A predictive convolutional neural network model for source-load forecasting in smart grids

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Abstract: - Smart grid engineering is the key for an optimized use of extensive energy resources which allows hybrid renewable energy sources (RES) to be optimally integrated, and their power generation efficiently dispatched to the grid over long distance DC transmission lines using the high voltage DC (HVDC) transmission technologies. In this context, it is crucial to determine the required number of generating units of wind turbines and photovoltaic arrays, and the associated storage capacity for standalone and/or grid connected hybrid microgrid. Typically, this is determined using a sizing algorithm based on the observation that the state of charge of battery power system should be periodically invariant in order to keep optimum cost. Given the intermittency of wind speed and solar irradiance, it is very challenging to accurately calibrate power production from wind turbines and photovoltaic arrays, at all times even under varying weather conditions. In this context, the convolution neural network (CNN) can symbolize a practical and reliable tool to precisely monitor and predict the wind speed and solar irradiance outputs and accordingly manage the power transfer switching between areas that have surplus of renewable energies to areas with energy shortage by initiating the energy management system (EMS) to dispatch power according to an anticipated schedule. The efficiency of the proposed CNN based model was tested using meteorological data related to Beirut city. The experimental results indicate that the mean absolute error related to wind speed and solar irradiance are low, demonstrating very high forecasting accuracy.

Key-Words: - Smart grid, convolution neural network, energy management system, wind energy forecasting, solar energy forecasting.

1 Introduction

Smart grid engineering is the key for an optimized use of extensive energy resources. A modernized electrical grid uses analogue or digital information and communications technology (ICT) [1]. The engineering work will result in enhancements and extensions to the existing grid, as well as the deployment and development of an extensive two-way communication system. Smart grid will also allow improving grid reliability and operation mainly by monitoring real-time power flow and improving voltage control to optimize efficient power delivery, eliminate waste, and oversupply [2].

Renewable energy accounted for 19% of global final energy demand in 2015, having risen by 0.17% per year since 2010 and contribute to the majority of the greenhouse gas emissions reduction that is needed between now and 2050 for keeping the average global surface temperature increase below 2 °C [3].

The fusion of renewable energy generation on the grid is a key topic of today's global power systems because it is aiming to reduce the CO2 emissions in order to stop or at least reduce the global warming effect. New "CO2-free" technologies are being investigated to fulfil the forecasted global energy demand growth [2], and new ways are being examined to integrate those technologies into the smart grid [4].

Managing the hybrid system in terms of the required number of active wind-turbines and photovoltaic arrays at any given time, as well as the associated storage capacity for on-grid hybrid microgrid, is a challenging task. This is usually done using an algorithm based on the observation that the state of charge of the battery power system should be periodically invariant and should keep the life cycle cost of the system minimum, while satisfying the given load power demand without rejection [5].

The hybrid renewable energy source (HRES) microgrid can be interfaced with the AC bus line and afterwards to the utility grid. However, under certain circumstances, it becomes economically beneficial, especially for large amount of power and over long distances, to transmit power over DC transmission lines [6]. Weather AC or DC, smart grid will introduce fundamental changes in the use of the traditional transmission and distribution (T&D) system and will create significant challenges. Some of the challenges are to reduce the grid congestion, ensure stability and security and optimize the use of transmission assets and cost generation source. Hence, the grid must be equipped with a smart transmission system that deploys advanced technologies such as flexible AC transmission systems (FACTS) or HVDC power electronic components to support power flow control and ensure stability [2]. With the introduction of HVDC stations using line-commutated converters or voltage source converters, electrical power can be transmitted over long distances at different power levels.

Utilizing internet of things (IoT) technology in smart grid is an important approach to integrate advanced sensing and communication technologies that can effectively avoid or reduce the damage of natural disasters to the transmission lines, improving the reliability of power transmission and reducing economic loss. The specific monitoring covers transmission tower leaning, conductor galloping, wind deviation, micro-meteorology, conductor icing, wind vibration, and conductor temperature [7].

One of the benefits of using smart grid solutions and applications, is that substations will be transformed from conventional to smart substations leading to more advanced local analytics and to more efficient management of vast amount of user data. Consequently, smart grid enables efficient transfer of surplus power generated from HRESs in existing locations to other remote locations.

The artificial intelligence techniques, such as expert systems (ESs), fuzzy logic (FL), and artificial neural networks (ANNs) have enhanced power electronics and power engineering providing powerful tools for design, simulation, control, estimation, fault diagnostics, and fault-tolerant control in modern smart grid and renewable energy systems [8].

The intermittency of wind speed and solar irradiance is very challenging for energy production especially in terms of its synchronization with the load demand, at any given time. The crucial role that the ANN technologies play lies in the accuracy of forecasting wind and solar data for a better effective power system management. The basic building block of ANNs is a simple processing unit called neuron organized in interconnected layers. The computational capabilities of ANNs are mainly determined by the connection weights, network architecture, and training algorithm [9].

With the recent developments in neural networks and deep learning new approaches based on deep architectures such as multilayer perceptron (MLP), convolutional neural network (CNN) and recurrent neural network (RNN) are being classified as the main three optimal forecasting methods that extract and learn wind profiles and solar patterns. In their architecture, each layer of the network has only forward connections with the subsequent layer. Depending on the role and position of a layer, input, hidden, and output layer types are the main elements of a feed forward neural network. An input or data fed to the input layers of MLP is processed by the hidden layers and the result is delivered at the output [10].

Neural networks have an activation function on each neuron that acts on the inputs received and generates an output, plus a backpropagation algorithm that optimizes the weights on each connection in a process to find the optimal combination for the output. Neural networks are non-linear which allows them to produce better results than linear models on wind and solar data time series [10]. RNNs are designed to process sequential data by, most importantly, sharing parameters between the different layers and neurons, generating cycles in the graph sequence of the network. In this sense, RNNs can devour extensive memory. In RNN each output is a function of the previous elements. Thus, the values in a specific step will influence its value in future steps. RNNs have the potential to learn from patterns in the time series to predict the future [10].

The effectiveness of using CNN for levelling energy load forecasting was demonstrated to be higher compared to those obtained by ANN, support vector machines (SVM), factored restricted Boltzmann (FCRBM), long short term memories (LSTM), and other deep learning architectures [11]. CNNs have the advantage of processing big data and addressing it in form of a two dimensional matrix, widely applied in the field of image processing or time series. CNN weight sharing network structure which is similar to a biological neural network can reduce the complexity of the network model and the number of weights [12]. Convolution networks extract relevant features from small areas of the matrix, by identifying short intervals of the time series that could bring relevant information to the prediction task. The information could be that some patterns are relevant for the future behavior of wind and solar series [13].

This paper is organized as follows: section 2 introduces the major components of a smart grid. Section 3 defines the hybrid sizing algorithm used in this paper. Section 4 discusses the control strategies and bus configurations in smart grids. Section 5 discusses the application of convolution neural network in multi-step time series wind speed and solar irradiance forecasting.

2 The Smart Grid Components

We shall first recall in a compact form the most important components of a smart grid, namely focusing on the interoperability between different SG components, the transmission systems monitoring and the communications systems.

2.1 Interoperability between different SG components

The interoperability between different smart grid components is vital. The framework shown in Table 1 below illustrates the general components of a smart grid at three basic levels: the electrical infrastructure level, the smart infrastructure level and the smart grid solution level.

TABLE 1 - SMART GRID TECHNOLOGY FRAMEWORK – FUNCTIONALITY.

	Utility Enterprise Applications
Smart Grid Solutions	**Operational Efficiency** **Reliability and Security** **Energy Efficiency** **Alternative Energy** **Consumer Participation**
Smart Infrastructure	Engineering and Operational Systems
	Communications Infrastructure
	Smart Sensors, Controllers, and Meters
Electrical Infrastructure	T&D Infrastructure
	Alternative energy sources RES, Storage
	Energy consumer home area network

While real power is supposed to flow throughout the subsystems, the information should flow through the different networks as shown in Fig. 1. The concept of the virtual power plant (VPP) is also shown, is a central control unit and a pure software-based layer. This layer communicates bi-directionally with the different components of the information flow and power flow layers, in order to coordinate all load-source and source-load transactions within the smart grid. In fact, the VPP can be seen as the brain of the smart grid.

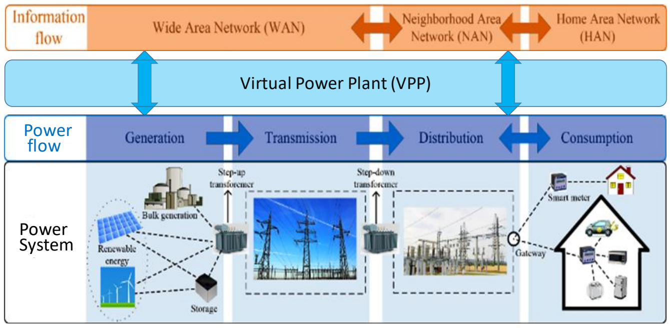

Fig. 1 Smart grid components. Modified from [14].

2.2 Transmission systems monitoring

The Internet of Things (IoT) technology is an important component in a smart grid. With an abundance of sensors all over the grid, a technology is needed to convey and process their data in real-time to the VPP. It is an important approach integrating advanced sensing and communication that monitors transmission tower leaning, conductor galloping, wind deviation, micro-meteorology, conductor icing, wind vibration, and conductor temperature. The devices deployments are shown in Fig. 2.

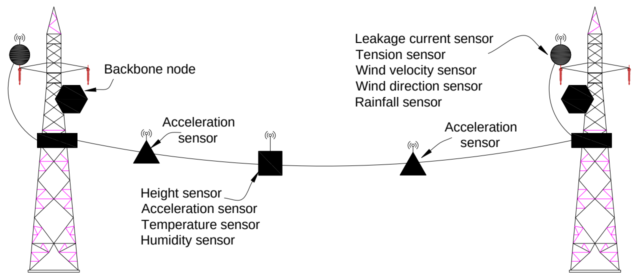

Fig. 2. The sensor deployment scheme of the power transmission line tower in a smart grid configuration.

2.2 Communications Systems

The smart grid encompasses three different types of networks as illustrated in Fig. 1, namely:

1. Home area network (HAN) extends communication to end points within the end-user home or business.
2. Neighborhood Area Network (NAN) for connecting multiple HANs to local access points.
3. Wide Area Network (WAN) for automation, distribution and for covering long-haul distances by providing communication links between the NANs and the utility systems to transfer information.

In addition, communication technologies can be classified into either wired or wireless. Traditionally, wired technologies are considered beneficial to wireless technologies in terms of reliability, security and bandwidth because cables are easier to protect from interference. On the other hand, wired equipment are generally cheaper and need less maintenance compared to wireless solutions. Nevertheless, wireless networks have low installation costs with minimal cabling, which provides network connectivity over wide areas, especially in those regions where no communication infrastructure exists.

3 Solar-Wind Microgrid Sizing

The power system considered in this work is composed of three parts: wind turbines, PV panels and a battery power bank. The two former units generate electricity, in accordance with the local wind and solar energy resources, to supply the load. The battery bank forms the energy storage system that can supply the load when there is shortage of electricity, and store the surplus power when the power generated exceeds the load. The energy storage system is essential to cover the shortage of the renewable energy's unpredictable and fluctuant nature, but its existence brings difficulties to the sizing problem.

In this work, we have used the simple microgrid-sizing algorithm proposed in [5]. The different steps of this algorithm are described below:

1. Load all weather data consisting of the hourly wind speed and solar radiation for a period of 3 years is loaded.
2. Compute the average daily curves of the collected wind speed and solar radiation data at the same hour every day.
3. Read the daily load power consumption profiles.
4. Load the different specifications of wind turbine, PV array and battery.
5. Start the algorithm initialization by calculating the power generated by both wind turbine and PV array.
6. Calculate all configurations of the system, i.e. numbers of solar panels, wind turbines and batteries, satisfying demand.
7. Find the optimal solution that has the smallest implementation and system cost, for different seasons.

4 Control Strategies of Microgrid

In order to balance the production and demand of electrical energy within the combination network of the existing power grid and renewable energies, the control strategies employed via the use of technologies and processes and advanced control protocols have to be implemented. These controls are needed to enhance the reliability of energy supply of the intermittent nature of the renewable sources (fluctuating sunshine and wind profile). The controls include strategies for the optimal power harnessing and effective energy management, power device control, intelligent control of energy transformation, and line faults management [15].

The HRESs must have the ability to mitigate the power quality issues to supply high-quality and more reliable steady power. The power quality and system stability can be achieved by an appropriate control technique embedded into the power converter control circuit [16].

The HRES microgrid can be interfaced with the AC bus line and afterwards to the utility grid directly or via a common DC bus by using the appropriate power converters. The AC bus-linked HRES configuration reduces the number of power conversion stages and losses in power transferred to the load/utility [16].

Physically, in HRES configuration, a group of PV panels are interfaced through a DC–DC converter to regulate their fluctuating DC output. The wind turbine coupled with a permanent magnet synchronous generator (PMSG) generates a three-phase AC voltage, and its amplitude and frequency vary with rotor speed. Therefore, the wind turbine generator is connected to the DC bus via a rectifier and DC–DC converter. The storage battery is connected to the DC bus through a bidirectional DC–DC converter to maintain a stable supply–demand balance at its rated capacity. The common DC bus collects the regulated power from various RESs to supply and maintain a constant DC voltage at the input terminal of the DC–AC inverter. A single DC–AC inverter is used to interface the common DC bus to the AC bus connected to the utility grid [16].

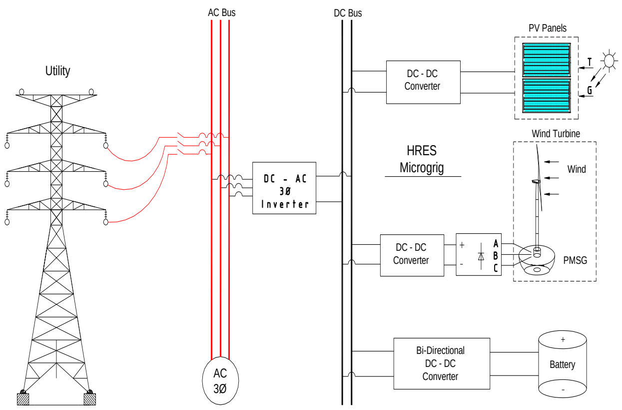

Fig. 3. Typical configuration of the DC and AC bus linked HRES.

5 Smart Microgrid Configuration

Putting all pieces together, the general architecture of a smart microgrid is illustrated in Fig. 4. Here substation A is connected to the HRES microgrid via a central switch, and to the communications master station via a control system. Power is transmitted from substation A to a remote substation B via a DC power transmission line.

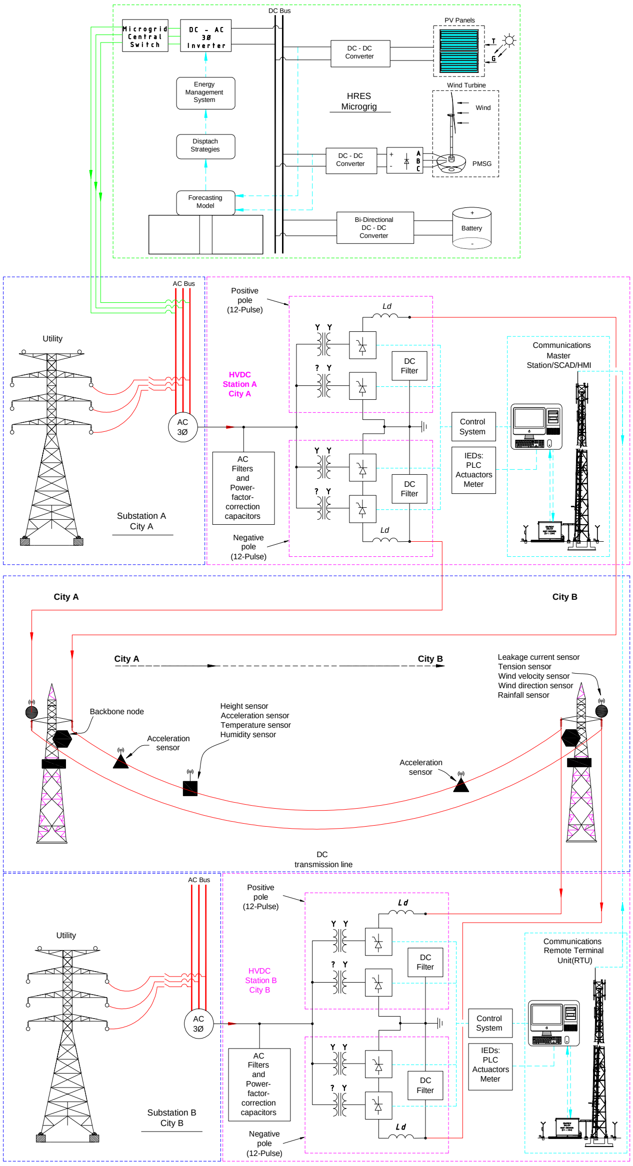

Fig. 4. Power generation, transmission, and distribution – overall single line diagram.

5 Convolutional Neural Network

5.1 CNN Structure

The structure of CNN is a feed-forward neural network. It uses the back-propagation algorithm to optimize the new structure to solve unknown parameters in the network. It starts with the pre-processing of the samples, and the required features are extracted and classified or determined by regression analysis in order to estimate the output [12].

The pre-processing is implemented using convolution filters that act repeatedly on the receptive field and extract the local features of the input matrix with the convolution kernel of the matrix. Furthermore, the pooling and flattening process calculates the average or maximum in each section of the convolved feature. After pooling, the dimension of the characteristic statistics is greatly decreased and the generalization ability of the model is increased. Thus, the basic structure of CNN consists of a convolution layer and a pooling layer. The neurons in the convolution layer are locally connected with the previous layer, and their local features are extracted. These extracted features are processed again by the pooling layer [12].

5.2 Proposed 1D CNN

In a 1D convolution neural network, the convolution layers read the input multi-time series signal using a kernel filter that processes small segments at a time, and steps across the entire segment input field. The pooling layer, then, takes the feature map projections and filter them to the most essential elements such as using a signal averaging or signal maximizing process. The output of the convolution and pooling layers network is one or more fully connected (FC) layers called the dense layer that interpret the internal representation and output a vector representing the multi-step time predicted [17]. This is illustrated in Fig. 5.

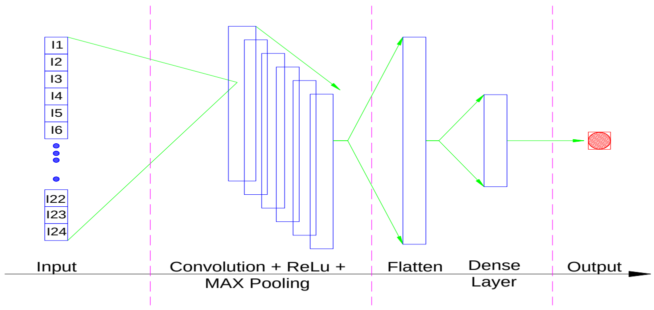

Fig. 5. The 1D CNN structure.

The development of the multi-step time series forecasting model with CNN starts by defining the prior hours/days subsequence data as input that enables the model to read and learn to extract features.

The 1D CNN model data consists of three segments [samples, time steps, features], whereby each sample consists of a specified number of time steps with one feature for each time step. The recorded dataset is divided into training and testing data. Hence, the shape of the training or testing dataset is [training/testing, time steps, features]. The first step is to flatten the data, i.e. to transform the 2D weather data into a 1D vector, and then iterate over the time steps whereby each iteration moves along one time steps and predicts the subsequent hours/days [17].

Furthermore, this multi-step series forecasting problem is an auto regression time series model which uses observations from previous time steps as an input to predict the value at the next time step. This results in accurate forecasts on a range of time series problems.

The built model consists of one convolution layer with different number of filters progressively incremented and a kernel size of 1. This means that the input sequence will be read with a convolutional operation one time step at a time and this operation will be performed according to the number of filters, followed by a pooling layer which will reduce these feature maps, before the internal representation is flattened to one vector. Finally, the outcome is

TABLE 2 – ALGORITHMIC STEPS OF THE PROPOSED CODE.

1:	Load and prepare dataset
2:	Fill in missing values
3:	Split the dataset into train and test sets
4:	Convert history into inputs and outputs
5:	Build the CNN model
6:	Set verbose=0; epochs=20; batch size =4
7:	Train the model on batch
8:	Make a forecast
9:	Evaluate the model through the Walk-forward validation
10:	Plot the actual vs. predicted and APE
11:	Print the MAE, RMSE values of error indicators $\mathrm{MAE} = \frac{1}{N}\sum_{n=1}^{N} \lvert yn - \hat{y}n \rvert$; $\mathrm{RMSE} = \sqrt{\frac{\sum_{n=1}^{N}(yn-\hat{y}n)2}{\mathrm{N}}}$
12:	Terminate

TABLE 3 - PARAMETER SETTINGS OF THE PROPOSED MODEL.

Parameter	Setting
1D convolution filter number	32
1D convolution kernel size	1
1D convolution filter number	64
1D convolution kernel size	1
1D convolution filter number	96
1D convolution kernel size	1
1D convolution filter number	112
1D convolution kernel size	1
1D convolution filter number	128
1D convolution kernel size	1
1D convolution filter number	144
1D convolution kernel size	1
Dense layer activation function (to limit output value range to [0, 1])	ReLU
Optimizer (extension of stochastic gradient descent (DSG), to adjust parameters)	Adaptive Moment Estimation (Adam)
Verbose (option for producing detailed logging information)	0

interpreted by a fully connected layer before the output layer predicts the next hours/days in the sequence [17]. The specific steps and parameters of the algorithm used in this paper are illustrated in Tables 2 and 3.

6 Case Study

The 1D convolution neural network model built according to Tables 2 and 3 is trained using real pre-processing data extracted from historical weather websites. The data extracted covers a period of 28270 hours related to wind speed [18] and 1160 days related to solar irradiance [19-20], from December 2016 to April 2019, for the city of Beirut. The dataset covering 28200 hours was used to train the model to predict the wind speed the next 70 hours (~3 days). In addition, the dataset covering the 1157 days was used to train the model to predict the solar irradiance the next 3 days.

6.1 Forecast Accuracy

The comparison of the wind speed for a 3 days forecast with existing multi-layer perceptron and WindNet older models based on the mean absolute error (MAE) and root mean square error (RMSE) indicators are tabulated in table 4, demonstrating the effectiveness of the proposed model providing the highest forecasting accuracy (0.69 compared to 0.80). The MAE and RMSE of the 3 days forecast for the solar irradiation data had an average MAE of 0.66. Based on historical weather data of wind speed and solar irradiance related to Beirut City [18-19], the 3 days forecast results related to wind speed are depicted in Fig. 6.

TABLE 4 - COMPARISON OF WIND SPEED 3 DAYS FORECAST RESULTS.

Test	MLP [14]	WindNet [14]	Proposed Model	
3 Days Forecast	**MAE**	**MAE**	**MAE**	**RMSE**
1:	0.951965	0.906002	0.672649	0.843
2:	0.749479	0.726946	0.687472	0.881
3:	0.883512	0.919904	0.697633	0.9
4:	0.725489	0.735706	0.691511	0.874
5:	1.00744	0.956887	0.706766	0.902
6:	0.845219	0.743931	0.676663	0.871
7:	0.877877	0.867812	0.705473	0.888
8:	0.832765	0.769551	0.684255	0.879
9:	0.800525	0.744625	0.686370	0.875
10:	0.742297	0.644439	0.750552	0.956
11:	0.751773	0.786698	0.668264	0.859
Average:	**0.833486**	**0.800227**	**0.693418**	**0.884**

6.2 Power Distribution and Load Demand

Based on historical weather data, the hybrid renewable energy microgird is sized according to the output power provided by the PV/Wind turbine energy sources as shown in Figures 7 and 8, and according the existing load demand as shown in Fig. 9.

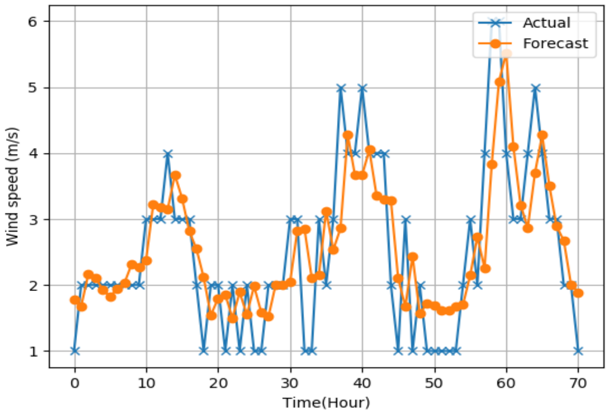

Fig. 6. Wind speed 3 days actual data vs. forecast.

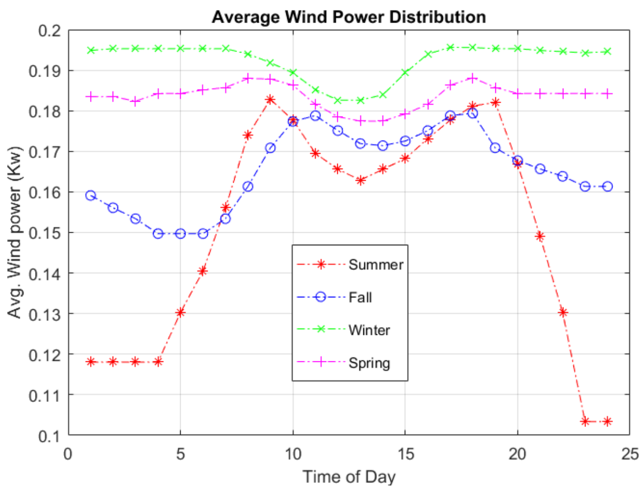

Fig. 7. Average wind power distribution.

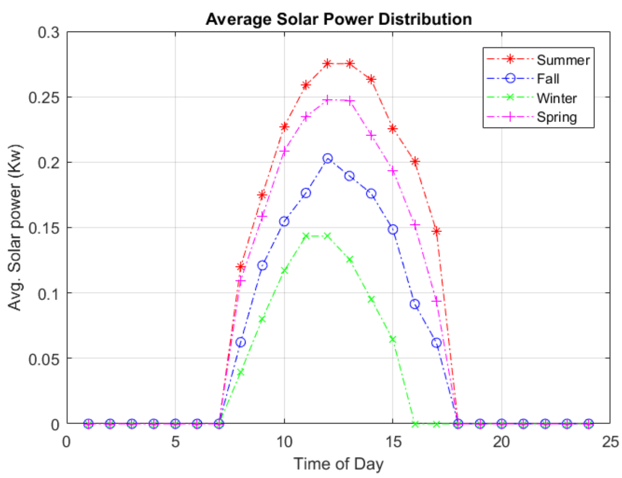

Fig. 8. Average solar power distribution.

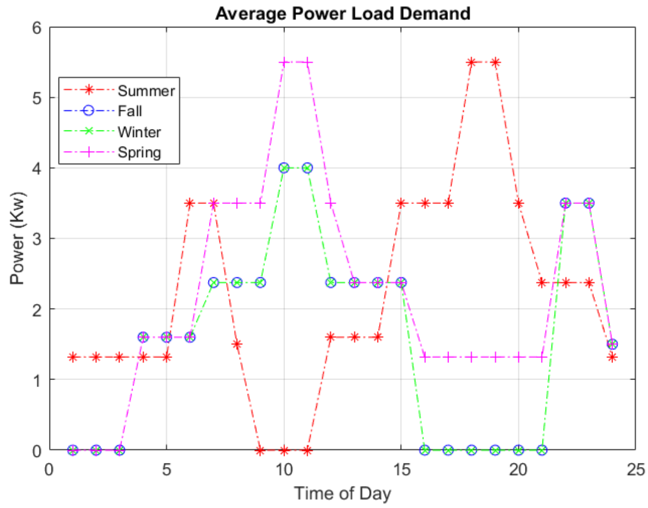

Fig. 9. Average power load demand.

6.3 Battery State of Charge

Using the proposed technique the battery's state of charge (SOC) is maintained constant at 50 % as shown in Fig. 10 during all seasons. This ensures a longer battery lifetime for the storage system.

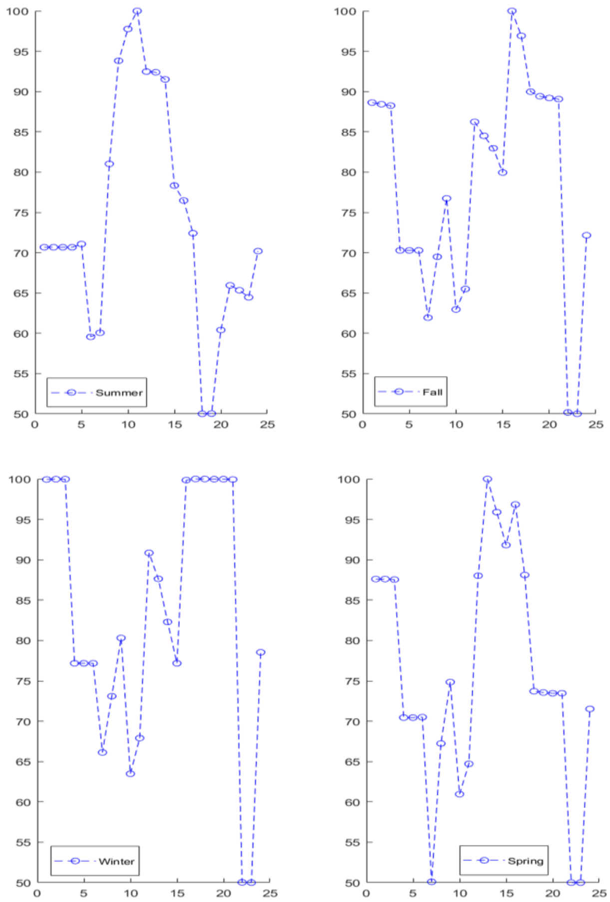

Fig. 10. Battery state of charge during all seasons.

6.2 System Life Cycle Cost

We have calculated the system life cycle cost with respect to the number of wind turbines, PV panels, and battery bank capacity. The prices are based on local providers of wind turbines and PV panels in Lebanon. The results are illustrated in Table 5.

TABLE 5 - SYSTEM LIFE CYCLE COST IN ALL SEASONS.

Season	N_{wind}	N_{PV}	# of Batteries	Battery Bank (Ah)	System Cost ($)
Summer	1	12	19	1903 67	20738 12
	2	11	18	1829 47	21467 10
	3	10	18	1755 26	22738 28
	4	9	17	1681 06	23467 26
	5	8	16	1606 86	24196 24
	6	8	15	1532 66	25630 21
Fall	1	13	10	1018 80	18411 51
	2	11	9	924 051	18774 46
	3	10	9	876 65	20521 83
	4	8	8	835 16	20884 80
	5	7	8	793 67	22632 16
	6	5	8	752 18	23674 53
Winter	1	21	12	1170 02	27533 0
	2	18	10	1031 54	26713 32
	3	15	9	893 05	26710 25
	4	12	8	754 56	26707 19
	5	9	6	616 07	25887 50
	6	7	6	584 68	27406 05
Spring	1	14	13	12667 29	25674 50
	2	12	12	11682 83	26715 42
	3	11	11	10698 37	28461 33
	4	10	10	971 40	30207 24
	5	9	9	872 94	31953 15
	6	7	8	774 50	32994 06

Based on table 5, the optimal configuration of the microgrid system is composed of 5 x 1KW wind turbines and 9x1.94 m^2 PV modules and 6 x 100 Ah batteries. Hence, the system provided has an optimum life cycle cost of $ 25887.50. In addition the system cost in each season is plotted in Fig. 11.

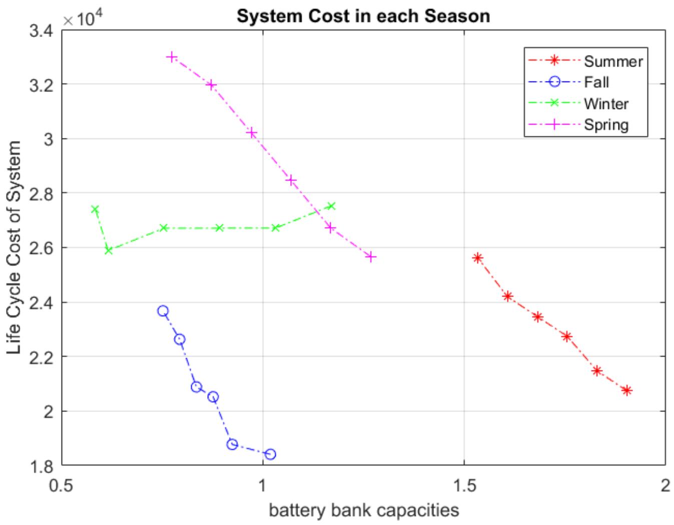

Fig. 11. System life cycle cost.

7 Conclusion

Smart grid technologies optimize the management of energies and real-time balance between electrical energy supply and demand sides. Thus, the reliability of power dispatching process highly depends on the energy management system and the energy sources availability. The most important features in developing the smart grid are the integration of renewable energy sources, such as solar and wind, to increase the electricity consumption and to guarantee the sustainability of the power system. However, the intermittency of wind speed and solar irradiance are very challenging to power production from wind turbines and photovoltaic arrays respectively. In this context, CNN proved to be a practical and reliable tool to precisely monitor and predict the wind speed and solar irradiance outputs and accordingly manage the power transfer switching between areas that have surplus renewable energies to areas that have shortage in energies. This is done by initiating the virtual power plant to dispatch power according to schedule. In addition, the effectiveness of the proposed model CNN was tested using meteorological data related to Beirut city, Lebanon. The experimental data were divided into training and testing datasets. The large amount of training dataset has proven the reliability of the model when tested on actual data recorded in the past. The experimental results indicate that the proposed model outperforms existing techniques by consistently demonstrating a higher forecasting accuracy.

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