Green Energy and Technology

Philip Pong *Editor*

Renewable Energy Resources and Conservation

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Green Energy and Technology

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Part I
Solar Energy and Photovoltaic Power Generation

Artificial Neural Network Application for the Prediction of Global Solar Radiation Inside a Greenhouse

Salah Bezari, Asma Adda, Sofiane Kherrour, and Reda Zarrit

1 Introduction

Solar energy is an amazing and sustainable resource that has the potential to revolutionize the way to meet various sectors' energy needs, especially in the greenhouse agricultural. The climate has a direct impact on agricultural productivity, particularly in greenhouse farming where a favorable microclimate is essential for good production. In this context, solar energy can be harnessed to power these structures and create a sustainable solution for the agricultural sector. For example, there is research on improving greenhouse systems by storing large-scale solar thermal energy to heating [1]. Renewable energy solutions like solar power are truly revolutionizing the way we meet our energy needs. It is, indeed, the irregular distributions of temperature, relative humidity, carbon dioxide concentration and solar radiation in the microclimate of greenhouse that can cause negative impacts on growth and quality. Nowadays, artificial neural networks are used in many applications of renewable energies such as desalination [2, 3], conditioning of greenhouses [4, 5], and solar energy [6, 7]. Several studies have been carried out on greenhouses, for example, to control the climate of the greenhouse [8], the thermal modeling of the climate of the greenhouse [9], and the prediction and estimation of the climatic factors of the greenhouse [10]. The local greenhouse climate can be predicted through knowledge of physics and information derived from data on inside and outside variables. It seems that Ferreira et al. [11] conducted a study on the use of RBF neural networks to model the indoor air temperature

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of a greenhouse. S. Zeng et al. [12] utilized several input parameters release to predict the temperature and humidity inside greenhouses. The results showed that the proposed model exhibited better adaptability and more satisfactory real time. R. Ahmad and his team [13] used a neural network model with the Levenberg-Marquardt algorithm to predict temperature and humidity in a greenhouse with natural ventilation. Kuzugudenli, E. [14] conducted a study in 2018 where they developed regression and artificial intelligence network models to predict relative humidity in greenhouses using monthly mean temperature, total precipitation, and altitude parameters from 177 weather stations in Turkey. In 2020, Escamilla-García et al. [15] conducted a review of artificial neural network (ANN) applications in greenhouse technology. This study developed a model based on an ANN for predicting incident solar radiation on a horizontal surface in an agricultural greenhouse.

2 Materials and Methods

2.1 Experimental Greenhouse

The experimental greenhouse, which is the subject of this work, is placed within the Applied Research Unit for Renewable Energies (URAER) located in the south of Algeria, city of Ghardaïa with latitude: +32.37°, longitude: +3.77°, and altitude of 450 m above mean sea level (see Fig. 1). This greenhouse is equipped with a set of sensors to measure the temperature, relative humidity, and solar radiation.

2.2 Modeling Procedure

In our study, neural networks were chosen to address greenhouse modeling, as previous studies have shown them to be useful and powerful tools to define such

Fig. 1 Greenhouse view in URAER site (Ghardaïa region)

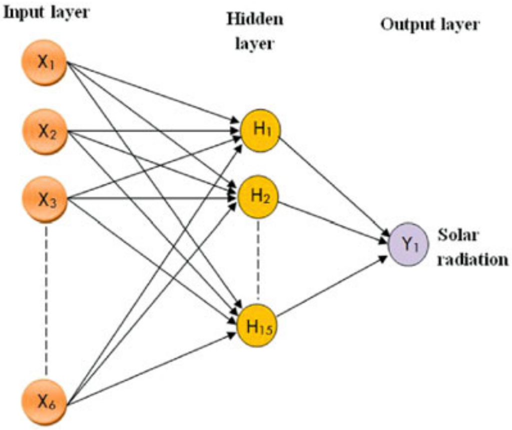

Fig. 2 ANN architecture

a system [4]. Solar radiation plays a major role in the climate of the greenhouse; it therefore constitutes the network output of the model studied. In this way, the model will try to predict the solar radiation incident on a horizontal surface inside the greenhouse depending on the variables used as input to the network, such as the temperature of the outside and inside air, the relative humidity, solar radiation, etc. Regarding the data sets used, the sampling time to obtain the measurements was 30 min, which corresponds to 145 measurement points in 72 h. The database used contains a monthly set of parameter values for 3 days for the month of the winter season (January). A Multilayer Perceptron (MLP) consists of at least three layers named input layer, output layer, and hidden layers (see Fig. 2).

To get the most accurate estimate of our model's performance, it is important to calculate the error. The best way to do this is by using statistical parameters such as the determination coefficient R, the root mean square error RMSE, and mean absolute error MAE. These parameters are frequently referenced in literature and can be calculated using specific equations outlined in references [2].

3 Results and Discussion

For the studied network, the Levenberg-Marquardt (LM) learning algorithm with 15 neurons in the hidden layer for the network (7-15-1) produced the best results, and it is used to generate the graphical output. The mean squared error (MSE) during the training of three phases (training, validation, and testing) is shown in Fig. 3. The backpropagation learning error plot explains that the error is high when the iteration is less and vice poured.

To some extent, errors in training, validation, and test sets indicate how well the performance of the trained network can be measured. Therefore, it is necessary to

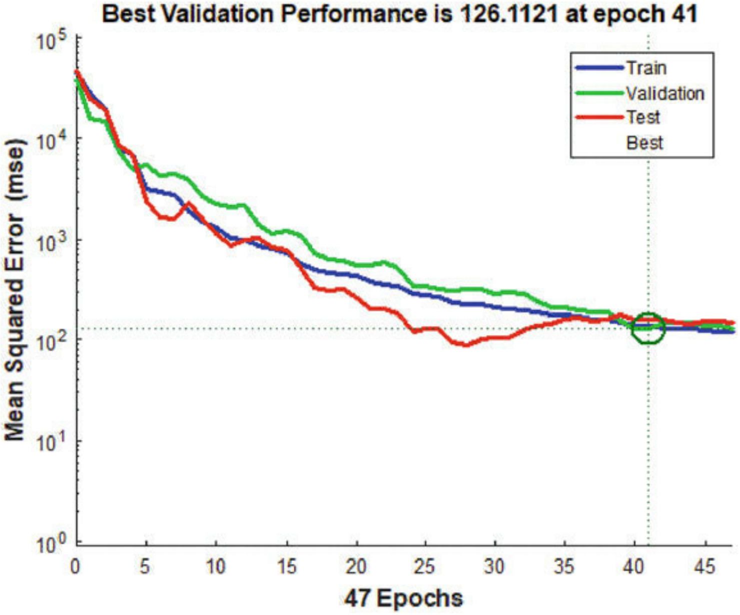

Fig. 3 Diagram of MSE as function the number of iteration (epochs)

study the response of the network by performing regression analysis, which is a measure of how the variance of the results is explained by the objectives.

The *R* values obtained for the target output from each estimated division are: (training 99.95%, validation 99.58%, test 99.32%, and overall 99.78%, as shown in Fig. 4. Through the regression, the ANN made good accuracy.

Figure 5 presents the comparison between the measured and predicted solar radiation inside the greenhouse using the MLP neural network. A comparison made between the results of the measured values and those observed according to the ANN model for the entire database shows a good correlation, which results in a coefficient of determination of 0.99. The model developed has a dynamic close to the system in the learning phase. On the other hand, in the test phase, the error seems significant even if overall the dynamics are respected and the estimated output presents some "peaks." The latter is due to the influence of the input elements on the solar radiation to the front of the greenhouse.

Table 1 presents the validation agreement plot for the inside greenhouse solar radiation with an agreement vector approaching the ideal $[\alpha, \beta, R] = [1.008, -0.0791, 0.997]$.

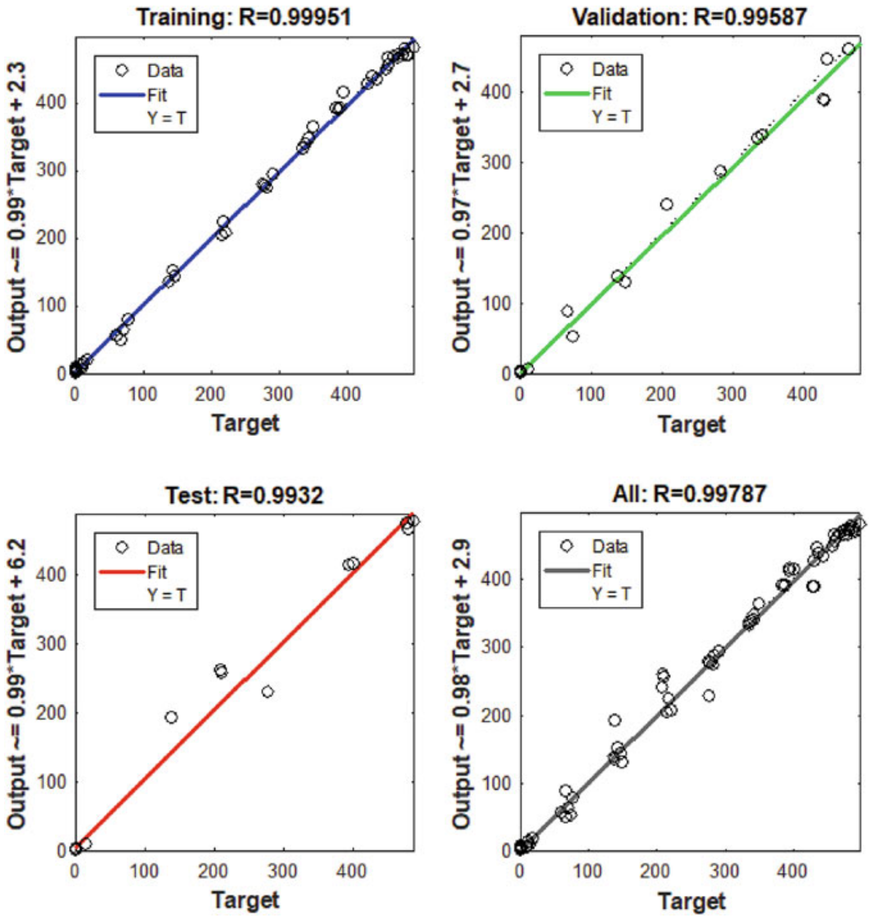

Fig. 4 Regression result of ANN training. (**a**) training, (**b**) validation, (**c**) test, and (**d**) all

4 Conclusions

Over the past decades, research and studies in greenhouse engineering have focused on reducing production costs and the need to reduce environmental impacts to ensure production quality.

In this study, we relied on a tunnel-type agricultural greenhouse covered with plastic film in a desert area in Ghardaïa. The greenhouse is equipped with several sensors and a climate station to record various parameters.

To manage and control the performance of solar greenhouse, an ANN model was developed to predict the solar radiation on a horizontal surface inside the greenhouse.

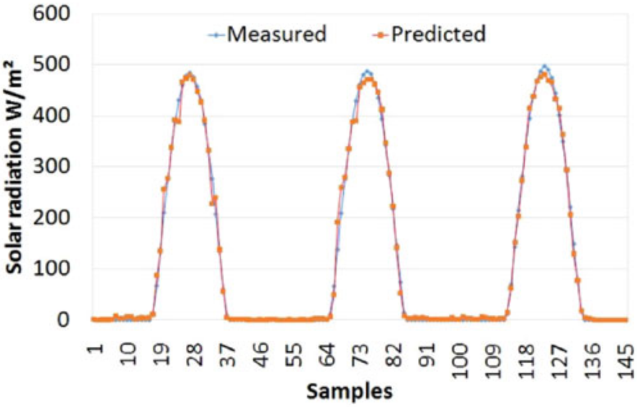

Fig. 5 Measured and predicted solar radiation in greenhouse

Table 1 Linear regression vectors [linear equation: $y^{\text{predict}} = \alpha y^{\text{exp}} + \beta$], R, RMSE, MAE

Parameter	α	β	R	RMSE	MAE
Inside solar radiation	1.008	−0.079	0.997	1.56	1.311

The results showed a high determination coefficient R and low error RMSE and MAE values, indicating that the ANN model is a reliable and powerful tool for simulating the complex performance of the greenhouse system.

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Prototype of a Solar Photovoltaic Charging Station Applied to the Propulsion of Artisanal Fishing Vessels in Arequipa, Peru

Juan José Milón Guzmán, Mario Enrique Díaz Coa, Jorge Antonio Molina Díaz, and Diego Alonso Valdivia Vera

1 Introduction

Currently there is a trend on concepts of electromobility as a measure that has been proposed to decarbonize transportation systems worldwide. This new concept of the use of electric motors brings with it various benefits such as the positive impact on the environment due to the elimination of polluting emissions, greater energy efficiency of all systems that use electric motors and lower acquisition costs. It is for these reasons that in various parts of the world the use of electric motors as part of electromobility is being promoted through policies, guidelines, and standards [1]. This new trend has been applied to various sectors such as marine transport. In Norway, for example, the propulsion of zero-emission marine vessels has been promoted by electrifying them and this has reduced consumption costs of fossil fuels with close to 98% of the electricity used coming from renewable energy. However, various limitations have been verified, such as the lack of charging stations to facilitate the autonomy of the vessels, which is why charging stations have been implemented in the ports [2]. Artisanal fishing in Peru is a sector that faces great problems related to the successful development of its activities. Nearly 90% of the artisanal vessels use gasoline as fuel in two-stroke engines, which is why one of the main expenses incurred is fuel, amounting to as much as 40 USD for a day's work. It has been identified that one of the needs in terms of extraction capacity and cost reduction is the use of electric propulsion systems [3]. It has since been verified that this type of electric motor with a power of 10 kW can mobilize a vessel supplying a combustion engine of up to 60 HP [4]. However, the use of such electric motors has a major weakness, which is the lack of recharging infrastructure for battery banks, since not all places, such as remote locations where access to electricity by network

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is limited, have a charging station. H. Wang et al. [5] investigated the potential benefits of applying solar panel systems to a Ferry, for which they calculated the life cycle of photovoltaic systems as a viable, economical, and environmentally sound solution to replace traditional systems such as diesel engine systems. It was determined thereby that the recovery period of the investment in the solar panel system is only 3 years. Y. D. Çağlar [6] evaluated the contribution of solar energy in marine vessels by designing solar panels on a Cargo Ship with a total length of 208.3 m, a hybrid system consisting of two diesel generators, 1274 solar panels, and an inverter. The photovoltaic system covered 38% of the fuel requirement of the vessel, which is equivalent to 73.53 T of fuel with an energy efficiency of 7.76%, and a recovery period of 7.2 years. In Ecuador, D. Umarani et al. [7] proposed to install a solar charging station in the open spaces of an educational campus in order to provide a constant power supply to mobile devices and laptops in open spaces using clean energy from the sun. Meanwhile, M. Shubham et al. [8] studied the charging of electric bicycles in workplaces through an off-grid system with a battery bank. In that study, a simulation was carried out using the Matlab software, and later the scenarios with a voltage of 12 V were compared to 24 V and 36 V, respectively. Peña and Céspedes [9] proposed the design of a photovoltaic solar charging station in a shopping center and undertook a technical-economic analysis of the charging station for electric vehicles. Over the years the demand for energy has increased, especially since the consumption of electricity is now used for mobility in ocean-going vessels [10, 11].

2 Experimental Model

The experimental model (Fig. 1) is made up of two battery banks, a storage system, a solar supply system, a charge control system, an electrical supply system, and a measurement and data acquisition system. The battery bank is made up of two movable metal structures that contain four batteries each, providing for a total of eight batteries. The structure of the battery bank has fast connectors that facilitate the connections between both banks, charge and discharge connections that will be used in the experimental tests. The batteries that were used are $LiFePO_4$, each of the batteries has an approximate weight of 32 kg, Model LIT 100-48S, Ultracell, 48 V, 100 A·h, 4800 W·h. These batteries were connected in parallel. The charge controller is the model MPPT 250|100, Victron Energy brand, 5800 W. The solar panels used are 370 W, 48 V, and 22 kg. A 5000 VA Victron Energy Multiplus 48|5000|70 model charger was used to charge the battery banks with the electricity grid and with an electric generator. This charger also serves as an inverter. Two Panther K0E4 4 kW electric generators (Inverter generator) and the 6 kW Yamaha EF7200DE generator (Inverterless generator) were used, both fueled by gasoline. Hioki CM7290 brand clamps were used for current measurement. The Data Acquisition System is a Keysight brand model DAQ970A.

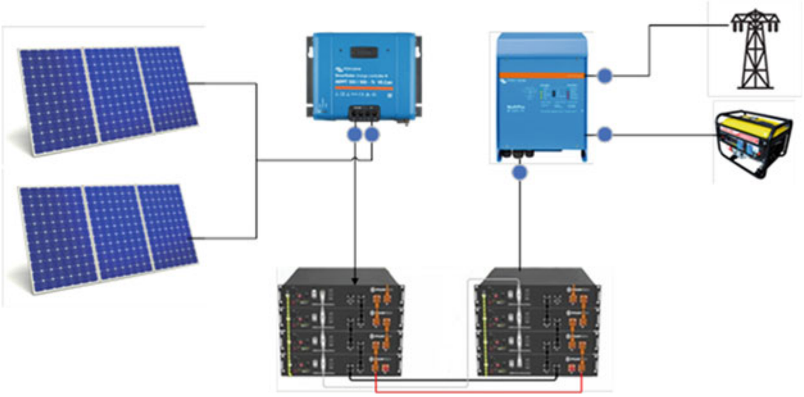

Fig. 1 Setup of the experimental model

The studied uncertainties [12] are Current ± 2%, Voltage ± 0.15%, Power ± 2%, Fuel mass ± 0.25%, and Irradiance ± 0.25%.

The Efficiency of the solar photovoltaic system is:

$$\eta_{\mathrm{solar}} =\cdot I/I_S\cdot A \tag{1}$$

V = Voltage [V]; I = current [A]; Is = Solar irradiance [W/m^2]; A = Area [m^2]

3 Results

The tests were conducted in September and October 2022 (Spring), with a peak solar irradiance of 1150 W/m^2 (Arequipa, Peru). The following graph details the charging time for each of the charging types for one bank (four batteries) and two battery banks (eight batteries). It should be noted that in the case of the charging time of the solar panels, the total time has been counted, that is, including the night hours when there is no presence of the sun. It can be highlighted that the types of load that have a shorter charging time are generators and the electrical network (Fig. 2).

Figure 3 shows the efficiencies calculated for four batteries with different charging methods. A great variation can be observed between each of the methods, the most efficient being the charge with the eight photovoltaic panels, which is close to 99% followed by the efficiency with four photovoltaic panels, with a lower efficiency. The load with the electrical network can also be observed, which is more stable and constant since a linear trend is displayed, finally the load efficiency with the generator can be visualized.

Figure 4 shows the efficiencies calculated for eight batteries with different charging methods. A great variation can be observed between each of the methods,

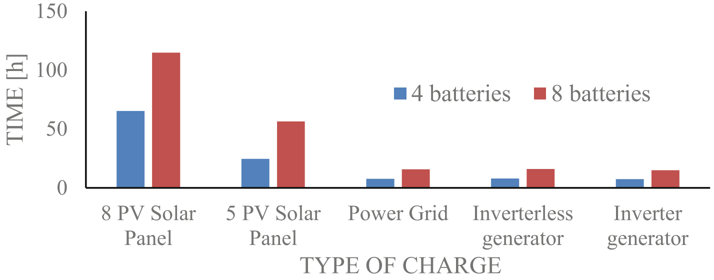

Fig. 2 Average efficiency of charging four and eight batteries

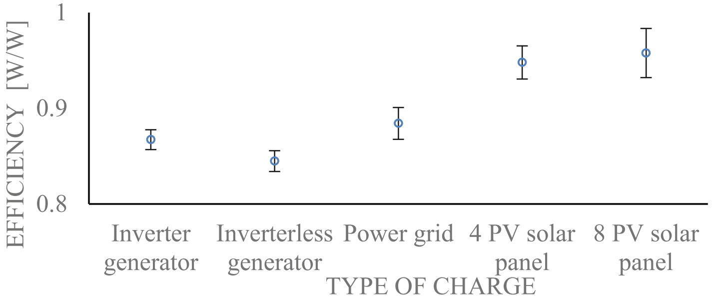

Fig. 3 Battery charge time according to type of charge

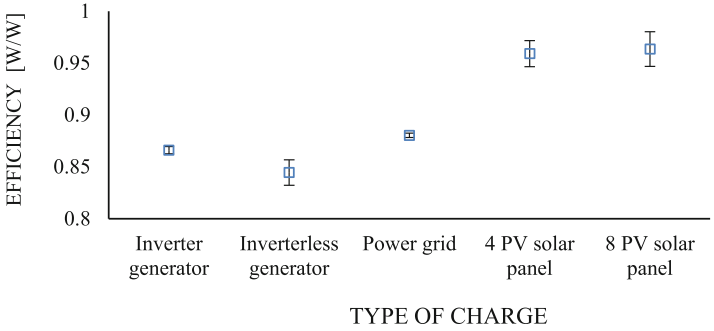

Fig. 4 Average efficiency of charging eight batteries

the most efficient being the charge with the eight photovoltaic panels, which is 96.4% followed by the efficiency with four photovoltaic panels that is 95.9%. It can also be seen that the uncertainties of the generators are less than those obtained by the four and eight photovoltaic panels. It can also be affirmed that the uncertainty of the electrical network is the lowest. It is for this reason that the efficiencies with uncertainties are very close to the average. For charging a battery bank, the Inverter generator was more efficient than the inverterless generator because the average power generated is closer to the rated power of the equipment, unlike the inverterless

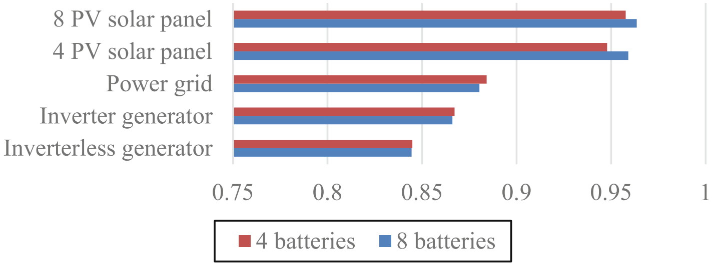

Fig. 5 Comparison of average efficiencies for four and eight batteries

generator whose efficiency decreased because the average power was further away from that of the rated power of the equipment.

Figure 5 presents a summary of the average charging efficiencies for four and eight batteries using the five previously mentioned charging methods. It can be highlighted that the lowest efficiencies correspond to the charge with generators, the charge with the inverterless generator being the lowest, which is close to 84% for the charge of four and eight batteries, compared to the charge with the Inverter generator, which is much more efficient since it represents an 86% average efficiency. It can also be seen that the electrical network is even more efficient and stable, with an average efficiency close to 88%. However, the most efficient means of charging is that of the solar panels where it can be seen that charging eight batteries with eight panels is the most efficient with 96.3% compared to charging with four panels where a slightly lower efficiency is obtained at 95.8 %.

Two (2) discharge tests of a battery bank (made up of four batteries) and two battery banks (totaling eight batteries) were carried out. In these tests, the discharge system with two inverters and discharge module was used. The discharge time of the bank of four batteries was 6 h. The average discharge voltage was 48 V, the average discharge current was −64 A, and the average discharge power was −3 kW. The discharge time of the bank of eight batteries was 8.6 h. The average discharge voltage was 48 V and the average discharge current was −90.8 A. The average discharge power for eight batteries was −4.4 kW. For the discharge test with the electric boat motor, a support structure was built in the laboratory to allow the motor to be anchored. A pool was also used in which the motor was submerged. After the pool was filled, the battery and throttle were connected to the motor.

4 Conclusions

The charging station was dimensioned using a charger inverter, photovoltaic panels, a charge controller, connection cables, and two electric generators. A prototype electric station used to charge two battery banks was built. The prototype was equipped with current and voltage sensors connected to the data acquisition system.

A total of ten load tests were considered using combinations of four photovoltaic panels, eight photovoltaic panels, an electrical network, a Panther K0E4 (Inverter generator) and a Yamaha EF 72000DE (inverterless generator) to charge them. The efficiencies and their respective uncertainties were calculated for charging four and eight batteries using the five charging methods. The lowest efficiencies correspond to charging with electric generators, obtaining efficiencies of 84% and 86% for charging four and eight batteries, respectively. The electrical network improves efficiency with values of up to 88%. Finally, the most efficient charging methods were with solar panels where it could be seen that charging eight batteries with eight panels is the most efficient with 96.35% compared to charging with four panels where a slightly lower efficiency is obtained, 95.7%. The charging time with photovoltaic panels is much longer than using the grid or electric generators, but, in terms of charging costs and efficiency, they produced very favorable results. The charging costs of a bank and two banks of batteries were evaluated in the charging station prototype, where it can be concluded that the cost of charging with the generators is much higher with costs between 85 PEN and 210 PEN. On the other hand, the cost of charging the battery banks using the domestic network is cheaper at 32 PEN and 34 PEN with domestic electrical networks of Arequipa and Matarani, respectively.

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Evaluation and Improvement of the Efficiency of a Self-Contained Photovoltaic System Applied to a Small Business in Arequipa, Peru

Juan José Milón Guzmán, Diego Andree Reynoso Yana, Holger Campos Paredes, and Jhonatan Orlando Macedo Luna

1 Introduction

For some years now, the issue of renewable energy and the necessary research for its efficient use has been widely discussed. The sun is an inexhaustible source of clean energy that is available to anyone who has the initiative to use it, but its use throughout the world is still low compared to conventional sources of power generation, such as fossil fuels. This scenario has caused PV costs to drop rapidly, averaging 13% and 18% per year between 2009 and 2014 for residential and nonresidential buildings, respectively. The unit cost of photovoltaic power has been reduced more than 20 times since 1973, going from 100 to 0.30 USD/Wp. These readjustments have allowed the use of this technology to become widespread and are now on the threshold of massive applications [1, 2]. A correct dimensioning of photovoltaic components determines that the highest efficiency of this can be achieved, although technical criteria such as the coupling of the consumption and solar power curves must be taken into account [3]. In commercial or industrial applications, it is possible to oversize the photovoltaic system without significantly affecting profitability, since a larger system can cover a possible increase in energy consumption in the future [4]. If the surpluses are very high, these will not contribute to the recovery of the investment, since there is no discharge to the public network [5]. According to Willborn [6], it is stated that within the commercial sector, small and medium-sized companies, as compared to larger commercial businesses, are the ones that can obtain a greater benefit in profitability from photovoltaic generation systems. This situation occurs because most of these companies have

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the bulk of their energy needs during the day. According to Herce [7], in a study applied in Portugal, the use of renewable resources for energy generation and its application under the category of self-consumption is very widespread in Europe, with the classic user of the energy system becoming a producer and consumer at the same time. Users under this category are now known as “prosumers.” As explained by Ramírez [8], the application of photovoltaic generation systems is more feasible in the economic field if they are applied to commercial sectors. Grid parity, which is the equality of grid energy prices and the energy generated by the photovoltaic system would be easily achieved by up to 88% of the total of the commercial sector, making the economic indicators favorable. According to Vásquez [9], to carry out the dimensioning of a photovoltaic system, the historical consumption of electrical energy must be analyzed, based on which it is possible to determine if the system deserves the implementation of an energy storage system (batteries). In his own work, Peralta [10] states that the constant supervision of the operation of the photovoltaic system must be carried out together with the installation of sensors that record the operating parameters such as voltage and current to determine the efficiency of the system. The main restriction of the photovoltaic systems that operate under the self-consumption model is that of not being able to inject surplus power into the electricity grid, which means that there is a considerable percentage of electrical power that is not consumed by the installation and therefore is considered lost. This percentage in countries with considerable photovoltaic development can reach 20% of the total energy generated [11]. In order to obtain maximum efficiency from photovoltaic systems, prosumers can increase the level of photovoltaic self-consumption in their facilities. One strategy to achieve this increase in self-consumption is to store excess generated energy that is not immediately consumed by the utility installation. This storage can occur through batteries or in domestic water heating systems [12, 13]. Kumar [14] explains that another means of reducing power fluctuations is by load shedding or reduction of charge, but that energy storage remains as one of the most effective methods of handling intermittency in PV systems. According to Abou [15], energy storage systems have been successfully used in cooperation with photovoltaic systems in isolated microgrids. Energy storage is viable and power can be delivered back to the facility when needed. Bhayo [16] explains that the storage of energy in batteries and its integration with photovoltaic systems ensures that the installation has an energy backup system. This means that when the photovoltaic generation is not enough to feed a load and there is a deficit of power, this is provided from the battery system to meet internal demand. However, battery systems are still expensive and represent about 54% of the total cost of capital. Saini [17] also explains that battery systems store the excess power generated by the photovoltaic system, functioning as an alternative electrical load during a low demand situation. On the other hand, when they are discharged and deliver the stored energy, they behave as an additional generator during peaks in demand.