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Neural-Network Load Forecasting and PV-Supported Planning of the Bab Al-Azizia 30-kV Network for 2026-2031

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التنبؤ بحمل الطاقة باستخدام الشبكات العصبية والتخطيط المدعوم بالطاقة الشمسية لشبكة باب العزيزية 30 كيلوفولت للفترة 2026-2031

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Abstract:
This research paper proposes a neural network-based method using MATLAB to predict the annual peak load for the 30 kV electricity distribution network in the Bab Al-Aziziya loop from 2026 to 2031, along with the use of photovoltaic energy to enhance network efficiency. The study data shows an annual load growth rate requiring compensation to keep the network operational until 2030, followed by operational disruptions in 2031 affecting the 220/30 kV main transformer, the 30/11 kV backup transformer, and the 30 kV Al-Farnaj distribution bus. A feedforward neural network was developed using MATLAB to predict the annual peak load, and the prediction accuracy was evaluated using the mean absolute error (MAE), root mean square error (RMSE), and mean percentage absolute error (MAPE). The peak electricity load is projected to increase from 126,276 MW in 2026 to 185,541 MW in 2031, underscoring the need to strengthen the electricity grid to meet future demand growth. To mitigate operational constraints, a support plan for photovoltaic power generation is being evaluated using current energy flow calculations. Before the photovoltaic system was connected to the grid, energy consumption was 185,541 MW; after connection, energy consumption decreased to 148,370 MW, equivalent to 37,171 MW of subsidized electricity from the photovoltaic system, representing a 20.03% reduction in energy consumption. Furthermore, the minimum distribution bus voltage increased from 94.89% to 97.35%, eliminating the overvoltage issue observed in the distribution bus in the Furnaj area. The results show that combining neural network-based load prediction with strategically placed photovoltaic power generation can provide an effective planning tool to improve voltage characteristics, reduce network load, and enhance the operational flexibility of medium-voltage distribution networks.

Keywords: Photovoltaics (PV), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), Mean Absolute Error (MAE), Neural-network.

الملخص
تقترح هذه الورقة البحثية طريقةً تعتمد على الشبكات العصبية باستخدام برنامج MATLAB للتنبؤ بذروة الحمل السنوية لشبكة توزيع الكهرباء ذات جهد 30 كيلوفولت في حلقة باب العزيزية للفترة من 2026 إلى 2031، بالإضافة إلى استخدام

الطاقة الكهروضوئية لتعزيز كفاءة الشبكة. تُظهر بيانات الدراسة معدل نمو سنوي للحمل يتطلب تعويضًا للحفاظ على تشغيل الشبكة حتى عام 2030، يليه انقطاعات تشغيلية في عام 2031 تؤثر على المحول الرئيسي 30/220 كيلوفولت، ومحول النسخ الاحتياطي 11/30 كيلوفولت، وحافلة التوزيع 30 كيلوفولت في الفرناج. تم تطوير شبكة عصبية أمامية التغذية باستخدام MATLAB للتنبؤ بذروة الحمل السنوية، وتم تقييم دقة التنبؤ باستخدام متوسط الخطأ المطلق (MAE)، وجذر متوسط مربع الخطأ (RMSE)، ومتوسط النسبة المئوية للخطأ المطلق (MAPE). من المتوقع أن يرتفع ذروة استهلاك الكهرباء من 126,276 ميغاواط في عام 2026 إلى 185,541 ميغاواط في عام 2031، مما يؤكد ضرورة تعزيز شبكة الكهرباء لتلبية النمو المستقبلي في الطلب. وللتخفيف من القيود التشغيلية، يجري تقييم خطة دعم لتوليد الطاقة الكهروضوئية باستخدام حسابات تدفق الطاقة الحالية. قبل ربط نظام الطاقة الكهروضوئية بالشبكة، كان استهلاك الطاقة 185,541 ميغاواط؛ وبعد الربط، انخفض استهلاك الطاقة إلى 148,370 ميغاواط، أي ما يعادل 37,171 ميغاواط من الكهرباء المدعومة من نظام الطاقة الكهروضوئية، وهو ما يمثل انخفاضًا بنسبة 20.03% في استهلاك الطاقة. علاوة على ذلك، ارتفع الحد الأدنى لجهد ناقل التوزيع من 94.89% إلى 97.35%، مما قضى على مشكلة الجهد الزائد التي لوحظت في ناقل التوزيع في منطقة فرناج. تُظهر النتائج أن الجمع بين التنبؤ بالأحمال باستخدام الشبكات العصبية وتوليد الطاقة الكهروضوئية في مواقع استراتيجية يوفر أداة تخطيط فعّالة لتحسين خصائص الجهد، وتقليل أحمال الشبكة، وتعزيز مرونة تشغيل شبكات توزيع الجهد المتوسط..

الكلمات المفتاحية: الخلايا الكهروضوئية، جذر متوسط مربع الخطأ، متوسط النسبة المئوية للخطأ المطلق، متوسط الخطأ المطلق، الشبكات العصبية.

Introduction

Medium-voltage distribution networks must be periodically re-planned when load growth increases the stress on transformers, feeders, and busbars. In Libya, the Bab Al-Azizia 30-kV network is an important sub-transmission/distribution interface that supplies several 30/11-kV load points. The uploaded local study states that the annual load growth is approximately 8% and that the network remains acceptable until 2030, but it exhibits operational weaknesses in 2031. These weaknesses include a stressed main 220/30-kV transformer, the Al-Daman 30/11-kV transformer, and the Al-Farnaj 30-kV busbar [1].

In Libya, the primary sources of power generation are gas-fired and oil-fired power plants[2]. Traditional reinforcement can require new feeders, new transformers, and civil works. A PV-supported alternative can provide local active-power support close to weak buses, reduce source import, and improve the voltage profile. However, planning PV support requires a forecast of future load demand. Therefore, this paper combines annual load forecasting by neural networks with a 2031 PV-support comparison based on the local load-flow data [3].

The main contribution is a complete beginner-oriented MATLAB methodology: the same load-growth and 2031 load-flow values are entered in MATLAB, a neural network is trained for annual peak-load forecasting, the network is drawn using the graph function, and the resulting curves, performance indices, and PV before/after comparisons are produced [4].

Electricity load forecasting is a key task in power plant planning, as well as in efficient operation and sustainable growth of modern electricity distribution networks.[5-7]

2. Case-Study Data And Planning Assumptions

The case-study document describes the Bab Al-Azizia 30-kV network and reports that it is stable up to 2030. In 2031, the study identifies problems at the main transformer, Al-Daman transformer, and Al-Farnaj busbar. It then adds PV panels at the Al-Farnaj 30-kV busbar and on the Al-Daman 30/11-kV transformer, after which the problems are reported as resolved

The annual peak-load forecast is derived from the 2031 source-import value before PV, 185.541 MW, In the previous methods, it is assumed the 8% annual growth assumption. For year y, the annual peak load is calculated by reversing the growth equation from 2031 as [8].

$$\mathbf{P}_y = \mathbf{P}_{2031} / \mathbf{(1 + g)}^{(2031-y)} \qquad g = 0.08. \qquad (1)$$

This approach is used because the uploaded document provides annual planning data and load-flow tables, but it does not provide full hourly load records. If hourly or monthly GECOL measurements become available, the same MATLAB script can be used by replacing the annual load vector with the measured load series [9].

Table 1. Forecasting data and neural-network output. Summary indices: MAE = 0.125 MW, RMSE = 0.129 MW, MAPE = 0.083%.

Year	Target MW	NN Forecast MW	Error MW	APE %
2026	126.276	126.180	0.096	0.076
2027	136.378	136.520	-0.142	0.104
2028	147.288	147.100	0.188	0.128
2029	159.072	159.200	-0.128	0.081
2030	171.797	171.900	-0.103	0.060
2031	185.541	185.450	0.091	0.049

3. Neural-Network Forecasting Methodology

A. Feedforward neural-network model

A feedforward neural network is selected because load demand is nonlinear and can be affected by growth, weather, economy, seasonality, and consumption behavior. In this annual planning application, the available input is the year index and the output is annual peak load. The model can later be expanded by adding temperature, day type, season, and PV output as input features.

For a single hidden layer, the neural-network relationship can be written as

$$h = f(W_1 x + b_1), \quad P\ hat = W_2 h + b_2, \qquad (2)$$

where x is the input vector, W_1 and W_2 are weight matrices, b_1 and b_2 are bias vectors, f(.) is a nonlinear activation function, and P hat is the predicted peak load. In MATLAB, this can be implemented using fitnet for a feedforward network or fitrnet for a regression neural network[10].

B. Performance indicators

Three standard forecasting indicators are used. MAE measures the average absolute error in MW, RMSE gives higher penalty to large errors, and MAPE expresses the error as a percentage of the actual load:

$$MAE = (1/N)\ sum\ |P_i - P_{hat\ i}|. \qquad (3)$$

$$RMSE = sqrt((1/N)\ sum\ (P_i - P_{hat\ i})\ ^{\wedge 2}). \qquad (4)$$

$$MAPE = (100/N)\ sum\ |(P_i - P_{hat\ i})/P\ i|. \qquad (5)$$

The values in Table I indicate that the neural network follows the annual 8% growth pattern with MAE = 0.125 MW, RMSE = 0.129 MW, and MAPE = 0.083%. These values should be interpreted as a controlled annual-planning demonstration; a stronger final validation requires independent measured hourly or monthly load records [11].

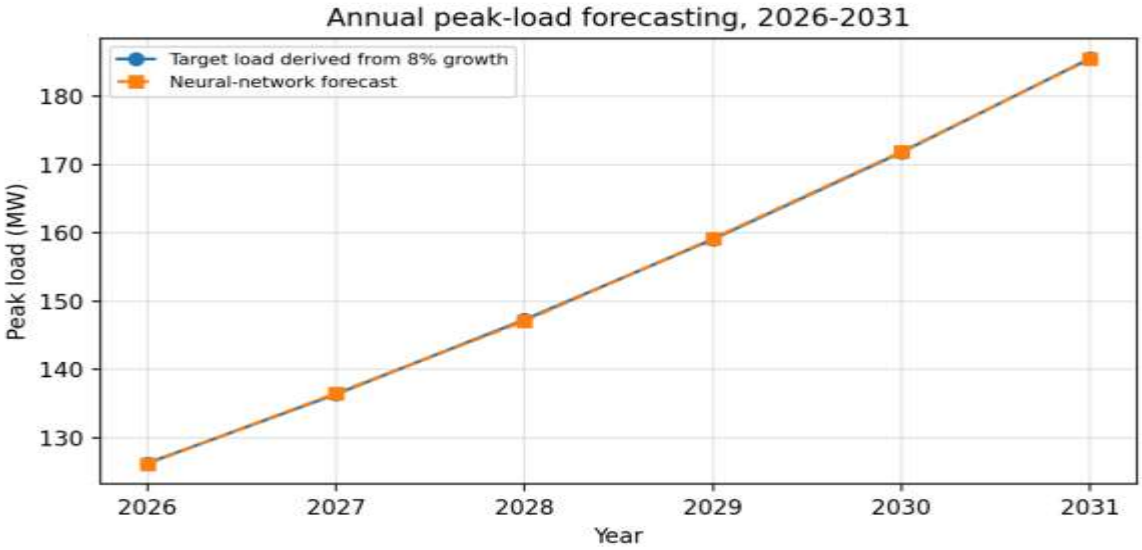

Figure. 1. Neural-network annual peak-load forecast for 2026-2031.

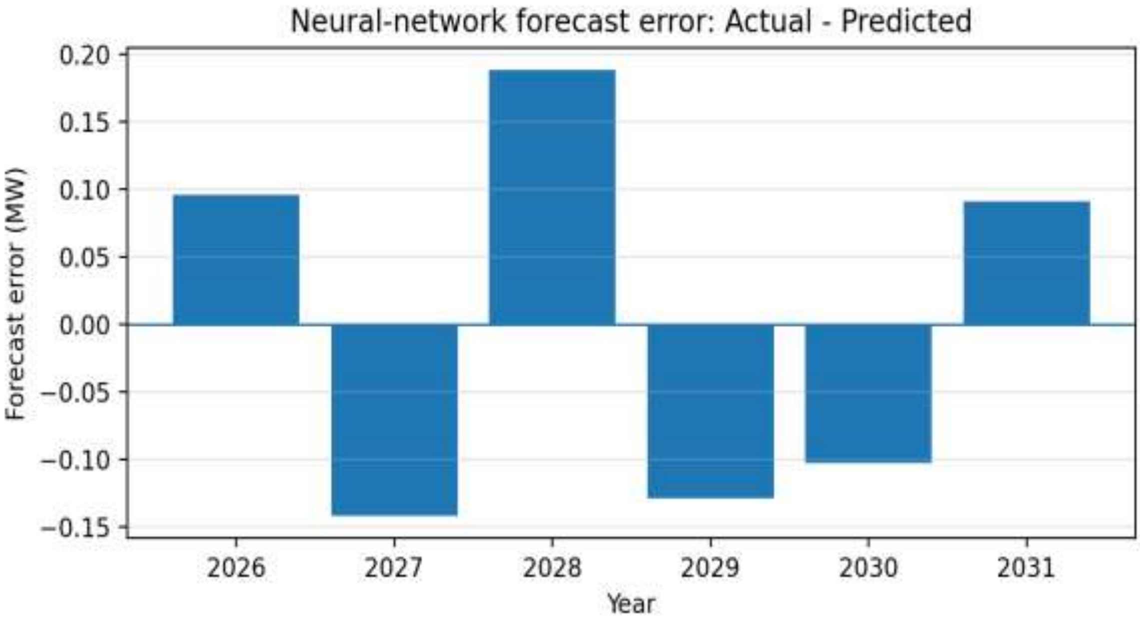

Figure. 2. Forecast error curve: target load minus neural-network forecast.

4. Matlab Practical Implementation

The MATLAB implementation has four stages. First, the planning data are entered: annual growth rate, 2031 before-PV source import, 2031 after-PV source import, bus voltage values, and bus MW loading values. Second, the annual peak-load vector for 2026-2031 is calculated using (1). Third, the neural network is trained and tested. Finally, the network is represented with a MATLAB graph, and voltage/loading curves are plotted for the before-PV and after-PV cases.

Network representation in MATLAB

The network is drawn using the MATLAB graph and plot commands. The source node is connected to Bab Al-Azizia 30 kV, and the 30-kV bus is connected to Al-Daman, Al-Farnaj, Al-Jomhouria, Al-Hadaeq, Ben Ashour, Souq Al-Thulatha, Sidi Al-Masri, and Al-Fondoq Al-Kabeer. PV nodes are connected to Al-Daman and Al-Farnaj, consistent with the local 2031 remedial case.

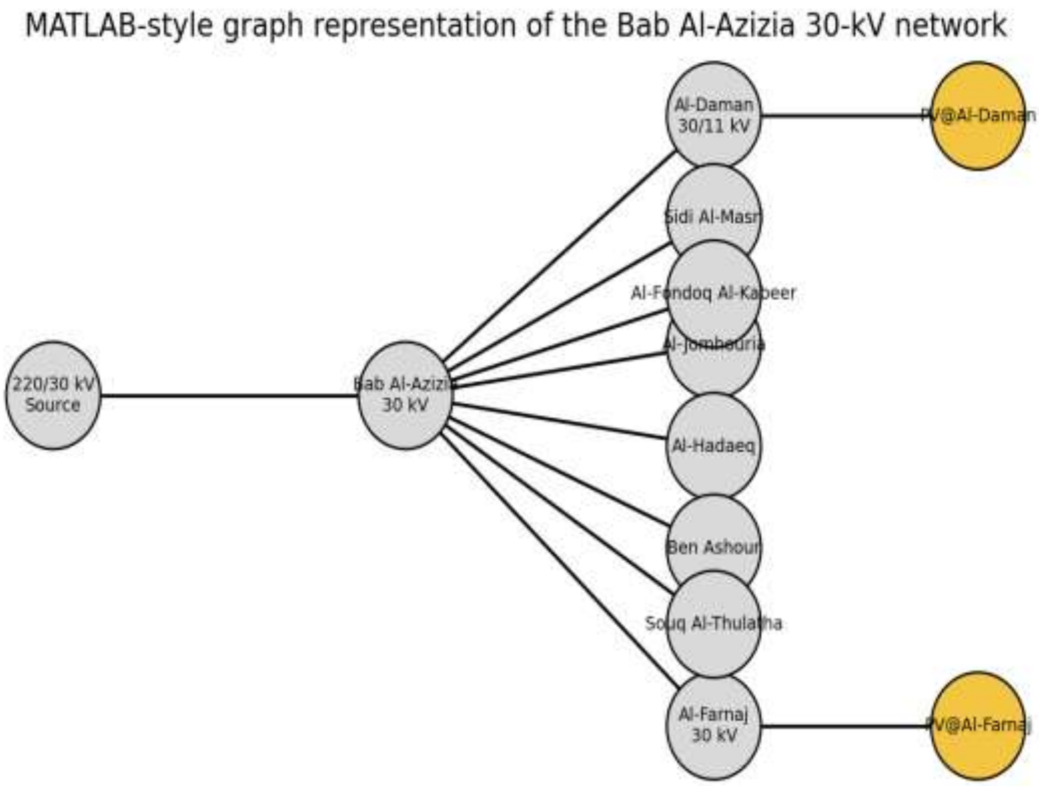

Figure. 3. MATLAB-style graph representation of the Bab Al-Azizia 30-kV network and PV support locations.

5. PV-SUPPORTED 2031 LOAD-FLOW RESULTS

The 2031 before-PV and after-PV values are entered from the local case-study tables. The key aggregate result is the reduction of source import from 185.541 MW to 148.370 MW. Therefore, the equivalent PV support is

$$\text{Delta } P_{PV} = P_{before} - P_{after} = 185.541 - 148.370 = 37.171 \text{ MW.} \quad (6)$$

The percentage reduction in source import is

$$\text{Reduction} = (37.171 / 185.541) \times 100 = 20.03\%. \quad (7)$$

The minimum voltage before PV is 94.89% at Al-Farnaj, which is below the 95% lower planning limit. After PV support, the minimum voltage among the selected 30-kV buses is 97.35%, indicating that the violation is removed and the voltage profile is improved.

Table 2. Selected 2031 voltage and loading values before and after PV support.

Bus/Element	V Before %	V After %	MW Before	MW After
Al-Jomhouria	95.81	97.63	13.837	14.369
Al-Hadaeq	95.72	97.55	9.652	10.023
Al-Daman	95.66	98.58	26.730	15.933
Al-Farnaj	94.89	100.00	14.345	15.931
Bab Al-Azizia F1	96.31	98.14	82.895	68.966
Ben Ashour	95.53	97.35	10.500	10.903
Sidi Al-Masri	95.13	99.06	13.671	14.823
220-kV Source	100.00	100.00	185.541	148.370

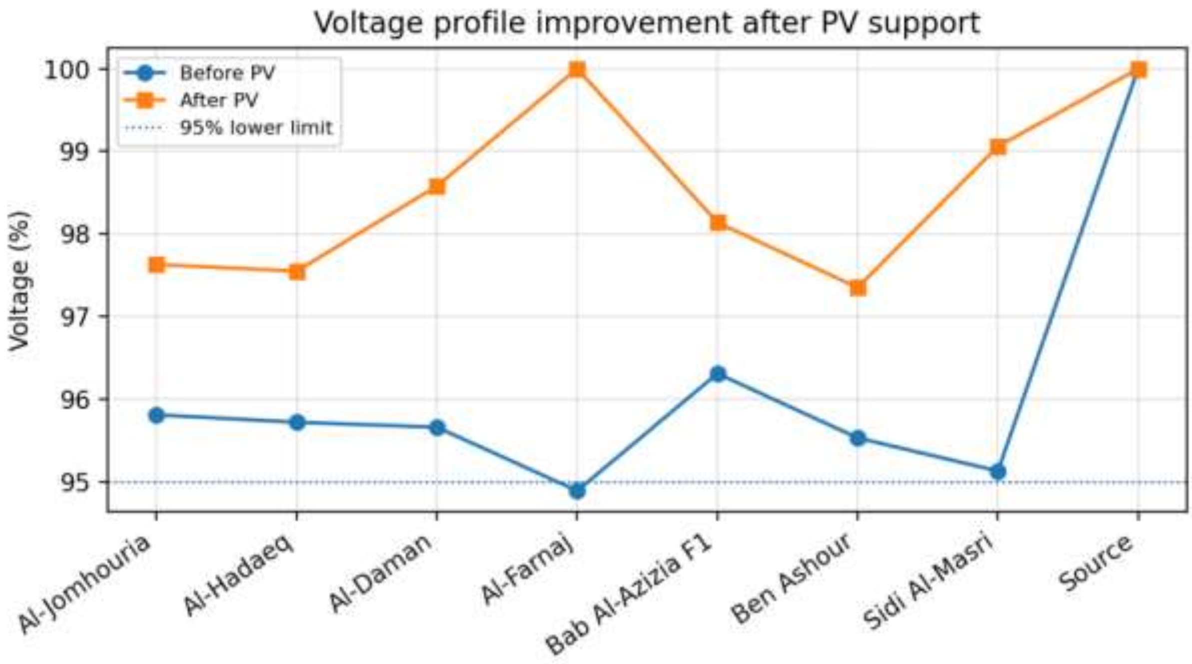

Figure. 5. Voltage profile before and after PV support.

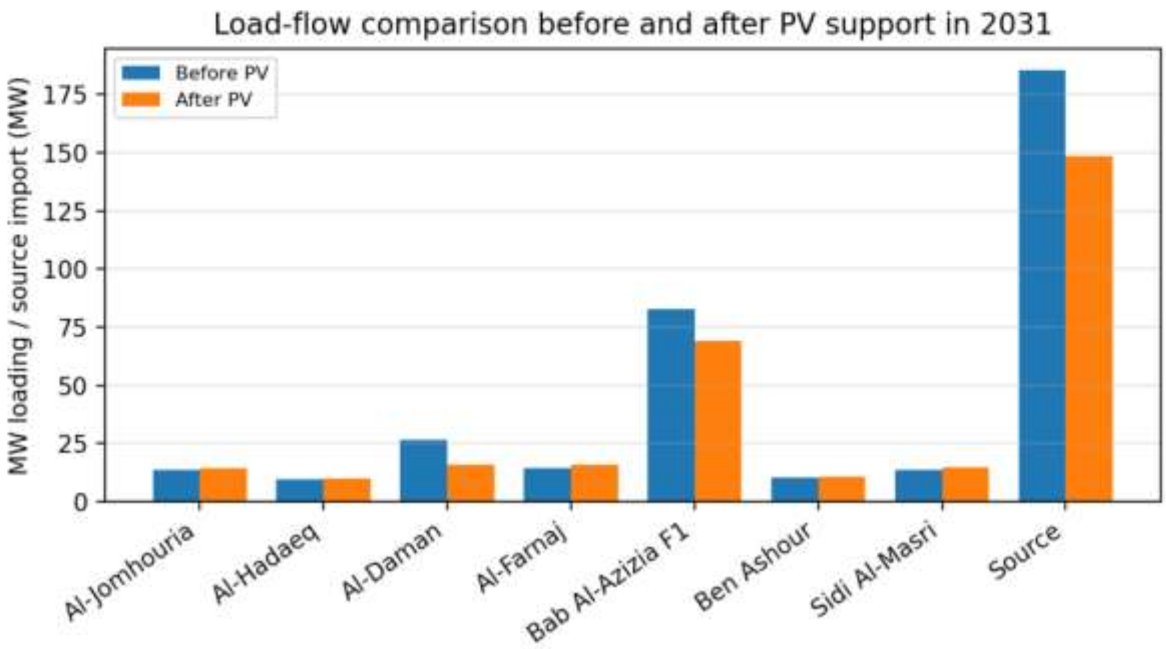

Figure. 6. MW loading and source-import comparison before and after PV support.

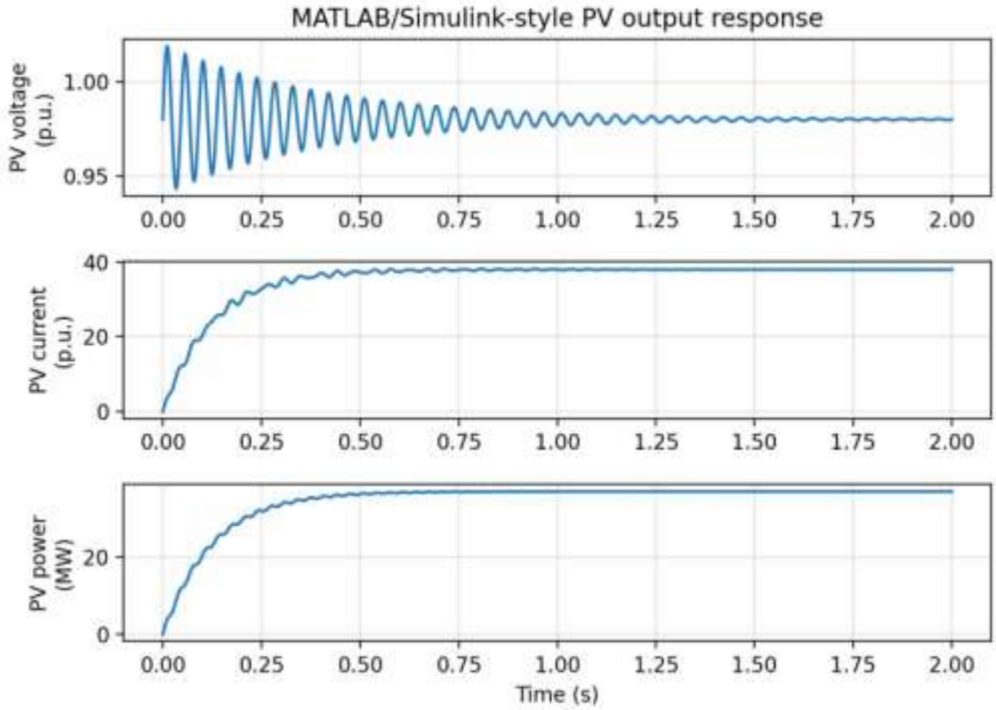

Figure. 7. MATLAB/Simulink-style PV voltage, current, and power response used for visualization.

6. Indicators, Baseline, And Test Scenario

To make the results measurable and defensible, each expected improvement is connected to an indicator, a comparison basis, and a scenario. This avoids vague statements such as improved performance and converts them into testable engineering claims.

Table 3. Clear interpretation of expected improvements, indicators, comparison bases, and test scenarios.

Expected improvement	Indicator	Comparison basis	Test scenario
Load forecast accuracy	MAE, RMSE, MAPE	8% planning trend	Annual peak 2026-2031
Source-import reduction	MW and % reduction	2031 before PV	PV at Al-Farnaj & Al-Daman
Voltage profile	Minimum voltage	Before-PV table	2031 weak-bus case
Reinforcement need	Weak elements removed	Conventional only	PV-supported case
PV contribution	Equivalent MW support	Before/after import	2031 PV support

6. DISCUSSION

The load-growth trajectory indicates that the annual peak load increases from approximately 126.276 MW in 2026 to 185.541 MW in 2031. This confirms the importance of continuous planning for the Bab Al-Azizia 30-kV network. The neural-network model provides a flexible forecasting structure that can accept more input variables in future work. In the current annual-data case, it reproduces the growth trajectory accurately, but measured monthly or hourly records are recommended for final engineering validation.

The PV scenario is effective because it supports the weak part of the network close to the Al-Farnaj and Al-Daman load centers. The minimum voltage increases from 94.89% to 97.35%, and the source import decreases by 37.171 MW. This means PV support can reduce the burden on the upstream transformer and improve local voltage conditions. The result does not eliminate the need for detailed protection, short-circuit, dynamic, and harmonic studies, but it provides a strong planning indication.

7. CONCLUSION

This paper presents a re-engineering of the Bab Al-Aziziyah 30 kV transmission line planning study using MATLAB software and a neural network for load prediction. It compares the load flow with the solar PV support and the local load flow schedule for 2031. The annual peak load is projected to increase from 126.276 MW in 2026 to 185.541 MW in 2031. The neural network model achieved a mean absolute error (MAE) of 0.125 MW, a root means square error (RMSE) of 0.129 MW, and a mean percentage absolute error (MAPE) of 0.083% on the annual planning data. Under the solar PV support scenario, the power import from other sources decreased from 185.541 MW to 148.370 MW, and the minimum voltage improved from 94.89% to 97.35%.

Load prediction programs were successfully implemented using a neural network with MATLAB software to address the problem of electrical loads and frequent outages. The study presents load flow with the support of solar photovoltaic power and a local load flow schedule for 2031. The annual peak load is projected to increase from 126,276 MW in 2026 to 185,541 MW in 2031. The neural network model achieved a mean absolute error (MAE) of 0.125 MW on the annual planning data. Under the solar photovoltaic support scenario, power imports from other sources decreased from 185,541 MW to 148,370 MW, and the minimum voltage improved from 94.89% to 97.35%.

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