostationary satellites. However, since these solar panels constantly face the Sun, they operate at relatively higher temperatures, which can lead to reduced efficiency. On the other hand, spin-stabilized satellites utilize cylindrical solar panels. These panels offer their own set of advantages and disadvantages. The spin-stabilized design allows the solar cells to cool down when they are in the satellite's shadow. As a result, these panels can maintain better efficiency compared to the flat solar panels used in three-axis body-stabilized satellites.



(a)



(b)

Figure 1. a) Flux density change over a year due to the sun distance to the earth b) sun incidence angle left vertical axis solid line, flux density right vertical line over a year.

Solar panels consist of a series and parallel connection of numerous solar cells. These solar cells are the fundamental building blocks that convert solar energy into electrical power. The need to produce sufficient power necessitates a large surface area of solar panels. However, this requirement must be balanced with the satellite's objective of being compact and lightweight. For this reason, careful consideration is given to the selection of solar panel type based on the satellite's stabilization mechanism.

Like all satellites, geostationary satellites with solar arrays are susceptible to various factors. As the Earth orbits the Sun, the distance between them varies from a minimum of 0.983 astronomical units (AUs), where 1 AU is the mean distance from the Earth to the Sun (approximately 149,597,870 km), to a maximum of 1.067 AU. This difference amounts to 12,518,000 km. If the energy received from the Sun at 1 AU is considered as 100%, the energy received by the geostationary satellite varies from approximately 97% to 103% due to the changing distance. These variations are depicted in Figure 1. a), illustrating the fluctuation in energy received by the solar arrays throughout the year. These changes in solar energy availability impact the power generation capacity of the solar arrays and must be accounted for in satellite system design and power management strategies. [15]

$$\left(\frac{H}{H_{constant}} = 1 + 0.33\cos\left(\frac{360(n-2)}{365.25}\right)\right) \qquad (1)$$

where; H radiant power density outside the Earth's atmosphere (W/m^2), H constant: solar constant 1353 W/m^2, n: day of the year n=1 on 1st of January.

The Earth's orbit is not perfectly circular, and the plane of the Earth's equator does not align precisely with the plane of its orbit, known as the ecliptic. This misalignment of the equatorial plane with the ecliptic plane gives rise to the Earth's seasons. This phenomenon is depicted in Figure 1b). This declination angle can be expressed in Equation 2.

$$\delta = 23° + \left(\frac{27}{60}\right)° + \sin\left[\frac{360\ d}{365.25}\right] \qquad (2)$$

where d: day of the year passed after the spring equinox which is March 21.

The solar cycle is a recurring pattern of solar activity that spans approximately 11 years. It is characterized by Sun's magnetic field variations, sunspot activity, and overall solar output. Throughout the solar cycle, the Sun undergoes periods of high and low activity, directly influencing the flux density of solar radiation reaching the Earth.

A geostationary satellite eclipse refers to the period when a satellite is in the Earth's shadow, causing a temporary loss of direct sunlight. Due to this fixed position, the satellite can experience eclipses when the Earth blocks the Sun's direct rays. The eclipse duration can be estimated, providing valuable information for power system design, battery performance assessment, and thermal design in geostationary satellites.

It is important to note that these eclipses persist for approximately 45 days in the geostationary orbit and occur twice per year. The maximum eclipse period was estimated to be around 69 minutes in practice [18].

Table 1. Categorized performance metrics of different solar cell technologies for space spplications

Solar Cell Technology	BOL effic. (% at 28°C)	Specific Power	Mass	Power coefficient	Radiation (P/P0)	Radiation (P/P0)	Radiation (P/P0)
Unit	(°C)	(W/m^2)	(kg/m^2)	(% / °C)	1x10^{14}	5x10^{14}	1x10^{15}
Si	13.7	185	0.55	-0.045	0.92	0.82	0.77
High ef. Si	16	216	0.28	-0.042	0.92	0.83	0.79
GaAs /GESJ	19	253	0.83	-0.022	0.90	0.85	0.75
GaInP^2/ GaAs/ GeDJ	22	297	0.85	-0.030	0.96	0.89	0.83
GaInP^2/ GaAs/ Ge TJ	25	337	0.85	-0.060	0.96	0.82	0.83
Hi 3J	28	378	0.86	-0.060	0.93	0.89	0.86

Satellite panels solar cells, commonly composed of silicon, are semiconductor materials capable of conducting electricity under specific conditions. When sunlight strikes the solar cell, the semiconductor material absorbs a portion of the light, transferring its energy. This energy absorption causes some electrons within the material to become free, allowing them to move and create a flow of electrons known as a current [16]. By understanding the current voltage and power-voltage characteristics, designers can optimize the solar cell's performance and harness its maximum power generation capabilities for various applications. [17]

There are various types of solar cells, with silicon and multijunction solar cells particularly interesting. Silicon solar cells are widely used and have been a predominant technology for many years. They are known for their reliability and reasonable efficiency in converting sunlight into electricity.Solar cells are designed to convert solar energy into electrical energy, utilizing the Sun's radiation, which is approximately 1360 W/m² at 1 AU (Astronomical Unit). These cells have varying conversion efficiency rates depending on the material used, ranging from 20% for silicon to 35% for the most efficient multijunction Ga-As cells. Additionally, factors such as cell aging and working temperatures can further reduce efficiency.

Considering all these factors, solar arrays positioned at 1 AU and accurately aligned with the Sun can generate approximately 150 to 400 W per m² of surface area. A combination of material characteristics, physical factors, and environmental conditions influences the overall efficiency of the solar array. Nonetheless, solar arrays remain a vital and efficient means of converting solar energy into usable electrical power for various satellite applications.

Table 1 provides a comprehensive overview of various solar cell technologies along with their respective performance metrics. These metrics include the Beginning-of-Life (BOL) efficiency at 28°C, specific power coefficient, and mass characteristics under different radiation conditions. The table outlines the solar cell technologies, each with its corresponding BOL efficiency percentage at 28°C, specific power coefficient, and mass values. Table 1 provides a comprehensive comparison of solar cell technologies based on their efficiency, power coefficient, mass, and radiation response, offering valuable information for selecting and optimizing solar cell technologies for space applications [18].

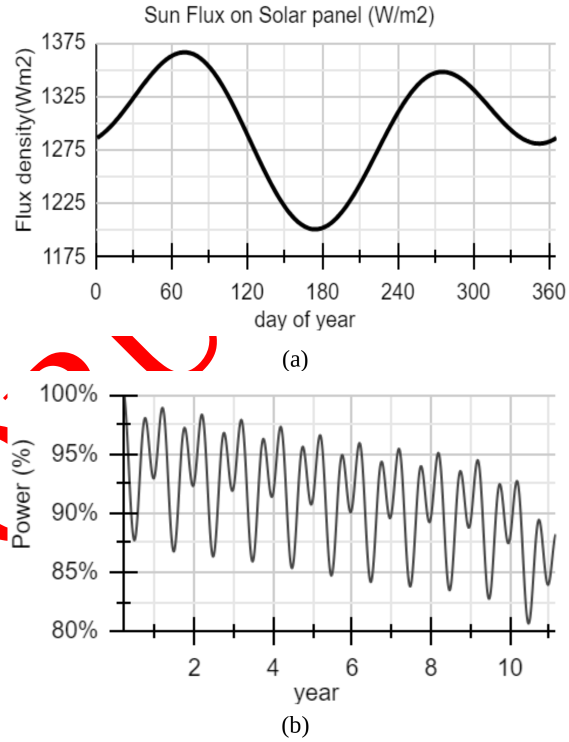


Figure 2. a) Sun flux density variation at geo altitude over a year b) Satellite solar panel lifetime power performance.

When combining the information depicted in Figure 1. a), which illustrates the variation in sun distance to Earth and its corresponding flux, with Figure 1. b), demonstrating the flux variation due to the Sun's incidence angle on the Earth's equator and the solar panel of the satellite, we obtain Figure 2. a). This resultant figure represents the flux density, which directly and significantly impacts the power generated by the solar panel. Analyzing Figure 2. a), we can assess the primary influencing factor on the solar panel's power generation capability [3, 19].

Suppose the effects of variations in solar distance, solar cycle, solar angle, temperature, and eclipses over a year were combined. In that case, new results are obtained, and the total solar energy available varies 12%—from a low of 89% to a high of 101% [20]. The effects of degradation on the solar cells and their optical coverings due to the space environment and a nominal nine-year satellite lifetime are shown in Figure 2. b. The size of a spacecraft subsystem is determined not only by the power needed to operate the equipment and its duty cycle but also by considering factors such as power requirements during eclipses and peak power consumption. Ensuring reliable power supply throughout the satellite's mission is crucial, considering the limited lifespan of solar cells and batteries. At the beginning of life, the power requirement should be considered the potential degradation in the solar array. This degradation is influenced by factors such as the orbit altitude and radiation environment.

When designing the power subsystem for a spacecraft, ensuring a continuous and reliable power supply throughout its planned lifetime is of utmost importance. A power margin of approximately 33% is incorporated into the design to achieve this. This means that the power subsystem is designed to provide an initial power capacity of approximately 133% of the maximum power demand required for normal operations, where 100% represents the power needed for standard functioning. By implementing this power margin, the satellite can sustain normal operations while accommodating any potential variations or increased power demands that may arise over its lifetime. This additional power capacity acts as a safety buffer, preventing the available power from dropping below the threshold necessary for smooth operation throughout the satellite's planned mission duration.

The spacecraft's power subsystem ensures a robust and reliable power supply over an extended period by strategically providing an initial power capacity that exceeds the immediate needs. This design approach considers potential changes in power requirements, solar panel degradation, and other factors that may affect power generation over the satellite's operational life. As a result, the spacecraft can operate efficiently and effectively, fulfilling its mission objectives with a stable and dependable power supply [21, 22].

3. POWER GENERATION MODELING USING NEURAL NETWORKS

Traditional analytical models used for solar panel power generation often rely on simplifications and assumptions that may not fully capture the complex and non-linear relationships inherent in the process. These limitations can result in inaccurate predictions, especially in scenarios with varying weather conditions and environmental factors. Consequently, optimizing the efficiency and reliability of solar energy utilization becomes challenging.

In recent years, advancements in artificial intelligence have paved the way for more sophisticated modeling techniques. Neural networks, a subset of machine learning algorithms inspired by the human brain's neural structure, have demonstrated significant potential in addressing the shortcomings of traditional analytical models. Unlike traditional approaches, neural networks excel at learning patterns and correlations directly from data, making them well-suited for capturing intricate relationships present in solar panel power generation.

By leveraging their powerful learning capabilities, neural networks can process vast amounts of historical data related to solar panel power output and associated environmental parameters. This includes data on solar irradiance, panel temperature, sun position, and other relevant factors. Through the training process, neural networks identify complex patterns and dependencies within the data, creating a model that can accurately predict solar panel power generation under various conditions.

The ability of neural networks to handle non-linear relationships and adapt to changing inputs makes them particularly valuable in scenarios with dynamic and uncertain solar energy generation patterns. As a result, these AI-based models offer superior accuracy and robustness compared to traditional analytical methods.

Furthermore, neural networks can be continually updated and fine-tuned as new data becomes available. This adaptability ensures that the model remains up-to-date and maintains its predictive capabilities over time. Businesses, energy providers, and policymakers can optimize solar energy utilization, improve energy planning, and enhance overall system efficiency by making informed and precise forecasts [23, 24, 25]. Hence, in this study, utilizing the neural network method was proposed to model and analyze the power generated by satellite solar panels.

3.1. Non-linear Autoregressive Neural Networks with Exogenous Input

A neural network model is constructed with appropriate input and output layers. Hidden layers with interconnected neurons enable the network to learn the underlying patterns and relationships between environmental factors and solar panel power generation.

Figure 3 illustrates the architecture of a neural network employing a single input with feedback.

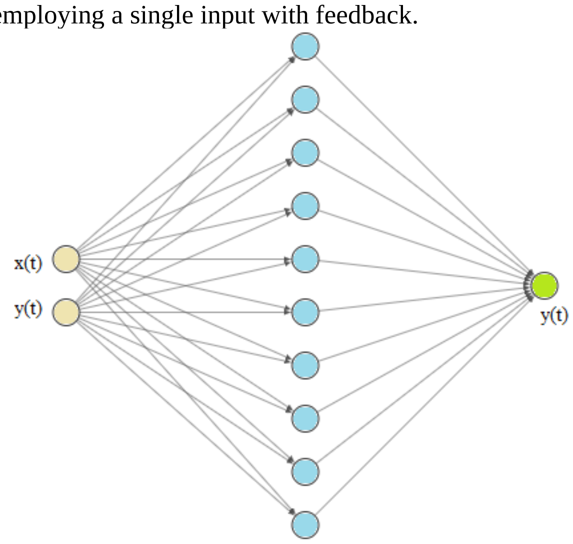


Figure 3. Non-linear Autoregressive Neural Networks with Exogenous Input

In certain time series problems, the goal is to predict future values of a given time series, denoted as y(t), by utilizing past values of both that time series and an additional related time series, denoted as x(t). This type of prediction is known as non-linear autoregressive with exogenous input. Mathematically, it can be expressed as follows:

$$y(t) = f(y(t-1), \ldots y(t-d), x(t-1), \ldots, x(t-d)) \quad (3)$$

In this context, the above mentioned network model was employed to predict future values of generated power by a solar panel based on previous instances of generated power. The model considers the historical data of both the solar panel's power output (y) and other relevant factors (x), such as environmental conditions, solar radiation, or panel orientation.

By analyzing the relationships between past power generation and the associated exogenous inputs, the network learns patterns and correlations to make predictions about future power generation. This predictive capability aids in optimizing power management, system planning, and decision-making processes related to solar energy utilization.

The network serves as a valuable tool in harnessing the potential of solar panels by providing insights into their performance dynamics and enabling accurate predictions of future power generation based on historical data.

3.1.1. Training and Validation

The collected data is split into training and validation sets. The neural network is trained using the training data, and the model's performance is assessed using the validation set. The network learns to accurately predict solar panel power output based on environmental inputs through an iterative process.

Mean Squared Error (MSE) are used as a performance indicators to evaluate the proposed model's predicted performance. These metrics quantify the accuracy and quality of the predictions by measuring the discrepancy between the predicted and actual values. The Mean Squared Error (MSE) is computed using the following equation 4:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_{actual} - y_{predicted})^2 \quad (4)$$

MSE considers the absolute differences between actual and predicted values. However, by squaring these differences, the MSE emphasizes larger errors and provides a measure of the average squared difference between the actual and predicted values.

In this study, the Levenberg-Marquardt training algorithm, which yielded superior results compared to other methods, was employed. The evaluation of training, validation, and testing results is based on two metrics: Mean Squared Error (MSE) and Regression R Values. MSE measures the average squared difference between predicted outputs and actual targets, with lower values indicating better accuracy (zero indicates no error). Regression R Values quantify the correlation between predicted outputs and targets, where an R-value of 1 indicates a close relationship, and 0 signifies a random relationship. By utilizing these evaluation metrics and the effective Levenberg-Marquardt training algorithm, our study aims to provide accurate and reliable predictions for solar panel power generation, further advancing the capabilities of neural network modeling in this domain.

3.2. Data Collection and Preprocessing

In our study, the actual power data of Satellite-A (Sat-A) operated at the designated orbital location over eight years was utilized. The power generated through Sat-A's solar panels is used explicitly for modeling purposes. The entire dataset covers a span of 8 years, ranging from January 1, 2015 to December 31, 2022.

Two distinct methodologies exist for utilizing satellite solar panel power data to train the neural network. The first approach involves predicting solar panel power values based on a comprehensive set of parameters encompassing telemetry, orbital data, and space environment conditions. These parameters include variables such as day of the year, sun flux density, sun incidence angle, satellite-to-sun distance/AU ratio, cell degradation factor, and panel temperature readings. Within this approach, the neural network's output signifies the predicted power values generated by the solar panels, while the parameters mentioned above constitute the network's input. Conversely, the second approach exclusively employs the actual generated power values as input. The network's output continues to represent the solar panel power, while the input consists solely of day-of-the-year values commencing from an established epoch.

Table 2 presents a detailed overview of the input and output values of the Sat-A dataset utilized for the training process. Each row corresponds to a specific day, providing information on parameters such as Sun angle, flux density, temperature, cell degradation, sun-satellite distance, and the corresponding power generated by the solar panel. The dataset spans 2922 days, encapsulating various conditions and factors contributing to solar panel power generation.

In this study, both approaches are implemented, and their respective outcomes are meticulously compared. The results shed light on the efficacy and performance of each approach, allowing for a comprehensive evaluation of their predictive capabilities in modeling satellite solar panel power generation.

This preprocessed data forms the foundation for training and validating the neural network model. By using this comprehensive dataset, we aim to develop a reliable and accurate model for predicting the power output of Sat-A's solar panels over time. The neural network model is trained and evaluated based on this dataset.

Table 2. Input and output values of Sat-A data for neural network training

Day	Sun angle (degree)	Flux Den (W/m^2)	Temperature (°C)	Cell degrade (%)	Sun-Sat Dist (AU)	Power (Watt)
1	-23.012	1397.642	28.0239	0.9999	0.983046	10999.885
2	-22.931	1397.649	28.0416	0.9998	0.983031	11004.321
…	…	…	…	…	…	…
2921	-23.012	1397.642	28.0196	0.9356	0.983121	10292.445
2922	-22.931	1397.649	28.0380	0.9356	0.983093	10297.616

It enables us to assess its forecasting performance and potential for predicting solar panel power generation in various conditions and scenarios.

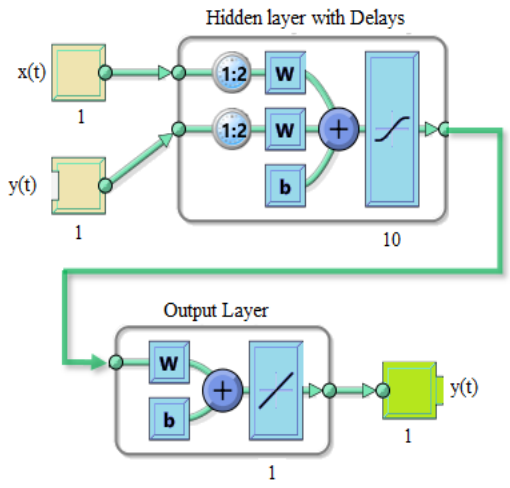
4. THE RESEARCH FINDINGS AND DISCUSSION

This study encompasses a data collection spanning 2922 days for Sat-A to facilitate neural network training for predictive purposes. The entire dataset is partitioned randomly into three distinct segments: 70% (2046) is allocated for training, 15% (438) for validation, and the remaining proportion for testing. During the training phase, the neural network undergoes adjustments in response to its computed errors. The validation subset evaluates the network's generalization capacity and prompts the cessation of training upon stagnation in performance enhancements. Conversely, the testing subset furnishes an independent assessment of the network's operational efficacy both during and post-training, all the while preserving the integrity of the training process.

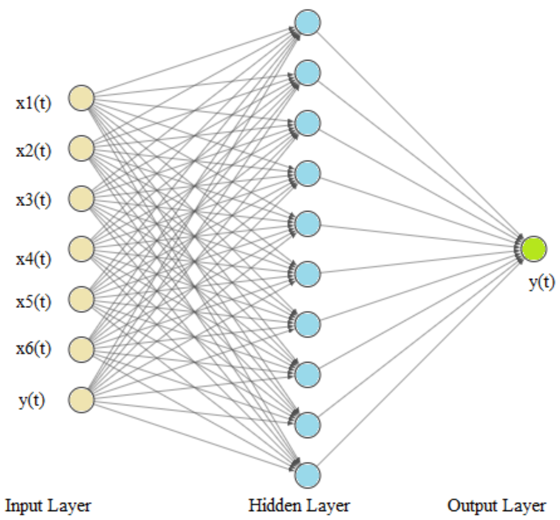
As previously delineated, the study encompasses two distinct modes of training: a single input paradigm involving only day values and a more comprehensive 6-input framework encompassing days, flux density, sun incidence angle, sun-satellite distance, temperature, and cell degradation as inputs.

Figure 4.a) illustrates a neural network architecture with a single input and 1 feedback (y(t)), featuring 10 hidden layers and a single output in Matlab form. Meanwhile, Figure 4.b) presents a network configuration with 6 inputs and 1 feedback (y(t)), incorporating 10 hidden layers and a sole output. Notably, both configurations incorporate a delay of 2 in their respective designs.

Figure 5 compares the actual and predicted values of Sat-A solar panel output over 8 years using the neural network time series model with a single input. The model employs a non-linear autoregressive with external (exogenous) input architecture. The lower portion of the figure illustrates the error, representing the difference between the observed and predicted values. Notably, the error values in the figure are minimal, indicating the model's effectiveness in accurately capturing the solar panel's power generation behavior.



(a)



(b)

Figure 4. a) the block diagram of the network generated for training with a single input and feedback, **b)** illustrates the networks utilized for training with six inputs and feedback.

The neural network model demonstrates its proficiency in predicting solar panel output with high precision and reliability, validating its successful performance in this context.

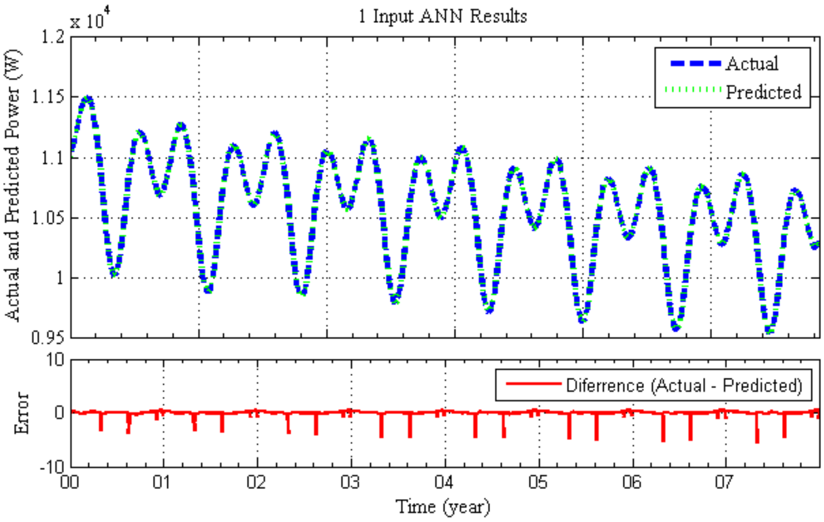


Figure 5. The upper part presents a comparison between predicted and actual power generated by the solar panels over an 8-year period, while the lower part illustrates the differences between them.

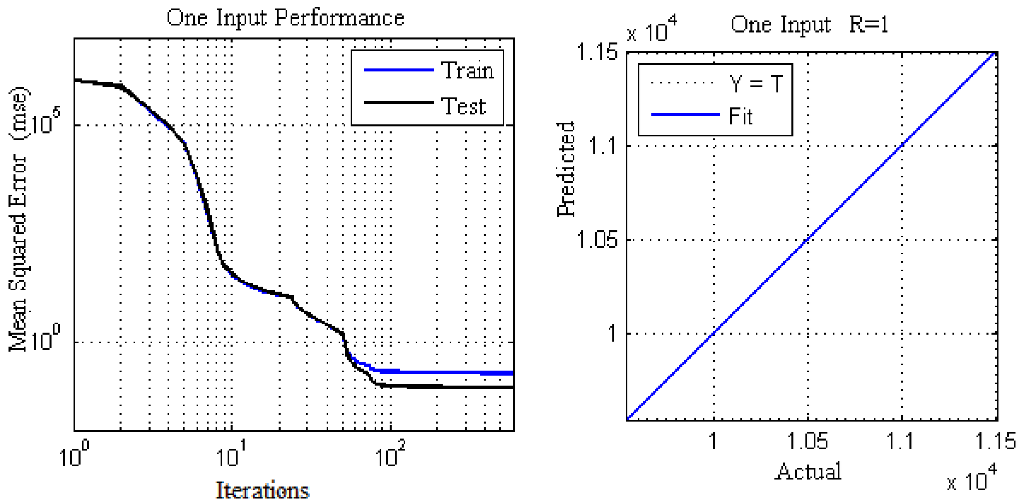


Figure 6. The left graph illustrates the performance of the single input model, while the right graph displays the regression value between the actual and predicted power.

Figure 6.the left side showcases the network's performance in the context of a single input with feedback. The Mean Squared Error (MSE) is quantified at 0.199. Figure 6.the right side illustrates the regression value at an impressive 0.9999. This exceptionally high regression value indicates an exceptional fit between predicted and actual data. Furthermore, the minimal value of MSE underscores the strong performance of the modeling approach.

In light of these findings, it is evident that the generated power of Sat-A solar panels is effectively and accurately modeled by utilizing the neural network. The combination of the high regression value and the low MSE demonstrates the reliability and precision of the neural network model in predicting solar panel power generation behavior. This success contributes to advancing our understanding and practical utilization of neural networks in analyzing and optimizing satellite solar panel performance.

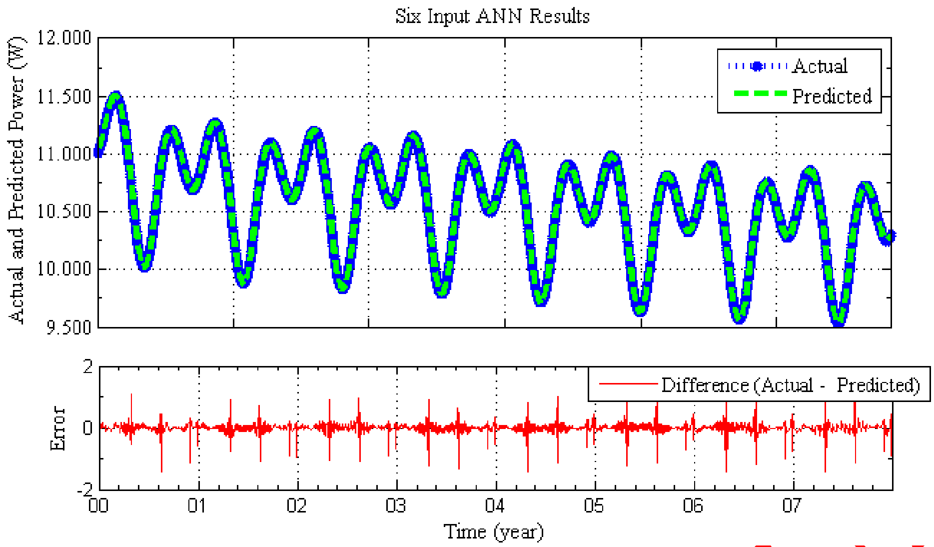


Figure 7. The upper portion presents an 8-year comparison between the predicted and actual power generated by the solar panels using six inputs. The lower part illustrates the differences between these values.

Figure 7. offers a comprehensive visual comparison between the observed and predicted values of Sat-A solar panel output over an 8-year duration. This analysis is conducted by applying a neural network time series model, incorporating 6 inputs encompassing the aforementioned critical data parameters. For enhanced accuracy, the model is structured with a non-linear autoregressive architecture featuring external (exogenous) input.

The upper segment of Figure 7. provides a detailed portrayal of the predicted and actual values of generated power derived from Sat-A solar panels throughout the 8-year span. This representation visually illustrates the model's predictive performance in capturing the intricate nuances of power generation behavior. The closeness between the predicted and actual values highlights the model's capability to accurately emulate the real-world solar panel power output.

Intriguingly, the lower section of the same figure illustrates the margin of error, revealing the disparity between the observed and predicted values. The remarkably low difference observed in this comparison indicates the model's exceptional precision in replicating actual solar panel power generation. This remarkable agreement between the predicted and actual data underscores the reliability and effectiveness of the neural network time series model.

The findings depicted in Figure 7 validate the chosen modeling approach's robustness and reinforce the significance of neural networks in understanding and forecasting satellite solar panel power generation dynamics. The successful alignment of predicted and actual values paves the way for enhanced decision-making and optimization in satellite power management.

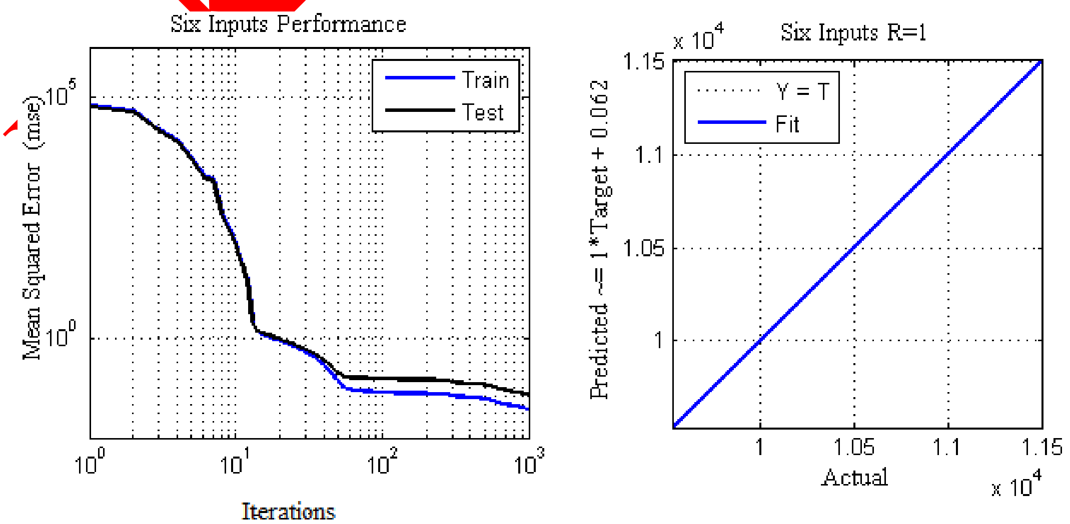


Figure 8. The left graph demonstrates the performance of the six-input model, while the right graph showcases the regression value indicating the correlation between the actual and predicted power.

Figure 8. the left graph provides insight into the behavior of the Mean Squared Error (MSE) alongside the number of iterations throughout the iterative modeling process, displayed on a logarithmic scale. As expected, the errors consistently diminish as the number of iterations increases. This pattern aligns with the anticipated trajectory of iterative optimization algorithms frequently utilized in training neural networks. The gradual decrease in errors over successive iterations signifies the model's progressive enhancement in prediction refinement. Through iterative learning, the neural network effectively fine-tunes its predictions, resulting in a notable reduction in MSE and a heightened precision in capturing the intricate power generation patterns of the solar panel.

Figure 8. the right graph unveils the comparison between observed and predicted power regression. The data points cluster closely around the 45-degree line, indicating a robust correlation between the predicted and actual solar array power. This striking proximity underscores the neural network's commendable accuracy in forecasting power generation, affirming its competence in accurately simulating the genuine power output behavior of the solar array.

The specific quantitative indicators also underscore the effectiveness of the model. The MSE is recorded at a value of 0.047, highlighting the minimal discrepancy between predicted and actual values. Simultaneously, the regression value (R) registers at an impressive 0.9999, showcasing the robust relationship between predicted and actual data points.

Upon scrutinizing the performance metrics of the 6-input model in contrast to the 1-input model, it becomes evident that the former exhibits slightly superior performance. The 6-input model showcases improved metrics, with an MSE of 0.047 compared to the 1-input model's 0.199. Moreover, the R values corresponding to the 6-input model also demonstrate an enhanced correlation. While the discrepancy between the two models is modest, these marginal improvements collectively contribute to the slightly superior prowess of the 6-input model.

The suggested neural network-based modeling approach has numerous benefits, including enhanced power estimation, increased efficiency in satellite mission planning, and improved resource management. Furthermore, the model's flexibility is evident since it can be consistently refined with new telemetry data, allowing it to stay quick and sensitive to changing circumstances while improving its capacity to make predictions. The proposed neural network modeling technique has been evaluated against other research areas, including the simulation of satellite temperature sensors [26], the control of spacecraft power systems [27], and methods for predicting time series data [28]. These comparisons demonstrate that our approach is both reliable and practically applicable, yielding positive results. This validation across different domains confirms the robustness and effectiveness of proposed neural network model in accurately predicting power generation in geostationary satellite solar panels.

The rationale for employing a neural network in this study lies in its capacity to effectively capture and model the complex and non-linear relationships inherent in the behavior of photovoltaic arrays. Traditional analytical models may have limitations in accurately representing the intricate dynamics of solar panel power generation. Neural networks, a form of artificial intelligence, have demonstrated promise in learning patterns from data and providing precise predictions. By leveraging the neural network's ability to adapt and learn from the dataset, the study aims to achieve a more accurate and reliable predictive model for the power generation of geostationary satellite solar panels. The neural network, particularly in the context of machine learning, offers the flexibility to discern patterns and relationships among various input parameters, such as time, temperature, flux density, sun angle, and satellite-to-sun distance. This, in turn, enhances the understanding and prediction of how these factors influence the power output of the photovoltaic arrays over time.

5. CONCLUSION

This study extensively investigated the complex dynamics of power generation in geostationary satellite solar panels, presenting an approach for modeling their output using neural networks. The effectiveness of the proposed technique in accurately forecasting power output holds substantial potential for optimizing resource allocation, refining satellite operations, and enhancing mission planning.

The findings of our research demonstrate the efficacy of the neural network-based model in accurately capturing the power generation patterns of geostationary satellite solar panels. A remarkable Mean Squared Error (MSE) of 0.0477 and a regression value of 0.9999 were achieved through the utilization of a non-linear autoregressive with exogenous input architecture. This level of performance underscores the robust correlation between predicted and actual power values.

The neural network-based model offers satellite operators a powerful tool for efficient resource management, mission planning, and operational decision-making. The accurate prediction of power output empowers operators to allocate resources more effectively and plan satellite activities with a heightened understanding of energy availability.

Nevertheless, like any scientific investigation, this study comes with its own set of limitations. The accuracy of the proposed model could be influenced by external factors, such as space weather conditions, short circuits in solar panel strings, or unforeseen anomalies in solar panel performance. Additionally, the model's predictive capability is constrained by the data on which it was trained. This limitation could hinder the model's ability to adapt to new and unique scenarios that were not represented in the training data. Addressing these constraints in future work could involve incorporating a wider range of data inputs and further refining the model to enhance its robustness and adaptability to various conditions.

For future research, there are promising avenues to explore. Similar neural network-based modeling techniques could be applied to solar panels on satellites in Low Earth Orbit (LEO) or other orbital configurations. Furthermore, the model could be refined by incorporating additional variables such as satellite orientation or environmental conditions, potentially enhancing its predictive accuracy. Additionally, exploring the feasibility of applying this approach to other space-based solar power systems holds the potential for advancing our understanding of power generation dynamics in various satellite environments.

In conclusion, our research showcases the potential of neural network-based modeling in understanding and predicting power generation in geostationary satellite solar panels. This approach enhances our comprehension of energy dynamics in space and has substantial implications for improving satellite operations. By continually refining and expanding upon this modeling technique, new insights into solar panel behavior and further optimize space-based energy utilization can be unlocked.

DECLARATION OF ETHICAL STANDARDS

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

AUTHORS' CONTRIBUTIONS

İbrahim ÖZ: Perofrmed the study, analyse the results and wrote the manuscript

Mehmet BULUT: Performed structural analysis and edited the article.

CONFLICT OF INTEREST

There is no conflict of interest in this study.

REFERENCES

[1] Verduci, R., Romano, V., Brunetti, G., Nia, N. Y., Carlo, A. D., Ciminelli, C., "Solar energy in space applications: review and technology perspectives". ***Advanced Energy Materials,*** 2200125, 12(29), (2022).

[2] Jones, P. A. and Spence, B. R., "Spacecraft solar array technology trends". ***IEEE Aerospace and Electronic Systems Magazine***, vol. 26, no. 8, pp. 17-28, (2011).

[3] Plis E. A. et al., "Effect of simulated geo environment on the properties of solar panel cover glasses,". ***IEEE Transactions on Plasma Science***, vol. 49, no. 5, pp. 1679-1685, (2021).

[4] Cho M. et al., "Spacecraft Charging analysis of large GEO satellites using MUSCAT," ***IEEE Transactions on Plasma Science***, vol. 40, no. 4, pp. 1248-1256, (2012).

[5] Cho, M. R., Ramasamy, T., Matsumoto, K., Toyoda, Y., Takahashi, M., "Laboratory tests on 110 V solar arrays in a simulated geosynchronous orbit environment," ***J. Spacecraft Rocket,*** vol. 40, no. 2, pp. 211–220, (2003).

[6] O. Safak, "Structural design and analysis of a solar array substrate for a GEO satellite," Projecte Final de Màster Oficial, UPC, Escola d'Enginyeria de Telecomunicació i Aeroespacial de Castelldefels, ***Departament de Ciència dels Materials i Enginyeria Metal·lúrgica***, (2013).

[7] Bermudez, A., Voarino, P., Raccurt, O., "Environments, needs and opportunities for future space photovoltaic power generation: A review", ***Applied Energy***, Volume 290, 116757, (2021).

[8] Sproewitz, T., Banik, U., Grundmann, JT. et al. "Concept for a Gossamer solar power array using thin-film photovoltaics." ***CEAS Space*** J 12, 125–135 (2020).

[9] Muhammad Z., Ekundayo O., "Simulation of photovoltaic (PV) power system performance of spacecraft in geostationary orbit using a prototype model.", **IOSR Journal of Applied Physics (IOSR-JAP)**, Volume 6, Issue 3 Ver. II, pp 20-26. (2014).

[10] Chetty, P., Vasagam, R., "Enhanced Power Generation by Optical Solar Reflectors on Geostationary Spinners," ***IEEE Transactions on Aerospace and Electronic Systems***, vol. AES-15, no. 1, pp. 119-124, Jan. (1979).

[11] Karadağ B., Arı Ali, Karadağ, M. "Derin öğrenme modellerinin sinirsel stil aktarımı performanslarının karşılaştırılması.", ***Politeknik Dergisi***, 24(4), 1611-1622., (2021).

[12] Aslay F., Özen, Ü. "Estimating soil temperature with artificial neural networks using meteorological parameters.", ***Journal Of Polytechnic-Politeknik Dergisi,*** 16(4), (2013).

[13] Kayci B., Demir B. E., Demir, F. (2023). Deep learning based fault detection and diagnosis in photovoltaic system using thermal images acquired by UAV. ***Politeknik Dergisi***, 1-1, (2023).

[14] Erdoğan, İ., Bilen, K., Kivrak, S. " Experimental investigation of the efficiency of solar panel over which water film flows.", ***Politeknik Dergisi***, 1-1, (2023).

[15] Abood, A., "A comprehensive solar angles simulation and calculation using matlab", International Journal of Energy and Environment, 367, 6(4), (2015).

[16] Ribah, A. Z., Ramayanti, S., "Power produced analysis of solar arrays in nadir pointing mode for low-earth equatorial micro-satellite conceptual design", In ***IOP Conference Series: Earth and Environmental Science*** (Vol. 284, No. 1, p. 012048). IOP Publishing, (2019).

[17] Maini, A. K., Agrawal, V. "Satellite technology: principles and applications", ***John Wiley & Sons***. (2011).

[18] Demirel, S., "Haberleşme uydusunun elektrik güç sisteminin modellenmesi ve analizi" (Doctoral dissertation, ***Sakarya Universitesi***, Turkey, (2017).

[19] D'Accolti, G., Beltrame, G., Ferrando, E., Riva, S., Vallini, L., "One year in-orbit data of the MITA Ga As on Ge solar array" ***In Space Power***, Vol. 502, p. 719, (2002).

[20] Sözbir, N., Bulut, M. "Prediction of the Solar Array Temperatures of Geostationary Earth Orbit Satellite by Using Analytical Methods.". ***9th International Conference on Recent Advances in Space Technologies (RAST)***, Istanbul, Turkey, , pp. 369-372, (2019).

[21] Kirkpatrick, D., "Space mission analysis and design", (Vol. 8). J. R. Wertz, W. J. Larson, & D. Klungle (Eds.). ***Torrance: Microcosm***. (1999).

[22] Cao, M., Zhang, T., Liu, Y., Yu, W., "A performance degradation model of solar cells in an on-orbit resource satellite based on peak currents", ***Solar Energy***, 189, 26-34, (2019).

[23] Khashei, M., Bijari, M., "An artificial neural network (p,d,q) model for time series forecasting". ***Expert Systems With Applications***, 37(1), 479-489. (2010).

[24] Lee, J., Kim, E., & Shin, K. G., "Design and management of satellite power systems". In 2013 ***IEEE 34th Real-Time Systems Symposium,*** pp. 97-106, (2013).

[25] Olawoyin, A., Chen, Y." Predicting the future with artificial neural network". ***Procedia Computer Science***, 140, 383-392. (2018).

[26] Abdelkhalek, H. S., Medhat, H., Ziedan, I., Amal, M., "Simulation and prediction for a satellite temperature sensors based on artificial neural network***". Journal of Aerospace Technology and Management***, 11. (2019).

[27] El-madany, H. T., Fahmy, F. H., El-Rahman, N. M., & Dorrah, H. T., "Spacecraft power system controller based on neural network". ***Acta Astronautica***, 69(7-8), 650-657, (2011).

[28] Hota, H. S., Handa, R., Shrivas, A. K. "Time series data prediction using sliding window based RBF neural network". ***International Journal of Computational Intelligence Research***, 13(5), 1145-1156, (2017).