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A Dynamic Nonlinear Autoregressive Exogenous Model to Analyze the Impact of Mobility during COVID-19 Pandemic on the Electricity Consumption Prediction in Jordan

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Due to the global COVID-19 pandemic, governments have adopted regulations and restrictions to prevent spreading the disease. Changes in socioeconomic status, lifestyle, mobility and consumer consumption behavior have resulted due to these restrictions. These changes caused the amount and pattern of electricity consumption to be affected during and after the pandemic. In this study, we developed a data-driven model of electricity consumption based on machine learning techniques to analyze the effect of Mobility during and after the pandemic on electricity consumption prediction, which has been considered along with other factors that typically affect electricity consumption, including historical load profile, weather measurements, and timing information. The Nonlinear Auto Regressive Exogenous (NARX), a recurring dynamic neural network with feedback, establishes the model. The model performance results show improved prediction performance when considering the mobility factor; the error residuals between the actual and forecasted max load values were lower than when not considering the Mobility. The test dataset's least Mean Square Error (MSE) was decreased by 43%. In addition, the regression values between actual and predicted values have improved when considering the mobility factor. The same applies to the R-value and Root Mean Squared Error (RMSE), with an improvement of 6.0% and 7.6%, respectively. For comparison purposes, two additional models were developed to verify the results using the Auto-Regressive Integrated Moving Average (ARIMA) and Long-Short Term Memory (LSTM), as well known models. These models also demonstrated improved prediction performance when considering the mobility factor. However, the NARX model exhibited the best results, with lower MSE and higher R values. The models considered in this study can be used to predict the electricity consumption values of other pandemics or another wave of COVID-19 to assist decision-makers in having higher consumption visibility, thus better planning resources, capacity, and costs.

Keywords: ARIMA, Electricity demand, LSTM, NARX, Recurring dynamic neural network

Introduction

The Corona virus disease 2019 (COVID-19) pandemic has impacted the world in numerous ways. The first case of COVID-19 was reported in Wuhan, China, in December 2019; after that, the number of cases and deaths increased gradually to reach most countries worldwide.[1] Since early 2020, with the propagation of the cases, individuals' and industries' behaviors and consumption have changed due to the government's defence regulations and orders, such as movement restrictions, lockdowns, and quarantine to eliminate and contain the virus spreading.[2] These actions have affected the demand and supply rates in many sectors, including health care, hospitality, transportation, energy, and education.[3]

Recent studies have been conducted to investigate the influence of the COVID-19 pandemic and the procedures and laws taken to restrict its spread in different sectors. For example, one of these studies involved a comprehensive analysis of the effect of COVID-19 on various aspects such as education, globalization, society, the environment, and the economy.[4] The study indicates that global economic growth will decline by 1.6% in 2020 and 3.2% in 2021. It also shows that the expected percentage of businesses that will shut down due to the pandemic is from 19% to 43% if it exists for a long time (i.e., more than eight weeks). In addition, the study estimated a 5% to 15% shrink in global foreign direct investment due to global closures in factories worldwide.[4] The pandemic has affected many countries, including the ones with the largest economies. For instance, in China, sectors that do not produce basic needs products such as electronics and apparel have faced severe disruptions, which resulted in a significant sales drop. Also, people started consuming and stocking only

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essential goods, besides the increasing demand for hand sanitizers and face masks. These fluctuations in customer consumption created a supply shortage for many products as suppliers could not meet the sudden demand changes for these products.[5]

In Jordan, an assessment report has been conducted by the International Labor Organization (ILO) and the United Nations Development Program (UNDP) to evaluate and assess the effect of COVID-19 on Jordan's economic status. One of their key findings was that all surveyed companies suffered from some challenges in cash flow and reduced market demand in many sectors, which forced many businesses and startups to close due to measures responding to COVID-19.[(6)] In addition to the global and local economic changes, the lockdown and movement restrictions have also affected people's lifestyles and daily mobility. Data collected from 128 countries showed a decline in mobility during a complete lockdown by 25%.[(7)] These decreasing mobility rates worldwide have changed, affected many sectors, and contributed to the economic situation and growth.

Energy consumption has been affected due to the socioeconomic changes caused by the pandemic. Socioeconomics includes the transformation of most activities (education, work, events) to be conducted remotely, besides restricting movement and traveling, along with the shutdown of most industrial activities. Electricity, a significant energy source and considered the power of most industrial and daily activities, is one of the most affected sectors due to the pandemic's socioeconomic changes and the changes in consumer consumption behavior. The amount and pattern of electricity consumption have changed during and after the pandemic in both the short and long term.[8] This makes the old model used for electricity prediction invalid, and the gap between the actual and predicted values increases.

Several studies show the effect of COVID-19 on the energy sector in general, while few studies have studied the impact on electricity consumption specifically. Electricity consumption has been affected in different countries due to the pandemic and its associated procedures and the actions taken to eliminate the spread of the virus.[9] In Jordan, the effect of COVID-19 on electricity consumption showed emerging changes in the pattern and amount of electrical consumption, indicating a decline in the minimum peak load by 13%[(10)] to 17.5%[(11)] compared to 2019. In addition, the mobility effect on energy consumption in Jordan has been statistically analyzed and modeled as a case study.[12] Such analyses and models presented have been advantageous to the related sector. However, the models utilized did not consider the dynamic behaviors, which led to a difference between the predicted and the actual consumption during the peak period and otherwise.

Big data and machine learning are two highly demanded topics where research around them is enormous and of great variety.[13] Machine learning techniques have recently been used in forecasting models for complex time series problems with multiple input variables that increase the efficiency and accuracy of prediction. For example, stacking machine learning models were developed using the Internet of Things[14] to forecast daily consumption. A study conducted in Turkey using the long-term forecast of electricity consumption was analyzed using eight models to investigate the effects of eight variables frequently used in electricity consumption forecasting studies.[15] Nonlinear Auto regression Neural Network (NARNN), Auto-Regressive Integrated Moving Average (ARIMA), and long-term memory (LSTM) techniques were utilized to forecast electricity demand values under the effect of COVID-19[(16)]; the LSTM approach showed the best performance. Using a rolling stochastic Auto-Regressive Integrated Moving Average with Exogenous (ARIMAX) model to predict the electricity consumption after the effect of the COVID-19 pandemic showed a reduced error from using the traditional ANN and ARIMAX models, which only use the historical demand data by up to 23.7%.[(17)]

The Nonlinear Auto Regressive Exogenous (NARX) model has been used in many studies for practical time series forecasting problems. To forecast the COVID-19 outbreak in Jordan, a NARX model was created[18], and results showed high accuracy with a root mean square error of approximately 28. Another application of the NARX method in forecasting power output from a photovoltaic system at a university in Egypt[19] indicated the importance of using NARX neural networks due to their efficiency in controlling nonlinear applications and their effectiveness in forecasting. The NARX model performance was evaluated by comparing the forecasted and measured data, and the results obtained by the NARX model were almost similar to the experimental ones. Also, the theoretical results were compared with the Neural Network (NN) model, where the NARX model showed better performance.

Electricity consumption amounts are usually related to the lagged load data, weather measurements, and timing information. Few studies have considered mobility measure data as a factor that affects electricity consumption during and after the COVID-19 pandemic. A multilayer feed-forward Artificial Neural Network (ANN) to predict the energy in Italy[3] was proposed, considering mobility measure as a factor. The extreme Gradient Boosting, Support Vector Regression, and ARIMAX models were used to predict electricity consumption during the COVID-19 pandemic in the microgrid-based educational buildings using public data, including Google Trends and Google Mobility, where adding these factors impacted the prediction accuracy positively.[20] The impact of the behavioral restrictions during the COVID-19 pandemic on electricity consumption in Turkey was studied using the modulated Fourier Series.[21] Results showed a decrease in demand and a notable shift in demand to nights. They emphasized the importance of developing new daily and weekly load forecasting approaches to consider the restrictions, including Mobility, which are required to match the supply-demand in the future.

In our study, NARX will be used to analyze the effect of Mobility during the COVID-19 pandemic on electricity consumption prediction in Jordan. A proposed model that considers the mobility measure reflects the socioeconomic changes caused by the pandemic. Other factors suggested by previous studies, such as historical load profile, weather measurement, and timing information, were also considered. The new model will improve the performance of electrical consumption forecasting by considering the mobility factor compared to the previous model, which only accounts for historical load profile, weather measurement, and timing information.

While some current studies also consider Mobility, they often use different approaches that primarily rely on linear or ensemble modeling techniques like multilayer feed-forward ANN, XG Boost, SVR, ARIMAX, and Fourier Series. These models may struggle to effectively capture mobility and electricity consumption's complex, nonlinear relationships. Our approach using NARX as a model in forecasting electricity consumption during the COVID-19 pandemic addresses this limitation by leveraging the NARX model's proficiency in capturing complex, nonlinear relationships in time series data, enabling better model performance results.

The suggested approach in this study has a significant contribution due to:

— After reviewing the existing literature and the current models considering the mobility factor during the pandemic in forecasting electricity consumption, the current approaches mainly rely on linear modeling techniques. This study uses the NARX model, which captures complex, nonlinear relationships.
— This study considers factors that typically affect electricity consumption, including historical load profile, weather measurements, and timing information. In addition, it considers Mobility as a factor to illustrate the impact of COVID-19 on electricity consumption. This inclusion is expected to improve the prediction model's performance compared to the previous model that did not incorporate Mobility.
— The suggested approach addresses Jordan's socioeconomic and environmental conditions during a pandemic, providing relevant insights into the region. These insights can be valuable for decision-makers to apply this model in similar situations.

Data Collection and Analysis

Electricity consumption in Jordan data before and during the COVID-19 pandemic was collected. The parameters considered in this study are shown in Table 1 below.

Mobility is considered a parameter in the second model, and it is classified into six categories:

— Grocery & Pharmacy: grocery markets, food warehouses, farmers markets, specialty food shops, drug stores, and pharmacies.
— Parks: local parks, national parks, public beaches, marinas, dog parks, plazas, and public gardens
— Transit stations: public transport hubs like subway, bus, and train stations.

Table 1 — Parameters considered in this study

Category	Parameters	Unit
Weather	Temperature of the day (Min, Avg, Max)	°C
	Total precipitation amount	mm
	Wind speed	Km/hr
	Wind Direction	Degrees
	Wind chill temperature	°C
	Humidity	%
	The feels-like temperature	°C
	Cloud cover	%
Load	Lagged observation of average loads	MWh
Timing	Day of the week (weekday or weekend)	1–7
Mobility	Mobility index	0–7

- Retail & recreation: restaurants, cafes, shopping centers, theme parks, museums, libraries, and movie theaters.
- Residential Mobility
- Workplaces Mobility

The response in the model is the maximum average electricity consumption load in Megawatt-Hours (MWh). The time horizon considered in this study spans from January 2017 to December 2020, while mobility data is available from February 2020 to August 2021, during and after the pandemic. The maximum average electricity consumption load data in Jordan has been obtained from a regional electricity company in Jordan. The weather measurements for the study period in Jordan are collected from an international website that provides access to a wide range of historical weather information for different locations. The Google COVID-19 Community Mobility database provides the mobility measure parameter.

The collected data has been organized, cleaned, and scaled to be fitted into the NARX model. The maximum average electricity consumption load data is plotted versus year, as shown in Fig. 1.

The load pattern for the year 2020 from mid of March to the end of June shows a decrease in electricity consumption compared to the exact times in other years considered in the study, 2017, 2018, and 2019, which is the period of the movement and lockdown restrictions that aimed to eliminate the COVID-19 pandemic's spread. After this period, the reopening and the dropping of most restriction orders increase the consumption to be similar to previous years' patterns in some months and behave in different patterns in others. For instance, the impact of COVID-19 on Jordan's electricity consumption is indicated by a sudden rise in consumption values during September 2020.

Nonlinear Autoregressive Exogenous Model

The Nonlinear Autoregressive Network with Exogenous Inputs (NARX) is a feedback-connected, recurrent dynamic network encompassing multiple network layers. The next value that depends on the previous values of the same series and the current and previous values of the driving (exogenous) series is the dependent output signal; the model also includes an error term to represent the prediction error.[22] The model can generally be expressed mathematically, as in Eq. (1).

$$y_t = F(y_{t-1}, y_{t-2}, y_{t-3}, \dots, u_t, u_{t-1}, u_{t-2}, u_{t-3}, \dots) + \epsilon_t \quad \dots (1)$$

where, y is the response, u is the external parameter, ε is the error term (sometimes called noise), and F is some nonlinear function. In our case, we used sigmoid and linear transfer functions. Information and data of u and previous values of y itself help predict the y value for the desired time.

The neural network is generally part of deep learning algorithms in which the network simulates the human neural system. The network works on training, validating, and testing the model to predict future events, recognize patterns, and classify & describe objects within the data. NARX network is like other neural networks, consisting of input, hidden, and output layers. It has two main architectures, the parallel (closed-loop) and the series-parallel (open-loop), as shown in Fig. 2. The closed-loop estimates the response based on exogenous parameters and past predicted model values.

In comparison, the open-loop predicted response is based on the parameter's current and historical values and the responses' actual historical values. The number of hidden layers can lead to the best predictive performance of the NARX model with the least error residuals, specifically the Least Mean Square Error (MSE), between the actual and predicted

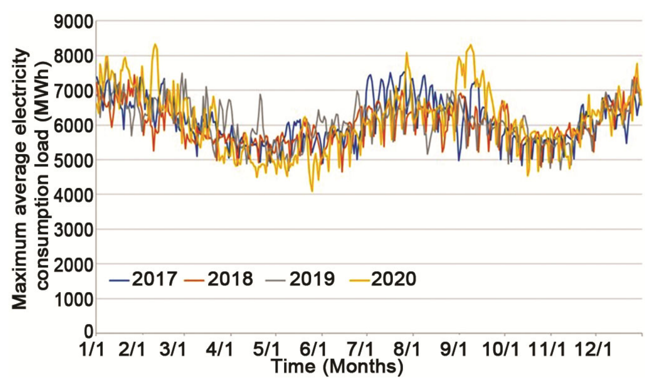

Fig. 1 — Maximum average electricity consumption per year

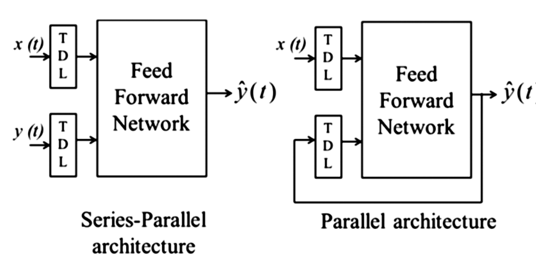

Fig. 2 — NARX neural network architecture[23]

amounts. Our study chose the NARX model due to the data's nonlinearity, fuzziness, and dynamicity. In addition, several factors were considered, adding more complexity to the model.

Methodology

The aim is to study the effect of Mobility measures during the COVID-19 pandemic on electricity consumption prediction in Jordan. A NARX model was developed for better electricity consumption forecasting, which considers multiple factors that typically affect electricity consumption, including historical load profile, weather measurements, and timing information. In addition, it considers Mobility as a factor to illustrate the pandemic's effects on electricity usage compared to the previous model that did not incorporate Mobility. The methodology followed in this work is shown in Fig. 3. The first step was collecting, cleaning, and scaling the data to prepare it for use in the model. After that, a MATLAB Neural Net Time Series app will be used to build and train the models.

Two models were created, the first without the mobility factor and the other with it. Predictors and responses should be selected from the imported dataset for each model. For the first model, which reflects the electricity consumption without considering the mobility data, the predictors are weather measurements and timing information, and the response is the maximum average electricity consumption load. The second model considered Mobility as a predictor besides the other factors mentioned before to reflect the effect of the socioeconomic changes due to COVID-19 on electricity consumption and the performance of the forecasting model in Jordan. After that, three sets of data—training, validation, and testing—were created from the data. Delay steps and the number of hidden neurons were chosen to achieve the best predictive performance of the NARX model. Two performance criteria were used, Least error residuals (least MSE), and the R-value of the regression analysis. Different numbers of combinations of the hidden neurons and delay steps in the 1 to 20 and 1 to 15, respectively,

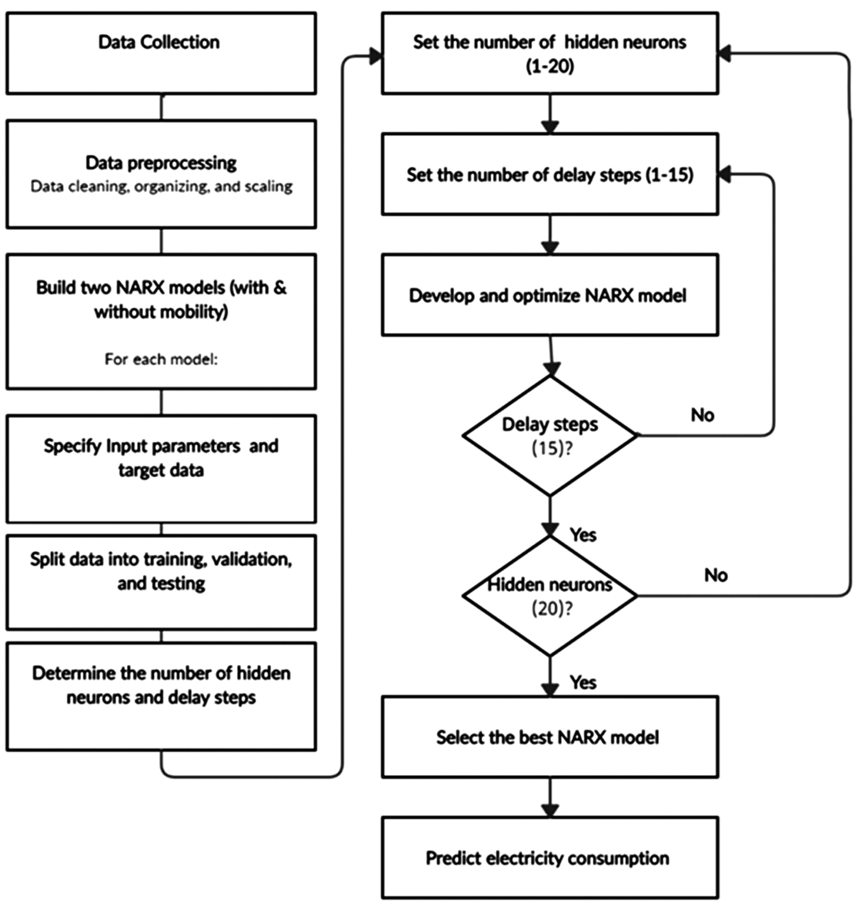

Fig. 3 — Flowchart of the NARX model development

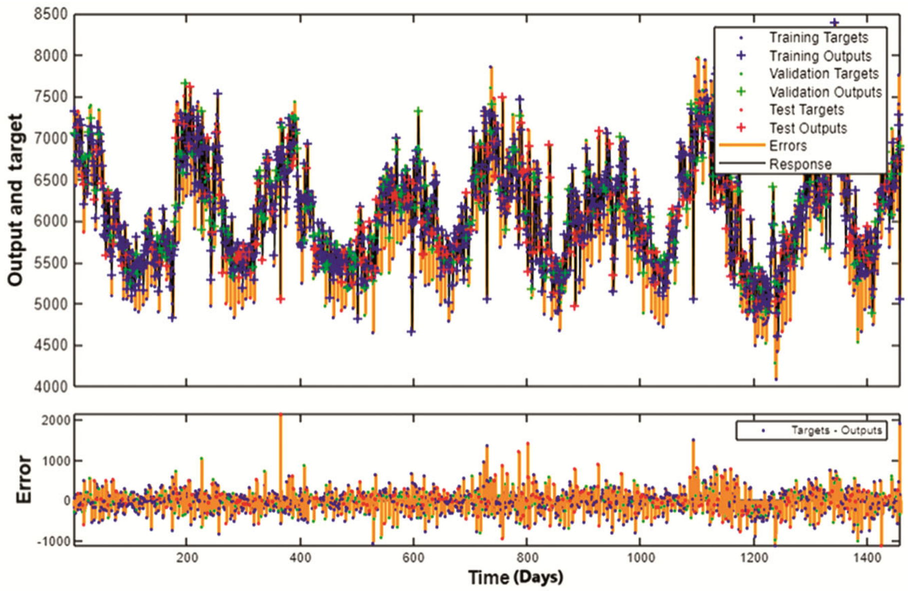

Fig. 4 — The prediction performance of the NARX model without Mobility

were tested to choose the best combination that leads to the best performance predicative NARX model.

Results and Discussion

A NARX model was built by following the above-proposed methodology. Three sets of data were randomly selected from the dataset: 70% for training, 15% for validation, and 15% for testing. The first model excluded the mobility factor to predict the maximum average electricity consumption load. Several sets of hidden neurons and delay steps were tested to determine the optimal combination. The best option that led to the least MSE was three hidden neurons and two delay steps. After training, validating, and testing the model, the MSE values for training, validating, and testing, respectively, were (8.5381e+04, 1.1112e+05, and 1.483e+05). In addition, the R-values, respectively, were (0.9024, 0.8851, and 0.8384), while the Root Mean Square Error (RMSE) of the model was 408.1, as shown in Figs 4–5.

For the second model, which considered the mobility measure, four hidden neurons and six delay steps were the optimal combination of delay steps and hidden neurons that produced the lowest MSE. The model performance results showed performance improvement where the values of MSE for each set were, respectively (5.6025e+04, 6.3784e+04, and 8.55258e+04). In addition, the R-values respectively were (0.9426, 0.9260, 0.8876), while the RMSE of the model was 377.12, as shown in Figs 6–7.

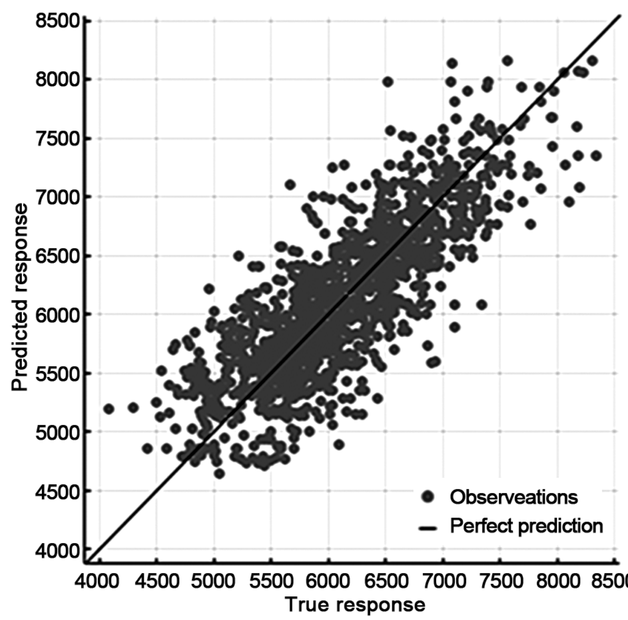

Fig. 5 — The prediction performance of the NARX model without Mobility (Regression analysis)

Incorporating the mobility measure as a predictor in the NARX model effectively improved its performance. For instance, the actual value of the maximum average electricity consumption load in Jordan on 4/9/2020 was 5319 MWh. The first model without Mobility predicted value was 5708 MWh with an error percentage of 7.32%. In comparison, the second model, with mobility factor, predicted value was 5354 MWh for the same day, with an error percentage of 0.66%. The percentages of

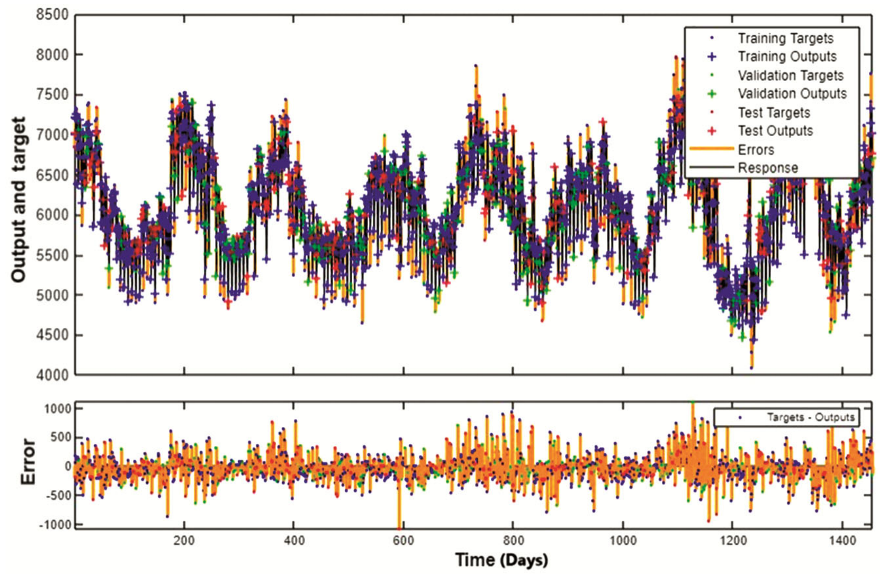

Fig. 6 — The prediction performance of the NARX model with mobility

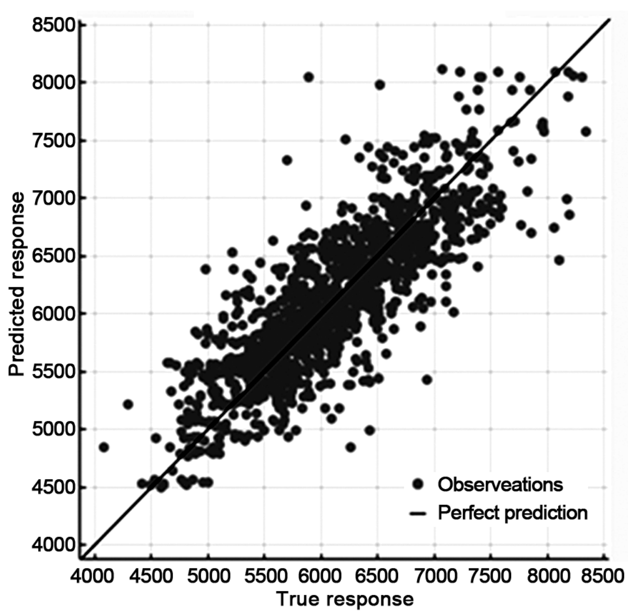

Fig. 7 — Prediction performance of the NARX model with Mobility (Regression analysis)

improvement in terms of MSE, R-values, and RMSE values for both models are summarized in Table 2.

The mobility factor improved the model's performance by lowering the error residuals between the actual and forecasted max load values. In addition, the regression analysis plot between actual and predicted values, Figs 6–7, indicates that the points got closer to the regressed diagonal line in the second model than the first one, which did not consider the mobility factor. The R-values improved by significant amounts compared to the R-values of the first model. The same applies to the RMSE values of the model, with an improvement of 7.6%. The goodness of fit of the first model, shown by the regression plot, is foggier, with the points being more dispersed compared to the second model, which offers a better fit.

The two models' performance values indicate that COVID-19 and its associated restrictions and lockdowns in Jordan influence electricity consumption. In addition, considering the mobility measure leads to a better electricity forecasting model. This model can be used for future prediction of the electricity consumption values in case of Mobility restrictions due to pandemics, crises, wars, or similar situations. The suggested approach can be implemented in practice by utilizing the NARX model as an effective methodology for generating predictions of electricity consumption. It incorporates the prediction model's mobility factor, historical load profiles, weather measurements, and timing information. These predictions can be invaluable for capacity planning, resource allocation, and policy decision-making.

Comparative Studies

To validate the results of the NARX model and for comparative purposes, two models have been developed to analyze the impact of Mobility during the COVID-19 pandemic on electricity consumption, utilizing the Auto-Regressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM) methods.

Table 2 — Improvements in percentages

Performance measure	Model 1 (without Mobility)	Model 2 (with Mobility)	Percentages of improvement
MSE (Training)	8.6e+04	5.6e+04	Decrease by 35%
MSE (Validation)	1.2e+05	6.4e+04	Decrease by 46%
MSE (Testing)	1.5e+05	8.6e+04	Decrease by 43%
R-value (Training)	0.90	0.95	Increase by 5.5%
R-value (Validation)	0.89	0.92	Increase by 3.6%
R-value (Testing)	0.84	0.89	Increase by 6.0%
RMSE	408.1	377.12	Decrease by 7.6%

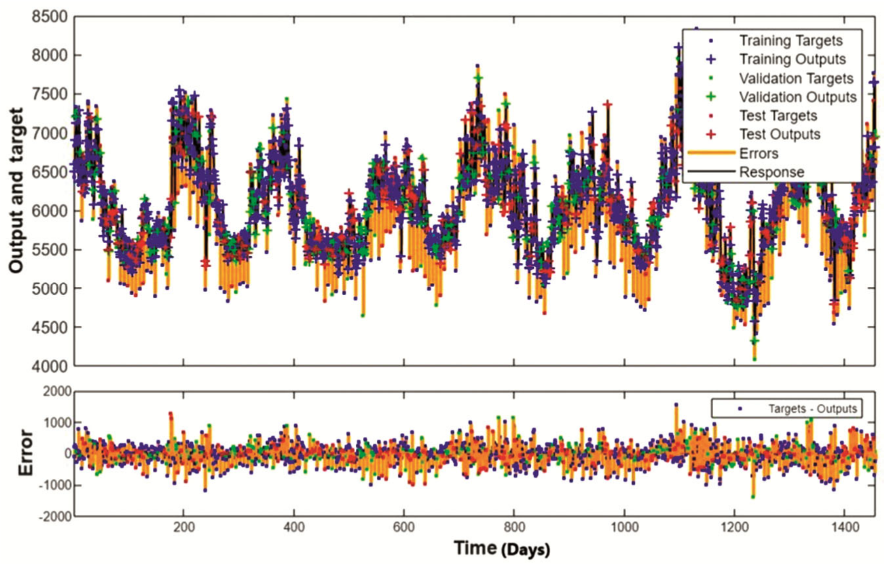

Fig. 8 — Time-series response for electricity consumption without considering mobility factor using the ARIMA model

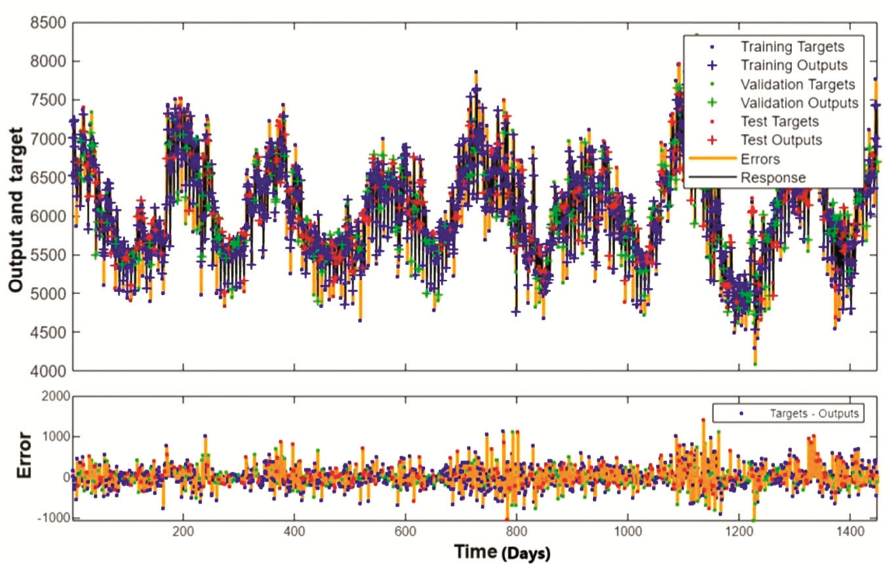

Fig. 9 — Time-series response for electricity consumption considering mobility factor using the ARIMA model

The ARIMA model was developed for both cases, with and without Mobility. The response of the time series for the actual and expected values, along with their associated errors for electricity consumption without considering the mobility factor, is shown in Fig. 8. At the same time, Fig. 9 displays the results considering the mobility factor. Comparing the two figures reveals a decrease in errors when considering

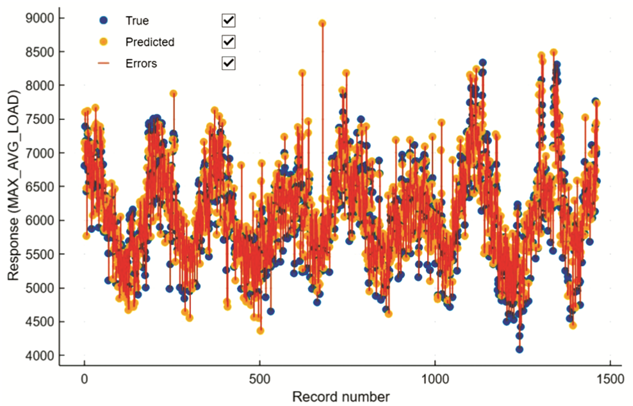

Fig. 10 — Time-series response for electricity consumption without considering mobility factor using the LSTM model

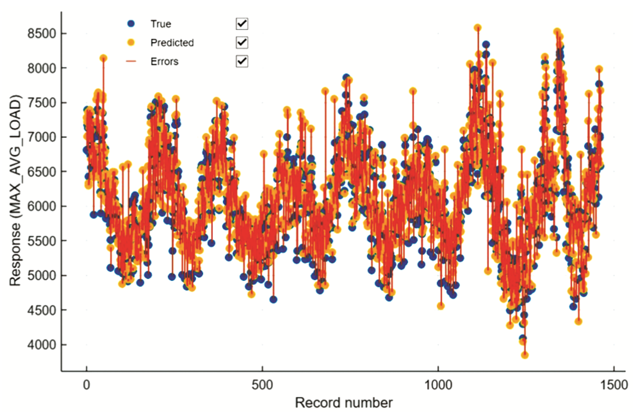

Fig. 11 — Time-series response for electricity consumption considering mobility factor using the LSTM model

the mobility factor. The MSE values for training, validation, and test were 1.0907e+05, 1.2254e+05, and 1.3184e+05, and the corresponding R values were 0.8755, 0.8747, and 0.8402 for the ARIMA model without considering the mobility factor. With the inclusion of the mobility factor, there was an improvement in results, with MSE values for training, validation, and test of 7.1588e+04, 9.1128e+04, and 1.0609e+05, and R values of 0.9218, 0.8907, and 0.8839,respectively.

The same conclusion can be drawn when developing LSTM models for both cases, with and without considering the mobility factor. The response of the time series for the actual and expected values and their associated errors for electricity consumption without considering the mobility factor is shown in Fig. 10. In contrast, Fig. 11 displays the results considering the mobility factor. When comparing them, we can observe a decrease in the error in the second case. Additionally, the MSE and R-value values support this conclusion. For validation, the MSE was 1.904e+05 in the first case, which decreased to 1.8452e+05 when considering Mobility in electricity consumption forecasting. The R values were 0.59 for the first case and improved to 0.61 for the second.

Table 3 — Overall model predictive performance

	Model 1 (without Mobility)		Model 2 (with Mobility)	
Model	MSE	R-value	MSE	R-value
NARX	1.2e+05	0.89	6.4e+04	0.92
ARIMA	1.2e+05	0.87	9.1e+04	0.89
LSTM	1.9e+05	0.59	1.84e+05	0.61

When comparing the results obtained from these two models with the NARX model, we can observe that the NARX Model exhibits better performance in terms of MSE and R. The differences between the three models for validation data as a comparison example are displayed in Table 3 below. In summary, we can conclude that all three models show better predictions when considering the mobility factor in the model. Among them, the NARX model performs the best, followed by ARIMA and then the LSTM model when comparing their MSE and R values.

Conclusions

In this study, a NARX model was created to study the effect of Mobility as a factor that reflects the socioeconomic changes caused by the pandemic on electricity consumption prediction in Jordan. Factors suggested by previous studies, including historical load profile, weather measurement, and timing information, were also considered. Adding the Mobility measure to the model improves electricity consumption prediction. Error residuals between the actual and forecasted max load values and the RMSE value were lower in the model with the inclusion of the Mobility measure compared to the model without it. Additionally, the R values were higher for the second model than for the first one (without the Mobility measure). To verify the results and for comparison purposes, two other models were built using ARIMA and LSTM models, which show the same conclusion as the NARX model, incorporating a mobility factor to enhance the prediction performance and accuracy of the model. The NARX model delivers the best results regarding MSE and R values among the other models, ARIMA and LSTM.

In future work, other machine learning approaches could be considered to build forecasting models for complex time series problems with multiple input variables to increase the efficiency and accuracy of the electricity consumption prediction. Additional correlation factors that could influence the amount of electricity consumed due to the pandemic can be studied.

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