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ARIMA Models in Solar Radiation Forecasting in Different Geographic Locations

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Abstract: The increasing demand for clean energy and the global shift towards renewable sources necessitate reliable solar radiation forecasting for the effective integration of solar energy into the energy system. Reliable solar radiation forecasting has become crucial for the design, planning, and operational management of energy systems, especially in the context of ambitious greenhouse gas emission goals. This paper presents a study on the application of auto-regressive integrated moving average (ARIMA) models for the seasonal forecasting of solar radiation in different climatic conditions. The performance and prediction capacity of ARIMA models are evaluated using data from Jordan and Poland. The essence of ARIMA modeling and analysis of the use of ARIMA models both as a reference model for evaluating other approaches and as a basic forecasting model for forecasting renewable energy generation are presented. The current state of renewable energy source utilization in selected countries and the adopted transition strategies to a more sustainable energy system are investigated. ARIMA models of two time series (for monthly and hourly data) are built for two locations and a forecast is developed. The research findings demonstrate that ARIMA models are suitable for solar radiation forecasting and can contribute to the stable long-term integration of solar energy into countries' systems. However, it is crucial to develop location-specific models due to the variability of solar radiation characteristics. This study provides insights into the use of ARIMA models for solar radiation forecasting and highlights their potential for supporting the planning and operation of energy systems.

Keywords: ARIMA; GHI; RES; forecasting; solar; energy; irradiance; photovoltaic; climatic conditions; Poland; Jordan

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1. Introduction

Global energy consumption is growing continuously, and even though fossil fuels (coal, gas, petroleum) are still the basis of production, their depletion and greenhouse effect have caused renewable energy sources (RES) to become more and more important. Energy Information Administration (EIA) projects that the share of renewables in US electricity generation mix will double by 2050 [1]. In Europe, the objective behind the European Green Deal (COM(2019) 640) is to become the world's first climate-neutral continent by 2050 [2].

Electricity production in 2021 amounted to a total of 28,466.3 TWh worldwide, including 7931 TWh from RES, with more than 50% from hydroelectric power plants (4273.8 TWh) [3]. However, the wind and the sun are the fastest growing sources of electricity, which, in 2021, were used to generate a tenth (10.3%) of the world's electricity [4]. In 2021, a record for the installation of new photovoltaic (PV) power plants was noted, contributing an additional 167.8 GW, and a total level of 940 GW was achieved [5]. Production of electricity from sunlight reached the value of 1023.10 TWh [6].

Solar energy is inexhaustible and theoretically, its potential far exceeds the worldwide energy demand [7]. However, solar power availability depends largely on geographical location [8]. More precisely, the production of energy from photovoltaic plants depends on the amount of solar radiation and environmental conditions (latitude, the presence of clouds, terrain and shading, aerosol concentration in the atmosphere, air humidity, temperature) [9]. However, it is believed that PV can strengthen its position in the mix of energy production of almost all countries.

Photovoltaic power potential is most often expressed in W/m^2 in a selected unit of time using the global horizontal irradiance (GHI), which relates to shortwave solar radiation and is the sum of direct (after taking into account the Sun's zenith angle) and diffuse horizontal irradiance. In addition, the integral of irradiance over a period of time, which is the sum of the energy falling on the surface in a given period, measured in J/m^2 or Wh/m^2. Similarly, it consists of direct, diffused, or reflected solar radiation. Shortwave downward radiation (SWDR, SDR) can also be analyzed. Sometimes, to assess the photovoltaic power, the radiation on a surface at a specific inclination angle and azimuth, global irradiation onto inclined plane (in Wh/m^2), is useful. To estimate the irradiance/irradiation, many models have been developed, taking into account, e.g., the relative distance between the Sun and the Earth during the year, the declination of the Sun, the rotation of the Earth around the polar axis, and its motion around the Sun [10]. Moreover, the irradiance under clear sky or all sky conditions can be considered. Solar radiation data are also provided in a dimensionless form: the clearness index.

Since photovoltaic panels differ in the materials from which they are manufactured, as well as in energy production technology and inverter efficiency, which implies an unequal performance potential, solar radiation analysis allows the comparison of conditions for different photovoltaic technologies. It does not require taking into account the specific design of the power plant (the parameters of photovoltaic panels and their orientation, i.e., tilt angle and azimuth) and operating mode. Solar radiation is believed to be the most important component for assessing the power potential at each location. It is sometimes assumed that the relationship between solar radiation and the energy generated by a photovoltaic panel is proportional [11]. On the other hand, planning the location and parameters of a specific PV installation, especially in cities, requires analysis and modeling of not only the GHI but the spatial and temporal distribution of solar radiation taking into account shading and reflections caused by buildings and other infrastructure and terrain objects [12].

One of the most important challenges for the efficient operation of power distribution systems is balancing supply and demand in real time [13]. For this reason, energy generated by photovoltaic systems requires forecasting solar radiation for the design, planning, and operational management of power systems in the short, medium, and long term and with high time resolution to reliably provide clean energy.

Solar power estimation can be performed through several types of forecasting methods. Recently, the most popular ones are derived from artificial intelligence and include neural networks (e.g., support vector machines (SVM), long short-term memory (LSTM) [14,15], back propagation neural networks [16], autoregressive neural networks [17,18], neural network autoregressive models with exogenous input [19]), swarm intelligence [20,21], and machine learning, including deep learning. Considering the data that underline modelling, the methods can be divided into two categories: physical, using numerical weather predictors and solar irradiation data, and statistical, forecasting solar power directly from historical data [22,22–24]. To overcome their drawbacks and emphasize the advantages, these models are often combined and proposed as hybrid models to increase the fitting and accuracy. The periodicity of solar irradiation also makes it possible to successfully explore time series auto-regressive integrated moving average (ARIMA) models [24–29].

ARIMA models, due to their versatility and simplicity, have been widely used in the field of energy and electrical systems. The main advantages of these models are accessibility and low computational complexity, the use of only previous observations of the time series and, at the same time, the possibility of embedding the model in the theory and/or in the process structure, and formal translation of the studied phenomenon. This, combined with the often-obtained sufficient quality and reliability of the forecasts, puts ARIMA models among the most popular approaches to predicting time series values in the power industry. However, it is very important to check the adequacy of the model with the available data. The quality of global solar radiation forecasts using ARIMA models depends on the characteristics of time series and random perturbations, the source of which is geographical location [30]. The results for each time refer only to a given climatic area and should not be directly extrapolated to other sites [31]. In order to compare the performance of ARIMA models, it is reasonable to test their performance in different climate varieties [32].

The aim of this paper is to test ARIMA models, evaluate their performance, and validate their prediction capacity for the seasonal forecasting of solar radiation in different climatic conditions. The need for further development of renewable energy is indisputable, but to achieve sustainable goals effectively, the strengths and weaknesses of a site must be taken into account. In this paper, prognostic models were built on the basis of data from countries with utterly different solar potential and GHI values—Jordan and Poland. Both countries have a keen interest in increasing the share of renewable energy in their energy mix and reducing dependence on fossil fuels. To achieve this goal, various initiatives have been pursued, such as building solar farms and energy windmills, as well as supporting the development of biomass and biogas. In recent years, Jordan and Poland have made significant progress in renewable energy production. Considering the solar energy production, according to the International Renewable Energy Agency (IRENA), Jordan's installed PV capacity has increased from just 6 MW in 2015 to 1521 MW in 2021, and Poland's in the same period from 108 MW to 6257 MW [33]. Despite significant differences in climatic conditions, solar energy production per capita varies little: 0.166 kW in Poland and 0.148 kW in Jordan.

This article is organized as follows. First, it presents the essence of ARIMA models. Then, it provides a solid review of papers on the use of ARIMA in solar radiation forecasting. Next, a case study is discussed, Polish and Jordanian policies on renewable energy development are cited, and the results of the numerical analysis are presented. The article ends with conclusions. The step-by-step research methodology is presented in Figure 1.

Stage one of the research is to investigate the essence of ARIMA modeling and to analyze the literature on the use of ARIMA models both as a reference model for evaluating other approaches and as a basic forecasting model for forecasting renewable energy generation. In stage two, the current state of RES utilization in selected countries and the adopted transition strategies to a more sustainable energy system are presented as the background of the study. In stage three, ARIMA models of two time series (for monthly and hourly data) were built for two locations and a forecast was developed. The final stage is a discussion of the results and conclusions.

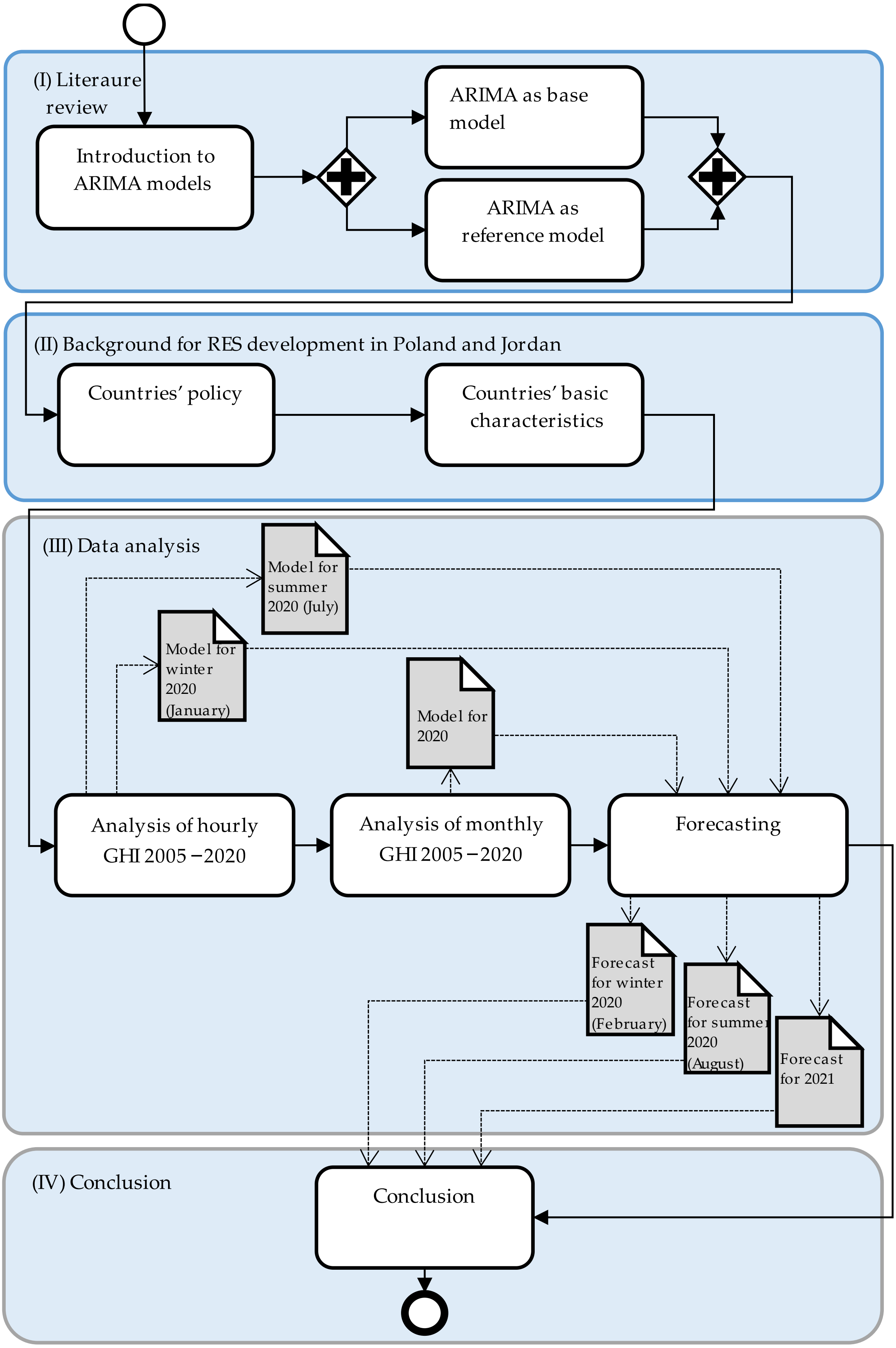


Figure 1. The step-by-step research methodology.

2. Method

Auto regression integrated moving average (ARIMA) models are a wide class of models of stochastic processes that are extensions of ARMA models including integration (I) to remove non-stationarity. ARMA models of time series y_t consist of (i) autoregression (AR), which involves a regression model of lagged time series values, and (ii) moving average (MA), which involves an error term as the linear combination of the previous error terms:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j e_{t-j}. \tag{1}$$

In the model in (1), y_{t-i} and e_{t-j} are the lagged past values and errors, Φ_i is the coefficient for the autoregressive component, θ_j is the coefficient for the moving average term, and p and q are orders and determine number of coefficient parameters.

ARMA(p,q) models can be applied on at least weakly stationary series, characterized by the finite and constant mean and variance, and the value of the covariance between the observations from two periods depending only on the lag. Therefore, adequate data preprocessing is an important stage when applying the approach to non-stationary series.

The most common method of removing non-stationarity in terms of the mean (e.g., trend) can be combined with the model. With B as the backward operator to indicate differencing, $B(y_t) = y_t - y_{t-1}$, the ARIMA(p,d,q) model with an integration (differencing) d to delete non-stationarity is expressed as follows:

$$\Phi_p(B)(1-B)^d y_t = \theta_q(B)e_t, \tag{2}$$

where:

$\Phi_p(B) = 1 - \Phi_1 B - \ldots - \Phi_p B^p$ is the moving average operator, represented as a polynomial in the backshift operator;
$\theta_q(B) = 1 - \theta_1 B - \ldots - \theta_q B^q$ is the autoregressive operator, represented as a polynomial in the backshift operator.

The SARIMA(p,d,q)(P,D,Q)s models include seasonality in time series, where s is the number of seasons in the seasonal cycle:

$$\Phi_P(B^s)\Phi_p(B)(1-B)^d(1-B^s)^D y_t = \Theta_Q(B^s)\theta_q(B)e_t, \tag{3}$$

where:
$\Phi_P(B^s) = 1 - \Phi_1 B^s - \ldots - \Phi_P B^{Ps}$ is the seasonal autoregressive operator;
$\Theta_Q(B^s) = 1 - \Theta_1 B^s - \ldots - \Theta_Q B^{Qs}$ is the seasonal moving average operator.

The ARIMA/SARIMA model describes the y_t using the preceding values of the y_t and the forecast error e_t. An extension of the classic ARIMA models includes a set of exogenous series $x_{i,t}$ as input variables, and is referred to as an ARIMAX:

$$y_t = \mu + \sum_i \frac{\omega_i(B)}{\delta_i(B)} B^{k_i} x_{i,t} + \frac{\theta_q(B)}{\Phi_p(B)} e_t, \tag{4}$$

where:

μ is a constant;
$\omega_i(B)$ is a numerator polynomial of the transfer function for the ith input series;
$\delta_i(B)$ is a denominator polynomial of the transfer function for the ith input series;
k_i is the pure delay for the effect of $x_{i,t}$. at time t.

The identification of an adequate ARIMA model relies on the proper identification of the autocorrelation and partial autocorrelation patterns. A common approach to determine the appropriate ARIMA structure is to sequentially compare models with different parameters to find the one that the best fulfils the fit criteria [34].

3. Background Literature

The importance of the problem of estimating electricity production from renewable sources has led to an increase in interest in renewable energy generation modeling and forecasting methods. With regard to solar energy, reviews on the recent applications of photovoltaic output forecasting have been presented, among others by Mellit et al. [35], Başaran et al. [36], Massaoudi et al. [37], and Ahmed et al. [11].

ARIMA models, as a result of their flexibility and relatively simple structure, have found wide application in energy management. The popularity of ARIMA models in solar forecasting is reflected in the number of articles on this topic: the IEEE, Scopus, and WoS databases accumulate nearly 840 such papers published between 2012 and 2022 (Figure 2). Numerous studies treat ARIMA models, one of the simplest forecasting models, as a reference to evaluate other, more complex multivariable models. Selected recent works from the period 2018–2022 are listed in Table 1.

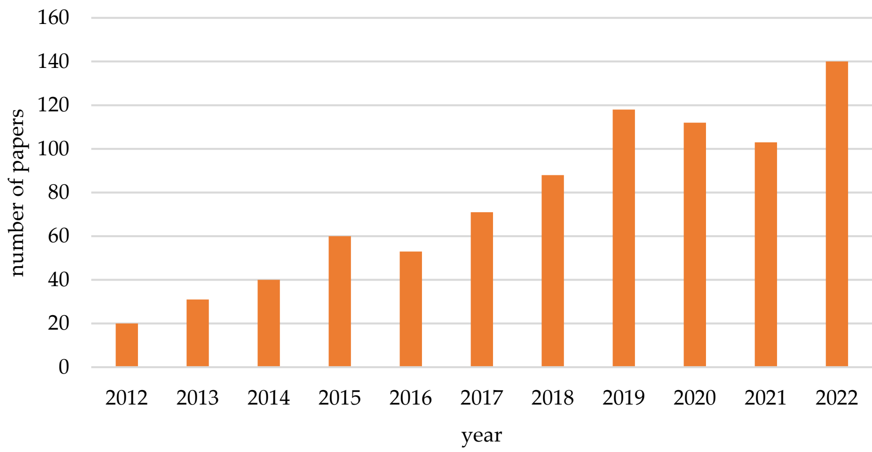


Figure 2. Number of papers on modeling and forecasting renewable energy generation in the period 2012–2022.

Table 1. ARIMA in solar radiation forecasting methods—literature review.

Title of the Article	Author (Year)	Focus	Methods
Very Short-Term Solar Irradiance Forecasting using Multilayered Long-Short Term Memory	Thirunavukkarasu et al. (2022) [38]	Solar irradiance at Melbourne airport	Improved multi-layered LSTM LSTM, SVM, ARMA, ARIMA, AR, MA
Dynamic Forecasting of Solar Energy Microgrid Systems Using Feature Engineering	Mohamed et al. (2022) [39]	PV farms' power based on the associated features in NWP	ARIMA MLR, XGBoost, LSTM
Comparison and Analysis of Solar Irradiance Forecasting Techniques	Mishra et al. (2022) [40]	National Renewable Energy Laboratory in Golden, Colorado	ARIMA, FL
Deep Learning and Statistical Methods for Short- and Long-Term Solar Irradiance Forecasting for Islamabad	Haider et al. (2022) [41]	GHI based on weather data in Islamabad, Pakistan	SARIMAX, Prophet, LSTM, CNN, ANN
Deep Attention ConvLSTM-Based Adaptive Fusion of Clear-Sky Physical Prior Knowledge and Multivariable Historical Information for Probabilistic Prediction of Photovoltaic Power	Bai et al. (2022) [42]	Clear-sky global irradiation	ConvLSTM, ARIMAX, CNN, LSTM, MLP, SVR, ELM, CART, GBDT
On Comparing Regressive and Artificial Neural Network Methods for Power System Forecast	Andreotti et al. (2021) [43]	Yearly PV power generation in Sicily and data from Gestore Servizi Energetici	AR, ANN
Solar PV Power Forecasting Using Traditional Methods and Machine Learning Techniques	Alam (2021) [44]	Power generation by PV modules at the University of Queensland campus in 1-day and 1-week horizons	CNN, multi-headed CNN, CNN LSTM, ARMA, MLR

Table 1. *Cont.*

Title of the Article	Author (Year)	Focus	Methods
A Study of 100kwp PV Plant Output Power Forecasting: A Case Study	Ananthu and Kashappa (2021) [45]	A day-ahead time forecast of a solar power PV plant at G.N.D.Engg.College, Bidar, India	LSTM, ARIMA, SARIMA, RNN, fbProphet
Day-Ahead Forecasting of the Percentage of Renewables Based on Time-Series Statistical Methods	Basmadjian et al. (2021) [23]	The percentage of different types of renewable energy sources in Germany	SARIMAX, SARIMA, ARIMA
Forecasting of Solar Power Volatility using GJR-GARCH method	Ghosh and Gupta (2021) [46]	PV power in a one-hour window at the University of Central Florida	AR, MA, ARIMA, GJR-GARCH
Day Ahead Solar Irradiance Forecasting Using Different Statistical Techniques	Garg et al. 2020 [47]	Monthly average irradiance of Bhadla, Jodhpur, India	MARKOV model, ARIMA, ANN
Day-ahead Energy Sharing Schedule for the P2P Prosumer Community Using LSTM and Swarm Intelligence	Zou et al. (2020) [21]	Day-ahead energy demand prediction and battery charge/discharge	LSTM PSO, ARIMA
A Derivative-Persistence Method for Real Time Photovoltaic Power Forecasting	Bozorg et al. (2020) [48]	Very short-term power production of a PV system in Switzerland	Derivative-persistence method, persistence, ARMA
The Impact of Prediction Errors in the Domestic Peak Power Demand Management	Mahmud et al. (2020) [49]	The domestic peak power demand system of PV, EV, and BESS	ARMA, ANN
Daily Electric Forecast for Various Indian Regions Using ANN	Singh et al. (2020) [50]	The day ahead forecasting of wind and solar generation and peak demand of various Indian regions	ANN, ANN-GA, AR, ARIMA
Time Series Forecasting of Total Daily Solar Energy Generation: A Comparative Analysis Between ARIMA and Machine Learning Techniques	Atique et al. (2020) [51]	The daily solar energy generation by panels at the Reese Technology Center of Texas Tech University	SARIMA, SVM, ANN
Global Solar Radiation Estimation and Climatic Variability Analysis Using Extreme Learning Machine Based Predictive Model	Hai et al. (2020) [52]	The daily solar radiation in the Cheliff Basin, Algeria	MLR, ARIMA
Day-Ahead Solar Irradiation Forecasting Utilizing Gramian Angular Field and Convolutional Long Short-Term Memory	Hong et al. (2020) [53]	A day-ahead forecast of GHI values in Fuhai, Taiwan	LSTM, ARIMA, CNN-LSTM
Modified Auto Regressive Technique for Univariate Time Series Prediction of Solar Irradiance	Marikkar et al. (2020) [25]	Solar irradiance from 10 min to 1 h prediction horizons in PV plant at the University of Peradeniya in Sri Lanka	Modified AR, CNN, LSTM
Short-term Forecasting of Solar Irradiance	Paulescu and Paulescu (2019) [54]	Nowcasting solar irradiance for evaluation models from perspectives of forecast accuracy, precision, data series granularity, and variability	Random walk with drift, MA, exponential smoothing, ARIMA, the two-state model
Global Solar Radiation Prediction by ANN Integrated with European Centre for Medium Range Weather Forecast Fields in Solar Rich Cities of Queensland Australia	Ghimire et al. (2019) [30]	Global incident solar radiation in five metropolitan sites in Australia	ML, ANN, SVR, GPML, GP, ARIMA, TM, TSFS
A Hybrid Approach for Short-Term PV Power Forecasting in Predictive Control Applications	Vrettos and Gehbauer (2019) [55]	Short-term forecasts with prediction horizons from 15 min to 1 day	SARIMA, ANN, hybrid SARIMA with ANN
Forecasting Solar Energy Generation and Load Consumption—A Method to Select the Forecasting	Nambiar et al. (2019) [56]	Load consumptions and solar energy generation on a university campus	ARIMA, SES, SVR, ANN, LSTM, LR
Comparison of Intraday Probabilistic Forecasting of Solar Irradiance Using Only Endogenous Data	David et al. (2018) [32]	GHI data recorded at six different locations around the world	ARMA, CARDS, NN, LMQR, WQR, QRNN, GARCHrls, SB, QRF, GBDT
Forecasting Solar Irradiance at Short Horizons: Frequency and Time Domain Models	Reikard and Hansen (2018) [29]	Irradiance and clear sky index data at very short horizons in six sites in the US	ARIMA, frequency domain, LR, persistence
Forecasting Solutions for Photovoltaic Power Plants in Romania	Oprea et al. (2018) [57]	Output of two PV plants in Romania	NN, ARIMA, data mining

Table 1. *Cont.*

Title of the Article	Author (Year)	Focus	Methods
Long-term Solar Irradiance Forecasting Approaches—A Comparative Study	Sharika et al. (2018) [58]	Solar irradiation in 10 min intervals in Sri Lanka	ARIMA, RFR, NN, LR, SVR
Short Term Forecasting of Solar Radiation and Power Output of 89.6 kwp Solar PV Power Plant	Das (2018) [59]	Total insolation received on the tilted surface for a short time horizon and PV power output	A model that utilizes anisotropic Klucher's, model, smart persistence model (SPM), and ARIMA

Abbreviations: ANN—artificial neural network, AR—auto regressive, ARMA—auto regression and moving average, ARIMA—auto regression integrated moving average, ARMArls—recursive least square ARMA, ARIMAX—auto regressive integrated moving average exogenous variable, BESS—battery energy storage system, CARDS—coupled autoregressive and dynamical system, CART—classification and regression tree, CNN—convolutional neural network, ConvLSTM—convolutional long short-term memory, ELM—extreme learning machine, EV—electric vehicle, FL—fuzzy logic, GBDT—gradient boosting decision tree, GA—genetic algorithm, GARCH—generalized autoregressive conditional heteroskedasticity, GARCHrls—recursive GARCH, GP—genetic programming, LMQR—linear model in quantile regression, LR—linear regression, LSTM—long short-term memory, MA—moving average, MLP—multilayer perceptron, MLR—multiple linear regressions, NAR—non-linear autoregressive, NN—neural network, NWP—numerical weather prediction, PSO—particle swarm optimization, QRF—quantile regression forest, QRNN—quantile regression neural network, RFR—random forest regression, RNN—recurrent neural network, SARIMA—seasonal auto regression integrated moving average, SB—sieve bootstrap, SES—simple exponential smoothing, SVR—support vector regression, TM—temperature model, TSFS—time series and Fourier series, WQR—weighted quantile regression.

The multitude of articles comparing different models and proposing new hybrid approaches shows that forecasting solar energy production is an ongoing challenge, and the selection of an appropriate forecasting method is still an unresolved task because the obtained results depend on many factors. In most cases, methods are compared by the mean squared error (MSE), root mean square error (RMSE), and mean absolute percentage error (MAPE), less often by R-values, and sometimes by total training time [53], Willmott's index [52], or forecast score [59]. The basic finding is that the errors increase for all models as the prediction horizon increases. In general, AI-derived forecasting methods achieve higher quality measured by forecasting errors [49], but in many cases, ARIMA models have errors only slightly higher and often less than 20% [43,60,61]. The ARIMA approach implies larger errors in cases of very short time horizons ranging from a few minutes up to few hours due to the high variability of solar radiation [48], but such a level of prediction errors in systems can be compensated for using battery energy storage systems [49,62]. Modified AR models can give good short-term solar irradiance forecasting results, as can NN methods [25]. ARIMA models definitely outperform the other statistical models [63].

Comparing different models does not always unequivocally reveal the best probabilistic model. As has been shown in a number of works, machine learning techniques can improve forecast accuracy [20,21]. However, this is not a principle [17,64]. There is not always a clear advantage for ANNs, especially when computational effort and input data requirement are taken into account. In addition, automatically applied machine learning methods based on processing large data sets can sometimes lead to over-fitting of the model and deterioration in the quality of the resulting predictions [27,28]. ARMA and NNs could present similar results both in terms of error and the distribution of the error [32]. ARIMA could sometimes perform better than machine learning techniques [58]. The choice between classical statistical methods and machine learning algorithms generally depends on the area of application and the data held [39]. Moreover, time and space dependencies of PV power must be considered [65]. The advantage of each approach may be relative and depends on the variability of a given time series resulting from the geographic location [30]. The value of combining different models is emphasized [58].

This allows us to conclude that ARIMA could be considered as a potential method for solar radiation forecasting (and indirect solar energy production), although an accurate model must be tailored to local conditions. The main advantage of ARIMA lies in its simplicity. AI methods, in the majority, require data related to the physical nature of the problem such as not only solar irradiance, but also, e.g., air temperature, humidity, wind direction and speed [44], rainfall, cloud cover, elevation, and azimuthal angle [66] and even albedo, vorticity, evaporation, and more [30]. ARIMA uses only previous data and reveals the series structure. The legitimacy of ARIMA models is confirmed by selected recent (2019–2022) ARIMA-only works listed in Table 2.

Table 2. A review of recent articles that employ the ARIMA method.

Title	Author (Year)	Focus	Models
Irradiance and Temperature Forecasting for Energy Harvesting Units in IoT Sensors using SARIMA-KF	Azzam et al. (2022) [67]	48 daily datapoints on irradiance of the sun for Ottawa, Ontario, Canada	ARIMA(0,1,1)(2,1,0)$_{48}$
Early Experience of the Generation Pattern of Grid Connected Solar PV System in Bangladesh: A SARIMA Analysis	Aziz and Chowdhury (2021) [68]	Electricity generation from a solar plant in Bangladesh	ARIMA(1,1,8)(0,1,0)$_{12}$
Forecasting and Analysis of Solar Power Output from Integrated Solar Energy and IoT System	Adli et al. (2021) [69]	Solar power output at Kampung Pulau Melaka, Kelantan, Malaysia	ARIMA(11,2,4)
Modeling Solar Radiation in Peninsular Malaysia Using ARIMA Model	Ismail et al. (2021) [70]	Daily solar radiation data in Peninsular Malaysia	ARIMA(1,1,2), ARIMA(2,1,1), ARIMA(1,1,3) depending on the state
Spatial Forecasting of Solar Radiation Using ARIMA Model	Shadab (2020) [71]	Monthly solar radiation prediction around Delhi in India	ARIMA(1,0,1)(0,1,1)$_{12}$, ARIMA(3,0,3)(0,1,1)$_{12}$, ARIMA(2,0,0)(0,1,1)$_{12}$, ARIMA(2,0,2)(1,1,1)$_{12}$, and many others, depending on the location
One Month-Ahead Forecasting of Mean Daily Global Solar Radiation Using Time Series Models	Belmahdi et al. (2020) [72]	Solar radiation in Tétouan, Morocco	ARMA(2,1) and ARIMA(0,2,1)
Solar Radiation Prediction for a Winter Day Using ARMA Model	Sansa et al. (2020) [73]	Solar radiation related to an industrial company in Barcelona	ARMA(3,3)
Photovoltaic Power Plant Production Operational Forecast Based on its Short-Term Forecasting Model	Khalyasmaa et al. (2020) [60]	Short-term 1 h forecasts of photovoltaic power plant generation in the south of Russia	AR(1), AR(2), ARMA(1,2)
Estimating Solar Power Plant Data Using Time Series Analysis Methods	Idman et al. (2020) [74]	Solar energy panels' production based on monthly average	AR, ARMA, SARIMA, Holt, Holt–Winters
A Guide to Solar Power Forecasting Using ARMA Models	Singh and Pozo (2019) [22]	One hour-ahead predictions of power output from a site in Australia	ARMA(p, q) for each of 14 hours of the day
Analysis of ARMA Solar Forecasting Models Using Ground Measurements and Satellite Images	Marchesoni-Acland et al. (2019) [31]	GHI 10 min granularity data recorded in six measuring stations in the Pampa Húmeda region in Uruguay	ARMA and ARMAX RLS, including as cloudiness and short-term local variability index as exogenous variables
Forecasting of Total Daily Solar Energy Generation Using ARIMA: A Case Study	Atique et al. (2019) [75]	The daily total solar energy generation of a 10kW solar panel installed in the Reese Research Center in Lubbock, TX	ARIMA(0,1,2)(1,0,1)$_{30}$

The works cited in Table 2 indicate that ARIMA can be considered as a potential method that can be successfully applied to the prediction of insolation data. The variety of models considered suggests the necessity of selecting a model each time in order to achieve high accuracy and reach the goal, but taking into account the data available. It was also proven that in order to obtain a high fit when using an ARIMA-type model, it is worth testing different models, not only taking into account geographic location, but also seasonal variation in insolation [61]. Sometimes, it is worth testing various ARIMA models with different time horizons [55] or exploring potential improvements in accuracy when the input data are normalized [29]. In the case of the ARIMA approach, the model selection is often made on the basis of error assessment [69] or AIC [52,68].

In this article, solar radiation data are used as a prerequisite for the outputs of all solar energy systems [76] in two locations: Poland and Jordan.

4. Results

4.1. Framework Conditions for the Development of Renewable Energy in Jordan and Poland

Goal 7 of sustainable development is to 'ensure access to affordable, reliable, sustainable, and modern energy for all'. Achieving this is crucial to all aspects of human life as well as for tackling climate change as increasing the share of renewables in energy mix can help reduce greenhouse gas emissions.

The targets for renewable energy production vary depending on the priorities of each country or region, but many governments aim to increase the share of RE in their overall electricity production. In the EU, Renewable Energy Directive 2018/2001/EU established a target of 20% RES in 2020 and at least 32% in 2030. However, in 2022, the European Commission's new 2030 climate targets include a proposal to increase the target to at least 45% of the energy mix (COM/2022/230).

According to the 2022 report on the achievement of the 2020 renewable energy target progress in deploying renewable energy, the EU reached a share of 22.1% in gross final energy consumption. Poland committed (2009/28/EC) to a target of 15% RES by 2020 and reached 16.1%, mainly thanks to biomass. It follows that Poland should take additional actions and investments to encourage faster deployment of other RES.

EU member states are required to submit national plans that outline their actions to achieve the energy and climate goals set at the EU level. In Poland, the development of renewable energy production is regulated by several acts, including:

- The Renewable Energy Sources Act of 2015;
- The Act on the National Energy and Climate Plan for years 2021–2030.

Examples of Jordan's laws that regulate the development of renewable energy production are:

- Renewable Energy & Energy Efficiency Law: Law No. (13) of 2012;
- The Updates of Renewable Energy & Energy Efficiency Law: Law No. (33) of 2014;
- Jordan General Electricity Law for the Year 2002;
- The Environmental Protection Law of 2017.

In conjunction with the efforts to develop renewable energy production, Jordan issued Law No. 13 on renewable energy in 2012 and its amendments in 2014. This law promotes renewable energy projects by clarifying the procedures related to the funding, implementation, and operation of renewable energy projects in Jordan. The Jordanian Ministry of Energy and Mineral Resources (MEMR) has developed the Master Strategy for Energy Sector 2020–2030 with a target for renewables to reach 31% of the total power generation and 14% of the total energy mix in Jordan by 2030 [77]. In the General Electricity Law for the Year 2002, MEMR confirmed that one of its main duties is to promote the generation and use of renewable energy. The ministry has established the Renewable Energy and Energy Efficiency Fund to provide partial funding for renewable energy projects, and exempted all systems and equipment of renewable energy from customs duties. However, some constraints remain present, such as the cost and the availability of funding for its implementation, the availability of the necessary infrastructure, especially for the systems connected to the electricity grid, managing the systems to maintain their efficiency, etc. [78].

Photovoltaic technology can play a key role in the transition to a more sustainable energy system [79] since it is characterized by a relatively low environmental impact, wide availability thanks to the possibility of installation in various locations, cost efficiency, and scalability. Combination with other energy technologies such as storage systems is especially promising.

4.2. Countries' Basic Characteristics

Jordan and Poland differ highly in irradiance values: Poland has an average daily GHI potential of 2.977 kWh/m^2 and Jordan receives twice as much irradiance, 6.018 kWh/m^2.

These countries are ranked 198th and 19th, respectively, out of 209 countries analyzed in the World Bank's ranking of global photovoltaic potential [9]. However, looking at the per capita capacity of photovoltaic installations, it is similar in both countries: 0.166 kW in Poland and 0.148 kW in Jordan. Brief characteristics of these countries are presented in Table 3.

Table 3. Characteristics of Jordan and Poland related to solar energy.

Variable	Jordan	Poland
Energy generation (GWh)	21,862 (2021)	166,557 (2021)
Energy generation per capita (MWh	2.129 (2021)	4.423 (2021)
Energy consumption (GWh)	19,689 (2021)	158,194 (2021)
Per capita electricity use (kWh)	1728 (2020)	4674 (2021)
Net electricity imports (imports minus exports) (TWh)	0.14 (2020)	1.45 (2021)
Electricity production from renewables (TWh)	3.17 (2020)	30.27 (2021)
Electricity production from fossil fuels (TWh)	16.41 (2020)	146.39 (2021)
Solar PV cumulative capacity (MW)	1520.57 (2021)	6256.75 (2021)
Solar PV cumulative capacity per capita (kWh)	0.1481 (2021)	0.1662 (2021)

Source: [6].

Jordan, with its high solar radiation intensity, has excellent conditions for the development of PV farms. It is estimated that installing 1 kilowatt peak (kWp) of PV systems at an optimal angle may result in 1750 kWh per year in some places [80]. Although a significant increase in installed PV capacity was recorded during the period 2011–2021, with a growth rate per annum of 185.0%, the country's potential is still underexploited. Figure 3 shows the cumulative installed photovoltaic capacity in Jordan compared to Poland. The annual growth rate in Poland in the period 2011–2021 was approximately 137.2% [3].

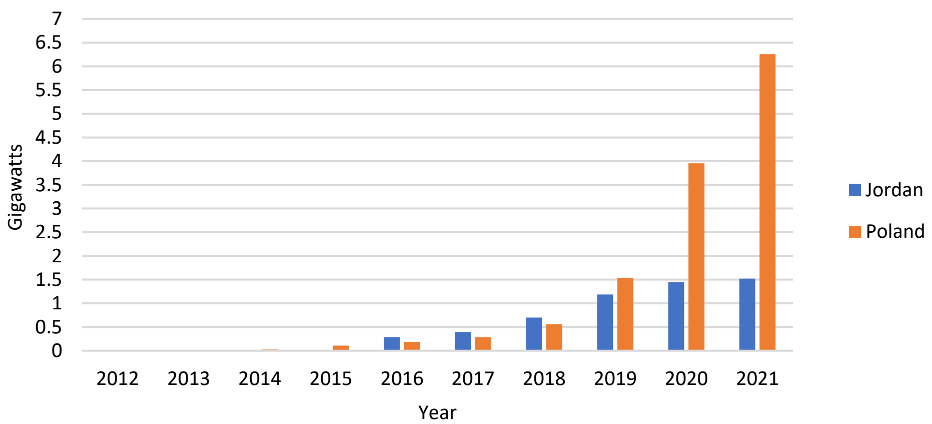


Figure 3. Cumulative installed solar capacity in Jordan and Poland. (Source: [6]).

Figure 4 shows the structure of the energy sources of the two countries, which is a function of geographic location and natural resources. Jordan does not have significant energy resources, and the country relies heavily on imports of gas to meet domestic electricity needs. Poland's electricity production is based on coal, which is supplied to the power sector by domestic mines and via imports. Both Poland and Jordan have a positive balance of electricity imports. Both countries are attempting to become independent from fossil fuels and are investing in and developing numerous projects to increase energy production from renewable sources.

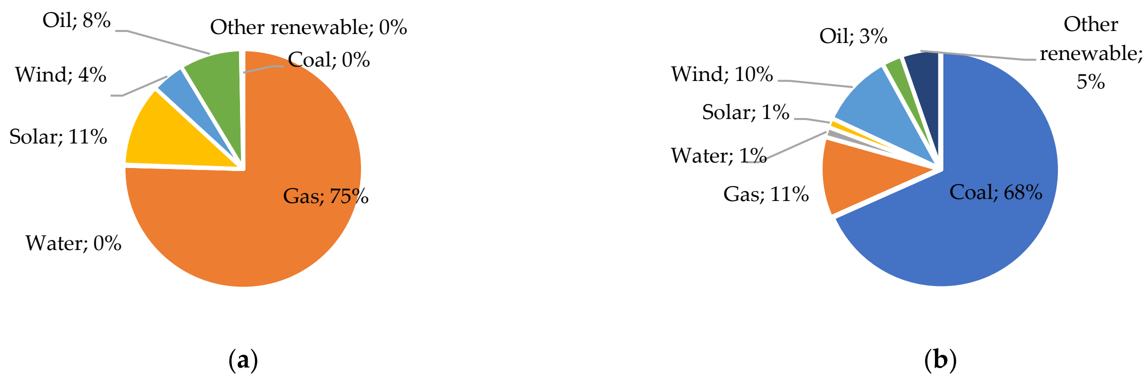


Figure 4. Sources of electricity: (**a**) Jordan; (**b**) Poland. (Source: [6]).

The results of the cited characteristics are the countries' places in global rankings. Statista's ranking of the renewable energy share of the total final energy consumption by country 2020 awards Poland with 14 and Jordan with 4 points. In contrast, considering CO_2 emissions in metric tons per capita, in 2021, Poland reached 8.58, while Jordan reached only 2.3.

This paper develops ARIMA irradiance models for Amman—31.954, 35.9354 (31°57′14.4″ N 35°56′07.4″ E)—and Warsaw—52.250000, 21.000000 (52°15′00.0″ N 21°00′00.0 ″ E)—using monthly and hourly data downloaded from the Joint Research Centre (JRC) solar radiation database PVGIS-SARAH2 (https://re.jrc.ec.europa.eu/pvg_tools/en/, accessed on 1 January 2023). SAS®® OnDemand for Academics was used in the models' estimation (https://welcome.oda.sas.com/home, accessed on 1 January 2023).

4.3. Research Results

First, irradiance models for hourly data were compared. JRC data on GHI from the period 2005–2020 were studied (140,256 observations). The values of hourly observations depend on the month, but more so on the time of day. Analyzing ACF and PACF of 16-year series, no significant values were observed at multiples of 365/366 (see Appendix A). Preliminary analysis did not reveal significant deviations in series trends or fluctuations in historical data that would indicate the existence of anomalies in any of the previous years. Thus, only the year 2020 can be taken as the base for model construction. In the example presented, the irradiance models were developed for observations recorded in January and July 2020 (744 observations each). A non-automatic, expert approach was used to select the ARIMA model. The values of irradiance in January in Amman and Warsaw are shown in Figure 5. The daily 24 h seasonality is the rationale for differentiating with a lag of 24. The model that is adequate for both cities due to the residuals, the values of the parameters that ensure stationarity, reversibility, and the significance of the parameters is ARIMA$(1,0,0)(0,1,1)_{24}$. The analogical analysis performed for the July time series showed that it can be described with the same model. However, radiation is much more stable in summer, and, thus, forecasting with ARIMA models is more effective and reliable. Models' parameters for hourly data and their fit are included in Table 4.

When evaluating the models, it is worth highlighting the differences in descriptive statistics values of irradiance in Amman and Warsaw. In Amman, in July, the average is 344.1557 (std. error: 21.18872; sum 256,051.8), while in January, the average is 115.224 (std. error: 67.58713; sum: 85,726.69). In Warsaw, the differences are more significant: the July average is 237.6998 (std. error: 96.43191; sum 176,848.6) and the January average is 29.60884 (std. error: 22.65059; sum 22,028.98).

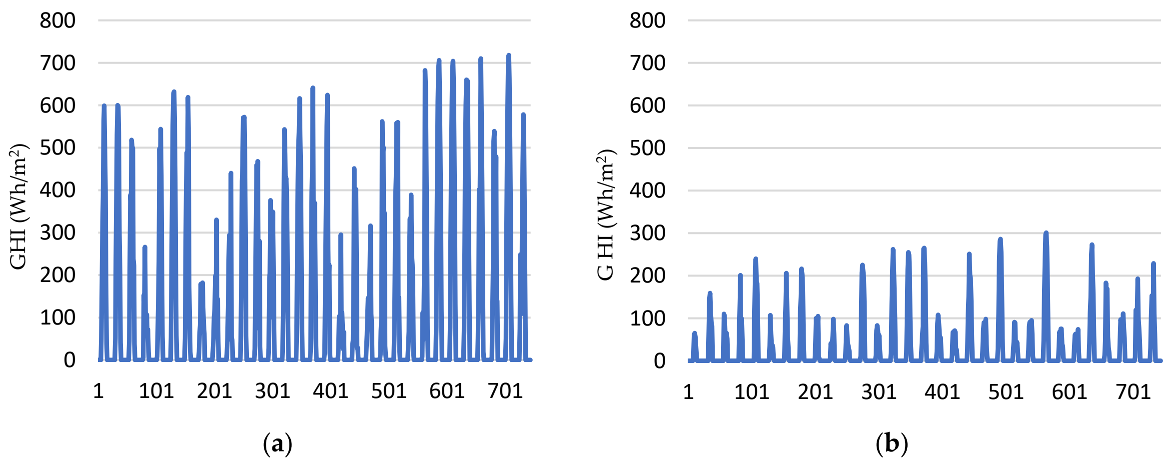


Figure 5. Hourly irradiance in January: (**a**) Amman; (**b**) Warsaw.

Table 4. Hourly data models.

	Amman	Warsaw
January	$(1-\Phi B)(1-B^{24})y_t = (1-\Theta B^{24})e_t$ $\Theta = 0.95803$ Std. error = 0.03972 $\Phi = 0.70207$ Std. error = 0.02554 Variance = 4568.02 Std. error = 67.58713 AIC = 8171.498 R^2 = 86.4%	$(1-\Phi B)(1-B^{24})y_t = (1-\Theta B^{24})e_t$ $\Theta = 0.92547$ Std. error = 0.02720 $\Phi = 0.77180$ Std. error = 0.02299 Variance = 513.0493 Std. error = 22.65059 AIC = 6585.634 R^2 = 85.4%
July	$(1-\Phi B)(1-B^{24})y_t = (1-\Theta B^{24})e_t$ $\Theta = 0.80959$ Std. error = 0.02488 $\Phi = 0.50886$ Std. error = 0.03221 Variance = 448.9619 Std. error = 21.18872 AIC = 6468.135 R^2 = 99.7%	$(1-\Phi B)(1-B^{24})y_t = (1-\Theta B^{24})e_t$ $\Theta = 0.88694$ Std. error = 0.02511 $\Phi = 0.66143$ Std. error = 0.02746 Variance = 9299.113 Std. error = 96.43191 AIC =8662.033 R^2 = 86.8%

The monthly data were considered, and the content of the analysis was the series of GHI in kWh/m^2 from the period 2005–2020 (192 observations). The time series of the monthly GHI pattern of in Amman and Warsaw are shown in Figure 6. The data, as can be seen, differ in average values (Amman 176.33; Warsaw 92.89) but have similar standard deviation (Amman 61.09; Warsaw 60.20). In Warsaw, larger random fluctuations can be noticed.

The strong seasonality, which gives excellent repeatability of the series values, is the rationale for conducting a seasonal differentiation with a lag of 12. The ACF and PACF patterns (see Appendix A) of the original y_t and differenced $(1-B^{12})y_t$ time series suggest seasonal MA models. Although the irradiance patterns are similar, in the case of Warsaw, the MA parameter exceeds the region ensuring the reversibility of the process. Thus, the GHI series in Warsaw was described by the seasonal AR model (since the finite-order moving average process can be represented as an infinite autoregressive process). The following models meet the assumptions of the ARIMA procedure regarding the parameters and residuals distribution: Amman, ARIMA(0,0,0)(0,1,1)$_{12}$ and Warsaw, ARIMA(0,0,0)(1,1,0)$_{12}$. The parameters and fit statistics are shown in Table 5.

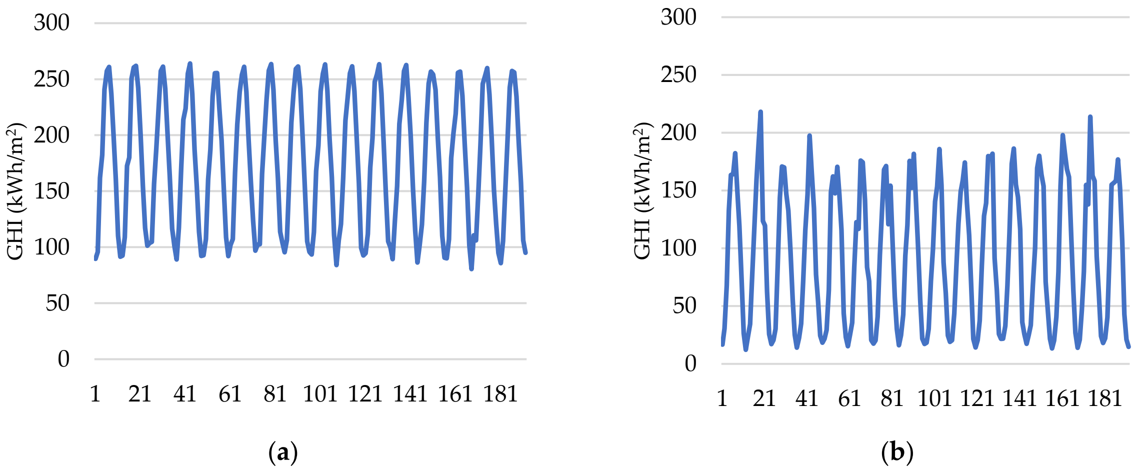


Figure 6. Monthly GHI: (**a**) Amman; (**b**) Warsaw.

Table 5. Monthly data models.

	Amman	Warsaw
model	$(1 - B^{12})y_t = (1 - \Theta B^{12})e_t$	$(1 - \Phi B^{12})(1 - B^{12})y_t = e_t$
parameters	$\Theta = 0.89108$ Std. error = 0.07438	$\Phi = -0.57432$ Std. error = 0.06150
fit statistics	Variance = 50.05613 Std. error = 7.075036 AIC = 1234.837 R^2 = 98.5%	Variance = 246.9536 Std. error = 15.71476 AIC = 1508.274R^2 = 93.0%

Figure 7 illustrates the fit of all the developed models.

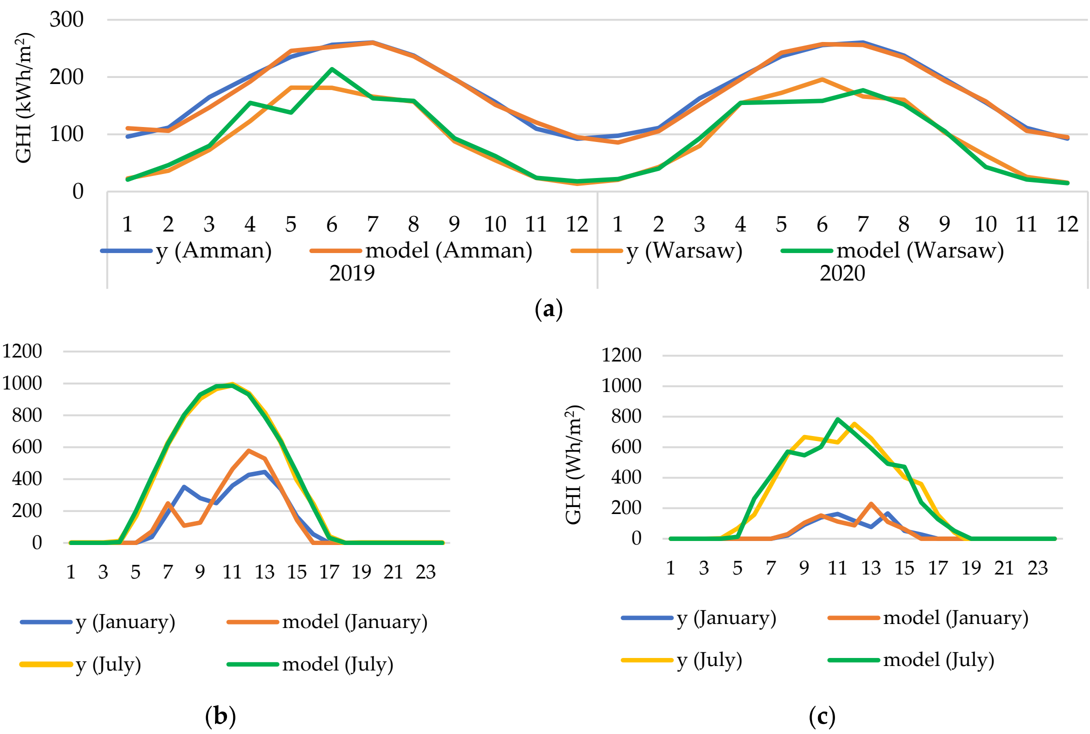
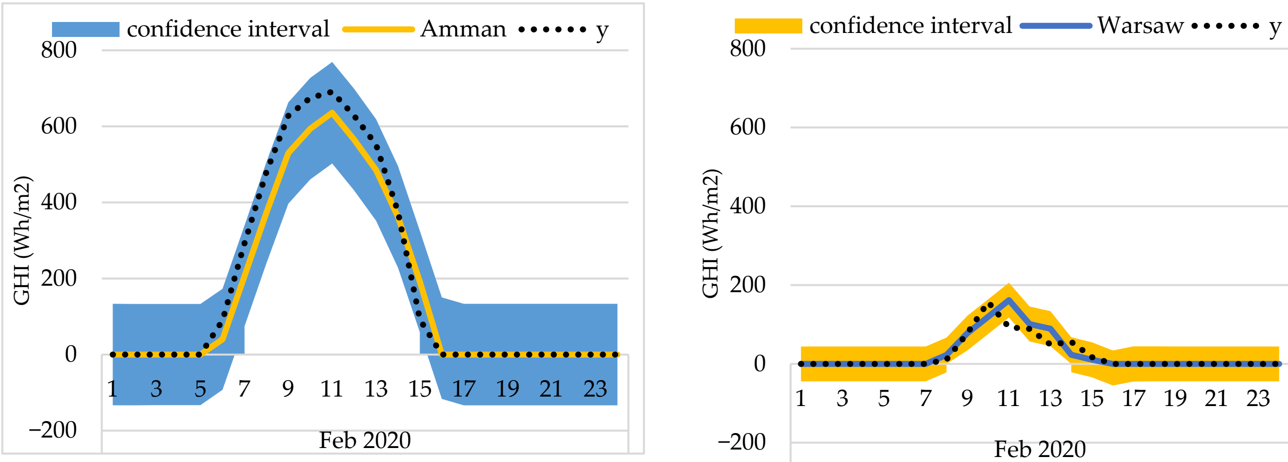


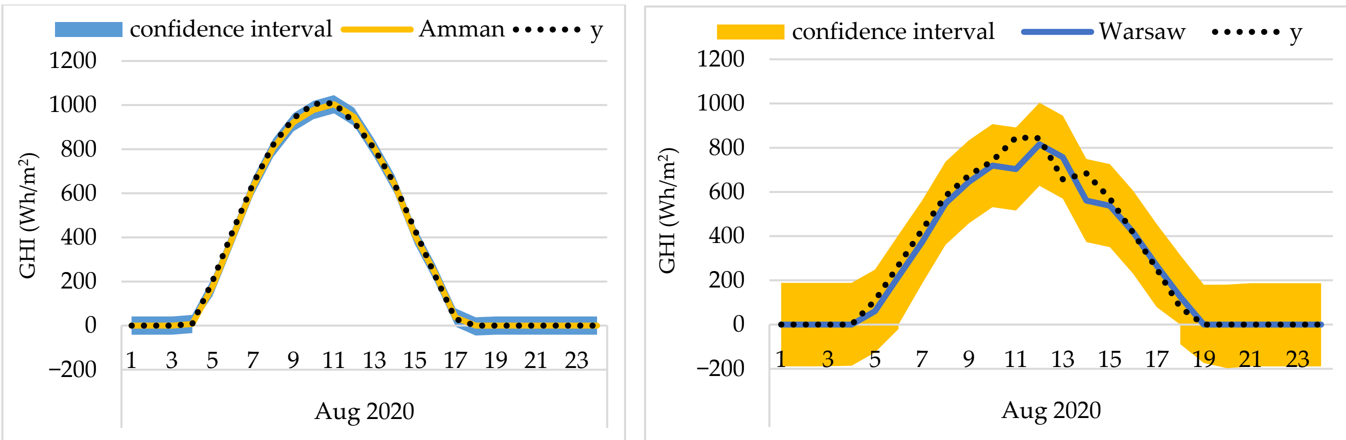
Figure 7. Model fit visualization: (**a**) monthly time series for Amman and Warsaw (2019–2020); (**b**) hourly time series—Amman (31st of January and July); (**c**) hourly time series—Warsaw (31st of January and July).

Analysis of the data presented allows the models to be used for monthly and hourly data during the summer months. Figure 8 presents forecasts for 2020 February 1st with a confidence interval based on hourly time series of (a) Amman and (b) Warsaw together with the observed values. Similarly, Figure 9 shows forecasts for 2020 August 1st with a confidence interval of 95%. It is worth noting the significant differences in the width of the confidence intervals.



(**a**) (**b**)

Figure 8. Forecasts for 2020 February 1st with confidence interval (95%) based on hourly time series of (**a**) Amman; (**b**) Warsaw.



(**a**) (**b**)

Figure 9. Forecasts for 2020 August 1st with confidence interval (95%) based on hourly time series of (**a**) Amman; (**b**) Warsaw.

For a clear assessment of the reliability of the forecasts and their applicability, the basic statistics obtained for the performed forecasts are presented in Table 6 (due to the availability of data for 2020 only).

Table 6. Basic forecast statistics.

	Amman	Warsaw
February	MSE = 2456.48 RMSE = 49.56 MAPE = 11.51% Std. Error = 51.77 R^2 = 98.3%	MSE = 381.09 RMSE = 19.52 MAPE = 16.59% Std. Error = 20.39 R^2 = 82.2%
August	MSE = 183.18 RMSE = 13.53 MAPE = 2.79% Std. Error = 14.14 R2 = 99.9%	MSE = 2508.97 RMSE = 50.09 MAPE = 9.08% Std. Error = 52.32 R^2 = 97.9%

Figure 10 shows the forecast for 2021 with 95% confidence intervals in Amman and Warsaw.

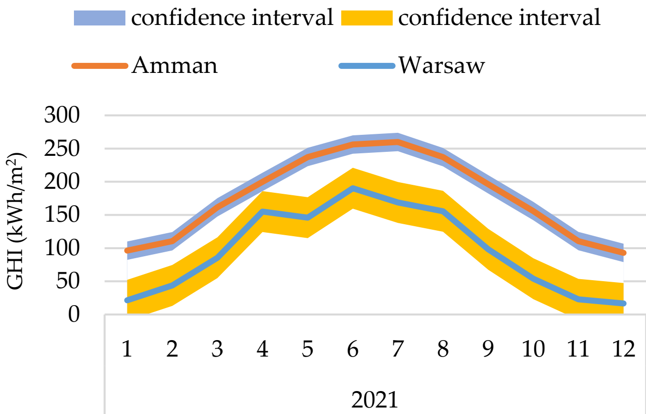


Figure 10. Forecasts for 2021 with confidence interval (95%) based on monthly time series of Amman and Warsaw.

The forecast was made for 2021 using the models described in Table 5. Since insolation data for 2021 were not available, the expected quality of the ex ante prognosis was illustrated with a 95% confidence interval, i.e., the true insolation value would be located in that interval with a probability of 95%. Such a graphical representation is more intuitive than numerical indicators and allows a visual assessment of the acceptability of the forecast. Both the forecasts for Amman and Warsaw should be considered acceptable given the assumed forecasting goal.

5. Discussion and Conclusions

The research reported in this article indicates the usefulness of ARIMA models for forecasting insolation in different geographical locations characterized by different climatic conditions. The capitals of Jordan and Poland, for which the level of average daily GHI differs more than twofold, were selected for analysis. Adequate ARIMA models were identified for both locations and the parameters for hourly and monthly time intervals were estimated. In the case of Amman, ARIMA$(1,0,0)(0,1,1)_{24}$ and ARIMA$(0,0,0)(0,1,1)_{12}$ models were obtained, respectively, and in the case of Warsaw, ARIMA$(1,0,0)(0,1,1)_{24}$ and ARIMA$(0,0,0)(1,1,0)_{12}$ models were obtained. The identified ARIMA models show the same structure for hourly data in both locations and a different structure for monthly data. Such a result indicates the necessity of identifying an adequate ARIMA model every time for locations with different climatic conditions.

The fit of the models and their predictive capacity were also evaluated. All models showed a very good fit to the data, as measured by the model's standard error of judgment and the R^2 coefficient of determination (R^2 > 85%). The models show a better fit for hourly data for the summer months in the case of both Amman and Warsaw.

All models showed satisfactory robustness in terms of their predictive capacity. Statistical evaluation of the forecast for hourly data confirms their high quality for both Amman and Warsaw (R^2 > 82%). More accurate forecasts were obtained for Amman (R^2 > 98%), which is due to the greater stability of insolation in this location. The least accurate, but still acceptable, forecast—as measured by the coefficient of determination R^2 (R^2 = 82.2%) and the MAPE error (MAPE = 16.59%)—was obtained for Warsaw in February, which is due to the small insolation values and variable atmospheric conditions at this time of year in this location. This resulted in small absolute values of forecast errors being translated into large relative forecast errors.

Year-ahead forecasts made for 2021 on the basis of monthly data show a high accuracy as determined by their confidence interval. At the same time, the confidence interval is narrower for the forecast in Amman. The differences in the observed results indicate that ARIMA models are best suited for forecasting in stable conditions (sunny or cloudy). The lower accuracy obtained in Warsaw may be an indication that if larger instabilities are observed, such models fail to provide satisfactory forecasts.

The results of modeling and forecasting insolation with ARIMA models presented in this article indicate that they are sufficiently accurate, especially for medium- and long-term forecasts, and may be effectively used for planning the harmonization of photovoltaic installations with the electric power system in different geographical locations. The method proposed in this article may also be used to predict the overall potential for reducing greenhouse gases through the development of photovoltaic systems at the level of power minigrids (with capacities in the megawatt range). However, this should be the subject of further detailed research [81].

The importance of solar irradiance forecasting for grid infrastructure exploitation and management is also worth highlighting. Reliable forecasting ensures that both technical (e.g., enhancing system dependability, proper power quality, smaller backup of energy storage) and economic (e.g., better matching of supply and demand, lower investment and operating costs, lower retribution cost) benefits can be achieved [82]. Despite notable progress, further research is needed in these directions.

It should be emphasized that for each geographic location, it is necessary to identify a suitable ARIMA model, estimate its parameters, assess the fit, and verify the model's forecasting ability.

Author Contributions: J.N. and E.C. were responsible for the study concept and research design; J.N., Ł.N., H.S.R., R.A. and R.M.A. developed the concept; E.C. performed computation and analysis; J.N., E.C., H.S.R., R.A. and R.M.A. were responsible for data interpretation; J.N. and Ł.N. discussed the results and contributed to the final manuscript; J.N., E.C., Ł.N., H.S.R., R.A. and R.M.A. wrote and edited the text. All authors have read and agreed to the published version of the manuscript.

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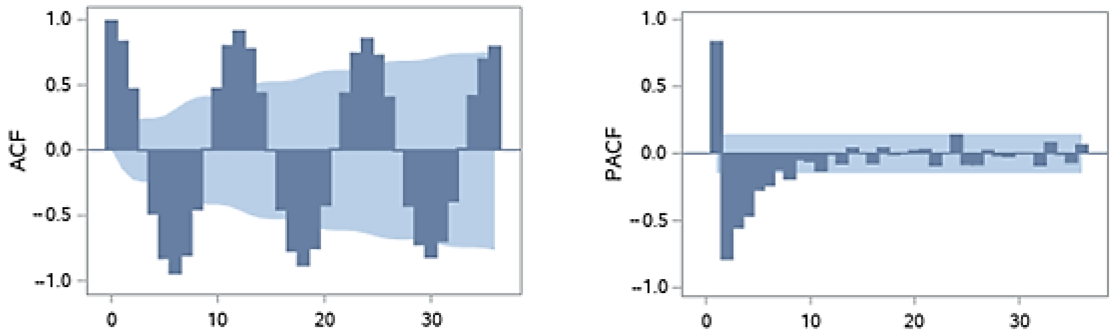
Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Publicly available datasets were analyzed in this study. These data are available in the Joint Research Centre (JRC) solar radiation database PVGIS-SARAH2: https://re.jrc.ec.europa.eu/pvg_tools/en/ (accessed on 1 January 2023).

Conflicts of Interest: The authors declare no conflict of interest.

Appendix A



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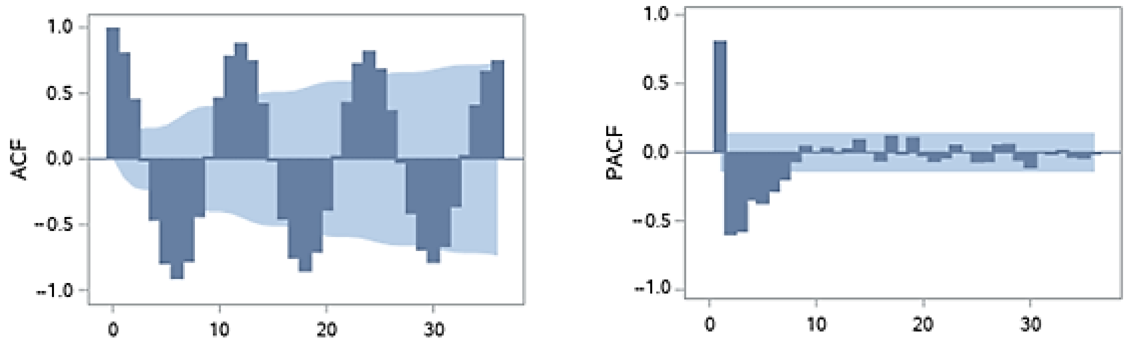
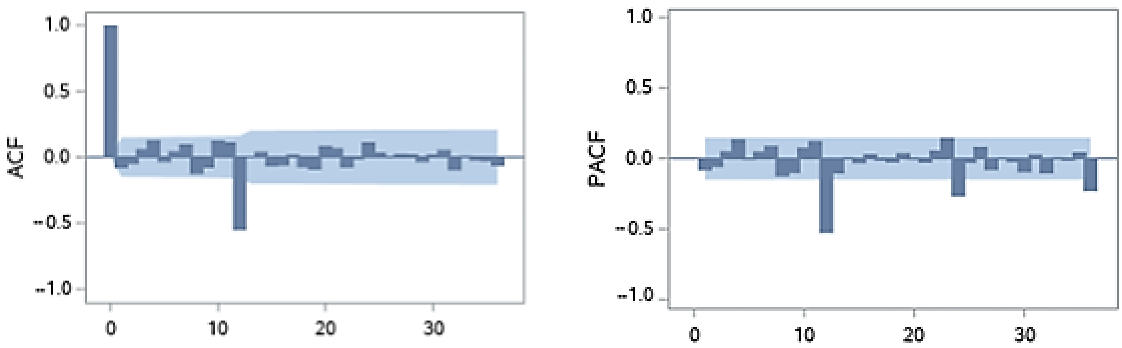


(**b**)

Figure A1. ACF and PACF of monthly y_t in (**a**) Jordan and (**b**) Poland.



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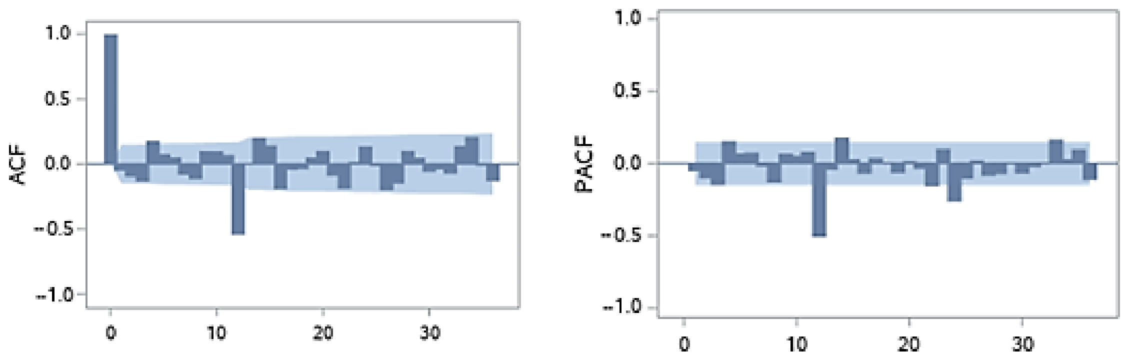
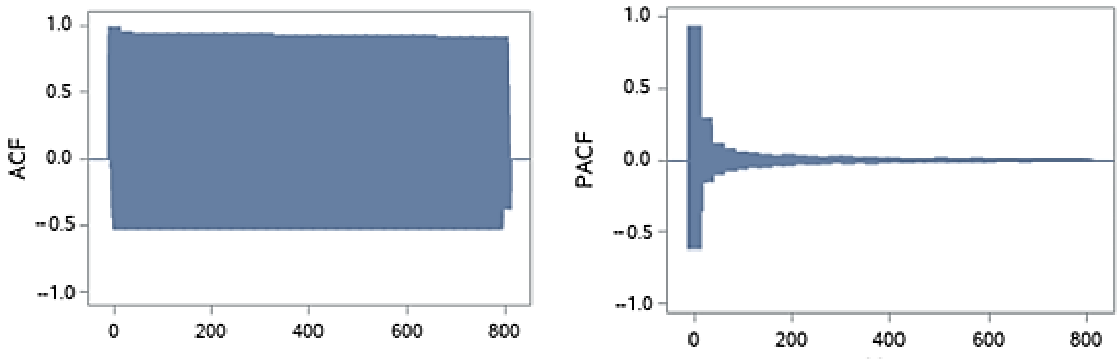


(**b**)

Figure A2. ACF and PACF of monthly $\left(1 - B^{12}\right)y_t$: (**a**) Jordan; (**b**) Poland.



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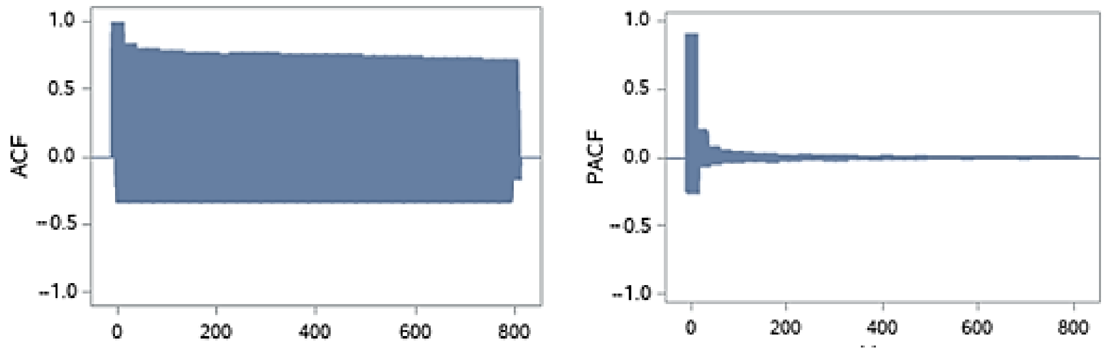
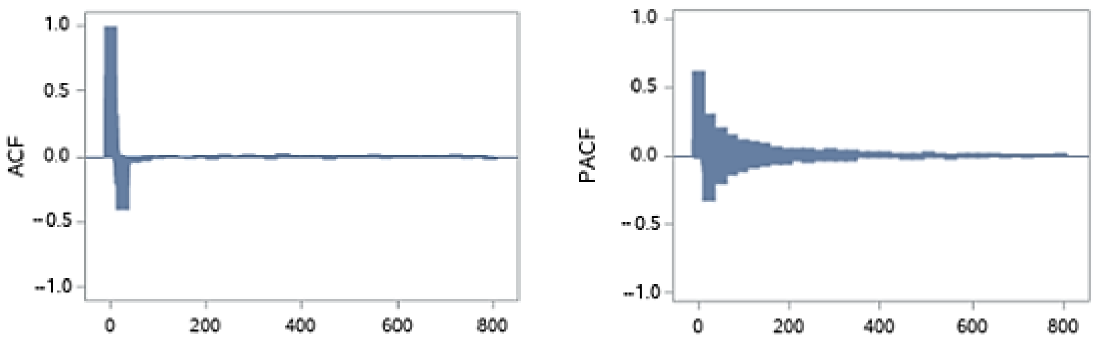


(**b**)

Figure A3. ACF and PACF of hourly y_t in (**a**) Jordan and (**b**) Poland.



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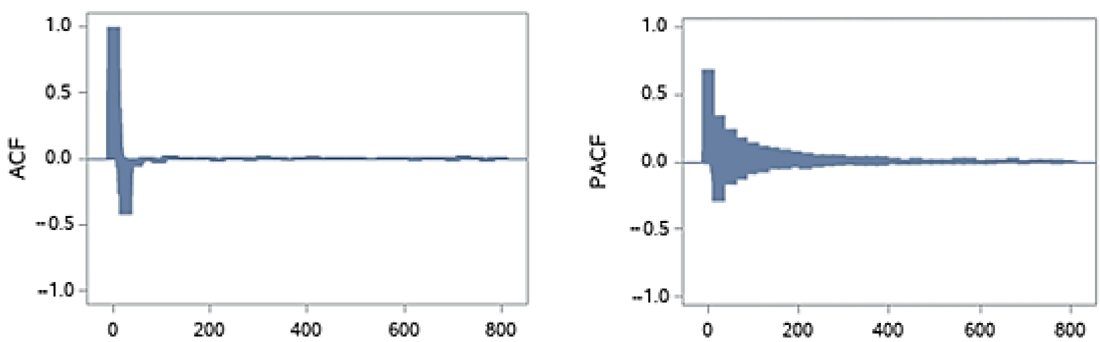
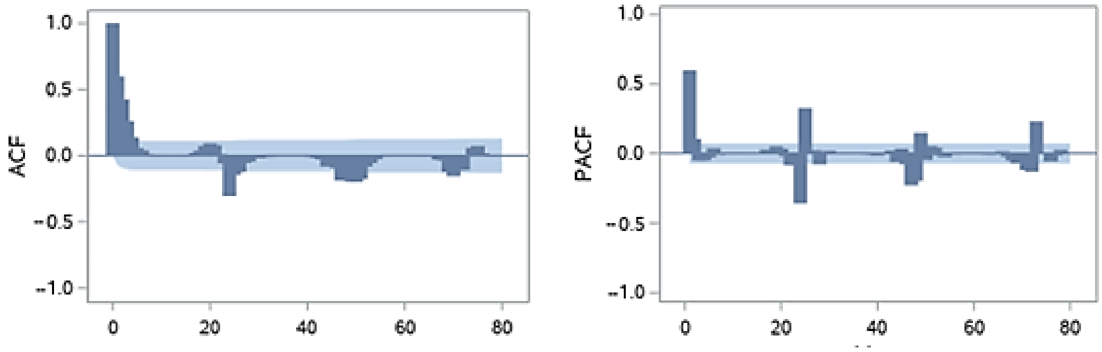


(**b**)

Figure A4. ACF and PACF of hourly $(1 - B^{24})y_t$: (**a**) Jordan; (**b**) Poland.



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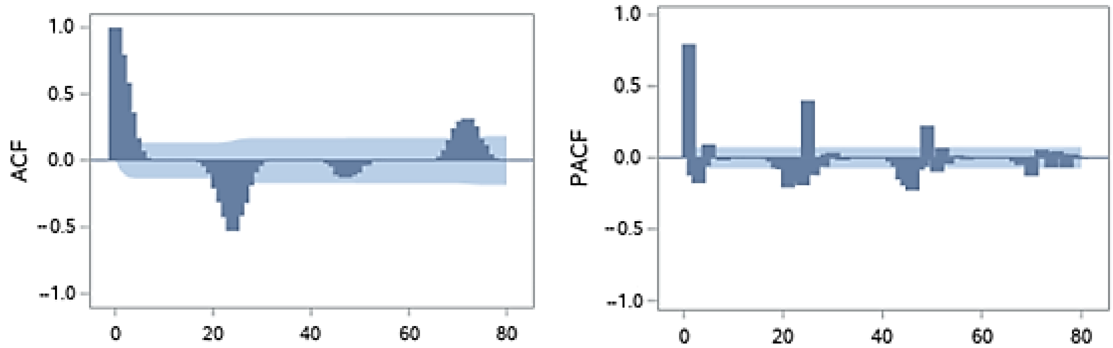
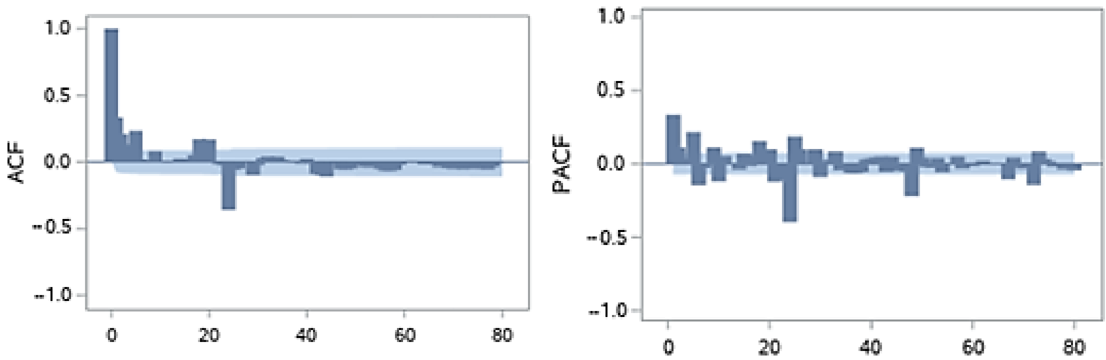


(**b**)

Figure A5. ACF and PACF of y_t in December 2020 $\left(1 - B^{24}\right)y_t$: (**a**) Jordan; (**b**) Poland.



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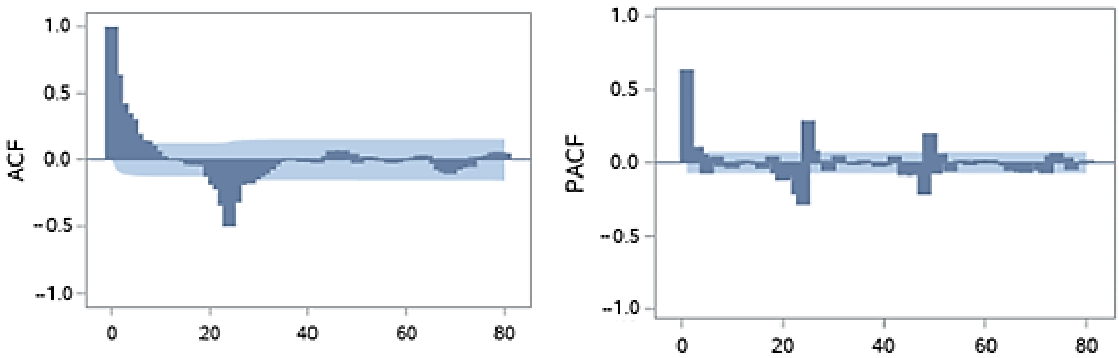

(**b**)

Figure A6. ACF and PACF of y_t July 2020 $\left(1 - B^{24}\right)y_t$: (**a**) Jordan; (**b**) Poland.

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