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Intelligent Control for Voltage Regulation in the Distribution Network Equipped with PV Farm

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Abstract: A combined PSO-ANN control is proposed in this work to achieve the best voltage regulation in a distribution network, based on quick response and minimum average voltage deviation. The Jordanian Sabha Distribution Network (JSDN) with PV Farms is used as a real case study to examine a voltage variation issue. Two STATCOMs are used to solve the voltage fluctuation problem on the network's three buses. The required reactive powers of STATCOMs for voltage regulation during load variation are calculated in offline mode using a particle swarm optimization (PSO) algorithm. Despite its high performance in solving voltage issue in the JSDN network, the PSO controller is unable to react promptly to dynamic changes in the network. An artificial neural network (ANN) is therefore suggested as an online mode controller for quick and efficient voltage regulation. The offline dataset is used to train the ANN for online voltage regulation utilizing the MATLAB-Tool Box. At an average voltage deviation (AVD) of 1.168%; (whereas an acceptable one is 6%), the results revealed the proposed ANN controller's competence for voltage regulation in the distribution network. Moreover, to find the best position based on an efficient voltage regulation, many sites for STATCOMs are taken into consideration.

Keywords: renewable energy; smart grids; distribution networks; STATCOMs; PV systems

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1. Introduction

Power systems have become more complicated as a result of renewable energy sources (RES) integration. RESs have become important due to their high economic benefits and environmental friendliness. Several policies have been developed to increase RES penetration and some of them have become alternative sources such as solar and wind energy [1]. In general, the growing demand for electric power consumption has created an urgent need to provide new environmentally friendly generation sources that meet these needs with economic benefits, such as RES [2]. Utilizing RES leads to a change in the power flow from one direction to bidirectional causing several problems, predominantly voltage deviation.

Voltage deviation is classified as a voltage rise problem that occurs at the generation peak with a light load or a voltage drop that happens at overloading on the network. Distributed generation sources play an important role in distribution systems. The utilization of distributed generation reduces the power loss and voltage drop and improves the voltage profile [3]. The distributed generation in the network can be utilized in a way to generate active power and reactive power, and the injection or absorption of reactive power helps in voltage profile improvement.

Plenty of research work has been published to mitigate the voltage deviation problem due to its effective significance. Reactive power compensation is one of the most important strategies that has been proposed, including static volt-ampere reactive (VAR) compensator (SVC) and on-load tap changer (OLTC) [4,5]. Furthermore, the studies showed that the

devices were optimally controlled by many methods, such as genetic algorithms and other optimization techniques. Power system problems are characterized by their nonlinear nature and thus the importance of using optimization algorithms is to find the optimal solution. To address the issue of optimal power dispatch, numerous metaheuristic optimization techniques were used [6,7]. Reactive power control approaches, electrical energy storage (ESS), and PV system active power reduction are the three primary categories that the authors of [8] presented for voltage regulation under high photo-voltaic (PV) penetration. When energy production is at its maximum, the ESS stores the extra energy and feeds it back into the grid when demand is at its peak. This helps in solving the voltage deviation issue. The second main category depends on the relation between the active power and the voltage of the PV inverter. A linear reduction in active power occurs after exceeding the voltage above a certain level. The reduction of active power should overcome the voltage rising during high PV penetration. Reactive power control was employed using devices such as SVC, static synchronous compensator (STATCOM), PV inverter, and switched capacitors (SC). In [9], a comparison was conducted between these three categories and the OLTC technique. The reactive power control technique proved its supremacy in response time and efficiency. The accommodating of the PV systems in the grid leads to bidirectional power flow. The authors in [10] proposed the PV inverter volt-var method to overcome the voltage deviation. The positive sequence sensitivity impedance matrix was implemented for the power flow calculation to compensate for the reactive power of the PV inverter. The simulated results showed that the proposed method improved the voltage profile and minimized the injected reactive power of the existing slack bus. In [11], the authors proposed a new voltage regulation technique that utilizes the reactive power compensation capability of PV inverters in addition to the locations of the PV system in the network. The proposed technique relies on power factor/active power and reactive power/voltage characteristic curves (Q(P) and Q(V) curves). The authors tested the proposed strategy and concluded that it gives the best results along with the Q(V) method, and recommended it for high PV penetration.

To train the nonparametric models for reducing the voltage variation in the distribution network equipped with a PV farm, the augmented grey wolf optimization (AGWO) algorithm was used [12]. The suggested method significantly decreased the network's voltage deviation. Merging techniques were proposed in [13,14] by using the feeder transformer electronic tap changer to adjust its voltage, and local PV inverters to compensate the reactive power of its buses and reduce the feeder's apparent power flow and losses. The proposed strategy showed the best result on voltage profile during the daytime. In [15], the authors proposed a merged strategy between OLTC of the distribution transformer and the reactive power compensation by PV inverters. It showed excellence in improving voltage regulation and power loss reduction under different loads/and PV penetration based on criteria of reactive power as a function of bus voltage. The proportional integral (PI) controller strategy was proposed in [16] to control STATCOM to regulate the bus voltage and improve the source power factor of the single-phase distribution system, and in [17] to mitigate the voltage sag, swell, and harmonics reduction in the wind generator. The simulated results proved the enhancement capability of the suggested method.

Artificial neural networks (ANN) have been used to mitigate many electrical problems. An ANN was used to manipulate state-of-the-art reactive power compensating devices to regulate line voltage with minimum response time and proved its high performance compared to conventional controllers such as a PI controller [18]. In [19], to overcome the problem of the particle inertia coefficient in a PSO algorithm for an ideal power flow for tools used in power system control, it proposed an enhanced fuzzy interface system. The PSO was suggested by the authors in [20] to regulate the functioning of switched capacitors with delta connections in an unbalanced radial medium-voltage distribution grid. The approach was successfully tested for an entire day on an actual unbalanced medium voltage network in Australia. In [21,22], the authors demonstrated that the PSO has successfully

handled several engineering issues with a higher mean fitness value, fewer variables to manipulate, and a quick execution time on average.

Many optimization algorithms were used to solve electrical power problems [23–27]. In [6], eight metaheuristics optimization algorithms were implemented to solve optimal power dispatch. The results showed that the moth–flame optimization algorithm (MFO) outperformed the tested algorithms. In [28], the authors proposed the volt-var and watt optimization algorithm (VVWO) to increase the PV penetration level and overcome its issues such as voltage deviation, line losses, active power demand curtailment, and reduce the operation period of classic reactive power compensators. The simulated results proved that the imposed algorithm mitigated the increment of PV penetration problems. In [29], the fuzzy-based improved comprehensive learning–particle swarm optimization algorithm (FBICLPSO) was proposed to achieve the optimal power flow of the IEEE 30 bus system using MATPOWER program. The implemented cost function included the reactive power compensation of the thyristor-controlled series compensator, the generator's steam flow, and a multi-fuel option to minimize the line losses and voltage deviation. The simulated results showed that the proposed method provided the minimum cost, computed time, line losses and voltage deviation. In [30], a new technique was proposed to overcome the time-consuming model of typical optimization algorithms. It adopted multi-agent deep reinforcement learning (MADRL) based on volt-var optimization (VVO) for voltage regulation and line loss reduction. The modified IEEE 13-bus with two units of single-phase PV sources and one unit of three-phase PV source was tested, in addition to IEEE 123-bus systems with six PV units. The simulated results proved the proposed technique's ability to improve the voltage profile and reduce the line losses with less computation time. In [31], the authors proposed grey wolf optimization (GWO) to compensate the reactive power of the PV inverter and OLTC to regulate the voltage on the tested 119-bus system. Three cases were considered: reactive power compensation of PV inverter, reactive power compensation of both PV inverter and OLTC, and no compensation. The outcome showed that the combined technique provides the best results in voltage profiles. In [32], GWO was proposed to enhance the voltage profile and reduce the active power losses of 33, 69 bus systems by optimizing the location and the capacity of PV–wind turbine units. The outcomes proved the algorithm's ability to enhance the voltage profile and reduce the losses by up to 50% in different conditions. The authors in [33] used an optimization algorithm to train the neural network for monitoring and control of distribution networks. This hybrid machine learning-optimization approach improves the efficiency of distribution system state estimation. In [34], for hyperspectral images, a feature extraction technique merging principal component analysis (PCA) and local binary pattern (LBP) is created. To efficiently implement a hyperspectral image classification approach, the kernel extreme learning machine (KELM) parameters are optimized using the gray wolf optimization algorithm with global search capabilities. Voltage violations are a significant barrier to integrating more rooftop solar energy into intelligent low-voltage distribution grids (LVDGs). To best utilize the reactive power capability of smart PV inverters while minimizing active power curtailment to reduce the voltage violation problem, the authors suggest a two-stage optimization process that consists of the feasible region search (FRS) step and particle swarm optimization (PSO) [35].

Based on quick response and the minimum possible average voltage variation, a hybrid PSO-ANN control strategy is proposed in this study to achieve optimal voltage regulation in the JSDN. This intelligent method is used on the static synchronous compensator (STATCOM) to obtain the best reactive power that can be provided in order to reduce voltage variation in the network.

The JSDN has nine buses and the following:

- Sabha substation of 132/33 kV, 30 MVA and two distribution lines of 35.87 km and 22.47 km.
- Safawi substation of 132/33 kV, 1.96 MVA with one distribution line of 58.57 km.

- Badiah PV Farm of 0.4/33 kV, 13 MW and three distribution lines of 0.83 km, 1.8 km and 1.16 km.
- Sabha load of 13.45 MW and 6.24 MVAR.
- Safawi load of 2.1 MW and 1.6 MVAR.
- Saliheah load of 12.75 MW and 8.1 MVAR.

The PSO algorithm is used in the offline mode to calculate the required reactive power and operation settings of the existing STATCOMs to solve the voltage deviation at intermediate buses of JSDN. To overcome the dynamic response problem of the PSO, the trained ANN is used in real-time to solve the voltage deviation at intermediate buses of JSDN.

The rest of the paper is organized as follows: Section 2 describes the model for the distribution network. A trained ANN for real-time voltage regulation is explained in Section 3. Section 4 presents results and discussion for PSO and the trained ANN. Section 5 concludes this work.

The Contributions of the Work

To address the problem of voltage variation, a real case study of the Jordanian Sabha Distribution Network (JSDN) with PV Farms was modeled. A PSO algorithm was applied to the JSDN model to determine the optimal STATCOMs' reference signals for voltage regulation. The low response of PSO to the real-time dynamic changes in the network was resolved by proposing the ANN as an online controller to fulfill the voltage regulation promptly and accurately. Due to the training of the ANN, using a sizable dataset produced via PSO, the suggested ANN was able to obtain a quite low average voltage deviation and so overcome the voltage fluctuation problem.

Table 1 introduces a comparison between the proposed ANN controller and different control techniques mentioned in the literature for voltage regulation in a distribution power network. Accordingly, the contributions to knowledge in this paper are as follows:

- The proposed ANN controller showed its high performance in solving the voltage deviation in the distribution network system equipped by PV Farm, without the need for complex equations.
- The proposed ANN controller has a high dynamic response compared to wind driven optimization (WDO) and the gravitational search algorithm (GSA), due to their search process.
- The AVD after the action of the proposed ANN controller is 1.168%; which is the smallest value compared to other methods.

Table 1. A Comparison between the proposed ANN and different control techniques.

Comparison Criterion	Proposed Work	Work in Ref. [23]			Work in Ref. [27]	Work in Ref. [4]
Method	ANN	Artificial Bee Colony (ABC)	Wind-Driven Optimization (WDO)	Gravitational Search Algorithm (GSA)	Artificial Bee Colony (ABC)	MiPower Software
Power system	9-bus JSDN	IEEE 9-bus standard	IEEE 9-bus standard	IEEE 9-bus standard	IEEE 9-bus standard	IEEE 9-bus standard
Voltage source	Two conventional sources With PV Farm	Conventional sources	Conventional sources	Conventional sources	Conventional sources	Conventional sources
The objective function of the technique	1	3	3	3	2	2
Load flow method	Newton Raphson	Newton Raphson	Newton Raphson	Newton Raphson	Newton Raphson	Newton Raphson
AVD (%)	1.168%	4.900%	4.000%	5.000%	4.790%	6.000%
Reactive power device	STATCOM	Network Power Flow	Network Power Flow	Network Power Flow	Network Power Flow	Series Capacitors

2. Distribution Network

The Irbid District Electricity Company (IDECO) in Jordan gave sufficient data that was used to model the JSDN integrated with a PV farm as a real case study. Based on a load flow analysis, the model was constructed using the MATLAB–Simulink environment and

validated using actual JSDN data. It was noted that the load bus voltage variation would eventually be resolved.

The analysis of the power flow is necessary to simulate a steady-state distribution electric grid. Based on network specifications, the power or load flow analysis is carried out using various numerical techniques to determine the voltages, power angles, and active and reactive powers of the already-existing buses in the network. Normally, the load flow analysis is implemented by nodal power balanced equations [36]. Iterative techniques are used to solve the power flow equations such as fast-decoupled, Newton–Raphson, and Gauss–Seidel methods.

Load Flow and Model of JSDN

The unknown variables in the n-buses distribution network can be solved by using the active and reactive power equations. To derive these power equations, the network is modeled using the admittance matrix (Y-bus) given in (1). Y-bus includes both line and bus values.

$$\mathbf{Y} = \begin{bmatrix} Y_{11} & \dots & Y_{1n} \\ : & & : \\ Y_{n1} & \dots & Y_{nn} \end{bmatrix} \tag{1}$$

The current and power equations at i-bus are as follows:

$$I_i = V_i Y_{ij} + \sum_{\substack{j=1 \\ j \neq i}}^{n} Y_{ij} V_j \tag{2}$$

$$P_i = \sum_{j=1}^{n} \left(|V_i||V_j||Y_{ij}| \cos(\theta_{ij} - \delta_i + \delta_j) \right) \tag{3}$$

$$Q_i = -\sum_{j=1}^{n} \left(|V_i||V_j||Y_{ij}| \sin(\theta_{ij} - \delta_i + \delta_j) \right) \tag{4}$$

where;

I_i: current at bus-i.
P_i: active power at bus-i.
Q_i: reactive power at bus-i.
V_i: voltage at bus-i.
V_j: voltage at bus-j.
Y_{ij}: admittance between bus-i and bus-j.
δ_{ij}: angle of admittance Y_{ij}.
δ_i: angle of ith bus voltage.
δ_j: angle of jth bus voltage.

Due to its significant precision, the JSDN's power flow calculations carried out via a sim power toolbox are based on the Newton–Raphson approach [37]. It is known as the sequential approximation method and it is based on the approximate Taylor's expansion. The Taylor's expansion estimate can be used to find the unknown (x) in the function f(x) = c, where "c" is a constant. The iterative equations can be written as follows:

$$\Delta P_i^{[k+1]} = \sum_{j=1}^{n} |V_i|^{[k]} |V_j|^{[k \text{ or } k+1]} |Y_{ij}| \cos(\theta_{ij} - \delta_i^{[k]} + \delta_j^{[k]}) - P_i^{[k]} \tag{5}$$

$$\Delta Q_i^{[k+1]} = -\sum_{j=1}^{n} |V_i|^{[k]} |V_j|^{[k \text{ or } k+1]} |Y_{ij}| \sin(\theta_{ij} - \delta_i^{[k]} + \delta_j^{[k]}) - Q_i^{[k]} \tag{6}$$

$$\mathbf{J^k} = \begin{bmatrix} \frac{\partial \Delta P_i^{[k]}}{\partial \delta_i} & \frac{\partial \Delta P_i^{[k]}}{\partial |V_i|} \\ \frac{\partial \Delta Q_i^{[k]}}{\partial \delta_i} & \frac{\partial \Delta Q_i^{[k]}}{\partial |V_i|} \end{bmatrix} \tag{7}$$

$$\begin{bmatrix} \Delta \delta_i^{[k]} \\ \Delta \left| V_i^{[k]} \right| \end{bmatrix} = J^{[k]^{-1}} \begin{bmatrix} \Delta P_i^{[k]} \\ \Delta Q_i^{[k]} \end{bmatrix} \tag{8}$$

$$\begin{bmatrix} \delta_i^{[k]} \\ \left| V_i^{[k]} \right| \end{bmatrix} = \begin{bmatrix} \delta_i^{[k-1]} \\ \left| V_i^{[k-1]} \right| \end{bmatrix} + \begin{bmatrix} \Delta \delta_i^{[k]} \\ \Delta \left| V_i^{[k]} \right| \end{bmatrix} \tag{9}$$

where;

k: iteration number and J: Jacobean matrix.
θ_{ij}: angle between bus-i and bus-j.
$\delta_i[k]$: angle of ith bus voltage at kth iteration.
$\delta_j[k]$: angle of jth bus voltage at kth iteration.

JSDN has the specifications given in Tables 2–4. The tables were validated by the IDECO based on the total power losses in every substation mentioned in the model. The data is used to build the Simulink model of JSDN shown in Figure 1. Every bus was labeled and specified to be ready for load flow calculations. JSDN includes Badiah PV Farm and it is considered a smart network. The used base power is 30 MVA and the base voltage is 33 kV for the load flow calculation setting. The results of load flow calculation at maximum generation and peak load are given in Table 5. It is observed that the load bus voltages were low and will be solved later on via STATCOM based on an ANN controller to reach almost unity p.u.

Table 2. Substations data in JSDN.

Substation	Substation Type	Bus Type	Power	Transformer Voltage
Sabha	Conventional	Swing	30 MVA	132/33 kV
Safawi	Conventional	Swing	1.96 MVA	132/33 kV
Badiah (1)	PV Farm	PV	1 MW	0.4/33 kV
Badiah (2)	PV Farm	PV	8 MW	0.4/33 kV
Badiah (3)	PV Farm	PV	4 MW	0.4/33 kV

Table 3. Load data in JSDN.

Load	Power	Reactive Power	Bus Type
Safawi	2.1 MW	1.60 MVAR	PQ (Active–Reactive power)
Salehiah	12.75 MW	8.10 MVAR	PQ
Sabha (1)	6.725 MW	3.27 MVAR	PQ
Sabha (2)	6.725 MW	3.27 MVAR	PQ

Table 4. Line Data in JSDN.

Line	r (Ω/Km)	l (H/Km)	Length (km)
Sabha distribution line (1)	0.2823	1.3127×10^{-3}	8.9677
Sabha distribution line (2)	0.2823	1.3127×10^{-3}	8.9677
Sabha distribution line (3)	0.2823	1.3127×10^{-3}	17.9346
Saliheah distribution line (1)	0.2823	1.3127×10^{-3}	11.2332
Saliheah distribution line (2)	0.2823	1.3127×10^{-3}	11.2332
Safawi distribution line (1)	0.2823	1.3127×10^{-3}	29.2836
Safawi distribution line (2)	0.2823	1.3127×10^{-3}	29.2836
Badiah distribution line (1)	0.1867	1.2516×10^{-3}	0.83
Badiah distribution line (2)	0.1867	1.3127×10^{-3}	1.80
Badiah distribution line (3)	0.1867	1.3127×10^{-3}	1.16

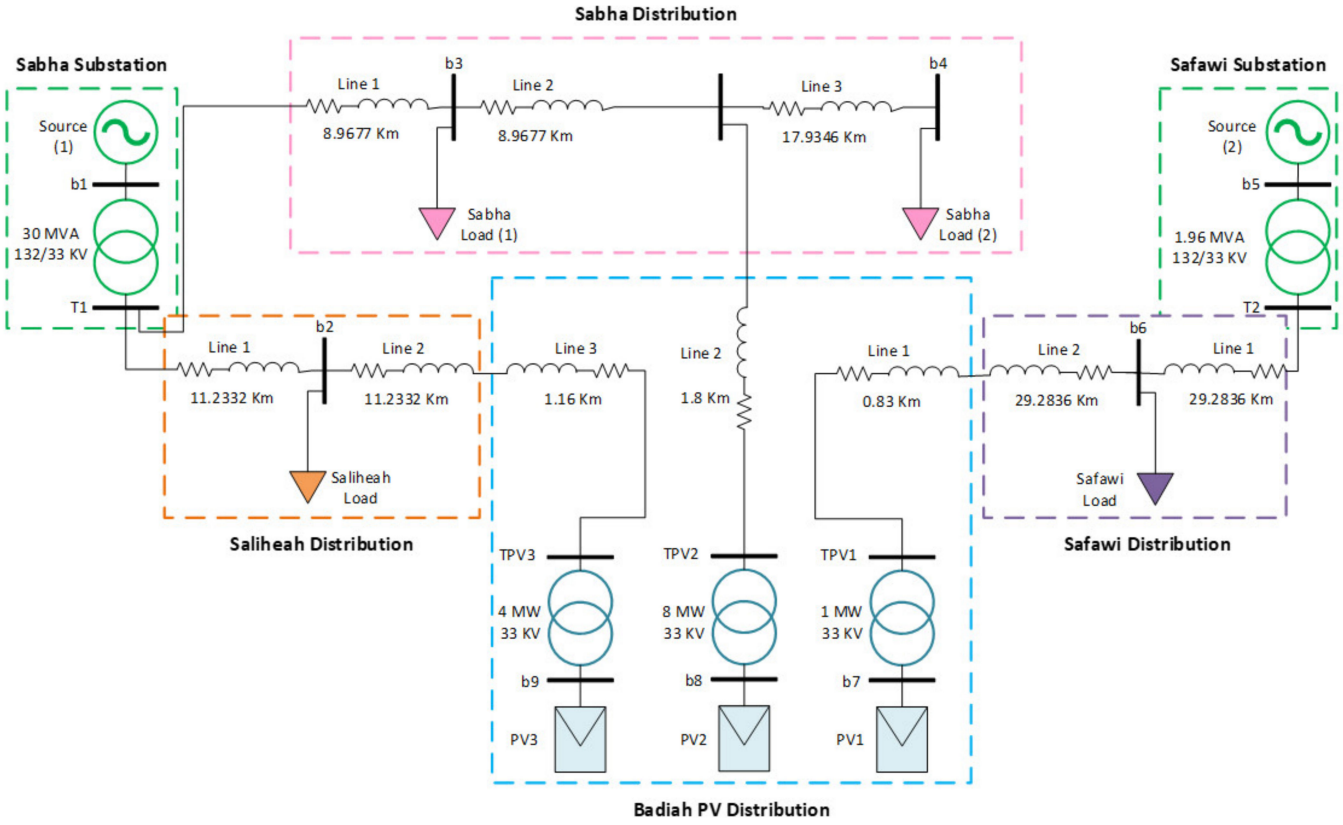


Figure 1. Single-line diagram of JSDN Simulink mode.

Table 5. Load flow calculations for JSDN, Obtained by Matlab–Simulink.

Block Type	Bus Type	Bus ID	Vbase (kV)	Vref (pu)	V-Angle (deg)	P (MW)	Q (Mvar)	Qmin (Mvar)	Qmax (Mvar)	V_LF (pu)	V-Angle_LF (deg)	P_LF (MW)	Q_LF (Mvar)
Vsrc	PV	b8	0.40	1	0.00	8.00	0.00	0.00	0.00	0.8245	−1.34	8.00	0.00
Bus	-	T1	33.00	1	0.00	0.00	0.00	0.00	0.00	0.8869	−5.35	0.00	0.00
Bus	-	T2	33.00	1	0.00	0.00	0.00	0.00	0.00	0.8154	−5.48	0.00	0.00
Bus	-	TPV1	33.00	1	0.00	0.00	0.00	0.00	0.00	0.7895	−4.37	0.00	0.00
Bus	-	TPV2	33.00	1	0.00	0.00	0.00	0.00	0.00	0.8246	−4.03	0.00	0.00
Bus	-	TPV3	33.00	1	0.00	0.00	0.00	0.00	0.00	0.8241	−4.75	0.00	0.00
Vsrc	PV	b9	0.40	1	0.00	4.00	0.00	0.00	0.00	0.8241	−2.06	4.00	0.00
RLC Load	PQ	b3	33.00	1	0.00	6.73	3.27	−Inf	Inf	0.8384	−5.54	6.73	3.27
RLC Load	PQ	b2	33.00	1	0.00	12.75	8.10	−Inf	Inf	0.8107	−6.39	12.75	8.10
Vsrc	swing	b5	132.00	1	1.00	1.46	0.00	−Inf	Inf	1	1.00	1.19	2.30
Vsrc	swing	b1	132.00	1	0.00	0.01	0.00	−Inf	Inf	1	0.00	16.06	21.57
Vsrc	PV	b7	0.40	1	0.00	1.00	0.00	0.00	0.00	0.7894	−1.43	1.00	0.00
RLC Load	PQ	b4	33.00	1	0.00	6.73	3.27	−Inf	Inf	0.7496	−7.31	6.73	3.27
RLC Load	PQ	b6	33.00	1	0.00	2.10	1.60	−Inf	Inf	0.7806	−5.46	2.10	1.60

The Simulink environment is used in this research to implement STATCOM in the load flow computation. After turning off the active power generation and determining how much reactive power is needed, the model is put into action.

The STATCOM in the Simulink can alter between inductive and capacitive modes depending on the polarity of the produced reactive power. The voltages of bus-2 at Saliheah

load, bus-3 at Sabha load-1, and bus-4 at Sabha load-2 in the JSDN will be regulated by STATCOM based on the ANN controller.

In this work, the PSO algorithm is used to determine the reactive power and operating settings of STATCOMs required for voltage regulation in the three buses of JSDN. The fitness (J) for PSO is developed and given below:

$$J = \sum_{n=2}^{4} |V_{ref} - V_n| \quad (10)$$

where;

V_{ref}: is the reference rated voltage and equals 1 p.u.
V_n: the bus voltage in JSDN.

To train ANN for solving real-time voltage deviation, the reference signals of the STATCOMs for 150 cases of deviation in three bus voltages are obtained using PSO. The percentage of voltage deviation (VD_n) in the bus is given by:

$$VD_n\% = \frac{V_{ref} - V_m}{V_{ref}} \times 100 \quad (11)$$

where;

V_{ref}: reference voltage.
V_m: measured bus voltage.
n: bus number.

The AVD at the three buses: 2, 3, and 4 is given by:

$$AVD\% = \frac{VD_2 + VD_3 + VD_4}{3} \quad (12)$$

3. ANN Training for Real-Time Voltage Regulation

Two STATCOMs are employed to solve the voltage deviation in JSDN equipped by PV Farm. The voltage deviation is mitigated at three buses in the network, shown in Figure 1: bus-2 (b2) of voltage V2 at Saliheah load, bus-3 (b3) of voltage V3 at Sabha load-1, and bus-4 (b4) of voltage V4 at Sabha load-2. In addition, different sites for STATCOMs are considered to obtain the optimal location for voltage regulation.

Although the PSO controller has a very high performance in solving the voltage regulation in the JSDN network, it is unable to respond right away to the dynamic changes in the network. Therefore, an ANN is proposed as an online mode to fulfill the voltage regulation quickly and accurately. Therefore, in this work, an ANN is trained and used to mitigate the real-time voltage deviation in JSDN, due to its high response compared to the PSO algorithm. The ANN can respond to different inputs and adapt its operation depending on the environment [38]. In this work, the ANN is trained by a Matlab-tool box and used for real-time solving of the voltage deviation in JSDN. It has two layers and ten neurons in the hidden layer, as shown in Figure 2. The dataset obtained by the PSO algorithm was used to train the ANN.

The training dataset consists of 150 cases for the deviation in three bus voltages and the reference signals of the STATCOMs. The input data to the ANN are the three bus voltages, divided into 70% for training, 15% for validation, and 15% for testing. Figure 3 shows the performance of the trained ANN in terms of the regression factor (R). The regression factor determines how close is between the dependent output variable and independent input variables. The training results of the ANN showed that a high regression factor was obtained, which is 0.96691 for training, 0.96527 for validation, and 0.97203 for testing.

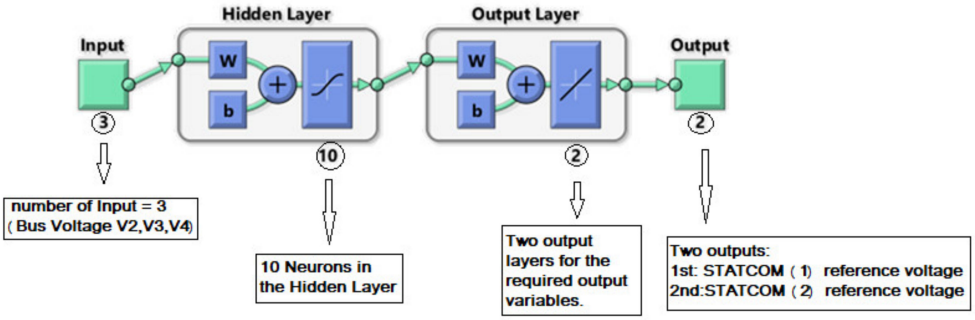


Figure 2. The ANN structure.

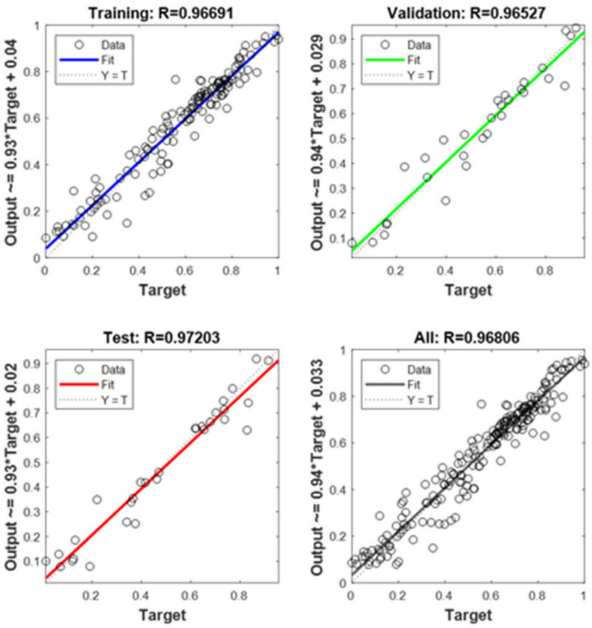


Figure 3. Performance of ANN training in terms of regression factor.

4. Results and Discussions

In this work, the voltage deviation is mitigated in an electric-distributed system, through the control of the reactive powers of STATCOMs. JSDN, equipped by PV Farm, is considered a real case study. In the first stage, the operating settings of the two STACOMs are determined in the off-mode using the PSO algorithm. In the second stage and to overcome the dynamic response problem of the PSO, the evaluated operating settings of STATCOMs obtained by the PSO are used to train the ANN, and in the third stage, the trained ANN is used in real-time to solve the voltage deviation at intermediate buses of JSDN. The ANN gives quick voltage regulation due to its high response compared to the PSO algorithm. The technical route for this work is presented in the schematical diagram shown in Figure 4.

4.1. PSO Results for Offline-Mode Voltage Regulation

The voltage deviation of JSDN has been mitigated in two stages; in the first stage, the PSO algorithm is used to evaluate the operating settings of the two STACOMs in the off-line mode for voltage regulation in the buses of JSDN. In the second stage, the online-mode voltage regulation is achieved using ANN.

To examine the capability of PSO, based on generating the appropriate parameters for STATCOMs to achieve voltage regulation at JSDN, different factors are considered. The load factors (LF) and the generation factors (GF) for the Badiah PV farm reflect the ratio of the generated power from the PV station and the load variation, respectively. Different locations for STATCOMs in the JSDN are proposed: two STATCOMs at TPV2 and TPV3

buses of Badiah PV farm, one STATCOM at TPV2 of Badiah PV farm, and one STATCOM at TPV3 of Badiah PV farm. Tables 6–8 give the bus voltages before and after the action of PSO on STATCOMs for different cases. When the two STATCOMs are employed at their maximum of 12.8127 and 11.4155 Mvars, the maximum capacity of STATCOMs is attained. Results validated the capability of the PSO algorithm to solve the voltage deviation in the JSND network. Table 9 gives the AVD after PSO action on STATCOMs located at different sites. It shows that the best solution for voltage regulation is obtained with the use of two STATCOMs at TPV2 and TPV3 buses of Badiah PV farm, at the average value of average voltage deviation (AVD) of 1.04606%.

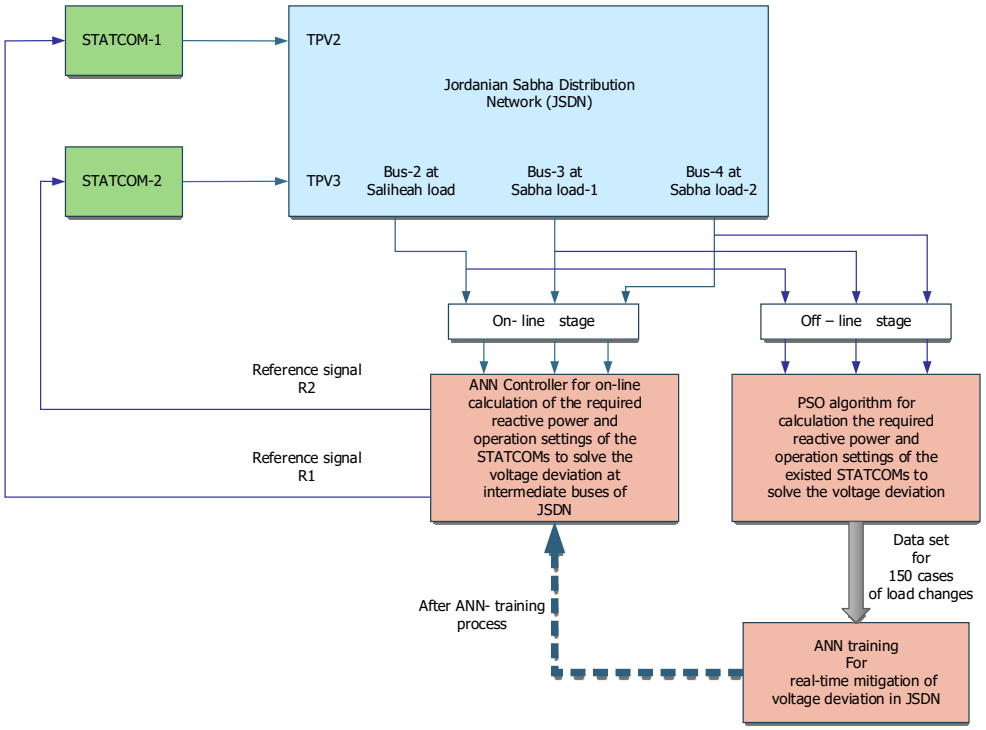


Figure 4. Schematic diagram of the technical route.

Table 6. PSO Results Using Two STATCOMs at TPV2 & TPV3 Buses of Badiah PV Farm.

GF for Badiah PV (%)	*LF* for Load Buses (%)	Before PSO Action on STATCOMs			After PSO Action on STATCOMs				
		Bus Voltages			Reactive Power (Q) Injected by STATCOMs		Bus Voltages		
		V2 (p.u)	V3 (p.u)	V4 (p.u)	Q1 (Mvar)	Q2 (Mvar)	V2 (p.u)	V3 (p.u)	V4 (p.u)
00.00	62.50	0.8815	0.8929	0.8315	9.5485	6.1048	0.9996	1.0160	0.9956
11.50	65.60	0.8779	0.8910	0.8289	8.5133	6.9070	0.9990	1.0106	0.9862
69.00	88.10	0.8376	0.8602	0.7825	11.6263	7.5437	0.9919	1.0188	0.9958
100.0	100.0	0.8107	0.8384	0.7496	12.5074	8.8633	0.9920	1.0207	0.9956
48.90	92.20	0.8200	0.8417	0.7520	11.7189	9.1284	0.9943	1.0146	0.9846
00.00	84.40	0.8224	0.8375	0.7446	11.1960	10.1363	1.0017	1.0113	0.9770
00.00	94.30	0.7886	0.8049	0.6931	12.8127	11.4155	1.0009	1.0122	0.9743
00.00	75.00	0.8498	0.8633	0.7852	11.7610	8.2713	1.0063	1.0230	0.9992
00.00	68.70	0.8663	0.8788	0.8095	10.4623	8.4285	1.0130	1.0242	1.0016
00.00	65.00	0.8755	0.8873	0.8228	10.1643	6.7321	1.0036	1.0198	0.9994

Table 7. PSO results using one STATCOM at TPV2 bus of Badiah PV Farm.

GF for Badiah PV (%)	*LF* for Load Buses (%)	Before PSO Action on STATCOMs			After PSO Action on STATCOMs			
		Bus Voltages			Reactive Power (Q) Injected by STATCOM	Bus Voltages		
		V2 (p.u)	V3 (p.u)	V4 (p.u)	Mvar	V2 (p.u)	V3 (p.u)	V4 (p.u)
00.00	62.50	0.8815	0.8929	0.8315	13.3455	0.9590	1.0128	1.0046
11.50	65.60	0.8779	0.8910	0.8289	14.4346	0.9614	1.0197	1.0145
69.00	88.10	0.8376	0.8602	0.7825	15.2543	0.9347	1.0059	0.9942
100.0	100.0	0.8107	0.8384	0.7496	16.1889	0.9210	1.0007	0.9868
48.90	92.20	0.8200	0.8417	0.7520	18.2280	0.9362	1.0148	1.0055
00.00	84.40	0.8224	0.8375	0.7446	17.3667	0.9336	1.0043	0.9896
00.00	94.30	0.7886	0.8049	0.6931	21.2012	0.9301	1.0132	1.0019
00.00	75.00	0.8498	0.8633	0.7852	14.9858	0.9420	1.0037	0.9897
00.00	68.70	0.8663	0.8788	0.8095	13.7970	0.9490	1.0057	0.9935
00.00	65.00	0.8755	0.8873	0.8228	13.8287	0.9565	1.0123	1.0034

Table 8. PSO results using one STATCOM at TPV3 bus of Badiah PV Farm.

GF for Badiah PV (%)	*LF* for Load Buses (%)	Before PSO Action on STATCOMs			After PSO Action on STATCOMs			
		Bus Voltages			Reactive Power (Q) Injected by STATCOM	Bus Voltages		
		V2 (p.u)	V3 (p.u)	V4 (p.u)	Mvar	V2 (p.u)	V3 (p.u)	V4 (p.u)
00.00	62.50	0.8815	0.8929	0.8315	23.0131	1.0797	1.0093	0.9559
11.50	65.60	0.8779	0.8910	0.8289	23.0491	1.0776	1.0082	0.9543
69.00	88.10	0.8376	0.8602	0.7825	25.6161	1.0689	0.9980	0.9335
100.0	100.0	0.8107	0.8384	0.7496	26.6781	1.0609	0.9896	0.9185
48.90	92.20	0.8200	0.8417	0.7520	27.8566	1.0715	0.9933	0.9207
00.00	84.40	0.8224	0.8375	0.7446	29.7715	1.0839	0.9964	0.9216
00.00	94.30	0.7886	0.8049	0.6931	35.9139	1.1018	0.9996	0.9154
00.00	75.00	0.8498	0.8633	0.7852	25.9790	1.0772	0.9992	0.9337
00.00	68.70	0.8663	0.8788	0.8095	21.4764	1.0587	0.9926	0.9324
00.00	65.00	0.8755	0.8873	0.8228	21.3333	1.0642	0.9984	0.9421

Table 9. Average voltage deviation after PSO action on STATCOMs at different locations.

GF for Badiah PV (%)	LF for Load Buses (%)	AVD% before PSO Action	AVD% after PSO Action		
			Two STATCOMs at TPV2 & TPV3	One STATCOM at TPV2	One STATCOM at TPV3
00.00	62.50	13.1376	0.6923	1.9458	4.4354
11.50	65.60	13.4067	0.8470	2.4270	4.3836
69.00	88.10	17.3211	1.0351	2.5643	4.5793
100.0	100.0	20.0420	1.1033	3.0946	5.0944
48.90	92.20	19.5440	1.1911	2.8016	5.2504
00.00	84.40	19.8506	1.2014	2.7010	5.5336
00.00	94.30	23.7782	1.2928	2.8327	6.2254
00.00	75.00	16.7223	1.0028	2.4008	4.8123
00.00	68.70	14.8481	1.2933	2.1087	4.4565
00.00	65.00	13.8129	0.8015	1.9726	4.1239
Average value of AVD		17.246	1.046	2.485	4.889

4.2. ANN Results for Online-Mode Voltage Regulation

From the results of the PSO algorithm for voltage regulation in Section 4.1, it is concluded that the best solution for voltage regulation is obtained with the use of two STATCOMs at TPV2 and TPV3 buses of Badiah PV farm. Therefore, the ANN is trained for voltage regulation by the data obtained from PSO, using two STATCOMs at Badiah PV farm. For different generation and load factors (GF and LF), Table 10 shows the AVD before and after ANN action on two STATCOMs. The ANN controller generates the required two reference voltages for STATCOM1 and STATCOM2 located at the TPV2 bus and TPV3 bus, respectively. These two references are used by the STATCOMs to provide the reactive power required for voltage regulation in the three buses of JSDN. It can be seen from Table 10 that the ANN controller can obtain the optimal operating settings of STATCOMs for voltage regulation. The average value of AVD after ANN action is 1.16834%, which is a very acceptable value (the acceptable one is 5%).

Table 10. Average voltage deviation for ANN controller using two STATCOMs.

GF for Badiah PV (%)	LF for Load Buses (%)	AVD% before ANN Action	AVD% after ANN Action
0	62.5	13.1376	1.0268
11.5	65.6	13.4067	0.9617
69	88.1	17.3211	0.8741
100	100	20.042	0.961
48.9	92.2	19.544	1.0045
0	84.4	19.8506	1.043
0	94.3	23.7782	2.1585
0	75	16.7223	1.7006
0	68.7	14.8481	1.0187
0	65	13.8129	0.9345
The average value of AVD		17.246%	1.168%

For the load and PV farm variations during the period of 5:49 a.m. to 4:00 a.m. shown in Figures 5 and 6, the AVD of the three bus voltages (at bus-2, bus-3, and bus-4) is given in Figure 7. Results are obtained by applying the ANN control on the two STATCOMs located at both TPV2 and TPV3 buses. The very low AVD for all hours of the day proved the high capability of ANN control to achieve voltage regulation. Additionally, the results showed that the AVD-curve for ANN is very close to the one of PSO, proving that the ANN was well trained to give high performance for voltage regulation. Figure 8 shows the voltage profile of the three bus voltages after ANN action during the period of 5:49 a.m. to 4:00 a.m., for changes in load and PV farm. The results have exposed the capability of the proposed ANN controller to regulate the bus voltages accurately and efficiently.

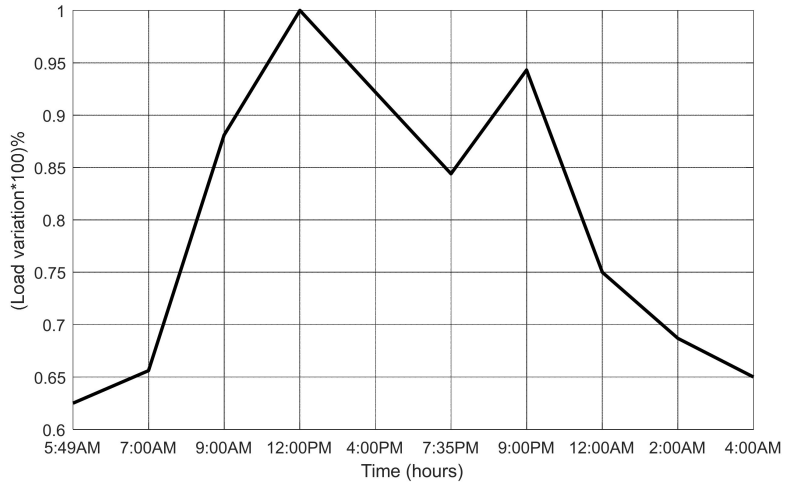


Figure 5. Load factor variations in the time domain.

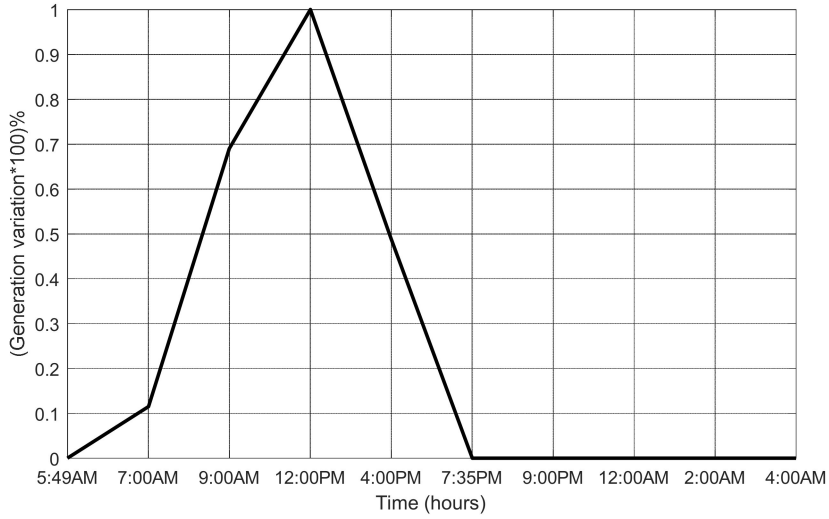


Figure 6. PV generator factor variations in the time domain.

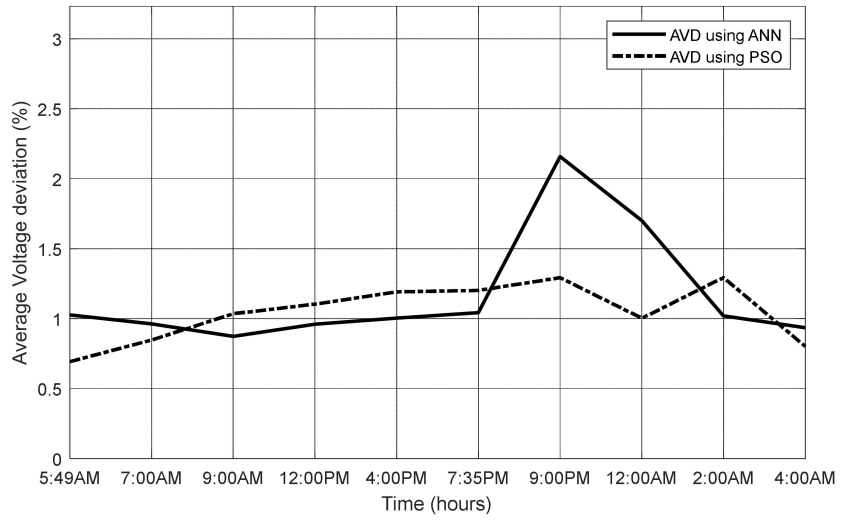


Figure 7. AVD using ANN control on two STATCOMs at TPV2 and TPV3.

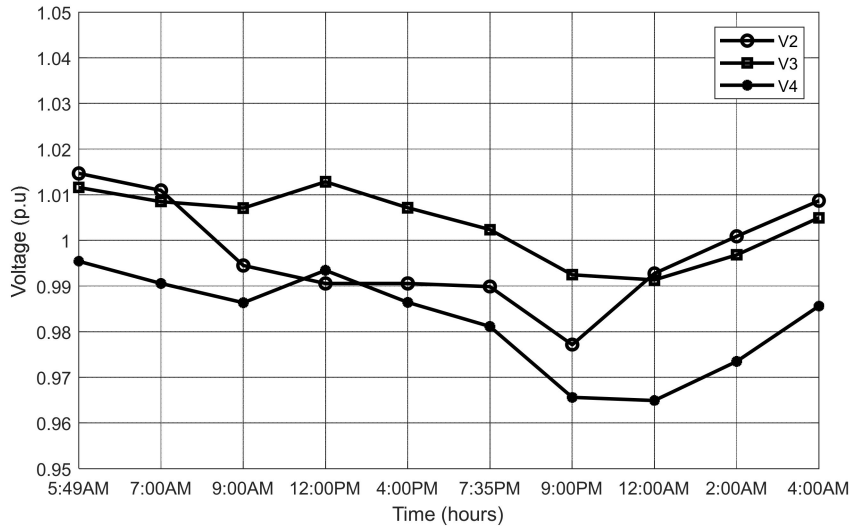


Figure 8. Voltage profiles of the three bus voltages after ANN Action.

5. Conclusions

In this paper, a high-performance technique is proposed to mitigate the voltage deviation that takes place in the Jordanian Sabha Distribution Network (JSDN) equipped with a PV farm. Two STATCOMs are employed to solve the voltage deviation at three buses of JSDN: bus-2 of voltage V2 at Saliheah load, bus-3 of voltage V3 at Sabha load-1, and bus-4 of voltage V4 at Sabha load-2. The required reactive power and operation settings of the STATCOMs are determined in the offline mode using the PSO algorithm. These datasets are applied to train the ANN for online voltage regulation. Different sites for STATCOMs are considered to obtain the optimal location based on voltage regulation. The results show that the presented technique has achieved high performance for voltage regulation by almost an AVD of 1.168%. The limitations behind this study are the number of load buses (three buses) in the network and the size of the PV farm (13 MW) in the JSDN, which affect the range of the generated reactive power and then the range of voltage deviation to be corrected.

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