Research Article

Model Predictive Control for Conventional Power Production Optimization and Voltage Rise Mitigation in Distribution Networks

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Abstract

The energy flow management in distribution networks started to worry grid operators since the challenge of exploiting natural resources such as solar irradiance and wind speed to produce electricity became a reality. Due to their intermittent nature, mismanagement of these resources can result in a severe bidirectional energy flow; likewise, notable imbalances between demand and generation in the electrical lines. Consequently, this may engender excessive energy losses and could violate electrical component characteristics. However, a predictive management of these resources can allow for the forecast of the different existing electrical device regulations beside the energy needed to be produced by conventional generations in a vertically-integrated system. For that purpose, we present in this paper a Model Predictive Control approach applied on a distribution feeder connected to renewable distributed generators and supplied by a High Voltage/Medium Voltage substation through transmission lines. We associated to this model a regulating algorithm for energy optimization and cost minimization. The control strategy outputs are the active and reactive energy predicted to be injected by the substation into the feeder. Finally, we evaluated the accurateness of the proposed method and we identified the parameters that affect its precision error.

Keywords: Biomass; energy management; energy storage; predictive control; reactive power; solar energy.

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1. Introduction

The incorporation of Distributed Generators (DGs) into Distribution Networks will relieve electricity supply from conventional production units that are getting more and more stressed by many factors: the increasing electricity demand, the limitation of power delivery capabilities and the expenses relative to the building of new transmission lines [1]. In other words, renewable DGs have the potential to raise the reliability of the system by alleviating substation transformers and most of the feeders during peak load periods. This support may result in extending the usable lifetime of the transformers, avoiding or delaying the construction of extra conventional power plants and diminishing the probability of distribution equipment's premature failing due to overloading.

However, the management of these DGs in the grid has been the challenge of many proposals as it brings up many constraints that need to be dealt with. In particular, dealing with this new configuration invites grid operators at the National Dispatching (ND) level to update their methods for predicting the power production of the following day from conventional and renewable power systems at the High Voltage (HV) level by considering the ones connected to Medium Voltage (MV) distribution networks. In fact, as they used to base their calculations on load demand prediction and daily energy cost evaluation, they will have to

add in the near future two other important parameters: 1) the energy production predicted to be delivered by the numerous DGs connected to distribution networks; 2) the hourly energy cost equation according to the wholesale energy market [2]. The latter is due to the strong dependence of many nations on fossil fuels that are imported from aboard, added to the electrical energy exchanged with bordering countries in spot markets.

To that end, and in order to facilitate the scheduling and dispatching task for vertically-integrated monopoly utilities, we propose in this work, to predict the needed active and reactive energy flow for each HV/MV transformer at the different Regional Dispatching (RD) levels. This makes the particularity of this work. In fact, when the injection of intermittent energies will increase in distribution feeders, the RDs will have to communicate the collected database from each substation to the ND of electrical energy to optimize the energy production from conventional resources. The latter will use it for decision support when predicting the hourly energy production profile curve of the country. In parallel, the RDs will have to evaluate the impact of DGs on distribution networks during the day. All this starts by predicting the energy that will be delivered by the renewable DGs, which may introduce us to the different variables influencing the safe behavior of the grid and help us define the rest of the needed energy to supply the different loads. To proceed, considering that those DGs are in the form of Photovoltaic Power System (PVPS), Battery Energy Storage System (BESS) and Biomass Generators (BGs), we have to start by predicting the key variables of our system that

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fluctuate continuously and suddenly, namely, the PVPS production and load demand.

In the relevant literature, there is a plethora of research regarding the PVPS generation and load demand forecast. Concerning the load demand prediction, a lot of studies have been reported in the literature proposing essentially mathematical models. D. Li and S.K. Jayaweera presented linear prediction models such as standard autoregressive and time varying autoregressive processes, according to different assumptions on the stationarity of customer load profile to model uncertainty in customer load demand [3]. Conversely, they ignored the impact of weather changes on forecast accuracies while building up their assumptions [4-5]. For the PVPS production prediction, a survey on the existing approaches to forecast solar irradiance has been done in [6-9].

In the present paper a Model Predictive Control (MPC) method is adopted. Its implementation procedure is defined through a detailed flowchart algorithm. Prediction results of PVPS production and load demand constitute the flowchart inputs while the active and reactive energy predicted to be injected by the distribution substation represent its outputs. The system objectives are: underpin forecast accuracy, maximize PVPS production consumption, optimize conventional power production, and minimize costs while meeting load demand and ensuring electric grid security. As a matter of fact, using predictions to anticipate electrical device regulations and prevent undesired events by an advanced energy flow management.
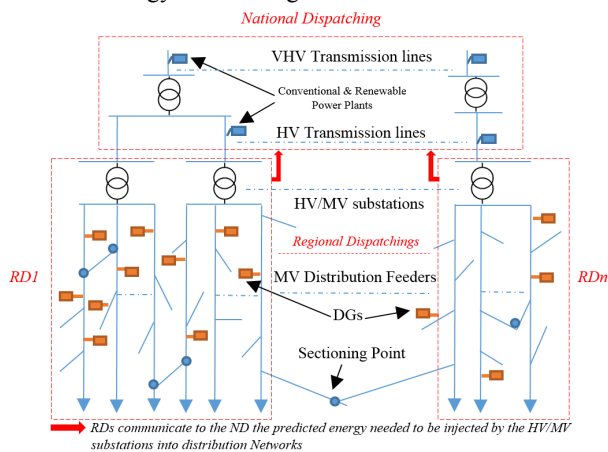

Fig. 1. Architecture of the distribution network under study

A significant number of studies based their predictive control strategies on MPC. For instance, E. Namor et al. [10] predicted the prosumers forecast consumption profile by using a non-parametric black-box method based on vector auto-regression. Furthermore, the authors relied on the BESS to improve the forecast response to the load by adding a function to alter the dispatch plan so that it will be with minimum variance using MPC [10]. Differently from [10], we ensured the response to the load through the day by four simultaneous or coupled means: the grid, the BESS, the PVPS and the BG. This has been done according to the energy tariffs variation and BESS state of charge (SOC) constraints. Also, the method proposed here for load demand prediction is different from the one adopted by [3-5; 10], as it considers temperature changes and day type impacts; moreover, it involves dynamic use of load demand historical database to reduce the precision error.

A contribution based on a comparable schematic diagram is reported in [11], where the objective was to control the BESS in a power distribution node using MPC, by letting the controlled node power profile track the curve established on the day-ahead. This was done while guaranteeing that the renewable energy sources (RESs) fluctuations seen at node level are smothered as much as possible, and the BESS SOC evolution is kept within the saturation limits. That is to say, the output of the cited controller in [11] is the BESS control profile, contrary to the control strategy proposed. Here we seek to obtain the substation active and reactive energy forecasts as system outputs. Similarly, we aim to keep the BESS SOC within the saturation limits.

After more in-depth searching in the literature, we found a control strategy close to the one presented here [12], but applied on a different architecture composed of private Microgrids (MGs) grouped together within a limited area and connected to the Distribution Network Operator (DNO) via one connection. In fact, in reference [12], a central controller was designed to deliver the optimal control strategy, which is communicated to each private MG using MPC. The common goals between [12] and the present paper are summarized in optimizing the energy coming from the grid, dealing with RESs and loads uncertainties, and maximizing available RES use. Yet, in our paper, the system under study is a MV distribution network, composed of many MV feeders interconnected by sectioning points and issued from different HV/MV substations Fig.1. To those feeders, different DGs are connected; this matter pushes grid operators to find the way to manage the energy flow in this kind of systems, more than ever under higher DGs penetration. Differently from [12], we coupled two main control strategies 1) the active power control and 2) the reactive power control resulting in a voltage and VAr (Volt/VAr) control to maintain voltage within acceptable bounds. A combination of those will allow us to raise the system reliability and enhance decision making accuracy. Furthermore, the Volt/VAr control strategy suggested here will ensure a predictive coordination taking into account the capabilities of the capacitor banks located along MV feeders additionally to the regulations of the On Load Tap Changers (OLTC) present at the HV/MV substations [13]. An approach has been conducted in [14] to elaborate an MPC-based dynamic Volt/VAr Control scheme for a MG connected renewable and conventional DGs. The authors used a simplified voltage prediction model to predict the voltage behavior of the system for a time horizon ahead. Hence, this was typically applied on islanded MGs.

As we can notice, each author has used MPC in its control strategy depending on the control variables and the system state that they wanted to forecast. Therefore, in all those cited studies, the control objective was based on the elaboration of a design that minimizes the cost function for MPC optimization problems which differs from the control strategy proposed here. To the best of our knowledge, there is no existing work dealing with this kind of architecture, using MPC combined to a flowchart algorithm for two parallel control strategies recognition. In fact, the working logic of proposed MPC is based on feedback from the prediction equation and on a continuous underpinning relying on a regular update of the State-Space Models (SSMs). The work presented will permit to predict the energy needed for each feeder, to handle efficiently the sectioning points, spread or store the additional RES production and predict the transmission lines peak to optimize conventional power production. Furthermore, those control strategies can avoid insecure voltage conditions in

distribution grids by predicting severe variations ahead of time.

The remainder of the paper is organized as follows. Section 2 presents the problem formulation concerning the active and reactive energy forecast at the MV feeder busbar. The optimization algorithm of our system is discussed in section 3. Section 4 is dedicated to resolve the problem through a case study, by simulating different scenarios to calculate the precision error of the method. Finally, the conclusion appears in section 5.

2. Problem Formulation

Our scope behind solving this problem is to retain the active and reactive power through the network balanced despite the growing presence of DGs. This means responding to load demand and maintaining frequency, voltage and angles of the feeder buses at the nominal rating values. This is because in such configurations, the dispersed nature of RESs impacts the quality of service, traduced by an increasing voltage variation along the feeders correlated to the amount of reverse power flow [15].

The current architecture of distribution power systems is designed for unidirectional power flows. Thus, attention has been directed toward dealing with this situation by extending the control infrastructure of distribution grids and adapting the existing one to this new configuration. For that purpose, we combined two predictive control strategies: active and Volt/VAr control. In cases where the reactive power control scheme fails to regulate voltages within acceptable bounds, the curtailment of the active power could solve the problem [13]. Furthermore, those control strategies will allow grid operators at the ND to predict the necessity of shedding some conventional power production units when DGs production efficiency is high.

To treat our problem, we focused on one single MV feeder modelled by a radial circuit, Fig.2, as distribution feeders are typically operated in a radial fashion [16]. We established an exhaustive theoretical investigation on the DGs connected to this feeder.

2.1 Active Energy Prediction

The voltage rise is more onerous when there is no demand on the system, as all DGs generation is exported back to the primary substation of the HV/MV substation [17]. As well, when this generation exceeds local demand, voltage levels also rise [18]; causing damage to consumers and grid equipment's if it exceeds the acceptable limits [19]. As a result, this phenomenon could impact the thermal rating of equipment's, system fault levels, OLTC capabilities and protection regulations [17; 20]. To deal with this, overvoltage must be managed in advance by curtailing active power injection [21]. Therefore, the prediction of active energy flow through distribution feeders is important to avoid such imbalances. The prediction of the active energy flow in a MV feeder is defined by the under mentioned equation:

$$X_{t+1,(1)} = AX_{t,(1)} + B\begin{pmatrix} U_{t,(1)} \\ U_{t,(2)} \end{pmatrix} + CP_{t,(1)} + Ew_{t,(1)} \qquad (1)$$

The matrices A, B, C and E represent the SSMs and the term $Ew_{t,(1)}$ represents random noise probably caused by sudden solar irradiance variability on the panel or by

temperature forecast errors, aside from problems linked to satellite images. The choice of using the SSMs formulation is due to the fact that they provide the best percent fit to the data aimed in comparison with ARX models for example [22], their identification is based on memory of past states and their structure is a good choice for quick estimation. Moreover, the SSMs have sufficient flexibility to model noise in comparison to ARX structure which is unable to independently model noise and system dynamics [22].

The system constraints are:

1) $0 \leq U_{t,(1)} \leq U_{MAX,(1)}$ for the BG energy production limits;

2) $U_{t,SOC\min,(2)} \leq U_{t,(2)} \leq U_{t,SOC\max,(2)}$ for the BESS.

2.2. Reactive Energy Prediction

The control of grid-connected systems focuses essentially on power factor gain and voltage variations mastery, which can guarantee the good quality of energy transfer [16]. Nevertheless, it ignores the importance of compensating reactive power and harmonics when the role of the existing compensation devices is insufficient. This is because in the actual distribution network, reactive power regulation is ensured essentially by switching capacitor banks and shunt capacitors installation due to their low costs [23]. However, with the integration of small-scale dispersed RESs in distribution networks, the reactive power flow can be regulated by inverters connected to PVPS, wind power systems and BGs that can also provide it. Consequently, a comprehensive optimization of reactive power generators in distribution networks becomes an important issue. In this section, we propose a combined Volt/VAr control strategy dealing with voltage variation and reactive capabilities. It is of vital importance to take into account the reactive power capability limits in grid-connected DGs in addition to the associated devices in such systems conducive to quantify their impact on reactive energy flow planning through distribution grids. Thus, reactive energy prediction will permit us to forecast the suitable existing devices regulation [15], deal with solar energy stochasticity, enhance voltage profiles and reduce energy losses.
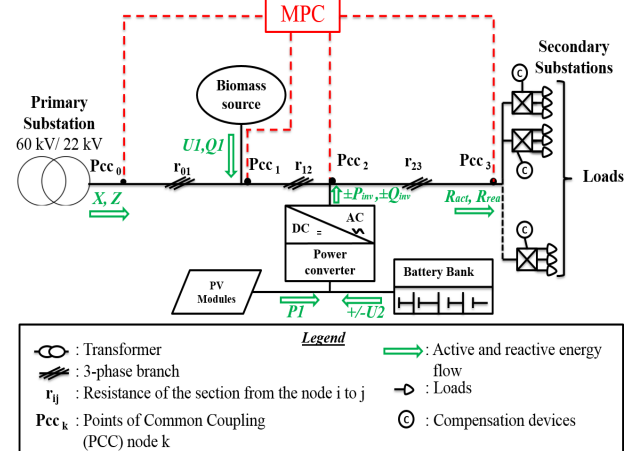

Fig. 2. Schematic diagram of the MV feeder under study

In line with Fig.2 and according to [20], the load flow equation relative to the reactive energy in our system is resumed as follows:

$$Q_{j+1} = Q_j - q_{j+1}^{(c)} + q_{j+1}^{(g)} \tag{2}$$

with $j \epsilon$ IN, $j \epsilon$ [0- 3].According to Fig.2, we get the systems (3) and (4):

$$\begin{cases} Q_1 = Q_0 - q_1^{(c)} + q_1^{(g)} \\ Q_2 = Q_1 - q_2^{(c)} + q_2^{(g)} \\ Q_3 = Q_2 - q_3^{(c)} + q_3^{(g)} \end{cases} \tag{3}$$

Then,

$$\begin{cases} Q_1 = Q_0 + q_{1,biomass}^{(g)} \\ Q_2 = Q_1 - q_{2,inv}^{(c)} + q_{2,inv}^{(g)} \\ Q_3 = Q_2 - q_{3,load}^{(c)} + q_{3,comp}^{(g)} \end{cases} \tag{4}$$

with $0 \le q_{3,comp}^{(g)} \le q_{max,comp}^{(g)}$. The system (4) is obtained considering the following:

On the one hand, as the BGs are usually synchronous machine-based [24], their excitation field has been adjusted to work on and not under the field of maximum stator current, maximum rotor voltage and prime mover limit Fig.3-(a), [25]. So they will not absorb reactive power. According to [25-26], Q_{1,S_s}^{sn1u} limited by I_1^{scsn} is expressed as:

$$Q_{1,S_s}^{sn1u} = \sqrt{\left(\left|V_{1,S_s}\right| I_1^{scsn}\right)^2 - \left(U_{t,(1)}\right)^2} \tag{5}$$

Then, Q_{1,S_s}^{sn2u} limited by E_1^{rvsn} can be derived as:

$$Q_{1,S_s}^{sn2u} = -\frac{\left|V_{1,S_s}\right|^2}{X_n^d} + \sqrt{\left(\frac{\left(\left|V_{1,S_s}\right| E_1^{rvsn}\right)}{X_n^d}\right)^2 - (U_{t,(1)})^2} \tag{6}$$
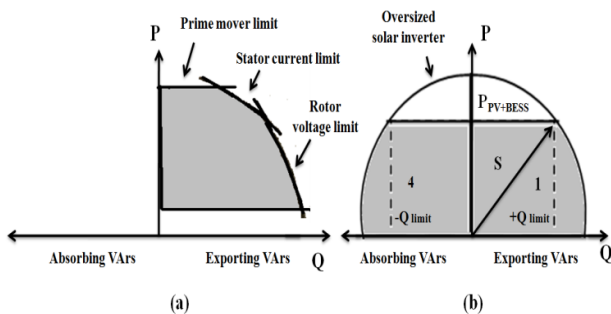
Fig. 3. Reactive capability limits of (a) the synchronous machine-based BG unit of the system under study (b) the inverter of the system under study

-*On the other hand*, the inverter has the capability to provide reactive power to the network, as well as the active power given by the PVPS or delivered by the BESS, Quadrant 1, Fig.3-(b). Moreover, the presence of the BESS may allow for the reactive power absorption and for full quadrant charging and discharging of real and reactive power [27]. In fact, this power depends on the inverter's apparent power ratings such as illustrated in Fig.3-(b) by a vector with magnitude S. To maximize active power capture through Maximum Power Point Tracking (MPPT), and maximum discharging BESS, $P_{PV+BESS}$, the reactive power limits are founded by projecting the end points of the segment down to the Q axis, the values are labelled by $-Q_{limit}$ and $+Q_{limit}$. Hence, the inverter can supply positive and negative reactive power, which means that it can behave as both an inductor (Quadrant 1) and a capacitor (Quadrant 4). Besides their continuous reactive power support, inverters can also operate very fast in comparison with capacitors that are susceptible to cause switching transients [28].

Then, we obtain from the three equations of system (4):

$$Q_3 = Q_0 - q_{3,load}^{(c)} - q_{2,inv}^{(c)} + q_{1,biomass}^{(g)} + q_{2,inv}^{(g)} + q_{3,comp}^{(g)} \tag{7}$$

To predict the reactive energy needed to be injected by the transformer $Q_0 - Q_3$, we have the following formulation:

$$Q_{t+1,transf} = q_{t+1,load}^{(c)} + q_{t+1,inv}^{(c)} - q_{t+1,biomass}^{(g)} - q_{t+1,inv}^{(g)} - q_{t+1,comp}^{(g)} \tag{8}$$

As our objective function is to minimize reactive energy coming from the transformer, we will ensure the equity generation/consumption by maximizing the reactive energy injected by the inverter and the BG respecting these constraints:

$$\begin{cases} q_{inv}^{(g),max} \le q_{load}^{(c)} \\ q_{biomass}^{(g),max} \le q_{load}^{(c)} \\ q_{inv}^{(g),max} + q_{biomass}^{(g),max} \le q_{load}^{(c)} \end{cases} \tag{9}$$

Those maximums are restricted by the current rating of the inverter, BG and compensating devices. Under a given active power generation $p^{(g)}$, the generated reactive energy is expressed as follows [29]:

$$q^{(g)} = T\sqrt{s^2 - (p^{(g)})^2} \tag{10}$$

T is the time interval length. Concerning the reactive energy consumed, it is expressed by the under mentioned equation for a given $p^{(g)}$ and a phase angle between current and voltage φ:

$$q^{(c)} = T.\tan\varphi.p^{(g)} \tag{11}$$

Thus, according to (8), (10), and (11), the reactive energy predicted to be delivered by the transformer is expressed as follows:

$$Z_{t+1,(1)} = D.Z_{t,(1)} + G.Q_{t,(1)} + H.Q_{t,inv}$$
(12)

with D, G and H the SSMs,

$$Q_{t,(1)} = T\sqrt{s_{biomass}^2 - \left(\frac{U_{t,(1)}}{T}\right)^2} \quad \text{and}$$

$$Q_{t,inv} = T\left[\sqrt{s_{inv}^2 - \left(\frac{U_{t,(2)}}{T}\right)^2} + \tan\varphi.P_{t,(1)}\right].$$

Note that, if we want to generate the maximum possible active energy, reactive energy delivery will be restrained by the connected inverter rating s_{inv} [29]. Accordingly, the equality and inequality constraints should be considered as:

$$\begin{cases} P_{t,(1)} = P_{t,MPPT} \\ \sqrt{\left(P_{t,(1)} + U_{t,(2)}\right)^2 + \left(Q_{t,inv}(g)\right)^2} \leq T.s_{inv} \end{cases}$$
(13)

It is assumed that the PV inverter will continue to offer reactive energy support during night hours and the needed energy to compensate for the inverter internal losses will be delivered by the BESS [30]. As a result, the required quantity of reactive power compensation by switching capacitors decreases gradually as the PVPS penetration level increases. For instance, the authors of the paper [28] proved that at a penetration rate of 30%, the reactive power injected by the switching capacitors wholly diminishes till disappearing for a rate of 50% PVPS penetration. Simultaneously, the amount of reactive power supplied by the substation is also progressively lower if the PVPS penetration increases and this is traduced by lower current through the feeder, resultantly, lower power losses [28].

To sum up, our prediction system relative to the active and reactive energies forecast is defined as follows:

$$\begin{cases} X_{t+1,(1)} = A.X_{t,(1)} + B.\begin{pmatrix} U_{t,(1)} \\ U_{t,(2)} \end{pmatrix} + C.P_{t,(1)} \\ Z_{t+1,(1)} = D.Z_{t,(1)} + G.Q_{t,(1)} + H.Q_{t,inv} \end{cases}$$
(14)

This prediction will allow us to avoid voltage sag and swell along the circuit. Additionally, it will permit us to keep the balance between active and reactive energy outputs at the primary substation level of the HV/MV substation, as $S_{t+1,(1)}$ is limited by the substation rating S_{MVA} :

$$T.S_{t+1,(1)} = \sqrt{X_{t+1,(1)}^2 + Z_{t+1,(1)}^2} \leq T.S_{MVA}$$

We assumed that the reverse power flow is not permitted through the transformer; we focused on forward power flow and sectioning points handling.

3. Prediction Algorithm

This paper proposes an algorithm, to predict the active and reactive energy supplied by the HV/MV substation to a MV distribution feeder including a PVPS, a BG and a BESS, Fig.2. The objectives of the algorithm are essentially minimizing conventional energy production and favouring the exploitation of renewable DGs with their auxiliary equipment's, while choosing the best compromise between energy price and time of use. The energy pricing is actually fixed for three time intervals in our country: on-peak, off-peak and mid-peak for energy distribution and vary during the day for energy purchase at higher voltages.

3.1 Algorithm Inputs definition

The equations used to forecast PVPS production and BESS SOC are defined in [6]. In what concerns the BG production, it is usually planned in advance by the producer. Regarding the method employed for load demand forecast, which represents the reference value of the MPC system, it has been introduced in [6]. The equations used in this method involve historical database, day type impact (special/ normal day) and weather conditions particularity. The main equation for active energy demand prediction is the following:

$$R_{t,act} = r_{t,y_{l-1}} \times \left(1 + \frac{1}{g_{\ell-1,1}}.N_t\right)^{g_{\ell,\ell-1}} \times F(T_{P,t}) \quad (15)$$

with,

$$N_t = \sum_{i=1}^{\ell-1} \frac{1}{g_{i,i-1}}\left[\frac{r_{t,y_i} - r_{t,y_{i-1}}}{r_{t,y_{i-1}}}\right]$$

and

$$\forall\, a, b \in \{1, 2..., \ell\}, a > b: g_{a,b} = y_a - y_b.$$

The instant t belongs to a normal or special day of the year ℓ. The y_i, where $i \in \{1, 2...,\ell\}$, are the different available years of normal or special days in our historical database beginning from y_1 the first available one to y_l the year when we need to predict the load demand r_t at the instant t. $T_{p,t}$ is the temperature predicted for the instant t. The function F is a weather dependent component, we expressed it as follows:

$$F(T_{P,t}) = (1+\alpha)^{\max(0,T_{P,t} - T_{moy})} \times (1+\beta)^{\max(0,T_{moy} - T_{P,t})} \quad (16)$$

where T_{moy} represents the average of the temperatures at the instant t of the normal years from i = 1 to ℓ. The parameters α and β represent the percentages of increase or decrease of the load demand at the instant t based on the temperature variation. The physical meaning of (16) is that the load demand predicted for the next time interval ΔT will be the same as the load demand for the same time interval of the last year marked up by the mean of yearly load demand evolution in the region object of study. However, we have to note that an exception appears if the temperature of the day object of prediction differs from that of last year's. That's

why we multiplied by the third term $F(T_{P,t})$: the scope behind is to amplify or downgrade the predicted load demand by the percentage of load demand increase or decrease corresponding to each degree Celsius in plus or in minus. For example, in South Africa, if the temperature decreases by 1 C°, electricity demand will increase

marginally by 1.03%. Conversely, if it increases by 1C° electricity demand will increase marginally by 0.55% [31].

Concerning the reference value for reactive energy demand tracking, $R_{t,rea}$, it is expressed as follows:

$$R_{t,rea} = T.\tan\varphi.R_{t,act} - q_{t,comp} \qquad (17)$$
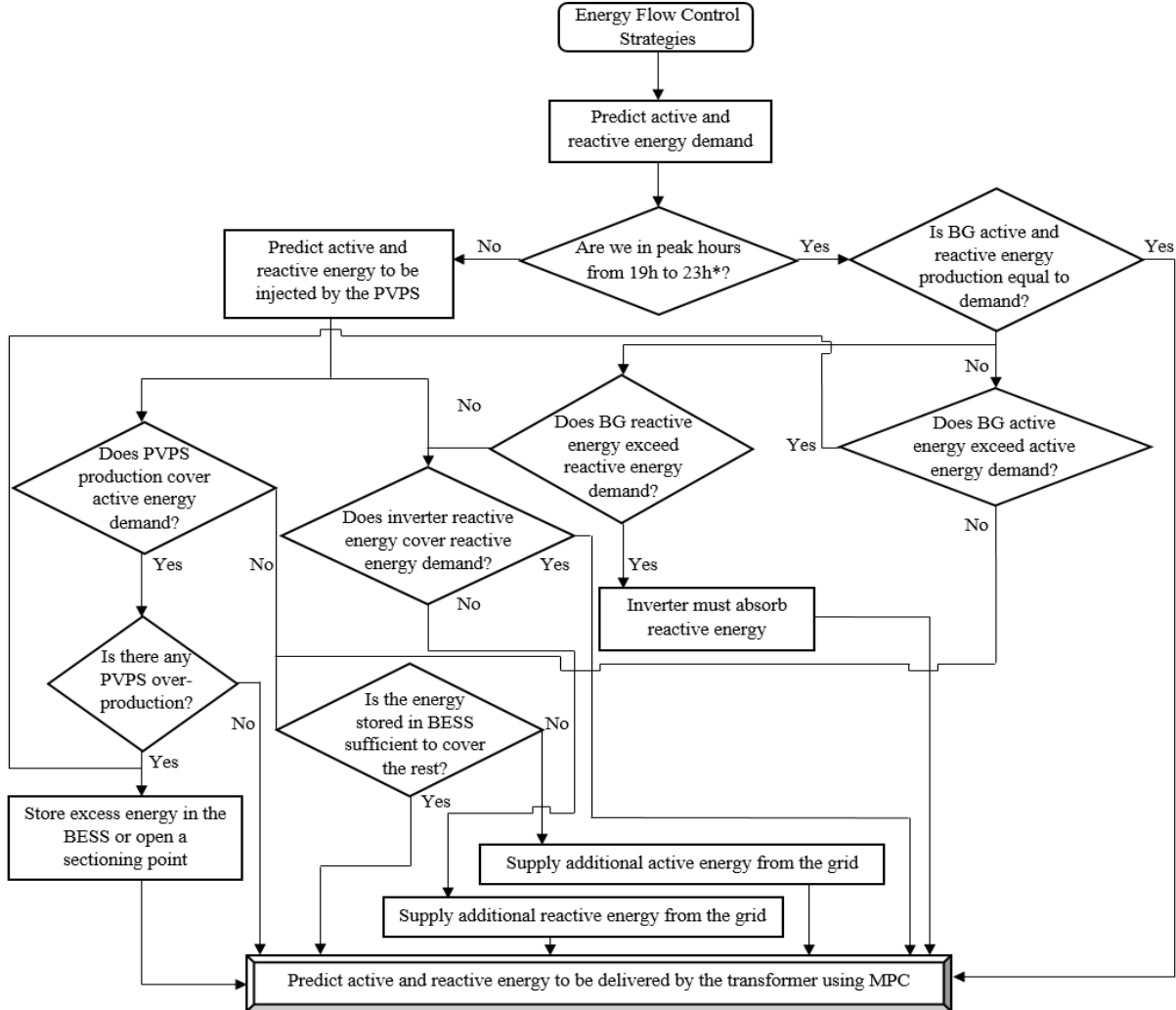
*The choice of 19h-23h is typical to Morocco as the peak of load demand is in this time interval, the logic of the algorithm could change according to the country energy prices variation during the day

Fig. 4. Active and reactive energy prediction algorithm flowchart

3.2. Algorithm description

The flowchart illustrated in Fig.4 explicit the implementation process of two control strategies adopted in parallel to solve the MPC system (14). We considered in this flowchart that the entire energy generated by the PVPS will be injected into the grid instantaneously, followed by the energy delivered from the BG especially in peak-hours when the energy cost is high in comparison with off-peak and mid-peak hours. Regarding the stored energy released when the PVPS production exceeds demand, it will be also used in peak hours particularly. However, if the BESS is full, the grid operator must handle the sectioning points to increase the load demand of the feeder, and then, save energy.

The reactive energy prediction process was inspired partially from Pukhrem's work as detailed in [32]. It considers that for a balanced reactive power supply network, two control methodologies exist. The first one focuses on controlling reactive power by fixing the power factor (cosφ)

for an injected active power. In this case, at low irradiance, reactive power control is needless as it creates extra line losses. This method can be used for overvoltage mitigation during high and low irradiance. However, when high irradiance level coincides with high peak demand, the voltage rise may not exceed the overvoltage limit. The second method aims at controlling reactive power by controlling instantaneously the local grid voltage which is a consequence of the PVPS production and load consumption in its vicinity. Nevertheless, if the bus voltage exceeds 1.1 p.u bound, the PVPS inverters which are positioned near to the transformer at the Point of Common Coupling (PCC), Fig.2, should help in mitigating the grid overvoltage by absorbing reactive energy from it. It can be achieved in the first case through increasing inverters reactive power.

We choose to integrate the BESS in our system to help reduce PVPS intermittency and avoid losses that can occur in case of PVPS overproduction. In addition, it will be

exploited to supply inverters with active energy when operating in night mode for reactive energy injection as explained in section II. Note that charging the battery directly from the grid is forbidden in the algorithm as the price of the stored energy is much higher than the cost of the electricity coming from the grid [33]. In addition, we must note that the algorithm respect the constraints related to inverter range limits and BESS SOC.

The presented algorithm lead to the overall energy efficiency improvement by making an optimal demand and supply control taking into account energy pricing. Concerning the communication between the system and the components of the grid, it will be ensured by a Power Line Communication (PLC) network connected to each node [34] as illustrated by the dashed redline in Fig.2. This line will communicate the different active and reactive energies besides the voltages at the PCC to the DNO. This will permit us detect and prevent voltage collapse ahead of time by predicting the appropriate sectioning points to open or close at the RD level or the conventional generation to handle at the ND level.

4. Problem Resolution

The system under study is a real MV distribution feeder including a PVPS of 800 kW composed of 8 inverters, 100kW each. Those inverters are not configured to work in night mode. The feeder considered is one of the five feeders issued from a HV/MV substation of 2×20MVA, its annual maximum peak load demand is 3.2 MW and its minimum is 0.9MW.

To evaluate the applicability of our contribution, we calculated the accuracy error of the method formulated above theoretically, we applied it on this case study considering 4 different scenarios to weigh up the goodness of fit between test and reference data and its relation to load demand forecast variation and weather prediction precision. The error will not be impacted by the absence of the BESS and the BG in our system as they are not intermittent.

5. Results and discussions

To fulfill our aim, we employed hereafter the MATLAB system identification toolbox as illustrated in [35], for each scenario. The inputs of our system are the load demand for t+1, the PVPS production for t+1 and the energy injected by the substation into the feeder at the instant t, for active and reactive energy separately. We assumed that the step time is T=10 min interval length, for 12960 step look-ahead horizons, as we proved by testing the prediction results on many time intervals from 10 min to 1 hour that the shorter the time interval is, the more accurate values the system gives [35]. We didn't went into intervals less than 10 min as the shorter time needed to handle (stop/start/reduce production) a conventional turbine connected to transmission lines is approximately 10 min on average [36]. The model was tested on the months 05/15, 08/15 and 11/15.

Scenario 1: Load Demand and PVPS production predictions are perfect- we compared here the results of (14) with the real active and reactive energy given by the transformer to see the extent to which they match the purpose as shown in Fig.5-(a) and Fig.5-(b).

Scenario 2: Load Demand is predicted and PVPS production prediction is perfect- for load demand prediction we used the formulations (15) and (17). As we didn't register any special temperature variation; we based the prediction only on load demand evolution from 2011 to 2015. The prediction results due to load demand imperfectness are illustrated on Fig.5-(c) and Fig.5-(d).

Scenario 3: Load Demand prediction is perfect and PVPS production is predicted- the PVPS production was calculated theoretically [6], assuming that temperature and irradiance forecast are perfect. In what concerns the power factor at the PCC of the PVPS, we considered it equal to the power factor at the instant t-1 for reactive energy computation. The results obtained are illustrated in Fig.5-(e) and Fig.5-(f).
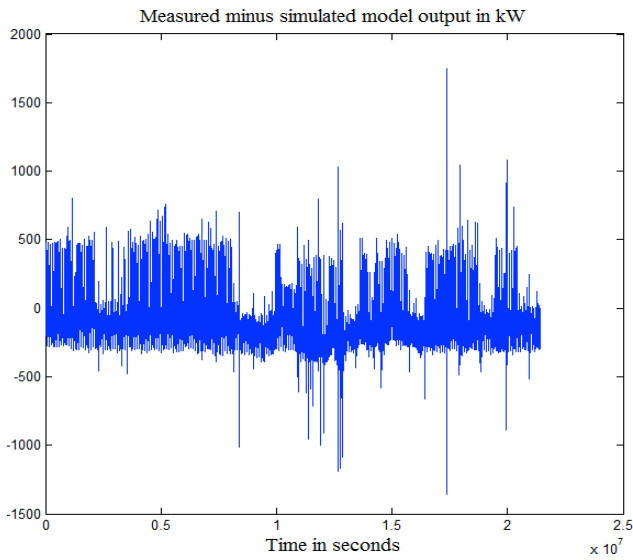
Scenario 4: Load Demand and PVPS production are predicted- considering the assumptions of scenarios 2 and 3, the prediction results of this scenario are illustrated in Fig.5-(g) and Fig.5-(h).

In the different figures of Fig.5, we can observe that sometimes the error is very important and this is the result of the absence or non acuteness of the value registered by the meter in the database. The figures (c), (d), (g) and (h) show less data because we eliminated some days corresponding to a non-successive normal or special days according to the logic of (15).
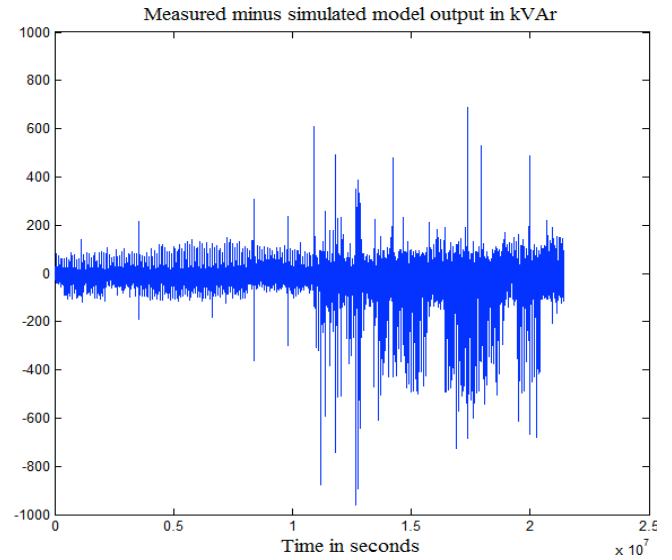
For the transformer active power prediction, the obtained results show that the scenarios 2 and 4 give the same percent fit to estimation data (FED), 82.45% as illustrated in Table 1.. This means that the prediction error of the method used to predict the active PVPS production is very small, same for the reactive PVPS production. This claim is supported by the results of the scenarios 1 and 3 where we can notice clearly that the error generated by the active PVPS production forecast is approximately 0.27% and neglected for the reactive PVPS production, while the load demand prediction is considered to be perfect. This is due to the absence of cloudy weather conditions that usually lead to sudden loss of production during the test months. In what concerns the accuracy error of the method employed for load demand prediction, we can see clearly by comparing the scenarios 1 and 2 that the active and reactive power prediction error is around 6% according to the basic results of scenario 1 which considers that all the inputs are exact. All in all, the active power prediction error of the MPC system proposed in this paper is 11.88% and 11.33% for the reactive power prediction. Those results can't be compared actually to any other method in the absence of a similar approach for short-term energy flow management with the same advantages.

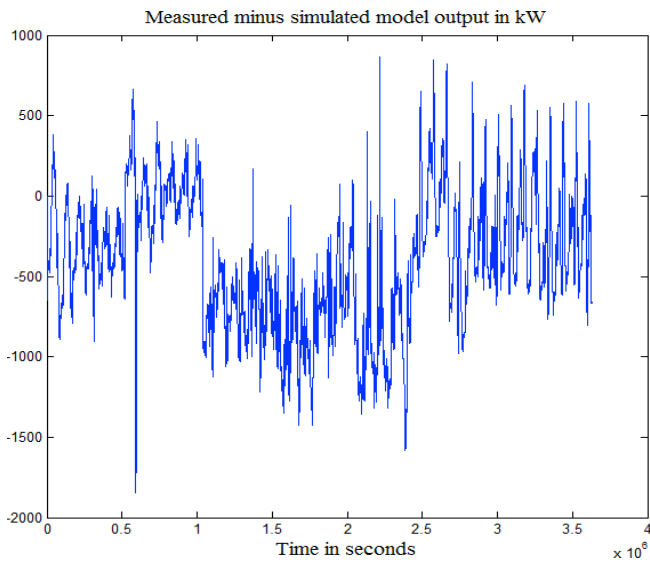**Table 1.** FED Comparison between the four scenarios

	Scenario1	Scenario2	Scenario3	Scenario4
Active Power prediction	88.12%	82.45%	87.85%	82.45%
Reactive Power prediction	88.67%	82.45%	88.67%	82.45%

(a)

(b)

(c)

(d)

(e) (f)

Measured minus simulated model output in kW
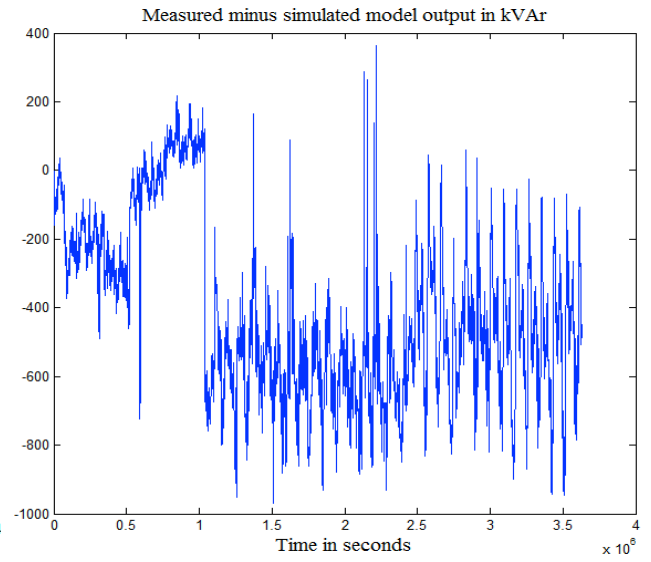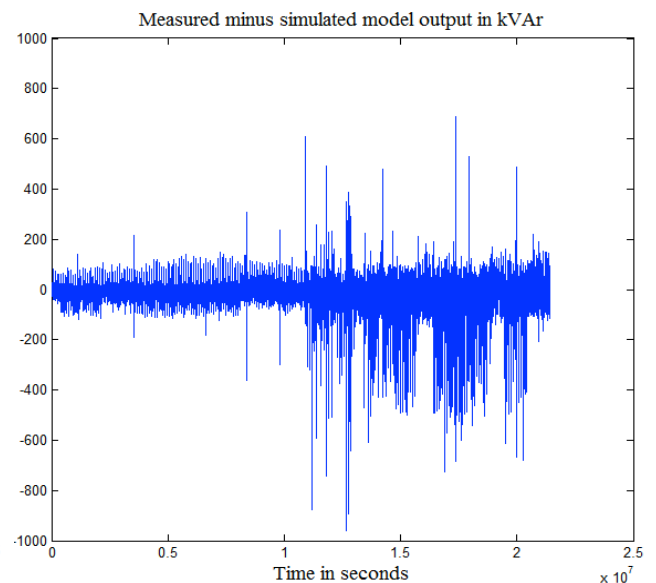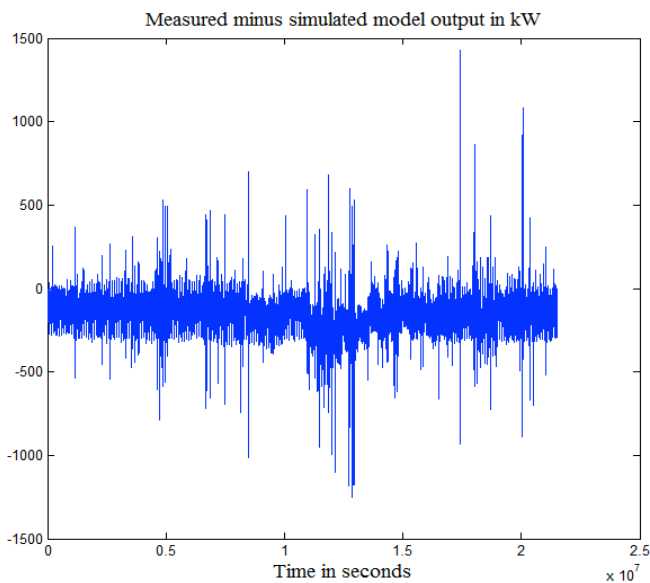

Measured minus simulated model output in kVAr
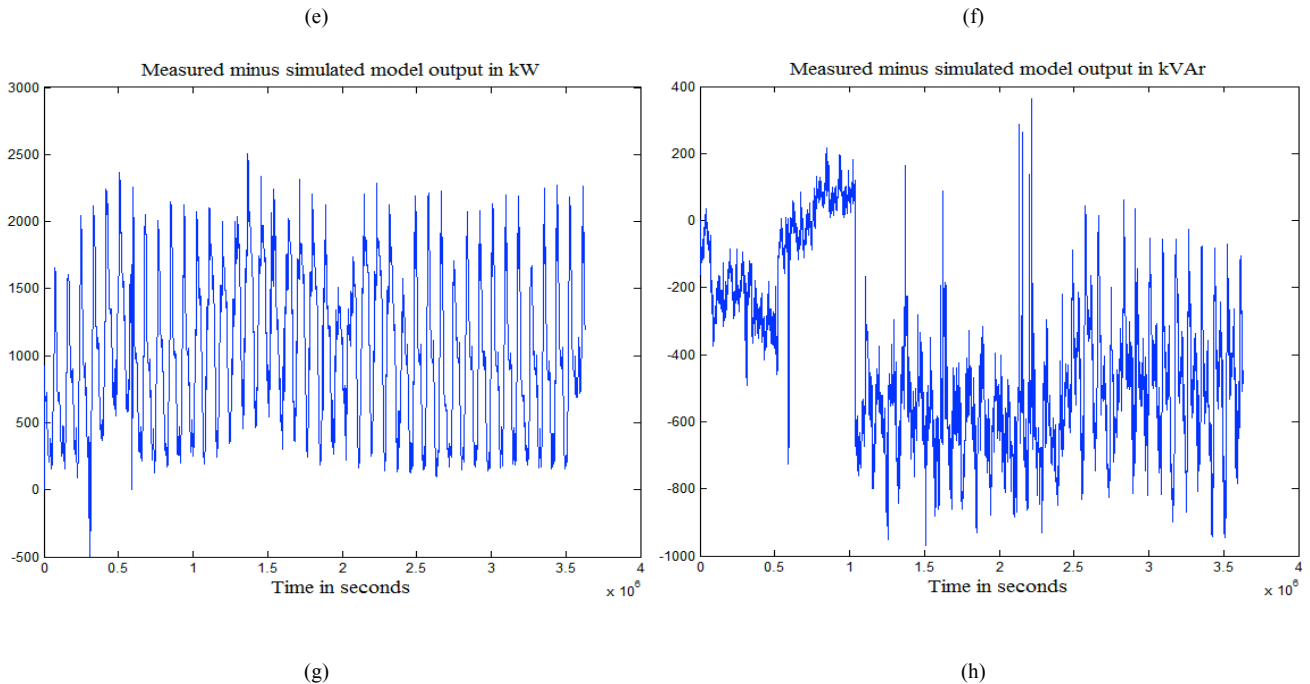

(g) (h)

Fig. 5. Simulation results from MatLab Software

6. Conclusion

In this study, we defined the equations that will allow us to predict the active and reactive energy needed to be supplied to the HV/MV substations from the transmission lines taking into consideration the impact of the high penetration of DGs in distribution networks. The methodology adopted to solve the problem was based on three fundamental steps. The first one is the load demand and PVPS production prediction. The second is the use of algorithm to optimize the energy use and price in a grid connected DGs. The last one is the integration of the predicted parameters into the system identification MATLAB Toolbox to run the system and update the SSMs to minimize the prediction error for discrete time intervals through the MPC. This is a flow diagram based control approach that gives good results in terms of energy flow forecast underpinning.

As a result, we obtained a forecast model that will allow a steady operation of the system with no excessive energy reserves. Furthermore, this will permit the planner to decide on the most convenient compromise between energy cost and energy saving. This method is suitable for any grid-connected DGs, we only need to change the peak hours in the algorithm flowchart as they vary from country to country depending on its dominant activity: industrial or domestic. Additionally, the weather conditions of the country may also push the user to enhance the algorithm logic as it was considered that the PVPS production potential is very promising which is the case in our country. To sum up our strategy is based on forecasting for regulating and optimizing either for natural monopolies or unbundled systems, it's all about energy saving.

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Nomenclature

$X_{t,(1)}$	Active energy injected by the transformer (kWh)
$U_{t,(1)}$	Active energy generated by the biomass (kWh)
$U_{t,(2)}$	Active energy absorbed/injected by BESS (kWh)
$P_{t,(1)}$	Active energy injected by PV panels (kWh)
Q_j	Reactive energy at the node j (kVArh)
$q_j^{(c)}$	Reactive energy absorbed at the node j (kVArh)
$q_j^{(g)}$	Reactive energy generated at the node j (kVArh)
$q_{f,comp}^{(g)}$	Reactive energy delivered by the compensation devices at node f (kVArh)
$q_{max,comp}^{(g)}$	Maximal reactive energy delivered by the compensation devices (kVArh)
Q_{1,S_s}^{sn1u}	Maximum reactive power injection at node 1 (kVAr)
Q_{1,S_s}^{sn2u}	Reactive power injection limit at node 1 (kVAr)

$q^{(g),\max}$ Maximal reactive energy generated (kVArh)

E_1^{rvsn} Maximum rotor voltage at node 1 (V)

I_1^{scsn} Maximum stator current at node 1 (A)

V_{1,S_s} System voltage at node 1 over S_s (V)

S_s System state

$S_{t,(1)}$ Apparent power capability of the transformer (kVA)

X_n^d Direct axis component of synchronous reactance for a synchronous machine