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Smart Forecasting of Photovoltaic Panel Power Output: A Neural Network Approach with an Interface Based on Arduino Board

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Abstract

The use of photovoltaic solar energy seems to be an essential asset and a necessity for the future with advantages such as abundance and availability. However, the outdoor exposure of photovoltaic modules brings together a complex combination of factors which cause their degradation. This results in a negative impact whether on the efficiency or on the characteristics of the panels, which means that even for the optimal temperature and radiation conditions, we will have electrical characteristics different from those of the panel nameplate, the case maximum power for example. The objective of this paper is to realize a system capable of forecasting the maximum power delivered from the photovoltaic field, knowing only the value of the temperature and the value of the solar radiation, whatever its state of degradation. We propose an approach based on an artificial intelligence technique. The acquisition circuit, implemented cost-effectively, will be detailed in this work. The results obtained will be also shown, validating the proposed approach. This integration of AI with renewable energy systems promises to enhance their efficiency and reliability.

Keywords: Artificial Intelligence, Neural Network, Photovoltaic (PV) Panels, Power Prediction.

1. Introduction

The integration of renewable energy sources into our electricity networks has gained considerable momentum in recent years. Photovoltaic (PV) panels, harnessing the abundant energy of the sun, have become a central player in this global transition to sustainability [1] [6] [7] [8]. Accurate forecasting of the production power of photovoltaic panels is essential to optimize energy production and network management [2] [3]. In this context, the article “Smart Forecasting of Photovoltaic Panel Power Output: A Neural Network Approach with an Interface Based on Arduino Board” looks at the innovative use of neural networks, as well as the Arduino board as a low-cost interface, to predict the power output of photovoltaic panels accurately and efficiently. Solar energy forecasting has been the focus of extensive research due to its implications for both small-scale residential installations [1] [4]and large-scale solar farms [3] [5]. Prior works have explored various techniques, from statistical methods to machine learning algorithms, to improve forecasting accuracy [9] [10] [11] [12] [13] [14] [15] [16]. Traditional time series analysis, autoregressive models, and weather-based models have been applied, but these approaches often encounter limitations in handling the inherent complexity of solar energy generation [17] [18] [19], which is influenced by factors like weather conditions, shading, and panel degradation. Consequently, there is a pressing need for advanced forecasting techniques that can adapt to real-world variations and provide reliable predictions for optimal energy utilization [20] [21] [22].

This article builds upon the foundations laid by previous research in solar energy forecasting and advances the field through the utilization of neural networks. Neural networks have demonstrated remarkable capabilities in handling complex, non-linear relationships within data, making them well-suited for forecasting tasks [23]. By integrating these neural networks with Arduino boards, the research aims to develop a practical and cost-effective solution for PV panel power output forecasting, thus addressing some of the challenges faced by existing forecasting methods.

In the following sections, we delve into the methodology, implementation, and results of this innovative approach, providing insights into how it contributes to the evolution of solar energy forecasting, with the potential to revolutionize the integration of PV panels into the global energy landscape.

2. System description

A GPV photovoltaic generator or a PV module is formed from the association of several PV cells in series and or in parallel [24]. When cells are connected in series, the voltages of each cell always add to the total voltage of the photovoltaic module. On the other hand, if the cells are connected in parallel, the amperage increases. Fig.1 shows a series/parallel connection of PV cells. The I(V) operating curve of a module is a curve deduced from the operating curve of an elementary cell by change of scale on the abscissa axis. The performance of a PV generator is determined from these characteristic curves. Panel (Fig.2).

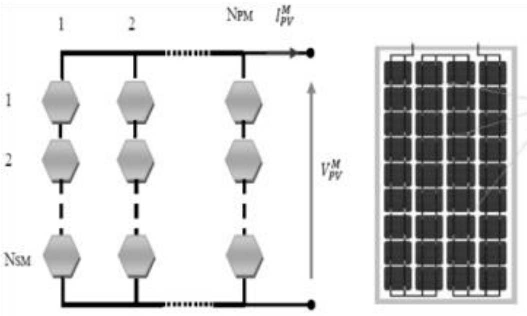

Fig.1. Connection of PV cells.

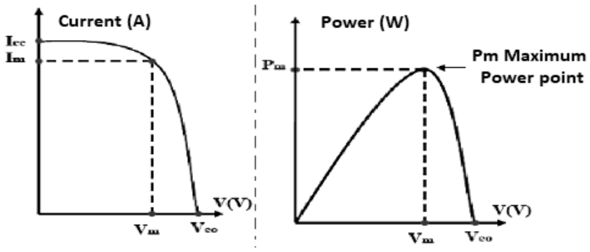

Fig 2. Caractéristics of PV panel.

Concerning our application system, we took two photovoltaic panels from the solar field installed at the LGEER laboratory of the University of Chlef. The characteristics of each module are shown in Fig.3. The series connection of the two panels gives us a source having a voltage of 100V and a current of 10A. Fig.4 shows the series wiring of these modules.

The degradation factors of a module or a PV field such as: corrosion, delamination, cracks and breakage of solar glass, significantly influence the characteristics of the modules [25] [26], which makes it impossible to predict their behavior even in the presence of nameplates. hence the objective of this work which is to predict the maximum power delivered by our system whatever the state of degradation of the module by knowing only the illumination values and the temperature. Fig.5 shows the degradation of one of these two photovoltaic modules. This requires us to go through two steps: • The first step concerns data acquisition. • the second part is intended for data processing

3. Data acquisition system

The data acquisition system is a set of devices interconnected in such a way as to automatically obtain a series of measurements on an object [27]. Data acquisition involves collecting measurements, digitizing them and storing them in vector or matrix form on a computer or other system containing memory [28] [29]. In this project we have to make five different measurements, which are:

- Illumination and temperature: these two parameters are provided from the metrological station installed at the LGEER laboratory. These measurements are recorded every 15 minutes via dedicated software.
- The voltage, current and power delivered by the two panels. To carry out these measurements, we created an algorithm and an electronic circuit, the details of these measurements will be discussed immediately afterwards.

Fig.3. The photovoltaic module nameplate of our system

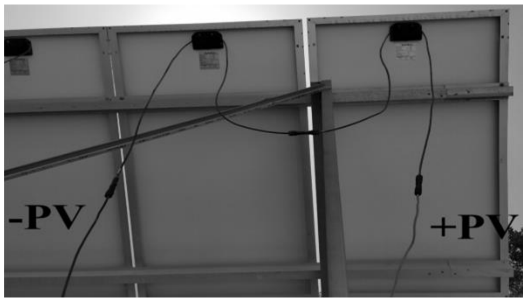

Fig.4.series wiring of two photovoltaic panels

Fig.5. Degraded PV module status

To reveal the maximum power, several measurements must be carried out (for a given illuminance and temperature) while varying the load progressively. This led us to create and manage a dynamic load

A. Dynamic load algorithm

To carry out several power measurements for a given illuminance and temperature. We must vary the load gradually; we have created what we call the dynamic load. To do this, use a buck converter (series chopper) between the source and the load and vary the voltage at the load terminal. Comes back as if we vary the load itself. The serial chopper switch is controlled by a PWM signal generated by the management algorithm of this acquisition step [30].

. In our work, we took 500 measurement points (one measurement every 0.25 seconds) for a given radiation (illumination) and temperature. These measurements are then repeated every 15 minutes for other radiation and temperature values. Note that for each 500 measurement points, the maximum power is taken. All measurements taken are carried out and recorded as a vector in MATLAB/Simulink. We carried out a 23-hour test which allowed us to take 44,000 measurement points (88 points of maximum power), which gives after processing 03 vectors of 84 elements for the learning phase (training and test) and 03 vectors of 04 elements for validation: • Radiation vector (illumination) E. • Temperature vector T. • Maximum power vector Pm. The algorithm that generates this acquisition step is shown in the Fig.6. Note that we used the Arduino Mega as an interface circuit and the duty cycle α of the Arduino PWM signal varies from 0 to 255. So to have 500 points we increment α by a value of 0.5.

B. Dynamic load circuit

Fig.7. represents the dynamic load circuit. The PV module delivers its energy into a load which gradually varies, according to the duty cycle α of the PWM command generated by the algorithm, of the PWM signal from the Arduino card having a frequency of 490 Hz. The load used in our circuit is a resistive load of 16 Ohm

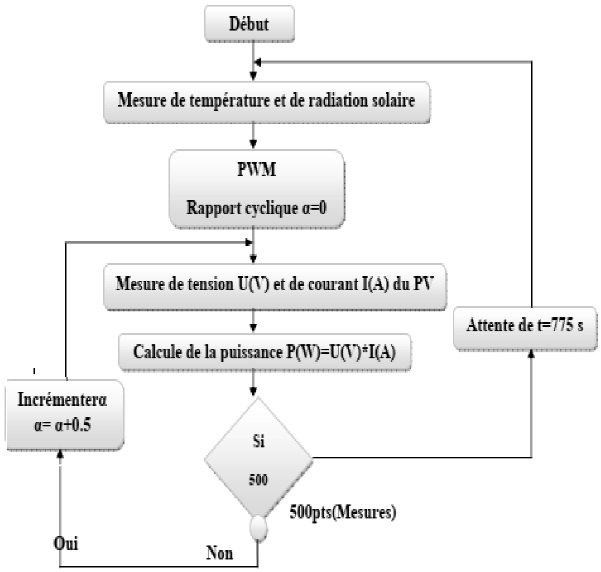

Fig.6. Flowchart of the data acquisition algorithm

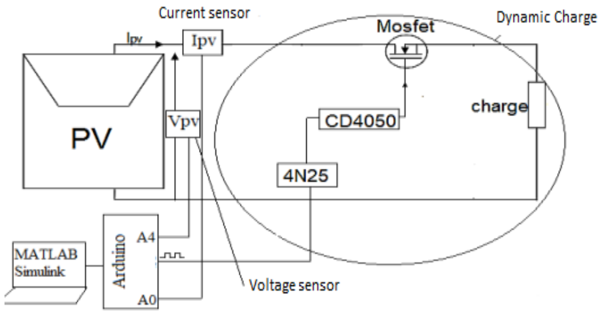

Fig.7. Dynamic load circuit

C. Interface card

The interface card plays the role of connection between the management program generated on MATLAB/Simulink and the external environment containing the sensors and the real system, while guaranteeing that this connection is in real time. The most adaptable and cheapest board that can fulfill this role is the Arduino MEGA board. It contains everything necessary for the operation of an interface circuit. For the Arduino card, to act as an interface with the MATLAB/Simulink software, a library dedicated to this purpose exists under this software.

The overall circuit of our implementation under ISIS/Proteus is shown in Fig.8. We note that for our Arduino MEGA; we are using:

- USB cable: for power supply and serial data connection between the real system and the MATLAB/Simulink program.
- Pin No. 2 which is used to trigger the trigger of our power switch. Pin A4 for reading the PV voltage from the voltage divider. Pin A0 for reading the PV current from the ACS712 sensor.

Fig.9 represents the installation of the overall assembly of the realization

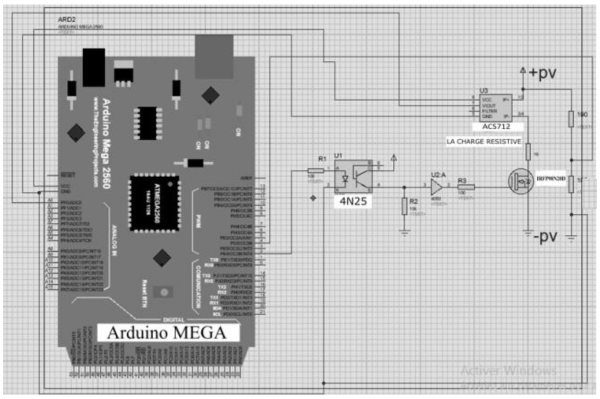

Fig.8. The circuit simulation in ISIS/Proteus

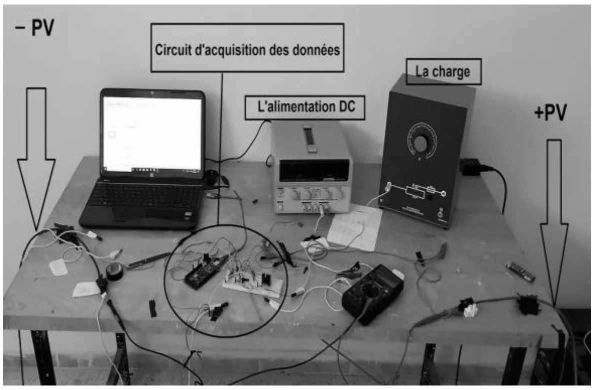

Fig.9. Real installation of the system

4. Data Processing

In this part, we use the data previously stored in the form of vectors to use them in the learning phase. The multilayer neural network “MLC back propagation” was chosen in this study because of its capacity for success in terms of prediction and optimization of models. Employing supervised learning requires knowledge of a desired output for any element of the input data set. The multi-layer “MLC backpropagation” model consists of three types of layers, the input layer, one or more hidden layers and an output layer [31] [32]. For our case, the input data are the temperature and illuminance values and the desired outputs are the maximum power values sorted from the first part by choosing the maximum value of the product between the current and the voltage for an illumination (radiation) and a given temperature.

A. Methodology and implementation

The first step is to identify the parameters to be used for the forecast models. The data is divided into three parts. 70% of the data is used for learning, 15% for the testing phase and 15% for validation. The implementation of an ANN model includes these three phases: learning, testing and validation. The aim of the learning or training phase is to determine the network parameters (weights and biases) using the optimization technique. The testing phase consists of verifying the network determined during the training phase on data not used during the latter, and examining the network's ability to generalize the training examples (by comparing the actual network output with the desired output). The validation phase is carried out on the last part of the data. In our work, we chose the data from the four tests which are chosen randomly to be used as validation data.

B. Design of our neural network

To simulate an application of supervised learning neural networks, we must import the data from the Excel file in the form of matrices previously recorded by the acquisition part. The data is broken down into two parts:

- The input vector is dimensioned in 84 rows and 2 columns:

1. the first column corresponding to the temperature data.
2. the second column corresponding to solar radiation data.

- The output vector is dimensioned in 84 lines and 1 column, this vector corresponding to the maximum power data.

We use the “newff” MLP Back-propagation neural network tool. We named our network by “Pmax”, the characteristics of our network are:

- Number of entries: in= [2*252]. (radiation and temperature)
- Number of outputs: out= [1*252]. (maximum power)
- Number of hidden layers s=2 the first layer contains 25 neurons and the second contains 35 neurons.
- The learning gain “α” lr =0.1.
- Training is divided into:

70% of the data for learning (training).
15% of the data for the test.
15% of the data for validation.

- The number of epochs equal to 10000, it allows defining the maximum allowed number of epochs “if it does not reach the objective after 10000 epochs stops.
- Goal= 1e-10.
- The method used: MLP Back-propagation.

Fig.10. summarizes these characteristics. The architecture of our network is shown in Fig.11. then Fig.12. illustrates the neural network during the learning phase.

After designing our neural network, the training phase revealed the performance shown in Fig.13 and Fig.14.

In Fig.13, we look at the mean square error (MSE) of the network for the training, validation and testing stages. According to this figure the least MSE in the validation step arrived at epoch 08 which has a validation performance equal to 18.2594. It is true that we can have a better performance than this by modifying the hyper-parameters but given our application, this is acceptable.

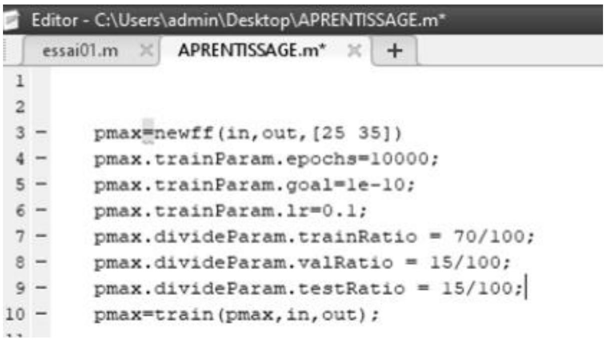

Fig.10. Pmax ANN parameters

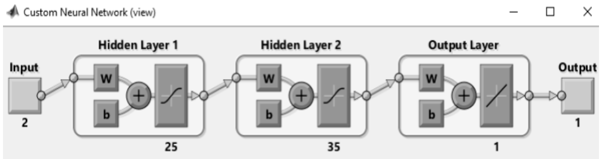

Fig.11. Pmax ANN architecture

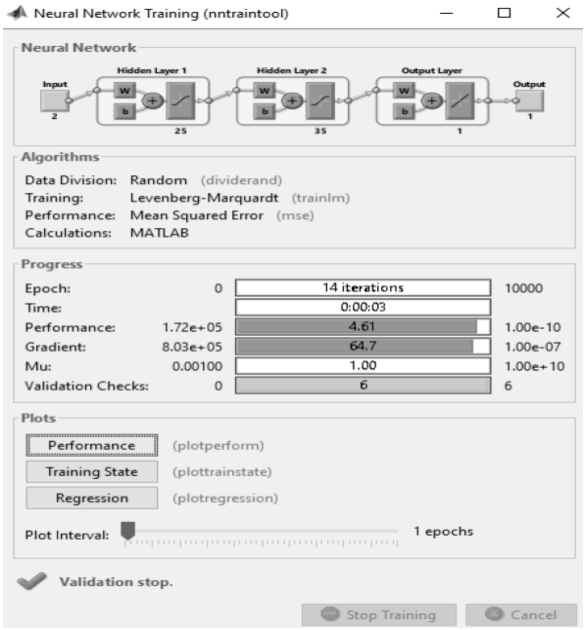

Fig12. the neural network during learning

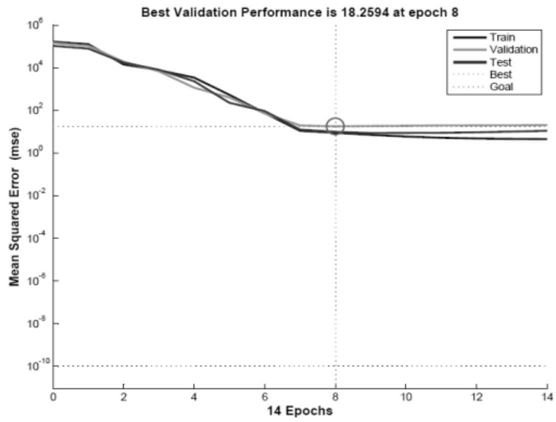

Fig.13. Pmax ANN architecture

For the regression, we obtain the result of Fig.14. This option allows examining the correlation between target values (measured Pmax) and output values (Pmax of our approach) for training, testing and validation. As shown in this Fig. we note

- Training - R = 0.9996:

The very high correlation (R = 0.9996) on the training set suggests that the model has successfully learned and captured the underlying patterns in the training data. This indicates strong agreement between the predicted and actual values during the training phase.

- Validation - R = 0.99943:

A high correlation (R = 0.99943) on the validation set is promising, demonstrating that the model generalizes well to unseen data. However, it's important to monitor for overfitting, ensuring that the model's performance on the validation set aligns with its performance on the training set.

- Test - R = 0.99963:

The very high correlation (R = 0.99963) on the test set is a positive sign, indicating that the model maintains its strong performance on new, unseen data. This suggests the model's ability to generalize to real-world scenarios.

- Total - R = 0.99957:

The overall correlation, combining training, validation, and test sets (R = 0.99957), reflects the model's consistency across the entire dataset. The extremely high correlation implies a robust and reliable predictive capability for the maximum power delivered by photovoltaic panels.

These high values of R suggest a very strong linear correlation between the values predicted by your neural network model and the actual values of the maximum power delivered by the photovoltaic modules. To achieve these high correlation coefficients, our model appears to have captured the general trend of the data well and accurately predicted the target variable. This indicates a close match between model predictions and actual observations, which is often a positive indicator of the quality of our regression model, whether linear or nonlinear.

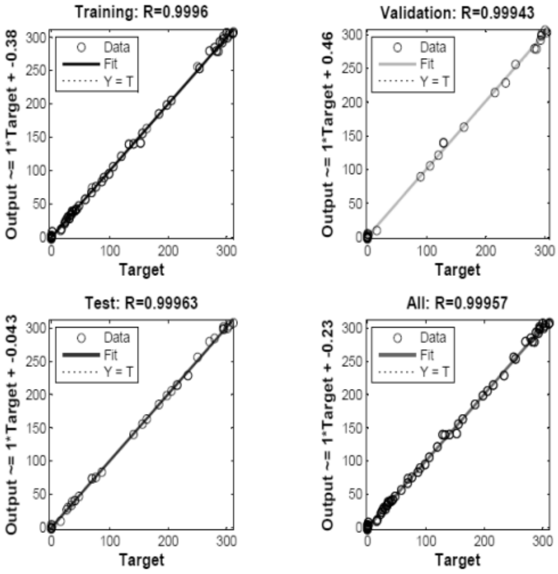

Fig.14. Pmax ANN architecture

5. Validation of results

This phase allows us to validate the processing phase. To do this, we have used two types of data:

1. Data (inputs, output) obtained during the acquisition part used in the learning phase.
2. Data (inputs, output) obtained during the acquisition part, which are not used in the learning phase.

In the first case, we use the first type of data, for example we take the data from Table I.

We test our network with the following command;

>> Pmax ([29.7000;368.0000])

The result obtained is shown in Fig.15. We noticed that the result is very close, which allows us to validate this test.

Now, let's move on to the second type of data, that is to say those which were not used in the learning phase. For this step we take the values from table II. Fig.16. illustrates the results obtained.

According to the results obtained from Fig.17. we notice that the values resulting from our approach are very close to those obtained during measurements of the real system, which validates the strategy adopted

Table I: Data used in the learning phase

Temperature	Solar Radiation	Maximum Power
29.7000	368.0000	140.6553

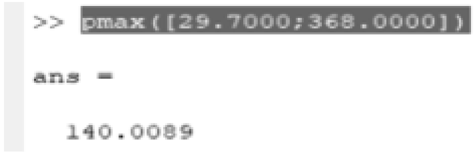

Fig.15. Test result (data used in the learning phase)

Table II: Data not used in the learning phase

Temperature	Solar Radiation	Maximum Power
37.8	221	43.5013275146484
37.2	177	40.4078559875488
26.8	230	89.9773101806641
27.6	274	105.909965515137

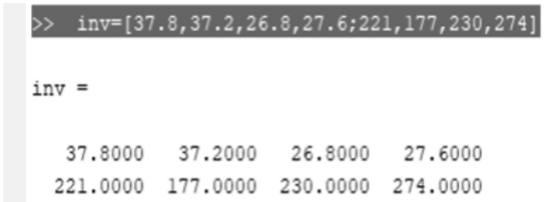

Fig.16. Test result (data not used in the learning phase)

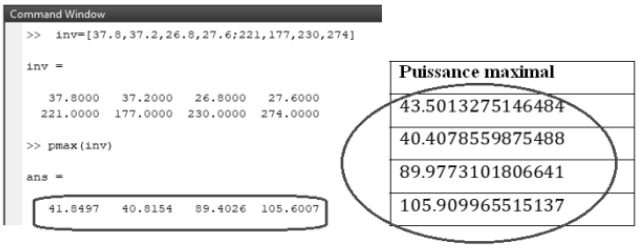

Fig.17. Test comparison between the results obtained by measurements and the results predicted by our approach

6. Conclusion

In conclusion, this study addresses the critical challenge of accurately forecasting the maximum power output from photovoltaic (PV) panels, considering the complex factors contributing to their degradation in outdoor environments. The results obtained from our neural network-based approach, complemented by a low-cost acquisition circuit and an algorithm for dynamic load creation, have demonstrated highly satisfying outcomes. The robust correlation coefficients achieved during the training, validation, and testing phases (R = 0.9996, R = 0.99943, R = 0.99963, respectively) underscore the effectiveness of our model in predicting the maximum power delivered by the photovoltaic field. These high correlation values indicate a strong linear relationship between the predicted and measured values, emphasizing the model's ability to generalize across varying conditions and states of degradation.

The integration of artificial intelligence (AI) into renewable energy systems, as exemplified in this work, holds promise for significantly enhancing both the efficiency and reliability of power predictions for photovoltaic panels. By utilizing a cost-effective acquisition circuit and leveraging the capabilities of neural networks, our approach demonstrates the potential to overcome the challenges posed by panel degradation, ultimately contributing to the optimization of renewable energy utilization. As the world continues to transition towards sustainable energy solutions, the findings presented in this paper contribute valuable insights to the field, offering a practical and effective methodology for improving the performance of photovoltaic systems through the application of AI techniques. The successful implementation of our approach encourages further exploration and adoption of AI-based solutions in renewable energy domains, paving the way for a more resilient and efficient energy future.

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