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Development and testing of a micro-grid excess power production forecasting algorithms

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Abstract

Traditional electricity grids lack flexibility in power generation and load operation in contrast to smart-micro grids that form semi-autonomous entities with energy management capabilities. Load forecasting is invaluable to smart micro-grids towards assisting the implementation of energy management schedules for cost-efficient and secure operation. In the present paper is examined the 24h forecasting of excess production in an existing micro-grid. Alternative input parameters are considered for achieving an accurate prediction. The prediction can be used for scheduling the charging process of a thermal storage during weekends based on excess power production levels.
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Keywords: micro-grid, forecasting, integration, artificial neural network

1. Introduction

The requirement for clean energy, energy efficiency and cost-efficient energy management has given rise to the investigation of transition from traditional energy distribution grids to smart micro-grids.

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In traditional electricity grids energy is produced centrally and distributed to the various energy consumers that are connected to the grid. Traditional grids lack flexibility in power generation and load operation [1]. A micro-grid comprises distributed energy sources, energy loads and storage components, thus forming a semi-autonomous entity with energy management capabilities. Moreover, a micro-grid can operate connected to the main grid or in island mode [2]. For the purpose of reliable and efficient operation the Energy Management System (EMS) has become an essential component of micro-grids [2, 3].

EMS assists in the optimization of power distribution within a micro-grid through the application of appropriate controls. Measuring and monitoring and control equipment connected through Information and Communication Technologies (ICT) are necessary for "building" an EMS. These assets combined with advanced energy management techniques make a micro-grid smart [1, 4-6]. A smart micro-grid communicates with its components and through the EMS controls its loads so as to achieve an efficient and cost-effective operation. In [7] an energy management algorithm is tested for optimum integration and operation of a PV array and a battery for serving a micro-grid's loads. In [8] two algorithms are proposed and tested on an existing micro-grid, one for energy scheduling and one for demand response. Increased efficiency and occupant satisfaction has been achieved by the EMS applied in a University Campus [5].

Load forecasting is invaluable to micro-grid energy management [5, 6, 8, 9]. Load forecasting for controlling charge and discharge of an electrical storage has been studied in [10] as well as in [11]. Depending on the forecasted period three types of forecasting are recognised [6, 9]:

- Short-term forecasting: 1h to 1week for optimum
- Medium-term forecasting: 1week to 1year
- Long-term forecasting: 1year to decades ahead

Two methods for load forecasting have been recognised in literature, statistic mathematical models and artificial intelligence models [6, 9]. Artificial Neural Networks (ANN) are artificial intelligence models widely used for forecasting providing high accuracy [6, 9]. ANN have been extensively used for short-term load prediction [9, 11]. In [12] a multi-layer perceptron neural network that uses load and weather data was applied in order to forecast the daily load of a suburban area. In [13] a feed forward artificial neural network for hourly demand prediction is tested and the proposed algorithm is able to achieve a high prediction accuracy.

In the present paper the 24h load forecasting of a micro-grid using artificial neural networks is examined. The purpose is to predict the day ahead excess production of the micro-grid so as to apply appropriate controls for its utilisation.

2. Case Study

The case study is the micro-grid of the Leaf Community, in Angeli di Rosora, Italy, Figure 1. The energy production sources connected to the grid are a micro-hydropower plant, of 48kWp, four rooftop PV installations of total 421.3kWp and a dual axis Solar Tracker of 18kWp. Five buildings are currently connected to the micro-grid, all equipped with ground water heat pumps (GWHP). A 224kWh electrical storage system and a thermal storage with heat capacity 523.25kWh/K are also part of the micro-grid. All the previously mentioned power loads, renewables and storage components are in parallel to one single Point of Delivery (POD). All nodes as well as the collective operation of the micro-grid is monitored and controlled via My Leaf web based platform.

The rooftop PVs are installed on four of the five interconnected buildings of the micro-grid. The production by each rooftop PV installation is consumed by the respective building first. If there is residual production, it is fed to the micro-grid. The production of the micro-hydropower plant is also fed to the micro-grid. When the production is not enough to cover the micro-grid's loads, energy is withdrawn from the main grid. Energy is also given to the main utility grid if the demand of the micro-grid has been fulfilled, storages are fully charged and there is excess production. Regarding the storages, both have been recently connected to the grid and their operation and integration are tested.

In the present paper the integration of the thermal storage with the micro-grid is studied. Specifically, the availability of excess production in the micro-grid during weekends is of interest, so as to schedule the charging of the thermal storage using this excess production. The thermal storage is connected to the Leaf Lab and the automation system for its charge and discharge was set considering this building. Currently, the automation system is set to charge the thermal storage during weekends, when there is excess production from Leaf Lab's PV. This kind of automation will charge the storage while energy is not needed form Leaf Lab, but it could be needed from the micro grid. Consequently, there is a requirement to change the settings so that the thermal storage will be charged when there is real excess production at micro-grid level. To this end, excess production of the micro-grid during weekends needs to be predicted in a robust way so that charging of the thermal storage is controlled accordingly.

Figure 1: Leaf micro-grid

2.1. System description

2.1.1 Ground water heat pumps

There are three water to water heat pumps in Leaf Lab. GWHP1 is connected to the chilled beams installed in the offices for space heating and cooling. GWHP2 and GWHP3 are connected to four HVAC units that service the offices, the laboratory and the warehouse.

The heat pumps are connected to the storage as shown in Figure 2. GWHP2 and GWHP3 are used for charging the thermal storage. When the thermal storage is discharged, thermal energy is provided to the chilled beams, thus avoiding activation of GWHP1 during the first three days of the week.

2.1.2 Thermal storage

The TES is a water tank with dimensions 12.3 X 11 X 3.4 m (400m³).The water tank is buried and insulated with16 cm of XPS. The heat stored is sensible heat intended to cover the thermal loads of Leaf Lab. The thermal storage is charged during weekends using the excess production of the Leaf Labs' rooftop PV installation. The excess production is used to operate GWHP2 and GWHP3

2.1.3 System settings

The charging process begins when there is an excess in Leaf Lab's PV power production over 60kW. This is the threshold for activation of GWHP3. After activation of GWHP3, if there is excess of 50kW, GWHP2 is activated.

The activation of the heat pumps for charging the thermal storage is allowed only during weekends from 8:00am to 16:00pm in winter and in weekends from 7:00am to 18:00pm in summer. The pumps are switched off at the end of each schedule or if PV production is significantly reduced over a sustained period of time. In case PV power is instantly reduced power is withdrawn from the grid in order to keep the heat pumps, which provide heat to the thermal storage, activated. For the deactivation of the heat pumps if the power from the grid is greater than 130kW GWHP3 is switched off and following this GWHP2 is switched off when energy withdrawn from the utility grid exceeds 90kW.
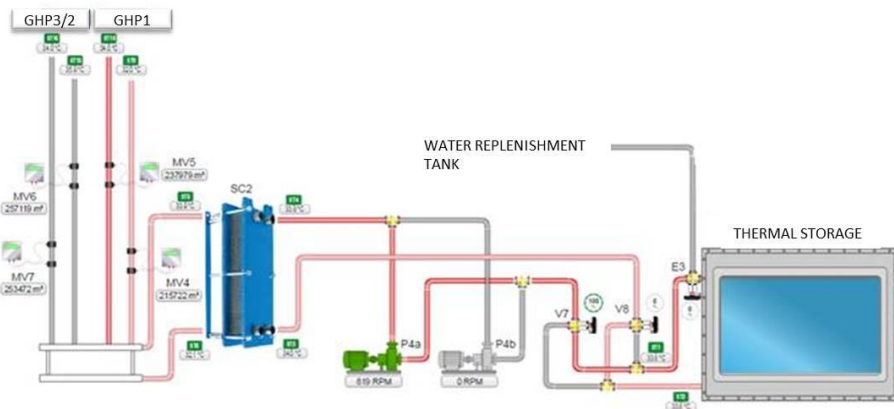

Figure 2: Thermal storage - GWHP connection schema

2.2. Data

Power data as well as environmental data have been collected from the My Leaf platform. The power production of each energy source and the power taken from and exported to the main grid are measured.

The total production of the micro-grid is:

$$P_{MG} = P_{LLPV} + P_{AEAPV} + P_{SUMMAPV} + P_{KITEPV} + P_{TUV} + P_{HYDRO4} \quad (1)$$

Where:

P_{LLPV} is the power production of the Leaf Lab PV, in kW

P_{AEAPV} is the power production of the AEA PV, in kW

$P_{SUMMAPV}$ is the power production of the SUMMA PV, in kW

P_{KITEPV} is the power production of the KITE PV, in kW

P_{TUV} is the power production of the solar tracker, in kW

P_{HYDRO4} is the power production of the micro-hydro power plant, in kW

The production of the micro-grid is self-consumed and excess production is given to the main grid. Since there

are measured data of the power exported to the grid, power production self-consumed at any time in the micro-grid can be calculated as follows:

$$P_{SC} = P_{MG} - P_{OUT} \quad (2)$$

Where:

P_{SC} is the power production self-consumed, in kW

P_{OUT} is the amount of excess power production that is fed to the main-grid, in kW

3. Methodology

The collected data is used for prediction of excess power of the micro-grid. There are two steps involved in this process. First a good prediction of excess production has to be achieved. For this purpose the Matlab [14] Neural Network (NN) tool is utilised. Alternative combinations of input parameters are tested so as to investigate which set of input parameters are suitable for achieving an accurate prediction of excess production.

3.1. NN model setup

3.1.1 Problem definition

The excess production of energy that can be used for charging the thermal storage can be determined from the measured data of power exported to the main grid. The prediction of excess production is a non-linear autoregressive problem. Past values of excess production as well as past values of day, time, irradiance, temperature and total production are used for prediction of excess power in 24h time horizon.

3.1.2 Input parameters

From equations (1) and (2) it can be deduced that excess production is related to parameters that determine production. For prediction of PV production, day of the week, time of day, temperature and radiation have been used as inputs [10, 15]. Prediction of hydro power production using as inputs the river water level and machine water level was attempted in [10] but a high accuracy prediction could not be achieved.

As a first step, day of the week, time of day and irradiance is used for prediction of excess production. In Figure 3 and Figure 4 it can be observed that there is a positive correlation between excess production and irradiance values, especially during peaks. Subsequently, a second prediction approach is tested using the first step's inputs plus ambient air temperature as input. A third prediction model is attempted using as input parameters the day of the week, the time of the day and total micro-grid production. It can be observed from Figure 5 that excess production follows the trend of total production.

Table 1: Input data for each prediction

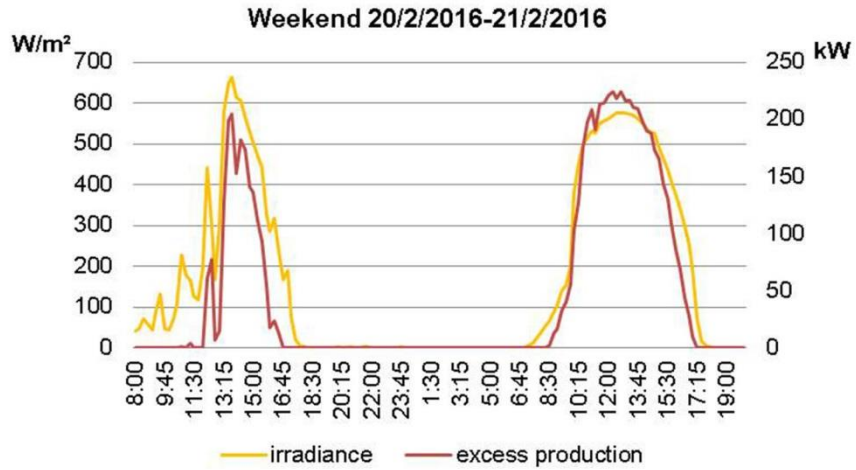|	Inputs	Target	Output
1st prediction	day of week time of day irradiance	excess production (P_{OUT})	excess production (P_{OUT})
2nd prediction	day of week time of day irradiance temperature	excess production (P_{OUT})	excess production (P_{OUT})
3rd prediction	day of week time of day micro-grid production	excess production (P_{OUT})	excess production (P_{OUT})

Figure 3: Excess production plotted along irradiance levels for the weekend 20/2-21/2 2016
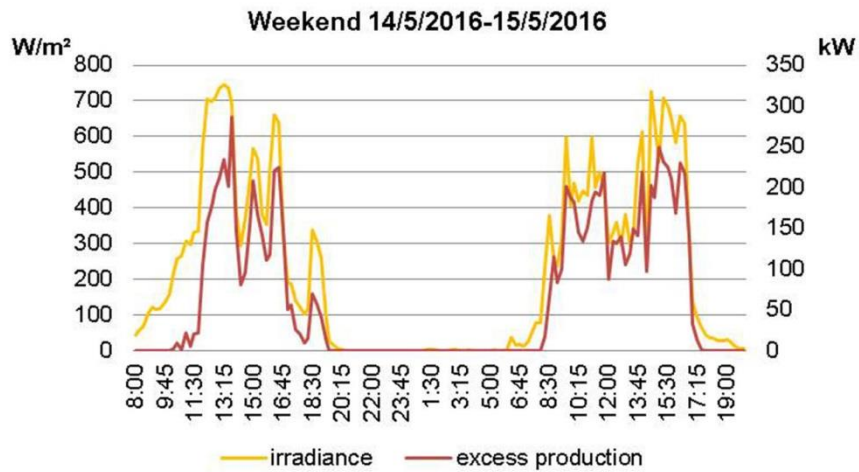

Figure 4: Excess production plotted along irradiance levels for the weekend 14/5-15/5 2016
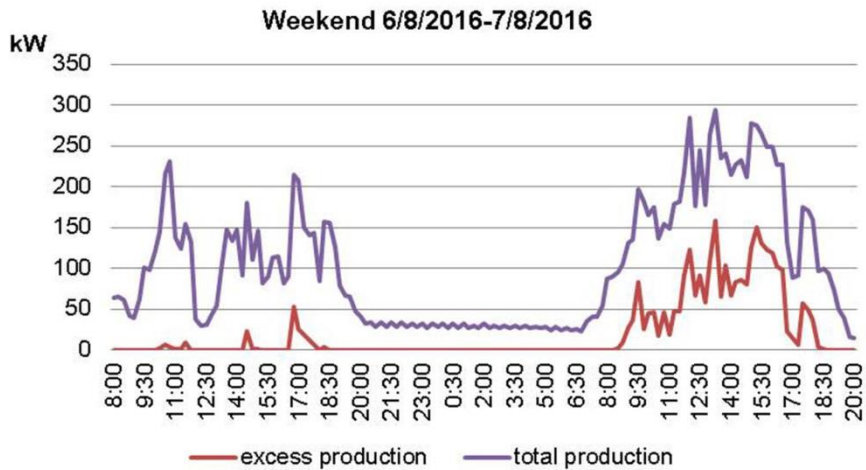
Figure 5: Excess production plotted along total production for the weekend 6/8 - 7/8 2016

4. Results and Discussion

The prediction results of a neural network with 30 hidden neurons and 5 delays are presented below. For training the network the Lavenberg-Marquardt algorithm was used. All prediction models achieve good results with the second one providing the best prediction results.

The first prediction with inputs day of the week, time of day and irradiance could achieve training regression R=0.96. A three-month period was used for training purposes, Figure 7.

The second prediction with input day of the week, time of day, irradiance and temperature resulted in training regression of R=0.98, Figure 6. Because of some gaps in temperature data, one-month period was used for training, Considering that only one month data is used for this specific prediction configuration, it can be concluded that using as inputs irradiance and temperature along with day of week and time of day can produce highly reliable results.

The third prediction with input day of the week, time of day and total micro-grid power production achieves training regression R=0.956, Figure 8.

The present work focuses on the thermal storage integration with the Leaf micro-grid. In this direction a first but necessary step is the prediction of excess power production that can be used for charging the storage. Having a reliable 24 hours excess power production forecasting model provides the basis for the design and implementation of advanced dynamic integrated control. In the Leaf micro-grid there is PV-power production and hydro-power production. Despite not using input data related to hydro-power production, a reliable prediction can be achieved using irradiance and temperature as input data along with time of day and day of week.

In future work, an appropriate control has to be designed for optimum utilisation of the prediction. Based on the requirement for 60kW for activation of the first heat pump, this can be the first threshold of excess power production of the micro-grid. The control system will have to take into account POD power levels where excess power is measured.

The control will also include an evaluation of the amount of time that excess production is over the thresholds. A decision making mechanism will guide the charging of the thermal storage based on available excess production and hours of availability during weekends. The target of the control will be the cost efficient integration of the thermal storage in the micro-grid.
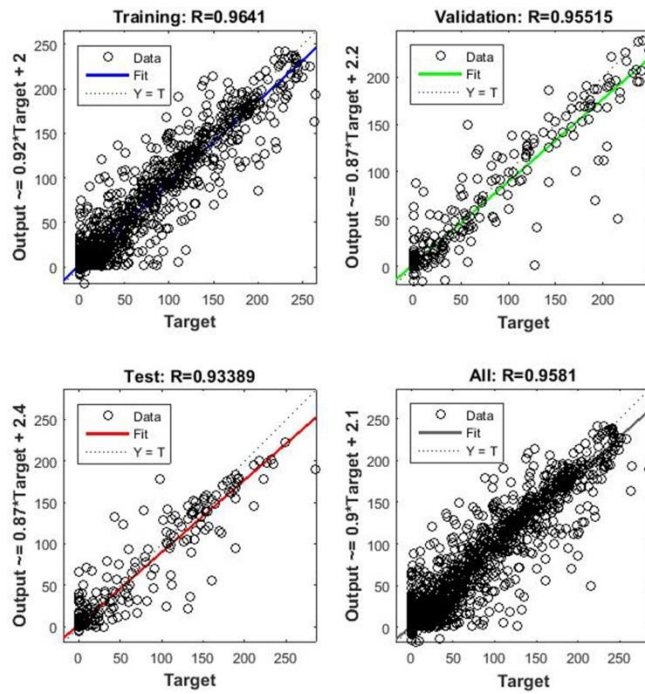
Figure 6: Prediction with irradiance and temperature input (data 23/1 - 29/2), 30 hidden neurons, 5 delays, Lavenberg-Marquardt algorithm
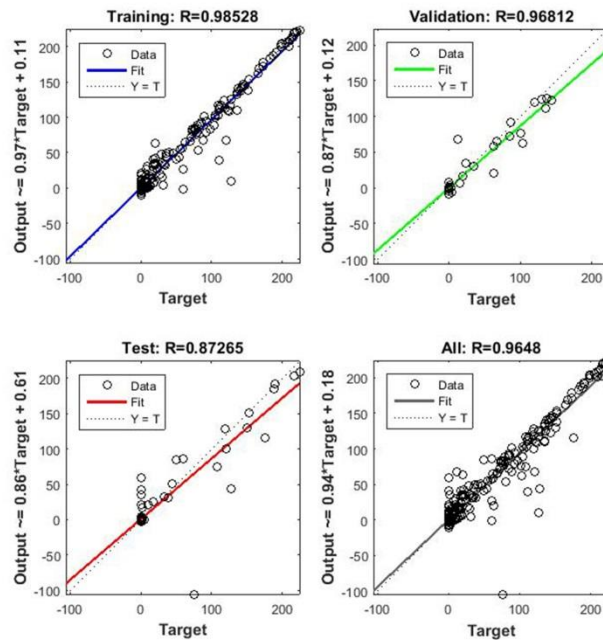
Figure 7: Prediction with irradiance input (data 3/5 - 26/7), 30 hidden neurons, 5 delays, Lavenberg-Marquardt algorithm
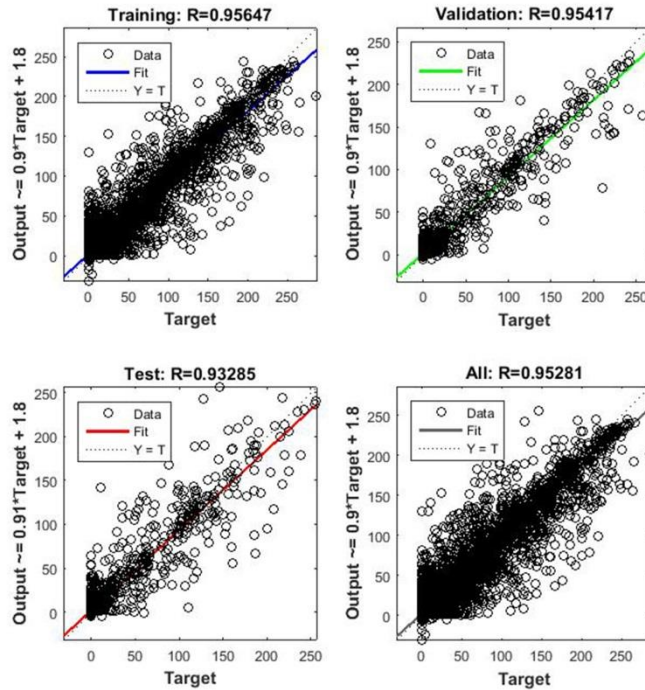
Figure 8: Prediction with production input (1 year data), 30 hidden neurons, 5 delays,
Lavenberg-Marquardt algorithm

5. Conclusion

In this paper, 24h excess power production forecasting of the Leaf micro-grid has been investigated using Neural Network Lavenberg-Marquardt algorithm. A robust and highly accurate prediction is achieved for various seasons using measurements of the environmental parameters of irradiance and temperature as inputs. Forecasted output is aimed at scheduling the process of charging thermal storage during weekends or other time intervals when excess power is significant and may be utilised by the micro-grid rather than exported into the main power grid.

Acknowledgements

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