Modelling and simulation of a predictive BESS controller based on load forecasting in a South European island power system

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Abstract:

Modern isolated power grids are constantly evolving to adopt smart grid concepts that can permit higher renewable energy penetration and energy management optimization, in the view of a sustainable RES based energy production EU policy with reduced pollutant emissions. Nevertheless, many islandic power systems like the islands in Southern Europe are still depending on oil-fired diesel engines, while the renewable energy production is limited due to financial, technical and environmental reasons. In this study, the power system of a typical non-interconnected South European island consisting of diesel generators and a PV farm is modelled and simulated. Scope of this paper is to examine the ability of a Battery Energy Storage System (BESS) to achieve load peak shaving combined with maximization of the PV power penetration into the grid leading to pre-planned zero curtailment. For this purpose, a novel peak shaving algorithm is developed and implemented into an Energy Management System (EMS), for optimal scheduling of the diesel engines. Thereinafter, dynamic simulations of the island's power system are carried out employing a predictive control strategy for different time scales, ranging from a supervisor BESS controller based on load forecasting, to a real-time battery power regulation. The predictive BESS controller is based on future consumption values forecasting, which in turn result from an Artificial Neural Network (ANN) and an optimization procedure taking into account PV power generation and a peak shaving threshold. Thus, a new diesel engine scheduling is obtained capable of replacing the maximum peak power demand with renewable power while at the same time load curve smoothening and reduced diesel generators ramps-up are achieved. The simulations are executed in APROS (Advanced Process Simulator) dynamic simulation platform, using built-in components for the BESS modelling, an external model for load forecasting and a user-developed EMS structure.

Keywords:

Artificial Neural Networks, Battery Energy Storage System, Energy Management System, Load Forecast, Peak Shaving, Renewable Energy.

1. Introduction

Nowadays, fundamental concepts related with energy production and consumption are continuously evolving and being reformed towards the forthcoming energy revolution based on smart energy networks predominance. Due to constant environmental regulations and limitations, energy utilities are enforced to implement changes and alter their policy in order to achieve a more sustainable and renewable based operation [1]. This task may be more feasible for large scale, highly interconnected grids, but this is not the case for smaller islanded grids, where renewable production can be a significant proportion compared to the total system production and excess energy cannot be exported. Through this perspective, islands' power networks, that resemble the future structure of distributed microgrids in islanded operation too, are highly dependent on precise forecasts and storage solutions, since grid stability and production/consumption balancing are met exclusively by the local power generation. This is primarily dependent on diesel generators. Abrupt changes in load conditions and sudden impulses of renewable energy injections into the grid are usually counterbalanced by commissioning more diesel generators for peak hour demand, forcing them to experience cold start-ups or to operate in variable power setpoints which result in fuel-consuming ramp-ups. Both of these operational conditions are strongly related to high operating costs and reduced diesel engine lifetime, which in turn have a negative effect on grid operators illustrated by the high cost of the produced electricity. In addition, as Chua et al. stated in [2], commercial and industrial customers are subject to monthly maximum demand charges which can be as high as 30% of the total electricity bills, thus peak shaving can be an efficient way to reduce those charges and relieve diesel generators from cost-intensive and energy-demanding ramps-up, accelerating from base to the peak load.

Concerning the aforementioned inherent difficulties in operating islanded grids and managing the power flows between production and consumption, battery energy storage systems (BESS) have proved to be a very promising option for smoothening those instabilities and enabling higher renewable power penetration simultaneously. However, the most suitable operation strategy of the BESS, which is determined by a centralized Energy Management System (EMS), is related with the shape of the load profile of the system and the type of renewable power generation. Thus, for an islandic power system, where the load profile presents a high peak in late night hours and high photovoltaic (PV) generation in daylight hours, peak shaving with BESS energy stored from PV generation seems a rational approach. Specifically, this is the case for most South European islands where the load profile is shaped mainly from activities related to tourism at night hours rather than energy devouring industries that operate during the daylight hours.

Many studies related with short term load forecasting for power grids implementing numerous methodologies and algorithms from the field of time-series forecasting have been published so far. Among them, Artificial Neural Networks (ANNs) that incorporate many versions is considered as a common approach [3,4,5] and is also adopted in this study. In order to evaluate the performance of neural networks and their capability to forecast accurately, some statistical indicators are used such as Mean Squared Error (MSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) with the last being the most common for comparison actions [5].

However, implementing such predictive energy management systems for large isolated power systems and grid scaled BESS can be more challenging due to inherent difficulties related with system stability. In studies such as [6], load forecasting was used for a system with high PV penetration. In other studies [7,8,9], a simple linear regression model for load forecasting has been implemented in order to achieve optimal operation of a grid-scaled BESS for the power network of Hawaii island, considering also the large number of installed PV capacity on rooftops at the distribution grid. Halfmann et al. [10], implemented a predictive real-time BESS control based on load forecasting with ANNs to provide both peak shaving and primary frequency control for the Germany power system at the same time. Predictive energy management systems for a microgrid consisting of grid-tied BESS with PV generation were also examined in [11,12], where load and PV generation forecasts were provided as input and used in combination with an optimization problem for minimizing renewable curtailment power or grid consumption and consequently the electricity cost. The cost reduction from the peak shaving ability of a grid-tied BESS was also studied in [13]. However, the ability for power exchange with the main power grid interconnection presents an operating advantage over isolated microgrids. According to those studies [10-13] the economic feasibility of BESS was remarked and validated, especially for their ability of peak shaving the load curve.

From the above review analysis, it makes clear that despite the wide spectrum of combination of energy management systems with BESS, their effectiveness is highly correlated with the optimization targets, the operational constraints, the specific characteristics of the load profile and the amount and type of installed renewable power. Regarding the present study, a novel predictive algorithm for peak shaving and diesel engine operation smoothing is proposed. This algorithm is combined with a load forecasting method and then integrated into a microgrid simulation model, including a detailed non-linear battery representation. In this way, the isolated power system of a South-European island is examined and the developed predictive open loop EMS with relatively simple implementation and low complexity is integrated into a dynamic simulation model. Compared to other studies mentioned before, the novel aspect of this study is the combined attributes of a machine learning method for load forecasting and a developed tailored made optimization algorithm with a custom modelled EMS and the dynamic simulation of a detailed Lithium (Li) battery model in Apros software. Therefore, a complete simulation framework for isolated power systems is proposed, combining load forecasting, predictive EMS algorithms and dynamic simulation models (see Fig. 5). Aim of this study is the development of a smart predictive control architecture for a BESS, based on load forecasting, for the optimum integration of PV power into an islanded power grid, through peak demand shaving and smoothening of the load curve.

2. Load Forecasting with Artificial Neural Network

A forecasting model is a necessary subsystem that needs to be implemented in a predictive energy management algorithm able to compensate for future events. In this study, such a model was developed for future consumption values forecasting by implementing a simple single-hidden layer feedforward neural network. This neural network structure was selected based on the well-known Kolmogorov theorem [14]. In this way, short-term load forecasting was mathematically formulated as a function fitting problem in which the hourly load time-series of a whole year were estimated. Specifically, the developed model was trained from past years load data (i.e. years 2014, 2015) provided from the South-European island's grid operator and the outputs were the load data for the next year (i.e. year 2016). A strong correlation between the trend of the load curve and the temperature data of the island was observed, making the latter as an appropriate input for the developed neural network model. The hourly temperature data was produced by the long validated CFSR [15] numerical weather model (NWM) from representative grid points near the most-highly inhabited areas of the island for the years examined, so that the correlation of weather phenomena with electricity consumption to be intensified.

The inputs of the feedforward neural network were determined based on common input variables for similar networks referred in load forecasting studies [3-7] and after a trial-and-error iterative procedure. Therefore, the inputs that were found to give the best results in terms of the MAPE defined as:

$$MAPE = \frac{1}{8760}\sum_{i=1}^{8760}\left|\frac{Forecsted\ Load_i - True\ Load_i}{True\ Load_i}\right| \tag{1}$$

where i) the 48 values of the hourly consumption data of the two previous days, ii) the 24 values of previous day temperature data, iii) 7 binary values corresponding to the day of the week and iv) a binary variable which was used as an index for weekend days and working days. The network output consisted of a 24-variable vector containing the next day's forecasted load values on an hourly basis. The structure of the developed networks is schematically depicted in Fig. 1.

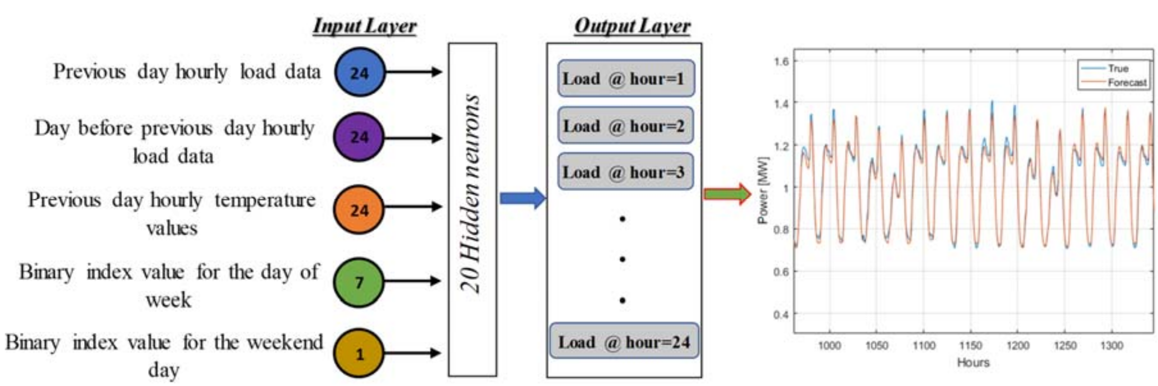

Fig. 1. Neural Network Structure

The input variables before the training procedure were scaled in the interval [0, 1] so that every input has the same weighting despite the different physical scales that are related with the type of input variable. For the same reasons, the binary values were chosen to be 0 or 1. For the training procedure, as it was stated above, data from years 2014 and 2015 were used in a backpropagation algorithm based on the *Levenberg-Marquardt* error minimization algorithm. In this way, after each iteration the neuron's weight matrix and biases vectors are updated based on the following equation:

$$\vec{x}_{k+1} = \vec{x}_k - [J^T J + \mu I] J^T \vec{e} \tag{2}$$

where J is the Jacobian matrix of the networks errors $\vec{e}$. The latter are calculated based on the difference of the networks output $\vec{y}$ from target values $\vec{t}$. The network's output vector from each layer is calculated as the weighted sum of the neuron's outputs from the previous layers and after being filtered from the logarithmic sigmoid activation function:

$$f(x) = \frac{1}{1+e^{-x}} \text{ and therefore } \vec{y} = f\left(\boldsymbol{W}\vec{u} + \vec{b}\right) \tag{3}$$

where $\vec{u}$ is the input vector and $\vec{b}$ the neuron's biases vector. The mean squared error (MSE) was used as a termination criterion for the training procedure. The evaluation of the network output with the target values was determined with the correlation coefficient R as it is shown in Fig. 2. The MSE parameter was first calculated for the validation data set, chosen to be around 4% of the training set, and then the overall network's performance was evaluated for the test set, which was not ever used in the training process.

After the network configuration procedure was completed and the best results were achieved, the correlation coefficient was found to be R=0.99189, which considered as an acceptable value. Thereinafter, the outputs were scaled back to their physical scales, the overall network's performance was evaluated for the test set and a *MAPE=1.7412%* was achieved. The results of the load forecast are presented in Fig. 2, where the real and forecasted load values are compared for the whole year and more specifically, during a typical week time period.

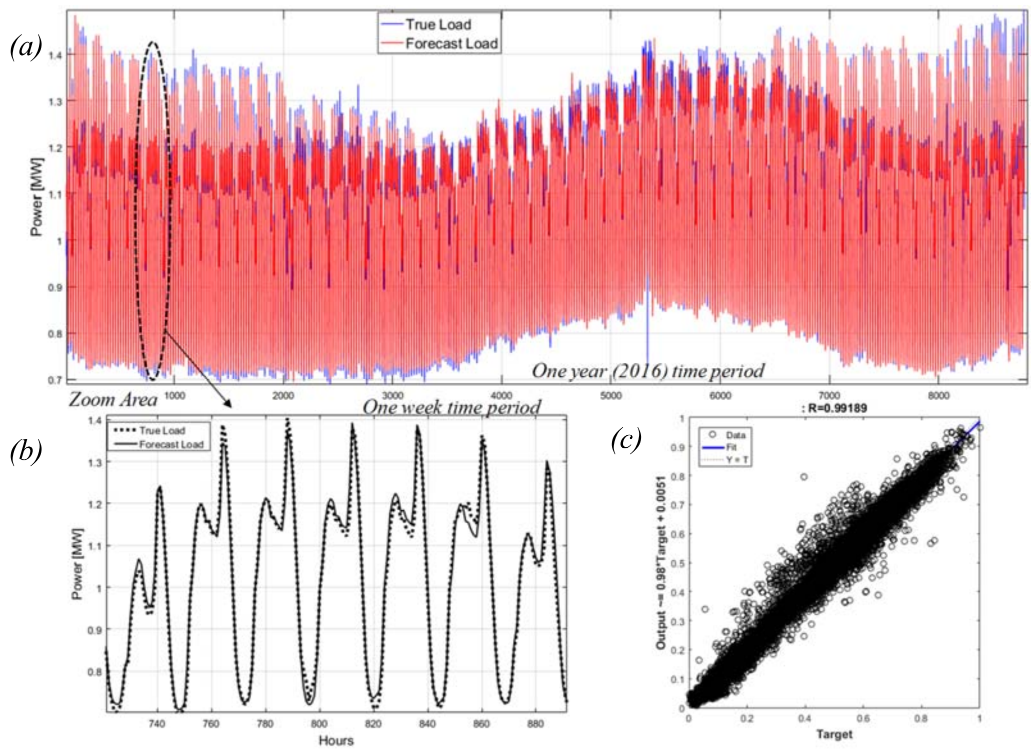

Fig. 2. Forecasting results for: a) the test year, b) a week time period, c) correlation coefficient

3. Peak shaving optimization algorithm and power system modelling

In this section, the developed peak shaving procedure is described. In order to take advantage of the load forecasting in the energy management of the island's power system and considering the shape of the load profile (Fig. 2), it is seen that especially for winter period, the peaked values of load are detected during the night hours where the renewable installed PV power is not available. The island's power system has maximum peak demand values about 1.3-1.5 MW, which are currently covered by the additional diesel generators that operate at low partial loads, while the installed capacity of PV power is approximately 300 kW, accounting for around 10% of the peak values. Therefore, in order to achieve zero curtailment and full renewable penetration to the grid, the diesel generators should operate at partial loads under variable conditions during daylight PV production period and at night, they should be capable of a steep and abrupt acceleration to cover the night peak demand. Both of the aforementioned cases contribute to diesel engine efficiency reduction, augmented emissions and pollutants levels and increased fuel consumption compared to a steadier operation. As a consequence of these is the increase in the electricity production cost.

3.1. Predictive peak shaving methodology

Regarding the above concerns, a BESS capable of saving renewable energy when it is not required and releasing it at night peak demands is a meaningful strategy. However, a BESS should operate with an optimum plan in order to be sized appropriately and minimize the pay-back period of the investment. In addition, considering that this would be a grid-scale BESS and that the installed renewable capacity in the island, for the time being, is not enough to cover the load curve at any point, the PV energy storage should be optimized. To achieve this, an optimization algorithm which is presented in Fig. 3 was developed and deployed:

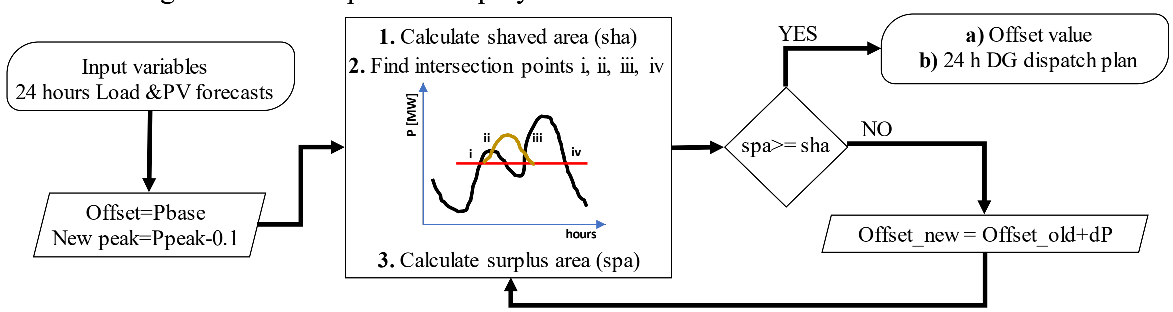

Fig. 3. Proposed algorithm for the diesel operation planning

Initially, the next day forecasted load curve and the PV production is used as input into the algorithm. The energy production of the installed PV plants is predicted using a simulation engine developed by Pfenninger et al. [16] and through which it is possible to obtain an hourly based production based on the irradiance intensity on the island while considering the power converter losses of the system at 10% based on a conservative assumption. As the purpose of this work is the evaluation of the performance of the neural network load forecasting module combined with the energy management of a BESS for peak shaving, the produced renewable energy is considered as a perfect forecast.

Subsequently, the peak shaving level is determined and then an offset initial value is set equal to the base forecasted load of each day. The latter is set equal to the daily minimum of load curve. In this study, the peak reduction level was set at 0.1 MW lower than the peak demand, defined as the maximum value of the daily load curve. The final offset value is obtained through an iterative procedure. At first step, the intersection of the combined PV and offset curves with the load curve at two points (points ii, iii in Fig. 3) have to be achieved. The combined PV and offset curve is the result of the PV production superimposition to the offset curve. The desired curve intersection is achieved by increasing the offset value by $dP=1\ kW$ (see Fig. 3). Then, a second criterion for the offset value determination is imposed: the artificial PV excess production has to be at least equal to the peak shaved area, as seen in Fig. 4. The second criterion is mathematically formulated as:

$$\int_{t_1}^{t_2} (P_{offset} + P_{PV})\, dt - \int_{t_3}^{t_4} P_{load}\, dt \leq \varepsilon \tag{4}$$

Where ε is a small value around 10^{-3}, t_1, t_2 are the intersection points of the combined curve with the load curve and t_3, t_4 are the intersection points of the peak reduction level with the load curve. The offset level is constantly increasing by dP, until sufficient surplus area (*spa* in Fig. 3) is created. This surplus energy can be spotted in Fig. 4d as the lighter area above the darker area, which represents the load area at the corresponding hours. The peak reduction level with the corresponding load curve of each day, define a shaved area (*sha* in Fig. 3) which is represented by the grey area of Fig. 4. In this way, the offset level determined from the algorithm acts as an “elevator” for the PV production curve and at the same time as an upper limit for the diesel operation during the off-peak hours. In order to calculate the above areas as more accurately as possible, a linear interpolation is considered between the hourly values of demand and production, which is quite close to the true case. Thus, it is possible to set a new 24-hour based operation plan for the diesel generators consisting of the offset value that is achieved from the algorithm and the new shaved peak, which are also the outputs of the procedure (Fig. 3).

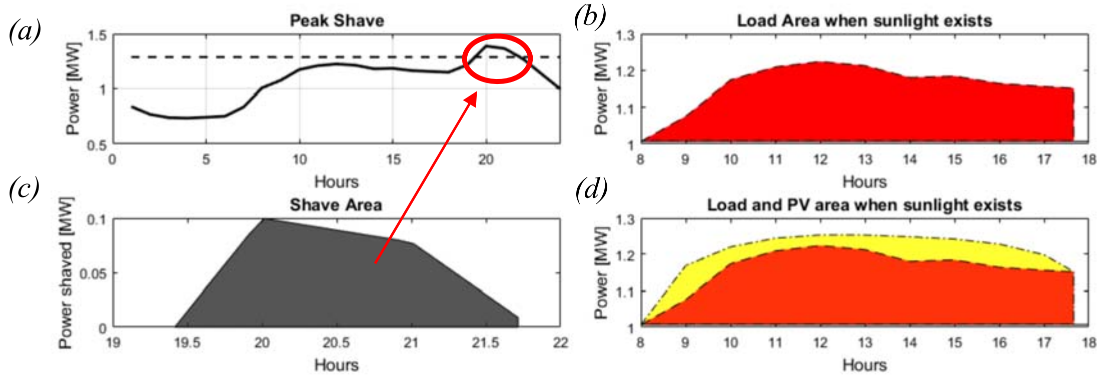

Fig. 4. Results for a typical winter day: a) load profile and peak shave level, b) area between load curve and offset level for sunlight time period, c) shaved energy, d) artificial excess PV energy

3.2. Apros BESS model with EMS

Thereafter, the predictive peak shaving algorithm described in previous sections was incorporated in the BESS energy management system, which was modelled in Apros software and simulated for the whole year. An Apros multi-cell Lithium battery module was employed in order to model the BESS. The basic equations [17] related to the Lithium battery model, are the following:

$$U(t) = V_{OC} \cdot n - \frac{n}{m}\left(R_{series} + R_{cycle} + R_{tr\_sh} + R_{tr\_ln}\right) \cdot I + n \cdot \Delta E(T) \tag{5}$$

$$C(t) = C(t - \Delta t) - I \cdot \frac{\Delta t}{3600} \tag{6}$$

$$N_{eq} = \int \frac{\frac{1}{2}|I|}{3600 \cdot C_{max}} \tag{7}$$

$$C_{max} = C_{nom} \cdot [1 - (f_{sl} + f_{cl})] \tag{8}$$

In the above equations, V_{OC} represents the open circuit voltage of each cell, which is a function of remaining capacity and is set at maximum capacity at about 4 V, n =199, m =169 are the number of cells in series and in parallel respectively, C_{nom} is the nominal capacity of the BESS which is set to 2000 Ah. C_{max} is the maximum remaining capacity of the battery, which is affected by battery aging and degradation effects, through coefficients f_{sl} and f_{cl} that represents the lifetime storage loss fraction and the lifetime cycle loss fraction respectively. C is the current battery capacity, which is updated at each simulation step. The latter is set equal to $\Delta t=0.2s$, in order to capture small scale dynamic transients in voltage $U(t)$ and current $I(t)$ parameters. The remaining capacity was also used with the current maximum capacity at every step for a state of charge (SoC) calculation, which in this study and based on recent advances in battery technology is allowed to be in the range 0-100%. The term $\Delta E(T)$ is related with the battery temperature and its effect on voltage, while the R_i parameters represent an internal resistance model of the battery that can be found in [17]. R_{series} is responsible for the instantaneous voltage drop in battery terminal voltage. The other component of series resistor,

R_{cycle}, is used to explain the increase in the battery resistance with cycling. The components R_{tr_sh} and R_{tr_ln} of the battery RC network are responsible for short and long-time transients in battery internal impedance respectively. The battery model operation is controlled by two PI controllers, one for battery charging control and one for discharging. The charge controller regulates the voltage level of an ideal DC source, which represents the DC to AC bus connection to the grid through the inverter module, so that the power system balance is preserved. The discharge controller regulated the set point of an iconic controllable load so that the battery could provide enough energy to the grid to account for system imbalances. The integrated simulation framework of the system examined in this study, is presented in Fig. 5.

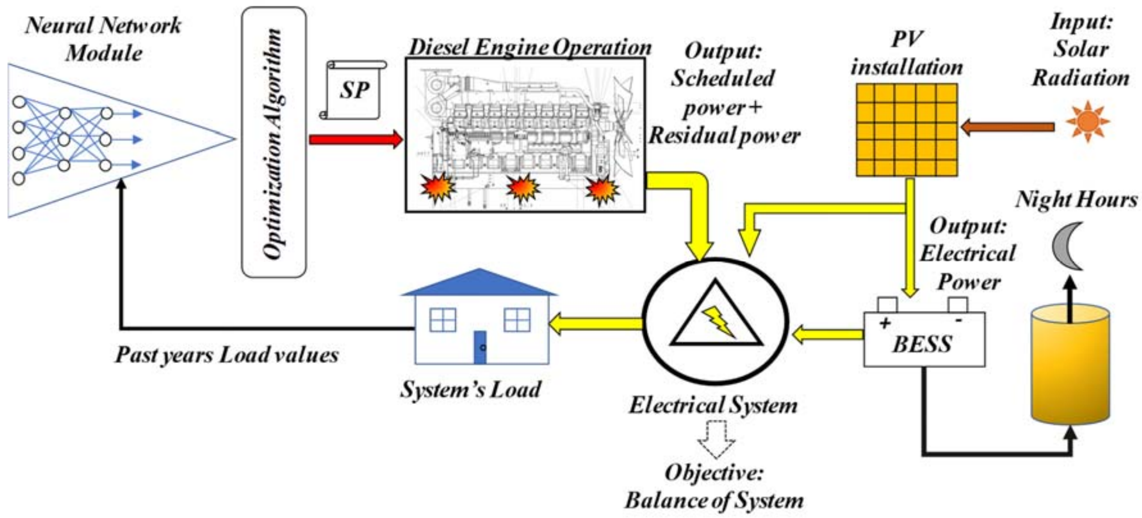

Fig. 5. System configuration and methodology procedure

The system inputs to the model are the 24-hour diesel generators setpoints for every day of the year, which are calculated in the previous section, the true demand curve of the island for 2016 and the perfect PV forecasted power values for the same year. The EMS that controls the system is formulated as a binary signal logic, which is responsible for the state of the BESS. In particular, when PV power available at daylight and at the same time the sum of the offset set-point of the diesel generators and the PV power is greater than the current load demand, the EMS defined a charging state for the battery. If PV power is not available or the aforementioned sum is less than the load demand, the battery should discharge as much energy as possible. In case that the offset set-point of the diesel generators is either greater than the load demand or the absolute value of the residual, defined as the diesel power plus the PV power minus the load demand, is smaller than 0.1 kW, then the BESS should be in idling mode and ready for a future incident. Thanks to this operation plan, not only is BESS charged with renewable energy that can be used at a next time, but also the false scheduling due to forecasting errors are compensated at the same time.

4. Results of the dynamic simulations

After the system model configuration is completed, the power system yearly operation is simulated with the rules and the operational strategies mentioned before. Thus, it is possible to estimate the performance of the predictive EMS algorithm regarding the impact of load forecasting to the real time operation of the BESS.

As it was described in the previous section, the system power balance was used as a criterion for power generation-consumption balancing and it was monitored in order to be constantly zero (i.e. no over/under production was allowed). For that reason, the battery power delivered to the system was controlled according to this specification. However, at specific times over the year period, the power balance was not achieved due to isolated large forecast errors or operational limitations owed to the state of charge of the battery. This surplus or deficit of energy was considered to be compensated by the diesel engines supposing a flexible operation with small deviations around their base scheduled operating point, as forecasted. A good overall performance of the system was obtained with a significant success in smoothening the load curve around the engines predicted operating points. As it makes clear in Fig. 6, the new achieved operation of the diesel engines consisted of basically two levels, one related with the offset obtained from the optimization algorithm and one owed to successful peak shaving implementation. In this picture, the simulation results are indicatively presented for a one-week duration, making possible the comparison of two different operational strategies of the diesel engines. The first approach namely "OLD Diesel" corresponds to the diesel engine operation if the system could absorb all possible PV energy production, meaning zero curtailment, despite the lack of load forecasting. The second approach namely "NEW Diesel" corresponds to the proposed methodology. According to Fig. 6, it is clear that the NEW Diesel operation curve is much smoother than the OLD one while the produced PV energy is completely absorbed by the system by supplying the artificially achieved excess PV power at the time periods of peak shaving. This ensures that all renewable energy produced is supplied to the grid resulting in a predicted and planned zero curtailment.

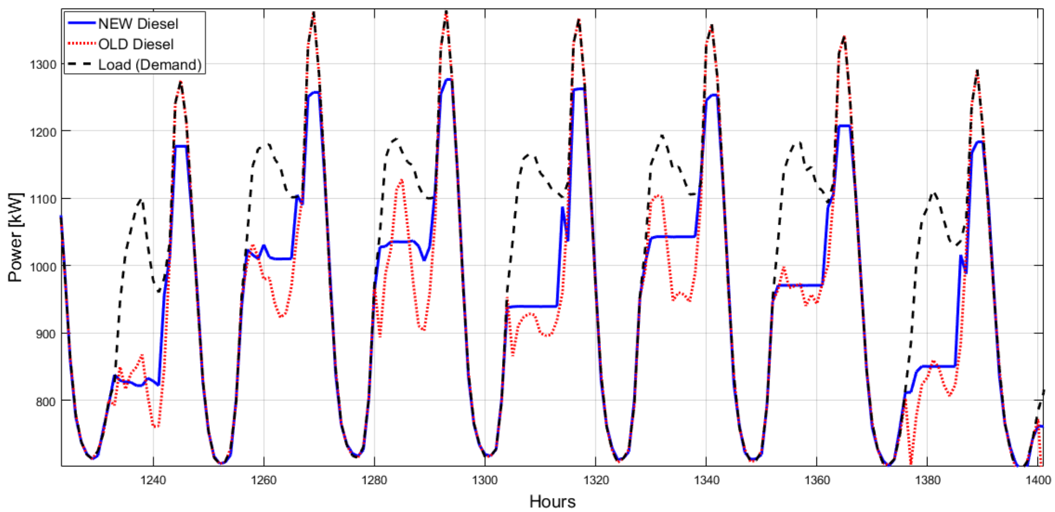

Fig. 6. Obtained diesel engine production curves for a typical winter week time period

In Fig. 7, the achieved results during a single day operation of the week presented in Fig. 6 are shown. As it is evident, with the proposed methodology the diesel engines operate in a more monotonic mode, owed to the calculated offset level and it is possible to avoid in a great extent the valleys and crests due to the PV generation at the specified time-periods. These time varying, and unplanned operating conditions are eliminated with the proposed BESS operation and this has a significant improvement to the magnitude and the gradient of the engine's ramp-up for the following peak event (Fig. 7). Under this scope, a more precise dispatch planning of the diesel engines can be obtained and the allocation of fewer additional engines to cover the ramp-up of the load curve can be achieved. In addition, the acceleration rate of the engines, depicted through the gradient of their operation at Fig. 6 is decreased. Provided that this is directly related with immense fuel consumption decreasing this gradient results in a less aggressive engine operation and a more cost-effective fuel consumption.

The aforementioned effects on the operation of the system are also depicted from the BESS side in Fig. 8a, where the correlation of the BESS delivered power, state of charge and PV production are presented. It is revealed that during the time period of PV production, the BESS stores energy that it is supplied later on during the peak demand. For that reason, the SoC of the BESS is around its daily maximum values right before the peak demand event and subsequently it supplies the daily maximum power when the peak demand event is reached. This fact is also depicted in Fig. 8a, where the maximum PV energy production is followed from the maximum value of the battery's SoC, which in turn is followed from the maximum value of the power delivered from the BESS. The latter, is also achieved at the same time of the maximum peak demand value, which is another indication that the peak demand is satisfied from the stored renewable energy. In addition, in Fig. 8b, it is observed that the EMS that controls the battery, operates the BESS according to the plan derived from the developed algorithm. This is obvious from the actual and the scheduled battery operation curves depicted in Fig. 8 b that present a similar pattern.

In order to evaluate the performance of our methodology for the whole year operation, (though it is applicable when the peak demand is misaligned with PV production which is the case for winter periods), a statistical indicator is employed. Specifically, the kurtosis feature is calculated for the reference case (Diesel + PV) and the case proposed (Diesel + BESS + Predictive EMS) by implementing the following formulas:

$$kurtosis = \frac{\sum_{k=1}^{K}(x(k) - x_m)^4}{(K-1){x_{std}}^4} \tag{9}$$

$$x_{std} = \sqrt{\frac{\sum_{k=1}^{K}(x(k) - x_m)^2}{K-1}} \tag{10}$$

$$x_m = \frac{1}{K}\sum_{k=1}^{K} x(k) \tag{11}$$

where *x(k)* is a signal series for *k=1,2,…,K*, and *K* is the number of data points, x_{std} the standard deviation and x_m the mean value. This feature which is commonly used in vibration analysis [18] for bearings health monitoring, expresses the quality of the data values distribution around the mean value of the dataset. The latter has a direct relation with the concertation of the data values around some central values and therefore it can be an indicator of the peak frequency of the signal. Thus, a signal with a high frequency of peaked values will typically have a greater kurtosis value compared to a smoother signal. Therefore, the quantification of the results of this approach is accomplished through the calculation of the kurtosis feature for the signals of interest in our study. Therefore, for the signals "NEW Diesel" and "OLD Diesel" depicted in Fig. 6 and as obtained from the simulations, the kurtosis values are: $kurtosis_{OLD\ Diesel} = 2.5416$ and $kurtosis_{NEW\ Diesel} = 2.1319$.

This reduction in kurtosis, accompanied by the probability distributions of the same signals which are depicted in Fig. 9, imply an improved performance of the power system for the whole year duration. In particular, observing the latter figure, two areas are easily distinguished: The one is related with the peak reduction success level as the frequencies around the peak demand values are considerably decreased, whereas the other area is related with the level of smoothness of the diesel engine operation. The intermediate power demand values with the proposed configuration are more uniformly distributed compared to the frequency distribution of the previous case.

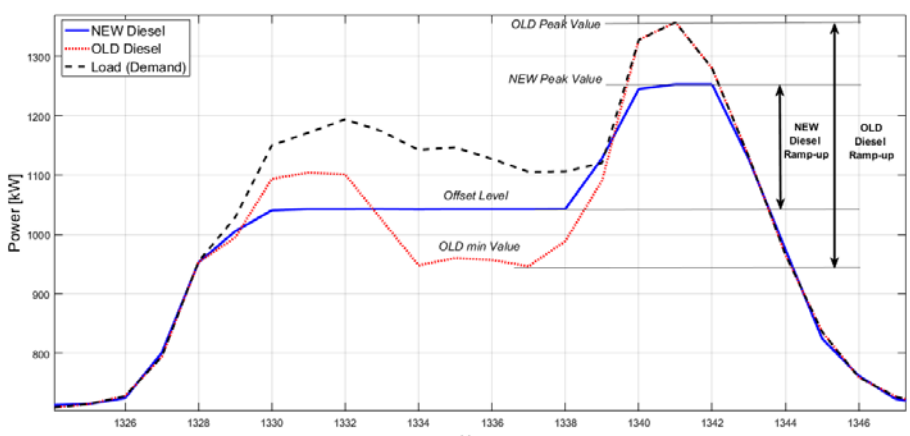

Fig. 7. Consumption and production obtained power curves for a single day time period from the week of Figure 6

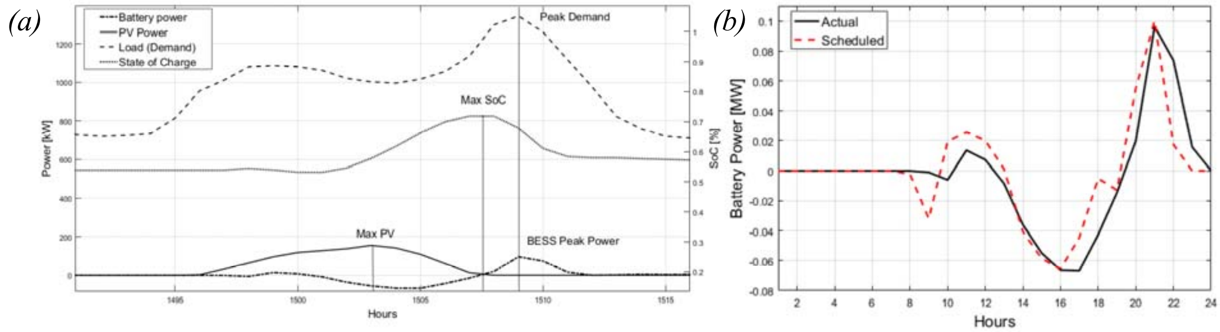

Fig. 8. a) BESS operation results after the dynamic simulation for a single day b) actual vs scheduled battery operation for the same day

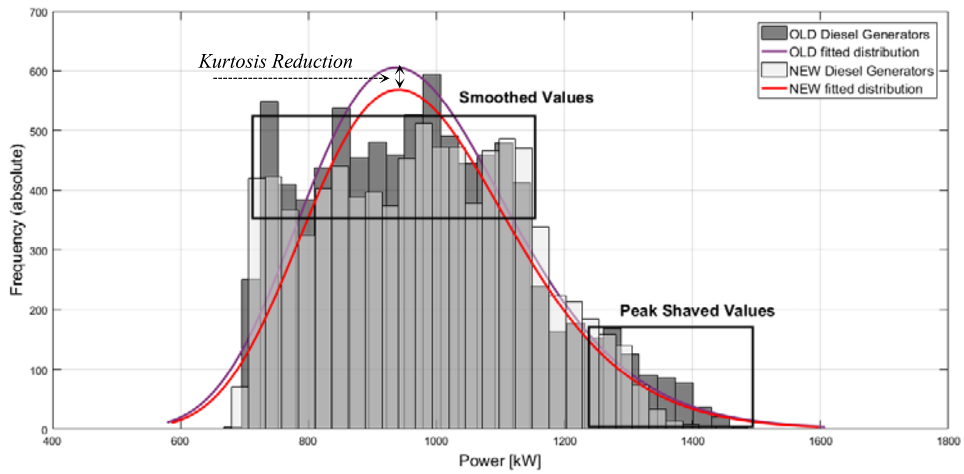

Fig. 9. Frequency histograms with fitted distributions of the diesel generators operation for the OLD and NEW case

5. Conclusions and Future work

In this study, a predictive EMS based on load forecasting was introduced and integrated with the operation of a BESS for peak demand reduction of a South-European islanded power grid. The results of the combined synergy of prediction and a new developed algorithm with real time control of the BESS, revealed that the peak shaving with renewable energy load levelling and smoothening in conjunction with a better diesel generators scheduling, can be achieved. Specifically, the load forecasting was realized by implementing a single-hidden layer feedforward neural network for day ahead hourly predictions and a *MAPE=1.7412%* was achieved. Moreover, an optimization algorithm for the appropriate operational strategy of diesel generators based on load forecasting was developed and implemented in Apros software for dynamic simulation. The system was simulated for a whole year and except from the peak shaving of the load curve by using stored PV energy, a significant reduction in the variability in diesel generators operation was also achieved. The proposed method reinforced the power grid ability to integrate renewable power in a more robust and planned way, leading to zero curtailment and possible cost reduction through fuel savings.

A future step for the improvement of this method could be the battery size optimization and the implementation of real PV power production forecasting. Also, the fuel consumption of the diesel generators incorporated into a techno economical study, could enlighten the economic feasibility of the proposed configuration, leading to the reduction of the number and capacity of the existing diesel generators.

Acknowledgements

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Abbreviations

ANN: Artificial Neural Network

BESS: Battery Energy Storage System

DG: Diesel Generator(s)

EMS: Energy Management System

MAE: Mean Absolute Error

MSE: Mean Squared Error

MAPE: Mean Absolute Percentage Error

NWM: Numerical Weather Model

PV: Photovoltaic

SoC: State of Charge

Nomenclature

$\vec{b}$ network neurons biases

C battery capacity at each time step, Ah

$\vec{e}$ network errors

f(x) neurons activation function

I battery current, A

J Jacobian matrix of the network errors

N battery charging cycles

P_{PV} PV produced power, kW

P_{offset} offset power level for the DG, kW

P_{load} true demand power of the island's power system, kW

R_i battery internal resistances, Ohm

R correlation coefficient

spa artificially created surplus area derived from the developed algorithm, MWh

sha shaved area created from the peak shaving level, MWh

$\vec{t}$ network target values

$\vec{u}$ network inputs

V_{OC} battery cell open circuit voltage, V

U voltage over BESS terminals, V

$\vec{x}_k$ vector of weight and biases at k iteration

$\vec{y}$ network outputs

Greek symbols

μ relaxation coefficient of Levenberg-Marquardt method

Δt simulation time step, s

Subscripts and superscripts

eq equivalent

m mean value

std standard deviation

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